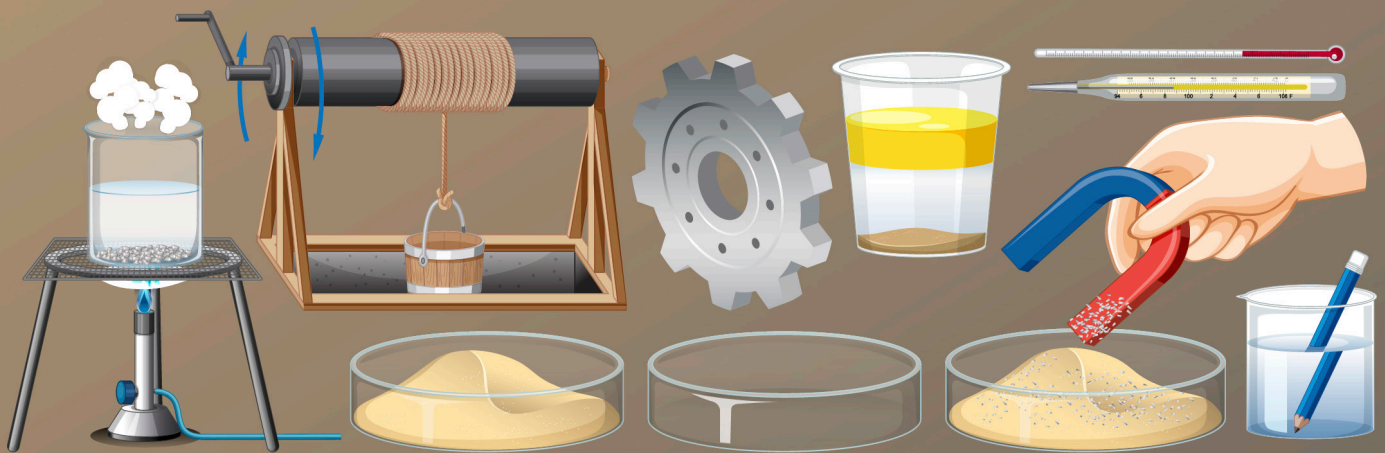




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## Response Surface-Based Optimization of Cutting Parameters in Wet Turning of Eggshell-Reinforced Aluminum Alloy 6351 Composite for Enhanced Temperature and Cutting Force Performance

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*Material Removal Rate, Numerical Optimization, Regression Equation, Response Surface Methodology, Surface Roughness*

### ABSTRACT

This work focused on response surface-based optimization of cutting parameters during wet turning to enhance temperature and cutting force performance of an eggshell-reinforced AA6351 composite. The Aluminum alloy eggshell reinforced composites were composed of 15% eggshell and 85% aluminum alloy. 2% crushed magnesium was mixed with molten metal to improve wettability through surface energy, interface energy, and surface tension reduction. The p-values of 0.0022 and 0.0078 for the temperature and CF response models, respectively, indicate that the cutting parameters in the model had a substantial impact on the responses. The significant influence of Vc on temperature and CF is demonstrated by P-values less than 0.0001 and 0.0003, respectively. Vc has a significant effect on temperature and CF and positively affects the way Fr, and Dc affect the responses. The high R<sup>2</sup> values of 0.9721 and adjusted R<sup>2</sup> of 0.9220 for CF, and 0.9534 R<sup>2</sup> and adjusted R<sup>2</sup> of 0.8696 for temperature, respectively, demonstrate how well the model fits the data for both variables. The optimal CF and temperature values, 128.117 N and 41.7652 °C, respectively, are obtained by turning operations on AAERC with input variables Vc, Fr and Dc set at 368.139 rpm, 0.389925 mm/min, and 0.322686 mm.

### INTRODUCTION

The objective of contemporary industry is to produce high-quality, reasonably priced goods quickly. This is achieved by combining computerized numerical equipment that can process data rapidly and correctly with automated and flexible manufacturing techniques. Machining is the process of using a single-point or multi-point cutting tool to remove extra metal or material off the exterior of the workpiece as chips. Turning is a metal cutting or machining technique used to create cylindrical shapes. The turning system requires a turning machine, a workpiece, and a computer numerically controlled (CNC). A critical step in ensuring optimal performance in a turning operation is selecting appropriate machining parameters.

A composite is created when two or more materials are combined, and it uses both of the materials' qualities to provide better mechanical and tribological qualities (Wesolowski *et al.*, 2020; Yi, 2018). One of the main characteristics of composite materials is their poor resistance to mechanical wear and their very poor electrical and thermal conductivity (Ambrosio *et al.*, 2016; Chairi *et al.*, 2023). The composite materials exhibit remarkable strength, low weight, and thermal expansion when compared to conventional engineering materials (Agarwal *et al.*, 2024; Shahruzzaman *et al.*, 2022). The matrix phase and reinforcement phase of composite materials are

the crucial stages (Yao *et al.*, 2019). The matrix serves a number of purposes, including giving the structure its rigidity and shape, binding the reinforcements together and distributing loads evenly among them, and isolating the reinforcements so that each one can act independently. Lightweight engineering materials are becoming more and more necessary for a variety of engineering applications (Hassan & Saeed, 2024; Xiong *et al.*, 2023). High strength-to-weight ratio materials are important because of the ability to improve performance, save resources, use less energy, and save costs in a variety of sectors (Sinha *et al.*, 2021; Vijayan *et al.*, 2023). Lightweight alloys are increasingly being used in the military, aerospace, and energy transportation sectors because they may save resources and lighten component weight (Miracle, 2019). One of the optional sources to satisfy these requirements is aluminum metal matrix composite. The main reason aluminum metal matrix composite (AMM) is preferred is because of its exceptional and dependable qualities, which include low weight, ease of manufacture, resistance to corrosion and wear, and more (Kar *et al.*, 2024; Kumar *et al.*, 2024). The reinforcing material is incorporated into a matrix and serves a structural purpose in MMC. It is also utilized to modify physical properties including heat conductivity, wear resistance, and friction coefficient. The RSM method is a statistical technique that is used in experiments to examine the effects of cutting factors

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including feed, depth of cut, and cutting speed. This work concentrated on the performance evaluation of wet turning of aluminum alloy 6351 eggshell reinforced composite for best temperature and cutting force using RSM approach.

**Response Surface Methodology**

Engineers and scientists have used response surface methodology (RSM) to identify optimal parameter choices for process and equipment designs. The RSM collects information and identifies key variables and interactions that impact the process response using the design of experiment (DoE) technique (Hadiyat *et al.*, 2022). Experiment optimization is crucial to research because it is a major determinant of process advancement and development. It entails determining the ideal combination of experimental parameters that produce the greatest outcome. RSM is based on a mathematical model that explains the connection between the independent factors and the response variable. Finding the optimal set of experimental settings that either maximizes or decreases the pertinent response variable is made easier by the model. RSM is a powerful tool for experiment optimization because it makes it possible to identify the optimal set of experimental conditions with the fewest number of repetitions. The study highlighted how effective RSM is at cutting down on the number of experiments needed for optimization, which saves money and yields quicker results. The RSM approach, which is popular for process optimization, works well in situations where engineers have complete

control over the levels and treatments of variables, such as in laboratory experiments, computer experiments, scientific method applications, and any other research setting where variables are under control. The optimum use of input parameters to create the greatest response in the production aspect employing metals is highly needed for high performance, especially given the considerable application of machining in engineering.

**LITERATURE REVIEW**

Aluminum metal matrix composites (AMMCs) are made to almost net shape and often need to be machined to improve performance and efficiency. The volume proportion of the reinforcement and matrix, the type of reinforcement, the reinforcement’s distribution within the matrix, and the reinforcement material all affect the machining properties. Compared to metal machining, AMMC machining produces distinct outcomes due to the strong and brittle reinforcement. The cutting tool, on the other hand, encounters matrix and reinforcing materials, which respond to machining in very different ways. Problems with AMMC machining include excessive and unoptimized cutting force performance and temperature, which either render the process unfeasible or result in an unprofitable production process. Therefore, it is crucial to optimize the cutting parameters of newly generated composites in order to maximize output and minimize wasteful material usage. Table 1 provides an overview of selected related works that focus on the utilization of AA6351 and different optimization strategies.

**Table 1:** Literature review table

Author	Study Objectives	Methods	Key Findings	Gaps/ Limitations
(Mohanavel <i>et al.</i> , 2025)	To investigate the tribological behavior of AA6351 reinforced with 20 wt.% AlN and optimize wear rate and friction using Taguchi methodology.	Fabricated AA6351–20 wt.% AlN composites via stir casting. Used Taguchi design to study effects of load, disc speed, and sliding distance on wear rate (WR) and coefficient of friction (COF). Parameters varied across three levels.	Sliding speed and disc speed were the most influential factors in minimizing WR and COF. Taguchi optimization effectively identified optimal conditions for improved tribological performance.	Study limited to one reinforcement ratio (20 wt.%); did not explore long-term wear behavior or effects of thermal cycling.
(Nwoziri <i>et al.</i> , 2024)	To assess the machinability of Al 6351/eggshell composite in dry turning using Response Surface Methodology (RSM).	Fabricated composite with 85% Al 6351 and 15% eggshell. Conducted dry turning experiments measuring cutting force (Fc), surface roughness (Ra), and material removal rate (MRR). Used RSM and ANOVA to model and optimize machining parameters.	Optimized parameters significantly improved machining performance. ANOVA showed strong statistical significance (P < 0.05) for models predicting Fc, Ra, and MRR. Numerical optimization identified ideal parameter combinations.	Study focused on a single reinforcement ratio (15% eggshell); thermal effects and long-term tool wear not explored.

(Dwivedi <i>et al.</i> , 2017)	To investigate the effect of precipitation hardening parameters on the microstructure and mechanical properties of AA2014/5 wt.% carbonized eggshell composites.	Electromagnetic stir casting of AA2014 with 5 wt.% carbonized eggshells; immediate extrusion at 60 MPa using a graphite-coated H13 steel die. Optimization of precipitation hardening parameters (solutionizing time: 4.5 h, aging temp: 250 °C, aging time: 13.5 h) using response surface methodology. Microstructural analysis and mechanical tests conducted.	Uniform distribution of carbonized eggshells after extrusion; grain refinement observed after optimized heat treatment; improved mechanical properties; trans-granular fracture mode; AA2014/eggshell composite had 5% lower density than pure AA2014; mechanical strength further enhanced post-treatment.	Agglomeration in non-extruded samples; study limited to 5 wt.% reinforcement; only one alloy (AA2014) and reinforcement level explored.
(Nwobi-Okoye <i>et al.</i> , 2019)	To model and optimize the production of Al 6351/eggshell reinforced composite by maximizing toughness and hardness using RSM, ANN, and genetic algorithms.	Employed Box-Behnken Design to develop RSM model; production variables included stirring speed, time, and preheat temperature. ANN was used to model property-process relationships; optimization carried out using NSGA-II algorithm.	Maximum toughness of 4.83 at hardness of 69.37; maximum toughness of 1.73 at hardness of 51.67. RSM and ANN models were accurate and effective. NSGA-II algorithm successfully optimized multi-objective output.	Focused only on two mechanical properties (toughness and hardness); effect of other reinforcements, compositions, or mechanical properties not studied.
(Mba <i>et al.</i> , 2025)	To optimize machining parameters for wet turning of Al 6351/eggshell composite using Response Surface Methodology (RSM).	Fabricated composite with 85% Al 6351 and 15% eggshell; added 2% magnesium powder to improve wettability. Used RSM and ANOVA to model and optimize cutting speed (Vc), feed rate (Fr), and depth of cut (Dc) for Material Removal Rate (MRR) and surface roughness (Ra).	Optimal machining parameters significantly improved MRR (1793.93 mm <sup>3</sup> /min) and reduced Ra (1.0689 μm). R <sup>2</sup> values of 0.9745 (MRR) and 0.9461 (Ra) indicated strong model fit. Cutting speed and feed rate had the most significant influence on both responses.	Study limited to a single reinforcement ratio (15% eggshell); thermal effects, tool wear, and broader material behavior under wet conditions not explored.
(Suresh Kumar <i>et al.</i> , 2014)	To optimize the electrical discharge machining (EDM) parameters for Al 6351–5% SiC–10% B <sub>4</sub> C hybrid composite using Grey Relational Analysis.	Conducted EDM experiments on the hybrid composite. Input parameters included pulse current, pulse on time, and voltage. Grey Relational Analysis was used to optimize multiple performance characteristics like material removal rate (MRR), surface roughness (SR), and overcut (OC).	Optimal EDM parameters were identified for improved MRR and reduced SR and OC. The hybrid composite exhibited favorable machinability characteristics under optimized conditions.	Study limited to specific reinforcement ratios (5% SiC, 10% B <sub>4</sub> C); thermal effects and tool wear behavior not extensively analyzed.

(Emumejaye <i>et al.</i> , 2025)	To evaluate the mechanical properties of aluminium composites reinforced with varying percentages of eggshell powder.	Prepared six composite samples with 0%, 2%, 4%, 6%, 8%, and 10% eggshell powder. Conducted tensile, impact, compressive, and hardness tests to assess mechanical performance.	Hardness improved with 4–10% eggshell addition (up to 19.31% increase). Sample with 6% eggshell (Sample D) showed the best overall mechanical performance. Demonstrated potential for lightweight, eco-friendly composites suitable for marine and sports applications.	Did not explore thermal or fatigue behavior; limited to mechanical testing under static conditions; long-term durability not assessed.
(Sushil Kumar <i>et al.</i> , 2020)	To optimize turning parameters for improving surface roughness in machining of Al 1275 alloy pistons using PCD cutting inserts	Experimental study using Taguchi L27 orthogonal array. Input parameters: spindle speed, feed rate, depth of cut, tool nose radius. Used ANOVA and S/N ratio for analysis; conducted confirmation tests to validate optimum cutting conditions.	Feed rate had the highest influence on surface finish, followed by tool nose radius; depth of cut had the least effect. Optimal settings (A3-B1-C3-D3) produced improved surface roughness (Ra: 4.5–5 μm). Results validated by confirmation test.	Focused only on surface roughness and a single material/tool pairing; other performance metrics like tool wear, MRR, energy use not analyzed.

**MATERIALS AND METHODS**

**Materials**

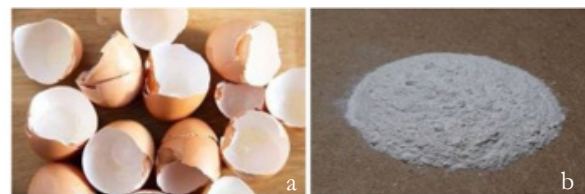
Figure 1 to figure 2 shows eggshells, eggshell powder, and mechanical stirrer respectively. The study used a veneer caliper, measuring tape, aluminum alloy 6351, eggshell waste, CNC lathe tool dynamometer, a CNC lathe machine (250 PCD Boxford CNC lathe machine), and other instruments and materials to accomplish its goals.

**Methods**

**Aluminum Alloy 6351 Eggshell Re-enforced Composite Preparation**

The collected eggshell samples were thoroughly cleaned to remove dust and other debris. After washing them with water, they were dried in an oven at 1000°C for one hour (Nwoziri *et al.*, 2024). The dried eggshells were ground and crushed until they cooled to room temperature, ensuring the finest particle size (Nwoziri *et al.*, 2024; Sushil Kumar *et al.*, 2020). The resulting powder was then sieved through meshes ranging from 106 to 850 microns to achieve a uniform particle size distribution (Mba *et al.*, 2025). The AAERCs were composed of 15% eggshell reinforcement and 85% aluminum alloy (Mba *et al.*, 2025; Nwoziri *et al.*, 2024). The weight of the eggshell powder was precisely measured using an electronic compact scale (Mba *et al.*, 2024). Wooden templates were used to create the sand mold with natural sand. The necessary amount of pulverized eggshell was kept warm in a furnace to enhance its wettability (Mba *et al.*, 2024). The aluminum was securely held with a temperature probe to ensure it melted completely, which was essential for

achieving optimal reinforcement when combined with the pulverized dried eggshell (Nwoziri *et al.*, 2024). An electric-powered crucible furnace, fueled by diesel, was used to melt the aluminum alloy at a temperature of 700°C ± 50°C (Nwoziri *et al.*, 2024). Aluminum was carefully placed in the furnace to cool and solidify into



**Figure 1:** a. Egg shells & b. Egg shell powder



**Figure 2:** Mechanical Stirring with furnace

a semi-solid state. To enhance the metal's wettability, 2% magnesium powder was added to the molten aluminum (Mba *et al.*, 2024). This process helps reduce surface tension, increase surface energy, and lower the matrix-reinforcement interface energy (Ren *et al.*, 2024). The dried eggshell particles were introduced into the semi-solid melt at various temperatures and stirring intervals. Once the mixture was superheated to  $750^{\circ}\text{C} \pm 50^{\circ}\text{C}$ , it was stirred with an automatic mechanical stirrer (Mishra & Tulasi, 2020; Singh *et al.*, 2022). The molten mixture was then poured into a prepared sand mold and left to harden, resulting in solid casts.

**Tool Material**

High Speed Steel (HSS) was selected for this experiment due to its ability to control cutting force and minimize heat generated during turning by the material's interaction with the work tool.

HSS is a crucial tool for achieving high surface quality during machining.

**Selection of Factors & Parameters**

There are three fundamental cutting factors that are commonly used during turning. The optimal control factor for cutting speed, feed rate, and depth of cut was determined experimentally in order to establish the optimal cutting force and temperature response.

**Experimental Design**

The experimental design aimed to select machining settings through various combinations across 15 runs, involving three components and three levels. The objective was to identify the optimal input factors for the best response. The Box-Behnken design (BBD) framework was used, encompassing 15 runs. Table 2 outlines the design levels and independent process variables.

**Table 2:** Independent process variable and design levels

Variables	Units	Low (-1)	Medium (0)	High (+1)
$V_c$	Rpm	180	450	720
$F_r$	mm/rev	0.2	0.3	0.4
$D_c$	Mm	0.2	0.4	0.6

**Experimental Framework**

Orthogonal turning experiments were performed using the multipurpose 250 PCD Boxford CNC lathe. This lathe is ideal for the turning process as its tool spindle moves linearly along the X, Y, and Z axes. A cylindrical workpiece, approximately 220 mm in diameter and made of AAERC, was secured in the universal chuck's three jaws. The study focused on three main control variables:  $V_c$ ,  $D_c$ , and  $F_r$ . Experimental trials were conducted with various combinations of these input variables. The MRR and Ra values were meticulously recorded for each trial. Accurate input parameter entry is crucial to ensure the precision of the turning process model.

**Cutting Operation Procedures**

The AAERC samples were first machined on a CNC lathe to obtain the necessary 22 mm diameter for experimental investigations according to the DOE. The chuck was secured, and the workpiece was centered. The tool holder, equipped with an HSS cutting insert, was adjusted accordingly before starting the machining process. Turning was initiated using the selected process control parameters from the DOE. The machining was performed on AAERC using these input parameters to determine the appropriate output values. The experimental CNC lathe setup and the machined aluminum A6351 reinforced with eggshell sample are shown in Figures 3 and 4, respectively.



**Figure 3:** Experimental setup (CNC lathe)



**Figure 4:** Al. A6351 Egg-shell machined sample

### RSM Methodology

The RSM was used to examine the data and identify the ideal combination level. The RSM approach focuses on the effective use of statistical techniques. The impact of input factors on the turning responses were assessed in this experiment using RSM. Design Expert was utilized for analysis in the experimental investigation. Temperature and cutting force were the two parameters whose performance are assessed. The following are the general procedures needed to carry out this experiment:

1. Establish the process's goal and a target value for its performance indicator. The process goal was to

minimize cutting force and temperature. Identify the design parameters that have an impact on the procedure. Parameters are readily controllable process factors that impact the performance measure.

2. Construct orthogonal arrays (OA) for the parameter design to show the number of conditions for every experiment.

3. Conduct the experiments outlined in the completed array in order to collect data by evaluating the response brought about by the performance measure's effect.

4. Conduct a thorough data analysis to ascertain how various parameters affect the performance metric.

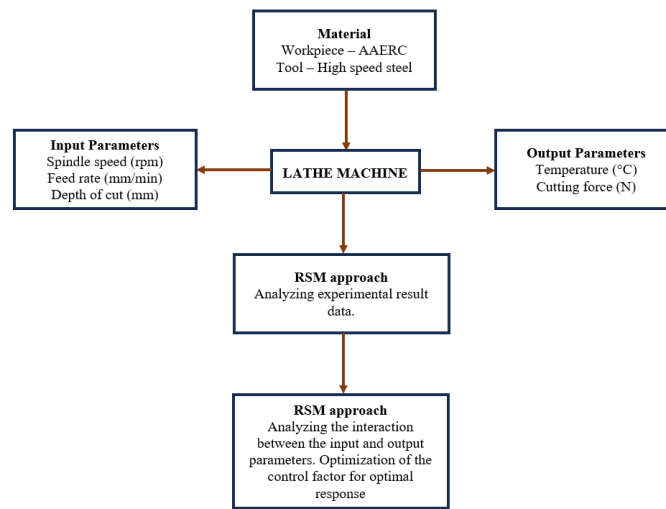


Figure 5: Overall methodology

### Modelling using Response Surface Methodology

Response Surface Methodology (RSM) is a set of sophisticated statistical and mathematical methods for process development, improvement, and optimization (Kaltenbach, 2021). Its main goal is to minimize variance and minimize experimental effort through robust design. RSM offers a more comprehensive analysis to help comprehend how different input components interact to affect one or more measurable outputs or reactions (Lamidi *et al.*, 2023). This makes RSM especially valuable when the goal is to fine-tune and optimize a process within a specific experimental region. The process begins with the systematic identification of the key input variables, also known as factors, and the desired output or response that needs to be optimized for the optimum process applications. Once these variables have been established, a well-planned experimental design is chosen using Box-Behnken Design. These designs ensure that the variables are altered in a systematic and efficient manner to yield data that can accurately explain the response.

A prediction model is created by fitting a second-order polynomial equation after data collection and experimentation. This model captures the independent effects of each variable as well as their quadratic and interaction effects. The general form of the model is represented in equation 1 (Khuri & Mukhopadhyay,

2010).

$$y = \beta_0 + \sum \beta_i x_i + \sum \beta_{ii} x_i^2 + \sum \beta_{ij} x_i x_j + \epsilon \quad \dots(1)$$

Where,

y is the predicted response,  $x_i$  represent the input variables,  $\beta$  terms are the regression coefficients indicating strength of each effect, and  $\epsilon$  is the experimental error or residual. Through careful interpretation of the graphical or numerical surface, which provides useful information about how the input variables interact and influence the response, one can determine the optimal levels of the input factors that yield the most desired result, such as maximizing a positive response like material strength or minimizing a negative one like cutting force. RSM helps engineers and researchers make well-informed judgments by facilitating the visualization of intricate interactions between variables and enabling precision in optimization (Hadiyat *et al.*, 2022; Suresh Kumar *et al.*, 2014).

## RESULTS AND DISCUSSIONS

### Experimental Investigation

The study investigated turning aluminum alloy 6351 eggshell reinforced composite using a variety of control input combinations in order to obtain the maximum response using the RSM technique. The RSM optimization research considers temperature and cutting force (CF) as response outputs, and it is the best method

**Table 3:** Final data table of the actual design after experiment.

Run	Control parameters			Responses	
	V <sub>C</sub>	F <sub>r</sub>	D <sub>C</sub>	Temp.	Cutting force
	(rpm)	(mm/min)	(mm)	(°C)	(N)
1	450	0.3	0.4	44.8	119.5
2	180	0.4	0.4	39.9	140.6
3	450	0.2	0.6	44.1	120.9
4	450	0.4	0.6	49.0	115.3
5	180	0.3	0.6	43.4	138.8
6	180	0.2	0.4	44.1	131.04
7	720	0.3	0.2	65.1	52.7
8	180	0.3	0.2	42.0	126.5
9	720	0.2	0.4	51.8	57.5
10	720	0.4	0.4	65.1	68.5
11	450	0.4	0.2	49.0	118.2
12	720	0.3	0.6	70.7	71.3
13	450	0.2	0.2	47.6	125.3
14	450	0.3	0.4	44.8	114.5
15	450	0.3	0.2	45.5	117.6

for selecting the ideal combination of parameters to get the best response value. The optimization research employed three levels of control factors including cutting speed, feed, and depth of cut process parameters.

Table 3 shows the final data collected after experimental runs using the 15-run combination of control parameter values. The runs were designed to find out how the cutting force and response temperature were impacted by the combination of input factors.

**Response Evaluation**

**Cutting Force (CF) Evaluation**

Cutting force is crucial in machining operations, particularly in turning. Excessive cutting forces can

accelerate tool wear, reduce tool life, increase costs, and affect production (Liu *et al.*, 2025). These forces also influence the surface finish of the workpiece, with higher forces potentially resulting in rougher surfaces (Binali *et al.*, 2023). Precision in machining is impacted by cutting forces, as uncontrollable factors can lead to size errors in parts (Wang *et al.*, 2021). High cutting forces can affect machine stability, causing vibrations that degrade surface quality and generate noise (Xing *et al.*, 2024). Therefore, optimizing cutting force is essential to enhance turning process productivity (Khlifi *et al.*, 2024). During each experimental run, a CNC lathe tool dynamometer was used to measure the cutting force.

**Table 4:** ANOVA table of CF

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	11947.10	9	1327.46	19.39	0.0022	significant
V <sub>C</sub>	10291.82	1	10291.82	150.31	< 0.0001	
F <sub>r</sub>	7.72	1	7.72	0.1128	0.7506	
D <sub>C</sub>	62.83	1	62.83	0.9176	0.3821	
V <sub>C</sub> ×F <sub>r</sub>	0.5184	1	0.5184	0.0076	0.9340	
V <sub>C</sub> ×D <sub>C</sub>	9.92	1	9.92	0.1449	0.7191	
F <sub>r</sub> ×D <sub>C</sub>	0.5625	1	0.5625	0.0082	0.9313	
V <sub>C</sub> <sup>2</sup>	1459.45	1	1459.45	21.31	0.0058	
F <sub>r</sub> <sup>2</sup>	15.26	1	15.26	0.2229	0.6567	
D <sub>C</sub> <sup>2</sup>	0.9982	1	0.9982	0.0146	0.9086	
Residual	342.35	5	68.47			
Lack of Fit	329.85	4	82.46	6.60	0.2831	not significant
Pure Error	12.50	1	12.50			
Cor Total	12289.46	14				

**Table 5:** Coefficients in terms of coded factors of CF

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	117.54	1	5.59	103.17	131.92	
$V_C$	-35.87	1	2.93	-43.39	-28.35	1.0000
$F_r$	0.9825	1	2.93	-6.54	8.50	1.0000
$D_C$	2.68	1	2.80	-4.51	9.86	1.02
$V_C \times F_r$	0.3600	1	4.14	-10.28	11.00	1.0000
$V_C \times D_C$	1.57	1	4.14	-9.06	12.21	1.0000
$F_r \times D_C$	0.3750	1	4.14	-10.26	11.01	1.0000
$V_C^2$	-20.50	1	4.44	-31.92	-9.09	1.08
$F_r^2$	2.10	1	4.44	-9.32	13.51	1.08
$D_C^2$	0.5561	1	4.61	-11.28	12.40	1.12

**Temperature Evaluation**

Temperature is an important consideration in machining operations, especially during turning. Careful temperature control is required during machining operations because high cutting temperatures can reduce tool life, speed up tool wear, and produce thermal softening, which raises operating costs and compromises dimensional accuracy

(Sivalingam *et al.*, 2023). The surface integrity of the workpiece may also erode due to high temperatures, which may result in unfavorable metallurgical changes and a decrease in mechanical qualities, lowering the product quality needed for best performance (Natarajan *et al.*, 2024). Furthermore, excessive heat-induced thermal expansion can lead to dimensional errors and part

**Table 6:** ANOVA table of Temp

Source	Sum of Squares	df	Mean Square	F-value	p-value	significant
Model	1190.23	9	132.25	11.37	0.0078	significant
$V_C$	867.36	1	867.36	74.57	0.0003	
$F_r$	29.64	1	29.64	2.55	0.1713	
$D_C$	3.97	1	3.97	0.3415	0.5843	
$V_C \times F_r$	76.56	1	76.56	6.58	0.0503	
$V_C \times D_C$	4.41	1	4.41	0.3791	0.5650	
$F_r \times D_C$	3.06	1	3.06	0.2633	0.6297	
$V_C^2$	170.30	1	170.30	14.64	0.0123	
$F_r^2$	2.63	1	2.63	0.2265	0.6542	
$D_C^2$	44.96	1	44.96	3.87	0.1065	
Residual	58.16	5	11.63			
Lack of Fit	58.16	4	14.54			
Pure Error	0.0000	1	0.0000			
Cor Total	1248.39	14				

**Table 7:** Coefficients in terms of coded factors of CF

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	44.33	1	2.30	38.40	50.25	
$V_C$	10.41	1	1.21	7.31	13.51	1.0000
$F_r$	1.92	1	1.21	-1.17	5.02	1.0000
$D_C$	0.6734	1	1.15	-2.29	3.64	1.02
$V_C \times F_r$	4.38	1	1.71	-0.0086	8.76	1.0000
$V_C \times D_C$	1.05	1	1.71	-3.33	5.43	1.0000
$F_r \times D_C$	0.8750	1	1.71	-3.51	5.26	1.0000
$V_C^2$	7.00	1	1.83	2.30	11.71	1.08
$F_r^2$	-0.8712	1	1.83	-5.58	3.83	1.08
$D_C^2$	3.73	1	1.90	-1.15	8.61	1.12

deformation (Pereira Guimarães *et al.*, 2022). The cutting environment may be hampered by persistently high temperatures, which could cause instability and raise the chance of chatter. Therefore, improved tool performance and machining quality require efficient temperature control (Zhang *et al.*, 2021).

**Response (CF & TEMP) Equations and Fit Statistics**  
Fit statistics, coded equations, and actual equations are all essential for optimizing and comprehending intricate turning machining operations, especially when it comes to predicting variables like temperature and cutting force (Zhang *et al.*, 2021). Fit statistics are crucial because they offer quantifiable proof of how well a mathematical

model captures actual experimental data. A model's statistical reliability and the amount of variance in the result it explains for high performance efficiency can be evaluated by looking at statistics like the F-value, the root mean square error (RMSE), the coefficient of determination ( $R^2$ ), and adjusted  $R^2$  (Jaurker *et al.*, 2023). When machining parameters are optimized for precision and effectiveness, a high  $R^2$  value means that most of the response variable's variability is captured by the model. Furthermore, by comparing several models or formulations objectively, these data enable the determination of which one offers the best prediction performance efficiency.

**Table 8:** Fit statistics of CF and Temp.

CF		TEMP	
R <sup>2</sup>	0.9721	R <sup>2</sup>	0.9534
Adjusted R <sup>2</sup>	0.9220	Adjusted R <sup>2</sup>	0.8696

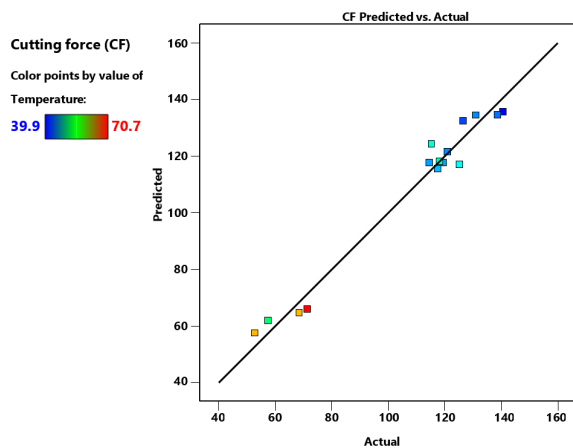
**Table 9:** Actual and coded equation for CF and Temp.

Responses	Coded factors equation
CF	$=+117.54-35.87 V_c+0.9825 F_r+2.68 D_c+(0.3600 V_c \times F_r)+(1.57 V_c \times D_c)+(0.3750 F_r \times D_c)-20.50 V_c^2+2.10 F_r^2+0.5561 D_c^2$
TEMP	$=+44.33+10.41 V_c+1.92 F_r+0.6734 D_c+(4.38 V_c \times F_r+(1.05 V_c \times D_c)+(0.8750 F_r \times D_c)+7.00 V_c^2-0.8712 F_r^2+3.73 D_c^2$
Responses	Actual factor equation
CF	$=+142.46186+0.104617 V_c-129.47935 F_r-16.48261 D_c+(0.013333 V_c \times F_r)+(0.029167 V_c \times D_c)+(18.75000 F_r \times D_c)-0.000281 V_c^2+209.67391 F_r^2+13.90217 D_c^2$
TEMP	$=+77.01987-0.104291 V_c-18.89493 F_r-93.14946 D_c+(0.162037 V_c \times F_r)+(0.019444 V_c \times D_c)+(43.75000 F_r \times D_c)+0.000096 V_c^2-87.11957 F_r^2+93.30163 D_c^2$

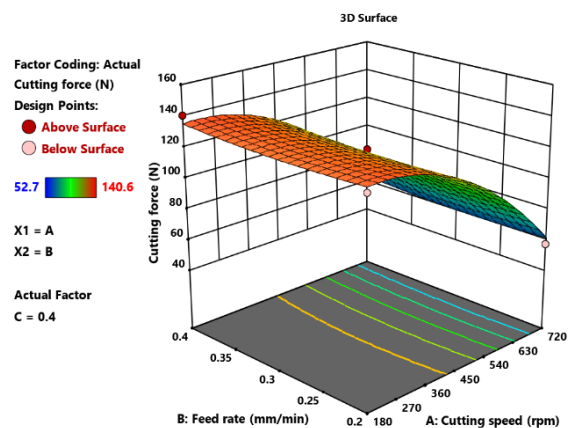
**Plot Evaluation of CF and Temp.**

The Predicted vs. Actual Plot compares the values predicted by the regression model with the actual experimental data as shown in Figure 7 and 10. A strong alignment along the 45-degree line indicates high model accuracy and minimal deviation. In this study the plot is used to validate the model's predictive capability for responses of cutting

force and temperature. 3D surface graphs make it easier to see how variables (temperature and force) are affected by combinations of cutting speed, feed rate, and depth of cut as shown in Figure 6 and 10. It facilitates the identification of ideal regions and nonlinear interactions. A contour plot was used to project the ideal parameter zones for each response as shown in Figure 8 and 11.



**Figure 6:** CF predicted vs actual



**Figure 7:** CF 3D surface

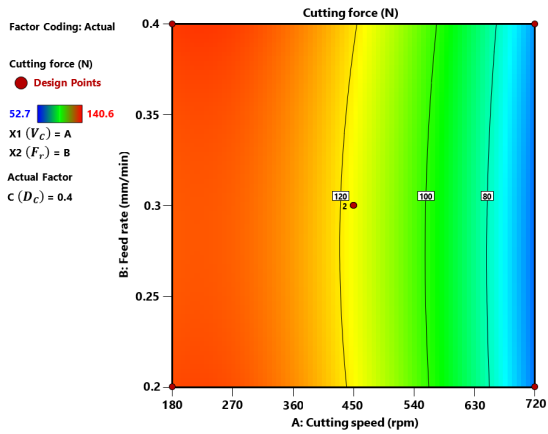


Figure 8: CF contour plot

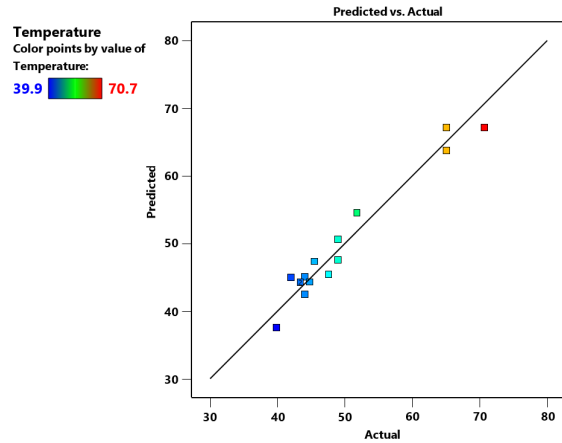


Figure 9: Temperature predicted vs actual

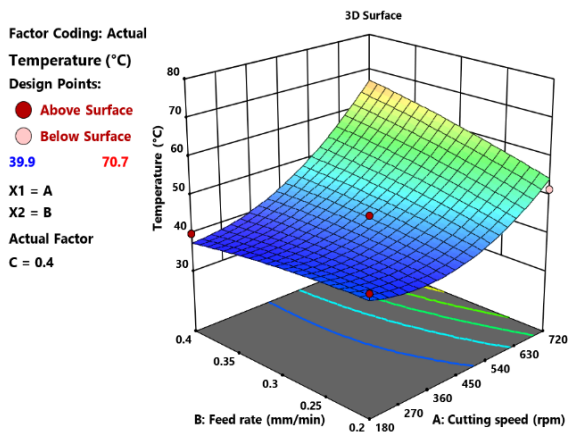


Figure 10: Temperature 3D surface

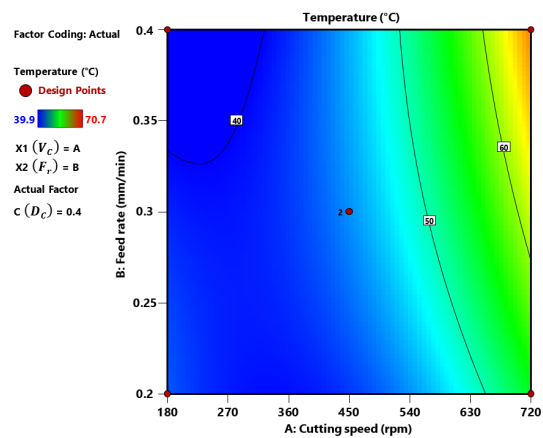


Figure 11: Temp. contour plot

### Desirability Plot

The function's primary goal is to optimize responses. Reducing or raising the response are the two main objectives of optimizing sets. Furthermore, a weighted geometric mean is used to represent the single predicted value for each response. Each response's single predicted value is represented by a weighted geometric mean. To achieve the ideal set of desired parameters, desirability function optimization involves anticipating and adjusting

the response. This function accepts the expected values for every reaction meter on a preferred, or least ideal to most ideal, scale from 0 to 1.

The machining parameters were effectively graphically optimized for the best response method at a desirability function of 1 as shown in Figure 13. The optimization depicted in Figure 14 and Figure 15 improves the machining process by adjusting parameters to attain the desired results, such as determining the optimal cutting

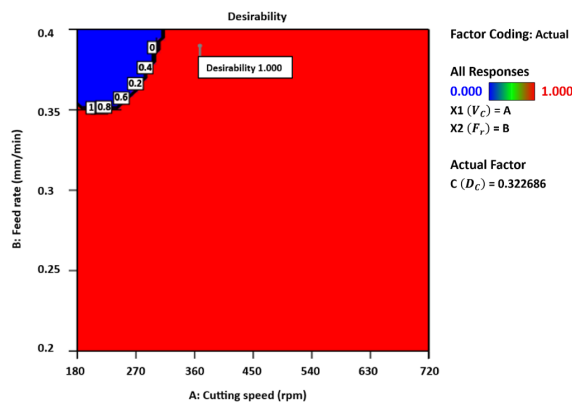


Figure 12: Optimal desirability

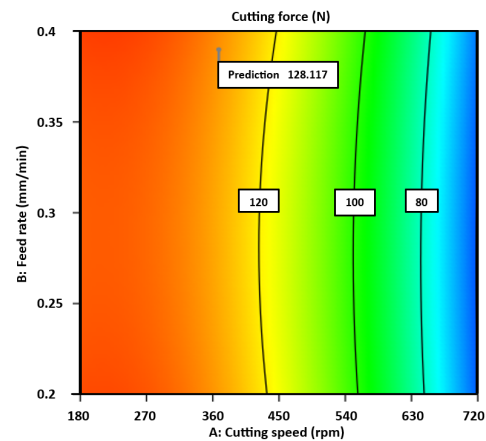
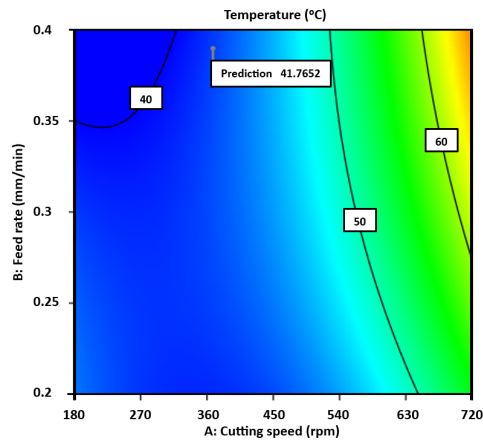


Figure 13: CF Optimal desirability plot



**Figure 14:** Temp. Optimal desirability plot

force and temperature respectively. From the solution of the combination of the 3 factor levels of  $V_C$ ,  $F_p$  and  $D_C$ , The ideal parameters were found to be 368.139 rpm of  $V_C$ , 0.389925 mm/min of  $F_p$  and 0.322686 mm of  $D_C$  to obtain the best response values of 41.7652 °C of temperature and 128.117 N of cutting force.

### Discussion

Tables 4 and 6 present the CF and Temperature ANOVA tables, which evaluate the impact of the factors and their interactions on the response's variable. The p-values for the two responses, temperature and CF, are 0.0022 and 0.0078, respectively, indicating that the variables in the models had a substantial impact on the responses. Tables 5 and 7 provide a statistical summary of regression models using temperature and CF as the dependent variables. A positive coefficient means that the reactions rise in tandem with these factors. A negative coefficient, on the other hand, indicates that a rise in these variables causes a fall in responses. The intercept shows the expected CF and temperature in coded form when all factors are zero, with a coefficient of 117.54 for CF and 44.33 for temperature. The low VIF values of 1, which guarantee the accuracy of the coefficient estimations, suggest that the model is free of major multicollinearity. CF and Temperature are significantly impacted by the factors VC, as evidenced by their respective p-values of <0.0001 and 0.0003. Table 8 presents the fit statistics for CF and temperature. The model fits the data quite well for both CF and temperature, as evidenced by the high R2 values of 0.9721 and adjusted R2 of 0.9220 for CF and 0.9534 R2 and adjusted R2 of 0.8696 for temperature, respectively. The equation illustrates how the input variables affect the responses. The coefficients and exponents show how sensitive the reactions are to variations in the parameters. The interaction term indicates a positive effect, indicating that the combined influence of these parameters affects the responses, negative coefficients imply that raising the parameters separately reduces the responses. The values of the input variables can be entered to forecast the coded and actual equations. The majority of the data points in the predictive model, as depicted in Figures 6 and 9,

are around the diagonal line, suggesting a substantial connection between the predicted and actual values. Each data point's closeness to the diagonal line highlights the importance of the model. The significance of this model makes it easier to optimize process parameters for the optimal response. The 3D surface indicates that there is no systematic bias in the model across the runs, which means that the errors aren't getting bigger or smaller throughout the course of the experiment. The CF contour map as observed in Figure 9 shows red for bigger cutting forces (up to 140.6 N) and blue for lower cutting forces (around 52.7 N). The color distribution illustrates how the force required for turning is affected by various combinations of feed rate and cutting speed. High cutting speeds and low feed rates produce little cutting force, as shown by the lower-left (blue) region. The hue changes to yellow, orange, and red as feed rates increase toward the upper right, signifying stronger cutting forces and it is expected since the tool workload increases when more material is engaged per unit of time.

Figure 11 shows the temperature contour plot, which explains that the dark blue area with low feed rate and cutting speed typically corresponds to lower cutting temperatures. At this setting, the rate of material removal is moderate, and the heat produced by plastic deformation and friction is largely contained. The cutting tool remains cooler as a result, improving tool life and thermal stability. Figure 12 illustrates the successful graphic optimization of the machining parameters for the optimal response method with a desirability function of 1. The optimization shown in Figures 13 and 14 enhances the machining process by modifying variables to achieve the intended outcomes, such as determining out the ideal cutting force and temperature, respectively. The combination of the three factor levels of VC, Fr, and DC was solved to yield the best response values, which were 128.117 N of cutting force and 41.7652 °C of temperature. The optimal values were found to be 0.322686 mm of DC, 0.389925 mm/min of Fr, and 368.139 rpm of VC.

### CONCLUSION

This research focused on response surface-based optimization of cutting parameters in wet turning of eggshell-reinforced aluminum alloy 6351 composite for enhanced temperature and cutting force performance. The study concentrated on applying RSM to determine the ideal VC, Fr, and DC input combination for the best cutting force and cut depth response. RSM was used to investigate how input parameters and response interacted during the AAERC wet turning process.

The factors in the models significantly influenced the responses, as seen by the p-values of 0.0022 and 0.0078 for the temperature and CF response models, respectively. The ANOVA indicates that the components VC have a significant effect on both CF and Temperature, as indicated by their respective p-values of less than 0.0001 and 0.0003, respectively. Temperature and CF are significantly influenced by VC, which also has a big

impact on how quickly Fr, and DC influence reactions. Graphical optimization was utilized to find the optimal response after combining the best input variables. The graphical approach offers a simple and intelligible visual depiction of how cutting force and temperature responses are influenced by the interaction of input variables such as VC, Fr, and DC. These maps show patterns, relationships, and ideal areas without depending just on equations or the results of solvers. Based on the optimization results, turning operations on AAERC with input variables VC, Fr, and DC set at 368.139 rpm, 0.389925 mm/min, and 0.322686 mm, respectively, yield the optimal values for CF and temperature, which are 128.117 N and 41.7652 °C, respectively. This study is important because it sheds light on the proper input parameters needed to produce the intended output parameters. The best cutting force and ideal temperature is guaranteed, and material waste is decreased through optimal input variable selection.

### Recommendations

Future studies could focus on expanding the application of AAERC in various machining processes and examining its performance under varied cooling and lubrication conditions. Applications in the aerospace, automotive, and precision manufacturing industries are possible; however, obstacles to broad adoption may include high material costs, the need for specialized equipment, and process optimization. Other biodegradable reinforcements that haven't been reinforced with AA6351 must be used to increase strength and characteristics, which will increase the supply of appropriate materials for engineering applications.

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