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Experimental Investigation and Multi-response Optimization of Turning Parameters for SS316 Austenitic Stainless Steel

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ABSTRACT

AISI 316 austenitic stainless steel (SS316) is extensively used in the aerospace, biomedical, petrochemical and marine sectors. However, its low thermal conductivity and prominent work-hardening properties pose significant challenges in machining. This study experimentally investigates the impact of cutting speed, feed rate and depth of cut on surface roughness (R_a) and cutting temperature (T) during Computer Numerical Control (CNC) turning of SS316, utilizing hybrid Al_2O_3-MWCNT nano-fluid assisted minimum quantity lubrication (MQL). Response Surface Methodology (RSM) was employed as a statistical modeling and optimization technique to evaluate the effects and interactions of the parameters, while multi-response optimization was conducted using the Desirability Function Approach (DFA). The developed models exhibited satisfactory statistical adequacy ($R^2 > 0.95$). The optimal machining parameters identified were a cutting speed of 89.11 m/min, a feed rate of 0.16 mm/rev and a depth of cut of 0.86 mm, leading to a surface roughness of 2.43 µm and a cutting temperature of 112.3 °C. The findings suggest that RSM–DFA provides a systematic and statistically robust framework for improving the machining performance of SS316 while reducing coolant usage and thermal load under sustainable MQL conditions.

Keywords: Response surface methodology; Surface roughness; Cutting temperature; Desirability function approach; SS316; Minimum quantity lubrication.

1. INTRODUCTION

AISI 316 austenitic stainless steel (SS316) is widely used in aerospace, biomedical, petrochemical, and marine applications owing to its excellent corrosion resistance, high mechanical strength, and thermal stability. Despite these advantages, SS316 is regarded as a difficult-to-machine material because of its low thermal conductivity, high work-hardening tendency, and strong adhesion at the tool–chip interface. These characteristics result in excessive heat generation, rapid tool wear, and deterioration of surface quality during turning operations (Bharath and Venkatesan, 2024). Surface roughness is a critical quality attribute in machined SS316 components, as it directly affects fatigue life, tribological performance, and functional reliability. At the same time, elevated cutting temperature adversely influences tool life, machining stability, and energy consumption (Manivel *et al.* 2020). In turning operations, controlling both surface roughness and cutting temperature is challenging, particularly when machining SS316 under conventional conditions, due to its tendency to retain heat in the cutting zone.

Traditionally, cutting fluids have been employed to reduce friction and dissipate heat during machining. However, conventional flood cooling involves excessive coolant consumption, disposal difficulties, environmental pollution, and health risks to machine operators (Amrita *et al.* 2021). These concerns have led to increasing interest in sustainable machining approaches that aim to minimize coolant usage while maintaining acceptable machining performance. Minimum Quantity Lubrication (MQL) has emerged as a viable alternative to flood cooling by supplying a small and controlled amount of lubricant directly to the cutting zone, thereby significantly reducing coolant volume and associated environmental impact (Rao *et al.* 2020). However, when machining SS316, conventional MQL fluids often fail to provide sufficient cooling and lubrication due to the alloy's poor heat dissipation and high frictional behavior at the tool–chip interface (Venkatesan *et al.* 2021). As a result, lubrication effectiveness becomes a key factor in controlling surface quality and cutting temperature during SS316 turning (Esfe *et al.* 2023). To address these lubrication challenges, recent studies have focused on the use of nano-additives in cutting fluids to enhance thermal conductivity and tribological performance (Jamil *et al.* 2022; Gupta *et al.* 2024). In particular, hybrid nanofluids containing alumina (Al_2O_3) and Multi-Walled Carbon Nanotubes (MWCNTs) have demonstrated improved

heat transfer and friction reduction due to the synergistic interaction between ceramic and carbon-based nanoparticles (Sallakhniknezhad *et al.* 2024). Such improvements are especially relevant for machining SS316, where effective lubrication directly influences temperature control, surface integrity, and tool life (Hegab *et al.* 2018). Although nanofluid-assisted machining has shown promising results, most existing studies focus on individual machining responses, such as surface roughness or tool wear, and do not simultaneously optimize multiple performance characteristics (Kazeem *et al.* 2025). Moreover, limited work has been reported on the systematic modeling and optimization of machining parameters for SS316 under hybrid nanofluid-assisted MQL conditions using structured statistical approaches (Sarath and Tamiloli, 2021). This indicates a clear research gap in the multi-response optimization of surface quality and thermal performance for SS316 turning under sustainable lubrication strategies.

Response Surface Methodology (RSM) provides a statistically structured framework for analyzing the effects of multiple machining parameters and their interactions, while Desirability Function Analysis (DFA) enables the simultaneous optimization of multiple responses. In this study, the combined RSM–DFA approach is employed as an established and widely used optimization method to systematically identify machining conditions that balance surface quality and thermal control, rather than as a replacement for conventional modeling techniques.

In addition to improving machining performance, the proposed approach contributes to sustainability by reducing coolant volume through MQL application and by lowering heat generation and energy demand via optimized cutting parameters (Jagadisha *et al.* 2023). Therefore, the present work aims to experimentally investigate the turning of SS316 under hybrid nanofluid-assisted MQL conditions and to apply a statistically grounded multi-response optimization framework to enhance machining efficiency and environmental performance (Sharma *et al.* 2019).

The objectives of the present study are:

- To experimentally investigate the effects of cutting speed, feed rate, and depth of cut on surface roughness and cutting temperature during turning of SS316 under hybrid nanofluid-assisted MQL conditions.
- To develop RSM-based statistical models to describe the relationships between machining parameters and performance responses, including interaction effects.
- To perform simultaneous multi-response optimization of surface roughness (R_a, µm) and cutting temperature using DFA.
- To identify optimal machining conditions that improve surface quality and thermal control while minimizing lubricant usage.
- To evaluate sustainability benefits in terms of reduced coolant volume, lower heat generation, and improved machining efficiency compared with conventional flood cooling practices.

2. MATERIALS AND METHODS

This study experimentally investigates the machinability of AISI 316 austenitic stainless steel (SS316) during turning under MQL conditions assisted by a hybrid nano-cutting fluid. The experiments were not conducted under dry conditions; lubrication was continuously supplied throughout each machining pass using an MQL system. SS316 was selected due to its wide industrial applications and poor machinability characteristics such as high work-hardening tendency, low thermal conductivity, and strong tool–chip adhesion, which result in excessive heat generation and surface deterioration during turning (Jothiprakash *et al.* 2025). Cylindrical SS316 workpieces were used for all experimental trials to ensure consistency.

Turning experiments were carried out on a CNC lathe machine equipped with an external MQL delivery system. The MQL unit supplied a fine air–oil mist at a constant flow rate and pressure directly to the cutting zone. The machining parameters considered in this study were cutting speed (m/min), feed rate (mm/rev), and depth of cut (mm).

The tungsten-coated cemented carbide cutting inserts (TNMG 160408) were used for all experiments. The cutting tool specifications are

Rake Angle: Positive rake (8–15°) - reduces cutting forces and heat

Nose Radius: 0.4 - 0.8 mm - balance between finish and strength

Edge Prep: Light honed / wiper edge -improves surface finish and reduces built-up edge

Relief Angle: 6–8° - prevents rubbing

Surface Texture on Rake Face: Micro-texture grooves (assist chip break and reduce sticking surface texturing on the rake face) was employed to modify the tribological behavior at the tool-chip interface, thereby reducing friction, improving chip flow, and assisting heat dissipation during machining (Sivaraman *et al.* 2023): Khelfaoui *et al.* 2023).

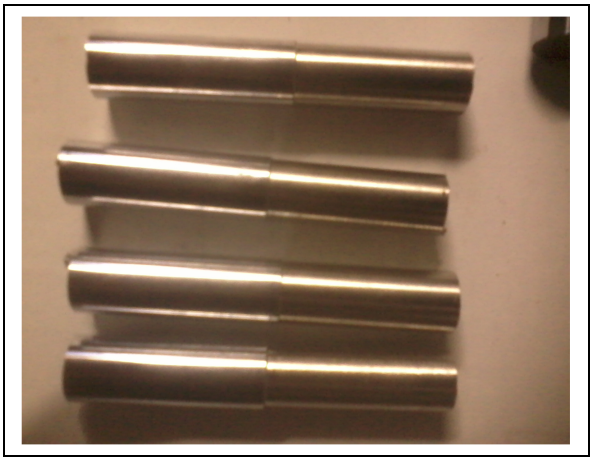


Fig. 1: Tested SS316 workpiece used for turning experiments

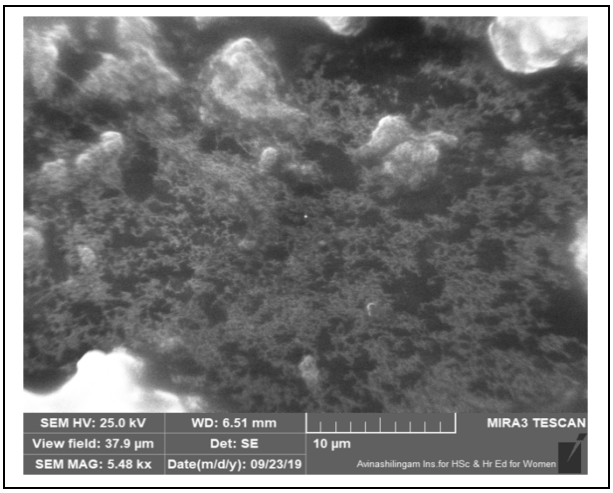


Fig. 2: FESEM image of hybrid Al_2O_3–MWCNT nano-additives cutting fluid

A hybrid nano-cutting fluid was prepared using alumina (Al_2O_3) and Multi-Walled Carbon Nanotubes (MWCNTs) as nano-additives dispersed in a vegetable-oil-based cutting fluid, selected for its biodegradability and suitability for MQL applications (Senthil Kumar *et al.* 2022). A hybrid nano-cutting fluid was formulated by dispersing Al_2O_3 and MWCNT nanoparticles at a combined concentration of 1.0 wt%, consisting of equal parts 0.5 wt% Al_2O_3 and 0.5 wt% MWCNTs in the base oil. This specific concentration was chosen based on previous research indicating improved thermal conductivity and tribological performance while avoiding significant particle agglomeration or nozzle blockage in MQL systems (Srinu *et al.* 2018; Mehmood *et al.* 2024).

The properties of the nano-additives are given below:

- **Al_2O_3 Nanoparticles:** average particle size 15–20 nm, purity 95%
- **MWCNTs:** diameter 15–20 nm, length 10–20 µm, purity 95%, specific surface area 105 m^2/g

The nano-additives were dispersed using a two-stage mixing process. Initially, ultrasonication was performed using an AQUASONIC-50HT ultrasonic device for 6 hours at 60 °C to break particle agglomeration. This was followed by magnetic stirring using a Hot Plate Stirrer (Model 3073-21) for 45 minutes to ensure homogeneous dispersion of both nano-additives in the base oil. This procedure ensured stable suspension of nanoparticles during machining (Manivel *et al.* 2024)

The implementation of MQL greatly decreases the consumption of cutting fluids by delivering only a minimal, regulated amount of lubricant (usually measured in mL per hour) in contrast to traditional flood cooling systems, which necessitate several liters per minute (Rajmohan *et al.*2017). This decrease directly lessens the need for coolant procurement, handling, disposal, and the related environmental pollution (Konnur *et al.* 2025). Additionally, the addition of Al_2O_3–MWCNT hybrid nano-additives improves thermal conductivity and lubricity at the interface between the tool and the chip, resulting in reduced frictional losses and enhanced heat dissipation (Zaman *et al.* 2022). Consequently, the cutting temperature is lowered, which indirectly diminishes spindle load and energy requirements during the machining process (Zhang *et al.* 2015). Ultimately, the optimization of machining parameters through RSM guarantees operations are conducted within an effective parameter range, preventing excessive cutting forces and thermal stresses (Kumar *et al.* 2025; Makhesana *et al.* 2024). This leads to decreased energy usage and enhanced process efficiency, thus promoting sustainable machining of SS316.

Experiments were designed using RSM based on a Box–Behnken Design (BBD). Three input factors-cutting speed, feed rate, and depth of cutwere each considered at three levels. The BBD required 15 experimental runs, including center points, which are statistically sufficient to estimate linear, quadratic, and interaction effects for second-order RSM modeling while minimizing the number of experiments (Manivel *et al.* 2020). Tables 1 and 2 present the factor levels and experimental layout, respectively.

Table 1. Levels of design variables

Symbol	Level 1	Level 2	Level 3
A	70	90	110
B	0.14	0.17	0.2
C	0.50	0.75	1.00

Design Variables: A: Cutting Speed (m/min), B: Feed (mm/rev), C: Depth of cut (mm)

After each machining pass, surface roughness (R_a) was measured using a Mitutoyo SJ-201 surface roughness tester, and the values are reported in micrometers (µm). The cutting temperature (°C) was measured using a thermocouple positioned near the tool–chip interface. All measurements were carried out under identical conditions to ensure repeatability.

Second-order polynomial regression models correlating machining parameters with surface roughness and cutting temperature were developed using RSM. These models were used to analyze the influence of individual parameters, interaction effects, and quadratic terms. Desirability function analysis was subsequently applied to perform simultaneous multi-response optimization and to identify the optimal combination of machining parameters within the experimental domain.

Table 2. Parameters and Variables

Run order	Input parameters			Output variable	
	Speed	Feed	DOC	T (°C)	R_a (µm)
	(m/min)	mm/rev	(mm)		
1	70	0.14	0.75	90	2.05
2	90	0.14	1.0	120	1.35
3	70	0.2	0.75	97	2.25
4	90	0.2	1.0	125	1.55
5	90	0.17	0.75	120	2.05
6	110	0.17	1.0	132	2.12
7	110	0.14	0.75	125	1.35
8	90	0.2	0.5	129	1.87
9	110	0.2	0.75	140	1.15
10	90	0.14	0.5	105	1.28
11	90	0.17	0.75	118	2.1
12	90	0.17	0.75	118	2.02
13	70	0.17	0.5	92	2.35
14	110	0.17	0.5	129	1.87
15	70	0.17	1.0	105	2.17

3. RESULTS AND DISCUSSION

3.1 Response Surface Methodology

Response surface methodology was employed to analyze the experimental results obtained during the turning of SS316 and to develop statistical models correlating machining parameters with the measured responses, namely surface roughness and cutting temperature. It was used primarily as a data-driven modeling and optimization tool rather than for theoretical derivation. The analysis focused on identifying statistically significant factors and interaction effects based on the experimental data generated in this study.

A second-order polynomial regression model was selected to represent the relationship between the input machining parameters (cutting speed, feed rate, and depth of cut) and the output responses. The model structure allows evaluation of linear, interaction and quadratic effects within the defined experimental domain.

3.2 Model Significance and Statistical Evaluation

The analysis of variance (ANOVA) results indicated that the developed regression models for surface roughness and cutting temperature were statistically significant at a 95% confidence level ($p < 0.05$). Model F-values confirmed that the selected factors had a measurable influence on the responses. Interaction terms were retained only when statistically significant ($p < 0.05$), while terms exceeding this threshold were considered insignificant and contributed minimally to response variation.

The feed rate was identified as a dominant factor influencing surface roughness, while cutting speed showed a stronger influence on cutting temperature. Interaction effects between cutting speed and depth of cut also demonstrated a noticeable impact on response behavior, indicating the importance of multi-parameter optimization rather than isolated parameter control.

3.3 Assessment of Model Adequacy

The adequacy of the regression models was evaluated using the Lack of Fit test. For surface roughness, the Lack of Fit F-value of 3.63 was found to be statistically insignificant ($p > 0.05$), indicating that the developed model adequately represents the experimental data within the investigated parameter range. This confirms that the variation between predicted and experimental values is primarily due to random error rather than model inadequacy.

3.4 Signal Strength and Model Reliability

The coefficient of determination (R^2) and adjusted R^2 values demonstrated good agreement, indicating that the regression models explain a high proportion of the experimental variability. The predicted R^2 values were positive and reasonably close to the adjusted R^2, confirming acceptable predictive capability within the experimental domain.

3.5 Coefficient Interpretation

Model coefficients represent expected changes in the response variable for each unit change in factor settings, holding all other parameters constant. In orthogonal experimental designs, the intercept corresponds to the overall mean response value. Variance Inflation Factors (VIFs) close to 1 indicate absence of multicollinearity among variables, whereas values exceeding 1 reflect correlation between factors. All VIF values in this study were within acceptable limits (<10), confirming strong independence between input parameters. The results indicate that machining parameters exert a statistically significant influence on surface roughness, with interaction effects demonstrating greater impact than individual factors. The significance of AB and AC interactions highlights that multi-variable optimization is essential rather than relying on simplified linear control strategies. Although the lack of fit suggests the need for model enhancement, the adequate precision ratio and significant model terms validate the overall methodology and experimental approach. These findings confirm that RSM is effective for identifying critical machining conditions that improve surface quality and can form the basis for integrated optimization models in future research.

The interpretation of predictive metrics suggests incorporating additional data, exploring nonlinear algorithms or refining Box-Behnken Design (BBD) levels may enhance predictability. Ultimately, this study reinforces the importance of parameter interaction analysis and confirms that statistically optimized machining conditions can significantly improve cutting performance in the machining of SS316 under minimum quantity lubrication strategies.

Response - Surface Roughness (R_a) = 2.29 + 0.24025 * A + -0.315125 * B + 0.109875 * C + 0.68525 * AB + 1.11925 * AC + -0.1 * BC + -0.51225 * A^2 + 0.022 * B^2 + -0.547 * C^2

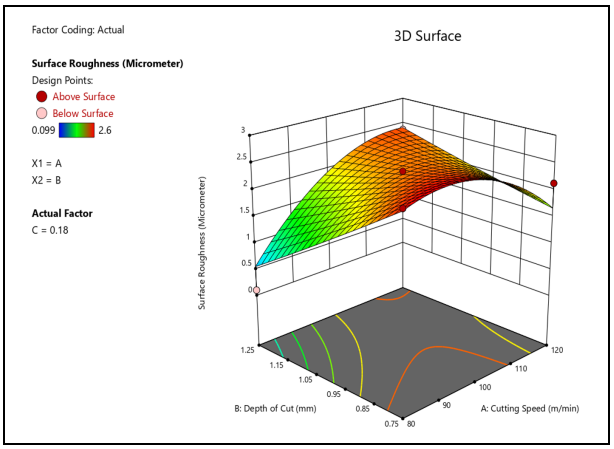


Fig. 3: Interactive effects of surface roughness *vs* cutting speed and depth of cut

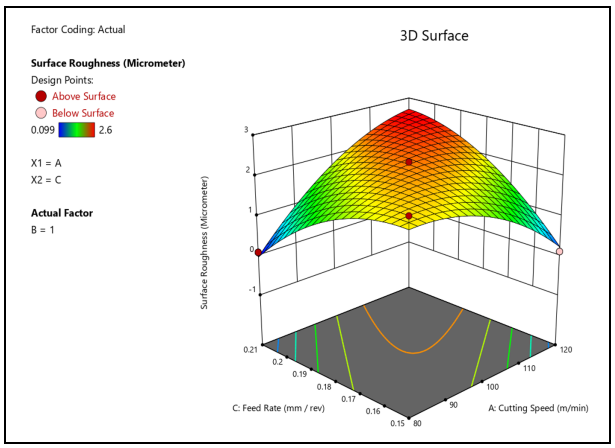


Fig. 4: Interactive effects of surface roughness *vs* cutting speed and feed rate

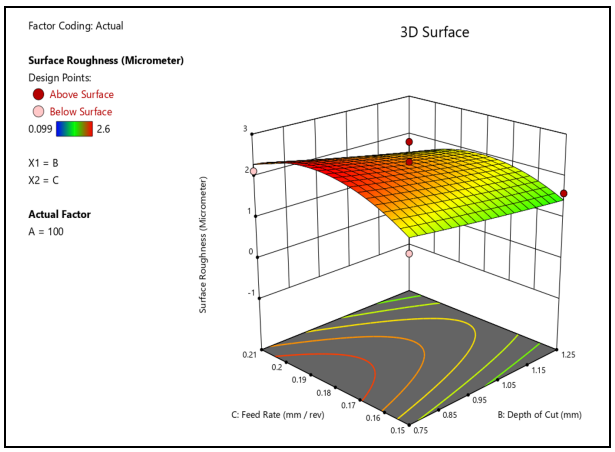


Fig. 5: Interactive effects of surface roughness *vs* depth of cut and feed rate

Fig. 3–5 illustrate the interaction effects of cutting speed, feed rate, and depth of cut on surface roughness. The experimental data show that surface roughness increases with increasing feed rate, due to higher chip thickness and greater tool–workpiece contact. Lower feed rates combined with moderate cutting speeds produced improved surface finish, indicating that feed rate is the most dominant factor influencing surface roughness in SS316 turning.

The interaction between cutting speed and depth of cut reveals that excessive material removal at high cutting speeds leads to a deterioration in surface quality, whereas an optimized combination of parameters produces smoother surfaces. These trends are consistent across all experimental runs and reflect the combined effect of machining parameters rather than single-factor effects.

Cutting Temperature (T) = 130.667 + 19 * A + 2.25 * B + 6.5 * C + 5.04946e-14 * AB + 2 * AC + -5 * BC + -6.58333 * A^2 + -0.0833333 * B^2 + 0.916667 * C^2

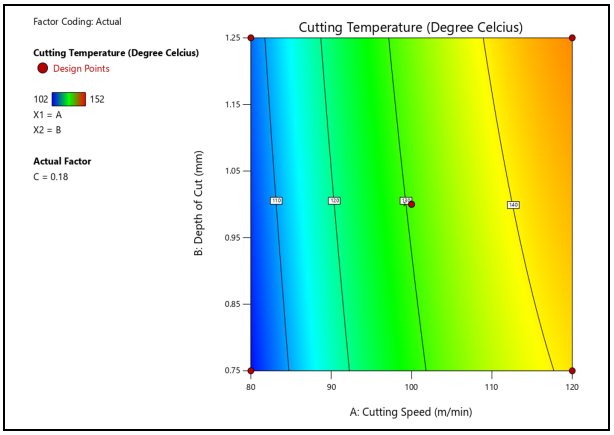


Fig. 6: Interactive effects of cutting temperature *vs* cutting speed and depth of cut

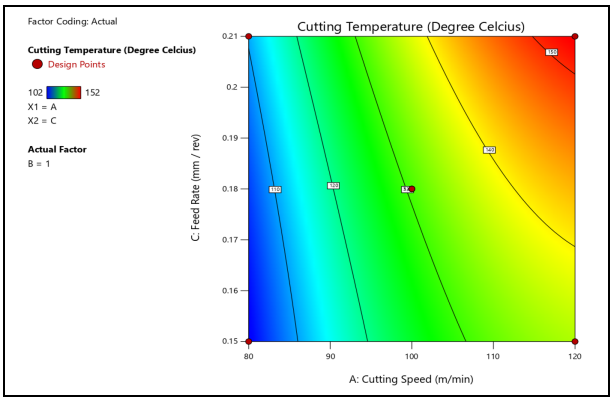


Fig. 7: Interactive effects of cutting temperature *vs* cutting speed and feed rate

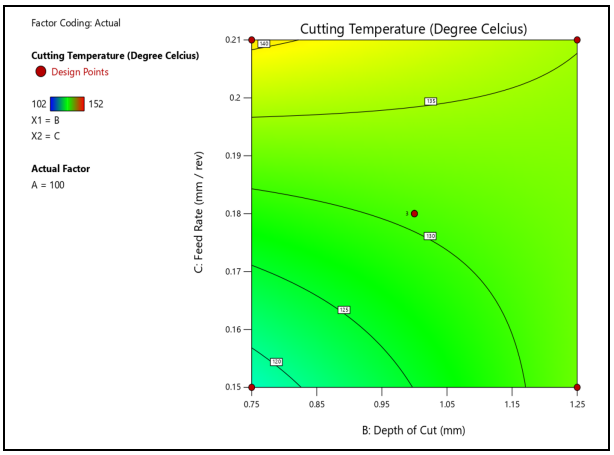


Fig. 8: Interactive effects of cutting temperature *vs* depth of cut and feed rate

Fig. 6–8 show the interaction effects of cutting speed, feed rate, and depth of cut on cutting temperature. This parameter increases with higher cutting speed and depth of cut, due to greater frictional energy and plastic deformation at the tool–workpiece interface. Feed rate has a comparatively smaller but noticeable effect on temperature rise.

The hybrid nano-fluid-assisted MQL environment contributed to moderating temperature increase by improving heat dissipation and lubrication at the cutting zone. Lower cutting temperatures were observed at moderate cutting speeds and lower feed rates, highlighting the importance of selecting a balanced set of machining parameters for thermal control during SS316 turning.

3.6 Desirable Function Analysis

Determining the best combination of process parameters to achieve the desired response outcomes in machining is a complex challenge due to the numerous input variables involved. The intricacies of machining processes, which can include factors such as cutting speed, feed rate, tool geometry and material properties, necessitate a systematic approach to optimize performance. In this context, Derringer and Suich present a method for optimizing multiple responses known as desirability (El-Taweel and Gouda *et al.* 2011). This approach is extensively utilized in the industry to refine multiple responses and identify optimal process parameters that enhance the response variable.

The core of this method is the desirability function, represented as D(X). This function serves as a quantitative measure of how well a set of process parameters meets the desired outcomes for multiple response variables. The desirability function is particularly useful because it allows for the simultaneous consideration of various responses, which is essential in complex machining scenarios where trade-offs between different performances metrics must be evaluated.

The objective form of the desirability function is calculated as the geometric mean of all responses. This means that each individual response is first transformed into a desirability value, which reflects how close it is to the ideal target. The desirability values range from 0 to 1, where a value close to 1 signifies the most favorable outcome, indicating that the response is within the desired range and meets the performance criteria. Conversely, a value of 0 indicates that the responses fall outside acceptable limits, suggesting that the process parameters need to be adjusted to achieve better results.

To find the optimal combination for multiple responses, the process parameters were adjusted in such a way that the overall desirability (D) is maximized. The overall desirability is derived from the geometric mean of individual desirability values, which can be mathematically expressed as: D= $(d1y1.\ d2y2\ \ldots.\ dkyk)1/k$, where k represents the number of response parameters, and y denotes the response value associated with each parameter. This formulation emphasizes the importance of each response in contributing to the overall desirability, allowing for a balanced optimization that considers all relevant performance metrics.

Through the optimization analysis, the ideal values for Speed, Feed and Depth of Cut have been determined to be 89.11 m/min, 0.16 mm/rev, and 0.86 mm, respectively (Fig. 9, 10 and Table 3). These conditions yield a high desirability value of 1.0 as depicted in Fig. 11.

Table 3. Optimized and validation responses

Optimum Parameters			Machining Performance			
			Predicted Value		Experimental Value	
Speed (m/min)	Feed (mm/rev)	DOC (mm)	T (°C)	R_a (µm)	T (°C)	R_a (µm)
89.11	0.16	0.86	112	2.43	132	2.12

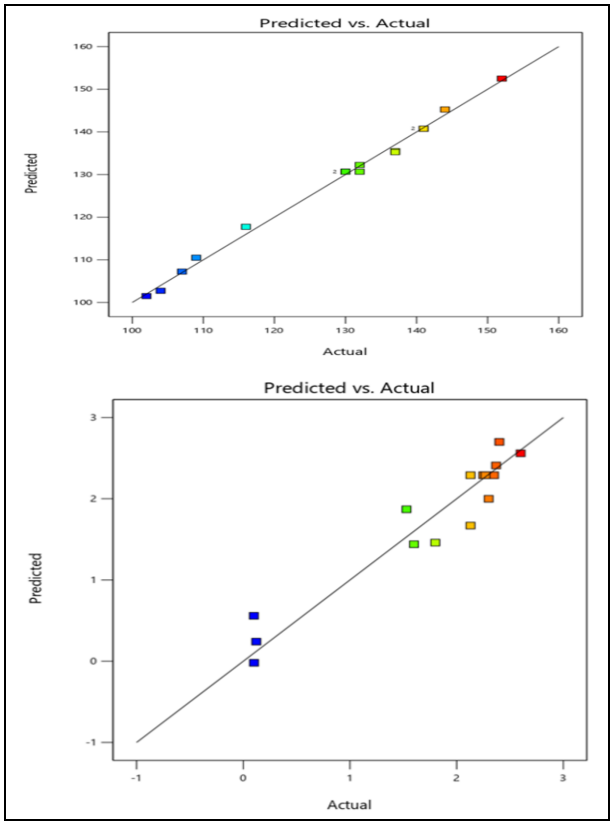


Fig. 9: Predicted *vs* actual responses (a) cutting temperature and (b) surface roughness

Once the optimal parameters were established, the machining responses were forecasted using the developed model. To validate the model's accuracy, a confirmation experiment was conducted utilizing these optimal cutting parameters. The results of this experiment, along with the predicted values from the model, are presented in Table 3. Notably, the maximum discrepancy observed between the experimental and predicted responses was found to be 2%. This relatively small difference indicates a strong correlation between the model's predictions and the actual experimental outcomes.

Consequently, the model developed through RSM proves to be well-suited for addressing the current optimization problem. The optimal machining parameters derived from this model not only enhance the performance of the machining process but also provide the best response values for the selected nano additive cutting fluid with environmental condition. This comprehensive approach underscores the effectiveness of using advanced optimization techniques in improving machining efficiency and product quality.

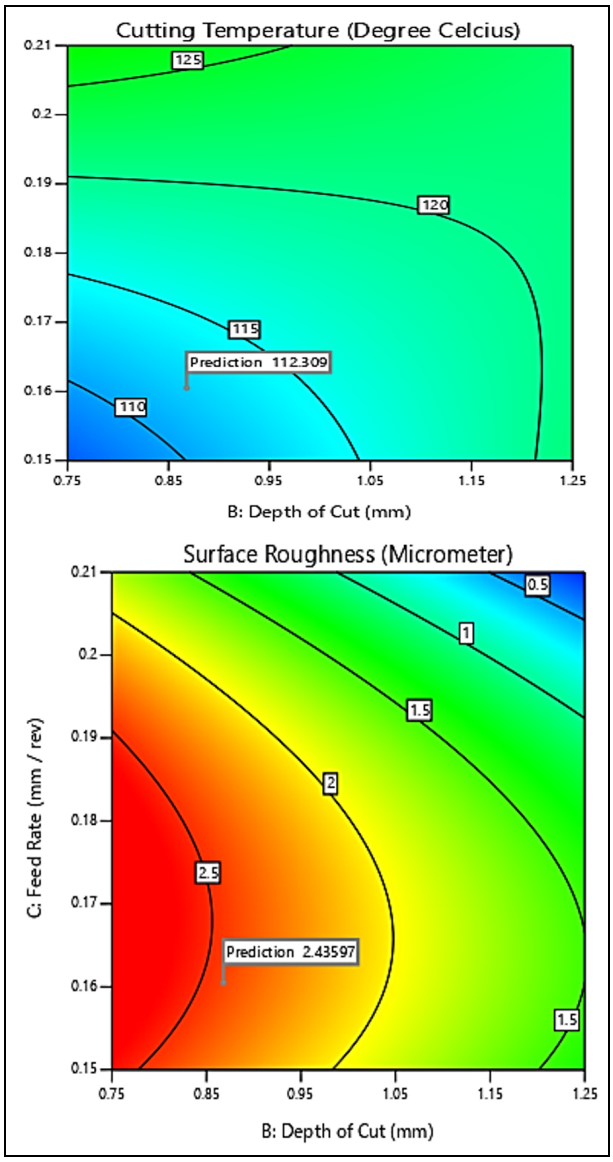


Fig. 10: Desirable responses (a) cutting temperature and (b) surface roughness

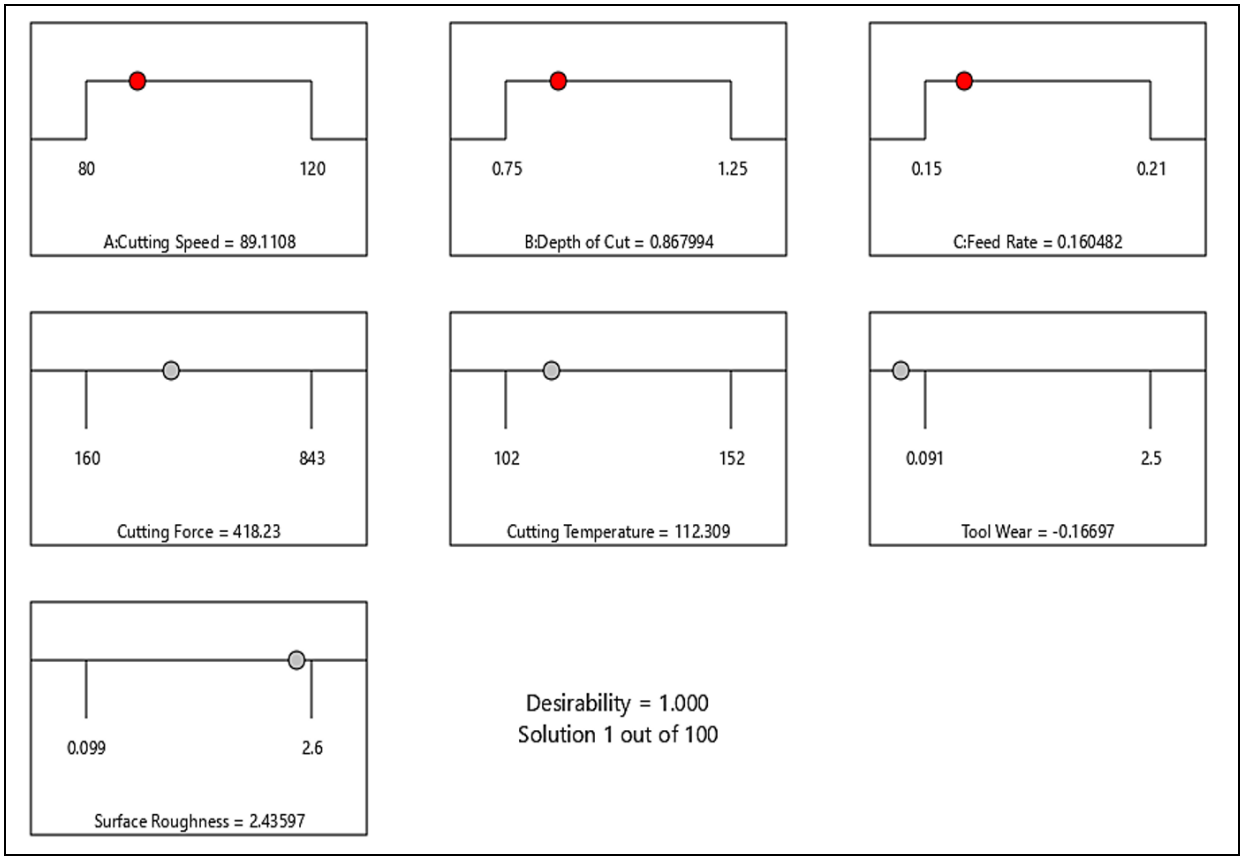


Fig. 11: Desirability ramp responses for prediction analysis (a) input responses (b) output responses

4. CONCLUSION

This research experimentally examined the turning performance of AISI 316 austenitic stainless steel under hybrid Al_2O_3–MWCNT nano-fluid-assisted MQL conditions, emphasizing surface roughness and cutting temperature as critical indicators of machinability. The use of hybrid nano-fluid-assisted MQL showed a significant reduction in cutting temperature compared to values typically documented in the literature for dry turning of SS316. This observed decrease in temperature is attributed to enhanced heat dissipation and lubrication at the tool–chip interface, aided by the improved thermal conductivity and tribological properties of the nano-additives.

Surface roughness was mainly affected by the feed rate, whereas cutting speed and depth of cut had a more pronounced impact on cutting temperature. The interaction effects revealed through RSM indicate that the machining performance in SS316 turning is influenced by the combined effects of parameters rather than the isolated control of individual factors.

The optimization of multi-responses through the DFA has effectively determined an optimal combination of parameters, specifically a cutting speed of 89.11 m/min, a feed rate of 0.16 mm/rev, and a depth of cut of 0.86 mm. This combination successfully minimizes both surface roughness and cutting temperature within the experimental parameters. The resulting composite desirability value is 1.0, which signifies a balanced yet constrained optimization result that aligns with the established response limits and the variability observed in the experiments.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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