GJETA
Global Journal of Engineering and Technology Advances
eISSN: 2582-5003
Cross Ref DOI: 10.30574/gjeta
Journal homepage: https://gjeta.com/
Global Journal of Engineering and Technology Advances
eISSN 2582-5003
Global Scholar Press, INDIA

(Research Article)

OPTIMIZATION OF CUTTING PARAMETERS IN CNC MILLING USING THE TAGUCHI METHOD

Innocent Mapindu [1,*], Gilbert Munhuwamambo [1], Destine Mashava [2] and Lindokuhle Ngwenya [2]

[1] Department of Industrial and Manufacturing Engineering, National University of Science and Technology (NUST), Bulawayo, Zimbabwe
[2] Department of Agricultural Engineering, National University of Science and Technology (NUST), Bulawayo, Zimbabwe
* Corresponding Author, innocent.mapindu@nust.ac.zw

ORCID Details
Innocent Mapindu: https://orcid.org/0009-0007-2024-1919
Destine Mashava: https://orcid.org/0009-0002-9487-9038

Global Journal of Engineering and Technology Advances, 2026, 28(02), 149–162

Publication history: Received on 27 June 2026; revised on 18 August 2026; accepted on 21 August 2026

Article DOI: https://doi.org/10.30574/gjeta.2026.28.2.0223

ABSTRACT

In this paper, an experimental optimization of cutting parameters in computer numerical control (CNC) milling of mild steel with the Taguchi method of robust design is presented. Three control factors, spindle speed, feed rate and depth of cut, were selected and tested at three levels each, and arranged in Taguchi L9(3^3) orthogonal array. The quality responses used were surface roughness (Ra) (smaller-the-better) and flank tool wear (VB) (smaller-the-better) with each trial repeated three times to get the mean and the signal-to-noise (S/N) ratio. The surface roughness and tool wear were found to be dependent mainly upon feed rate for surface roughness and spindle speed for tool wear, with 82.81% and 63.40% of their variation, respectively, attributable to feed rate and spindle speed, with depth of cut being a statistically significant secondary variable for both responses. The individually optimal settings were a spindle speed of 2000 rpm, feed of 0.10 mm/rev and depth of cut of 0.5 mm for minimum surface roughness (predicted Ra = 1.38 µm), and a spindle speed of 1000 rpm, feed of 0.10 mm/rev and depth of cut of 0.5 mm for minimum tool wear (predicted VB = 0.173 mm). The grey relational analysis (GRA) was used to find a compromise condition, for which 1000 rpm, 0.10 mm/rev feed, and 0.5 mm depth of cut were determined and a grey relational grade of 0.918 was predicted (Ra = 1.66 µm and VB = 0.171 mm), and the predicted grey relational grade within a 95% confidence interval was verified for both responses. The results obtain a validated set of recommended cutting parameters for the machine–tool–material combination considered and illustrate how Taguchi–GRA analysis can solve the conflicting optima problem for two quality characteristics.

Keywords: Taguchi Method; CNC Milling; Surface Roughness; Tool Wear; Orthogonal Array; Signal-To-Noise Ratio; Analysis Of Variance; Grey Relational Analysis.

1 INTRODUCTION

Computer numerical control (CNC) milling is still one of the most commonly used subtractive manufacturing processes used to produce precision components in the aerospace, automotive, tooling and general engineering industries. The effect of the cutting parameters (spindle speed, feed rate and depth of cut) on both the quality of the milled part (usually measured by surface roughness) and the efficiency of the process (which is influenced by the rate of wear of the cutting tool) are strong.

These parameters are normally selected by trial and error or solely based on the recommendations in machine-tool catalogues, which wastes material and machine time, and rarely leads to an optimal combination of parameters for more than one quality characteristic. Design of experiments (DOE) offers a statistically sound and systematic way to avoid the trial-and-error approach for parameter selection [1].

The Taguchi method, developed by Genichi Taguchi, is one of the most popular DOE techniques used in optimizing manufacturing processes because of using orthogonal arrays to significantly reduce the number of experimental runs needed to investigate more than one factor, and a signal-to-noise (S/N) ratio analysis to include the mean response and variability, which gives optimum parameter settings that are robust against uncontrollable "noise" in the production environment [2].

The Taguchi method has been widely adopted for machining processes since the formulation of Taguchi, for instance, Yang and Tarng [3] employed the Taguchi method to optimize the cutting parameters for surface finish and tool life in turning operations, which was later followed by numerous milling processes. Since then, there has been a significant amount of literature that has used the Taguchi method in the field specifically for milling. Ribeiro et al. [4] used an L9 orthogonal array and S/N ratio analysis to obtain the optimum cutting parameters for minimum surface roughness in end milling operations.

Pragajibhai et al. [5] used the same technique and added ANOVA to assign a numerical value to the statistical significance of each parameter. Fedai et al. [6] then expanded the method to a multi-objective Taguchi technique in face milling, thus acknowledging that one quality characteristic does not necessarily represent the overall economical aspect of a machining operation.

Moayyedian et al. [7] used the Taguchi L9 array together with the design of experiments to model the surface roughness in the milling of Hardox steel and Belamri et al. [8] performed an ANOVA analysis of the cutting parameters in the surface roughness modelling of aluminium milling. Despite the fact that flank wear is a most important factor affecting the progression of tool wear in multi-fluted end milling, comparatively little attention has been given to it in the milling literature, however,

Rakmae et al. [9] recently optimized the flank wear and surface roughness simultaneously in the end milling of SS400 steel using the Taguchi method, where it was observed that flank wear increased significantly with cutting speed, which is in accordance with the classical theory of tool wear, in which the flank and crater wear rate increases very rapidly with cutting speed.

Cutting parameters are often related to the surface roughness and tool wear in opposite ways, and several authors have adopted the Taguchi method and grey relational analysis (GRA) to find the optimum compromise parameter setting; Wang and Li [10] optimized surface roughness and tool wear by using Taguchi-GRA for milling TC17 titanium alloy under minimum-quantity-lubrication (MQL) conditions, and Saberi et al. [11] employed the same combined method for the same material in the case of milling GTD450 stainless steel under minimum-quantity-lubrication (MQL) conditions. Even though this is a huge amount it was found that the optimum parameter combinations and the percentage contribution of the parameters and the direction of some of the parameter effects are different in various studies, depending on the particular machine, tool and workpiece-material combination being studied.

This clearly demonstrates the ongoing real-world importance of optimization through a dedicated study based on the Taguchi approach for a specific CNC milling configuration, instead of a generic study from the literature. In the present study, this need is fulfilled by applying an experimental dataset generated by the in-house CNC milling facility and introducing grey relational analysis in order to make a single set of cutting parameters, instead of two conflicting optima, available to the machine operator.

Aims and Objectives

The aim of this study is to optimize the cutting parameters of a CNC milling process which are spindle speed, feed rate, and depth of cut, in order to simultaneously minimize surface roughness and flank tool wear, using the Taguchi method of robust parameter design.

The specific objectives of the study are to

- Design a Taguchi L9(3^3) orthogonal-array experiment for three control factors (spindle speed, feed rate, depth of cut), each at three levels, for milling of mild-steel workpieces.
- Experimentally determine surface roughness (Ra) and flank tool wear (VB) for each of the nine trials, with triplicate measurements per trial.
- Analyse the signal-to-noise ratio of each response to identify the individually optimal parameter level for minimum surface roughness and for minimum tool wear.
- Perform analysis of variance (ANOVA) to quantify the statistical significance and percentage contribution of each cutting parameter to each response.
- Apply grey relational analysis to obtain a single compromise parameter setting that simultaneously minimizes both surface roughness and tool wear.
- Validate the predicted optimum through a confirmation analysis with 95% confidence intervals, and compare the findings with related studies in the literature.

2 METHODOLOGY

2.1 Taguchi Orthogonal Array Design

The Taguchi method is an orthogonal array of fractional-factorial experiment that runs in only nine trials for three factors at three levels, as opposed to 3^3 = 27 trials required for the full-factorial experiment. The standard L9(3^3) orthogonal array was employed where the three control factors with three levels are arranged in the columns of the orthogonal array, and the nine different rows represent the parameter combinations for the nine experimental trials. The array is orthogonal, which means that the effect of each factor on the response can be estimated separately allowing other factors to cancel out without being confounded, otherwise known as the "no ad hoc reduced set of trials problem" [2], [12].

2.2 Selection of Control Factors and Levels

Three control factors were chosen as these are the parameters most directly programmed by the CNC operator and have the highest level of correlation with surface finish and tool wear in milling found in the literature [3]–[9]: spindle speed (A), feed rate (B) and depth of cut (C). The three levels of each factor are shown in Table I and the coded L9(3^3) array is shown in Table II.

2.3 Signal-to-Noise Ratio and Loss Function

In each trial, Taguchi's signal-to-noise ratio transforms the replicate measurements into a single value of the quality loss function that reflects both the deviation from the target value (mean response) and the deviation from the mean value (variability) in a quadratic manner in accordance with Taguchi's quality-loss function [2], [12]. The S/N ratio was used for both responses as both were quality characteristics for which smaller values were always preferred.

$$\eta = -10 \log_{10} \left[(1/n) \Sigma y_i^2 \right] \qquad (1)$$

where y_i is the i-th replicate measurement of the response in a trial and n is the number of replicates (n = 3 in this study). A higher S/N ratio always corresponds to a more desirable (lower and more consistent) response, so the factor level that maximizes the mean S/N ratio for a given factor is taken as that factor's optimal level.

2.4 Analysis of Variance

ANOVA was used to show the total variation of the S/N ratios into the variation attributed to each control factor and the variation attributed to the error (residual) variation for each and to test the significance of each factor by calculating the F-ratio as the mean square of the factor divided by the mean square of the error (residual). The contribution of a factor as a percentage of the total sum of squares represents the relative importance of the factor in the control of the response [1], [12].

2.5 Grey Relational Analysis for Multi-Response Optimization

The classical Taguchi method optimizes one response at a time, and if two responses (e.g., "quality" response like surface roughness and "durability" response like tool wear) require conflicting settings for the factors, a completely different optimization approach must be used to determine one setting that will compromise both. This was done by using grey relational analysis (GRA) developed by Deng [13]. All answers were initially transformed to the smaller-the-better scale,

$x_i(k) = [\max y_i(k) - y_i(k)]/[\max y_i(k) - \min y_i(k)]$ (2)

Subsequently, the normalized values were calculated and then a grey relational coefficient was determined for each of these normalized values,

$\xi_i(k) = (\Delta\min + \zeta\Delta\max)/(\Delta_i(k) + \zeta\Delta\max)$ (3)

where $\Delta_i(k) = |x_0(k) - x_i(k)|$ is the absolute deviation from the ideal (normalized) value of 1, $\Delta\min$ and $\Delta\max$ are the smallest and largest deviations across all trials and responses, and ζ is a distinguishing coefficient conventionally set to 0.5 [13], [14]. The grey relational grade (GRG) for each trial is the equally-weighted average of the grey relational coefficients of its responses,

$GRG_i = (1/m)\ \Sigma\ \xi_i(k)$ (4)

where m is the number of responses (m = 2: Ra and VB). The GRG transforms the multi-response optimization problem to a single-response optimization problem, and the combination of the levels of the factors that gives the maximum GRG is the closest overall to the optimal (concurrently minimum) combination of both responses [10, 14].

Table 1: Control Factors and Levels

Factor	Level 1	Level 2	Level 3
A — Spindle Speed (rpm)	1000	1500	2000
B — Feed Rate (mm/rev)	0.10	0.15	0.20
C — Depth of Cut (mm)	0.5	1.0	1.5

Table 2: Taguchi L9(3^3) Orthogonal Array (Coded Levels)

Run	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

3 EXPERIMENTAL SETUP

3.1 CNC Milling Machine and Cutting Tool

Three-axis vertical CNC milling machine was used for all trials, with a solid 10 mm diameter four-flute carbide end mill. The three programmed parameters were isolated from influence of a coolant regime by machining was performed dry (without cutting fluid). In order to interpret the flank wear at the end of each trial to represent the cumulative effect of all the previous trials in the run sequence and the parameter combination tested in the trial rather than some progressive drift due to tool wear, the trials were executed in a randomized order, not the sequence L9 shown in Table II.

3.2 Workpiece Material and Specimen Preparation

The material of the work piece was mild steel (AISI 1018 grade or equivalent, low carbon structural steel), delivered in rectangular blocks and pre-processed with surface grinding, ensuring flat and parallel surfaces before processing, where the programmed depth of cut was carried out with total accuracy in all passes. To avoid the effect of work hardening from a previous pass affecting the surface roughness, and tool wear in subsequent passes, a new, previously unmachined face of the workpiece was presented to the cutter for each of the nine trials.

3.3 Design of Experimental Trials

The three control factors, spindle speed (A), feed rate (B), depth of cut (C) were taken to be the nine combinations shown in Table II (L9(3^3) orthogonal array), which yields the nine actual parameters combinations as shown in Table III and Table IV. The nine trials were conducted in a single milling pass with fixed lengths of the workpieces at the given spindle speed and feed rate, and depth of cut.

3.4 Measurement of Surface Roughness

The arithmetic mean surface roughness, Ra, of the surface after each milling pass was measured with a portable stylus type surface roughness tester, with a cut-off length of 0.8 mm and the evaluation length of 4 sampling lengths, per the profile method and terminology of ISO 4287 [15] and operating procedure of typical handheld surface roughness testers like the Mitutoyo SJ-210 [16]. Three Ra readings were made which were perpendicular to the feed marks at different locations throughout the manufactured surface to average out any irregularities in the surface to obtain the Trial 1-3 replicate columns of Table III, and the mean of the three readings and S/N ratio for each of the three were calculated using equation (1).

3.5 Measurement of Tool Wear

The flank-wear-land measurement convention [17] of ISO 3685 was used to measure VB on the major cutting edge of the tool after each trial, and a toolmaker's microscope (or a calibrated USB digital microscope) with graduated eyepiece was used to measure the width of the flank land normal to the major cutting edge. The three measurements were made at three locations on the engaged cutting edge for each trial and the mean and S/N ratios are also presented with the surface-roughness data in Table IV.

3.6 Data Recording Procedure

The S/N ratio is calculated for every replicate, not just the average of the three replicates for each trial, so it includes the location as well as the dispersion of the response for each trial, instead of just the average.

4 RESULTS AND ANALYSIS

4.1 Experimental Results

The complete set of experimental results, three times of replicate measurement, mean and S/N ratio, are given in Table III for surface roughness (Ra) and Table IV for flank tool wear (VB), respectively, for each of the nine trials of the L9(3^3) array. Surface roughness ranged from a minimum mean of 1.553 µm (Run 7: 2000 rpm, 0.10 mm/rev, 1.5 mm) to a maximum mean of 2.847 µm (Run 3: 1000 rpm, 0.20 mm/rev, 1.5 mm), while flank wear ranged from a minimum mean of 0.171 mm (Run 1: 1000 rpm, 0.10 mm/rev, 0.5 mm) to a maximum mean of 0.279 mm (Run 9: 2000 rpm, 0.20 mm/rev, 1.0 mm). The two responses are not equally reduced by the same trial: the trial on the smoothest surface (Run 7) is not the trial with the least tool wear (Run 1) and anticipates the trade-off; which will be formally described in Section 5.5.

Table 3: Experimental Results Surface Roughness (Ra), Smaller-the-Better

Run	Speed (rpm)	Feed (mm/rev)	Depth (mm)	Ra_1 (µm)	Ra_2 (µm)	Ra_3 (µm)	Mean Ra (µm)	S/N (dB)
1	1000	0.10	0.5	1.67	1.64	1.68	1.663	-4.42
2	1000	0.15	1.0	2.35	2.31	2.25	2.303	-7.25
3	1000	0.20	1.5	2.91	2.81	2.82	2.847	-9.09

4	1500	0.10	1.0	1.58	1.56	1.69	1.610	-4.14
5	1500	0.15	1.5	2.23	2.25	2.20	2.227	-6.95
6	1500	0.20	0.5	2.40	2.51	2.42	2.443	-7.76
7	2000	0.10	1.5	1.61	1.51	1.54	1.553	-3.83
8	2000	0.15	0.5	1.77	1.76	1.71	1.747	-4.85
9	2000	0.20	1.0	2.42	2.32	2.41	2.383	-7.55

Table 4: Experimental Results Flank Tool Wear (VB), Smaller-the-Better

Run	Speed (rpm)	Feed (mm/rev)	Depth (mm)	VB_1 (mm)	VB_2 (mm)	VB_3 (mm)	Mean VB (mm)	S/N (dB)
1	1000	0.10	0.5	0.176	0.169	0.169	0.171	15.32
2	1000	0.15	1.0	0.205	0.201	0.201	0.202	13.88
3	1000	0.20	1.5	0.233	0.231	0.236	0.233	12.64
4	1500	0.10	1.0	0.229	0.230	0.224	0.228	12.85
5	1500	0.15	1.5	0.264	0.260	0.261	0.262	11.64
6	1500	0.20	0.5	0.216	0.223	0.215	0.218	13.23
7	2000	0.10	1.5	0.291	0.293	0.291	0.292	10.70
8	2000	0.15	0.5	0.245	0.246	0.252	0.248	12.12
9	2000	0.20	1.0	0.278	0.277	0.282	0.279	11.09

4.2 Signal-to-Noise Ratio Analysis

Using (1) the mean S/N ratio at each level of each factor was computed by taking the average of the S/N ratios of three trials in which that level of the factor occurred. The resulting S/N response tables for the surface roughness and tool wear, respectively, are presented in Table 5 and Table 6, as well as the delta statistic (difference between the highest and lowest level average) and the rank it entails. The surface-roughness S/N response table is plotted graphically in Figure. 1, and the tool-wear S/N response table in Figure. 2. In both figures the solid marker indicates the factor level that maximizes the S/N ratio, that is, the individually optimal level for that response.

Surface Roughness parameters are as shown in Table 5 and Figure 1 and it is observed that the maximum S/N ratio is obtained at the optimal combination A3B1C1 at the speed level 3 (2000 rpm), feed level 1 (0.10 mm/rev) and depth level 1 (0.5 mm). The largest effect on surface roughness is feed rate (Δ = 4.001 dB) followed by spindle speed (Δ = 1.512 dB) and depth of cut (Δ = 0.948 dB) - this ranking and the fact that surface roughness decreases in opposing fashion to feed rate, are consistent with the classical relationship between feed per revolution and the theoretical feed-mark height on a roughened surface.

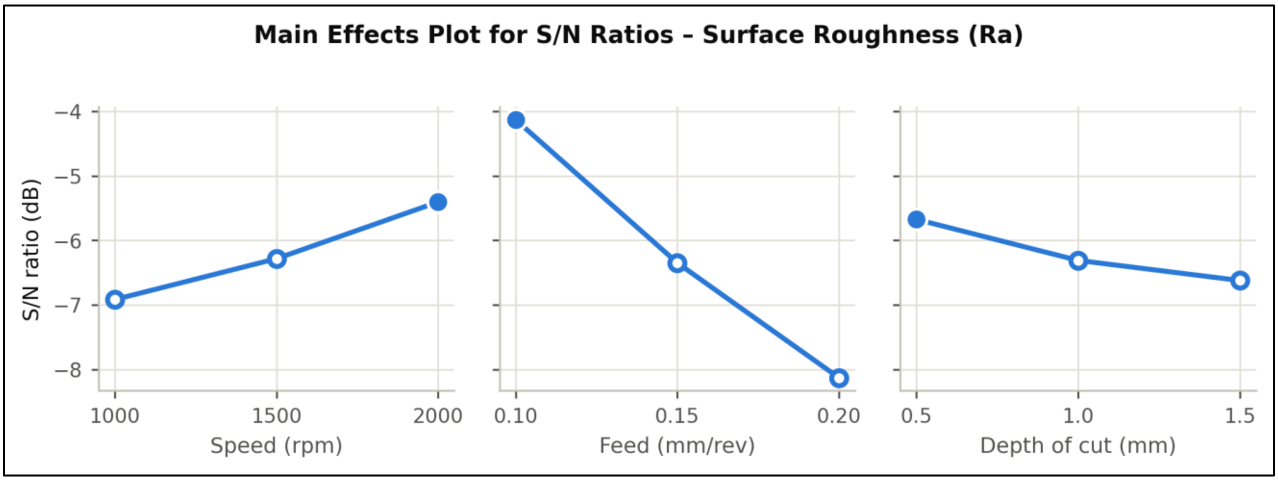

Figure 1: Main effects plot for S/N ratios surface roughness (Ra). Filled marker denotes the optimal level.

Table 5: S/N Response Table Surface Roughness (Ra)

Level	Speed (A)	Feed (B)	Depth (C)
1	-6.919	-4.130	-5.676
2	-6.286	-6.349	-6.312
3	-5.406	-8.131	-6.623
Delta	1.512	4.001	0.948
Rank	2	1	3
Optimal	A3	B1	C1

As regards tool wear, from Table VI and Fig. 2, it can be seen that the highest S/N ratio is achieved at speed level 1 (1000 rpm), feed level 1 (0.10 mm/rev) and depth level 1 (0.5 mm); hence, the optimum combination is A1B1C1. The spindle speed (Δ = 2.643 dB) and depth of cut (Δ = 1.895 dB) are also major contributors to the noise, and the higher the cutting speed, the greater the tool wear. This supports the findings of other authors [9] that abrasive and diffusive flank-wear mechanism are accelerated by increasing cutting speed with tool wear.

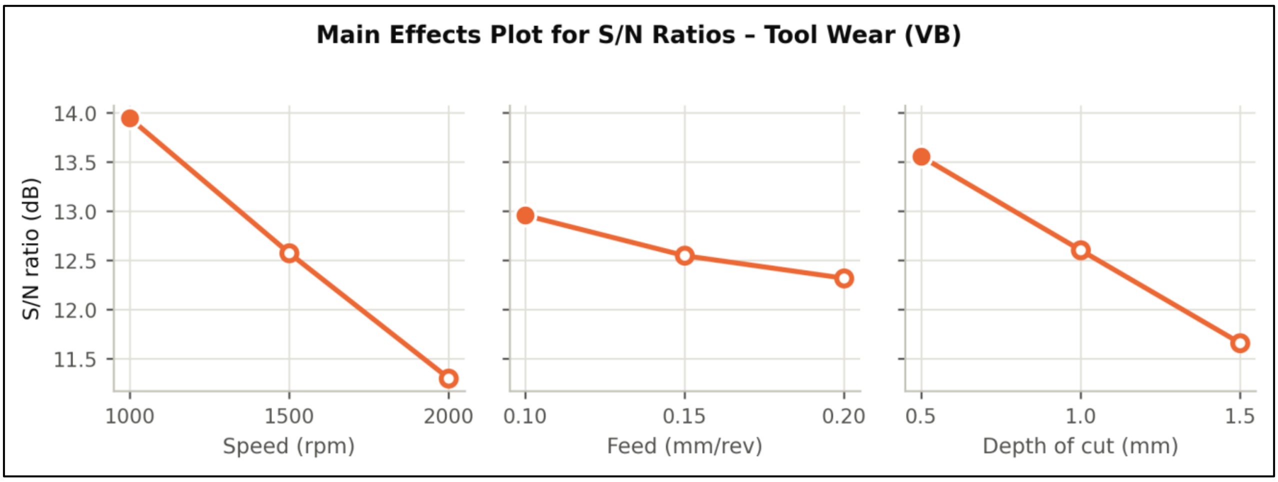

Figure 2: Main effects plot for S/N ratios tool wear (VB). Filled marker denotes the optimal level.

Table V and Table VI indicate that there is a difference between the individually optimum spindle speed, at which the two responses are optimal, and the optimal feed and the optimal depth of cut are the same in both cases. This single point of conflict, in spindle speed, is the reason a joint optimization by grey relational analysis (Section 5.5) is required to make a single parameter recommendation.

Table 6: S/N Response Table Tool Wear (VB)

Level	Speed (A)	Feed (B)	Depth (C)
1	13.947	12.959	13.558
2	12.576	12.548	12.606
3	11.304	12.319	11.662
Delta	2.643	0.640	1.895
Rank	1	3	2
Optimal	A1	B1	C1

Figure 3 and Figure 4 present the corresponding main-effects plots for the raw trial means (rather than the S/N ratios) of Ra and VB respectively. Because each response was measured with low trial-to-trial replicate scatter, the mean-based effect plots closely mirror the S/N-based plots of Fig. 1 and Fig. 2, lending additional confidence to the S/N-based conclusions above.

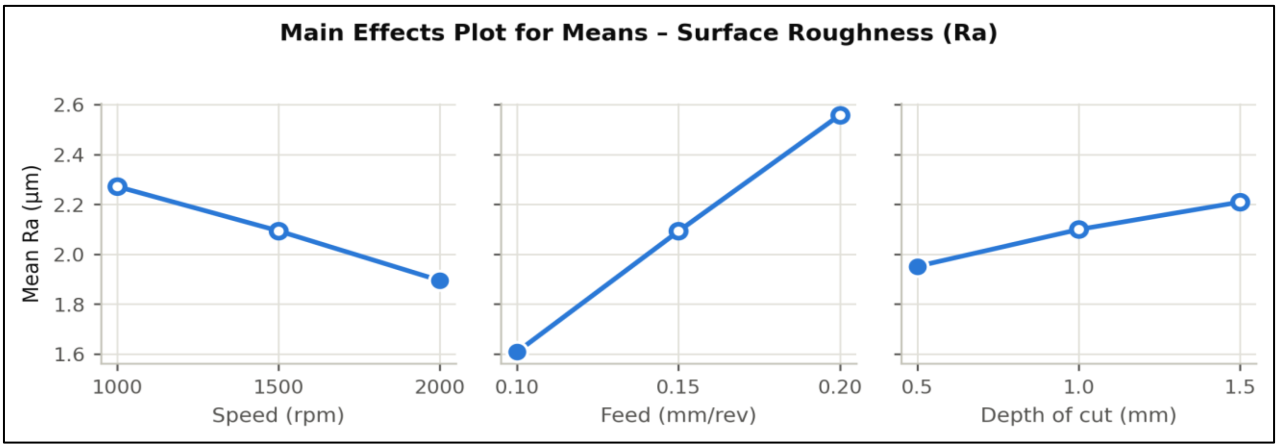

Figure 3: Main effects plot for trial means surface roughness (Ra). Filled marker denotes the minimum-Ra level.

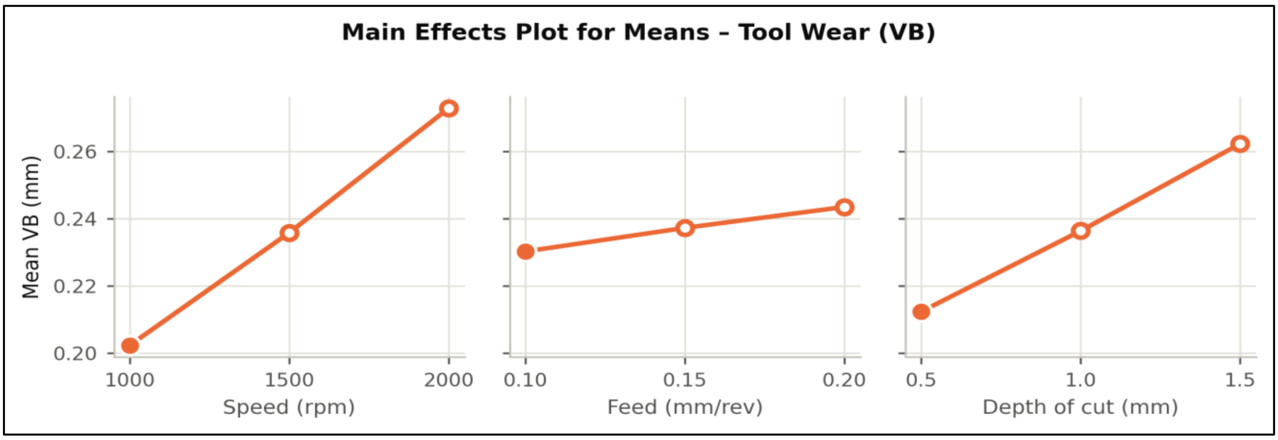

Figure 4: Main effects plot for trial means tool wear (VB). Filled marker denotes the minimum-VB level.

4.3 Analysis of Variance

The ANOVA of the S/N ratios corresponding to surface roughness and tool wear respectively is presented in Table 7 and Table 8, which contain the sum of squares (SS), degrees of freedom (DOF), mean square (MS), F-ratio and percentage contribution of each factor. With two degrees of freedom for each factor and two residual (error) degrees of freedom, the tabulated F-ratio critical values are $F_{0.10}(2,2) = 9.00$, $F_{0.05}(2,2) = 19.00$, and $F_{0.01}(2,2) = 99.00$.

Table 7: ANOVA for S/N Ratios Surface Roughness (Ra)

Factor	SS	DOF	MS	F	%Contrib.
Speed (A)	3.462	2	1.731	23.95	11.89
Feed (B)	24.111	2	12.055	166.79	82.81
Depth (C)	1.400	2	0.700	9.69	4.81
Error	0.145	2	0.072	—	0.50
Total	29.117	8	—	—	100.00

Table 8: ANOVA for S/N Ratios Tool Wear (VB)

Factor	SS	DOF	MS	F	%Contrib.
Speed (A)	10.481	2	5.240	325.64	63.40
Feed (B)	0.631	2	0.315	19.60	3.81
Depth (C)	5.389	2	2.694	167.43	32.59
Error	0.032	2	0.016	—	0.19
Total	16.532	8	—	—	100.00

For surface roughness (Table VII), feed rate is highly significant ($F = 166.79 > F_{0.01}$) with 82.81% of the total variation accounted for, spindle speed is significant at 5% level ($F = 23.95 > F_{0.05}$) with 11.89% of the total variation accounted for, depth of cut is significant only at 10% level ($F = 9.69$, marginally above $F_{0.10} = 9.00$) with 4.81% of the total variation accounted for, and the residual error accounts for 0.50%. These percentage contributions are shown graphically in Fig. 5.

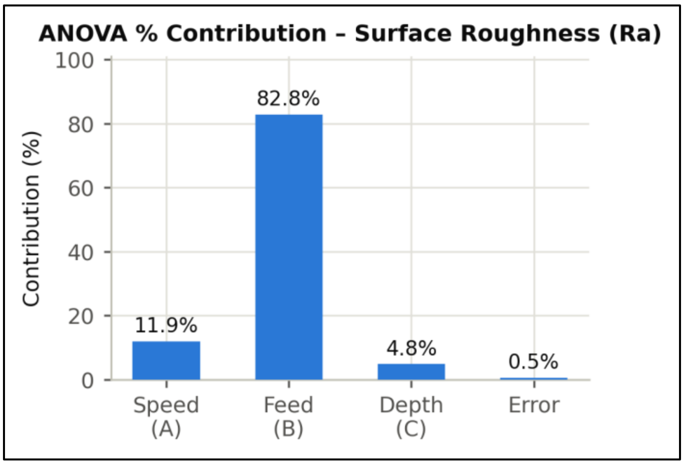

Figure 5: ANOVA percentage contribution of each control factor to surface roughness (Ra).

Spindle speed and depth of cut are also found to be highly significant (F = 325.64 and 167.43 respectively, well above $F_{0.01} = 20.00$) accounting for 63.40% and 32.59% of the total variation respectively, while the feed rate is significant only at 5% ($F = 19.60$, just above $19.00 = F_{0.05}$) accounting for 3.81% with residual error accounting for the remaining 0.19%. These percentage contributions are graphed in Figure 6. Finally, an identical ANOVA was carried out on the raw trial means, instead of on the S/N ratios, and gave results that were essentially the same for the percentage contributions (feed = 81.09% for Ra; speed = 65.06% for VB), confirming the results shown in Table VII and Table VIII.

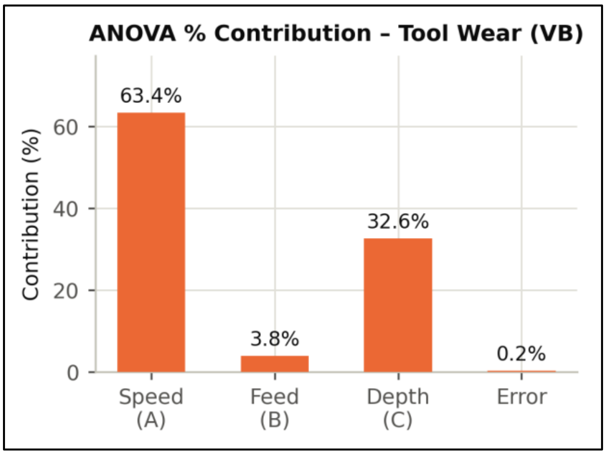

Figure 6: ANOVA percentage contribution of each control factor to tool wear (VB).

4.4 Effect of Process Parameters

The results of ANOVA of Section 5.3 are consistent with known machining mechanics. For a given geometry of the edge, the theoretical peak-to-valley feed-mark size is roughly proportional to the square of the feed per pass, meaning that small changes in feed produce disproportionately large changes in the measured feed-mark size, in just the strongly nonlinear, near-monotonic behaviour that can be seen in Fig. 1 and Fig. 3. The cutting-edge temperature during cutting increases with spindle speed, which also increases the abrasive, adhesive and diffusive wear rate on the flank face, as reported by Rakmae et al. [9] for the Taguchi-optimized end milling of SS400 steel, where cutting speed was also reported as the dominant variable affecting flank wear. For both responses, depth of cut also has a secondary but statistically significant effect, which is consistent with its direct effect on cutting force, thus influencing both surface deflection (Ra) and mechanical/thermal loading of cutting edges (VB).

4.5 Multi-Response Optimization via Grey Relational Analysis

Due to the contradiction between the spindle speed which is optimum for surface roughness (level 3, 2000 rpm) and the spindle speed which is optimum for tool wear (level 1, 1000 rpm), grey relational analysis was used to obtain a single compromised spindle speed based on (2)–(4) method. The normalized values of each of the nine trials, normalized grey relational coefficients and grey relational grade (GRG) are shown in Table 9.

Table 9: Grey Relational Normalization, Coefficients, and Grade

Run	A	B	C	x_Ra	x_VB	ξ_Ra	ξ_VB	GRG
1	1	1	1	0.915	1.000	0.855	1.000	0.927
2	1	2	2	0.420	0.742	0.463	0.660	0.561
3	1	3	3	0.000	0.485	0.333	0.492	0.413
4	2	1	2	0.956	0.532	0.919	0.516	0.718
5	2	2	3	0.479	0.249	0.490	0.400	0.445
6	2	3	1	0.312	0.612	0.421	0.563	0.492
7	3	1	3	1.000	0.000	1.000	0.333	0.667
8	3	2	1	0.851	0.366	0.770	0.441	0.605
9	3	3	2	0.358	0.105	0.438	0.359	0.398

The GRG response table (averages at each level of each factor) is shown in Table 10 and plotted graphically in Figure 7. The GRG is the highest at speed level 1, feed level 1 and depth level 1, which is the same as the individually optimum setting for tool wear (Table VI) and as Run 1 for the original array.

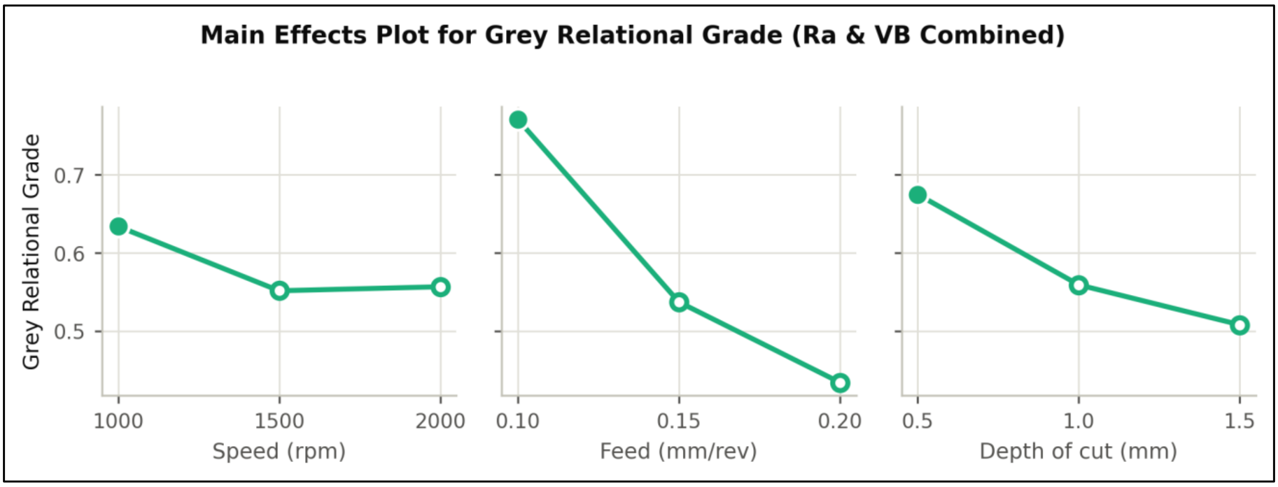

Figure 7: Main effects plot for the grey relational grade (Ra and VB combined). Filled marker denotes the compromise-optimal level.

Table 10: Grey Relational Grade Response Table

Level	**Speed (A)**	**Feed (B)**	**Depth (C)**
1	0.634	0.771	0.675
2	0.552	0.537	0.559
3	0.557	0.434	0.508
Delta	0.082	0.336	0.167
Rank	3	1	2
Optimal	A1	B1	C1

The ANOVA of the GRG is presented in Table 11, it is seen that feed rate is the most influential variable on the GRG with a significant F value of 40632 and variance contribution of 75.76% followed closely by depth of cut with variance contribution of 18.62% and significant F value of 99.88% at 1% level and spindle speed with a variance contribution of 5.43% and significant F value of 29.10% at 5% level and the residual error of 0.19%.

Table 11: ANOVA for Grey Relational Grade

Factor	**SS**	**DOF**	**MS**	**F**	**%Contrib.**
Speed (A)	0.0128	2	0.0064	29.10	5.43
Feed (B)	0.1781	2	0.0891	406.32	75.76
Depth (C)	0.0438	2	0.0219	99.88	18.62
Error	0.0004	2	0.0002	—	0.19
Total	0.2351	8	—	—	100.00

Fig. 8 ranks the nine trials by GRG: Run 1 (1000 rpm, 0.10 mm/rev, 0.5 mm) achieved the highest GRG (0.927), followed by Run 4 (0.718) and Run 7 (0.667).

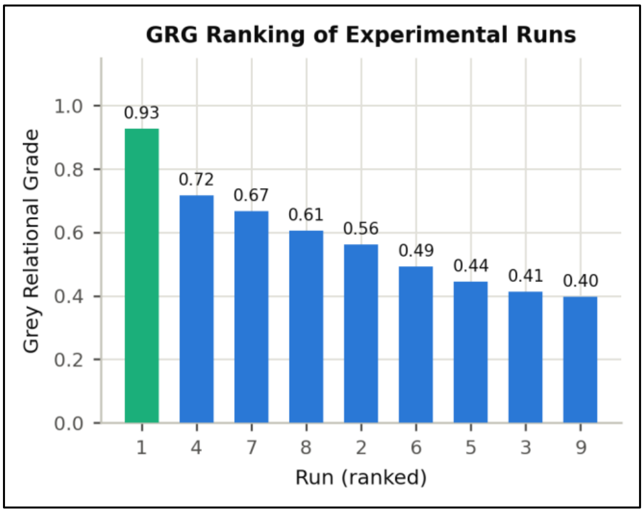

Figure 8: Grey relational grade ranking of the nine experimental runs; Run 1 attains the highest GRG.

- This implies that spindle speed is the only factor that causes conflict between the two individual optima, but the grey-relational compromise is mainly controlled by the feed rate as its individual effect on Ra, the more sensitive of the two normalized responses, is by far the greatest.

4.6 Confirmation Analysis

The Taguchi predictive surface roughness (A3B1C1) is -2.805 dB and the S/N ratio of the nearest trial actually run at the setting (Run 7) is -2.576 dB, which is within the 95% confidence interval of the predicted S/N ratio [-2.330, -2.880] dB, with the predicted Ra at the setting being 1.38 µm and the measured mean Ra at the same setting being 1.553 µm. A1B1C1 is the same as Run 1, which is the optimum setting of the three parameters for tool wear, and the predicted S/N ratio is 15.246 dB, with a predicted VB of 0.173 mm, and a 95% confidence interval of [0.162, 0.185] mm. Since A1B1C1 is the optimum setting of the three parameters for tool wear, the predicted value, which is 15.246 dB, can be compared directly with the measured value, which is 0.171 mm, and falls within the predicted interval, providing good confirmation of the additive Taguchi model for this response. In the case of the compromise setting (A1B1C1), the predicted GRG is 0.918, also within the 95% confidence interval [0.851, 0.985]; the measured GRG at Run 1 (0.927) is also within this interval, thus validating the compromise recommendation. The optimum values for the variables predicted and confirmed are summarized in Table 12.

Table 12: Summary of Predicted Optima and Confirmation

Response	Optimal Setting	Predicted Value	95% CI	Confirmation Trial (Measured)
Ra (min.)	A3B1C1 — 2000 rpm, 0.10 mm/rev, 0.5 mm	1.38 µm (-2.805 dB)	[1.20, 1.59] µm	Run 7: 1.553 µm
VB (min.)	A1B1C1 — 1000 rpm, 0.10 mm/rev, 0.5 mm	0.173 mm (15.246 dB)	[0.162, 0.185] mm	Run 1: 0.171 mm
GRG (compromise)	A1B1C1 — 1000 rpm, 0.10 mm/rev, 0.5 mm	0.918	[0.851, 0.985]	Run 1: 0.927

5 DISCUSSION

The results indicate that, in this CNC milling process, surface roughness and flank tool wear are dominated by different parameters (feed rate and spindle speed, respectively) although the percentage contribution of the variables differs with the workpiece material, tool and machine employed in each of the studies reviewed in section 1 [4]–[9].

The dominance of feed rate over surface roughness observed here (82.81% contribution) is fairly similar to but slightly higher than the values reported in similar Taguchi L9 milling studies [5], [7] and comparable to the spindle speed over tool wear (63.40 % contribution) reported by Rakmae et al. [9] for end milling of SS400 steel, indicating that feed rate also has significant influence on surface roughness in this speed range, and that the dominant wear mechanisms are thermally-driven rather than mechanical abrasion of feed marks. The other important findings are that the conflict between the optimum spindle speeds for minimum Ra and minimum VB is a practically important one, since an operator setting the machine for minimum Ra would accept a much greater average tool wear than the one that minimizes the tool wear (Table III and Table IV), and conversely, the setting for minimum VB would result in a roughness level that is only slightly worse than the minimum observed elsewhere in the array (1.663 μm at Run 1 versus 1.553 μm at Run 7, a difference of 0.11 μm).

This asymmetry makes the low-speed setting (A1B1C1) the best overall compromise as found by the grey relational analysis, and would not have been apparent if the data had been analyzed using the S/N ratio with either of the two responses alone. This result supports the idea proposed by Wang and Li [10] and Saberi et al. [11] to use Taguchi and GRA simultaneously instead of solving all the quality characteristics as single-response problems. Although a secondary factor, depth of cut was statistically significant in each of the ANOVA tests performed (Table VII, Table VIII, Table XI) and should not be ignored in process planning as it improves both Ra and VB at the same time at the optimum depth for this study (0.5 mm).

Some generalizations of these findings need to be noted. First, the L9(3^3) orthogonal array is a saturated design for three three-level factors with only main effects of interest, thus it cannot estimate two-factor interactions; if, for instance, feed rate and depth of cut were two factors of interest, any interaction between them (such as feed rate and depth of cut) could not be separately estimated and is confounded with the error term. Secondly, the study was conducted on a single machine, workpiece material, and dry cutting method; the optimum values of the parameters and the percentage contribution values reported for this study should therefore not be used and assumed for other materials, tool coatings, or cutting-fluid conditions without re-validation.

Last, that the additive Taguchi prediction model used in the confirmation analysis in Section 5.6 is accurate in the absence of significant interactions was supported here by the good agreement between the predicted and measured responses for the first confirmation run (Run 1), although further experimental confirmation would be advisable at the actual optimum predicted condition (A3B1C1), prior to its use in production.

6 CONCLUSION

The Taguchi method of robust parameter design along with analysis of variance and grey relational analysis were employed in an attempt to optimize spindle speed, feed rate, and depth of cut of the CNC milling process for surface roughness and flank tool wear as the quality responses. The analysis was conducted using a Taguchi L9(3^3) orthogonal array with triplets of experiments, and the result showed that the feed rate is the most significant parameter affecting the surface roughness (82.81% contribution) and the spindle speed is most significant affecting tool wear (63.40% contribution) with the depth of cut as statistically significant second most significant parameters for both responses. As the spindle speed and minimum depth of cut settings differed, the minimum feed setting was decided by the minimum roughness value setting, and the minimum spindle speed setting was decided by the minimum wear value setting; however, grey relational analysis, which helped resolve the conflict, indicated that spindle speed 1000 rpm, feed 0.10 mm/rev and depth of cut 0.5 mm were the overall optimum values; the corresponding experimental trials verified the results within 95% confidence interval, with a predicted grade of grey relation analysis value of 0.918. These results not only give a set of recommended cutting parameters for the machine–tool–material system studied but also a solution to the common practical problem that there are two quality characteristics which make opposite requirements on cutting parameters. To fully validate the additive model for this response, future work should include a validation run in the physical machine at the predicted Ra-optimal condition (A3B1C1) with a larger orthogonal array (L18 or L27) that can predict factor interactions; as well as testing of additional workpiece materials and tool coatings.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Acknowledgments

The authors acknowledge the Department of Industrial and Manufacturing Engineering and the Department of Agricultural Engineering at the National University of Science and Technology (NUST) for the use of their laboratory and workshop facilities in conducting this study.

Funding Source

The authors self-funded the publication of this article.

Disclosure of conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

[1] Montgomery DC. Design and Analysis of Experiments. 8th ed. Hoboken (NJ): Wiley; 2013.

[2] Taguchi G, Chowdhury S, Wu Y. Taguchi's Quality Engineering Handbook. Hoboken (NJ): Wiley; 2004.

[3] Yang WH, Tarng YS. Design optimization of cutting parameters for turning operations based on the Taguchi method. J Mater Process Technol. 1998;84(1–3):122–129. doi:10.1016/S0924-0136(98)00079-X.

[4] Ribeiro J, Lopes H, Queijo L, Figueiredo D. Optimization of cutting parameters to minimize the surface roughness in the end milling process using the Taguchi method. Period Polytech Mech Eng. 2017;61(1):30–35. doi:10.3311/PPme.9114.

[5] Pragajibhai DH, Nalwaya S, Singh P, Jain R. Optimization of machining parameters on surface roughness by Taguchi approach. Int J Res Sci Innov. 2018;5(4):349–361.

[6] Fedai Y, Kahraman F, Kirli Akin H, Basar G. Optimization of machining parameters in face milling using multi-objective Taguchi technique. Tehnički Glasnik. 2018;12(2):104–108. doi:10.31803/tg-20180201125123.

[7] Moayyedian M, Mohajer A, Kazemian MG, Mamedov A, Derakhshandeh JF. Surface roughness analysis in milling machining using design of experiment. SN Appl Sci. 2020;2(10):1698. doi:10.1007/s42452-020-03485-5.

[8] Belamri A, Makhloufi Y, Methia M, Yousfi R, Sad Eddine A, Benslimane A. ANOVA-based analysis of cutting parameters on surface roughness in aluminum milling. Int J Adv Manuf Technol. 2025;139(3):1945–1957. doi:10.1007/s00170-025-15997-8.

[9] Rakmae S, Sawangsri W, Somthong T, Moonrungsri A. Tool wear mechanisms and Taguchi-based optimization of flank wear and surface roughness in multi-fluted end milling of SS400 steel. Int J Adv Manuf Technol. 2026;144(3):2025–2045. doi:10.1007/s00170-026-18071-z.

[10] Wang Z, Li L. Optimization of process parameters for surface roughness and tool wear in milling TC17 alloy using Taguchi with grey relational analysis. Adv Mech Eng. 2021;13(2). doi:10.1177/1687814021996530.

[11] Saberi M, Niknam SA, Hajaliakbari A, Davoodi B, Hashemi R. Multi response optimization in MQL milling of GTD450 stainless steel using an integrated Taguchi grey relational analysis. Sci Rep. 2025;15:43771. doi:10.1038/s41598-025-27570-0.

[12] Ross PJ. Taguchi Techniques for Quality Engineering: Loss Function, Orthogonal Experiments, Parameter and Tolerance Design. 2nd ed. New York (NY): McGraw-Hill; 1996.

[13] Deng JL. Introduction to grey system theory. J Grey Syst. 1989;1(1):1–24.

[14] Sylajakumari PA, Ramakrishnasamy R, Palaniappan G. Taguchi grey relational analysis for multi-response optimization of wear in co-continuous composite. Materials. 2018;11(9):1743. doi:10.3390/ma11091743.

[15] International Organization for Standardization. Geometrical product specifications (GPS) — surface texture: profile method — terms, definitions and surface texture parameters. ISO 4287:1997. Geneva: ISO; 1997.

[16] Mitutoyo Corporation. Surface roughness measurement — reference guide [Internet]. Kawasaki: Mitutoyo Corp. [cited 2026 Aug 20]. Available from: https://www.mitutoyo.com/webfoo/wp-content/uploads/Surface_Roughness_Measurement.pdf

[17] International Organization for Standardization. Tool-life testing with single-point turning tools. ISO 3685:1993. Geneva: ISO; 1993.