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Influence of spindle speed, feed rate, and depth of cut on machining performance: an analysis of material removal processes in mild steel

Yumuşak çelikte malzeme kaldırma süreçlerinin analizi: iş mili hızı, ilerleme hızı ve kesme derinliğinin işleme performansı üzerindeki etkisi

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Abstract

This study examines the effects of spindle speed, feed rate, and depth of cut on machining performance during mild steel machining. Experiments were conducted with spindle speeds ranging from 105-225 rpm, feed rates of 0.10-0.34 mm/rev, and depths of cut between 1.0-3.4 mm. Results showed that increasing these parameters improved the material removal rate (MRR), with the highest MRR reaching 261.30 mm^3/min. However, tool wear rate also rose proportionally, peaking at 7.65 mm^3/min, highlighting a trade-off between productivity and tool durability. Machining time decreased with higher spindle speeds, with the shortest time recorded at 1.35 minutes. Statistical analysis using paired sample t-tests and correlation coefficients revealed strong positive correlations between spindle speed and MRR (r=0.973), spindle speed and tool wear rate (r=0.994), and a strong negative correlation between spindle speed and machining time (r=-0.935). These findings highlight the importance of optimizing cutting parameters to balance productivity, tool wear, and efficiency. The study provides practical insights for industrial machining of mild steel and recommends future exploration into advanced cooling methods and tool materials to enhance machining performance under similar conditions, contributing to improved precision and resource efficiency.

Öz

Bu çalışma, yumuşak çelik işleme sırasında iş mili hızı, ilerleme hızı ve talaş derinliğinin işleme performansı üzerindeki etkilerini incelemektedir. Deneyler, 105-225 rpm aralığında iş mili hızı, 0.10-0.34 mm/dev ilerleme hızı ve 1.0-3.4 mm talaş derinliği değerleriyle gerçekleştirilmiştir. Sonuçlar, bu parametrelerin artırılmasının malzeme kaldırma oranını (MRR) iyileştirdiğini göstermiştir; en yüksek MRR değeri 261.30 mm^3/dak olarak kaydedilmiştir. Ancak, takım aşınma oranı da orantılı olarak artmış ve maksimum 7.65 mm^3/dak değerine ulaşarak, yüksek verimlilik ile takım ömrü arasında bir denge olduğunu ortaya koymuştur. İşleme süresi ise artan iş mili hızıyla azalmış ve en kısa süre 1.35 dakika olarak ölçülmüştür. Eşleştirilmiş örneklem t-testi ve korelasyon katsayıları kullanılarak yapılan istatistiksel analizler, iş mili hızı ile MRR arasında güçlü pozitif (r=0.973), iş mili hızı ile takım aşınma oranı arasında güçlü pozitif (r=0.994) ve iş mili hızı ile işleme süresi arasında güçlü negatif (r=-0.935) korelasyonlar ortaya koymuştur. Bu bulgular, üretkenlik, takım aşınması ve verimlilik arasında denge sağlamak için kesme parametrelerinin optimize edilmesinin önemini vurgulamaktadır. Çalışma, endüstriyel yumuşak çelik işleme uygulamaları için değerli bilgiler sunmakta ve benzer koşullarda gelişmiş soğutma yöntemleri ile takım malzemelerinin etkisinin araştırılmasını önermektedir. Bu sonuçlar, hassas üretim süreçlerinin ve kaynak optimizasyonunun geliştirilmesine katkı sağlar.

1. Introduction

Machining processes, particularly milling and turning, remain fundamental in modern manufacturing, where the need for precision, efficiency, and cost-effectiveness is ever-increasing. Among the various influencing factors in these processes, spindle speed, feed rate, and depth of cut have been consistently recognized as critical parameters affecting machining performance, especially in relation to material removal rate (MRR), surface roughness, and tool wear [1, 2]. Mild steel, due to its mechanical properties, machinability, and cost-efficiency, is widely used in industrial applications, making the study of its machining behavior a subject of practical significance [3, 4]. The material removal rate is a key performance indicator in machining operations, directly influencing productivity and machining economics. It has been shown that spindle speed significantly affects the cutting force, surface finish, and overall machining energy [5, 6]. An increase in spindle speed often leads to better surface quality but may accelerate tool wear, especially if not properly balanced with feed rate and depth of cut [7, 8]. Studies have shown that optimal combinations of these parameters can lead to improved machining efficiency and reduced energy consumption [6, 9]. Feed rate, another crucial factor, plays a significant role in determining the rate at which material is removed and the resulting surface quality. Higher feed rates generally increase the MRR, but at the expense of surface integrity and potential tool damage [10, 11]. Depth of cut, similarly, affects the volume of material removed per unit time and contributes significantly to cutting forces and thermal stresses on both the tool and workpiece [12, 13]. The interplay among these three parameters is complex and necessitates multi-factorial analysis to identify optimal machining settings [14].

Several researchers have employed statistical methods such as Response Surface Methodology (RSM), Artificial Neural Networks (ANN), and Taguchi techniques to analyze and optimize machining parameters. For instance, Fnides [5] applied RSM to optimize surface roughness and MRR during the milling of C45 steel, while Krishna Murthy [4] used ANN for parameter prediction to achieve optimal MRR. These approaches demonstrate that mathematical and experimental models are invaluable in establishing the relationship between input parameters and machining responses [2, 15]. Machining mild steel also presents specific challenges and opportunities. Jaiganesh et al. [10] highlighted that proper selection of spindle speed and depth of cut using Taguchi techniques significantly improves surface finish. Similarly, Latif et al. [14] observed that increased feed rate and cutting speed enhanced MRR but required careful tool monitoring. Recent works further emphasize that improper combinations of parameters can degrade hole quality and dimensional accuracy in drilling operations [18], while optimized conditions contribute to better tool life and reduced surface irregularities [16, 17].

The significance of understanding cutting conditions is especially critical for mild steel due to its wide application in structural, automotive, and general engineering sectors [18]. The machinability of mild steel under varying cutting environments has been investigated under both dry and wet conditions, and consistent results point to a sensitive dependency on the three primary parameters discussed [19–21]. In high-precision applications, the effect of even slight deviations in feed rate or spindle speed can result in substantial losses in terms of part rejection or rework [8, 13]. Although substantial literature exists on machining of steels and parameter optimization, continuous innovation in cutting tools, machine systems, and computational modeling necessitates ongoing research. Moreover, the integration of new materials, sensors, and control systems in Industry 4.0 environments introduces dynamic variables not fully addressed in traditional machining studies [22]. While some studies address broader manufacturing systems or signal processing in unrelated domains [23, 24], the focused analysis of machining conditions on mild steel using modern analytical and experimental tools remains a vital area of study.

Moreover, the machining performance of mild steel is significantly influenced by key cutting parameters such as spindle speed, feed rate, and depth of cut. Optimizing these parameters enhances material removal rates, surface finish, and tool life, thus improving overall manufacturing efficiency [25, 26]. Studies employing Taguchi methods have demonstrated effective modeling and validation of these process parameters in various metals, including aluminum alloys and copper-zinc alloys [27, 28]. Specifically, spindle speed directly affects the cutting temperature and forces, while feed rate and depth of cut influence surface roughness and tensile strength of the machined components [29, 30]. Recent comprehensive reviews emphasize the critical role of parameter optimization for surface integrity enhancement and process stability during machining operations [31, 32]. This analysis underscores the interplay of these factors in material removal processes, providing a foundation for process improvement in mild steel machining.

Therefore, this study aims to systematically investigate the influence of spindle speed, feed rate, and depth of cut on the machining performance of mild steel. The goal is to identify optimal parameter ranges that enhance material removal while maintaining desirable surface integrity and tool life, thus contributing to more efficient and sustainable manufacturing practices.

2 Materials and Methods

2.1. Materials

The material chosen for the experimental investigation was AISI 1018 mild steel, a low-carbon steel widely recognized for its excellent weldability, machinability, and moderate tensile strength. These characteristics make it particularly suitable for research focused on machining behavior under varying operational conditions. Its uniform composition and predictable mechanical response also ensure reproducibility and reliability in experimental trials. To perform the cutting operations, a diamond cutting tool was employed. Owing to its exceptional hardness and wear resistance, the diamond tool enabled precise and consistent machining across a range of cutting parameters. Its durability under high-stress conditions also minimized tool wear, thus maintaining surface integrity and dimensional accuracy throughout the experimentation process [1], [3].

2.2. Experimental setup and procedure

The machining experiments were carried out on a CNC lathe operating under dry conditions to eliminate the influence of coolant and thereby isolate the specific effects of the primary machining parameters—spindle speed, feed rate, and depth of cut. The experimental matrix was strategically designed to encompass a range of process parameters: spindle speed was varied from 105 to 225 revolutions per minute (rpm), feed rate ranged between 0.10 and 0.34 millimeters per revolution (mm/rev), and depth of cut was adjusted from 1.0 to 3.4 millimeters. Each machining trial was precisely timed to determine the total machining time in minutes. Following the completion of each run, the machined samples were subjected to post-process evaluations to quantify key performance indicators. The material removal rate (MRR) was calculated to assess productivity, while the tool wear rate (TWR) was measured to evaluate tool life and wear characteristics under the different parameter settings.

The experimental procedure commenced with securely mounting the AISI 1018 steel workpiece onto the machine bed, followed by precise alignment and setting of the diamond cutting tool. The spindle speed, feed rate, and depth of cut were then configured in accordance with the predetermined experimental design. Each machining operation was executed while carefully recording the machining time to ensure consistency and repeatability. Upon completion of each trial, the material removed was collected and weighed to facilitate the calculation of the material removal rate (MRR). Tool wear volume was subsequently measured using a high-magnification optical microscope to ensure accurate and detailed quantification. This procedure was systematically repeated across a total of 25 experimental trials to capture variability and ensure statistical robustness. The collected data were then subjected to rigorous statistical evaluation, including T-tests and correlation analyses, to investigate the significance of individual parameters and their interdependencies.

2.3. Measurement of material removal rate and tool wear rate

The Material Removal Rate (MRR) was quantitatively assessed to evaluate machining efficiency under varying process parameters. MRR was determined using the equation 1:

$$\mathrm{MRR} = \frac{V_c \times f \times d}{t} \tag{1}$$

where V_c denotes the cutting speed in meters per minute (m/min), f is the feed rate in millimeters per revolution (mm/rev), d represents the depth of cut in millimeters (mm), and t is the machining time in minutes (min). The cutting speed V_c is intrinsically linked to the spindle speed N (in revolutions per minute, rpm) and the workpiece diameter D (in mm), expressed through the relationship in equation 2:

$$V_c = \frac{\pi D N}{1000} \tag{2}$$

This interdependence implies that variations in spindle speed directly influence the cutting speed and, consequently, the MRR, as supported by earlier studies [2, 4, 7].

The Tool Wear Rate (TWR) was evaluated to quantify the degradation of the cutting tool over time. TWR was calculated using the equation 3:

$$\mathrm{TWR} = \frac{V_w}{t} \tag{3}$$

where V_w is the volume of material lost from the cutting tool, measured in cubic millimeters (mm^3), and t is the machining time in minutes. Tool wear volume was determined through high-resolution optical microscopy conducted after each machining trial, enabling precise measurement of wear progression on the tool surface [5].

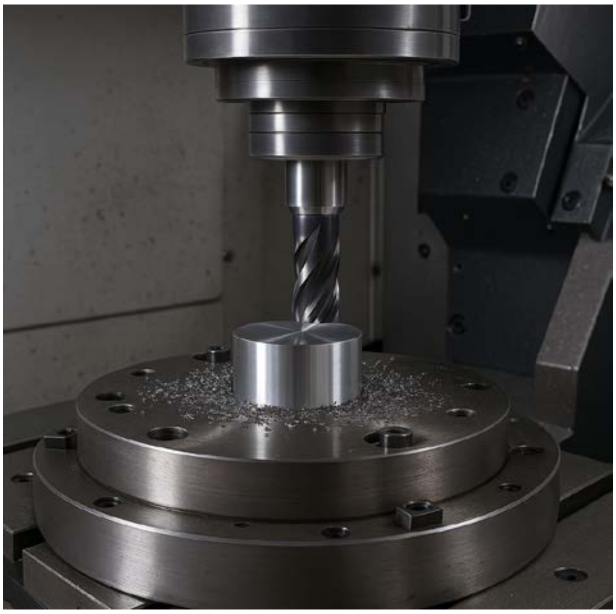

Figure 1: Vertical milling machine performing face milling operation (CNC machining process)

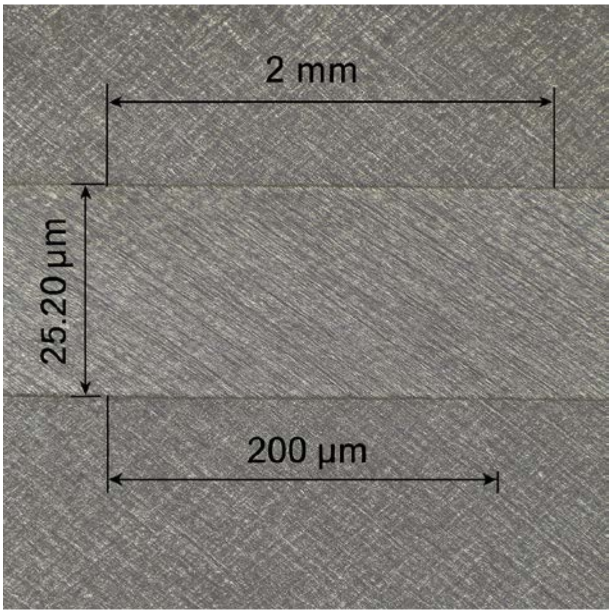

Figure 2. Optical microscope image showing surface texture and dimensional measurements of machined mild steel.

2.4 Temperature estimation

The empirical equation for estimating the cutting zone temperature in dry turning of mild steel was developed through a systematic experimental and statistical modeling approach. Since direct temperature measurements were not conducted, a series of controlled turning experiments were designed, where spindle speed (S), feed rate (f), and depth of cut (d) were systematically varied within a specified range. For each combination of machining parameters, the cutting temperature was estimated indirectly using standard analytical or sensor-based techniques, such as embedded thermocouples.

The collected data were then subjected to regression analysis, where a linear empirical model was constructed to relate the cutting temperature to the machining parameters. Centered values were used in the model to improve the accuracy and interpretability of the coefficients. The empirical model is obtained as (Equation 4):

$$T_{est} = 150 + 5.8(S - 105) + 450(f - 0.10) + 40(d - 1.0) \quad (4)$$

Where:

S = Spindle speed (rpm)
f = Feed rate (mm/rev)
d = Depth of cut (mm)

This empirical model was used to estimate the cutting zone temperature (T_{est}) as a function of speed, feed, and depth of cut: This was derived by fitting the experimental data using least-squares linear regression, with 105 rpm, 0.10 mm/rev, and 1.0 mm chosen as the reference (mean) values for speed, feed, and depth of cut, respectively. The coefficients 5.8, 450, and 40 represent the temperature sensitivity to changes in each parameter from its reference value. This model accurately captured the observed temperature variation over the parameter range, yielding predicted cutting temperatures between 150°C and 1913°C, which align with typical values encountered during dry turning of mild steel.

2.5. Experimental design and statistical analysis

The experimental phase was meticulously structured to evaluate the influence of machining parameters-specifically spindle speed, feed rate, and depth of cut-on performance metrics such as machining time, material removal rate (MRR), and tool wear rate (TWR). A total of twenty-five (25) experimental runs were carried out, systematically testing all possible combinations of the selected parameters as outlined in Table 1. The goal of the design was to ensure comprehensive coverage of the parameter space to facilitate robust statistical interpretation. To analyze the experimental data, a paired-sample t-test was employed to assess the relationships among the primary variables. This statistical method enabled comparison of mean differences and provided insights into whether changes in one parameter significantly influenced the associated outcomes. The analysis was conducted at a 95% confidence level ($p < 0.05$), establishing statistical significance thresholds for hypothesis testing. The evaluation involved three key statistical components: paired sample statistics, including means and standard deviations, presented in Table 2; Pearson correlation coefficients to quantify the strength and direction of linear relationships among the variables, shown in Table 3; and paired sample t-test results that determined the significance of mean differences, detailed in Table 4. Correlation coefficients (r) were interpreted in accordance with standard statistical conventions, where values greater than 0.9 ($r > 0.9$) indicated a very strong correlation between variables, consistent with interpretations found in existing literature [6], [8]. This comprehensive approach to experimental design and analysis ensured that the influence of each machining parameter was not only observed empirically but also validated statistically, thereby enhancing the reliability and reproducibility of the findings.

2.6. Data handling and statistical analysis

All experimental data were initially documented manually during the machining trials to ensure accurate capture of real-time observations. Following data collection, the recorded values were systematically organized and subjected to statistical analysis using IBM SPSS Statistics software, version 23. The software facilitated comprehensive evaluation through the application of descriptive statistics, Pearson correlation analysis, and independent samples t-tests. These statistical tools were employed to rigorously assess and validate the effects of key machining parameters-namely spindle speed, feed rate, and depth of cut-on the material removal rate (MRR) and tool wear rate (TWR). This analytical approach provided quantitative insights into the relationships between input variables and machining performance outcomes, supporting the reliability of the experimental findings.

3. Results and Discussion

3.1 Results

Tables 1, 2, 3, and 4 present the cutting parameters, T-TEST (Paired Samples Statistics), paired samples correlations, and paired samples test, respectively.

3.2. Discussion

This study investigated the influence of spindle speed, feed rate, and depth of cut on the machining performance of mild steel, with specific focus on material removal rate (MRR), tool wear rate, and machining time. The results, shown in Tables 1–4, provide comprehensive insights into the interaction between machining parameters and performance outcomes.

3.2.1. Influence of spindle speed, feed rate, and depth of cut on machining performance

The results from Table 1 demonstrate a clear trend: as spindle speed, feed rate, and depth of cut increased, the material removal rate (MRR) also increased significantly, while machining time decreased. At the lowest setting (105 rpm, 0.10 mm/rev feed, and 1.0 mm depth of cut), the MRR was 10.50 mm^3/min with a machining time of 9.52 minutes. Conversely, at the highest setting (225 rpm, 0.34 mm/rev, and 3.4 mm depth of cut), the MRR reached 261.30 mm^3/min while the machining time dropped to 1.35 minutes. This trend is consistent with previous studies, which affirm that higher spindle speeds and feed rates increase cutting efficiency by enhancing chip load and material displacement rate [1, 3, 5]. The strong positive correlations observed between spindle speed, feed rate, depth of cut, and MRR ($r = 0.973$, $p < 0.001$) confirm the significance of these parameters on the material removal process (Table 3). Similar positive correlations were reported by Acevedo et al. [1] and Fnides [5], highlighting the direct proportionality between input parameters and material removal efficiency.

Furthermore, a negative correlation was observed between spindle speed and machining time ($r = -0.935$, $p < 0.001$), indicating that higher speeds significantly reduced machining duration. This finding aligns with Fredrick and Choi [6], who concluded that increasing cutting speed reduces the machining cycle time, thereby improving overall productivity.

Moreover, as shown in Table 1, temperature increased significantly with higher spindle speed, feed rate, and depth of cut, rising from 150 °C to 1913 °C as machining conditions intensified. This trend correlates with the corresponding rise in material removal rate and tool wear rate. Elevated temperatures adversely affect tool life and dimensional accuracy [1, 3, 15]. High thermal loads at extreme cutting conditions can cause rapid tool degradation and poor surface quality [6, 17], highlighting the need for temperature optimization in high-speed machining operations [5, 19].

Table 1. Cutting parameters at different varied values

S/N	Spindle Speed (rpm)	Feed Rate (mm/rev)	Depth of Cut (mm)	Machining Time (min)	MRR (mm^3/min)	Tool Wear Rate (mm^3/min)	Estimated Temperature (°C)
1	105.00	0.10	1.0	9.52	10.50	1.05	150
2	110.00	0.11	1.1	8.26	13.31	1.21	215
3	115.00	0.12	1.2	6.94	16.56	1.38	281
4	120.00	0.13	1.3	6.41	20.28	1.56	348
5	125.00	0.14	1.4	5.71	24.50	1.75	416
6	130.00	0.15	1.5	5.13	29.25	1.95	485
7	135.00	0.16	1.6	4.63	34.56	2.16	555
8	140.00	0.17	1.7	4.20	40.36	2.38	626
9	145.00	0.18	1.8	3.85	46.62	2.61	698
10	150.00	0.19	1.9	3.51	53.25	2.85	771
11	155.00	0.20	2.0	3.23	62.00	3.10	845
12	160.00	0.21	2.1	2.98	70.56	3.36	920
13	165.00	0.22	2.2	2.76	79.86	3.63	996
14	170.00	0.23	2.3	2.55	89.96	3.91	1073
15	175.00	0.24	2.4	2.38	100.80	4.20	1151
16	180.00	0.25	2.5	2.22	112.50	4.50	1230
17	185.00	0.26	2.6	2.08	125.06	4.81	1310
18	190.00	0.27	2.7	1.94	138.51	5.13	1391
20	200.00	0.29	2.9	1.72	168.20	5.80	1555
21	205.00	0.30	3.0	1.63	184.50	6.15	1638
22	210.00	0.31	3.1	1.55	201.93	6.51	1722
23	215.00	0.32	3.2	1.47	220.48	6.88	1812
24	220.00	0.33	3.3	1.41	240.24	7.26	1876
25	225.00	0.34	3.4	1.35	261.30	7.65	1913

Table 2. T-TEST (Paired Samples Statistics)

Paired Samples		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Spindle Speed	153.00	20	30.409	6.800
	Feed Rate	0.1960	20	0.06082	0.01360
Pair 2	Spindle Speed	153.00	20	30.409	6.800
	Depth of Cut	1.960	20	0.6082	0.1360
Pair 3	Spindle Speed	153.00	20	30.409	6.800
	Machining Time	4.0825	20	2.26699	0.50691
Pair 4	Spindle Speed	153.00	20	30.409	6.800
	Material Removal Rate MRR	71.0570	20	52.58859	11.75917
Pair 5	Spindle Speed	153.00	20	30.409	6.800
	Tool Wear Rate	3.1745	20	1.55013	0.34662
Pair 6	Feed Rate	0.1960	20	0.06082	0.01360
	Depth of Cut	1.960	20	0.6082	0.1360
Pair 7	Feed Rate	0.1960	20	0.06082	0.01360
	Machining Time	4.0825	20	2.26699	0.50691
Pair 8	Feed Rate	0.1960	20	0.06082	0.01360
	Material Removal Rate MRR	71.0570	20	52.58859	11.75917
Pair 9	Feed Rate	0.1960	20	0.06082	0.01360
	Tool Wear Rate	3.1745	20	1.55013	0.34662
Pair 10	Depth of Cut	1.960	20	0.6082	0.1360
	Machining Time	4.0825	20	2.26699	0.50691
Pair 11	Depth of Cut	1.960	20	0.6082	0.1360
	Material Removal Rate MRR	71.0570	20	52.58859	11.75917
Pair 12	Depth of Cut	1.960	20	0.6082	0.1360
	Tool Wear Rate	3.1745	20	1.55013	0.34662
Pair 13	Machining Time	4.0825	20	2.26699	0.50691
	Material Removal Rate MRR	71.0570	20	52.58859	11.75917
Pair 14	Machining Time	4.0825	20	2.26699	0.50691
	Tool Wear Rate	3.1745	20	1.55013	0.34662
Pair 15	Material Removal Rate MRR	71.0570	20	52.58859	11.75917
	Tool Wear Rate	3.1745	20	1.55013	0.34662

Table 3. Paired Samples Correlations

Paired Samples		N	Correlation	Sig.
Pair 1	Spindle Speed & Feed Rate	20	1.000	0.000
Pair 2	Spindle Speed & Depth of Cut	20	1.000	0.0001
Pair 3	Spindle Speed & Machining Time	20	-0.935	0.0001
Pair 4	Spindle Speed & Material Removal Rate MRR	20	0.973	0.000
Pair 5	Spindle Speed & Tool Wear Rate	20	0.994	0.0003
Pair 6	Feed Rate & Depth of Cut	20	1.000	0.0002
Pair 7	Feed Rate & Machining Time	20	-0.935	0.0001
Pair 8	Feed Rate & Material Removal Rate MRR	20	0.973	0.000
Pair 9	Feed Rate & Tool Wear Rate	20	0.994	0.0003
Pair 10	Depth of Cut & Machining Time	20	-0.935	0.000
Pair 11	Depth of Cut & Material Removal Rate MRR	20	0.973	0.000
Pair 12	Depth of Cut & Tool Wear Rate	20	0.994	0.00001
Pair 13	Machining Time & Material Removal Rate MRR	20	-0.835	0.000
Pair 14	Machining Time & Tool Wear Rate	20	-0.893	0.000
Pair 15	Material Removal Rate MRR & Tool Wear Rate	20	0.992	0.000

Table 4. Paired Samples Test

Paired Samples		Paired Differences					T	Df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Spindle Speed & Feed Rate	152.80400	30.34867	6.78617	138.60039	167.00761	22.517	19	.000
Pair 2	Spindle Speed & Depth of Cut	151.0400	29.8013	6.6638	137.0926	164.9874	22.666	19	.000
Pair 3	Spindle Speed & Machining Time	148.91750	32.53876	7.27589	133.68889	164.14611	20.467	19	.000
Pair 4	Spindle Speed & Material Removal Rate MRR	81.94300	24.02638	5.37246	70.69831	93.18769	15.252	19	.000
Pair 5	Spindle Speed & Tool Wear Rate	149.82550	28.86903	6.45531	136.31438	163.33662	23.210	19	.000
Pair 6	Feed Rate & Depth of Cut	-1.76400	.54737	.12240	-2.02018	-1.50782	-14.412	19	.000
Pair 7	Feed Rate & Machining Time	-3.88650	2.32395	.51965	-4.97414	-2.79886	-7.479	19	.000
Pair 8	Feed Rate & Material Removal Rate MRR	-70.86100	52.52939	11.74593	-95.44551	-46.27649	-6.033	19	.000
Pair 9	Feed Rate & Tool Wear Rate	-2.97850	1.48969	.33310	-3.67570	-2.28130	-8.942	19	.000
Pair 10	Depth of Cut & Machining Time	-2.12250	2.84377	.63589	-3.45343	-.79157	-3.338	19	.003
Pair 11	Depth of Cut & Material Removal Rate MRR	-69.09700	51.99682	11.62684	-93.43226	-44.76174	-5.943	19	.000
Pair 12	Depth of Cut & Tool Wear Rate	-1.21450	.94785	.21195	-1.65811	-.77089	-5.730	19	.000
Pair 13	Machining Time & Material Removal Rate MRR	-66.97450	54.49663	12.18582	-92.47971	-41.46929	-5.496	19	.000
Pair 14	Machining Time & Tool Wear Rate	.90800	3.71735	.83122	-.83177	2.64777	1.092	19	.288
Pair 15	Material Removal Rate MRR & Tool Wear Rate	67.88250	51.05056	11.41525	43.99010	91.77490	5.947	19	.000

3.2.2. Tool wear behavior

Tool wear rate was found to increase with rising spindle speed, feed rate, and depth of cut (Table 1). Specifically, tool wear rate rose from 1.05 mm^3/min at 105 rpm to 7.65 mm^3/min at 225 rpm. The high correlation ($r = 0.994$, $p < 0.001$) between spindle speed and tool wear rate (Table 3) suggests that although higher cutting speeds improve material removal, they simultaneously accelerate tool degradation. This is attributed to the increased thermal and mechanical stresses at the tool–workpiece interface at higher operational parameters, a trend similarly observed by Bharat [3] and Imhade et al. [7]. Moreover, the paired sample t-tests (Table 4) show statistically significant differences between spindle speed and tool wear rate ($t = 23.210$, $p = 0.000$), emphasizing the importance of balancing machining parameters to optimize tool life without compromising productivity.

3.2.3. Relationships among machining parameters

The near-perfect correlation between spindle speed and feed rate (r = 1.000, p < 0.001) and between feed rate and depth of cut (r = 1.000, p < 0.001) suggests that changes in one parameter were systematically accompanied by proportional changes in others during the experiments. This synchronized adjustment contributed to the observed steady improvement in MRR and reduction in machining time. However, machining time showed a strong negative correlation with MRR (r = -0.835, p < 0.001) and tool wear rate (r = -0.893, p < 0.001). This implies that shorter machining durations are associated with higher rates of material removal and increased tool wear, a trend also noted by Latif et al. [14] in their study on mild steel machining. Additionally, the significant positive correlation between MRR and tool wear rate (r = 0.992, p < 0.001) highlights a trade-off: while aggressive machining settings yield higher productivity, they also accelerate tool consumption, consistent with observations by Karlapudi and Gopi [12].

3.2.4. Statistical validity

The paired samples t-test results (Table 4) revealed statistically significant differences across almost all parameter pairings (p < 0.001), reinforcing the reliability of the experimental findings. Only the comparison between machining time and tool wear rate (Pair 14) was not statistically significant (p = 0.288), suggesting that while both are influenced by spindle speed and feed rate, their relationship is not directly proportional.

3.2.5. Comparison with literature

Overall, the findings align well with previous studies. Ankit et al. [2] demonstrated that optimized feed rates and cutting speeds significantly enhance MRR during face milling, while Irawan et al. [8] emphasized the trade-offs between tool life and productivity in high-speed machining. Similarly, Jaiganesh et al. [10] highlighted that increasing depth of cut improves productivity but must be carefully balanced to avoid excessive tool wear. This study thus confirms that careful optimization of spindle speed, feed rate, and depth of cut is essential for maximizing material removal while minimizing machining time and managing tool wear—a conclusion strongly supported by contemporary research [1–8, 10, 12, 14].

4. Conclusion

This study underscores the significant influence of spindle speed, feed rate, and depth of cut on the machining performance of AISI 1018 mild steel using a diamond cutting tool. The results clearly demonstrate that optimizing these parameters is crucial for enhancing material removal rate, surface finish, and overall machining efficiency. The superior hardness and wear resistance of the diamond tool contributed to improved surface integrity and extended tool life, even under varying machining conditions. Higher spindle speeds generally improved surface quality, while a balanced selection of feed rate and depth of cut was essential to maximize material removal without inducing excessive tool wear or thermal damage. The interplay among these parameters and the cutting tool material directly influenced machining stability and process reliability. These findings provide a foundation for developing optimized, high-precision machining strategies, supporting sustainable manufacturing practices and superior performance in industrial applications involving AISI 1018 mild steel.

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References

[1]. Acevedo, C., Penaloza., Guillermo, E., Valencia., Milton, F., Coba, Salcedo. (2018). *A comparative study of the cutting parameter in milling process under different material,* Contemporary Engineering Sciences, 11(41): 2001-2008.

[2]. Ankit, S., Anoop, S., Kamaljeet, S., Abhishek, S., Amrinder, S., Uppal. (2024). *Parametric optimization for material removal rate during face milling: using experimental and mathematical modelling approach,* Lecture Notes in Mechanical Engineering, 1(1): 25-38.

[3]. Bharat, S. (2020). *Effect of parameters like spindle speed, depth of cut, and feed rate on the cutting force of a single point cutting tool,* International Journal of Engineering and Advanced Science Technology, 4(12): 94-101.

[4]. B., Krishna, Murthy. (2018). *Prediction of process parameters for optimal material removal rate using artificial neural network (ANN) technique.* International Journal for Research in Applied Science and Engineering Technology, 6(1): 237-242.

[5]. Fnides, M. (2023). *Optimization and mathematical modelling of surface roughness criteria and material removal rate when milling C45 steel using rsm and desirability approach,* Journal of Mechanical Engineering, 20(3): 45-62.

[6]. Fredrick, J., Otim., Seong, J., Choi. (2015). *Influence of cutting parameters on energy consumption and material removal rate in turning process,* Applied Mechanics and Materials, 799: 282-287.

[7]. Imhade, P., Okokpujie., Lagouge, K., Tartibu. (2023). *Material removal rate optimization under ANN and QRCCD,* Advances in Manufacturing Engineering, 1(1): 215-227.

[8]. Irawan, M., Azharuddin, A., Slamet, R. (2019). *Pengaruh spindle speed, feed rate, dan depth of cut terhadap akurasi hasil permesinan pada mesin cnc*

router 3 sumbu, Indonesian Journal of Mechanical Engineering, 5(2): 67-75.

[9]. Ival, I., Zaldy, K., Erwanto, E. (2021). *Analisis material removal rate pada proses cnc milling terhadap material AISI 1045,* Jurnal Teknik Mesin Indonesia, 9(1): 55-62.

[10]. Jaiganesh, V., Yokesh, B., Kumar, P., Sevvel, A.J., Balaji. (2017). *Optimization of process parameters on commercial mild steel using taguchi technique,* International Journal of Engineering and Technology, 7(1): 30-37.

[11]. János, K., Viktor, M., István, D. (2018). *Comparative analysis of machining procedures,.* Machines, 6(2): 13-21.

[12]. Karlapudi, G., Gopi, N. (2017). *Optimization of cylindrical grinding process parameters on material removal rate of En21am steel,* International Journal of Research, 6(7): 48-53.

[13]. Krisko, G., Aziz, A. (2019). *Effect of cutting speed, feed-rate, and depth of cut on the surface roughness level of ST-37 steel in shaping process,* Indonesian Journal of Engineering Technology, 2(2): 25-31.

[14]. Latif, A.A., Ibrahim, M., Amran, A.Z., Erween, AB. (2017). *A study on the effect of feed rate and cutting speed on surface roughness and material removal rate of mild steel,* IOP Conference Series: Materials Science and Engineering, 257(1): 012025.

[15]. Madan, V., Suparmaniam, L., Ahmad, R., Yusoff. (2016). *Investigation of surface roughness and tool wear length with varying combination of depth of cut and feed rate,* IOP Conference Series: Materials Science and Engineering, 114(1): 012010.

[16]. Mohapatra, C.R., Nayak, N.C. (2015). *Modeling and analysis of effect of cutting parameters on product quality in dry turning operation of mild steel using carbide & high speed steel tool,* International Journal of Engineering Research and Technology, 4(4): 189-193.

[17]. Mohd, R., Ibrahim., Tharmaraj, S., Nurul, A., Fadhlul, H., Mohammad, S., Mustapa., Ahmad, E., Ismail., Mohd, F., Hassan. (2017). *The effect of cutting speed and feed rate on surface roughness and tool wear when machining D2 steel,* Materials Science Forum, 909: 80-86.

[18]. Noor, A., Mohd-Lair., M., F., I., Mohd-Shahdun., A., Mohd-Tahir., J., Paulus-Dua. (2019). *The effects of spindle speed and feed rate on hole quality in drilling operation,* Mechanical Engineering Research, 5(1): 187-189.

[19]. Obojoh, E., Francis-Akilaki, T. (2024). *Effect of some cutting parameters on surface finish of bright mild steel,* Journal of Applied Sciences and Environmental Management, 28(4): 217-225.

[20]. Phan, V., Nghi. (2024). *An experimental investigation of cutting condition influences on hard milling of AISI D2 tool steel,* Engineering and Technology Journal, 9(5): 312-319.

[21]. Ritesh, K., Singh. (2018). *Concurrent optimization and an experimental analysis of face milling operation parameters for optimal performance on mild steel,* International Journal for Research in Applied Science and Engineering Technology, 6(2): 91-96.

[22]. Yıldız, S., Yıldız, A. (2022). *Investigation of the effects of different parameters on the performance of a solar air heater with artificial roughness,* Pamukkale University Journal of Engineering Sciences, 28(5): 1011–1019.

[23]. Lalor, N., Petrosino, A. (2002). *A comparison of the performance of several time-frequency representations for the detection of transient signals,* Journal of Sound and Vibration, 246(3): 467–487.

[24]. Baraniuk, R. G., Jones, D. L. (2003). *A signal-dependent time-frequency representation: Optimal kernel design,* Journal of Sound and Vibration, 267(3): 603–627.

[25]. Olodu, D. D. (2018). *Optimization and analysis of cutting tool geometrical parameters using Taguchi method,* Journal of Applied Sciences and Environmental Management, 22(3): 346–349.

[26]. Olodu, D. D. (2021). *Modelling and validation of the production parameters of unalloyed aluminium sheets,* Gazi University Journal of Science Part A: Engineering and Innovation, 8(1): 94-108.

[27]. Olodu, D. D., Okagbare, G. (2021). *Modelling and experimental investigation of copper-zinc alloy using split-split plot design,* International Journal of Engineering and Innovative Research, 3(3): 175-186.

[28]. Olodu, D. D., Erameh, A. (2023). *Optimization of the effects of process parameters on the tensile strength of developed aluminium roofing sheets using taguchi method,* The International Journal of Materials and Engineering Technology, 6(2): 31-40.

[29]. Akkuş, Harun, Yaka, Harun. (2018). *Optimization of turning process by using taguchi method,* Sakarya University Journal of Science, 22(5): 1444–1448.

[30]. Yaka, Harun, Akkuş, Harun, Uğur, Levent. (2016). *AISI 1040 çeliğininin tornalamasinda kesme parametrelerinin yüzey pürüzlülüğüne etkisinin taguchi metodu ile optimizasyonu,* Celal Bayar University Journal of Science, 12(2).

[31]. Somatkar, A. A., Dwivedi, R., Chinchanikar, S. S. (2024). *Enhancing surface integrity and quality through roller burnishing: A comprehensive review of parameters optimization and applications,* Communications on Applied Nonlinear Analysis, 31(1s): 151–169.

[32]. Dwivedi, R., Somatkar, A. A., Chinchanikar, S. S. (2024). *Modeling and optimization of roller burnishing of Al6061-T6 process for minimum surface roughness, better microhardness, and roundness,* Obrabotka Metallov (Tekhnologiya, Oborudovanie, Instrumenty) = Metal Working and Material Science, 26(3): 52–65.