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Enhancing Machining Performance: A Study on Taguchi ANOVA and Grey Relational Analysis

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Abstract

This study aims to optimize surface roughness (Ra) and material removal rate (MRR) in machining processes by analyzing the effects of cutting parameters: speed, feed rate, and depth of cut. The primary objectives include identifying optimal parameter settings to minimize Ra and maximize MRR, and understanding the relative significance of each parameter. The study's hypotheses propose that variations in speed, feed rate, and depth of cut significantly influence Ra and MRR, with feed rate expected to have the greatest impact.

The methodology involves conducting 27 experimental runs based on a Taguchi L27 orthogonal array. Surface roughness and MRR were measured for each run, and corresponding signal-to-noise (S/N) ratios were calculated using the "lower is better" criterion for Ra and the "larger is better" criterion for MRR. Analysis of variance (ANOVA) was performed to determine the significance and contribution of each factor. For surface roughness (Ra), the smallest value was 0.58 micrometers with an S/N ratio of 4.7314, while the highest value was 1.86 micrometers with an S/N ratio of -5.3903.

Regarding the material removal rate (MRR), the highest value recorded was 8007.751 mm^3/min with an S/N ratio of 78.07021, and the lowest was 1113.927 mm^3/min with an S/N ratio of 60.93713. ANOVA analysis revealed the statistical significance of each factor and its interactions, highlighting the critical parameters for process

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optimization. Additionally, the Grey Relational Analysis (GRA) was utilized to refine the selection and prioritization between minimizing surface roughness and maximizing the material removal rate.
Furthermore, to strike a balance between surface finish and material removal rate, it is recommended to consider higher feed rates and depth of cut, along with lower cutting speeds. Future studies should explore additional factors, such as tool wear and material properties to enhance machining performance.
Keywords: Machining Optimization, Experimental Design, Taguchi Method, ANOVA Analysis, Grey Relational Analysis (GRA), Surface Roughness, Material Removal Rate (MRR).

تحسين أداء عمليات التشغيل: دراسة حول تحليل التباين باستخدام طريقة تاغوشي وتحليل العلاقات الرمادية

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الملخص

تهدف هذه الدراسة إلى تحسين خشونة السطح (Ra) ومعدل إزالة المادة (MRR) في عمليات التشغيل من خلال تحليل تأثير معايير القطع: سرعة القطع، معدل التغذية، وعمق القطع. تتمثل الأهداف الرئيسة في تحديد الإعدادات المثلى للمعلمات بهدف تقليل خشونة السطح وزيادة معدل إزالة المادة، إضافةً إلى فهم الأهمية النسبية لكل معلمة. وقد افترضت الدراسة أن التغيرات في سرعة القطع، معدل التغذية، وعمق القطع تؤثر بشكل ملحوظ على كل من Ra وMRR، مع توقع أن يكون لمعدل التغذية التأثير الأكبر. تعتمد المنهجية على تنفيذ 27 تجربة باستخدام مصفوفة تاغوتشي .L27 تم قياس خشونة السطح ومعدل إزالة المادة لكل تجربة، كما تم حساب نسب الإشارة إلى الضوضاء (S/N)باستخدام معيار "الأقل أفضل" لـRa ، ومعيار "الأكبر أفضل" لـ .MRR وتم إجراء تحليل التباين (ANOVA) لتحديد دلالة وتأثير كل عامل. بالنسبة لخشونة السطح

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(Ra)، كان أقل قيمة مسجلة 0.58 مايكرومتر بنسبة S/N بلغت 4.7314، في حين بلغت أعلى قيمة 1.86 مايكرومتر بنسبة S/N مقدارها −5.3903. أما بالنسبة لمعدل إزالة المادة(MRR) ، فقد بلغت أعلى قيمة 8007.751 مم³/دقيقة بنسبة S/N مقدارها 78.07021، في حين كانت أقل قيمة 1113.927 مم³/دقيقة بنسبة S/N مقدارها 60.93713. أظهر تحليل ANOVA الأهمية الإحصائية لكل عامل وتفاعلاته، مما أبرز المعلمات الحرجة لعملية التحسين. كما تم استخدام تحليل العلاقة الرمادية (GRA) لتعزيز اختيار وتحليل الأولويات بين تقليل خشونة السطح وزيادة معدل إزالة المادة. ولتحقيق توازن بين جودة السطح ومعدل الإنتاج، توصي الدراسة باعتماد معدلات تغذية وعمق قطع أعلى، إلى جانب سرعات قطع منخفضة.
وتقترح الدراسة أن تتناول الأبحاث المستقبلية عوامل إضافية مثل تآكل الأداة وخصائص المواد لتعزيز أداء عمليات التشغيل.

الكلمات المفتاحية :تحسين التشغيل، التصميم التجريبي، طريقة تاغوتشي، تحليل التباين ANOVA، تحليل العلاقة الرمادية(GRA) ، خشونة السطح، معدل إزالة المادة(MRR) .

Introduction

Surface roughness is crucial in ensuring the precision of the workpiece. In manufacturing, achieving the best possible surface finish without incurring additional costs is always sought after. The Material Removal Rate (MRR) is inversely proportional to surface roughness, meaning the industry aims to achieve the lowest surface roughness while maintaining the highest MRR. This balance is essential because it directly impacts the efficiency and cost-effectiveness of the production process.

This study addresses a significant gap in the current literature: the lack of comprehensive research on the simultaneous optimization of surface roughness and MRR in the turning process of aluminum alloys. Specifically, it examines whether cutting speed, feed rate, and depth of cut significantly influence these two critical parameters and identifies the optimal values for each during operation.

Primary Objective: To optimize cutting speed, feed rate, and depth of cut to achieve the best possible surface roughness and maximum MRR in the turning process of aluminum alloy.

http://www.doi.org/10.62341/joae2727

Secondary Objective: To develop and validate a predictive regression model for surface roughness and MRR using the Taguchi method and Grey Relational Analysis (GRA).
The hypothesis of this study is that cutting speed, feed rate, and depth of cut significantly impact both surface roughness and MRR. The study aims to identify an optimal combination of these parameters using the Taguchi method, calculate the signal-to-noise ratio, perform Analysis of Variance (ANOVA) to assess the impact, and finally optimize the balance between MRR and surface roughness using the Grey Relational Coefficient (GRC).

Literature Review

Pradeep Kumar, K. Thirumurugan [1] studied the end milling process of titanium alloys and achieved optimal standards that could produce significantly good surface roughness while reducing tooling costs. The control variables were spindle speed, feed rate, depth of cut, and tool. They used an L27 (3^13) orthogonal array and analysis of variance (ANOVA) to identify the significant factors affecting surface roughness.
Vishal Parashar [2] conducted experiments on EN19 steel grade material using a coated carbide tool to optimize surface roughness using the Taguchi method. He found that spindle speed is the main factor affecting surface roughness, with increasing spindle speed resulting in reduced surface roughness and vice versa.
S. Sakthivelu [3] In his research, conducted experiments on Aluminum Alloy 7075 T6 using a CNC milling machine and High-Speed Steel (HSS) cutting tool. He found that feed rate is the most significant factor for surface roughness, while depth of cut is the most important factor for material removal rate.
Devesh Pratap Singh [4] used the Taguchi methodology to determine optimal machining conditions for surface roughness in aluminum CNC turning operations. He found that feed rate was the most significantly affecting factor, contributing 54.65%, followed by cutting speed at 34.67%, and depth of cut at 10.47%. Optimal machining parameters for surface roughness (Ra) were a spindle speed of 800 rpm, a feed rate of 40mm/min, and a depth of cut of 0.5mm.
Madhav Murthy [5] investigated the effect of various cutting parameters on the surface finish of Al6061 aluminum alloy using a

http://www.doi.org/10.62341/joae2727

CNC LT-16 turner with a carbide-tipped tool. He found that feed rate was the most significant factor influencing surface roughness, while the remaining three factors considered were not significant.
Mohsin Iqbal Qazi and Rehman Akhtar [6] studied the effect of shielded metal arc welding (SMAW) parameters on the evolution of mechanical properties, such as tensile strength, impact toughness, and hardness, as well as angular distortion in a welded joint from SA 516 grade 70. They analyzed and optimized parameters using the Taguchi method and Grey relational analysis. Nine experiments were conducted using an L9 orthogonal array, and results showed significant improvements in mechanical responses.
In the same context of multi-response optimization, a recent study titled [7] further validated the strength of this hybrid methodology. Although applied to welding rather than machining, the study addressed a similar challenge—balancing multiple quality characteristics such as tensile strength, elongation, and hardness—using an L9 orthogonal array and Grey Relational Analysis to derive an optimal setting under conflicting performance requirements. The findings confirmed that the Taguchi–GRA framework is a robust decision-making approach for optimizing processes in which improving one response may adversely affect another, which aligns with machining studies aiming to improve both surface roughness and material removal rate.
This literature review provides valuable insights into the factors influencing surface roughness and material removal rate across milling, turning, and welding processes. It highlights the significance of parameters such as spindle speed, feed rate, and depth of cut, as well as optimization techniques, such as the Taguchi method, in achieving desired outcomes.

Methodology

Workpiece Material

The workpiece material used in this study is an aluminum alloy. The chemical composition of the aluminum alloy is as follows:

Table 1. Chemical composition of the aluminum alloy workpiece (wt%).

Al	Cu	Mg	Si	Fe	Mn	Other
95.85%	0.4%	1%	0.25%	0.7%	0.5%	0.4%

http://www.doi.org/10.62341/joae2727

For the experiments, samples of this aluminum alloy were prepared with a consistent length and diameter to ensure uniformity in the turning process. The dimensions of the workpieces were chosen to be 100 mm in length and 20 mm in diameter, which are suitable for the capabilities of the CNC lathe used.

Surface Roughness Measurement

Surface roughness is a critical quality attribute in turning operations. The surface roughness of each machined workpiece was measured using a Mitutoyo Surftest SJ-210 surface roughness tester (Figure 1). This instrument provides precise measurements of surface finish, enabling accurate evaluation of the effects of cutting parameters. The measurements were taken at multiple locations on each workpiece to ensure reliability and repeatability of the data.

Fig.1.: Mitutoyo Surftest SJ-210 surface roughness tester

Material Removal Rate Calculation

Material removal rate (MRR) is a vital performance metric in machining processes, representing the volume of material removed per unit time. MRR was calculated using the following formula:

$$MRR = \frac{W_{bt} - W_{at}}{\rho * t} \qquad (1)$$

Where:

- W_{bt}- is the weight of the workpiece before machining.
- W_{at} - is the weight of the workpiece after machining.

http://www.doi.org/10.62341/joae2727

- ρ - is the density of the workpiece material, which for the aluminum alloy used is approximately 2.7 g/cm³.
- t- is the machining time.

Taguchi Method

In this study, the Taguchi method was used for experimental design. The Taguchi design is a collection of methodologies that include the inherent variability of materials and manufacturing processes during the design phase. Since the 1980s, this technique has become common in many American and European industries [8].

The Taguchi design enables multiple factors to be analyzed at the same time, aiming to identify a nominal design point that is insensitive to variations in the production environment. This method not only considers controlled factors but also includes noise factors, making it effective for enhancing manufacturing yield and product reliability. The Taguchi method is distinguished by its use of balanced (orthogonal) experimental groups, which improves the efficiency of fractional factorial designs.

In this study, three factors were selected to examine their impacts on material removal rate (MRR) and surface roughness: cutting speed, feed rate, and depth of cut. Each factor was categorized into three levels as presented in Table 2

Table 2. Process parameter levels and response factors

Process parameters	Level 1	Level 2	Level 3	Process response factors
Speed (s) (rpm)	1700	1900	2100	surface roughness (Ra)
Feed (f) (mm/rev)	0.1	0.125	0.15	material removal rate (MRR)
Depth of cut (d) (mm)	0.2	0.3	0.4	

This setup produced 27 samples, enabling a thorough investigation of these parameters. The signal-to-noise (S/N) ratio was used to analyze the results, with different formulas applied based on the desired outcome.

Lower-is-better (LB) for surface roughness:

$$S/N_{LB} = -10 log\left(\frac{1}{r}\sum_{i=1}^{r} yi^2\right) \quad (2)$$

http://www.doi.org/10.62341/joae2727

Nominal-is-better (NB) for variance

$$S/N_{NB1} = -10\log Ve \text{ (Variance only)} \quad (3)$$

$$S/N_{NB2} = 10\log\left(\frac{\mathrm{Vm-Ve}}{\mathrm{rVe}}\right) \text{ (Mean of Variance)} \quad (4)$$

Higher is better (HB) for MRR:

$$S/NHB = -10log\left(\frac{1}{r}\sum_{i=1}^{r}\frac{1}{yi^2}\right) \quad (5)$$

In this study, the "lower is better" formula was used for surface roughness, while the "higher is better" formula was applied to material removal rate. This dual approach enabled balanced optimization of both quality characteristics.

ANOVA Method

Analysis of variance (ANOVA) is an important statistical method used with the Taguchi method to analyze experimental data objectively. The column effect in Taguchi's approach acts as a simplified version of ANOVA, highlighting columns that significantly influence the response.

ANOVA assesses the significance of cutting parameters on surface roughness, providing a clear understanding of the impact and significance level of each factor. An F-test is used to determine the importance of design parameters on the quality characteristic, with F>4indicating a significant effect. ANOVA can be calculated based on the overall sum of squares (SS) from the total mean of the signal-to-noise (S/N) ratio, as shown in equation (6):

$$F = \frac{\sum_{j=1}^{q}\sum_{i=1}^{m}(\left(\frac{\frac{S}{N}}{N}\right)_{ij} - \left(\frac{\frac{S}{N}}{N}\right))^2}{\sum_{i=1}^{m}\sum_{j=1}^{q}(\left(\frac{\frac{S}{N}}{N}\right)_{ij} - \left(\frac{\frac{S}{N}}{N}\right))^2} \quad (6)$$

Where (m) is the total number of experiments, (q) is the number of repetitions of each level of the factor, $(\frac{S/N}{N})_{ij}$ is the calculated value in a row, and (N) is the total number of samples.

http://www.doi.org/10.62341/joae2727

The sum of squares (SS) is decomposed into the sum of squares due to each factor (SS_F) and the sum of squares due to error (SSe), shown in equations (7), (8) and otherwise (9) respectively:

$$SS_F = T - \sum_{j=1}^{q} F_j \tag{7}$$

$$SS_F = \sum_{i=1}^{m} \sum_{j=1}^{q} F_{ij} - SS_F \tag{8}$$

$$SS = \sum\nolimits_{i=1}^{m} [(\frac{S}{N})_i]^2 - \frac{1}{m} - [\sum_{i=1}^{m} (\frac{S}{N})_i]^2 \tag{9}$$

Where (F) stands for an experiment factor (parameter), (j) indicates the level number of that specific factor, and (T) denotes the total sum of squares.

The expected sum of squares (SS') for each factor is provided by (10):

$$SS' = \frac{SS_F}{DF_F} \tag{10}$$

Where (DF_F) is the degree of freedom for each factor, which is the number of its levels minus one.

Statistically, the F-test, named after R.A. Fisher, is used to determine which process parameter has a significant effect on the quality characteristic. The F-value, calculated as the ratio of the variance for each factor to the variance due to error, indicates significance. Typically, when the calculated F-value exceeds the tabulated F-value, it signifies a significant effect of the process parameter on the quality characteristic.

The percentage contribution (P) to the total variation is determined for each factor using equation (11).

$$P = \left(\frac{SS_i}{SS_{Total}}\right) X100 \tag{11}$$

http://www.doi.org/10.62341/joae2727

Where (SS_i) is the sum of squares for factor (i) and (SS_{Total}) is the total sum of squares.
Higher values of (P) indicate that the factor has a larger effect on the response variability.
In the analysis of variance (ANOVA) conducted to optimize surface roughness (Ra) and material removal rate (MRR) in CNC turning of aluminum alloy, the *pp*-value plays a crucial role in determining the statistical significance of the factors under investigation. The *p*-value is a probability measure that helps determine whether the observed effects in the response variables (Ra and MRR) are due to the factors considered in the experiment or are a result of random variation.
The *p*-value is compared against a predetermined significance level, commonly set at 0.05. This threshold is used to decide whether to reject the null hypothesis that a factor does not affect the response variable.

- p-value < 0.05: If the *p*-value is less than 0.05, it indicates that there is strong evidence against the null hypothesis, suggesting that the factor has a statistically significant effect on the response variable. In this case, we can conclude that the factor contributes significantly to the response's variability.
- p-value ≥ 0.05: If the *p*-value is greater than or equal to 0.05, it suggests that there is not enough evidence to reject the null hypothesis. This implies that the factor does not have a statistically significant effect on the response variable, and any observed effect is likely due to random variation.

Grey Relational Grade Method (GRG)

The Grey Relational Grade (GRG) method is a powerful analytical tool used in multi-criteria decision-making processes, particularly in engineering and optimization. It is based on the principles of grey relational analysis, which aim to quantify the relationship between multiple factors or variables, often in the presence of uncertainty or variability.
The GRG method is particularly beneficial in situations where multiple quality characteristics need to be optimized simultaneously, as it offers a systematic approach to evaluating the effectiveness of different experimental configurations. By providing a clear indication of the relationship between input variables and

http://www.doi.org/10.62341/joae2727

performance metrics, the GRG method helps engineers and decision-makers make informed choices to enhance system efficiency and effectiveness.
Here is the formatting of the equations depending on the objective of this paper, the maximization of the material removal rate (MRR) is of interest. Therefore, the larger-the-better criterion is selected for these quality characteristics
and normalized results can be expressed as Equation (12):

$$y_j^*(q) = \frac{y_j(q) - \min y_j(q)}{\max y_j\,(q) - \min y_j(q)} \tag{12}$$

Further, surface roughness (Ra) needs to be minimized, the smaller-the-better is used, as expressed in Equation (13):

$$y_j^*(q) = \frac{\max y_j\,(q) - y_j(q)}{\max y_j\,(q) - \min y_j(q)} \tag{13}$$

Where:
- y_j*(q)- are the generated grey relational values.
- Max $y(q)$ and Min $y_i(q)$ are the largest and smallest values of $y_j(q)$ for the *(q)* observation, respectively.
- q =2 is the number of response variables.

The twenty-seven observations of the experiments are in comparability sequence $y(q)$, where j=1, 2, ...,27. The best normalized results should be equal to 1; therefore, for achieving better performance, a larger value of normalized results is expected. Data normalization is followed by the calculation of grey relational coefficients (GRC), which display the relationship between the desirable and the real experimental normalized results. The expression of GRC $\xi(q)$ is determined as follows:

$$\xi\left(y_j^*(q), y_0^*(q)\right) = \frac{\Delta_{min}(q) + \zeta\Delta_{max}(q)}{\Delta_{0j}(q) + \zeta\Delta_{max}(q)} \tag{14}$$

Where:
- $\Delta_{0i}(q) = \left|y_0^*(q) - y_j^*(q)\right|$ is the deviation sequence, defined as the absolute difference between the reference sequence $y_0*(q)$ and the comparability sequence $y_j*(q)$.

http://www.doi.org/10.62341/joae2727

- The identification or distinguishing coefficient ζ takes a value in the range [0,1], and in this paper, it was set as 0.5 [9].

Results and Discussion

The surface roughness (Ra) and corresponding signal-to-noise (S/N) ratio for each experimental run are presented in the Table 3.The S/N ratio is calculated using a "lower is better" formula to minimize surface roughness.

Table 3. Surface Roughness and S/N Ratio Results

EXP. No	Surface Roughness (Ra)	S/N Ratio of Ra
1	0.82	1.7237
2	0.94	0.5374
3	0.96	0.3546
4	1.12	-0.9844
5	1.06	-0.5061
6	1.1	-0.8279
7	1.44	-3.1672
8	1.54	-3.7504
9	1.5	-3.5218
10	0.86	1.3100
11	0.92	0.7242
12	0.76	2.3837
13	1.04	-0.3407
14	1.2	-1.5836
15	1.1	-0.8279
16	1.44	-3.1672
17	1.6	-4.0824
18	1.5	-3.5218
19	0.88	1.1103
20	0.78	2.1581
21	1.16	-1.2892
22	1.08	-0.6685
23	1.14	-1.1381
24	1.26	-2.0074
25	0.58	4.7314
26	1.42	-3.0458
27	1.86	-5.3903

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The experimental results for surface roughness (Ra) reveal the variations in the quality of the machined surfaces under different cutting conditions. Lower Ra values are desirable for a smoother surface finish. From the data, it is observed that:

- The lowest surface roughness value is 0.58 µm (Experiment No. 25) with an S/N ratio of 4.7314, indicating the best surface finish achieved.
- The highest surface roughness value is 1.86 µm (Experiment No. 27) with an S/N ratio of -5.3903, indicating the roughest surface finish.

The S/N ratio helps identify the optimal setting for minimizing surface roughness by converting the variability into a measure that can be used to compare results across different experiments. A higher S/N ratio indicates better performance in the context of minimizing surface roughness.

- Experiment No. 25 shows the highest S/N ratio of 4.7314, indicating the most effective parameter setting for achieving low surface roughness.
- Experiment No. 27 shows the lowest S/N ratio of -5.3903, indicating the least effective parameter setting.

Taguchi Analysis: Surface Roughness (Ra) versus Speed, Feed, and Depth of Cut

The Taguchi method uses the signal-to-noise (S/N) ratio to identify the optimal levels of process parameters that minimize surface roughness. The "smaller is better" criterion is employed to analyze the S/N ratios. The obtained response values are presented in Table.4

Table 4. S/N Ratios Response Surface Roughness versus Speed, Feed, and Depth of Cut

Level	Speed (rpm)	Feed (mm/rev)	Depth of Cut (mm)
1	-1.12690	1.00145	0.06084
2	-1.01174	-0.98716	-1.18740
3	-0.61547	-2.76839	-1.62754
Delta	0.51142	3.76984	1.68838
Rank	3	1	2

http://www.doi.org/10.62341/joae2727

Analysis of S/N Ratios

- Speed: The difference (Delta) between the highest and lowest S/N ratios for speed is 0.51142, indicating it has a moderate impact on surface roughness.
- Feed: With a Delta of 3.76984, feed has the most significant impact on surface roughness, ranking first.
- Depth of Cut: The Delta for depth of cut is 1.68838, showing it also has a considerable impact, ranking second.

Figure 2illustrates the Signal to Noise Ratios (S/N) of surface roughness (Ra).

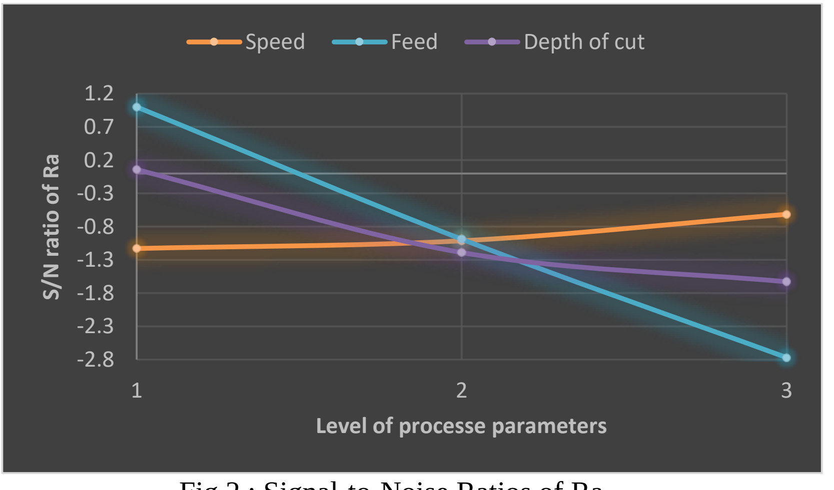

Fig.2.: Signal-to-Noise Ratios of Ra

Table 4 displays the mean surface roughness values for each level of the process parameters.

Table 5. Means of Response Surface Roughness

Level	Speed (rpm)	Feed (mm/rev)	Depth of Cut (mm)
1	1.1644	0.8978	1.0289
2	1.1578	1.1222	1.1778
3	1.1289	1.4311	1.2444
Delta	0.0356	0.5333	0.2156
Rank	3	1	2

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Analysis of Means

- Speed: The difference (Delta) in the means for speed is 0.0356, suggesting it has the least influence on surface roughness among the three factors.
- Feed: Feed has the highest Delta value (0.5333), confirming it as the most influential factor.
- Depth of Cut: The Delta for depth of cut is 0.2156, indicating it has a moderate influence.

As depicted in Figure 3, the mean surface roughness (Ra) is shown for varying levels of the process parameters.

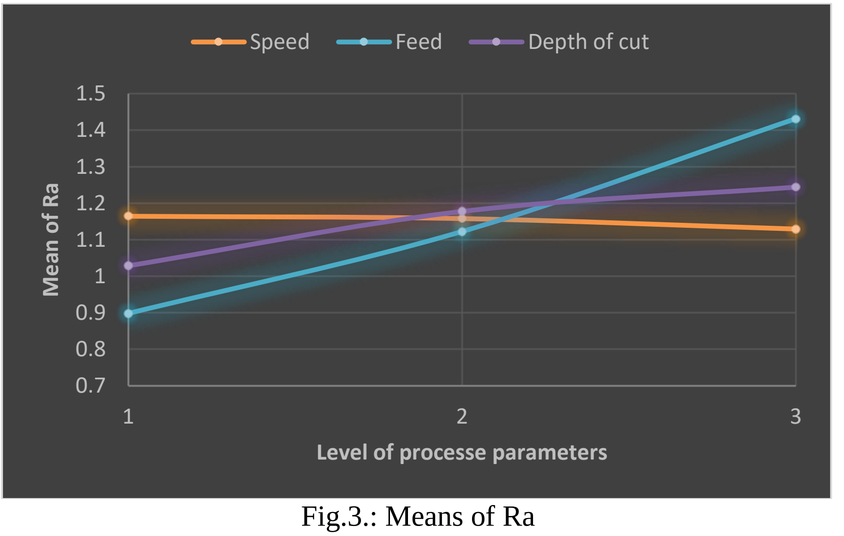

Fig.3.: Means of Ra

Material Removal Rate (MRR) Analysis

The material removal rate (MRR) values and their corresponding S/N ratios for different experimental conditions are presented in the Table 6:

Table 6. The Material Removal Rate and S/N Ratio Results

EXP. No	MRR (mm³/min)	S/N ratio of MRR
1	1113.927	60.93713
2	1672.129	64.4654
3	2022.443	66.11753
4	2780.859	68.88358
5	4176.76	72.41679
6	5040.271	74.04908

http://www.doi.org/10.62341/joae2727

EXP. No	MRR (mm³/min)	S/N ratio of MRR
7	4130.586	72.32023
8	6592.809	76.38141
9	7948.858	78.00609
10	1125.464	61.02663
11	1678.186	64.4968
12	2013.394	66.07858
13	2804.612	68.95746
14	4184.776	72.43344
15	5044.795	74.05687
16	4429.516	72.92713
17	6591.404	76.37956
18	7929.227	77.98462
19	1130.441	61.06496
20	1688.163	64.54829
21	2029.229	66.14662
22	2824.407	69.01855
23	4213.281	72.49241
24	5068.549	74.09767
25	4460.748	72.98815
26	6649.026	76.45516
27	8007.751	78.07021

The MRR data showcase the relationship between the machining parameters and the material removal rate, an essential factor in assessing the machining process's efficiency.

1. Highest MRR: Experiment 27 achieved the highest MRR at 8007.75 mm³/min, resulting in the highest S/N ratio of 78.070. This indicates that the parameters used in this experiment were the most effective for maximizing MRR.
2. Lowest MRR: Experiment 1 recorded the lowest MRR at 1113.9 mm³/min with an S/N ratio of 60.9. This suggests that the parameter settings for this experiment were the least effective for material removal.
3. Effect of Parameters:
   - Speed (rpm): Contrary to typical expectations, the data do not indicate a substantial impact of speed level on MRR.

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Higher speed levels do not consistently yield significantly higher MRR.

- Feed Rate (mm/rev): Increasing the feed rate generally leads to higher MRR. This is evident from the higher MRR values seen in experiments with higher feed levels (e.g., Experiment 9 at feed level 3).
- Depth of Cut (mm): Larger depths of cut significantly impact the MRR, contributing to higher values. This is supported by the results of Experiment 27, which combined a high feed rate and depth of cut.

4. Optimal Conditions: The optimal conditions for maximizing MRR appear to involve a combination of higher feed rate and depth of cut, as demonstrated by Experiment 27.

Material Removal Rate (MRR) Analysis: Speed (rpm) versus Feed (mm/rev) and Depth of Cut (mm)

The material removal rate (MRR) data and corresponding signal-to-noise (S/N) ratios for different levels of speed, feed rate, and depth of cut are summarized in Table 7.

Table 7. S/N Ratios: Response of MRR versus Speed, Feed, and Depth of Cut

Level	Speed (rpm)	Feed (mm/rev)	Depth of Cut (mm)
1	70.40	63.88	67.57
2	70.48	71.82	71.12
3	70.54	75.72	72.73
Delta	0.14	11.85	5.16
Rank	3	1	2

1. Effect of Speed on MRR:
    - The data suggests that increasing the speed leads to a higher material removal rate. This is evident from the trend in S/N ratios: higher speeds correspond to larger S/N ratios, indicating better performance.
2. Effect of Feed Rate and Depth of Cut on MRR:
    - Similarly, increasing the feed rate and depth of cut also positively impact the material removal rate. This is supported by the observed trend in the S/N ratios, where higher values of feed rate and depth of cut correspond to larger S/N ratios.
3. Optimal Conditions for MRR:

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- The optimal condition for maximizing MRR appears to involve a combination of high speed, feed rate, and depth of cut, as indicated by the highest S/N ratio and lowest rank for Level 3 in all parameters.

As shown in Figure 4, the Signal to Noise Ratios (S/N) of MRR are displayed.

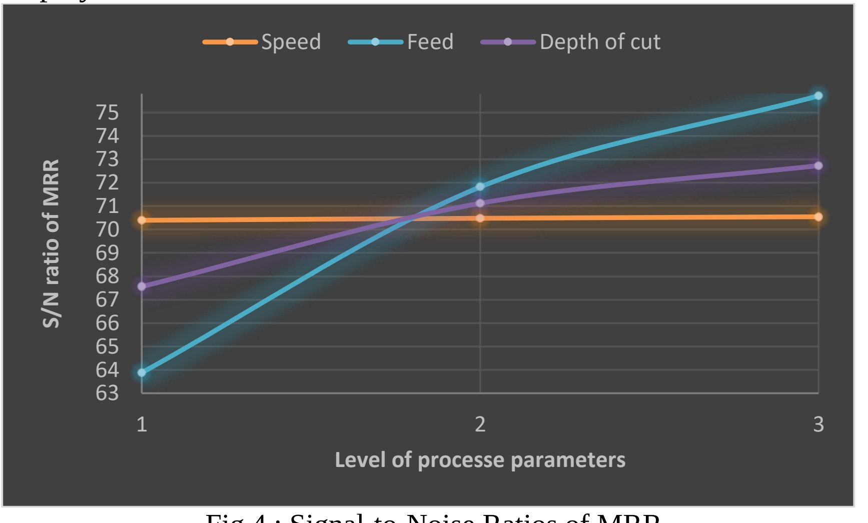

Fig.4.: Signal-to-Noise Ratios of MRR

Material Removal Rate (MRR) Analysis Means

The material removal rate (MRR) data and corresponding means for different levels of speed, feed rate, and depth of cut are summarized in Table 8 below:

Table 8. Means of MRR

Level	Speed (rpm)	Feed (mm/rev)	Depth of Cut (mm)
1	3942	1608	2756
2	3978	4015	4161
3	4008	6304	5012
Delta	66	4696	2256
Rank	3	1	2

1. Optimal Conditions for MRR

Similar to the S/N ratio analysis, the means also indicate that the highest MRR values are achieved at Level 3 for all parameters, suggesting that higher values of speed, feed rate, and depth of cut contribute to better material removal rates.

2. Effect of Speed on MRR

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Increasing the speed leads to higher MRR values, as observed from the increasing trend in MRR values across different speed levels.

3. Effect of Feed Rate and Depth of Cut on MRR:
   Similarly, increasing the feed rate and depth of cut also positively affect the material removal rate, resulting in higher MRR values at higher levels of these parameters.

Figure 5 illustrates the MRR means for different levels of the process parameters.

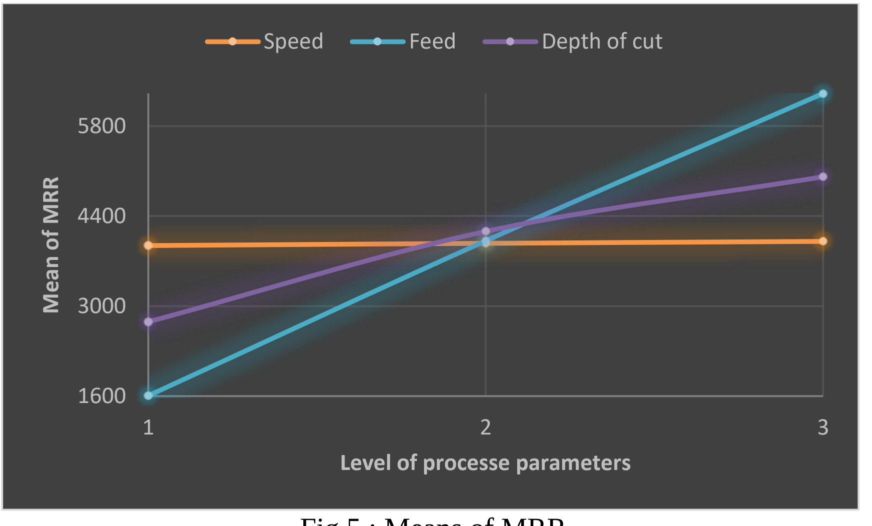

Fig.5.: Means of MRR

Analysis of Variance (ANOVA) for Surface Roughness (Ra) versus Speed (rpm), Feed (mm/rev), and Depth of Cut (mm)

The analysis of variance (ANOVA) table for surface roughness (Ra) versus speed, feed, and depth of cut is presented in Table 9.

Table 9. Analysis of Variance for Surface Roughness

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Speed (rpm)	2	0.00643	0.27%	0.00643	0.003215	0.07	0.930
Feed (mm/rev)	2	1.29070	53.70%	1.29070	0.645348	14.55	0.000

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Depth of Cut (mm)	2	0.2192 3	9.12%	0.2192 3	0.10961 5	2.47	0.11 0
Error	20	0.8871 4	36.91%	0.8871 4	0.04435 7		
Total	26	2.4035 0	100.00%	0.0064 3	0.00321 5		

Interpretation

1. Speed (rpm)
   The p-value for speed is 0.930, indicating that speed does not have a significant effect on surface roughness (Ra). Its contribution to Ra variation is minimal, accounting for only 0.27%.
2. Feed (mm/rev)
   The p-value for feed is 0.000, suggesting that feed rate significantly influences surface roughness. It accounts for 53.70% of the variation in Ra, indicating a strong effect.
3. Depth of Cut (mm)
   The p-value for depth of cut is 0.110, indicating that it does not have a significant effect on Ra. However, it still accounts for 9.12% of the variation in Ra, though this contribution is not statistically significant.

The interaction plot for surface roughness (Ra) in Figure 5 shows how the interaction among process parameters (speed, feed rate, and depth of cut) affects surface roughness. This plot provides insight into whether the combined effect of these parameters is additive or if there are significant interactions that influence the outcome.
The plot shows that as speed increases, the effect of feed rate on surface roughness becomes more pronounced. At lower speeds, feed rate has a moderate impact on surface roughness, whereas at higher speeds, the variation in surface roughness with feed rate is more significant.
This suggests a synergistic interaction in which higher speeds amplify the effect of feed rate on surface roughness.
The interaction plot indicates that changes in depth of cut have a consistent impact on surface roughness across different speed levels. However, at higher speeds, surface roughness decreases slightly with increasing depth of cut, suggesting a potential interaction effect.

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This pattern suggests that the depth of cut's influence on surface roughness is relatively stable, but higher speeds can mitigate some of the roughness induced by deeper cuts.
The plot shows a significant interaction between feed rate and depth of cut. At lower feed rates, increasing the depth of cut leads to a moderate increase in surface roughness. However, at higher feed rates, the increase in surface roughness with depth of cut is more pronounced.
This indicates a multiplicative interaction effect, in which the combined high levels of feed rate and depth of cut exacerbate surface roughness more than either factor alone.
Overall, feed rate appears to be the most influential factor affecting surface roughness, followed by depth of cut. Speed, on the other hand, has minimal impact on Ra in this analysis.

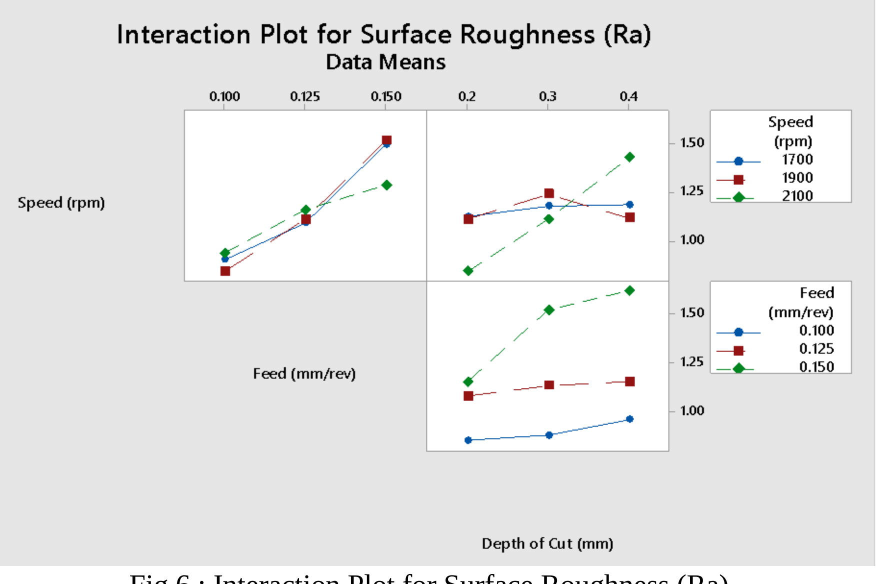

Fig.6.: Interaction Plot for Surface Roughness (Ra)

Residual Plots for Surface Roughness (Ra)

The residual plots for surface roughness (Ra) shown in Figure 6 are crucial for evaluating the regression model's assumptions and overall fit. These plots help in assessing normality, independence, and homoscedasticity of the residuals. Key Observations from the Residual Plots:

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- Normal Probability Plot: The points closely follow the diagonal line, indicating that the residuals are approximately normally distributed.
- Residuals versus Fitted Values: The residuals are randomly scattered around zero, suggesting that the assumptions of linearity and homoscedasticity are likely satisfied.
- Histogram of Residuals: The histogram is symmetric and bell-shaped, supporting the assumption of normally distributed residuals.
- Residuals versus Order of Observations: The residuals show no systematic pattern, indicating independence. These observations suggest that the regression model for surface roughness (Ra) is valid and reliable, and that it meets the necessary assumptions.

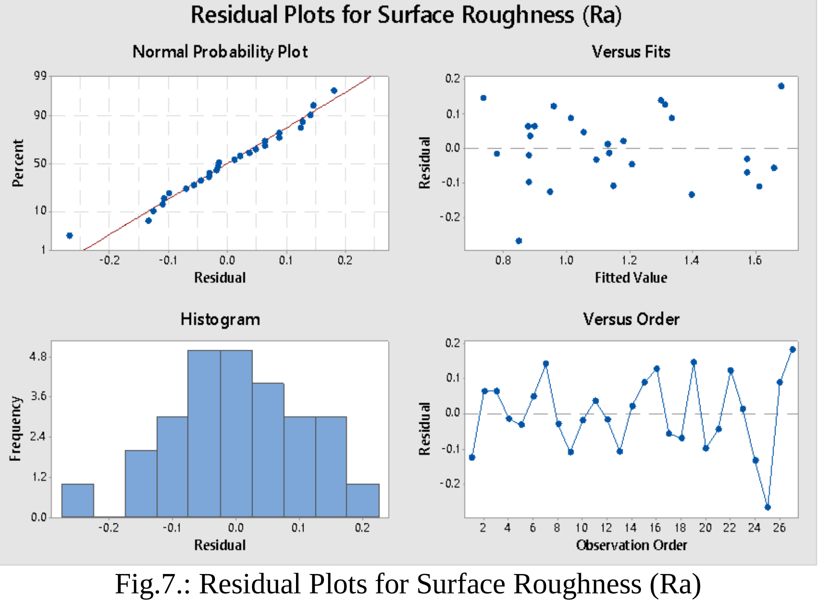

Fig.7.: Residual Plots for Surface Roughness (Ra)

Analysis of Variance (ANOVA) for Material Removal Rate (MRR) versus Speed (rpm), Feed (mm/rev), and Depth of Cut (mm)

The analysis of variance (ANOVA) table for material removal rate (MRR) versus speed, feed, and depth of cut is presented **in Table 10.**

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Table 10. Analysis of Variance for Material Removal Rate (MRR)

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Speed (rpm)	2	19584	0.02%	19584	9792	0.03	0.96
Feed (mm/rev)	2	99268780	77.32%	99268780	49634390	172.88	0.00
Depth of Cut (mm)	2	23363557	18.20%	23363557	11681778	40.69	0.00
Error	20	5742197	4.47%	5742197	287110		
Total	26	128394118	100.00%				
Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Speed (rpm)	2	19584	0.02%	19584	9792	0.03	0.96

Interpretation

1. Speed (rpm)
   The p-value for speed is 0.967, indicating that speed does not have a significant effect on surface roughness (Ra). It contributes a negligible 0.02% to the variation in Ra, with a low F-value of 0.03.
2. Feed (mm/rev)
   The p-value for feed rate is 0.000, indicating its significant influence on surface roughness (Ra). It contributes a substantial 77.32% to the variation in Ra, with a high F-value of 172.88.
3. Depth of Cut (mm)
   The p-value for depth of cut is also 0.000, signifying its significant effect on surface roughness (Ra). It contributes 18.20% of the variation in Ra, with an F-value of 40.69.

Interaction Effects

The provided interaction plot in Figure 7 illustrates the material removal rate (MRR) in mm^3/min as a function of three machining parameters: spindle speed (rpm), feed rate (mm/rev), and depth of cut (mm). The plot displays three two-way interactions:

Interaction between Speed and Feed

The top-left subplot shows the relationship between speed and feed rate. MRR increases with both higher feed rates and speeds.

Interaction between Speed and Depth of Cut

The top-right subplot indicates that MRR grows with both increasing depth of cut and speed. The effect of speed on MRR becomes more pronounced at higher depths of cut.

http://www.doi.org/10.62341/joae2727

Interaction between Feed and Depth of Cut

The bottom subplot demonstrates the combined impact of feed rate and depth of cut. Higher feed rates and greater depths of cut both contribute to a higher MRR, with a significant interaction effect observed.

The interaction effects highlight how changes in one parameter influence the impact of another, emphasizing the importance of optimizing these parameters concurrently to achieve efficient material removal in machining processes.

Overall, all three factors (speed, feed rate, and depth of cut) significantly affect material removal rate, with depth of cut being the most influential, followed by feed rate and speed.

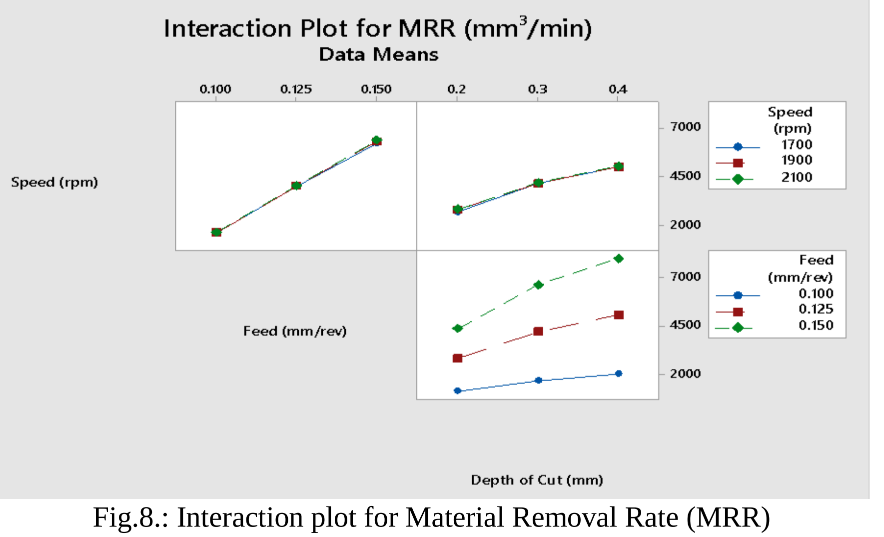

Fig.8.: Interaction plot for Material Removal Rate (MRR)

Residual Plots for Material Removal Rate (MRR)

The residual plots for MRR (mm^3/min) as shown in Figure 8 provide a comprehensive diagnostic evaluation of the regression model assumptions and performance.

- Normal Probability Plot: The points closely follow a straight line, suggesting that the residuals are approximately normally distributed, though there are deviations at the extremes indicating potential outliers.
- Versus Fits: The plot of residuals against fitted values shows no clear pattern, implying that the variance of the residuals

is constant and that the model is well-fitted without any discernible bias.

- Histogram: The histogram of residuals shows a roughly symmetric distribution around zero, supporting the assumption of normality but indicating a slight skew with a higher frequency of negative residuals.
- Versus Order: The residuals plotted against the observation order display a random scatter, suggesting that there are no significant time-related patterns or autocorrelation in the residuals.

Overall, these plots indicate that the model assumptions are largely satisfied, but attention should be given to the potential outliers and slight deviations from normality.

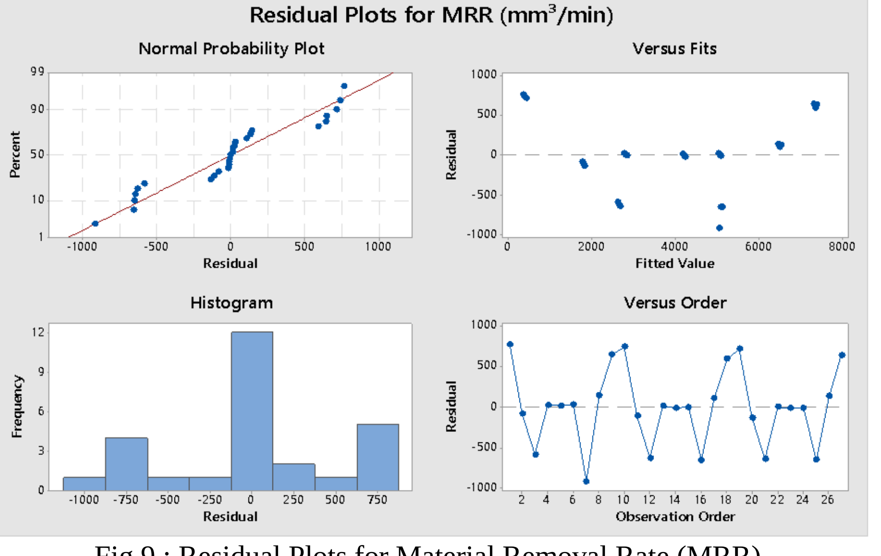

Fig.9.: Residual Plots for Material Removal Rate (MRR)

Multi-Response Optimization based on GRA

In this research work, an attempt is made to compare multi-objective optimization performed by GRG and to validate the results through confirmatory experiments.

The steps are discussed in detail in the optimization methodology section. First, the S/N ratios

depicted in Tables (2) and (5) are normalized using Equations (12) and (13).

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The Grey relational coefficient (GRC) of individual responses is computed using Equation (14).

The grey relational grade is calculated in Table 11:

Table 11. Calculated Normalized, GRC and GRG for 27 experiments

EXP. No	Normalization		GRC		Grey Relational Grade	
	Ra	MRR	Ra	MRR	GRG	Rank
1	0.297155	-1	0.415681	0.2	0.307841	26
2	0.414357	-0.79407	0.460557	0.217954	0.339255	20
3	0.432424	-0.69764	0.468351	0.227517	0.347934	19
4	0.564708	-0.53619	0.534592	0.245556	0.390074	15
5	0.517458	-0.32997	0.508884	0.273228	0.391056	14
6	0.549245	-0.2347	0.525898	0.288234	0.407066	13
7	0.780372	-0.33561	0.694803	0.272389	0.483596	8
8	0.837987	-0.09857	0.755272	0.31278	0.534026	3
9	0.815403	-0.00374	0.730357	0.332504	0.53143	4
10	0.338027	-0.99478	0.430303	0.200419	0.315361	23
11	0.395902	-0.79223	0.452858	0.218128	0.335493	21
12	0.231948	-0.69991	0.394306	0.227282	0.310794	24
13	0.501112	-0.53188	0.500557	0.246077	0.373317	18
14	0.623914	-0.329	0.57072	0.273374	0.422047	10
15	0.549245	-0.23425	0.525898	0.28831	0.407104	12
16	0.780372	-0.30018	0.694803	0.277749	0.486276	7
17	0.870787	-0.09868	0.794643	0.312758	0.553701	2
18	0.815403	-0.005	0.730357	0.332227	0.531292	5
19	0.357756	-0.99254	0.437735	0.200599	0.319167	22
20	0.254239	-0.78923	0.401361	0.218414	0.309888	25
21	0.594821	-0.69594	0.552377	0.227693	0.390035	16
22	0.533499	-0.52832	0.51733	0.24651	0.38192	17
23	0.579896	-0.32556	0.543417	0.273889	0.408653	11
24	0.665783	-0.23186	0.599364	0.288706	0.444035	9
25	0	-0.29662	0.333333	0.2783	0.305817	27
26	0.76837	-0.09427	0.683405	0.313624	0.498515	6
27	1	0	1	0.333333	0.666667	1

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Analysis of Grey Relational Grade (GRG)

The optimization process aimed to determine the optimal combination of speed, feed, and depth of cut based on the Grey Relational Grade (GRG). Since a higher GRG value indicates a performance closer to the ideal sequence, the "larger-is-better" criterion was applied to analyze the signal-to-noise (S/N) ratios. The response table for these ratios is presented in Table 12

Table 12. Signal to Noise Ratios for GRG

Level	Speed (rpm)	Feed (mm/rev)	Depth of Cut (mm)
1	-7.798	-9.636	-8.682
2	-7.823	-7.909	-7.678
3	-7.924	-6	-7.185
Delta	0.126	3.636	1.496
Rank	3	1	2

The Signal-to-Noise (S/N) ratios, indicating the performance of each parameter combination, were of the larger-is-better type. Looking at the Response Table for Signal-to-Noise Ratios, we observe that Level 3 for Feed (mm/rev) has the highest S/N ratio, followed by Level 3 for Depth of Cut (mm) and Level 1 for Speed (rpm). This suggests that Level 3 for Feed, Level 3 for Depth of Cut, and Level 1 for Speed are associated with better performance, as illustrated in Figure 10.

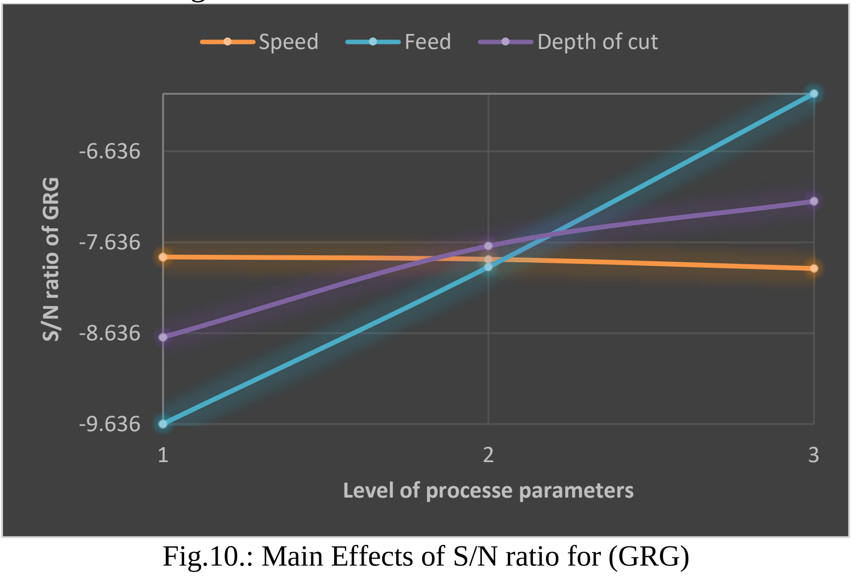

Fig.10.: Main Effects of S/N ratio for (GRG)

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To verify these results, the mean response values for the GRG were also analyzed. The response table for means is presented in Table 12.

Table 12. Means of GRG

Level	Speed (rpm)	Feed (mm/rev)	Depth of Cut (mm)
1	0.4147	0.3306	0.3737
2	0.415	0.4028	0.4214
3	0.4139	0.5101	0.4485
Delta	0.0012	0.1795	0.0748
Rank	3	1	2

Similarly, in the Response Table for Means, which provides the average performance at each parameter level, we find that Level 3 for Feed has the highest mean, indicating better performance, followed by Level 3 for Depth of Cut and Level 2 for Speed, as shown in Figure 11.

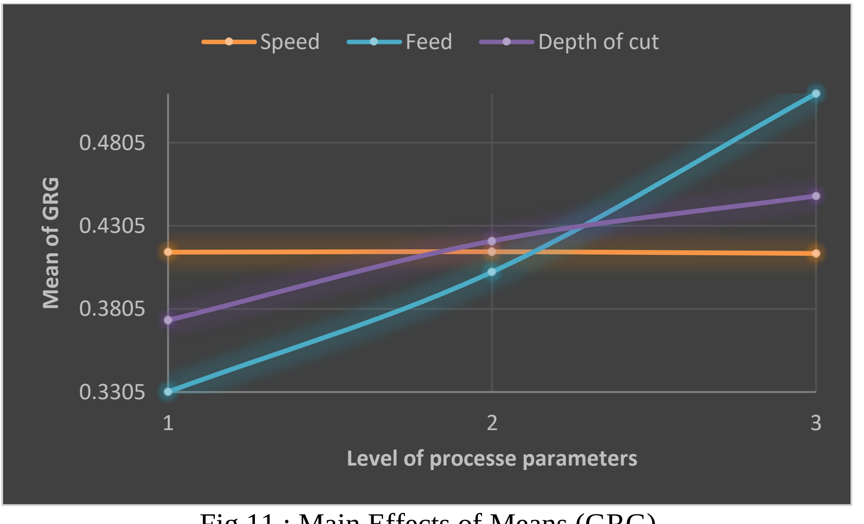

Fig.11.: Main Effects of Means (GRG)

Analyzing the Delta values, which represent the difference between the highest and lowest S/N ratios or means, we observe that Feed (mm/rev) has the highest impact on performance, followed by Depth of Cut (mm), and then Speed (rpm). Based on these results, we can conclude that, for this specific optimization goal, the most favorable parameter combinations are Level 3 for Feed, Level 3 for Depth of Cut, and Level 1 for Speed in terms of S/N ratio or Level 2 for Speed

http://www.doi.org/10.62341/joae2727

in terms of means. Adjusting these parameters to their respective levels can enhance the overall performance of the process.

Conclusion

This study comprehensively analyzed the effects of machining parameters on surface roughness (Ra) and material removal rate (MRR) using experimental data and statistical methods. Key findings include:

1. Surface Roughness Analysis

- The lowest Ra value of 0.58 µm was achieved in Experiment No. 25, indicating the best surface finish.
- Feed rate was identified as the most significant factor influencing Ra, contributing 53.70% to the variation in surface roughness. Depth of cut also had a considerable impact, while speed had a minimal effect.

2. Material Removal Rate Analysis

- The highest MRR of 8007.751 mm³/min was observed in Experiment No. 27, suggesting the most efficient parameter settings.
- The feed rate significantly influenced the material removal rate (MRR), accounting for 77.32% of its variation. This was followed by the depth of cut, which contributed 18.20%. The speed factor had an almost negligible effect, accounting for only 0.02% of the variation.

3. Taguchi Method:

- The analysis of the Signal-to-Noise (S/N) ratio using the Taguchi method for surface roughness indicated that lower feed rates and lower depth of cut levels, combined with the highest speed, result in improved surface finishes.
- For MRR, higher values of speed, feed rate, and depth of cut were optimal.

4. ANOVA confirmed the significant effects of feed rate and depth of cut on both Ra and MRR, emphasizing the need to control these parameters to achieve desired outcomes carefully.
5. Grey Relational Analysis (GRA) provided a balanced approach to simultaneously optimize both surface roughness (Ra) and material removal rate (MRR). The optimal parameter combination involved the first level of speed for Signal-to-

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Noise (S/N) ratio considerations and the second level for means, along with high levels of feed rate and depth of cut. Overall, this study highlights the critical role of feed rate and depth of cut in determining machining performance. By applying the Taguchi method and ANOVA, coupled with GRA for multi-response optimization, manufacturers can achieve a balance between surface quality and process efficiency. These findings of precision machining by providing a systematic approach to parameter optimization.

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