DOI: 10.21062/mft.2026.029 http://www.journalmt.com

Comparative Surface Roughness Performance of Al7075, Al6061, and Al5052 in End Milling Using Taguchi L16 S/N and Anova

Richard A M Napitupulu (0000-0003-2936-1224), Siwan Edi Amanta Perangin-angin (0009-0007-3049-4581)
Department of Mechanical Engineering, University HKBP Nommensen, Jalan Dr. Sutomo No. 4-A, Medan, Medan, 20235, Nort Sumatra, Indonesia. E-mail: richard.napitupulu@uhn.ac.id

This study examines the effects of cutting parameters on surface roughness (Ra) for three aluminum alloys AL7075, AL6061, and AL5052 using a Taguchi L16 (4^3) design, smaller-is-better signal-to-noise (S/N) analysis, and ANOVA. Experiments were conducted on a 3-axis CNC milling machine with a 2-flute Ø6 mm carbide end mill. Overall, AL7075 produced the smoothest surface (minimum Ra = 0.143 µm), followed by AL6061 and AL5052. The observed trends are consistent with machining mechanics: increasing cutting speed suppresses built-up edge (BUE) and vibration, whereas larger feed and depth of cut (doc) increase chip load and tool deflection. For AL7075, doc and feed were the principal factors (borderline significant in S/N-ANOVA); the mean-optimal setting was S3–F1–D3 = Spindle L3 (N = 2500 rpm), Feed L1 (f = 150 mm.min^{-1}), doc L3 (0.8 mm), while the robust-optimal setting was S4–F1–D3 = Spindle L4 (N = 3500 rpm), Feed L1 (f = 150 mm.min^{-1}), doc L3 (0.8 mm). For AL6061, spindle speed was strongly dominant (≈80.5% contribution; $p < 0.001$), with S3–F1–D1 = 2500 rpm, 150 mm.min^{-1}, 0.4 mm as the mean optimal and S3–F1–D2 = 2500 rpm, 150 mm.min^{-1}, 0.6 mm as the robust-optimal combination. For AL5052, factor contributions were relatively balanced and not significant at $\alpha = 0.05$; the mean optimal setting was S4–F2–D3 = 3500 rpm, 250 mm.min^{-1}, 0.8 mm, whereas S/N indicated S1–F4–D4 = 500 rpm, 450 mm.min^{-1}, 1.0 mm (requiring confirmation tests). Across alloys, doc and spindle speed emerged as the most practically influential factors. These results establish ANOVA validated mean and robust (S/N) settings as process guidelines to minimize Ra; confirmation tests are recommended.

Keywords: Aluminum alloys, CNC milling, Surface roughness, Taguchi method, Signal-to-noise ratio

1 Introduction

The development of modern manufacturing industries particularly in the automotive, aerospace, and energy sectors demands Computer Numerical Control (CNC) milling processes that are not only precise and efficient but also sustainable. One of the key indicators of machining quality is surface roughness (Ra), which directly affects fatigue resistance, tribological properties, joint integrity, and component service life [1,2]. The primary cutting parameters spindle speed (cutting speed, Vc), feed per tooth (fz), and depth of cut (ap) are often cited as the dominant factors governing Ra, although their contributions vary depending on the aluminum alloy, cutting conditions, and tool geometry employed Numerous studies based on classical Design of Experiments (DOE) have been conducted to optimize the surface quality of aluminum. For Al6061-T6, the integration of the Taguchi method and Grey Relational Analysis (GRA) reportedly reduced Ra by 21.7%, decreased specific cutting energy (SCE) by up to 11.4%, and narrowed burr width by 6.2% [3,4].

Other work on Al6061 SiCp metal matrix composites (MMC) using a Taguchi L25 design confirms that feed rate is the most dominant factor affecting Ra and cutting forces [5]. Similar studies on Al7075-T6 using Taguchi L18 and Response Surface Methodology (RSM) show that spindle speed makes the largest contribution (37.12%) to Ra, whereas material removal rate (MRR) is more strongly influenced by feed rate (41.68%) and depth of cut (47.29%); the optimum combination produced Ra of 0.159 µm with MRR of 32.019 g/min [6]. Other studies likewise emphasize the significant influence of depth of cut and of parameter interactions on surface quality in Al7075[7,8]. Meanwhile, the softer Al5052 tends to be susceptible to built-up edge (BUE), which can worsen the surface finish if the cutting speed is too low, or the feed is too small.

In addition, several advanced machining strategies have been explored. Ultrasonic Vibration-Assisted Milling (UVAM) combined with Minimum Quantity Lubrication (MQL) on Al7075-T6 has been shown to yield lower Ra than conventional machining Likewise, combining high-speed cutting (HSC) with high-feed milling (HFM) can improve surface integrity, reduce cutting forces, and produce more favorable residual stresses, although the direct effect on Ra is not always significant [9]. Multi-objective optimization has also been widely investigated, including joint optimization of Ra, SCE, and burr, to achieve both energy efficiency and optimal surface quality, as reported in Heliyon (2024) and the Journal of Cleaner Production (2024) [3,10].

With the advent of Industry 4.0, Artificial Intelligence (AI) and Machine Learning (ML) approaches are increasingly used. Vibration-based Extreme Learning Machine (ELM) models have demonstrated Ra prediction with an average error of 5.09% [11], while Bayesian Quantile Regression (BQR) leveraging multi-source data can map Ra sensitivity to cutting parameters with higher accuracy than classical regression [12]. Studies using Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) have also achieved prediction errors below 10%, although industrial deployment remains constrained by the need for large datasets and the high cost of sensors [1,13]. Balonji et al. showed that ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) hybridized with Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) can significantly improve Ra prediction performance for Al6061[14]. Recent comprehensive reviews also affirm that a major trend in current research is integrating classical DOE (Taguchi, RSM, ANOVA) with soft-computing methods (ANN, fuzzy logic, GA, PSO) to deliver more accurate and practical prediction and optimization frameworks [15]. Beyond aluminum, several studies have highlighted the importance of Ra prediction for other materials. For example, research on grinding and polishing of aero-engine components has shown that appropriate process parameter selection can improve surface quality by up to 25% compared with conventional grinding methods [16].

Moreover, in high-torque milling operations commonly used for wind-turbine components, ANFIS-based applications have been deployed for real-time prediction, monitoring, and control of Ra, underscoring the importance of surface roughness control as a process performance indicator. In addition, deep-learning approaches with sensor fusion have been used to simultaneously predict tool wear and Ra, indicating the potential of AI for online surface-quality monitoring [17,18]. Another line of research that integrates Principal Component Analysis (PCA) and Grey Relational Analysis (GRA) for multi-response optimization has reported effectiveness in improving surface quality, MRR, and tool wear in metal milling—supporting the broader trend of combining classical statistical methods with AI in modern machining [19]. Recent reviews emphasize the diversity of methods, parameters, and equipment setups used in aluminum-alloy machining, which complicates direct cross-study comparisons [20]. Most research still focuses on a single alloy (e.g., Al6061 or Al7075) with Taguchi/ANOVA/RSM, rather than conducting comparative analyses across multiple alloys within a single, unified framework using the same tooling [21–23]. Cross-alloy comparisons are typically limited to only two alloys and without a uniform Taguchi–ANOVA design, so a tri-alloy comparison (6061–7075–5052) with identical tooling has not yet been reported [24,25]. To date, most studies examine only one type of aluminum alloy, such as Al6061 or Al7075. Existing investigations also employ different tools and cutting parameters, making direct comparison difficult. Although there are some studies comparing two alloys, such as Al5052 and Al7075, there is still no research that specifically examines the three popular alloys Al6061, Al7075, and Al5052 using the same tool (carbide 2-flute straight end-mill) and a uniform statistical methodology such as Taguchi–ANOVA.

Therefore, this study aims to compare the effects of spindle speed, feed rate, and depth of cut on surface roughness (Ra) across three widely used aluminum alloys Al6061, Al7075, and Al5052. Experiments are performed using a carbide 2-flute straight end mill under a Taguchi design, and the results are analyzed using signal-to-noise (S/N) ratios, ANOVA, and regression. The expected outcomes are alloy-specific sensitivity patterns spindle-speed dominance for Al6061, a feed–depth-of-cut co-dominance for Al7075, and a more balanced contribution of all three parameters for Al5052. These findings are intended to provide practical guidance for selecting CNC milling parameters for aluminum and to supply baseline data for validating AI/ML-based predictive models, thereby bridging classical DOE methods with data-driven predictive machining toward precise, efficient, and sustainable CNC operations.

2 Methodology

2.1 Materials and Equipment

The work materials consisted of aluminum alloys Al6061, Al7075, and Al5052 with uniform dimensions. Machining was performed on a 3-axis CNC milling machine using a carbide 2-flute straight end mil Ø6 mm. Cutting conditions were kept dry and consistent throughout the experiments. The laboratory was maintained at room temperature. Workholding employed a precision vise; the clamping torque was standardized using a torque wrench. Spindle runout was verified to be < 5 μm using a dial indicator. Surface roughness (Ra) was measured using a surface roughness tester SRT6210 with measurement parameters compliant with ISO 4287 (the cut-off λc and tracing length Lt were recorded). Each surface was measured at three distinct locations; the response value for analysis was taken as the mean of the three readings (Ra). To ensure measurement reproducibility, a brief Gauge R&R

study (≤ 10 dummy specimens) was conducted prior to the main experiments to verify the repeatability and reproducibility of the instrument, targeting a measurement-variation contribution < 10% of the total variation. The study employs three aluminum alloys Al6061, Al7075, and Al5052 in uniformly sized work-piece blocks. Machining is performed on a 3-axis CNC milling machine using a 6 mm-diameter carbide 2-flute straight end mill, in accordance with standard end-milling practice for aluminum.

Fig. 1 *Carbide 2-flute straight end mill (a); 3-axis CNC milling (b)*

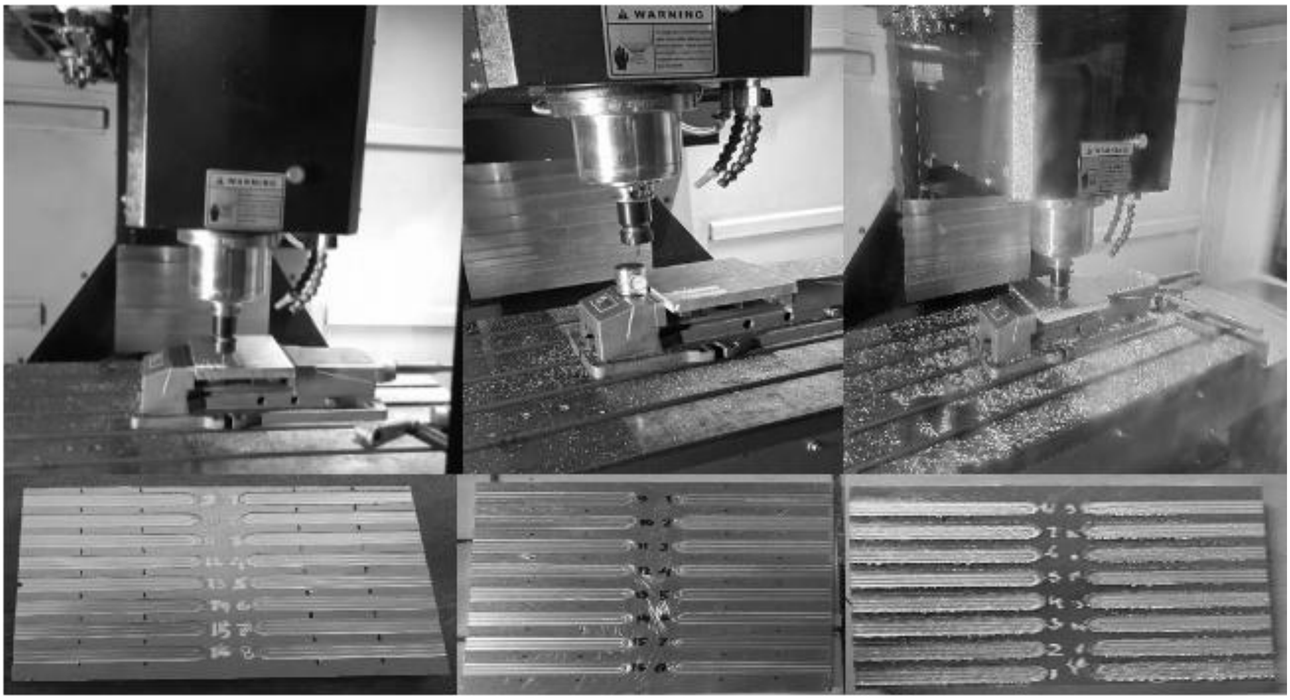

Fig. 2 *Machining process: Al7075 (a), Al6061 (b), Al5052 (c)*

Tab. 1 *Chemical composition of aluminum alloy 6061 (wt%)*

	UOM	Si	Fe	Cu	Mn	Mg	Cr	Zn	Ti	Others each
Min	%	0.4	0.7	0.15	0.15	0.8	0.04	0.25	0.15	0.15
Max	%	0.8	0.7	0.4	0.15	1.2	0.35	0.25	0.15	0.15

Tab. 2 *Chemical composition of aluminum alloy 7075 (wt%)*

	UOM	Si	Fe	Cu	Mn	Mg	Cr	Zn	Ti	Others each
Min	%	0.000	0.000	1.200	0.000	2.100	0.180	5.100	0.000	0.000
Max	%	0.026	0.098	1.630	0.002	2.655	0.198	5.730	0.031	0.028

Tab. 3 *Chemical composition of aluminum alloy 5052 (wt%)*

	UOM	Si	Fe	Cu	Mn	Mg	Cr	Zn	Ti	Others each
Min	%	0.25	0.4	0.1	0.1	2.2	0.15	0.1	0.15	0.13
Max	%	0.25	0.4	0.1	0.1	2.8	0.35	0.1	0.15	0.13

The chemical composition data for Al6061, Al7075, and Al5052 in Tables 1 - 3 are sourced from the supplier's Material Test Certificates (MTCs) and are used as the basis for quality traceability as well as a reference for analyzing the relationship between composition, machining behavior, and Ra.

Surface roughness (Ra) was measured using an SRT6210 digital surface-roughness tester, with at least three replicate measurements taken on each surface.

2.2 Cutting Factors and Levels

The study focuses on three primary process factors, each evaluated at four levels. The numerical levels were specified according to the researcher's predefined experimental draft/design

Tab. 4 *Machining parameters*

Parameter	Level			
	L1	L2	L3	L4
Spindle speed (rpm) (S)	500	1500	2500	3500
Feed rate (mm/min) (F)	150	250	350	450
Depth of cut (mm) (D)	0.4	0.6	0.8	1.0

2.3 Experimental Design

The experimental design employs a Taguchi Orthogonal Array L16(4^3), comprising four levels for three factors (1, 2, 3), as shown in Table 5. Experiments were executed by alloy L16 cycle for Al6061, one for Al7075, and one for Al5052. Tool-wear control was implemented by using a new tool at the start of each alloy block, or by monitoring flank wear (VB) and replacing the tool when the preset criterion was reached, as illustrated in Figure 1.

Tab. 5 *Taguchi Orthogonal Array L16(4^3)*

Experiment No.	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	2
6	2	2	1
7	2	3	4
8	2	4	3
9	3	1	3
10	3	2	4
11	3	3	1
12	3	4	2
13	4	1	4
14	4	2	3
15	4	3	2
16	4	4	1

The Taguchi method provides a practical, systematic framework for designing experiments with a minimal number of runs to identify factor combinations that maximize quality and minimize cost. In essence, we choose robust control-factor settings (insensitive to noise/disturbance factors) by maximizing the signal-to-noise (S/N) ratio computed from replications at each level combination. The S/N ratio simultaneously captures the mean and the variation of the response; its formulation is selected according to the engineering objective Larger-the-better (LTB), smaller-the-better (STB), or nominal-the-best (NTB). In all cases, a higher S/N value is preferred. Here are the S/N ($\log_{10}$ based) formulas for a trial with nnn replications and responses $y_1\ldots,y_n$ Notation general:

Smaller-the-better (STB) - minimize response [22]:

$$\mathrm{S/N_{STB}} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (1)$$

Larger-the-better (LTB) - maximize response [22]:

$$\mathrm{S/N_{LTB}} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \quad (2)$$

Nominal-the-best (NTB) - target a specific value with small variations [22]:

$$\mathrm{S/N_{NTB}} = 10\log_{10}\left(\frac{\mu^2}{s^2}\right) \quad (3)$$

Response Surface Methodology (RSM) is a statistical approach used to model and analyze how multiple independent variables (factors) influence a dependent variable (response). It is widely applied in engineering, science, and other applied fields to optimize processes, design experiments efficiently, and build predictive models that forecast outcomes under various scenarios. The core of RSM is constructing a mathematical–statistical model that approximates the response surface, i.e., the relationship between input factors and the response. The goal is to identify factor settings that yield an optimal response (maximum or minimum), thereby reducing cost, improving performance, and increasing process efficiency. RSM's applications span new product development, optimization of manufacturing parameters, efficient experimental design, and the analysis of complex systems in engineering, chemistry, biology, and agriculture.[4]:

$$y = \varphi(x_1, x_2, \ldots x_n) + \varepsilon \quad (4)$$

For k input variables, the input–output relationship is commonly approximated by a second order (quadratic) polynomial model.

$$= \beta_0 + \sum_{i=1}^{k} \beta_i x_i \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{ij}^{k} \beta_{ij} x_i x_j + \varepsilon \qquad (5)$$

Where:
xi…The coded variables,
βi…The first order (linear) coefficients,
βii…The quadratic coefficients,
βij…The interaction coefficients,
ε…The statistical error term, typically assumed to have zero mean.

Tab. 6 *Surface roughness test results for Al7075, Al6061, and Al5052*

No	Spindle Speed (rpm)	Feed rate (mm/min)	DOC (mm)	Ra Avg (μm) 7075	Ra Avg (μm) 6061	Ra Avg (μm) 5052
1	500	150	0.4	0.334	1.428	4.995
2	500	250	0.6	0.886	2.417	4.593
3	500	350	0.8	0.261	3.465	4.106
4	500	450	1.0	0.858	4.664	5.909
5	1500	150	0.6	0.655	0.384	3.265
6	1500	250	0.4	0.817	0.563	3.569
7	1500	350	1.0	0.450	1.645	4.567
8	1500	450	0.8	0.472	1.329	3.942
9	2500	150	0.8	0.159	0.442	4.380
10	2500	250	1.0	0.523	0.453	4.064
11	2500	350	0.4	0.434	0.343	3.253
12	2500	450	0.6	0.404	0.282	6.050
13	3500	150	1.0	0.143	0.453	6.562
14	3500	250	0.8	0.291	0.420	1.478
15	3500	350	0.6	0.660	0.439	3.191
16	3500	450	0.4	0.527	0.431	3.424

Surface roughness (Ra) testing in milling three aluminum alloys (AA7075, AA6061, AA5052) with 16 parameter combinations showed that the smoothest performance was obtained for 7075 with mean Ra (0.492 µm), followed by 6061 (1.197 µm) and 5052 (4.209 µm). The minimum Ra values for each material were 0.143 µm (7075) at 3500 rpm, feed 150 mm/min, and DOC 1.0 mm; 0.282 µm (6061) at 2500 rpm, feed 450 mm/min, and DOC 0.6 mm; and 1.478 µm (5052) at 3500 rpm, feed 250 mm/min, and DOC 0.8 mm. In general, increasing spindle speed reduced Ra in 6061; for example, mean Ra decreased from 2.99 µm (500 rpm) to 0.38–0.44 µm at 2500–3500 rpm, whereas increasing feed increased Ra (6061) (0.68 µm at feed 150 mm/min; 1.68 µm at feed 450 mm/min). A larger DOC also tended to increase Ra (6061) (0.69 µm for DOC 0.4 mm; 1.80 µm for DOC 1.0 mm).

For 7075, a medium DOC (0.8 mm) yielded the lowest average Ra (≈0.296 µm), indicating more stable chip formation; for 5052, the combination of high n (3500 rpm), moderate feed (250 mm/min), and medium DOC (0.8 mm) minimized adhesion/BUE and produced the lowest Ra. These patterns are consistent with prior machining mechanics, where higher cutting speed suppresses built-up edge and vibration, while larger feed and DOC increase chip load, cutting forces, and tool deflection, degrading the surface finish; accordingly, the recommended finishing strategies are: for 7075 use n ≥ 2500–3500 rpm with low feed (150–250 mm/min) and DOC 0.8–1.0 mm; for 6061 use n ≥ 2500 rpm, low feed (150–250 mm/min), and DOC ≤ 0.6–0.8 mm; for 5052 prioritize high n (3500 rpm), moderate feed (250 mm/min), and DOC 0.8 mm

3 Results and Discussion

Taguchi Analysis: Ra_Avg versus Spindle; Feed; DOC.

Tab. 7 *Taguchi Analysis Ra_Avg versus Spindle; Feed; DOC 7075*

Level	Spindle speed (rpm)	Feed rate (mm/min)	DOC (mm)
1	0.5847	0.3227	0.5278
2	0.5984	0.6292	0.6514
3	0.3803	0.4512	0.2958
4	0.4051	0.5653	0.4935
Delta	0.2181	0.3065	0.3557
Rank	3	2	1

Tab. 8 *Response Table for Signal-to-Noise Ratios 7075*

Level	Spindle speed (rpm)	Feed rate (mm/min)	DOC (mm)
1	5.898	11.514	6.026
2	4.723	4.791	4.049
3	9.172	7.368	11.220
4	9.201	5.320	7.698
Delta	4.478	6.723	7.170
Rank	3	2	1

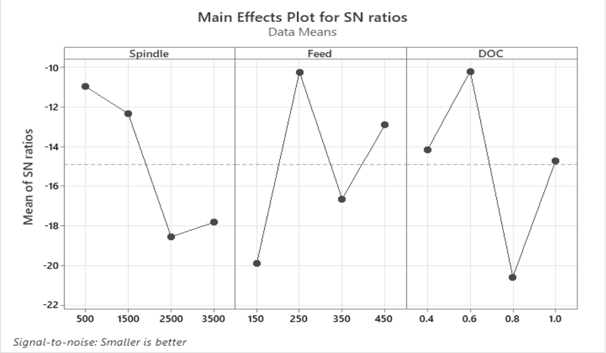

Fig. 3 *Mean surface roughness at each parameter level 7075*

For AL7075, Taguchi (smaller-is-better) indicates the influence order DOC > Feed > Spindle (ΔMeans: 0.3557 > 0.3065 > 0.2181; ΔS/N: 7.170 > 6.723 > 4.478). The mean-optimal setting to minimize Ra is S3–F1–D3, whereas the robust (highest S/N) setting is S4–F1–D3. Mechanistically, DOC is most decisive because it alters chip thickness and system stiffness (promoting vibration/BUE when too large); Feed has a moderate effect; and Spindle shows that Level 3 yields the lowest mean while Level 4 provides greater robustness.

The S/N main-effects plot indicates that, for the most robust (highest S/N) surface finish, the settings should be Spindle = 500 rpm, Feed = 250 mm/min, and DOC = 0.6 mm, with the factor influence ordered as DOC = Feed > Spindle.

Regression Equation in Uncoded Units 7075:

$$\begin{aligned} Ra\_7075 = {} & 0.72 + 0.000181\ Speed + 0.00085\ Feed - 1.15\ Doc + 0.000000\ Speed2 - 0.000005\ Feed2 + \\ & 0.46\ Doc2 - 0.000000\ Speed*Feed - 0.000304\ Speed*Doc + 0.00293\ Feed*Doc \end{aligned} \tag{6}$$

Tab. 9 *Response Table for Means 6061*

Level	Spindle speed (rpm)	Feed rate (mm/min)	DOC (mm)
1	2.9938	0.6772	0.6917
2	0.9807	0.9635	0.8807
3	0.3804	1.4735	1.4145
4	0.4360	1.6768	1.8041
Delta	2.6134	0.9997	1.1123
Rank	1	3	2

Tab. 10 *Response Table for Means 6061*

Level	Spindle speed (rpm)	Feed rate (mm/min)	DOC (mm)
1	-8.7623	4.7127	4.4819
2	1.5795	2.8048	4.6298
3	8.4532	0.2460	0.1961
4	7.0103	0.5173	-1.0270
Delta	17.2156	4.4668	5.6567
Rank	1	3	2

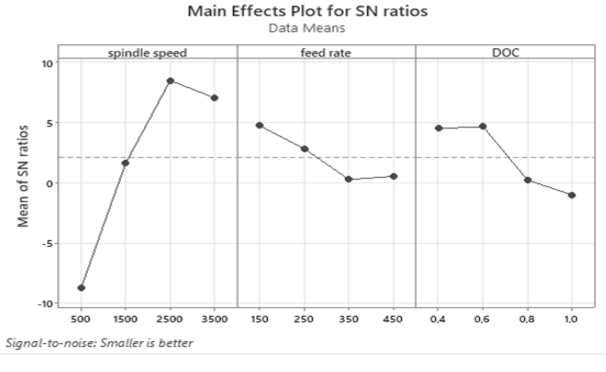

Fig. 4 *Mean surface roughness at each parameter level 6061*

For AL6061, Taguchi (smaller-is-better) ranks the factors Spindle > DOC > Feed (ΔMeans: 2.6134 > 1.1123 > 0.9997; ΔS/N: 17.2156 > 5.6567 > 4.4668). The mean-optimal setting to minimize Ra is S3–F1–D1 (Spindle L3 = 0.3804; Feed L1 = 0.6772; DOC L1 = 0.6917), whereas the robust (highest S/N) setting is S3–F1–D2 (Spindle L3 = 8.4532; Feed L1 = 4.7127; DOC L2 = 4.6298). Technically, spindle speed most strongly governs BUE formation/removal in 6061 and thus exerts the largest effect; Feed is relatively least influential; DOC is intermediate L1 yields the lowest mean Ra, but L2 is more stable (higher S/N).

The S/N main-effects plot indicates that the most robust settings are spindle 2500 rpm, feed 150 mm/min, and DOC 0.6 mm (with 0.4 mm also performing well), with the factor influence ordered approximately Spindle > Feed > DOC.

Regression Equation in Uncoded Units 5052:

$$\begin{gathered}\mathrm{Ra\_6061} = 0.117 - 0.001087\ \mathrm{Speed} + 0.00767\ \mathrm{Feed} + 2.23\ \mathrm{Doc} + 0.000001\ \mathrm{Speed2} - 0.000002\ \mathrm{Feed2} + \\ 1.254\ \mathrm{Doc2} - 0.000003\ \mathrm{Speed{*}Feed\ rate} - 0.001500\ \mathrm{Speed{*}Doc} - 0.00068\ \mathrm{Feed{*}Doc}\end{gathered} \tag{7}$$

Tab. 11 *Response Table for Means 5052*

Level	Spindle speed (rpm)	Feed rate (mm/min)	DOC (mm)
1	4.901	4.800	3.810
2	3.836	3.426	4.275
3	4.436	3.779	3.476
4	3.664	4.831	5.276
Delta	1.237	1.405	1.799
Rank	3	2	1

Tab. 12 *Response Table for Signal-to-Noise Ratios 5052*

Level	Spindle speed (rpm)	Feed rate (mm/min)	DOC (mm)
1	13.728	13.354	11.489
2	11.609	9.966	12.309
3	12.722	11.446	10.101
4	10.125	13.418	14.286
Delta	3.602	3.452	4.185
Rank	2	3	1

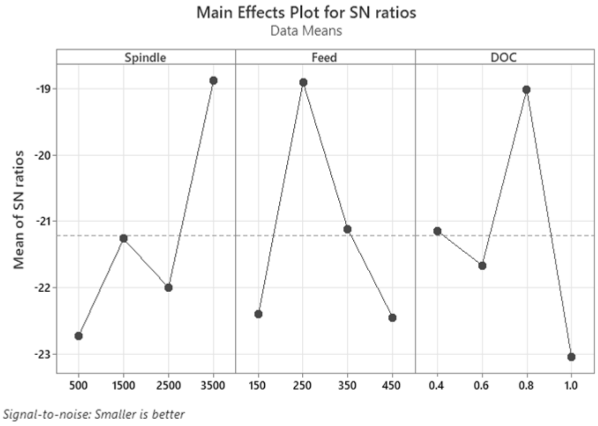

Fig. 5 *Mean surface roughness at each parameter level 5052*

The order of influence (Means) is DOC > Feed > Spindle (Δ: 1.799 > 1.405 > 1.237). The mean-optimal setting is S4–F2–D3 → 3500 rpm, 250 mm/min, 0.8 mm. Based on the S/N table provided, the order is DOC > Spindle > Feed (Δ: 4.185 > 3.602 > 3.452), with the robust optimum S1–F4–D4 → 500 rpm, 450 mm/min, 1.0 mm. Confirmation tests are required because the DOC direction in the S/N results differs from that in the Means.

From the Main Effects plot for the S/N ratio, the robust operating condition is obtained at 3500 rpm spindle speed, 250 mm/min feed, and 0.8 mm depth of cut (S4–F2–D3). The contribution order inferred from the S/N trends is Feed ≈ DOC, both exceeding the effect of Spindle speed.

$$\begin{gathered}\mathrm{Ra\_5052} = 9.54 - 0.00246\ \mathrm{Speed} - 0.0129\ \mathrm{Feed} - 7.6\ \mathrm{Doc} + 0.000000\ \mathrm{Speed2} + 0.000061\ \mathrm{Feed2} + 8.34 \\ \mathrm{Doc2} - 0.000001\ \mathrm{Speed{*}Feed} + 0.00236\ \mathrm{Speed{*}Doc} - 0.0246\ \mathrm{Feed{*}Doc}\end{gathered} \tag{8}$$

Across materials, surface quality is most influenced by DOC and Spindle (Feed is least). A “safe/robust” starting point common to all three alloys is S3–F1–D3 (2500 rpm, 150 mm/min, 0.8 mm), followed by alloy-specific fine-tuning: 6061 tends to finish smoother at small–medium DOC (D1/D2), whereas 5052 performs best at high spindle speed and medium DOC (S4–D3). Perform confirmation tests (≥ 3 replications) on the selected combinations and re-verify the 5052 S/N table to ensure consistency with the smaller-the-better criterion.

Tab. 13 *ANOVA results for the S/N ratio response 7075*

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Spindle	3	62.86	18.39%	62.86	20.953	2.23	0.185
Feed	3	111.87	32.72%	111.87	37.291	3.97	0.071
DOC	3	110.80	32.41%	110.80	36.934	3.93	0.072
Error	6	56.34	16.48%	56.34	9.390		
Total	15	341.87	100.00%				

Contributions (%SS): Feed 32.72%, DOC 32.41%, Spindle 18.39%, Error 16.48%. F-tests: Spindle $F = 2.23$; $p = 0.185$ (not significant), Feed $F = 3.97$; $p = 0.071$ (near significant), DOC $F = 3.93$; $p = 0.072$ (near significant). Ra is most influenced by Feed and DOC (both borderline at $\alpha \approx 0.10$), whereas Spindle has the weakest effect. Tight control of DOC and Feed is therefore more important. The robust setting is consistent with S4–F1–D3.

Tab. 14 *Analysis of Variance (ANOVA) for S/N ratio 6061*

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Spindle	3	730.93	80.49%	730.93	243.644	65.62	0.000
Feed	3	53.05	5.84%	53.05	17.683	4.76	0.050
DOC	3	101.89	11.22%	101.89	33.963	9.15	0.012
Error	6	22.28	2.45%	22.28	3.713		
Total	15	908.15	100.00%				

Contributions (%SS): Spindle 80.49% (dominant), DOC 11.22%, Feed 5.84%, Error 2.45%. F-tests: Spindle $F = 65.62$; $p < 0.001$ (strongly significant), DOC $F = 9.15$; $p = 0.012$ (significant), Feed $F = 4.76$; $p = 0.050$. Interpretation: Ra is determined almost entirely by Spindle, followed by DOC, with Feed having the smallest effect. This implies that controlling spindle speed (around S3 = 2500 rpm) and a medium DOC (D2 = 0.6 mm) is critical. Robust setting: S3–F1–D2; for the lowest mean, S3–F1–D1.

Tab. 15 *Analysis of Variance (ANOVA) for S/N ratio 5052*

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Spindle	3	28.66	20.78%	28.66	9.554	1.45	0.318
Feed	3	33.12	24.02%	33.12	11.041	1.68	0.269
DOC	3	36.72	26.63%	36.72	12.239	1.86	0.237
Error	6	39.40	28.57%	39.40	6.567		
Total	15	137.90	100.00%				

Contributions: DOC 26.63%, Feed 24.02%, Spindle 20.78%, Error 28.57% (largest). F-tests: Spindle $F = 1.45$; $p = 0.318$, Feed $F = 1.68$; $p = 0.269$, DOC $F = 1.86$; $p = 0.237$ all not significant. The relative variation/noise is high, so individual factor effects are not statistically demonstrated at $\alpha = 0.05$. A practical ordering remains DOC ≥ Feed > Spindle, but additional replications, improved Ra measurement repeatability, or wider factor ranges are needed for clearer effect separation. In the meantime, follow the most consistent mean result: S4–F2–D3. From the ANOVA comparisons, the factor most influencing robustness (S/N) is Spindle for 6061 strongly significant, Feed and DOC for 7075, while 5052 is dominated by noise. Process-control priorities: tightly control Spindle for 6061; control DOC and Feed for 7075; for 5052, increase replications and improve measurement repeatability

4 Conclusions

This study compared the sensitivity of cutting parameters to surface roughness (Ra) in three aluminum alloys (AL7075, AL6061, AL5052) using a Taguchi L16 design, S/N (smaller-is-better) analysis, and ANOVA, with a carbide 2-flute straight end mill, Ø6 mm and factor levels spindle 500-3500 rpm, feed 150-450 mm/min, DOC 0.4-1.0 mm. In general, AL7075 provided the smoothest finish (Ra_min = 0.143 μm), followed by AL6061 (0.282 μm) and AL5052 (1.478 μm). The factor-influence order is material-specific, summarized as follows.

- Al6061, Spindle speed is the dominant factor (highest ΔMeans; ANOVA S/N contribution = 80.5%, $p < 0.001$), followed by depth of cut (DOC, $p = 0.012$), while feed rate is the least influential ($p = 0.050$). The mean-optimal setting (minimum Ra) is S3–F1–D1 (2500 rpm, 150 mm/min, 0.4 mm), whereas the robust-optimal setting (highest S/N ratio) is S3–F1–D2 (2500 rpm, 150 mm/min, 0.6 mm)
- AL705, Depth of cut and feed rate are the most influential factors (highest ΔMeans and ΔS/N), while the ANOVA S/N results are borderline significant ($p \approx 0.07$). The mean-optimal setting is S3–F1–D3 (2500 rpm, 150 mm/min, 0.8 mm), whereas the robust-optimal setting is S4–F1–D3 (3500 rpm, 150 mm/min, 0.8 mm).
- AL5052, all three factors contribute at relatively similar magnitudes based on ΔMeans (DOC > Feed > Spindle), but none are statistically significant in the ANOVA S/N analysis ($p > 0.23$; Error contribution =

28.6%), indicating relatively high experimental noise. The mean-optimal setting is S4–F2–D3 (3500 rpm, 250 mm/min, 0.8 mm). The robust-optimal setting derived from the S/N table is S1–F4–D4 (500 rpm, 450 mm/min, 1.0 mm); however, this combination requires additional confirmation tests

Cross-material practical pattern. DOC and Spindle are the principal levers for surface-finish quality; Feed is comparatively less influential. A safe, cross-material starting recipe is S3-F1-D3 (2500 rpm, 150 mm/min, 0.8 mm), followed by alloy-specific fine-tuning: for 6061, reduce DOC (D1/D2); for 5052, increase Spindle (S4) and select medium DOC (D3). Mechanistic interpretation. Higher spindle speed suppresses BUE and vibration in 6061; a medium DOC stabilizes chip formation in 7075; 5052, being tougher and more prone to adhesion, benefits from high spindle with medium DOC for finishing. Limitations. The study used a single tool geometry, dry cutting conditions, and limited replications-particularly for 5052-which may constrain statistical power and generality. Future work should expand replication, explore coolant/MQL conditions, and assess alternative tool geometries

References

[1] YAU, H.T., KUO, P.H., HONG, S.W. (2024). Milling Wear Prediction Using an Artificial Neural Network Model. In: *Engineering Applications of Artificial Intelligence*, Vol. 135, pp. 108686. DOI 10.1016/j.engappai.2024.108686.

[2] KUNDRÁK, J., MARKOPOULOS, A.P., MAKKAI, T., KARKALOS, N.E. (2019). Effect of Edge Geometry on Cutting Forces in Face Milling with Different Feed Rates. In: *Manufacturing Technology*, Vol. 19, No. 6, pp. 984 – 992. DOI 10.21062/ujep/407.2019/a/1213-2489/MT/19/6/984.

[3] ZAIDI, S.R., BUTT, S.I., KHAN, M.A., FARAZ, M.I., JAFFERY, S.H.I., PETRU, J. (2024). Sustainability Assessment of Machining Al 6061-T6 Using Taguchi-Grey Relation Integrated Approach. In: *Heliyon*, Vol. 10, pp. e33726. DOI 10.1016/j.heliyon.2024.e33726.

[4] MARTOWIBOWO, S.Y., KASWADI, A., LUBIS, G.S. (2017). Application of Taguchi Method-Moldflow-Particle Swarm Optimization for Plastic Injection Process Parameters Optimization. In: *Manufacturing Technology*, Vol. 17, pp. 512 – 519.

[5] UMAMAHESWARARAO, P., RAVI SANKAR, B., NANCHARAIAH, T. (2019). Multi Objective Optimization of Process Parameters of Al 6061-SiCp Metal Matrix Composite in End Milling-Hybrid GRA-PCA Approach. In: *Materials Today: Proceedings*, Vol. 26, pp. 696 – 700. DOI 10.1016/j.matpr.2019.12.407.

[6] TRAN, C.C., LUU, V.T., NGUYEN, V.T., TRAN, V.T., TRAN, V.T., VU, H.D. (2023). Multi-Objective Optimization of CNC Milling Parameters of 7075 Aluminium Alloy Using Response Surface Methodology. In: *Jordan Journal of Mechanical and Industrial Engineering*, Vol. 17, No. 3, pp. 393 – 402. DOI 10.59038/jjmie/170308.

[7] IKHRIES, I.I., AL-SHAWABKEH, A.F. (2024). Novel Methods for Optimizing CNC Aluminum Alloy Machining Parameters in Polymer Mold Cavities. In: *International Journal of Lightweight Materials and Manufacture*, Vol. 7, pp. 507 – 519. DOI 10.1016/j.ijlmm.2024.03.002.

[8] URBIKAIN PELAYO, G., OLVERA-TREJO, D., LUO, M., LÓPEZ DE LACALLE, L.N., ELÍAS-ZUÑIGA, A. (2021). Surface Roughness Prediction with New Barrel-Shape Mills Considering Runout: Modelling and Validation. In: *Measurement*, Vol. 173, pp. 108670. DOI 10.1016/j.measurement.2020.108670.

[9] KUHLMANN, G., BORYSENKO, D., SÖLTER, J., KARPUSCHEWSKI, B. (2024). Simultaneous High-Speed Cutting and High-Feed Milling: An Investigation on Surface Integrity. In: *Procedia CIRP*, Vol. 123, pp. 59 – 64. DOI 10.1016/j.procir.2024.05.013.

[10] JIA, S., WANG, S., LI, S., CAI, W., LIU, Y., BAI, S., LI, Z.S. (2024). Integrated Multi-Objective Optimization of Rough and Finish Cutting Parameters in Plane Milling for Sustainable Machining Considering Efficiency, Energy, and Quality. In: *Journal of Cleaner Production*, Vol. 471, pp. 143406. DOI 10.1016/j.jclepro.2024.143406.

[11] YAO, Z., ZHANG, P., LUO, M. (2024). Extreme Learning Machine Oriented Surface Roughness Prediction at Continuous Cutting Positions Based on Monitored Acceleration. In: *Mechanical Systems and Signal Processing*, Vol. 219, pp. 111633. DOI 10.1016/j.ymssp.2024.111633.

[12] LIU, W.C., WANG, P., YOU, Y.P. (2023). Surface Roughness Prediction Using Multi-Source Heterogeneous Data and Bayesian Quantile Regression in Milling Process. In: *Journal of Manufacturing Processes*, Vol. 95, pp. 446 – 460. DOI 10.1016/j.jmapro.2023.04.038.

[13] YANG, H., ZHENG, H., ZHANG, T. (2024). A Review of Artificial Intelligent Methods for Machined Surface Roughness Prediction. In: *Tribology International*, Vol. 199, pp. 109935. DOI 10.1016/j.triboint.2024.109935.

[14] BALONJI, S., TARTIBU, L.K., OKOKPUJIE, I.P. (2023). Prediction Analysis of Surface Roughness of Aluminum Al6061 in End Milling CNC Machine Using Soft Computing Techniques. In: *Applied Sciences*, Vol. 13, pp. 4147. DOI 10.3390/app13074147.

[15] TRINH, V.L. (2024). A Review of the Surface Roughness Prediction Methods in Finishing Machining. In: *Engineering, Technology & Applied Science Research*, Vol. 14, pp. 15297 – 15304. DOI 10.48084/etasr.7710.

[16] ZHAO, T., SHI, Y., LIN, X., DUAN, J., SUN, P., ZHANG, J. (2014). Surface Roughness Prediction and Parameters Optimization in Grinding and Polishing Process for IBR of Aero-Engine. In: *International Journal of Advanced Manufacturing Technology*, Vol. 74, pp. 653 – 663. DOI 10.1007/s00170-014-6020-3.

[17] HUANG, P.M., LEE, C.H. (2021). Estimation of Tool Wear and Surface Roughness Development Using Deep Learning and Sensors Fusion. In: *Sensors*, Vol. 21, pp. 5338. DOI 10.3390/s21165338.

[18] CHARDE, M.M., NAJAN, T.P., CEPOVA, L., JADHAV, A.D., RASH, N.S. (2025). Predictive Modelling of Surface Roughness in Grinding Operations Using Machine Learning Techniques. In: *Manufacturing Technology*, Vol. 25, pp. 14 – 23. DOI 10.21062/mft.2025.006.

[19] QAZI, M.I., ABAS, M., KHAN, R., SALEEM, W., PRUNCU, C.I., OMAIR, M. (2021). Experimental Investigation and Multi-Response Optimization of Machinability of AA5005H34 Using Composite Desirability Coupled with PCA. In: *Metals*, Vol. 11, pp. 235. DOI 10.3390/met11020235.

[20] PIMENOV, D.Y., KIRAN, M., KHANNA, N., PINTAUDE, G., VASCO, M.C., DA SILVA, L.R.R., GIASIN, K. (2023). Review of Improvement of Machinability and Surface Integrity in Machining on Aluminum Alloys. In: *International Journal of Advanced Manufacturing Technology*, Vol. 129, pp. 1 – 32. Springer, London. DOI 10.1007/s00170-023-12630-4.

[21] ZAIDI, S.R., UL QADIR, N., JAFFERY, S.H.I., KHAN, M.A., KHAN, M., PETRU, J. (2022). Statistical Analysis of Machining Parameters on Burr Formation, Surface Roughness and Energy Consumption During Milling of Aluminium Alloy Al 6061-T6. In: *Materials*, Vol. 15, pp. 8065. DOI 10.3390/ma15228065.

[22] ȚÎȚU, A.M., SANDU, A.V., POP, A.B., ȚÎȚU, S., FRĂȚILĂ, D.N., CEOCEA, C., BOROIU, A. (2020). Design of Experiment in the Milling Process of Aluminum Alloys in the Aerospace Industry. In: *Applied Sciences*, Vol. 10, pp. 6951. DOI 10.3390/app10196951.

[23] SATHISH, T. (2024). Taguchi and ANOVA-Based Optimization of CNC Milling Parameters for Aluminium 7075 Alloy. In: *Journal of Environmental Nanotechnology*, Vol. 13, pp. 72 – 77. DOI 10.13074/jent.2024.03.241508.

[24] SIREGAR, I., SAEDON, J., ADENAN, M.S. (2025). Milling Performance of Selective Laser Melted Ti6Al4V: A Taguchi Approach for Surface Roughness Optimization. In: *Manufacturing Technology*, Vol. 25, pp. 230 – 238. DOI 10.21062/mft.2025.030.

[25] PUL, M. (2017). Comparison of Surface Roughness and Tool Wear in Turning of 7075, 6061 and 2024 Aluminum Alloys. In: *International Journal of Engineering Research and Development*, Vol. 9, pp. 65 – 75. DOI 10.29137/umagd.351746.

[26] ELSHAER, R.N., EL-ATY, A.A., SAYED, E.M., BARAKAT, A.F., SOBH, A.S. (2024). Optimization of Machining Parameters for Turning Operation of Heat-Treated Ti-6Al-3Mo-2Nb-2Sn-2Zr-1.5Cr Alloy by Taguchi Method. In: *Scientific Reports*, Vol. 14, pp. 1 – 14. DOI 10.1038/s41598-024-65786-8.