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Optimization of Machining Parameters of FG300 Flange Using ANOVA Technique under MQL

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ABSTRACT- The machining of FG300 gray cast iron flanges is critical in various industrial applications, requiring optimized parameters to enhance surface quality, reduce tool wear, and improve efficiency. The goal of this research is to maximise cutting depth, feed rate, and speed using a Minimum Quantity Lubrication (MQL) system, which is a sustainable substitute for traditional cooling techniques. MQL minimizes lubricant consumption while ensuring effective cooling and lubrication, contributing to sustainable manufacturing. Turning experiments were conducted using carbide cutting tools under controlled MQL conditions. Tool wear and surface roughness (Ra) were examined as important performance metrics. The statistical significance of the machining parameters and their impact on the responses were evaluated using the Analysis of Variance (ANOVA) approach. The findings show that cutting speed has the greatest impact, followed by feed rate and cut depth. The optimized parameters led to improved surface finish, reduced tool wear, and enhanced machining efficiency. This study provides a systematic approach for optimizing machining parameters under MQL conditions, offering valuable insights for industries seeking to enhance productivity while reducing costs and environmental impact. The findings demonstrate that ANOVA-based optimization under MQL can significantly improve the machining of FG300 flanges, making it a promising approach for sustainable and high-precision manufacturing.

KEYWORDS- Minimum Quantity Lubrication (MQL), Surface roughness, Analysis of Variance

I. INTRODUCTION

Drilling is a fundamental machining process used to create or enlarge cylindrical holes in solid materials through the application of multi-point cutting tools, typically twist drills—the most widely used among various types. As manufacturing technologies evolve, the dual focus on enhancing productivity and maintaining high product quality has become increasingly critical. Productivity is often measured by the Material Removal Rate (MRR), whereas quality is evaluated based on surface characteristics such as surface roughness. [12] Improving both productivity and quality requires careful adjustment of machining parameters[1][2][4]. Many researchers have investigated the influence of drilling variables to optimize performance outputs like MRR and surface finish. Among these, MRR is a primary indicator of productivity, influenced by both the machine tool and the selected process parameters. Surface roughness, in turn, is significantly impacted by MRR, creating a trade-off that necessitates optimization. [3]

In precision-focused sectors such as aerospace, achieving accurate and high-quality drilled holes is vital. To this end, statistical approaches like the Taguchi method are frequently used to examine how changes in input parameters affect performance metrics. [5] Several cutting conditions—tool geometry, cutting speed, feed rate, depth of cut, and type of coolant—play critical roles in determining the overall efficiency and output quality of the process. [6] [13] Among these, the use of an appropriate coolant, especially under Minimum Quantity Lubrication (MQL) conditions, is essential for minimizing tool wear and improving surface finish.

This study aims to optimize the machining parameters during drilling of cast iron components on a Vertical Machining Centre (VMC) under MQL conditions using a semisynthetic cutting fluid. The objectives include reducing surface roughness, increasing MRR, and minimizing machining time. The Taguchi design of experiments will be used for structuring the trials, and Analysis of Variance (ANOVA) will be applied to identify statistically significant factors influencing the outcomes.

In industrial manufacturing, casting is typically followed by subtractive processes such as drilling. The VMC is a widely adopted platform for such operations due to its precision and adaptability. While previous studies have addressed MQL-based drilling with various lubricants, limited research exists specifically on FG300 grade flange castings using semisynthetic fluids.[7] [8] Therefore, this research focuses on optimizing drilling parameters for FG300 flanges under MQL conditions, with the goal of improving output characteristics and enhancing overall process efficiency.

II. RELEVANCE

In manufacturing, the process typically begins with casting, followed by material removal operations. For metal components, drilling is a fundamental machining operation often performed on a Vertical Machining Centre (VMC), which is widely used for producing precise drilled features. This study aims to optimize the machining parameters—specifically focusing on surface roughness, material removal rate (MRR), and machining time—during the drilling of FG300 cast iron flanges under Minimum Quantity Lubrication (MQL) conditions. To evaluate and enhance these performance measures, statistical tools such as ANOVA and the Taguchi method are employed. The primary objective is to achieve improved machining efficiency by minimizing surface irregularities and maximizing MRR, contributing to cost-effective manufacturing.

While various researchers have explored the use of MQL with different cutting fluids, limited work has been reported on FG300 flange castings using semi-synthetic lubricants. [9] [10] [11] Therefore, this research is directed at optimizing machining parameters on a vertical machining centre and examining their influence on performance outputs when using a semi-synthetic cutting fluid under MQL conditions.

III. METHODOLOGY

- Selection of drilling parameters, their levels, and corresponding performance indicators based on an extensive literature review and practical insights from industry practices for experimental setup.
- Determination of the machining path using the part drawing, followed by simulation of the VMC (Vertical Machining Center) program on the same machine to verify accuracy prior to execution.
- Formulation of the experimental plan by designing appropriate trials for the chosen parameters and their respective levels.
- Execution of the machining trials in line with the experimental design.
- Evaluation of experimental data to identify the parameters that significantly affect the performance outcomes.
- Application of statistical analysis tools to develop the correlation between process variables and output characteristics.
- Determination of the most favorable combination of process parameters to achieve optimal performance.
- Experimental validation of the optimized parameters through confirmation tests.

Table 1: Process parameters with levels.

Parameter	Unit	Level1	Level 2	Level 3
Speed	mm/rev	1200	1800	2400
Feed	mm/rev	0.15	0.20	0.25
Flow rate	ml/hr	50	60	

The Table 1 shows the selected process parameters with their levels.

Table 2: Parametric combinations (Taguchi Method)

Sr. No.	Speed	Feed	Flow Rate
1	N1	R1	50
2	N1	R2	50
3	N1	R3	50
4	N2	R1	50
5	N2	R2	50
6	N2	R3	50
7	N3	R1	50
8	N3	R2	50
9	N3	R3	50
10	N1	R1	60
11	N1	R2	60
12	N1	R3	60
13	N2	R1	60
14	N2	R2	60
15	N2	R3	60
16	N3	R1	60
17	N3	R2	60
18	N3	R3	60

The Table 2 shows the Parametric combinations (Taguchi Method) for experiment.

Selection of Process Parameters- The levels of these parameters are decided on the basis of self-initial experiments, literature survey as well as input from the production engineers who are using CNC machine.

IV. EXPERIMENTAL OUTCOMES AND IDENTIFICATION OF KEY MACHINING FACTORS AFFECTING SURFACE ROUGHNESS VIA ANOVA

The internal surface roughness of the specimen was evaluated using a Mitutoyo surface roughness tester, with a stroke length of 0.25 × 5 µm. The table displays the Signal-to-Noise ratio for the surface roughness, derived from the average values of two experimental repetitions.

Table 3: Process parameters and their levels

Exp. No	Ra		
	First trial	Second trial	Avg. Ra value
1	1.9285	1.9305	1.9295
2	1.8777	1.8797	1.8787
3	1.8278	1.8278	1.8278
4	2.4612	2.4632	2.4622
5	2.4115	2.4112	2.4113
6	2.3615	2.3595	2.3605
7	2.9938	2.9958	2.9948
8	2.944	2.944	2.9440
9	2.8922	2.8942	2.8932
10	3.2516	3.2488	3.2502
11	3.1993	3.1993	3.1993
12	3.1485	3.1485	3.1485
13	3.7828	3.7828	3.7828
14	3.732	3.732	3.7320
15	3.6812	3.6812	3.6812
16	4.3165	4.3145	4.3155
17	4.2647	4.2647	4.2647
18	4.2124	4.2151	4.2138

The Table 3 shows the experimental trials conducted for surface roughness.

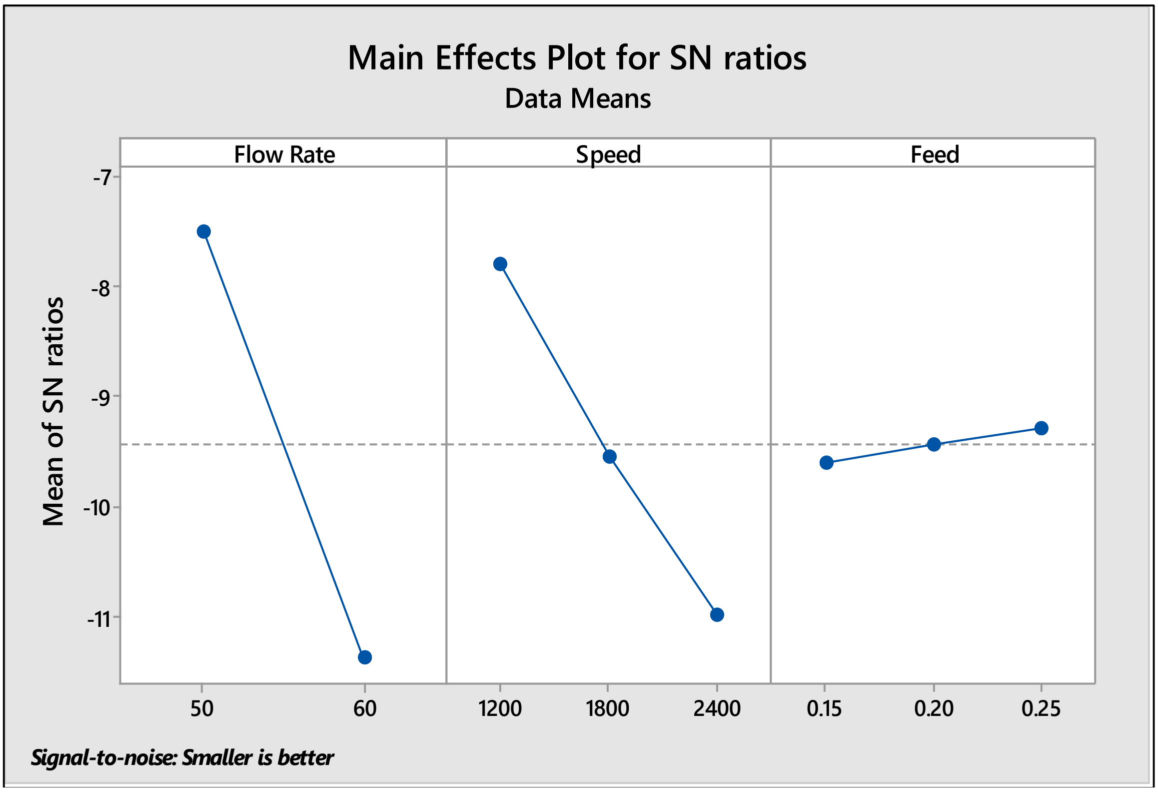

Figure 1: Graph of S/N ratio for surface roughness

The Figure 1 displays the average S/N values on the Y-axis and the varying levels of machining parameters on the X-axis. From the graph, it is evident that surface roughness tends to rise with higher cutting speeds and decreases as the feed rate increases. Additionally, the lowest surface roughness is observed when the lubricant flow rate is set at 50 ml/h.

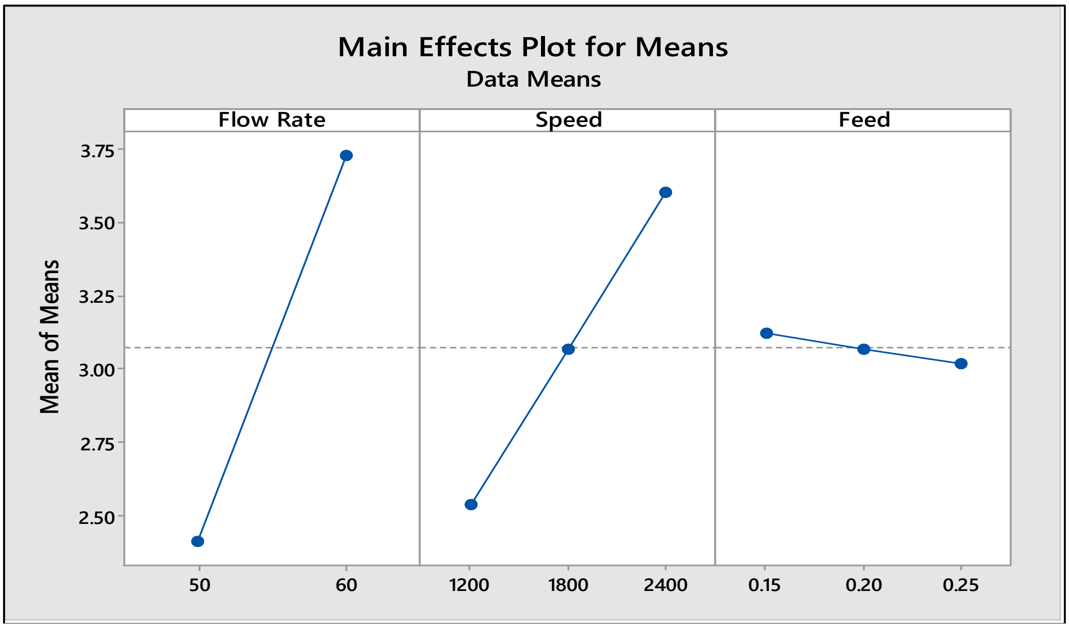

Figure 2: Graph for the means

The Figure 2 describes Flow Rate and Speed are influential factors. Feed has minimal impact on the mean response. The steeper the slope, the greater the factor's effect on the outcome.

Table 4: ANOVA for Ra

Source	DF	Seq.SS	Adj.SS	Adj.MS	F value	P value	% contribution
Flow rate	1	7.8487	7.8487	7.8487	7.06385E+09	0.000	69.55
Speed	2	3.4048	3.40481	1.70240	1.53216E+09	0.000	30.17
Feed	2	0.0310	0.03101	0.01550	13953750	0.000	0.27
Error	12	0.000	0.000	0.000			
Total	17	11.2845					

From the above Table 4 it is clear that, Flow Rate and Speed are the dominant factors affecting Ra, while Feed has a minimal but statistically detectable effect.

Table 5: Signal-to-Noise Ratio Table for Ra,

Levels	Flow rate	Speed	Feed
1	-7.499	-7.788	-9.593
2	-11.379	-9.541	-9.440
3		-10.988	-9.284
Delta	3.880	3.200	0.309
Rank	1	2	3

Table 6: Table for Means for Ra value

Level	Flow rate	Speed	Feed
1	2.411	2.539	3.123
2	3.732	3.072	3.072
3		3.604	3.021
Delta	1.321	1.065	0.102
Rank	1	2	3

Tables 5 and 6 clearly indicate that coolant flow rate has the greatest impact on surface roughness, with cutting speed and feed rate exerting comparatively lesser influence.

V. IDENTIFICATION OF KEY MACHINING PARAMETERS AFFECTING CIRCULARITY THROUGH ANOVA ANALYSIS

Table 7: Observed Outcomes of MRR

Exp. No	MRR		
	First trial	Second trial	Avg. MRR value
1	1404	1404	1404
2	1889	1889	1889
3	2375	2375	2375
4	2014	2014	2014
5	2500	2500	2500
6	2986	2986	2986
7	2625	2625	2625
8	3111	3111	3111
9	3596	3596	3596
10	1385	1385	1385
11	1870	1870	1870
12	2356	2356	2356
13	1995	1995	1995
14	2481	2481	2481
15	2966	2966	2966
16	2606	2606	2606
17	3091	3091	3091
18	3750	3750	3750

The Table 7 shows the experimental trials conducted for MRR

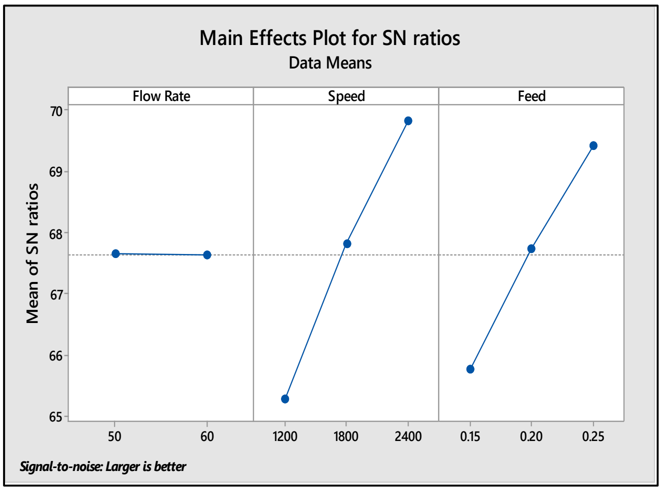

Figure 3: Main effect plot of S/N ratio for MRR

Figure 4: Main effect plot for means for MRR

From Figure 3 and Figure 4, it is clear that, the circularity increases with the increase in the speed and the feed with changing drilling cycle and tool grade that also effect on the circularity.

In continuous drilling cycle circularity decreases and in peck drilling cycle it increases. Coolant supply has very small effect on circularity.

Table 8: ANOVA for MRR

Source	DF	Seq. SS	Adj. SS	Adj.MS	F value	P value	% contribution
Speed	2	62.217	62.2172	31.1086	237.42	0.000	59.81
Feed	2	40.218	40.2181	20.1090	153.47	0.000	38.66
Flow rate	1	0.003	0.0032	0.0032	0.02	0.879	0.002
Error	12	1.572	1.5724	0.1310			
Total	17	104.01					

From Table 8 it is clear that, the Flow Rate and Speed are the dominant factors affecting Ra, while Feed has a minimal but statistically detectable effect.

Table 9: Table for S/N Ratios for MRR, Smaller is better

Level	Flow rate	Speed	Feed
1	67.65	65.28	65.76
2	67.63	67.81	67.75
3		69.83	69.42
Delta	0.03	4.54	3.66
Rank	3	1	2

Table 10: Table for Means

Level	Flow rate	Speed	Feed
1	2500	1880	2005
2	2500	2490	2490
3		3130	3005
Delta	0	1250	1000
Rank	3	1	2

Table 9 presents rankings derived from delta statistics, where delta represents the total variation between the highest and lowest mean values for each factor, regardless of intermediate fluctuations. These values help in assessing the relative influence of each parameter. A higher delta and corresponding rank indicate a stronger impact on the response. The data reveals that speed has the most substantial effect on material removal rate (MRR), followed by feed, with flow rate having the least influence. Table 10 describes Speed is the most influential factor, followed by Feed, while Flow Rate shows no effect on the response based on mean values.

Determination of significant process parameters for straightness (radial deviation) by ANOVA method

Table 11: Experimental results of time for machining

Exp. No	Time		
	First trial	Second trial	Avg. Time value
1	3.53	3.54	3.54
2	3.39	3.38	3.39
3	3.24	3.24	3.24
4	3.51	3.49	3.50
5	3.35	3.35	3.35
6	3.20	3.21	3.20
7	3.46	3.46	3.46
8	3.31	3.31	3.31
9	3.19	3.13	3.16
10	3.53	3.53	3.53
11	3.38	3.38	3.38
12	3.18	3.25	3.22
13	3.48	3.48	3.48
14	3.33	3.33	3.33
15	3.18	3.18	3.18
16	3.44	3.44	3.44
17	3.29	3.29	3.29
18	3.20	3.20	3.20

The Table 11 shows the experimental trials conducted for MRR

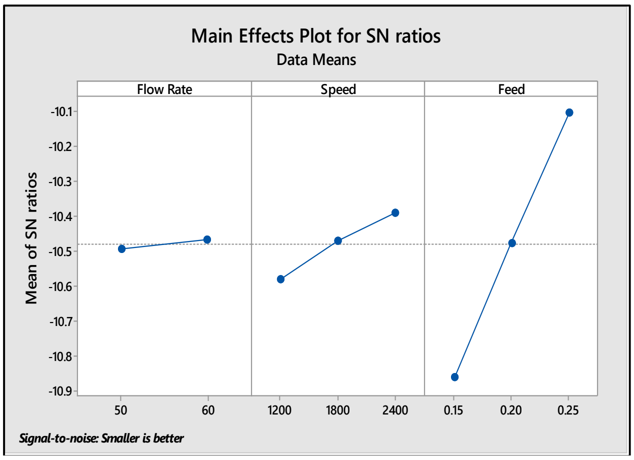

Figure 5: Graph of S/N ratio for time for machining

In the above Figure 5, the X-axis represents various levels, while the Y-axis shows the average S/N ratio. From the graph, it is clear that machining time tends to increase as both speed and feed are increased. The flow rate has a minimal impact on the machining time.

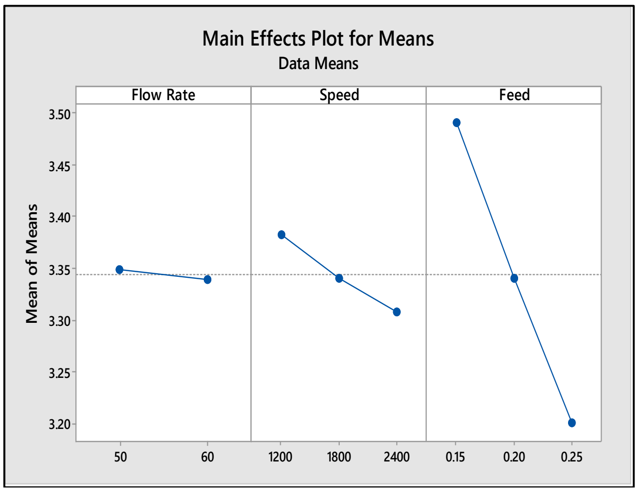

Figure 6: Graph of S/N ratio for time for machining

In the main effect plot for the S/N ratio of machining time, the X-axis represents different levels of the process parameters, while the Y-axis displays the average S/N ratio. As seen in Figure 6, machining time increases with higher values of speed and feed, while the flow rate has a negligible effect on machining time

Figure 7: Graph of means for time for machining

The Figure 7 describes, Feed has the most significant influence on reducing the response, followed by Speed, while Flow Rate has little impact.

Table 12: Analysis of variance for time for machining

Source	DF	Seq. SS	Adj. SS	Adj.MS	F value	P value	% contribution
Flow rate	1	0.000435	0.000435	0.000435	2.18	0.165	0.15
Speed	2	0.016760	0.016760	0.008380	41.99	0.000	6.11
Feed	2	0.254428	0.254428	0.127214	637.44	0.000	92.85
Error	12	0.002395	0.002395	0.000200			
Total	17	0.274018					

Table 12 describes Feed is the dominant factor affecting machining time, followed by Speed, while Flow Rate has negligible impact.

Table 13: Table for S/N Ratios for time for machining, smaller is better

Level	Flow rate	Speed	Feed
1	-10.49	-10.58	-10.86
2	-10.47	-10.47	-10.48
3		-10.39	-10.10
Delta	0.02	0.19	0.76
Rank	3	2	1

Table 14: Table for S/N Ratios for

Level	Flow rate	Speed	Feed
1	3.349	3.383	3.492
2	3.339	3.341	3.341
3		3.309	3.200
Delta	0.010	0.075	0.291
Rank	3	2	1

Table 14 describes Feed is the most influential factor affecting process stability, followed by Speed, while Flow Rate has minimal effect on the S/N ratio.

VI. PREDICTED OUTCOME BY TAGUCHI METHOD

Once the best combination of process parameters has been determined, the following step involves forecasting and validating the expected improvements in performance outcomes using these settings. The recommended configurations for each performance measure are outlined below:

- For surface roughness: N1-R3-Flow rate 1
- For MRR: N1-R1
- For machining time: N3-R3-Flow rate 1

Confirmation experiments are conducted to validate the conclusions derived from the analysis.

VII. ESTIMATION OF OPTIMAL SURFACE ROUGHNESS VALUES USING THE REGRESSION EQUATION

After establishing the ideal machining parameter values, the next phase focused on estimating the expected enhancement in surface roughness and verifying these estimates through a confirmation experiment. This step is crucial for ensuring the consistency and reliability of the analytical findings. Table 15 illustrates how surface roughness is influenced by the selected process parameters.

Table 15: Coefficient of factor for Ra

Term	Coefficient
Constant	-5.58667
Flow rate	0.132067
S	0.000888
F	-1.01667

Regression Equation

The regression model for predicting surface roughness (Ra) is given as:

$Ra = -5.58667 + 0.132067 \times \text{flow rate} + 0.000888 \times \text{speed} - 1.01667 \times \text{feed}$

The model's performance is reflected in its statistical indicators, with $R^2 = 100\%$ and adjusted $R^2 = 100\%$, demonstrating a strong fit and confirming the reliability of the regression equation. After accounting for significant variables, the model successfully explains 88.34% of the variability in surface roughness.

Using the optimal parameters—flow rate = 50 ml/hr, cutting speed = 1200 rpm, and feed = 0.25 mm/min—the estimated surface roughness is calculated as:

$Ra = -5.58667 + (0.132067 \times 50) + (0.000888 \times 1200) - (1.01667 \times 0.25) = 1.82\ \mu m$

Predicted of optimal value of MRR by using following regression equation

Once the optimal level of the geometry parameters is identified, the final step is to predict and validate the improvement of the performance measures using the optimal level, i.e. for MRR N1-R1. The confirmation experiment is conducted to validate the conclusions derived during the analysis phase. Table 16 presents the relationship between MRR and process parameters.

Table 16: Coefficient of factor for MRR

Term	Coefficient
Constant	-1375
Flow rate	0
S	1.0417
F	10000

Regression Equation

MRR= -1375 + 1.0417 * Speed + 10000* feed.

For this model R2 value = 99.72%, R2 (adj) = 99.66%

This suggests that the model is desirable and that, when important parameters are taken into account, the model explains 96.93% of the variability.

MRR= -1375 + 1.0417 * 1200 + 10000* 0.15.

= 1375 mm3/min

Predicted of optimal value of time for machining by using following regression equation

Predicting and validating the improvement of the performance measures using the optimal level—that is, for straightness N3-R3-flow rate 2—comes last after the ideal level of the geometry parameters has been determined. The confirmation experiment's goal is to validate the findings from the analysis stage.

The first order polynomial was used to link the answer with the factors. Table 17 illustrates the connection between straightness and process parameters.

Table 17: Coefficient of factor for time for machining

Term	Coefficient
Constant	4.0926
Flow rate	-0.000983
S	0.000062
F	-2.9116

Regression Equation

Time = 4.0926 - 0.000983-* Flow rate -0.000062*speed-2.9116*feed

For this model R2 value = 99.05%, R2 (adj) = 98.85% this indicate that the model is desirable and 92.46%variability is explained by the model after considering significant parameters.

Time = 4.0926 - 0.000983 *60 - 0.000062 *2400 - 2.9116 *0.25

= 3.156

Table 18: Coefficient of factor for time for Ra

	Prediction	Experiment
Level	N1-R3-Flow rate 1	
surface roughness	1.82	1.8278

The experiments were performed using the optimal settings for each parameter. Table 18 presents a comparison between the forecasted and observed values recorded during the experimental run. The close alignment between the predicted and measured surface roughness confirms the effectiveness of the chosen control parameter optimization.

Table 19: Confirmation of experiments for MRR

	Prediction	Experiment
Level	N1-R1	
MRR	1375	1385

The experimental trials were carried out using the most favorable level of each parameter. Table 19 provides a comparison between the estimated and actual circularity outcomes obtained during testing. The close match between the predicted and measured values suggests that the control parameters were effectively optimized.

Table 20: Confirmation of experiments for Time for machining

	Prediction	Experiment
Level	N3-R3- flow rate 1	
Straightness	3.156	3.16

The Table 20 describes confirmation test supports the validity of the model, with only a small deviation between predicted and actual results.

VIII. CONCLUSIONS

Conclusions Drawn from the Experimental Study:

- The analysis of surface roughness data indicates that flow rate has the most substantial effect among the tested parameters, while cutting speed and feed rate have moderate and minimal influences, respectively.
- The most effective parameter combination for achieving the lowest surface roughness was identified as 1200 rpm spindle speed, 0.25 mm/min feed rate, and a coolant flow of 50 ml/hr (S1-F3-Flow Rate 1). ANOVA results show that the flow rate is responsible for 69.55% of the variation in roughness, speed for 30.17%, and feed for only 0.27%.
- In the analysis of Material Removal Rate (MRR), cutting speed was found to be the primary influencing factor, with feed rate having a lesser impact, while the coolant flow rate showed minimal effect.
- The greatest MRR was obtained at the lowest levels of both speed and feed (S1-F1). ANOVA indicated that speed contributed 59.81% to the variability in MRR, feed rate 38.66%, and flow rate a minimal percentage.
- Among the parameters studied, feed rate had the strongest influence on machining time, whereas speed and flow rate were less impactful.
- The shortest machining time occurred at the highest speed setting (S3), highest feed rate (F3), and medium coolant flow (Flow Rate 2). ANOVA analysis determined that feed rate contributed 92.85% to the reduction in machining time, with speed and flow rate contributing 6.11% and 0.15%, respectively.
- Implementing the optimized machining parameters under the MQL system led to a significant enhancement in operational performance, increasing the flange output rate from approximately 80% to 90%. Moreover, coolant expenses were reduced, and rejection rates dropped from roughly 32% to about 12–13% monthly.

IX. FUTURE SCOPE

Following areas for research in future are identified from the findings of this experimentation.

- By experimenting with different grades of coolants, effects on quality of the hole can be studied.
- An investigation on wear of tool can be carried out with different tool grades.
- By using different coolant types, effects on quality of the hole can be studied.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest

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