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Experimental Study and Optimization of lathe Machining Parameters

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ABSTRACT
In modern manufacturing, optimizing machining parameters is crucial for enhancing productivity, reducing costs, and improving surface quality. Turning, a widely used metal cutting process, often suffers from inefficiencies due to poor parameter selection, leading to increased tool wear and energy use. This study investigated how machining variables like cutting speed, feed rate, depth of cut, and spindle speed affect the Material Removal Rate (MRR), aiming to determine the optimal combination for maximum efficiency. Central Composite Design (CCD) of Response Surface Methodology (RSM) was used to model and optimize the machining process. Thirty experimental runs were conducted on a conventional lathe, varying the selected parameters within practical limits. MRR was calculated for each run, and regression modeling was applied to develop a predictive quadratic model. Analysis of Variance (ANOVA) confirmed the statistical significance of the model and highlighted the contribution of each parameter. Findings showed that feed rate and depth of cut had the most significant influence on MRR, followed by cutting speed, with spindle speed having a moderate effect. The optimal machining conditions were identified as: cutting speed of 170.89 m/min, feed rate of 0.49 mm/rev, depth of cut of 1.14 mm, and spindle speed of 751.13 rpm, achieving a maximum MRR of 2.46%. The developed model can serve as a predictive tool to set machining parameters, reducing guesswork and improving efficiency. Future research could extend this approach to include other factors such as surface roughness, tool wear, for comprehensive process optimization.

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INTRODUCTION

Lathe machines are among the oldest and most fundamental machine tools in the history of mechanical engineering and manufacturing. Their development marked a significant turning point in human capability to shape, refine, and produce functional components for various applications (Jain & Bose, 2022). What makes lathe machines particularly valuable is their versatility and adaptability. Whether manually operated or computer-controlled (CNC lathes), they are capable of executing complex machining tasks with remarkable accuracy. However, the efficiency, precision, and overall quality of the output from a lathe are not solely dependent on the machine's capability. Much of the performance is dictated by the selection and control of machining parameters specifically, cutting speed, feed rate, depth of cut, and spindle speed. Optimizing these parameters plays a crucial role in improving the machining quality, reducing production costs, and extending tool life (Miller & Robinson, 2017). Several notable studies across the globe have explored the optimization and performance enhancement of lathe machines to improve machining efficiency and surface quality. They have also analyzed the effects of cutting parameters such as spindle speed, feed rate, and depth of cut on tool wear and material removal rate. Suresh et al. (2020) investigated the influence of these parameters on surface roughness, concluding that lower feed rates and optimal spindle speeds significantly enhance machining precision. Patel and Sharma (2019) utilized response surface methodology (RSM) and Taguchi techniques to optimize cutting conditions, demonstrating that proper parameter selection reduces machining time and operational costs. Awasare (2025) explored the optimization techniques and performance parameters that enhance the efficiency and accuracy of lathe machining. The study focuses on variables that have a major impact on surface finish and material removal rate, including spindle speed, feed rate, depth of cut, and tool material. Computational simulations and experimental analyses were conducted to evaluate machining performance under various conditions. The results indicated that optimized parameters lead to improved productivity and reduced tool wear. Amiebenomo et al. (2023) is an optimization study in which the surface roughness of AISI 1018 mild steel is minimized with the aid of the response surface methodology. The effect of process parameters like cutting speed, feed rate, depth of cut, and bearing clearance was analyzed to ascertain how the surface finish properties of mild steel can be improved. Bagaber & Yusoff (2017) studied the influence of cutting parameters such as cutting speed, feed rate, and depth of cut on surface roughness, and machining time of coated carbide tool in dry turning of stainless steel 316. It was shown that feed rate had dominant influence, followed by depth of cut, while cutting speed had slight influence on surface roughness. Bello et al. (2024) investigated the effect of cutting fluids on tool-work interface temperature during the turning of 6061 aluminum alloy. Nur et al. (2017) undertook cutting tests to optimize cutting parameters in order to achieve higher material removal rate when turning Al-11% Si base alloy with a PVD coated carbide tool on a two-axis CNC lathe in dry cutting environment. It was reported that increased material removal rate was obtained when the cutting speed and feed rate increased. Singh et al. (2017) used the Taguchi method to optimized cutting conditions for achieving lower surface roughness during the CNC turning of AISI 316 austenitic stainless steel with carbide inserts coated with titanium nitride coating (TiN) under dry cutting. Results show that surface roughness was highly influenced by feed rate, while depth of cut had minimal effect on surface roughness while cutting speed had least influence on surface roughness. Salgar et al. (2017) achieved minimum surface roughness and higher material removal rate using the Taguchi method to optimize cutting parameters such as cutting speed, depth of cut, and feed rate in the turning of AISI 1018 steel. Dhanalakshmi & Rameshbabu (2020) utilized the Taguchi method to optimize cutting parameters such as cutting speed, depth of cut, and feed rate in CNC turning of LM 25 aluminium alloy to achieve high material removal rate, low surface roughness values, and reduced machining cost. It was found that feed rate had more effect on the MRR when compared to cutting speed and depth of cut. Recent studies have applied advanced optimization techniques to enhance machining performance across various materials. Such include Rao & Venkaiah (2015) who optimized machining parameters for Nimonic-263 alloy using Response Surface Methodology (RSM) combined with Particle Swarm Optimization. Mohanraj et al. (2024) used the RSM desirability approach to optimize Wire Electrical Discharge Machining (WEDM) for mild steel, improving cutting efficiency and surface quality. Saha et al. (2024) applied RSM and a MOGA-ANN hybrid to optimize electrochemical machining parameters for Inconel 718. Nguyen (2024) compared Taguchi-based RSM and Artificial Neural Networks (ANN) for optimizing shredder blade geometry, highlighting their predictive strengths. Geleso et al. (2025) focused on optimizing spindle speed, feed rate, and depth of cut for C45 steel using RSM, targeting improvements in surface roughness and material removal rate (MRR).

The studies reviewed showed that machining parameters significantly influence material removal rate, surface roughness, machining time, and tool wear, with feed rate and cutting speed identified as the influential factors. The observed effects vary with workpiece material, tooling, and machining conditions, making it difficult to generalize the findings. Also, most of the studies focused on surface finish or multi-response optimization rather than systematically examining material removal rate (MRR) as the primary response. Therefore, the combined influence of cutting speed, feed rate, spindle speed, and depth of cut on material removal rate under practical conditions remains insufficiently resolved. While past studies have explored individual effects or used methods like RSM and Taguchi for various materials, just few have focused exclusively on MRR as the primary response variable. Besides, there is limited research that integrates all four key parameters under realistic machining conditions for low-carbon steels. This study aims to address this gap by analyzing their combined influence on material removal rate (MRR).

MATERIALS AND METHODS

In this study, mild steel with dimensions of 25 mm by 150 mm was selected as the workpiece material, while a cemented carbide cutting tool was employed. Turning operations were carried out on a lathe machine using a cutting tool with a rake angle of 25°. The tool was securely mounted on the tool post, and the mild steel workpiece was held firmly in place using a 3-jaw chuck. The cutting parameters were varied within the following ranges: cutting speed from 19.61 to 221.32 m/min, feed rate from 0.46 to 0.56 mm/rev, depth of cut from 0.05 to 1.50 mm, and spindle speed between 165 and 1800 rpm. A soluble oil cutting fluid, consisting of 20% oil mixed in water and 80% mineral oil, was used during the turning process. To determine the material removal rate (MRR), the diameter of the workpiece was measured before and after each trial. These values were then applied to Equation (1) to calculate the MRR for each experimental run.

$$MRR = \pi D_{avg} dfN \quad (mm^3/min) \tag{1}$$

Where $D_{avg} = \left(\frac{D_i - D_f}{2}\right)$ in mm, D_i = Initial diameter (mm), D_f = Final diameter (mm), f = Feed rate (mm/rev), N=Spindle speed (rpm), d = Depth of cut (mm).

Spindle speed of a milling machine is selected to give the desired peripheral speed of cutter expressed in revolution per minute (r.p.m) while Cutting speed of a milling cutter is its peripheral linear speed resulting from the operation expressed in meters per minute (m/min).

Each experimental run was carried out by setting the machining parameters according to the specifications outlined in the design matrix. Key observations, including the material removal rate (MRR), were calculated for every trial and recorded to support statistical evaluation and model formulation. The experimental design matrix was created using Design Expert Software (Version 11, Stat-Ease Inc., Minneapolis, USA), employing a four-factor, five-level randomized central composite design (RCCD). This resulted in a total of 30 runs, which included 12 factorial points, 12 axial (or star) points which represent three axial levels per factor and 6 center point replications, to accurately estimate error and assess process consistency. The selected ranges of input variables for the machining parameters are presented in Table 1.

Table 1: Input Variable and Levels

Independent Variabe	Symbols	Levels	
		-1	+1
Cutting Speed (m/min)	A	19.61	221.32
Feed Rate (mm/rev)	B	0.46	0.56
Depth Cut (mm)	C	0.05	1.50
Spindle Speed (rpm)	D	165	1800

The experimental analysis was carry out to assess the combined effect of cutting speed, feed rate, depth of cut, and spindle speed on the material removal rate (MRR).

RESULTS AND DISCUSSION

The design matrix and the experimental results corresponding to the four cutting parameters such as cutting speed, feed rate, depth of cut, and spindle speed are presented in Table 2 and 3 respectively.

Table 2: Design Matrix of Variables

Run	Cutting Speed (m/min)	Feed Rate (mm/rev)	Depth of Cut (mm)	Spindle Speed (rpm)	Run	Cutting Speed (m/min)	Feed Rate (mm/rev)	Depth of Cut (mm)	Spindle Speed (rpm)
1	170.89	0.48	1.14	573.75	16	120.46	0.51	1.50	982.50
2	70.04	0.48	0.41	573.75	17	170.89	0.54	1.14	1391.25
3	170.89	0.48	1.14	1391.25	18	170.89	0.54	0.41	573.75
4	120.46	0.56	0.77	982.50	19	120.46	0.46	0.77	982.50
5	170.89	0.54	0.41	1391.25	20	19.61	0.51	0.77	982.50
6	170.89	0.54	1.14	573.75	21	170.89	0.48	0.41	1391.25
7	120.46	0.51	0.77	982.50	22	120.46	0.51	0.05	982.50
8	70.04	0.54	1.14	573.75	23	120.46	0.51	0.77	1800.00
9	70.04	0.54	0.41	573.75	24	170.89	0.48	0.41	573.75
10	70.04	0.48	1.14	573.75	25	120.46	0.51	0.77	982.50
11	70.04	0.48	0.41	1391.25	26	70.04	0.48	1.14	1391.25
12	120.46	0.51	0.77	982.50	27	120.46	0.51	0.77	982.50
13	120.46	0.51	0.77	982.50	28	70.04	0.54	1.14	1391.25
14	120.46	0.51	0.77	165.00	29	221.32	0.51	0.77	982.50
15	70.04	0.54	0.41	1391.25	30	120.46	0.51	0.77	982.50

Table 3: Effects of Machining Variables on MRR of Mild Steel Iron Rod

Run	Factors				Response	
	Cutting Speed (m/min)	Feed Rate (mm/rev)	Depth of Cut (mm)	Spindle Speed (rpm)	MRR (x10^3 mm³/min)	
					Actual	Predicted
1	170.89	0.48	1.14	573.75	2.41	2.41
2	70.04	0.48	0.41	573.75	0.96	0.94
3	170.89	0.48	1.14	1391.25	1.76	1.78
4	120.46	0.56	0.77	982.50	1.00	0.97
5	170.89	0.54	0.41	1391.25	1.11	1.15
6	170.89	0.54	1.14	573.75	1.22	1.20
7	120.46	0.51	0.77	982.50	2.00	2.11
8	70.04	0.54	1.14	573.75	1.20	1.28
9	70.04	0.54	0.41	573.75	1.35	1.37
10	70.04	0.48	1.14	573.75	1.75	1.74
11	70.04	0.48	0.41	1391.25	0.89	0.94
12	120.46	0.51	0.77	982.50	2.22	2.11
13	120.46	0.51	0.77	982.50	2.01	2.11
14	120.46	0.51	0.77	165.00	1.05	1.00
15	70.04	0.54	0.41	1391.25	2.01	1.99
16	120.46	0.51	1.50	982.50	2.09	2.09
17	170.89	0.54	1.14	1391.25	1.20	1.20
18	170.89	0.54	0.41	573.75	0.70	0.70
19	120.46	0.46	0.77	982.50	1.11	1.13
20	19.61	0.51	0.77	982.50	1.73	1.71
21	170.89	0.48	0.41	1391.25	0.95	0.84
22	120.46	0.51	0.05	982.50	1.25	1.24
23	120.46	0.51	0.77	1800.00	0.95	0.99
24	170.89	0.48	0.41	573.75	0.96	1.02
25	120.46	0.51	0.77	982.50	2.14	2.11
26	70.04	0.48	1.14	1391.25	1.32	1.30
27	120.46	0.51	0.77	982.50	2.17	2.11
28	70.04	0.54	1.14	1391.25	1.49	1.46
29	221.32	0.51	0.77	982.50	1.51	1.52
30	120.46	0.51	0.77	982.50	2.09	2.11

The actual experimental material removal rate (MRR) values obtained during the machining of the mild steel rod ranged from 0.70 x 10^3mm^3/min to 2.41 x 10^3 mm^3/min. On one hand, the highest MRR of 2.41 x 10^3 mm^3/min was achieved at a cutting speed of 170.89 m/min, feed rate of 0.48 mm/rev, depth of cut of 1.14 mm, and spindle speed of 573.75 rpm. On the other hand, the lowest MRR of 0.70 x 10^3 mm^3/min occurred under the same cutting speed and spindle speed, but with a feed rate of 0.54 mm/rev and a reduced depth of cut of 0.41 mm. The summary statistics for the Material Removal Rates (MRRs) obtained from the machining of the mild steel rod are recorded in Table 4.

Table 4: Summary Statistics of MRRs of Mild Steel Iron Rod Machining

Source	SD	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	0.4903	0.1630	0.0291	-0.1478	8.24	
2FI	0.4419	0.4833	0.2114	0.1189	6.33	
Quadratic	0.0708	0.9895	0.9797	0.9631	0.2651	Suggested
Cubic	0.0776	0.9941	0.9757	0.9274	0.5217	Aliased

SD = Standard Deviation

In Table 4, a quadratic model provided the best fit for the Material Removal Rates (MRRs) during the machining of mild steel rods, with an R^2 value of 0.9895. This is attributed to the cubic model being aliased in the response surface methodology, based on the assumption that cubic effects are negligible. A strong correlation was also observed between the adjusted R^2 of 0.9797 and the predicted R^2 of 0.9631, with a difference of less than 20%, signifying good agreement between the experimental and the predicted results. This strong alignment is further confirmed by the predicted versus actual plot shown in Figure 1.

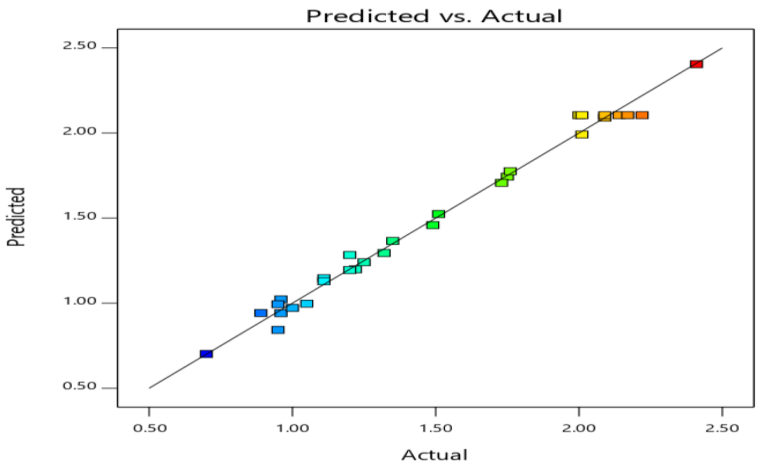

Figure 1: Actual vs. predicted plot for MRRs of mild steel iron rod

Analysis of Variance (ANOVA) for MRR

Analysis of Variance (ANOVA) was used to evaluate the significance and suitability of the model describing the machining process. Mean squares were determined by dividing the sum of squares for each source such as the model and the error by their respective degrees of freedom. A p-value below 0.05 indicates that the result is statistically significant and not due to random variation, suggesting that the model term has a meaningful effect on the response variable (Ahmad et al., 2017). The ANOVA results for the Material Removal Rate (MRR) during the machining of the mild steel rod are presented in Table 5.

Table 5: The material removal rate ANOVA for mild steel iron rod

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	7.11	14	0.5076	101.21	< 0.0001*
A - Cutting speed	0.0504	1	0.0504	10.05	0.0063*
B - Feed rate	0.0368	1	0.0368	7.34	0.0162*
C - Depth cut	1.08	1	1.08	216.08	< 0.0001*
D - Spindle speed	0.0000	1	0.0000	0.0033	0.9548
AB	0.5550	1	0.5550	110.66	< 0.0001*
AC	0.3364	1	0.3364	67.07	< 0.0001*
AD	0.0324	1	0.0324	6.46	0.0226*
BC	0.7832	1	0.7832	156.16	< 0.0001*
BD	0.3906	1	0.3906	77.88	< 0.0001*
CD	0.2025	1	0.2025	40.37	< 0.0001*
A^2	0.4102	1	0.4102	81.79	< 0.0001*
B^2	1.91	1	1.91	379.82	< 0.0001*
C^2	0.3306	1	0.3306	65.92	< 0.0001*
D^2	2.11	1	2.11	420.49	< 0.0001*
Residual	0.0752	15	0.0050		
Lack of Fit	0.0363	10	0.0036	0.4658	0.8578
Pure Error	0.0390	5	0.0078		
Cor Total	7.18	29			

*=significant

The empirical model developed using Response Surface Methodology (RSM) in terms of coded factors illustrates the influence and interaction of the machining parameters on Material Removal Rate (MRR) during the machining of mild steel rods. In the model, coefficients associated with single factors indicate the individual effect of each variable, while those involving two factors represent their interactive effects, and the second-order terms account for quadratic influences. The mathematical representation of the MRR model in coded form is provided in Equation 2.

$$MRR = 2.11 - 0.0458A - 0.0392B + 0.2125C - 0.0008D - 0.1862AB + 0.1450AC - 0.0450AD - 0.2213BC + 0.1563BD - 0.1125CD - 0.1223A^2 - 0.2635B^2 - 0.1098C^2 - 0.2773D^2 \quad (2)$$

Based on the model in Equation (2), among the primary factors, cutting speed (A), feed rate (B), and spindle speed (D) negatively influenced the Material Removal Rate (MRR) while depth of cut (C) had a positive effect. Depth of cut (C) exhibited the most significant impact, reflected by the highest coefficient value whereas spindle speed (D) had the least influence, with the lowest coefficient. Regarding the interaction terms, AB, AD, BC, and CD showed negative effects on MRR, while interactions between AC and BD had positive effects. Additionally, all quadratic terms negatively affected the MRR. The characteristics and reliability of the MRR model for the machining process are further explained using the fit statistics presented in Table 6.

Table 6: Fit Statistics of MRRs of mild steel iron rod machining

Statistics	Value
Standard deviation (%)	0.0708
Mean (%)	1.49
C.V (%)	4.76
R^2	0.9895
Adequate Precision	34.0138

The effects of the variables interactions are presented in Figure 2a to 2l using both the 3-dimensional response surface plot and the 2- dimensional contour plots.

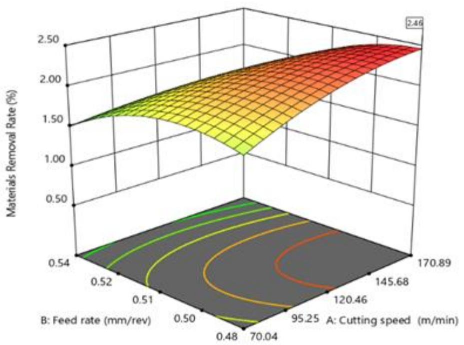

Figure. 2a. Response plot showing effect of interaction between cutting speed and feed rate

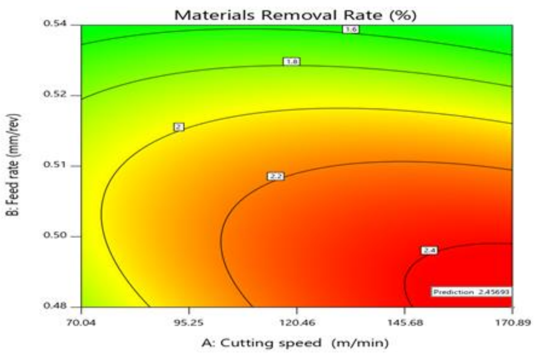

Figure 2b. Contour plot showing effect of interaction between cutting speed and feed rate

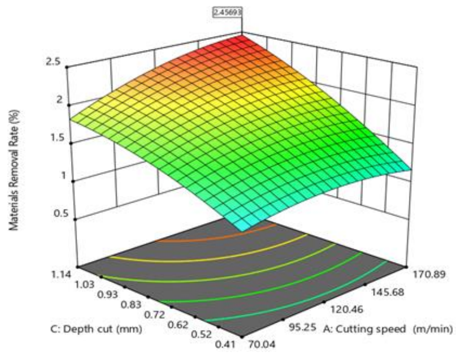

Figure 2c. Response plot showing effect of interaction between cutting speed and depth of cut

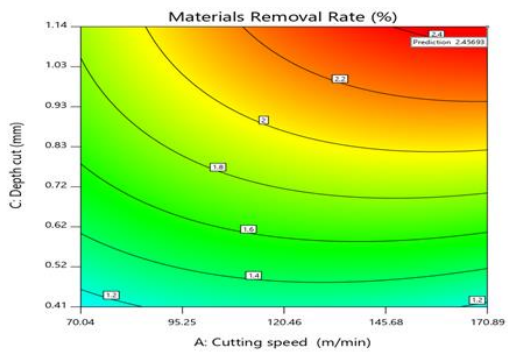

Figure 2d. Contour plot showing effect of interaction between cutting speed and depth of cut

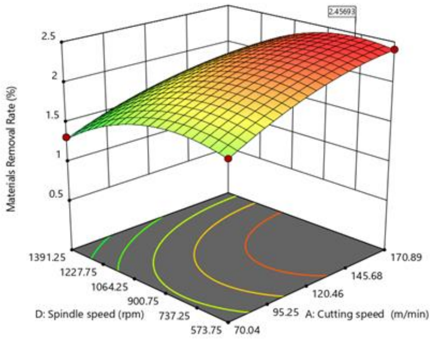

Figure 2e. Response plot showing effect of interaction between cutting speed and spindle speed

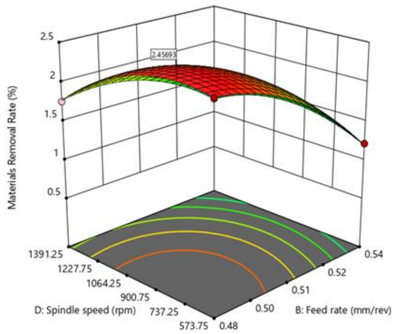

Figure 2i. Response plot showing effect of interaction between feed rate and spindle speed

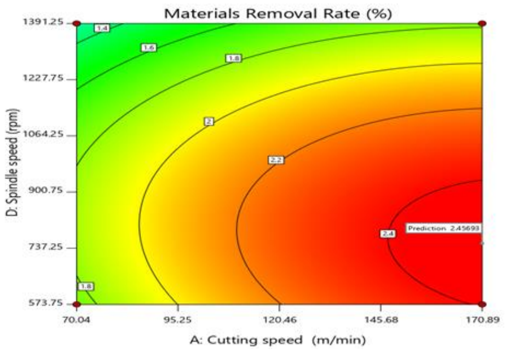

Figure 2f. Response plot showing effect of interaction between cutting speed and spindle speed

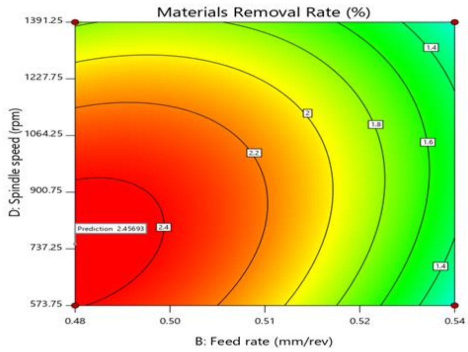

Figure 2j. Response plot showing effect of interaction between feed rate and spindle speed

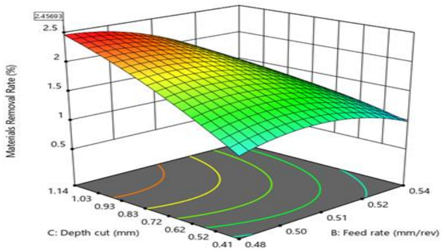

Figure 2g. Response plot showing effect of interaction between feed rate and depth of cut

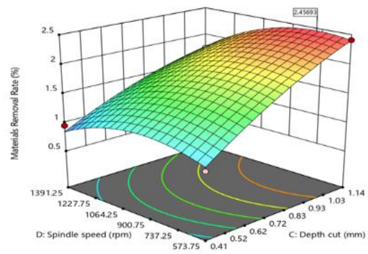

Figure 2k. Response plot showing effect of interaction between depths of cut and spindle speed

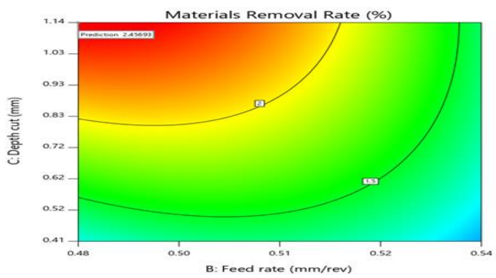

Figure 2h. Contour plot showing effect of interaction between feed rate and depth of cut

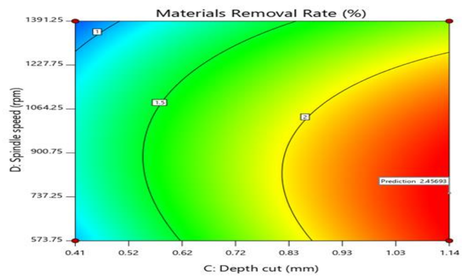

Figure 2l. Response plot showing effect of interaction between depths of cut and spindle speed

The response and contour plot in Figure 2(a-b) shows the effect of cutting speed and feed rate interaction on the MRR of mild steel at constant depth of cut and spindle speed. The plot reveals that increasing both parameters simultaneously lead to a decrease in MRR. In Figure 2(c-d), with constant feed rate and spindle speed, a simultaneous increase in cutting speed and depth of cut led to a corresponding rise in MRR. Figure 2(e-f) represents the effect of cutting speed and spindle speed at fixed feed rate and depth of cut. The implication is that increasing both parameters reduces MRR. In Figure 2(g-h), the combined increase in feed rate and depth of cut at constant cutting speed and spindle speed causes a decline in MRR. Figure 2(i-j) shows that increasing feed rate and spindle speed at fixed cutting speed and depth of cut give rise to higher MRR. Lastly, Figure 2(k-l) reveals that a simultaneous increase in depth of cut and spindle speed, while keeping constant the cutting speed and feed rate, led to a reduction in MRR.

The optimal condition obtained from the analysis furnished us with a maximum MRR of 2.46 x 10^3 mm^3/min obtained at a cutting speed of 170.89 m/min, feed rate of 0.49 mm/rev, depth of cut of 1.14 mm, and a spindle speed of 751.13 rpm.

CONCLUSION

This study highlights the vital role of machining parameter optimization in enhancing the efficiency of turning operations. Using Central Composite Design (CCD) within the Response Surface Methodology (RSM), the effects of cutting speed, feed rate, depth of cut, and spindle speed on material removal rate (MRR) were methodically analyzed. A robust quadratic regression model was also developed, and ANOVA confirmed its statistical significance. Among the parameters studied, feed rate and depth of cut were found to have the most significant effect on material removal rate (MRR), followed by cutting speed and spindle speed. The study demonstrates the effectiveness of RSM in minimizing trial and error and promoting data driven decisions in machining. For future research, exploring the use of such performance indicators like tool wear, surface roughness through multi-objective optimization would provide a more all-inclusive evaluation of machining performance.

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