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Optimization of CNC Turning Parameters for Surface Roughness of Brass 36000 Using the Taguchi Method

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Abstract

Brass is widely used in industrial applications due to its excellent machinability and durability, making it well suited for CNC turning operations. Although numerous studies have investigated the optimization of turning parameters, variations in machine tools and cutting conditions often lead to differing conclusions. This study aims to optimize surface roughness in the CNC turning of Brass 36000 using the Taguchi method. An L9 orthogonal array was employed to evaluate the effects of spindle speed, feed rate, depth of cut, and coolant type. Experimental data were analyzed using signal-to-noise (S/N) ratio analysis and analysis of variance (ANOVA) to identify the most influential parameters and optimal cutting conditions. The results indicate that feed rate is the dominant factor affecting surface roughness, contributing to 95.54% of the total variation, followed by spindle speed (1.88%), depth of cut (0.33%), and coolant type (0.18%). The optimal machining parameters were determined as a spindle speed of 1700 rpm, feed rate of 0.1 mm/rev, depth of cut of 1.0 mm, and the use of synthetic coolant (GT41), resulting in a minimum surface roughness of 0.67 µm. These findings demonstrate that precise control of feed rate is critical for achieving improved surface quality in CNC turning of brass.

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1. Introduction

Recent advances in manufacturing technologies have accelerated the adoption of computer numerical control (CNC) machining as a primary production route for high-precision components. Compared with conventional machining, CNC-based processes offer improved dimensional accuracy, repeatability, productivity, and reduced operator dependency, making them indispensable in modern manufacturing environments [1], [2]. Among these processes, CNC turning remains a critical operation for producing rotational components, as it directly influences dimensional accuracy, surface integrity, and overall component performance [3].

Brass is widely recognized as one of the most machinable engineering materials due to its favorable combination of mechanical strength, corrosion resistance, thermal conductivity, and excellent chip-forming characteristics. These properties make brass particularly suitable for CNC machining applications in industries such as plumbing, electrical systems, healthcare equipment, and precision mechanical components. In CNC turning, brass workpieces are progressively machined according to predefined tool paths generated from computer-aided design (CAD) models, enabling the efficient production of complex geometries with controlled surface quality.

The performance of CNC turning operations is commonly evaluated using two key response variables: surface roughness, typically expressed as the arithmetic average roughness (Ra), and material removal rate (MRR). Surface roughness is a critical indicator of surface integrity and directly affects fatigue life, wear resistance, and functional performance, while MRR represents productivity and machining efficiency [3], [4]. These responses are strongly influenced by cutting parameters such as spindle speed, feed rate, depth of cut (DOC), and lubrication or coolant conditions. The relationship between surface quality and productivity is inherently complex, as improvements in one response often come at the expense of the other, necessitating systematic optimization strategies.

Numerous studies have investigated the optimization of turning parameters using statistical and experimental approaches. For example, grey relational analysis has been applied to multi-

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response optimization problems, with some studies reporting depth of cut as the most influential parameter, followed by cutting speed and feed rate, for combined responses such as surface roughness, MRR, and tool wear [5]. Other investigations on mild steel turning have shown that feed rate is the dominant factor affecting surface roughness, while spindle speed exhibits a comparatively weaker influence [6]. In non-traditional machining contexts, such as electrical discharge grinding, machining parameters such as peak current and pulse-on time have been reported to significantly affect MRR, albeit with trade-offs in machining time and surface quality [7].

Despite extensive research, inconsistencies remain across reported findings. These variations arise from differences in machine tool characteristics, cutting tool geometry and coatings, material properties, lubrication strategies, and selected parameter ranges. Consequently, optimization results derived for one machine–tool–material system cannot be directly generalized to others. This underscores the importance of conducting machine- and material-specific experimental studies to obtain reliable and practically applicable optimization outcomes.

Design of experiments (DoE) techniques and response surface methodology (RSM) are widely employed to model and optimize machining responses by quantifying the relationships between cutting parameters and performance metrics such as Ra and MRR [3], [8]. Taguchi methods, grey relational analysis (GRA), and hybrid approaches have been successfully applied to reduce experimental effort while identifying robust parameter combinations for multi-response optimization [9], [10]. More recently, advanced surrogate-based and machine-learning-assisted methods, including artificial neural networks and genetic algorithms, have been explored to capture nonlinear interactions and enhance predictive accuracy [11], [12], [13]. While these approaches have produced reliable regression models and optimization maps for aluminum alloys, steels, polymers, and composite materials, comparable predictive models specifically for brass turning on modern CNC lathes remain limited in the open literature [4], [13].

The variability in machinability behavior across material classes, combined with the strong influence of cutting conditions and lubrication modes, indicates that regression models developed for other materials cannot be reliably transferred to brass machining applications [3], [14]. Therefore, there is a clear need for an experimentally driven, material-specific investigation that systematically evaluates the effects of primary turning parameters and establishes validated predictive models for both surface quality and productivity.

Accordingly, the objective of this study is to experimentally quantify the effects of spindle speed, feed rate, depth of cut, and coolant condition on surface roughness (Ra) and material removal rate (MRR) during CNC turning of Brass 36000. The study further aims to identify the optimal combination of process parameters using statistical optimization techniques and to develop multivariate regression models capable of predicting Ra and MRR within the investigated parameter ranges. By focusing on brass turning under controlled CNC conditions, this work seeks to provide actionable optimization guidance and predictive tools relevant to industrial practice.

2. Methods

2.1. Experimental design

The Taguchi method was employed in this study to systematically identify optimal machining parameters for the CNC turning process. The Taguchi approach has been widely applied in machining optimization studies due to its effectiveness in reducing the number of experimental runs while maintaining statistical reliability [15]. All experiments were carried out on a CNC turning machine equipped with a GSK 980TDi controller along with AISI 1005 steel TiN coated tool.

Four machining parameters were selected as control factors, each investigated at three levels: spindle speed, feed rate, depth of cut, and coolant type. The coolant conditions consisted of compressed air (7 Bar), synthetic coolant (GT41), and mineral engine oil (Shell Advance AX5 10W-30). These parameters were chosen based on their known influence on surface quality and machining performance.

The parameter levels were determined according to cutting tool manufacturer recommendations and preliminary calculations, ensuring compatibility with the machine tool and cutting insert. The cemented carbide insert CNMG 120408 TF IC 707 was used in this study. According to the manufacturer's data sheet, the recommended cutting conditions for this insert include cutting speeds of 180–300 m/min, feed rates of 0.12–0.35 mm/rev, and depth of cut values of 1–4 mm. The selected experimental levels were chosen within or close to these recommended ranges to ensure stable and safe machining conditions. The investigated factors and their levels are summarized in Table 1.

Table 1. Machining parameters and levels

No.	Control factor	Level 1	Level 2	Level 3
1	Spindle speed (rpm)	1300	1500	1700
2	Feed rate (mm/rev)	0.1	0.15	0.2
3	Depth of cut (mm)	0.4	0.7	1
4	Coolant type	Compressed air (7 bar)	Synthetic coolant (GT41)	Engine oil (10W-30)

2.2. Materials and equipment

The cutting tool used in the turning operation was a cemented carbide insert CNMG 120408 TF IC 707, mounted on a standard lathe tool holder. The workpiece material was Brass 36000 (free-machining brass), selected due to its widespread industrial use and favorable machinability characteristics. The chemical composition of Brass 36000, according to ASTM B16, is presented in Table 2 [15].

The workpiece geometry, tool holder, and cutting insert are shown in Figure 1, while the CNC turning machine, surface roughness measuring instrument, and machined samples are shown in Figure 2. A total of nine Brass 36000 specimens were prepared for the experimental study, corresponding to the L9 Taguchi orthogonal array. Each specimen had an overall length of 100 mm and an initial diameter of 16 mm. The specimens were machined into stepped profiles with diameters of 5 mm, 7 mm, and 9 mm, each step having a height of 8 mm.

Surface roughness measurements were conducted at three different locations on each specimen, and the average value was used for analysis to minimize measurement uncertainty. The experimental setup followed a structured L9 orthogonal array design with three replications to improve data reliability and statistical robustness.

Table 2. Chemical composition of Brass 36000

	Cu(%)	Fe(%)	Pb(%)	Zn(%)
Min / Max	60–63	0.35	2.5 - 3	Balance
Nominal	61.5	-	2.7	35. 4

(a) (b) (c)

Figure 1. Experimental components used in the CNC turning process: (a) Brass 36000 workpiece, (b) lathe tool holder, and (c) CNMG 120408 TF IC 707 cutting insert

(a) (b) (c)

Figure 2. Experimental setup and measurement equipment: (a) CNC turning machine (GSK 980TDi), (b) surface roughness tester (Mitutoyo SJ-310), and (c) machined test specimens

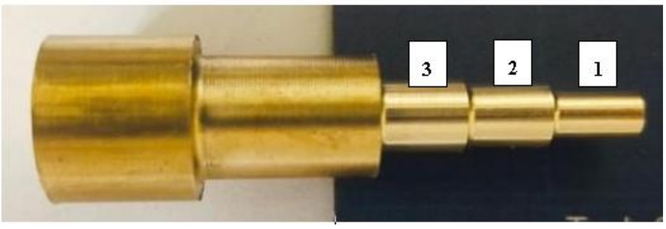

Figure 3. Stepped Brass 36000 workpiece geometry showing the three machined measurement sections used for surface roughness evaluation

(a) (b) (c)

Figure 4. CNC turning operations under different coolant conditions: (a) compressed air (7 bar), (b) synthetic coolant (GT41), and (c) engine oil (10W-30).

Figure 5. Surface roughness measurement procedure using the Mitutoyo SJ-310 tester.

The deviation from the nominal surface used in surface roughness evaluation is illustrated in Figure 3, while the machining processes under different coolant conditions and the surface roughness measurement procedure using a Mitutoyo SJ-310 tester are shown in Figures 4 and 5, respectively.

2.3. Measurement of surface roughness

Surface roughness is defined as the average vertical deviation of a machined surface from its nominal profile over a specified evaluation length [16]. Among the various roughness parameters, the arithmetic average roughness (R_a) is the most widely used due to its simplicity and effectiveness in representing overall surface quality. The arithmetic average roughness is expressed as:

$$Ra = \int_0^{L_m} \frac{|y|}{L_m} dx \tag{1}$$

Where Ra is the arithmetic average roughness (μm), $|y|$ is the absolute vertical deviation from the nominal surface (μm), and L_m is the evaluation length over which the surface profile is measured.

A schematic representation of the surface profile and the vertical deviations used in the calculation of surface roughness is shown in Figure 6.

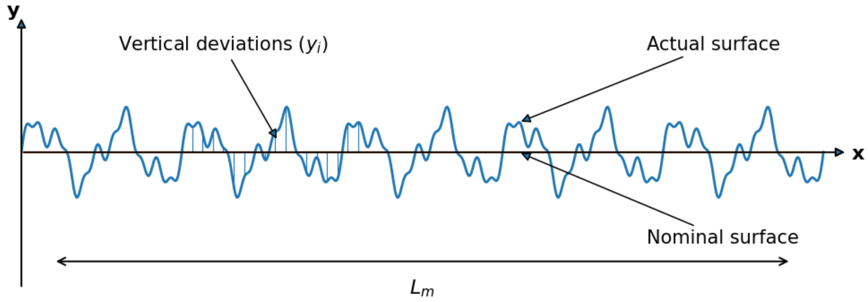

Figure 6. Schematic illustration of surface profile showing deviation from the nominal surface used in surface roughness evaluation

2.4. Material removal rate

Material Removal Rate (MRR) is defined as the volume of material removed per unit time during a machining process and is a key indicator of machining efficiency and productivity [16], [17]. In turning operations, MRR reflects the effectiveness of the selected cutting parameters in achieving higher production rates without compromising process stability.

In this study, the material removal rate was calculated using the following relationship:

$$\mathrm{MRR} = \frac{\mathrm{V}}{\mathrm{t}} \tag{2}$$

In Eq. (2), MRR denotes the material removal rate expressed in mm^3/min, V represents the volume of material removed in mm^3, and t is the machining time required to remove that volume, measured in minutes.

2.5. Confidence interval analysis

Confidence interval (CI) analysis was conducted to assess the reliability and precision of the optimized experimental results. A confidence interval defines the range within which the true mean value of the response variable is expected to lie with a specified level of confidence, typically 95%. This analysis is essential for validating the statistical significance and robustness of the optimization results.

The confidence interval for the optimized response was calculated using the following expression:

$$\mathrm{CI_{opt}} = \sqrt{\frac{\mathrm{F_{\alpha;v1_{v2}}} \times \mathrm{MS_E}}{\mathrm{n_{eff}}}} \tag{3}$$

In Eq. (3), $\mathrm{F}_{\alpha;(v_1,v_2)}$ represents the F-value at the selected significance level $\alpha$with degrees of freedom v_1 and v_2, $\mathrm{MS_E}$ denotes the mean square error obtained from the ANOVA results, and $\mathrm{n_{eff}}$ is the effective number of observations used in the confidence interval calculation.

3. Results and Discussion

An experimental investigation was conducted on Brass 36000 workpieces machined using a CNC turning process. A total of nine experimental runs were performed following an L9 Taguchi orthogonal array, with each experiment replicated three times to ensure measurement reliability. For each specimen, surface roughness was measured at three different locations, and the average value was reported. The test specimens had an overall length of 100 mm and an initial diameter of 16 mm. Each specimen was turned into stepped profiles with diameters of 5 mm, 7 mm, and 9 mm, each having a step height of 8 mm. The machining configurations, coolant conditions, and surface roughness measurement procedure are illustrated in Figures 5 and 6.

3.1. Surface roughness and material removal rate

Table 3 presents the experimental results for surface roughness (R_a) and material removal rate (MRR) for each combination of spindle speed, feed rate, depth of cut (DOC), and coolant type.

Table 3. Experimental results of Ra and MRR for each machining condition

Spindel Speed (rpm)	Feed rate (mm/rev)	DOC (mm)	Coolant Type	Surface Roughness (µm)	MRR mm^3/min
1300	0.1	0.4	compressed air	0.92	720.00
1300	0.15	0.7	coolant	1.38	1619.99
1300	0.2	1	engine oil	1.88	2619.56
1500	0.1	0.7	engine oil	0.84	1309.78
1500	0.15	1	compressed air	1.20	2323.01
1500	0.2	0.4	coolant	1.86	1465.71
1700	0.1	1	coolant	0.67	2051.99
1700	0.15	0.4	engine oil	1.16	1295.99
1700	0.2	0.7	compressed air	1.90	2512.64

The reported surface roughness values are the average of three measurements taken at different locations on each specimen, and these results were used to evaluate the influence of the selected machining parameters on surface roughness. The minimum surface roughness value of 0.67 µm was achieved at a spindle speed of 1700 rpm, a feed rate of 0.1 mm/rev, a depth of cut of 1 mm, and the use of synthetic coolant (GT41).

The observed reduction in surface roughness at higher spindle speeds can be attributed to improved cutting stability and reduced vibration, which result in finer surface textures and smaller tool marks. However, excessively high spindle speeds may also increase cutting temperature and material removal rate, potentially leading to surface degradation due to thermal effects at the tool–chip interface [18]. Within the investigated range, higher spindle speed generally improved surface finish.

Feed rate exhibited a strong influence on surface roughness. Lower feed rates produced smoother surfaces due to reduced chip thickness and more uniform material removal. In contrast, increasing the feed rate led to higher surface roughness values, as the cutting tool advanced more rapidly through the material, generating larger chips and more pronounced feed marks on the machined surface.

Depth of cut showed a comparatively smaller effect on surface roughness. Lower depth of cut values resulted in smoother surfaces due to reduced cutting forces and tool loading, while higher depth of cut slightly increased surface roughness. The influence of coolant type was relatively minor compared with the cutting parameters.

These findings are consistent with previous studies on brass machining, which reported that feed rate is the most influential parameter affecting surface roughness, followed by spindle speed and depth of cut [19], [20]. The combined effects of spindle speed and feed rate on surface roughness are further illustrated in the three-dimensional surface plot shown in Figure 7.

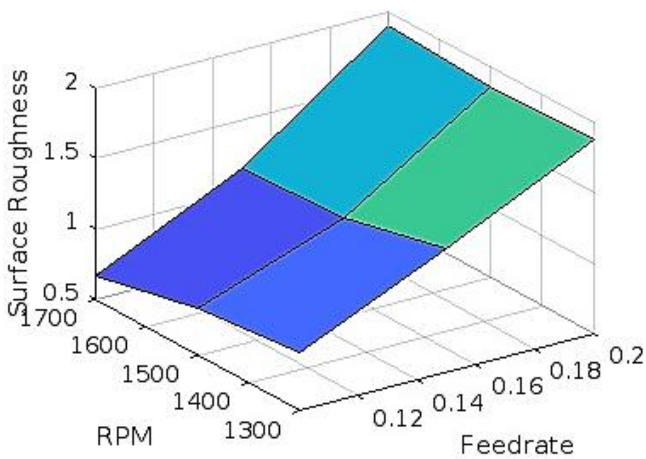

Figure 7. Three-dimensional surface plot of surface roughness

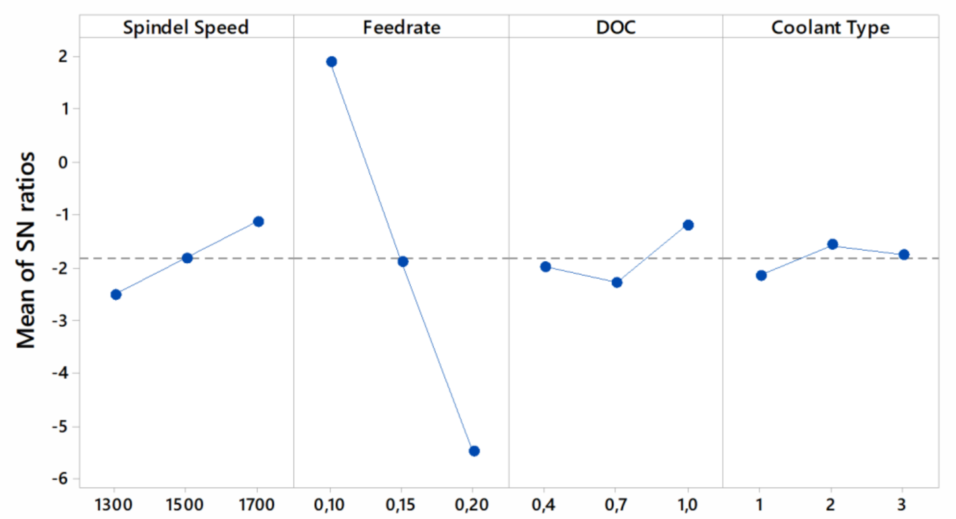

Figure 8. Main effects plot of signal-to-noise (S/N) ratios for surface roughness using the "smaller-is-better" criterion

3.2. Signal to noise ratio analysis

The signal-to-noise (S/N) ratio is employed in the Taguchi method to evaluate process quality by accounting for both the mean response and its variability. In machining applications, S/N analysis is particularly useful for identifying robust parameter settings that minimize sensitivity to uncontrollable variations. In this study, the "smaller-is-better" criterion was adopted to minimize surface roughness.

Figure 8 shows the main effects plot of S/N ratios for surface roughness. The results indicate that the minimum surface roughness is achieved at a spindle speed of 1700 rpm, a feed rate of 0.1 mm/rev, a depth of cut of 0.7 mm, and the use of synthetic coolant (GT41). Among all parameters, feed rate exhibits the most pronounced effect on surface roughness, as evidenced by the steepest slope in the S/N plot. Reducing the feed rate to 0.1 mm/rev significantly improves surface finish. Spindle speed and depth of cut show moderate influences, while the effect of coolant type is relatively small within the investigated range. The response tables for S/N ratios and mean values are presented in Table 4. The delta values clearly indicate that feed rate is the most influential factor, with the highest delta value of 7.389, followed by spindle speed (1.39), depth of cut (1.09), and coolant type (0.575). Accordingly, the factors are ranked in the order: feed rate (Rank 1), spindle speed (Rank 2), depth of cut (Rank 3), and coolant type (Rank 4). The optimal factor levels determined from the S/N analysis are spindle speed at Level 3, feed rate at Level 2, depth of cut at Level 3, and coolant type at Level 3.

$$\text{Surface roughness } = 0.390 - 0.000375\mathrm{X}_1 + 10.7\,\mathrm{X}_2 - 0.106\mathrm{X}_3 - 0.0233\mathrm{X}_4 \quad (4)$$

where the constant of X_2 is feed rate, while the coefficients X_1 and X_3 are spindle speed and depth of cut respectively. In the regression model, X_1 represents the spindle speed (rpm), X_2 denotes the feed rate (mm/rev), X_3 refers to the depth of cut (mm), and X_4 corresponds to the coolant type, where 1 represents compressed air (7 bar), 2 denotes synthetic coolant, and 3 represents engine oil.

Table 4. Response tables for signal-to-noise (S/N) ratios and mean surface roughness values for different machining parameters

Surface Roughness								
	Response Table for Signal to Noise Ratios				Response Table for Means			
Level	**S. Speed**	**Feed rate**	**DOC**	**Coolant**	**S. Speed**	**Feed rate**	**DOC**	**Coolant**
1	-2.519	1.906	-1.985	-2.145	1.3933	0.81	1.3133	134
2	-1.82	-1.89	-2.286	-1.57	1.3	1.2467	1.3733	13033
3	-1.129	-5.483	-1.196	-1.753	1.2433	1.88	1.25	1.2933
Delta	1.39	7.389	1.09	0.575	0.15	1.07	0.1233	00467
Rank	2	1	3	4	2	1	3	4

The obtained linear regression on equation (4) shows a positive coefficient for feed rate and negative coefficients for spindle speed and depth of cut, indicating that increasing feed rate increases surface roughness, whereas higher spindle speed and lower cutting load tend to reduce it. The regression model is statistically significant, with a P-value < 0.05, confirming the reliability of the relationship between the machining parameters and surface roughness. These findings are consistent with previous studies, which also identified feed rate as the dominant factor affecting surface roughness in turning operations [1], [20], [21], [22].

The S/N ratio analysis demonstrates the effectiveness of the Taguchi method in identifying robust machining conditions and confirms that precise control of feed rate is critical for minimizing surface roughness in the CNC turning of Brass 36000. This is consistent with previous research [23], which also used the Taguchi method in surface roughness optimization research for turning processes.

3.3. Analysis of variance (ANOVA) for surface roughness

Table 5. Analysis of variance (ANOVA) results for surface roughness

Source	DF	Adj SS	Adj MS	F-value	P-value	Contribution (%)
Model	4	1.7604	0.4401	47.36	0.001	—
Spindle Speed	1	0.0338	0.0338	3.63	0.129	1.88
Feed Rate	1	1.7174	1.7174	184.8	< 0.001	95.54
Depth of Cut (DOC)	1	0.006	0.006	0.65	0.466	0.33
Coolant Type	1	0.0033	0.0033	0.35	0.585	0.18
Error	4	0.0372	0.0093	—	—	2.07
Total	8	1.7976	—	—	—	100

Analysis of variance (ANOVA) was performed to statistically evaluate the significance and relative contribution of each machining parameter to surface roughness variation. The analysis was conducted at a 95% confidence level, where a parameter is considered statistically significant when the corresponding P-value is less than 0.05. The ANOVA results for surface roughness are summarized in Table 5.

The results indicate that the overall regression model is statistically significant, with an F-value of 47.36 and a P-value of 0.001, confirming a strong relationship between the selected machining parameters and surface roughness. Among the individual factors, feed rate is the only parameter with a statistically significant effect on surface roughness ($P < 0.05$). Feed rate exhibits the highest contribution, accounting for 95.54% of the total variation, and shows a very large F-value of 184.8, indicating a dominant influence on surface quality. In contrast, spindle speed, depth of cut, and coolant type show P-values greater than 0.05, indicating that their effects are not statistically significant within the investigated parameter ranges. Their respective contributions to surface roughness variation are relatively small, amounting to 1.88% for spindle speed, 0.33% for depth of cut, and 0.18% for coolant type.

These findings clearly demonstrate that feed rate is the dominant controlling factor affecting surface roughness in the CNC turning of Brass 36000 under the tested conditions, while the influence of the other parameters is comparatively minor. This statistical evidence strongly supports the trends observed in the S/N ratio analysis and confirms the critical importance of feed rate control in achieving improved surface finish.

3.3. Regression analysis for surface roughness

Regression analysis was employed to develop a predictive model describing the relationship between surface roughness and the selected machining parameters. A linear regression model was formulated to estimate surface roughness as a function of spindle speed, feed rate, depth of cut, and coolant type.

Model adequacy was evaluated using a normal probability plot of residuals, as shown in Figure 9. The residuals closely follow the normal probability reference line, indicating that the assumption of normality is satisfied and that the linear regression model is appropriate for representing the experimental data.

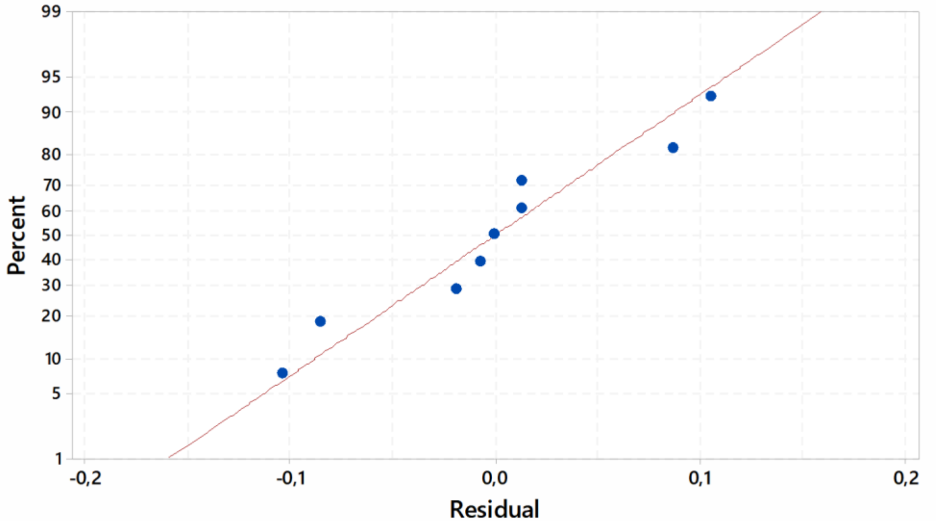

Figure 9. Normal probability plot of residuals for surface roughness

3.4. Optimal prediction for surface roughness

The optimal surface roughness value was predicted using the Taguchi method based on the mean response values of the significant factors. The predicted response was calculated using:

$$\hat{n} = n_m + \sum_{i=1}^{q} (\bar{n}_i - n_m) \tag{4}$$

where n_m is the overall mean surface roughness and $\bar{n}_i$ is the mean surface roughness at the optimal level of each factor. Substituting the corresponding values yields a predicted optimal surface roughness of:

$$SR_{opt} = 1.31 + (1.24 - 1.31) + (1.25 - 1.31) + (1.30 - 1.31)$$

$$SR_{opt} = 0.67\mu m$$

This predicted value is in good agreement with the experimental observations.

3.5. Confidence interval analysis

To assess the reliability of the predicted optimal surface roughness, a confidence interval analysis was performed. The effective number of observations was calculated as:

$$n_{eff} = \frac{\text{Total Number of Experiment}}{1 + \text{Sum of the Degrees of Freedom}}$$

$$n_{eff} = \frac{27}{1 + 2 + 2 + 2 + 2} = 3$$

Using the F-table value ($F_{0.05;3;23}$ = 3.03) and the mean square error obtained from ANOVA, the confidence interval was determined as:

$$CI_{opt} = \sqrt{\frac{F_{\alpha;v1_{v2}} \times MS_E}{n_{eff}}}$$

$$CI_{opt} = \sqrt{\frac{3.03 \times 0.0093}{3}} = 0.0096$$

Accordingly, the 95% confidence interval for the mean surface roughness is:

$$\bar{x} - CI \leq \mu_{confirm} \leq \bar{x} + CI$$
$$0.6733 - 0.096 \leq \mu_{confirm} \leq 0.6733 + 0.096$$
$$0.6604 \leq \mu_{confirm} \leq 0.679$$

The narrow confidence interval indicates that the predicted optimal surface roughness is statistically reliable and confirms the robustness of the optimized machining parameters.

The regression equation generated in this study found that the highest coefficient value was for feed rate, indicating that feed rate has a very strong influence on surface roughness. This result aligns with previous research [1], which also stated that feed rate plays an important role in minimizing surface roughness [1]. This research also demonstrated the effectiveness of the Taguchi method in turning process optimization research. This is consistent with previous research [23], which also used the Taguchi method in surface roughness optimization research for turning processes [23].

4. Conclusions

This study applied the Taguchi method to optimize CNC turning parameters for minimizing surface roughness in the machining of Brass 36000 using a CNC GSK 980TDi machine. The optimal parameter combination was identified as a spindle speed of 1700 rpm, feed rate of 0.1 mm/rev, depth of cut of 1.0 mm, and the use of synthetic coolant (GT41), resulting in a minimum surface roughness of approximately 0.67 µm. Statistical analysis revealed that feed rate is the dominant factor influencing surface roughness, contributing 95.54% to the total variation in the response. This finding confirms that controlling feed rate is critical for achieving superior surface quality in brass turning operations. In comparison, spindle speed exhibited a relatively minor influence with a contribution of 1.88%, while depth of cut and coolant type had negligible effects, contributing 0.33% and 0.18%, respectively, within the investigated parameter ranges.

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