Experimental Optimization of Surface Roughness in Milling of AISI 304 Stainless Steel on A CNC Vertical Machining Center

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Highlights

- \triangleright Studies show that the use of coolant fluid has a negative effect on surface roughness, leading to an increase in roughness rather than an improvement in surface quality.
- \triangleright The results obtained from validation experiments align with the calculated confidence interval values, indicating that the Taguchi method has been effectively used in the experimental design and optimization processes.
- Experimental results demonstrate that the feed rate (F) is the most influential factor affecting surface roughness.

AISI 304 Paslanmaz Çeliğinin CNC Dik İşleme Merkezinde Frezelenmesinde Yüzey Pürüzlülüğünün Deneysel Optimizasyonu

1. Introduction

Stainless steels are increasingly being used in various fields such as medicine, aviation, nuclear energy, food, and defense industries. Modifications in their composition, made to meet the mechanical and chemical properties required for specific applications, significantly affect their machinability. The high tensile strength, corrosion resistance, low thermal conductivity, ductile nature, and the presence of high amounts of strength-enhancing elements like chromium, nickel, and molybdenum are primary factors that make machining stainless steel challenging. Additionally, the tendency of stainless steel to work hard during machining is a critical issue that complicates manufacturing processes. Consequently, the difficulties in machinability pose significant challenges for manufacturers (Anonymous, 1997; Bahadur, Kumar, and Chowdhury, 2004).

AISI 304 stainless steel, despite its low machinability due to its properties, is widely used in the manufacturing industry. The primary goal of manufacturing is to transform raw materials into finished products, employing various technological methods in the process. Machining (e.g., turning, milling) is one of these methods, which removes material in the form of chips to achieve the desired shape (Belejchak, 1997; Kasap, 2001). In the manufacturing industry, the primary objective is to produce parts of the desired quality at minimum cost and in the shortest possible time. Among the modern manufacturing methods developed for this purpose, milling is one of the most commonly used techniques (Dilipak and Yılmaz, 2012; Yılmaz, 2009).

Incorrect selection of cutting parameters can lead to the loss of workpieces and the wear of cutting tools, causing financial losses. Surface quality, which plays a crucial role in determining the functionality of a product, can enhance the wear resistance and fatigue strength of materials. However, it can also significantly impact production costs (Guvercin and Yildiz, 2018; Uğur, 2019).

Therefore, measuring and characterizing surface roughness is of great importance for optimizing machining processes. In the literature, various studies have been conducted on such optimizations using AISI 304 stainless steel.

Bodur (2022) examined the effects of cutting speed, feed rate, and depth of cut parameters on surface roughness and power consumption during turning of AISI 304 stainless steel, conducting a detailed statistical analysis of these effects. The results showed that the feed rate plays a significant role in surface quality, while all three parameters were found to be decisive in terms of power consumption (Bodur, 2022). Özbek et al. (2017) compared the machinability of AISI 304 and AISI 316 stainless steels using uncoated tungsten carbide cutting tools in turning experiments. The study, which found that AISI 316 steel is more difficult to machine than AISI 304, highlighted differences between the two materials in terms of surface roughness and cutting tool wear (Özbek, Çiçek, Gülesin, and Özbek, 2017).

Kuram (2016), focusing on the performance of coated cutting tools, studied the effects of different coating types on surface roughness, tool wear, and cutting forces during milling of AISI 304 stainless steel. The experiments showed that TiCN + TiN-coated tools provided the best performance, while AlTiN-coated tools resulted in the highest wear and surface roughness values (Kuram, 2016). Similarly, Tekaslan et al. (2011) experimentally measured cutting forces during turning operations and compared these values with theoretical models. The study emphasized that theoretical calculations did not exactly match the experimental results and that experimental methods were more reliable (Tekaslan, Gerger, Günay, and Şeker, 2011). Tekaslan et al. (2008) investigated the surface roughness of AISI 304 stainless steel samples processed with different cutting parameters and noted that the optimal cutting speed was between 50-75 m/min. The study also showed that surface roughness deteriorated as the feed rate increased. It was concluded that appropriate cutting parameters should be selected to improve surface quality and reduce tool wear (Tekaslan, Gerger, & Şeker, 2008).

Although AISI 304 stainless steel has a wide range of industrial applications, studies on milling in the literature are relatively scarce. In this study, AISI 304 stainless steel was machined using parameters determined by the Taguchi method, both under wet and dry conditions, on a CNC milling machine. The study aims to investigate surface roughness and the parameters affecting surface roughness.

2. Material and Method

2.1. Test Pieces

For the experiments, AISI 304 stainless steel, with a hardness value ranging between 200-220 HV (Vickers Hardness), was used as the main material. The dimensions of the test pieces are presented in Figure 1. Its chemical composition and mechanical properties are provided in Tables 1 and 2, respectively.

2.2. Machinery and Equipment

The research investigated the effect of processing parameters on the surface quality of face milling of AISI 304 steel. In the experiments, a Frontier MCV 650 brand 3-axis CNC machining center with a motor power of 10 kW and a maximum spindle speed of 15,000 rpm was used. The experiments utilized an ER32UM D18 tool holder along with a 3-flute end mill featuring a 20 mm diameter and a length of 100 mm. The end mill's cutting edges were equipped with OKE

APKT1035PDSR tungsten carbide inserts used for stainless steel and steel application as shown in Figure 1. APKT1035 inserts are widely used standard inserts in the milling operations for the manufacturing industry. The overall dimensions of these inserts are 10x6.7x3.5 mm.

Figure 1. Milling Machine, Tool Holder, and Cutting Insert.

Two different processes were performed during the experiments: some were conducted using coolant, while others were performed as dry machining (without coolant).

The CNC machining coolant consisted of specially formulated chemical additives designed for optimal compound concentration.

The coolant mixture ratios were determined according to the manufacturer's recommendations to ensure the best lubrication and cooling properties. This controlled environment allowed for a consistent comparison between dry and wet machining processes. The experiments aimed to analyze how the presence or absence of coolant impacts surface roughness under varying cutting conditions.

Table 1. Chemical Composition of AISI 304 Stainless Steel (Şahin, Cakan, Tutar, and Şahin, 2023)

Hardness	Tensile Strength	Yield Strength (MPa)	Elongation	
'HV)	(MPa)		$(\min, \frac{9}{6})$	
200-220	515-740	205	60	

Table 2. Mechanical Properties of AISI 304 Stainless Steel

2.3. Experimental Parameters

The experiments were conducted in two different modes: using wet and dry machining. The machining parameters are provided in Table 3. The cutting parameters used in the experiments were selected by considering the catalog values of the OKE APKT1035PDSR hard metal inserts mounted on the end mill and the preliminary experiments. For the experimental design, the Taguchi L18 orthogonal array was applied.

In this study, the Taguchi L18 $(2^{\wedge}1 \frac{3^{\wedge}3}{3^{\wedge}3})$ orthogonal array (OA) was used. The experimental design included 18 cutting operations involving two different cooling methods, three cutting speeds (3000, 3500, and 4000 m/min), three feed rates (750, 1000, and 1250 mm/min), and three cutting depths (0.1, 0.15, and 0.2 mm). Based on the surface roughness values obtained after the experiments, S/N (Signal-to-Noise) ratios were calculated using the "smaller-is-better" equation.

Table 3. Machining Parameters and Levels

$$
S_{N} = -10 \log_{\frac{1}{n}}^{\frac{1}{n}} \sum_{i=1}^{n} y_{i}^{2}
$$
 (1)

2.4. Measuring Devices and Methods

The surface roughness values (Ra) obtained during the experiments were measured using a Mitutoyo SJ-210 surface roughness measurement device, by the DIN EN ISO 16610-21 standard (Figure 2). The surface roughness measurements were based on the average of five different readings taken from each sample, which were then used for statistical analysis.

Figure 2. Surface Roughness Measurement Device

3. Results and Discussion

According to the experimental plan, the first 9 experiments were conducted using coolant, with varying cutting speeds, feed rates, and cutting depth values. The subsequent experiments, from 9 to 18, were performed under dry machining conditions. For both coolant-assisted and dry conditions, a new cutting insert was used for each cutting speed.

3.1. Surface Roughness

The surface roughness results obtained from the experiments are presented in Table 4.

3.2. Determination of the optimum cutting condition

The optimal cutting performance in milling operations was determined using Signal-to-Noise (S/N) ratio analysis. This analysis facilitated the identification of delta statistics and ranking based on the results. The average results are presented in Table 5, where cutting speed ranked first (Rank 1) and was identified as the most influential factor on surface roughness. It was followed by spindle speed, cutting depth, and finally, the cooling factor in terms of their impact on surface roughness.

As summarized in Table 5, the S/N ratio analysis highlights the varying effects of different cutting parameters on surface roughness during milling operations. The rankings reveal the relative importance of these parameters in shaping the desired cutting performance outcomes.

The effects of cutting factors on Ra (surface roughness) are illustrated in Figure 3. The factors shown in the graph are the two most influential factors on Ra, determined based on variance analysis results.

Figure 4 displays the main effects plot for the mean S/N ratios of surface roughness (Ra). According to Figure 4, the second level of cooling (A_2) , the third level of spindle speed (B_3) , the first level of feed rate (C_1) , and the second level of cutting depth (D_2) yield the minimum Ra values. Based on the mean analysis (Table 5), the levels of the variables (A_2, B_3, C_1, D_2) are the optimum levels for achieving minimum Ra. This is also evident in the main effects plot for the S/N ratio presented in Figure 4.

The study demonstrated the positive effect of dry cutting on surface roughness. This effect is believed to be related to the low thermal conductivity of stainless steel. During dry machining, heat is largely transferred to the chips, which helps prevent excessive temperature increases in the machining zone. The absence of coolant also aids in avoiding sudden temperature fluctuations, which is thought to improve surface quality. Coolants, on the other hand, can negatively affect surface morphology and tool geometry due to rapid cooling and thermal shocks. A review of the literature revealed that researchers such as Nguyen et al. (2020); Shelar and Shaikh (2018); Chockalingam and Wee (2012) and Ozcelik, Kuram, and Simsek (2011) have reported findings consistent with the results of this study.

Surface Plot of Raivs C. B

Figure 3. The Effect of Cutting Factors on Surface Roughness (Ra)

Figure 4. Response Graph for S/N Ratios of Surface Roughness (Ra)

Test No	$\mathbf A$	\bf{B}	$\mathbf C$	\mathbf{D}	Surface roughness (μm)	S/N Ratio (dB)	Tahmini Ra
1	$\mathbf{1}$	3000	750	0,1	0,521	5,6566	0,512733
$\mathfrak{2}$	$\mathbf{1}$	3000	1000	0,2	0,454	6,8512	0,516833
3	$\mathbf{1}$	3000	1250	0,15	0,705	3,0387	0,816200
$\overline{\mathbf{4}}$	$\mathbf{1}$	3500	750	0,1	0,523	5,6333	0,574000
5	$\mathbf{1}$	3500	1000	0,2	0,583	4,6836	0,578100
6	$\mathbf{1}$	3500	1250	0,15	0,932	0,6154	0,877467
$\overline{7}$	$\mathbf{1}$	4000	750	0,15	0,450	6,9280	0,327867
$\,8\,$	1	4000	1000	0,2	0,435	7,2302	0,435000
9	1	4000	1250	0,1	0,814	1,7832	0,779800
10	$\overline{2}$	3000	750	0,2	0,420	7,5267	0,430456
11	$\mathfrak{2}$	3000	1000	0,1	0,710	2,9724	0,583022
12	2	3000	1250	0,15	0,827	1,6457	0,779356
13	$\sqrt{2}$	3500	750	0,15	0,395	8,0725	0,472522
14	$\mathbf{2}$	3500	1000	0,2	0,639	3,8873	0,579656
15	$\mathbf{2}$	3500	1250	0,1	0,935	0,5875	0,924456
16	$\overline{2}$	4000	750	0,2	0,337	9,4422	0,329422
17	$\overline{2}$	4000	1000	0,1	0,353	9,0544	0,481989
18	$\mathbf{2}$	4000	1250	0,15	0,643	3,8385	0,678322

Table 4. Experimental Surface Roughness Results and Calculated S/N Ratios

3.3. Analysis of Variance (ANOVA)

The primary purpose of using Analysis of Variance (ANOVA) in this research was to identify the significant effects of milling parameters on the performance characteristics of machined surfaces (Bilge and Motorcu, 2017). This study employed ANOVA to examine how cooling, spindle speed, feed rate, and cutting depth influence surface roughness. The analysis was conducted at a 5% significance level and within a 95% confidence interval.

In ANOVA, the significance of control factors is determined by evaluating the F-values associated with each factor. The ANOVA results for surface roughness are summarized in Table 6. The analysis revealed that, based on the percentage contribution rates, feed rate (F) was identified as the most influential factor affecting surface roughness, contributing 70.04%.

In summary, this study used ANOVA as a statistical tool to determine the significant effects of various milling parameters on surface roughness. The results presented in Table 6 highlight the substantial impact of coolant usage on performance characteristics, emphasizing its dominant role in shaping the properties of machined surfaces.

3.4. Regression analysis

Regression analysis is a crucial tool for modeling and analyzing relationships between a dependent variable and one or more independent variables. In this study, regression analysis was used to derive equations for predicting surface roughness. These predictions were formulated within the framework of a linear model. The calculated linear equations related to surface roughness are presented in Table 7.

Level		H	В	
	4,713	4,615	7,210	4,281
2	5,225	3,913	5,780	5,337
3		6,379	1,918	5,290
Delta	0,512	2,466	5,292	1,055
Rank				

Table 5. Response Table for Signal to Noise Ratios: Averages and Importance Levels for Surface Roughness

Source	DF	Contribution	Adi SS	Adj MS	F-Value	P-Value
Cooling $1 \text{ On} / 2 \text{ Off}$		0.22%	0,001401	0,001401	0.17	0.692
S(1/min)		12,73%	0,080605	0,040303	4.77	0.035
F (mm/min)		70.04%	0.443446	0.221723	26.24	0,000
a (mm)		3,66%	0.023148	0.011574	1.37	0,298
Error	10	13.35%	0,084509	0.008451		
Total	17	100.00%				

Table 7. Regression Equation for Ra

This study focused on predicting surface roughness by utilizing regression analysis to establish predictive equations. These equations, formulated within the structure of a linear model, provide a quantitative basis for predicting surface roughness and are summarized in Table 7.

3.5. Fitted plots assessment

Figure 5 illustrates the fit plot comparing predicted and actual Ra values. This graph highlights the deviation between the actual and predicted values. Specifically, the proximity of the residuals to the diagonal line indicates the significance of the model. This closeness suggests that the model adequately represents the data and confirms its statistical relevance.

Furthermore, the R² value calculated for the relationship between predicted and actual Ra responses was found to be 0.87, while the P-value from the ANOVA for regression was determined to be 0.002, indicating a statistically significant difference. These coefficients demonstrate a strong linear relationship between the two response variables.

An R² value of 87% for Ra emphasizes a substantial correlation between the predicted and observed values, highlighting the model's reliability in capturing and explaining variability in the data.

Figure 5. Comparison of Predicted Values and Experimental Results for Ra Output Parameters

3.6. Validation Experiments and Determination of Quality Losses

In the Taguchi method, validation experiments and the identification of quality losses constitute the final stage of the process, aimed at analyzing quality characteristics (Samtaş and Korucu, 2019). The main objective of validation experiments is to verify the accuracy of the results obtained during the analysis. These experiments aim to evaluate specific combinations of factors and levels, determined by the cumulative effects of the control factors. (Hill and Lewicki, 2006; Mandal, Doloi, Mondal, and Das, 2011). The contribution of each factor is accounted for in the total effect.

In the Taguchi optimization method, conducting at least one validation experiment is mandatory to verify the optimized conditions (Roy, 1990). The lowest surface $\eta_g = \overline{\eta_g} + (A_2 - \overline{\eta_g}) + (B_3 - \overline{\eta_g}) + (C_1 - \overline{\eta_g}) + (D_2 - \overline{\eta_g})$ (6)

roughness is attained by optimizing the influential factors within the ideal parameter combination. Therefore, considering the individual effects of control factors, the minimum surface roughness value (Rac) for the A₂B₃C₁D₂ combination (A₂ = Dry machining, B₃ = 4000 rpm, $C_1 = 750$ mm/min, $D_2 = 0.15$ mm) is calculated using the following equations (Fowlkes and Creveling, 1995):

Here, A_2 , B_3 , C_1 , and D_2 represent the S/N ratios at the optimal levels of the factors. $\overline{\eta}_g$ indicates the average S/N ratio for all factors, while η_g represents the S/N ratio calculated for the optimal levels. Considering these values, the minimum surface roughness value (Rac) was determined to be 0.347 μm.

 $Ra_C = 10^{-\eta_g/20}$ (7)

Table 8. Regression Equation for Ra

$$
CI = \sqrt{F_{\alpha;1;\nu_e}} \chi V_{ep} \chi \left(\frac{1}{n_{eff}} + \frac{1}{r}\right)
$$
 (8)

In this context, $F_{\alpha:1}$, V_{ep} is the F ratio of the significance level α, α is the significance level, 1- α is the confidence interval, V_e is the degree of freedom of the error, V_{ep} indicates the variance of the error, r represents the number of validation experiments, and n_{eff} is the number of effectively measured results (Liu, Chang and Yamagata, 2010).

$$
n_{eff} = \frac{N}{1 + [V_t]}
$$
\n(9)

Here, N represents the total number of experiments (18), and V_t is the total degrees of freedom for the process parameters considered in the average calculation, based on Table 5. Accordingly, neff was calculated as 2.25 (Pınar, Atik and Çavdar, 2010). For the evaluation conducted at a 95% confidence interval for surface roughness, with α =0.05 and V_e =18, the F value from the table was determined as $F_{\alpha:1}$, V_e =4.96. Using Eq. (8) and Eq. (9), the confidence interval (CI) was calculated to be 0.181. The result of the validation experiments for surface roughness, conducted with a

95% confidence interval, is expected to fall within (0.347 ± 0.181) μm or between 0.166-0.528 μm. To evaluate the performance of the experimental studies carried out in this research, three validation experiments were conducted using the optimal conditions. In the validation experiments conducted under optimal levels $(A_2B_3C_1D_2)$, the surface roughness values were obtained as 0.3, 0.33, and 0.37 μm, respectively, with an average value calculated as 0.33 μm.

Table 8 compares the surface roughness values obtained through experiments and predictions based on the optimal combinations. Additionally, the $A_2B_3C_1D_3$ combination was selected as the initial combination from the 18 experiments. Table 9 presents the performance comparison between the initial and optimal conditions. The average value obtained from the validation experiments, 0.33 μm, lies within the predicted range of 0.166–0.528 μm. This result confirms that the control factors analyzed in this study are both statistically significant and reliable.

Table 9. Performance Comparison Between Initial and Optimal Combination

	Initial combination	Optimal combination		
		Prediction	Verification	
Level	$A_2B_3C_1D_3$	$A_2B_3C_1D_2$	$A_2B_3C_1D_2$	
$Ra_{m}(\mu m)$	0,337	$0,347 \pm 0,181$	0,33	
Quality loss			%2,5	

The quality characteristic of this experiment was improved from $0.337 \mu m (A_2B_3C_1D_3,$ initial combination) to $0.333 \mu m$ (A₂B₃C₁D₂, optimal combination), as indicated in Table 9. The quality losses between the initial and optimal combinations for surface roughness can be determined using the quality loss function ratio. This ratio indicates that for every 3 dB improvement in quality, the quality loss is reduced by half. The quality loss function is computed using the equation shown below. (Fowlkes and Creveling, 1995).

$$
\frac{L_{opt}(y)}{L_{ini}(y)} \approx \left(\frac{1}{2}\right)^{\Delta \eta} / 3
$$
\n(10)

Here, $L_{opt(y)}$ and $L_{init(y)}$ represent the optimal and initial combinations, respectively. Δη is the difference between the S/N ratios of the optimal and initial combinations. The difference in S/N ratios, which can be used to evaluate the quality loss for the optimal combination in the verification experiments, was found to be 0,11 $[\Delta \eta = 0, 11 (= 9.55 - 9.44)]$. The quality loss of the verification test was calculated as 0.25 using Equation (10). Thus, the quality loss for the optimal combination is only 2,5% of that of the initial combination. Therefore, the quality loss for surface roughness was reduced by 97,5% using the Taguchi method for optimization.

4. Conclusion

This study investigates how the surface roughness of AISI 304 stainless steel is affected by different surface machining conditions during milling operations.

The following results were obtained:

According to the experimental results, the optimal combination of surface milling parameters was determined as $A_2B_3C_1D_2$ ($A_2 = Dry$ machining, $B_3 =$ 4000 rpm, $C_1 = 750$ mm/min, $D_2 = 0.15$ mm).

Experimental results showed that the feed rate (F) was the most influential factor on surface roughness, with a contribution rate of 70.04%. This was followed by spindle speed (S (rpm)) with a contribution rate of 12.73%.

The observed values from the validation experiments fell within the calculated confidence interval (CI), demonstrating the successful application of the Taguchi method.

Using the optimal combination, the quality loss of the surface roughness was reduced to 2.5%.

The initial surface roughness value of 0.337 μm was reduced to 0.333 μm through validation experiments conducted under optimal conditions.

The study showed that the use of coolant fluid had a negative effect on surface roughness, leading to an increase in roughness instead of improving surface quality.

Across all experiments, the highest surface roughness (Ra = 0.9346) was observed under wet machining conditions with a cutting speed of 3500 rpm, a feed rate of 1250 mm/min, and a cutting depth of 0.1 mm.

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Author Contributions:

Dalmış (ISD); Formal analysis–ISD; Investigation-Serdar Osman Yılmaz (SOY); Experimental performance– SOY; Data collection- Beyza Avcı (BA); Processing– ISD and BA; Literature review- BA; Writing– ISD and BA; Review and editing– SOY and SD.

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