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Optimizing Machining Parameters for End Milling 316l Stainless Steel under Dry Conditions

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Abstract— ***The manufacturing industry employs various metal cutting processes for part machining, with end milling being a prevalent method. Surface roughness significantly impacts the quality of machined parts, influencing properties such as wear resistance, ductility, tensile strength, and fatigue strength. This dissertation investigates the influence of cutting process parameters—cutting speed, feed rate, and depth of cut—on response variables including cutting force, surface roughness, and material removal rate (MRR). The objective is to optimize these parameters to achieve lower cutting force, reduced surface roughness, and higher MRR. Experiments were conducted on 316L stainless steel using a CNC milling machine equipped with TiSiN-coated solid carbide end mills. The Taguchi L9 design and ANOVA methods were utilized to identify the optimal parameter settings. Grey Relation Analysis (GRA) was also applied to evaluate the multiple performance characteristics and determine the optimal combination of parameters. Analysis of Variance (ANOVA) determined the significant influence of each parameter on the response variables. The findings indicate that depth of cut predominantly affects cutting force and surface roughness, while both depth of cut and feed rate significantly impact MRR. Optimal parameter settings are recommended based on varying priorities of MRR and surface roughness. This study provides valuable insights for enhancing machining efficiency and quality in industrial applications of 316L stainless steel.***

Index Terms— ***Dry Milling, ANOVA, Taguchi, Surface roughness, Cutting force, MRR.***

I. INTRODUCTION

In modern production environments, bridging the gap between productivity and quality is paramount. This study is centered on the optimization of machining process parameters applicable to the end milling of 316L Stainless Steel under dry machining conditions. Due to the material's inherent machinability challenges, identifying optimal process parameters is crucial for improving operational efficiency and product quality. The research endeavors to explore the utilization of neural networks in predicting tool wear and surface roughness in end milling procedures, with the overarching goal of augmenting surface quality and material removal rates. This endeavor involved optimizing cutting speed, feed rate, and depth of cut parameters. Additionally, the study conducted a comparative assessment of four optimization methodologies—Principal Components Analysis (PCA), Utility Theory, Grey Relational Analysis (GRA), and the Taguchi Optimization Principle—to assess their effectiveness in multi-objective optimization within CNC end milling. The outcomes underscore the pivotal role of depth of cut in diminishing surface roughness [1-4].

The investigation optimizes milling parameters for AISI 1040 steel through the application of the Taguchi method. The study successfully achieves desired levels of surface roughness, regardless of whether coated or uncoated inserts are employed. [5] The review of literature underscores the importance of improving surface roughness in AISI 316L stainless steel machining. It accentuates the predominant impact of the feed rate on surface roughness, while indicating that the influence of cutting speed on surface roughness outcomes is comparatively marginal [6]. The research endeavors to optimize the face milling process of stainless steel 316 utilizing the Taguchi method in conjunction with analysis of variance (ANOVA). The primary objective is to determine the optimal machining parameters that yield superior surface roughness (Ra) and material removal rate (MRR) under diverse coating conditions [7]. The study introduces a cost-effective, versatile multi-sensor tool condition monitoring system aimed at precise forecasts of tool wear. Experimental data validates its accuracy. Future research will focus on enhancing system calibration and advancing data analysis techniques [8]. The study investigates multiple techniques including Singular Value Decomposition (SVD), Pseudo Inverse, Kalman filter, and empirical methods to indirectly ascertain forces in machining, particularly cutting forces, tool wear, and condition monitoring. The aim is to enhance the estimation of cutting forces for optimal tool design, supplemented by statistical analysis [9]. The research aims to determine the most effective cutting parameters for enhancing overall performance, reducing tool wear, and improving metal removal and wear rate during the milling of Ti-6Al-4V Alloy. This is achieved through the utilization of a genetic algorithm [10]. Additionally, it enhances cutting parameters for a CNC turning machine to address surface inspection challenges, employing ANOVA to evaluate the influence of parameters on surface roughness (Ra) and material removal rate (MRR), leading to enhanced MRR and reduced surface roughness [11]. This study investigates the application of vegetable oil

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in Minimum Quantity Lubrication (MQL) setups for machining AISI O2 steel. It utilizes Taguchi, GRA, and RSM methodologies to enhance cutting tool performance and reduce wear. Achieving an impressive predictive accuracy of 0.9963 R-squared value, the research makes significant strides in promoting sustainable manufacturing practices [12]. The study emphasizes temperature forecasting, tool wear analysis, and power consumption assessment, advocating for dry machining for health and environmental reasons. Utilizing Taguchi methods in experimental setup, it incorporates Response Surface Methodology (RSM), Box-Behnken Design (BBD), and Multi-Objective Genetic Algorithm (MOGA) to fine-tune machining variables. The experimental outcomes closely align with forecasts, demonstrating an error margin of under 4% [13]. The investigation utilizes Taguchi methodology alongside Grey Relational Analysis (GRA) to optimize various objectives in the end milling process of enset fiber composites. It delineates the optimal surface roughness achieved at lower spindle speed and feed rate settings, highlighting the influence of depth of cut on surface roughness and feed rate on material removal rate [14]. The study surpasses previous research by refining milling force coefficients and cutter run-out parameters, showcasing heightened predictive precision compared to the conventional average force approach. These findings imply broader effectiveness across diverse milling conditions and methodologies [15].

II. METHODS AND MATERIALS

The research systematically examines the effects of cutting speed, feed rate, and depth of cut on critical performance metrics: cutting force, surface roughness, and material removal rate (MRR). Employing Analysis of Variance (ANOVA), the study statistically dissects the influence of each process parameter on machining performance, offering a quantitative evaluation of their significance.

Utilizing the Taguchi L9 orthogonal array, the experimental design minimizes the number of trials while ensuring comprehensive analysis. This method identifies robust parameter configurations that enhance performance across varied machining conditions.

Employing a distinctive orthogonal array design, the Taguchi method enables a comprehensive exploration of the entire parameter space while minimizing the number of required experiments. Analysis of Variance (ANOVA) is utilized to determine the most significant factor impacting the response. The study adopts a "Smaller-the-better" criterion for evaluating surface roughness and cutting force, and a "Higher-the-better" criterion for assessing material removal rate.

The calculations for Signal-to-Noise (S/N) ratios are conducted using the following formulas:

Table 1 Chemical Analysis of 316l Stainless Steel

Grade	C%	M%	P%	Si%	Ni%	Cr%	N%	Mo%
316L	0.023	0.005	0.043	0.26	10.03	16.25	0.038	2.02

Employing a distinctive orthogonal array design, the Taguchi method enables a comprehensive exploration of the entire parameter space while minimizing the number of required experiments. Analysis of Variance (ANOVA) is utilized to determine the most significant factor impacting the response. The study adopts a "Smaller-the-better" criterion for evaluating surface roughness and cutting force, and a "Higher-the-better" criterion for assessing material removal rate.

The calculations for Signal-to-Noise (S/N) ratios are conducted using the following formulas:

$\frac{S}{N} = -10 \log \frac{1}{n} \Sigma^{n} y^2$ ……….. For lower the better Characteristics (Eq. 1)

$\frac{S}{N} = -10 \log \frac{1}{n} \Sigma^{n} \frac{1}{y^2}$ ………. For higher the better Characteristics (Eq. 2)

In the experimental setup, we conducted machining operations on 316L Stainless Steel employing a CNC milling machine outfitted with TiSiN-coated solid carbide end mills. We systematically adjusted the cutting process parameters throughout the experimental runs, while measuring and recording the response variables.

Subsequently, we analyzed the experimental data using ANOVA and GRA techniques to pinpoint the optimal machining parameters and assess their significance. Figure 1 depicts the measurement setup for cutting force analysis, comprising a Kistler dynamometer, a charge amplifier, a data acquisition system, and data processing software.

The dynamometer is employed to gauge the forces and torque in action. Positioned on the machine bed, the dynamometer interfaces with an amplification unit and a PC running Dynoware software, facilitating the logging and exportation of cutting force data. The data acquisition system, utilizing Dynoware software, is employed for subsequent analysis.

Figure 1 Experimental setup

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Table 1 presents the chemical properties of stainless steel 316L. End mill slotting employs a four-flute cutter with an 8mm diameter, coated in TiSiN.

Table 2 presents the attributes of an end mill cutter made of solid carbide and coated with TiSiN.

Table 2 End Mill Cutter Technical Specifications

Sr. No.	Description	Specification
1	Material	Solid Caride
2	No. of flutes	4
3	Diameter of tool	8 mm
4	Helix Angle	35
5	Manufacturer	SURPASS
6	Coating	TiSiN
7	Maximum cutting speed	1990 rpm
8	Hardness	55 HRC
9	feed/tooth for slotting	0.08

The experimental setup comprised three levels and three criteria, specifically evaluating cutting force, surface roughness (Ra), and material removal rate (MRR). The control parameters included cutting speed, feed rate, and depth of cut. Utilizing Taguchi's design methodology, an L9 orthogonal array was employed, resulting in nine experimental trials for each coating type. Detailed information on the process parameters and their respective levels is presented in Table 3.

Table 3 Process Parameter and Their Levels

Factors	Units	Level 1	Level 2	Level 3
Cutting Speed (Vc)	RPM	1400	1600	1800
Depth of cut (d)	mm	0.2	0.4	0.5
Feed rate (f)	mm/rev	0.025	0.04	0.055

Table 4 Observations for L9 Experimentation

Sr. No.	d (mm)	f (mm/rev)	Vc (RPM)	t (Sec.)	F_c (N)	SR (μm)	MRR (cc/min)
1	0.2	0.025	1400	85.7	47.61	0.14	4.748
2	0.2	0.04	1600	46.87	48.22	0.142	8.683
3	0.2	0.055	1800	30.3	54.47	0.146	13.43
4	0.4	0.025	1600	75	79.96	0.206	10.85
5	0.4	0.04	1800	41.67	83.16	0.171	19.53
6	0.4	0.055	1400	38.96	88.81	0.184	20.89
7	0.5	0.025	1800	66.67	87.89	0.156	12.21
8	0.5	0.04	1400	53.57	115.8	0.151	15.19
9	0.5	0.055	1600	34.09	121	0.168	17.87

III. RESULTS AND DISCUSSION

Analysis of Variance (ANOVA) is the predominant statistical method utilized in experimental results to quantify the percentage contribution of each factor. Examination of the ANOVA table for a specific analysis aid in identifying the factors requiring control and those that do not.

The ANOVA analysis, detailed in Table 5, highlights the significant factors affecting cutting force. Depth of cut emerges as the most influential, contributing 87.92%, followed by feed rate at 7.03%, with cutting speed making the least contribution at 2.45%. The ANOVA table for cutting force reveals that cutting speed and depth of cut are indeed significant factors, with p-values of 0.029, exceeding the 0.05 threshold for a 95% confidence level. Additionally, their F-values of 33.75 greatly surpass the critical F-value of 4.46. However, despite its contribution factor of 7.03%, feed rate does not hold significance, as its p-value is higher than 0.05.

Table 5 Analysis of Variance for Cutting Force

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
d (mm)	2	5114.9	87.92%	5114.9	2557.47	33.75	0.029
f (mm/rev)	2	409.1	7.03%	409.1	204.55	2.7	0.27
Vc (RPM)	2	142.4	2.45%	142.4	71.22	0.94	0.515
Error	2	151.5	2.60%	151.5	75.77		
Total	8	5818	100.00%				

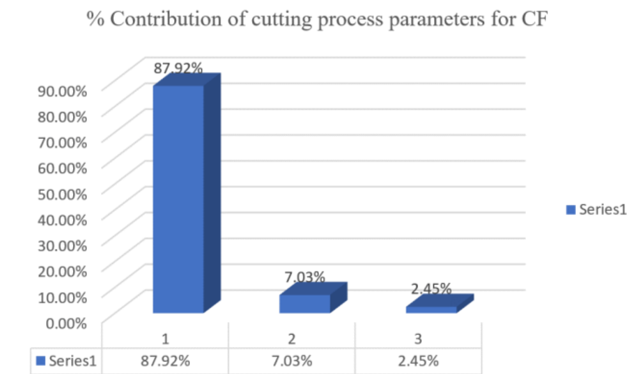

Figure 2: % Contribution of Cutting Process Parameters for Cutting Force

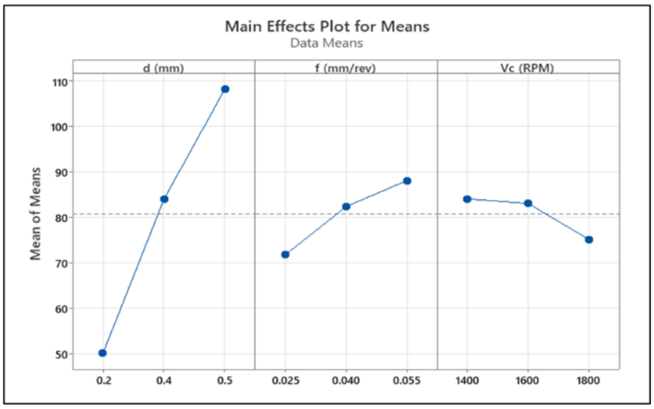

Figure 3: Main Effect Plot for Cutting Force

Figure 3 illustrates the average cutting force values across different depths of cut, feed rates, and cutting speeds, as detailed in Table 4.4. Notably, a cutting speed of 1800 RPM (level 3) yields the lowest average cutting force of 75.17 N, while a cutting speed of 1400 RPM (level 1) corresponds to the highest cutting force of 84.07 N. Thus, maintaining the cutting speed at level 3 is advisable for minimizing cutting forces. Regarding the depth of cut (mm), level 1 produces the lowest average cutting force of 50.1 N, whereas level 3 (0.5 mm) results in the highest cutting force of 108.23 N. Consequently, it is recommended to set the depth of cut at level 1 to mitigate cutting forces. Analyzing the graph, it is evident that a feed rate of 0.025 mm/rev (level 1) yields the lowest cutting force of 71.82 N, whereas a feed rate of 0.055 mm/rev (level 3) corresponds to the highest cutting force of 88.09 N. Therefore, opting for a feed rate at level 3 is preferable for minimizing cutting forces.

Table 5 Response Table for Means of Cutting Force

Level	Depth of Cut (mm)	Feed Rate (mm/rev)	Cutting Speed (RPM)
1	50.1	71.82	84.07
2	83.98	82.39	83.06
3	108.23	88.09	75.17
Delta	58.13	16.27	8.9
Rank	1	2	3

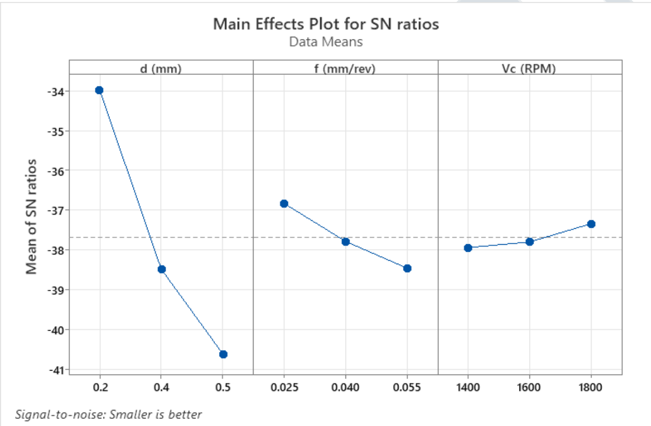

Figure 4 Main Effect Plot for S/N Ratio of Cutting Force

Figure 4 illustrates the main effects graphs. From these plots, one can forecast the optimal levels of milling parameters for the S/N ratio of cutting force. Notably, for achieving the maximum S/N ratio, it is observed that level 3 for cutting speed, level 1 for depth of cut, and level 1 for feed rate are ideal. Lower cutting force correlates with a preferable S/N ratio, as evidenced by the main effect plot for the S/N ratio of cutting force.

The ANOVA analysis presented in Table 6 delineates the distribution of data means. Notably, depth of cut exhibits a substantial contribution of 79.18% to surface roughness, whereas feed rate and cutting speed only contribute 7.59% and 10.25%, respectively. The ANOVA table for surface roughness, as depicted in Table 4.5, underscores the prominence of depth of cut as the most significant factor. This assertion is supported by its p-value of 0.036, falling below the critical threshold of 0.05 at a 95% confidence level. Moreover, its corresponding F-value of 26.6 significantly exceeds the tabulated F-value [at (2, 8) = 4.46], further substantiating its significance. In contrast, feed rate and cutting speed exhibit insignificance, with p-values exceeding 0.05 and F-values of 0.282 and 0.225, respectively, both notably below the table F-value [at (2, 8) = 4.46].

Table 6 Analysis of Variance for Surface Roughness

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
d (mm)	2	0.003033	79.18%	0.003	0.00152	26.6	0.036
f (mm/rev)	2	0.000291	7.59%	0.0003	0.00015	2.55	0.282
Vc (RPM)	2	0.000393	10.25%	0.0004	0.0002	3.44	0.225
Error	2	0.000114	2.98%	0.0001	5.7E-05		
Total	8	0.00383	100.00%				

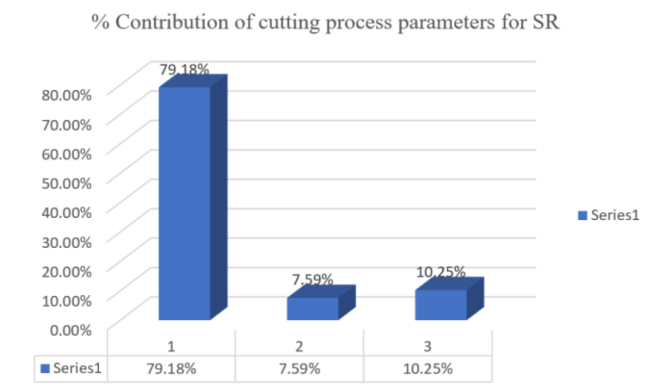

Figure 5 % Contribution of Cutting Process Parameters for SR

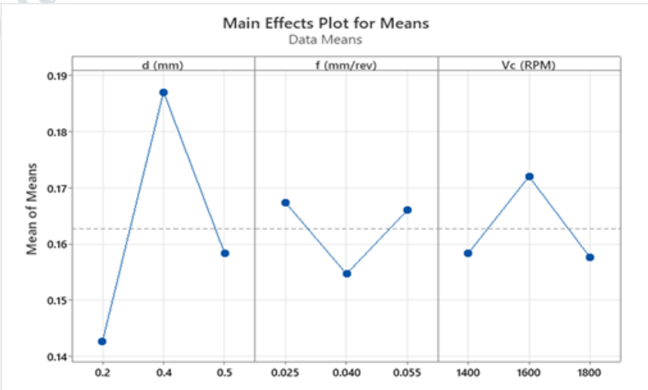

Figure 6 Main Effect Plot for Surface Roughness

Figure 6 presents the average Surface Roughness (SR) values across different levels of Cutting Speed, Feed Rate, and Depth of Cut [refer to Table 6]. The data demonstrates that a Depth of Cut at level 1 (0.2 mm) results in the lowest average SR value of 0.1427 µm, whereas level 2 (0.4 mm) produces the highest SR value of 0.187 µm. Consequently,

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maintaining the Depth of Cut at level 1 is advisable for achieving lower SR values. Regarding Feed Rate (mm/rev), level 2 exhibits the lowest average SR value of 0.1547 µm, while level 1 (0.025 mm/rev) yields the highest SR value of 0.1673 µm, indicating that Feed Rate should be set at level 2. The graph further illustrates that Cutting Speed at level 3 (1800 RPM) provides the lowest SR value of 0.1577 µm. Conversely, level 2 (1400 RPM) results in the highest SR value of 0.172 µm, with level 1 (1400 RPM) producing an intermediate SR value of 0.1583 µm. Therefore, to achieve minimal SR values, Cutting Speed should be maintained at level 3.

Table 7 Response Table for Means of SR

Level	Depth of Cut(mm)	Feed Rate (mm/rev)	Cutting Speed (RPM)
1	0.1427	0.1673	0.1583
2	0.187	0.1547	0.172
3	0.1583	0.166	0.1577
Delta	0.0443	0.0127	0.0143
Rank	1	2	3

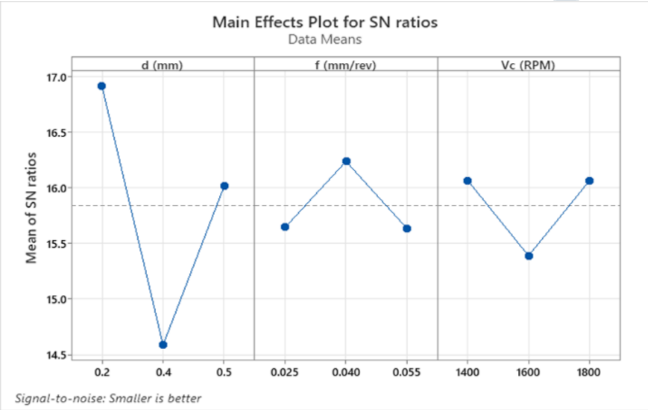

Figure 7 Main Effect Plot for S/N Ratio of Cutting Force

Figure 7 displays the main effects graphs for the milling parameters. Optimal milling parameter levels are identified from the main effects plot for the signal-to-noise (S/N) ratio of surface roughness (SR). The plot indicates that the highest S/N ratio values are achieved at cutting speed level 3, depth of cut level 3, and feed rate level 1. To minimize SR, a higher S/N ratio is preferable, as illustrated in the main effects plot for the S/N ratio of SR.

The analysis of variance (ANOVA) for the data means is presented in Table 8. The results indicate that the feed rate accounts for 45.99% of the contribution, while the depth of cut contributes 48.80%. In contrast, the cutting speed contributes only 4.57% to the material removal rate (MRR). Figure 8 displays the Minitab 21 interface with ANOVA results for MRR, which closely align with the calculated values. Figure 9 illustrates the percentage contribution of the cutting process parameters to the MRR.

Table 8 Analysis of Variance for MRR

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
d (mm)	2	107.855	48.80%	107.86	53.9273	76.7	0.013
f (mm/rev)	2	101.655	45.99%	101.66	50.8276	72.3	0.014
Vc (RPM)	2	10.101	4.57%	10.101	5.0505	7.18	0.122
Error	2	1.406	0.64%	1.406	0.703		
Total	8	221.017	100.00%				

Table 9 Response Table for Means of SR

Level	Depth of Cut (mm)	Feed Rate (mm/rev)	Cutting Speed (RPM)
1	8.954	9.269	13.609
2	17.09	14.468	12.468
3	15.09	17.397	15.057
Delta	8.136	8.127	2.589
Rank	1	2	3

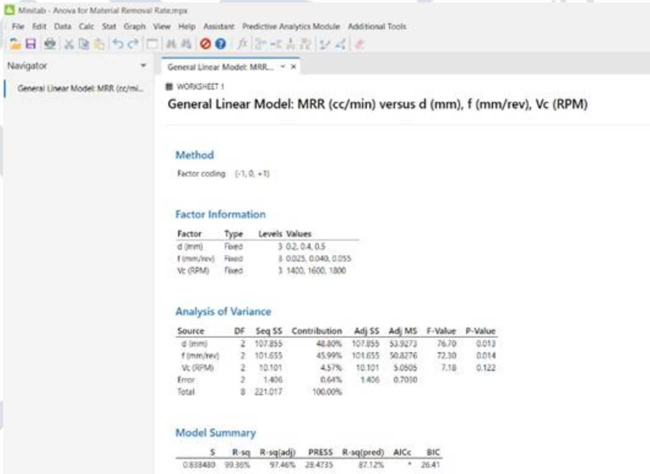

Figure 8 Minitab 21 Window with ANOVA Results for Surface MRR

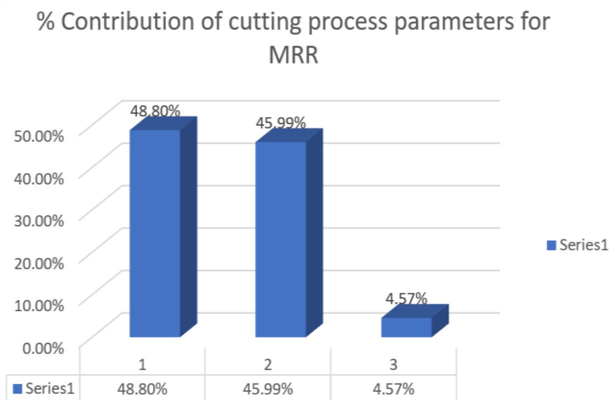

Figure 9 Contribution of Cutting Process Parameters for MRR

Figure 10 presents the average Material Removal Rate (MRR) values corresponding to different levels of Depth of Cut, Feed Rate, and Cutting Speed, as detailed in Table 9. The data indicate that the second level of Depth of Cut, specifically 0.4 mm, yields the highest average MRR value of 17.09 cc/min. Conversely, the first level, 0.2 mm, results in the lowest MRR value of 8.954 cc/min. Therefore, it is evident that a Depth of Cut of 0.4 mm should be maintained to achieve the highest MRR values.

Figure 10 Main Effect Plot for Material Removal Rate

In the context of feed rate (mm/rev), the experimental data indicates that at level 3, with a feed rate of 0.055 mm/rev, the highest average material removal rate (MRR) of 17.397 cc/min is achieved. Conversely, level 2, with a feed rate of 0.04 mm/rev, results in an intermediate MRR of 14.468 cc/min, while level 1, with a feed rate of 0.025 mm/rev, produces the lowest MRR of 9.269 cc/min. Therefore, maintaining the feed rate at level 3 is recommended to achieve the highest MRR. As illustrated in the accompanying graph, a depth of cut at level 3, corresponding to 0.5 mm, results in the highest MRR of 15.057 cc/min. In contrast, level 2, with a depth of cut of 0.4 mm, yields the lowest MRR of 12.468 cc/min, and level 1, with a depth of cut of 0.2 mm, provides an intermediate MRR of 13.609 cc/min. Hence, to maximize the MRR, the depth of cut should be optimized at level 3.

Figure 11 presents the main effects plots. The optimal levels for milling parameters are inferred from the main effects plot for the signal-to-noise (S/N) ratio of Material Removal Rate (MRR). The plots indicate that the maximum S/N ratio value is achieved at level 3 for cutting speed, level 2 for depth of cut, and level 3 for feed rate. A higher S/N ratio correlates with improved MRR, as demonstrated in the main effects plot for the S/N ratio of MRR.

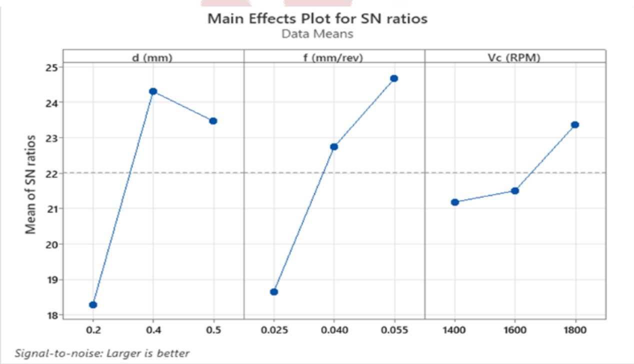

Figure 11 Main Effect Plot for S/N Ratio of MRR

A. Grey Relational Analysis (GRA)

Step 1: Grey Relational Generation

In the first step of grey relational generation normalize the experimental data according to the type of output response. For data pre-processing in the GRA process, "the lower cutting force, lower SR and the higher MRR" are the indication of better performance in hard milling operation. Then, it has a characteristic of the "higher is better" if the target value of original sequence is infinite. The original sequence can be normalized as following.

$$X_i^0(z) = \frac{\mathrm{Max}X_i^0(z) - X_i^0(z)}{\mathrm{Max}X_i^0(z) - \mathrm{Min}X_i^0(z)} \text{ ..... Lower The Better.... (4.1)}$$

$$X_i^0(z) = \frac{X_i^0(z) - \mathrm{Min}\, X_i^0(z)}{\mathrm{Max}X_i^0(z) - \mathrm{Min}X_i^0(z)} \text{.... Higher The Better.... (4.2)}$$

Equation 1st is used for lower the better characteristics, i.e., for Fe and SR, equation 2nd is used for higher the better characteristics, i.e., for MRR. Next step is to find out, the deviation sequence.

Step II: Deviation Sequence

$\Delta_{0i}(k) = x_0{*}(k) - x_i{*}(k)$ .... (4.3)

$X_0{*}(k) = 1$ .... (Maximum normalized value)

Step III: Grey Relational Coefficient

The grey relational coefficient can be calculated by using following equation.

$\xi_i(z) = \frac{\Delta_{min} + \zeta\Delta_{max}}{(\Delta_{0i}(z) + \zeta\Delta_{max})}$........... (4.4)

Where,

$\xi_i(z)$ = Grey Relational Coefficient

$\Delta min = mix\| x_0(z) - x_i(z) \| = \|1 - 1\| = 0$

$\Delta max = max\| x_0(z) - x_i(z) \| = \|1 - 0\| = 1$

ζ = distinguishing coefficient between [0, 1] = (0.5) selected.

$\Delta_{0i}(z)$ = Deviation sequence

$\Delta_{0i}(z) = \| x_{0*}(z) - x_{i*}(z) \|$

$x_i{*}(z) = 1$ .... (Maximum normalized value)

Where, $\Delta 0i$ (z) is the deviation sequence $x_0{*}(z)$ of the reference sequence and the x_0 (z) comparability sequence.

Step IV: Grey Relational Grade (γi)

The grey relational grade can be calculated by using following equation. gamma

$\gamma_i = \Sigma\, W_i(z) * \xi_i(z)$

Where,

γ_i = Grey relational grade

Wi = Weightage given to response variable

If the GRG has greater value, it shows that the concerned parameter combination is very nearer to the optimum value.

The analysis was done to determine the cutting force and surface roughness performance characteristics by assuming that lower is better and higher is better, respectively, and that MRR is better. Normalized values are presented in Table 9, deviation sequence Δ_{0i} and GRC are listed in Table 10, and GRG is listed in Table 11. Table 11 lists the predicted GRG

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for F_c, MRR, and SR, respectively, using different weight combinations of W1, W2, and W3. Applying the criterion of lowers is better features for Fc and SR respectively and higher is better characteristics for MRR yields the comparability sequence or normalizing value. Therefore, table 10 presents the normalized findings (for Fc, SR, and MRR) between 0 and 1 obtained for the L9 array together with observations.

Table 10 Normalizing Values for Cutting Force, MRR and SR

Sr. No.	d (mm)	f (mm/rev)	Vc (RPM)	F_c(N)	SR (µm)	MRR (cc/min)	Normalizing Values		
							F_c (N)	SR (µm)	MRR (cc/min)
1	0.2	0.025	1400	47.61	0.14	4.748	0	0	0
2	0.2	0.04	1600	48.22	0.142	8.683	0.008	0.03	0.244
3	0.2	0.055	1800	54.47	0.146	13.43	0.093	0.091	0.538
4	0.4	0.025	1600	79.96	0.206	10.85	0.441	1	0.378
5	0.4	0.04	1800	83.16	0.171	19.53	0.484	0.47	0.916
6	0.4	0.055	1400	88.81	0.184	20.89	0.561	0.667	1
7	0.5	0.025	1800	87.89	0.156	12.21	0.549	0.242	0.462
8	0.5	0.04	1400	115.8	0.151	15.19	0.929	0.167	0.647
9	0.5	0.055	1600	121	0.168	17.87	1	0.424	0.813

Table 11 Deviation Sequence and GRC for CF, MRR and SR

Deviation Sequence			Grey Relational Coefficient		
F_c (N)	SR (µm)	MRR (cc/min)	F_c (N)	SR (µm)	MRR (cc/min)
1	1	1	0.3333	0.33333	0.3333
0.992	0.97	0.756	0.3351	0.34014	0.3981
0.907	0.909	0.462	0.3554	0.35486	0.5198
0.559	0	0.622	0.4721	1.0000	0.4457
0.516	0.53	0.084	0.4921	0.48544	0.8562
0.439	0.333	0	0.5325	0.60024	1.0000
0.451	0.758	0.538	0.5258	0.39746	0.4817
0.071	0.833	0.353	0.8757	0.37509	0.5862
0	0.576	0.187	1.0000	0.46468	0.7278

Table 12 GRG and Order for CF, MRR and SR

Sr. No.	GRG W1 = 0.33, W2 = 0.33, W3 = 0.33	Order	GRG W1 = 0.25, W2 = 0.50, W3 = 0.25	Order	GRG W1 = 0.25, W2 = 0.25, W3 = 0.50	Order
1	0.1100	9	0.1111	9	0.1111	9
2	0.1181	8	0.1178	8	0.1226	8
3	0.1353	7	0.1321	7	0.1458	7
4	0.2110	3	0.2431	1	0.1970	5
5	0.2017	5	0.1933	4	0.2242	3
6	0.2346	2	0.2277	2	0.2611	1
7	0.1545	6	0.1502	6	0.1572	6
8	0.2021	4	0.1843	5	0.2019	4
9	0.2412	1	0.2214	3	0.2434	2

B. Parametric Level Optimization for Input Process Parameters

A. *Grey Relational Analysis (W = 0.54, W = 0.03, W = 0.43)*

With a given weights for F_c, MRR and SR run no. 4 (refer table 12) has the highest GRG value equal to 0.2412 with F_c = 121 N, MRR = 17.87 cc/min and SR = 0.168 µm. Thus, predicted optimum milling cutting process parameter levels setting by GRA are cutting speed at level 2; depth of cut at level 2 and feed rate at level 3, i.e., V-2, d-2 and f-3.

Table 13 Comparison between Grey Grade and Mean Prediction

Weights	Level	Initial process parameters	Optimum process parameters	
			Prediction	Experiment
		D-1, F-1 and v-1	D-2, f-3 and v-2	D-2, f-3 and v-2
a)	CF (N)	47.61	-	121
	MRR (cc/min)	4.748	-	17.87
	SR(µm)	0.14	-	0.168
	GRG	0.3300	0.7329	0.7235
	Improvement of the GRG		0.4029	
b)	CF (N)	47.61	-	79.96
	MRR (cc/min)	4.748	-	10.85
	SR(µm)	0.14	-	0.206
	GRG	0.3333	0.7243	0.7294
	Improvement of the GRG		0.3961	
c)	CF (N)	47.61	-	88.81
	MRR (cc/min)	4.748	-	20.89
	SR(µm)	0.14	-	0.184
	GRG	0.3333	0.7329	0.7438
	Improvement of the GRG		0.4105	

Figure 12 shows the graph and summary of average GRG for all cutting process parameter at each level respectively. The prediction of optimum cutting process parameter levels with response means approach c - 3d - 3 and f-3, gives as these levels have highest GRG values among respective groups. A confirmative test is taken with results Fc = 121 N, MRR = 17.87 cc/min and SR = 0.168 µm. This gives the GRG 0.7235. The results are shown in table 13.

Figure 12 Main Effect Plot for Material Removal Rate

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B. Grey Relational Analysis (W = 0.25, W = 0.50, W = 0.25)

With a given weights for Fc, MRR and SR run no. 4 (refer table 12) has the highest GRG value equal to 0.7293 with F_c = 79.96 N, MRR = 10.85 cc/min and SR = 0.206 µm. Thus, predicted optimum cutting process parameter levels setting by GRA are cutting speed at level 3; depth of cut at level 2 and feed rate at level 3, i.e., V_c-2, d-1 and f-1.

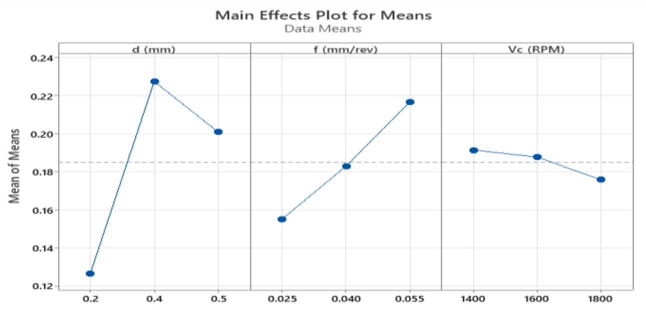

Figure 15 Grey Relational Vs Cutting Process Parameters

Figure 13 shows the graph and summary of average GRG for all cutting process parameter at each level respectively. The prediction of optimum cutting process parameter levels with response means approach V_c – 2, d-1 and f-1, gives as these levels have highest GRG values among respective groups. A confirmative test is taken with results F_c = 79.96 N, SR = 0.206 µm and MRR = 10.85 cc/min. This gives the GRG - 0.7294. The results are shown in table 4.14.

C. Grey Relational Analysis (W = 0.25, W = 0.25, W = 0.50)

With a given weights for F_c, MRR and SR run no. 6 (refer table 12) has the highest GRG value equal to 0.7438 with F = 88.81N, MRR = 20.89 cc/min and SR = 0.184 µm. Thus, predicted optimum cutting process parameter levels setting by GRA are cutting speed at level 1; depth of cut at level 2 and feed rate at level 3, i.e., V_c-1, d-2 and f-3.

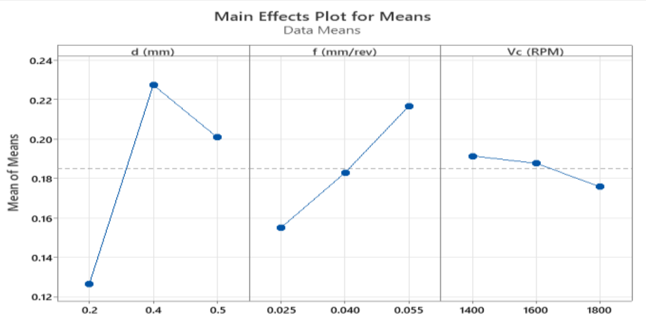

Figure 16 Grey Relational Vs Cutting Process Parameters

Figure 16 shows the graph and summary of average GRG for all cutting process parameter at each level respectively. The prediction of optimum cutting process parameter levels with response means approach d-2, f-3 and V_c-1 gives as these levels have highest GRG values among respective groups. An experimental test is taken with results F_c= 88.81, MRR = 20.89 cc/min and SR = 0.184 µm. This gives the GRG-0.6212. The results are shown in table 15.

IV. CONCLUSION

The depth of cut significantly affects cutting force (87.92%), while the impact of feed rate and cutting speed is minimal (7.03% and 9.24%, respectively). Analysis of the S/N ratio for cutting force predicts the optimal combination of milling parameters to be Vc = 1400 RPM, d = 0.5 mm, and f = 0.055 mm/rev, yielding the highest S/N ratio. Surface roughness is largely influenced by the depth of cut (79.18%), with feed rate and cutting speed having lesser effects (7.59% and 10.25%, respectively). S/N ratio analysis for surface roughness suggests the optimal combination of hard milling parameters as Vc = 1800 RPM, d = 0.2 mm, and f = 0.040 mm/rev, producing the maximum S/N ratio. Material removal rate (MRR) is significantly impacted by feed rate (45.99%) and depth of cut (48.80%), while cutting speed contributes minimally (4.57%). Analysis of the S/N ratio for MRR indicates the best combination of hard milling parameters to be Vc = 1800 RPM, d = 0.4 mm, and f = 0.055 mm/rev, yielding the highest S/N ratio.

The ideal configuration is determined by assigning equal weights to F, SR, and MRR, with a cutting speed of 1400 RPM, a cut depth of 0.5 mm, and a feed rate of 0.055 mm/rev. Setting the parameters to cut at 1800 RPM, cut depth of 0.4 mm, and feed rate of 0.055 mm/rev is recommended when MRR is prioritized. Setting the parameters to cut at 1800 RPM, cut depth of 0.2 mm, and feed rate of 0.040 mm/rev is recommended when SR is prioritized.

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