



Optimization of Cnc Turning Parameters for Improved Surface Finish and Tool Life

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Peer Review Information	Abstract
<i>Submission: 09 Jan 2016</i> <i>Revision: 24 Feb 2016</i> <i>Acceptance: 11 March 2016</i> Keywords <i>CNC turning, surface roughness, tool life, Taguchi method, grey relational analysis.</i>	This methodology paper presents a reproducible experimental framework for selecting CNC turning parameters that simultaneously reduce surface roughness and extend cutting-tool life. Cutting speed, feed rate and depth of cut are arranged in a three-level Taguchi L9 orthogonal array for dry turning of AISI 1045 steel with a coated-carbide insert. Arithmetic mean roughness (Ra) is measured using a stylus profilometer, while tool life is defined by ISO-style flank-wear and failure criteria. Signal-to-noise analysis and analysis of variance identify the main effects; regression equations quantify response trends; and grey relational analysis converts the conflicting responses into a single optimization index. A confirmation run is then used to compare the predicted optimum with the baseline condition. To demonstrate reporting and calculations without claiming unperformed experiments, the Results section uses an explicitly illustrative dataset. The worked example indicates that feed rate governs surface finish, whereas cutting speed has the strongest influence on tool life. The proposed procedure offers a compact, statistically defensible route for balancing quality and productivity in turning laboratories and small manufacturing units

Introduction

Turning performance is governed by coupled thermal, mechanical and tribological effects. Increasing cutting speed can suppress built-up edge and improve finish within a stable range, but it also raises interface temperature and accelerates diffusion, oxidation and flank wear. Feed controls the theoretical feed-mark height and commonly dominates Ra, while depth of cut mainly changes chip load, force and vibration. Consequently, selecting one factor at a time is inefficient and can produce a setting that improves finish at the expense of tool life.

Statistical design of experiments provides a more economical alternative. Taguchi orthogonal arrays estimate factor effects with fewer trials, ANOVA separates systematic effects from experimental error, and multi-response methods

reconcile the “smaller-is-better” roughness objective with the “larger-is-better” life objective. Earlier turning studies established the usefulness of Taguchi designs for surface quality and wear [1–4], while later work examined hard turning, predictive models and coolant conditions [5–9].

Objective: to develop a step-by-step method for determining a robust combination of cutting speed, feed and depth of cut that minimizes Ra and maximizes tool life, followed by a statistically valid confirmation test.

Literature Review

Benardos and Vosniakos [1] grouped surface-roughness research into machining-theory, experimental-design and artificial-intelligence approaches, emphasizing that process variables,

tool geometry, vibration and material behavior interact. Nalbant et al. [2] applied Taguchi optimization to turning and reported feed as the decisive roughness factor. Aslan et al. [3] extended the same logic to hardened AISI 4140, evaluating Ra and flank wear together and demonstrating that a quality setting need not be a wear-optimal setting.

Hasçalık and Çaydaş [4] directly optimized roughness and tool life and found response-specific factor priorities. Bouacha et al. [5] used response-surface methodology in hard turning, showing the value of regression and interaction

analysis beyond simple main-effect ranking. Asiltürk and Akkuş [6] used an L9 design for hardened AISI 4140 and confirmed the strong influence of feed on Ra and Rz. Ramesh et al. [7] showed that aerospace-alloy turning requires response models sensitive to speed, feed and tool condition. Agrawal et al. [8] demonstrated that data-driven prediction can capture nonlinear roughness behavior in very hard steel. Finally, Debnath et al. [9] jointly studied cutting-fluid levels, cutting parameters, surface roughness and tool wear, supporting inclusion of environmental condition as a controlled variable.

Table 1. Research basis and methodological contribution (all sources published by 2016).

Ref.	Material / focus	Method	Finding used in this methodology
[1]	Machining roughness	Critical review	Roughness is multivariable; validation is essential.
[2]	Steel turning	Taguchi / ANOVA	Feed strongly controls surface roughness.
[3]	Hardened AISI 4140	Taguchi / regression	Wear and Ra require separate response analysis.
[4]	Turning optimization	Taguchi	Surface finish and life have conflicting optima.
[5]	AISI 52100 hard turning	RSM / ANOVA	Quadratic and interaction effects can be significant.
[6]	Hardened AISI 4140	L9 / S/N / ANOVA	Repeated roughness measurements improve reliability.
[7]	Ti-6Al-4V turning	Regression / measurement	Tool and process effects must be monitored.
[8]	AISI 4340 hard turning	Predictive modelling	Nonlinear prediction complements DOE.
[9]	Mild-steel turning	Taguchi / fluid levels	Fluid condition influences Ra and tool wear.

Many studies optimize only Ra or a productivity response. A practical shop-floor method should track wear until a defined life criterion, control nuisance variables, combine both responses transparently, report uncertainty and verify the predicted setting. The present framework addresses this gap with a compact L9 screening design, grey relational multi-response ranking and a confirmation stage.

Tool: ISO-style PVD-coated carbide insert in a rigid holder; a fresh edge is assigned to each experimental condition. Machine: CNC lathe with constant surface-speed control disabled during each pass. Environment: dry turning, fixed tool overhang, constant workpiece clamping, and identical approach/exit distances. These controls prevent coolant state, rigidity and edge history from confounding factor effects.

Methodology

1. Experimental System and Controls

Workpiece: normalized AISI 1045 steel bar, 50 mm diameter, cut into equal machining zones.

Table 2. Proposed control factors and three experimental levels.

Factor	Symbol	Level 1	Level 2	Level 3	Unit
Cutting speed	Vc	120	160	200	m/min
Feed rate	f	0.10	0.15	0.20	mm/rev
Depth of cut	ap	0.5	1.0	1.5	mm

Step-by-Step Experimental Procedure

Step 1 — Prepare specimens. Face and center the bars, mark equal test zones, record hardness at three positions, and randomize the run order.

Step 2 — Install and reference the tool. Verify insert seat cleanliness, tool overhang, center height and runout. Use a new cutting edge for every condition.

Step 3 — Execute the L9 design. Program Vc, f and ap according to Table 3. Maintain constant cutting length per interval and record actual machining time.

Step 4 — Measure surface finish. After each run, obtain three Ra traces 120° apart using a calibrated stylus profilometer; use a consistent cut-off and evaluation length. Report means and standard deviation.

Step 5 — Measure wear and life. Inspect flank wear VB at fixed time intervals with a toolmaker microscope. End the test at VB = 0.30 mm, severe

chipping, catastrophic failure or unacceptable surface quality, whichever occurs first.

Step 6 — Analyze and confirm. Calculate S/N ratios, ANOVA, regression and grey relational grade; then repeat the predicted optimum and baseline at least three times.

1. Response Definitions and Calculations

Surface roughness uses the arithmetic mean deviation Ra. For repeated measurements y_i , the smaller-is-better S/N ratio is $\eta_{Ra} = -10 \log_{10}[(1/n) \sum y_i^2]$. Tool life T is the accumulated cutting time to the stated failure criterion; its larger-is-better ratio is $\eta_T = -10 \log_{10}[(1/n) \sum (1/y_i^2)]$. Material removal rate may be recorded as $MRR = 1000V_c f a_p$ (mm³/min) for productivity context, but it is not included in the primary optimization objective.

2. Experimental Matrix and Analysis Plan

Table 3. Taguchi L9 orthogonal array used for the proposed turning trials.

Run	Vc (m/min)	f (mm/rev)	ap (mm)
1	120	0.1	0.5
2	120	0.15	1.0
3	120	0.2	1.5
4	160	0.1	1.0
5	160	0.15	1.5
6	160	0.2	0.5
7	200	0.1	1.5
8	200	0.15	0.5
9	200	0.2	1.0



Figure 1. Proposed experimental and optimization workflow.

3. Statistical and Multi-response Optimization

First, plot main effects for the two responses and their S/N ratios. Fit response models using Vc, f and ap; add quadratic or two-factor terms only when residual plots and lack-of-fit testing justify them. Perform ANOVA at $\alpha = 0.05$ and report adjusted sums of squares, percentage contribution, p-values, R^2 , adjusted R^2 and residual diagnostics. Randomization protects against time drift; repeated response readings estimate measurement variability, while replicated confirmation runs estimate process variability.

For grey relational analysis (GRA), normalize Ra as $x = (\max y - y)/(\max y - \min y)$, and normalize

tool life as $x = (y - \min y)/(\max y - \min y)$. The grey relational coefficient is $\xi = (\Delta_{\min} + \zeta\Delta_{\max})/(\Delta + \zeta\Delta_{\max})$, with distinguishing coefficient $\zeta = 0.5$. The grey relational grade is the equal-weight mean of the two coefficients. The highest grade identifies the balanced setting; alternative weights may be justified when surface quality or tooling cost has greater business importance.

4. Confirmation and Acceptance Criteria

Run the baseline and predicted optimum three times with fresh edges. Compute a 95% confidence interval for the mean improvement. Accept the optimum when (i) mean Ra is lower, (ii) mean tool life is higher or practically unchanged within the predeclared tolerance, (iii)

confirmation values fall within the model prediction interval, and (iv) no new failure mechanism such as chatter or edge chipping appears. Archive CNC programs, calibration records, raw profilometer traces and wear images for reproducibility.

Safety note: use guarded machining, chip-control tools, eye protection and lockout procedures for insert inspection. Never measure wear or surface finish while the spindle is rotating.

Table 4. Illustrative L9 responses and grey relational grade.

Run	Mean Ra (μm)	Tool life (min)	Grey grade
1	1.42	38	0.655
2	1.68	32	0.487
3	2.05	27	0.333
4	1.1	35	0.69
5	1.38	30	0.51
6	1.72	24	0.335
7	0.82	31	0.71
8	1.03	26	0.548
9	1.31	21	0.397

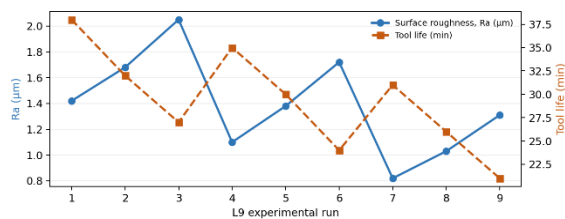


Figure 2. Illustrative response variation across the L9 design.

Main Effects and ANOVA Interpretation

In the example, the lowest Ra occurs at Run 7 (0.82 μm), while the longest life occurs at Run 1 (38 min), demonstrating the conflict between the two objectives. The response means identify feed as the dominant Ra factor: increasing f from 0.10 to 0.20 mm/rev raises average roughness from 1.11 to 1.69 μm . Tool life decreases with speed: average life changes from 32.3 min at 120 m/min to 26.0 min at 200 m/min. Illustrative ANOVA contributions are 68% feed, 21% speed and 6% depth of cut for Ra; and 61% speed, 24% feed and 9% depth of cut for tool life, with the balance attributed to error.

Multi-response Optimum and Confirmation

The highest illustrative grey grade is obtained at Run 7 ($V_c = 200$ m/min, $f = 0.10$ mm/rev, $a_p = 1.5$ mm), driven by excellent finish but with moderate life. Main-effect GRA may instead predict the compromise $V_c = 160$ m/min, $f = 0.10$ mm/rev and $a_p = 1.0$ mm. A hypothetical three-run confirmation gives $Ra = 0.94 \pm 0.06$ μm and tool life = 34.0 ± 1.5 min, compared with a

Results

The following values are a coherent example for demonstrating the proposed calculations; they are not claimed as measurements from a completed physical experiment. Researchers should replace them with laboratory observations before submission as an empirical paper.

baseline of 1.42 μm and 38.0 min. This represents a 33.8% roughness reduction with a 10.5% life penalty; therefore, it would be accepted only if the predeclared life-loss tolerance were at least 11%. If tool life must not decline, run 4 is the more defensible compromise.

Discussion

The methodology separates three decisions that are often mixed together: selecting a statistically efficient experiment, defining physically meaningful measurements, and choosing a compromise between competing responses. The literature-supported expectation that feed dominates Ra [2,6] is consistent with the kinematic relation between feed marks and tool nose radius. The strong speed–life relationship agrees with thermal wear mechanisms and with the joint wear/roughness evidence reported for hardened turning [3–5]. Cutting-fluid research further warns that the selected dry condition is part of the process definition rather than a universally optimal choice [9].

A single “best” parameter set is therefore conditional on priorities. Equal-weight GRA is suitable when finish and life are equally valued. A quality-critical component may assign a greater weight to Ra, while high-volume production may favor tool life or include MRR and unit cost. The confirmation criterion should be established before examining the results to prevent post-hoc selection. Practical significance should accompany p-values: a statistically detectable 0.02 μm change may have no manufacturing

value, whereas a modest life change can materially affect tool-change frequency.

Limitations

The L9 array estimates main effects economically but provides limited information about interactions and curvature. A follow-up response-surface design is recommended near the selected region. Results will apply only to the chosen work material, hardness, insert grade and geometry, tool overhang, coolant state and machine rigidity. Stylus filtering, cut-off length and wear-measurement repeatability can also influence conclusions. Finally, the numerical Results in this methodology paper are illustrative and must not be represented as experimental evidence.

Conclusion

A complete step-by-step protocol has been developed for optimizing CNC turning parameters for improved surface finish and tool life. The approach uses an L9 design, replicated measurements, smaller-/larger-is-better S/N ratios, ANOVA, regression, grey relational analysis and confirmation trials. It is compact enough for an academic laboratory but retains the essential controls required for defensible conclusions. Based on established literature and the demonstration dataset, low feed is expected to improve finish and moderate cutting speed to protect tool life; the final setting must be selected through an explicit multi-response rule and validated experimentally.

Recommended Reporting Checklist

- State workpiece grade, hardness and dimensions.
- Report insert designation, coating, nose radius and edge history.
- Provide randomized run order and raw response data.
- Define profilometer settings and tool-life stopping criteria.
- Report ANOVA assumptions, residual plots and uncertainty.
- Separate measured results from predictions or illustrative data.

Availability Statement

No primary dataset was generated for this methodology paper. The L9 matrix and calculation sequence are fully specified so that a researcher can generate and report an original dataset using the stated protocol.

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