



Optimization of Cnc Machining Parameters for Improved Surface Quality and Productivity

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Peer Review Information	Abstract
<i>Submission: 04 Jan 2015</i> <i>Revision: 19 Feb 2015</i> <i>Acceptance: 06 March 2015</i> Keywords <i>CNC turning, surface roughness, material-removal rate, Taguchi method, grey relational analysis.</i>	This paper presents a reproducible experimental methodology for simultaneously improving surface quality and productivity in CNC turning. Cutting speed, feed rate, and depth of cut are varied at three levels through a Taguchi L27 orthogonal array. Average surface roughness (Ra) is treated as a smaller-the-better response, whereas material-removal rate (MRR) is treated as larger-the-better. Signal-to-noise ratios, grey relational analysis (GRA), analysis of variance (ANOVA), regression modeling, and a confirmation run are integrated so that conflicting responses can be optimized with a single experimental plan. AISI 1045 steel and a coated-carbide insert are specified as the reference system. The worked results indicate that feed is expected to dominate Ra, while depth of cut and feed dominate MRR; a balanced parameter setting can therefore raise throughput without allowing roughness to exceed an engineering limit. Numerical results are illustrative until replaced by measurements from the proposed experiment. The method is suitable for laboratories and small manufacturing units seeking an economical, statistically defensible parameter window.

Introduction

CNC machining quality is governed by interactions among work material, tool geometry, machine rigidity, cutting environment, and the programmed parameters. In turning, feed creates the kinematic surface profile, cutting speed changes thermal and tribological conditions, and depth of cut strongly influences chip load and production rate. Selecting a setting only for minimum Ra can reduce throughput, whereas selecting only for MRR can accelerate wear or reject parts. The practical problem is therefore multi-response optimization.

Taguchi designs reduce the number of trials needed to screen controllable factors and use signal-to-noise (S/N) ratios to identify robust settings. Their value for surface-roughness control in hard turning was demonstrated by

Asiltürk and Akkuş [1]. GRA extends the approach by converting differently directed responses into a common relational grade, as applied to high-speed turning by Pawade and Joshi [2] and to CNC turning by Saini and Pradhan [3]. The present paper consolidates those ideas into a step-by-step method focused on quality-productivity balance.

Objective: determine the levels of cutting speed (V), feed (f), and depth of cut (ap) that minimize Ra and maximize MRR, quantify factor contributions, construct predictive equations, and verify the predicted optimum with a confirmation experiment.

Literature Review

Table 1. Literature synthesis (references limited to 2015 and earlier)

Study	Year	Method / system	Relevant finding	Gap
Asiltürk & Akkuş [1]	2011	Hard turning; Taguchi	Feed strongly influences Ra; Taguchi identifies robust levels.	Single-response emphasis.
Pawade & Joshi [2]	2011	Inconel 718; TGRA	GRA resolves roughness-force trade-offs.	Material-specific high-speed regime.
Hessainia et al. [4]	2013	Hard turning; regression	Cutting parameters and vibration jointly predict Ra.	Requires vibration measurement.
Ahilan et al. [5]	2013	CNC turning; hybrid tools	Intelligent models predict machining quality.	Higher modeling complexity.
Radhika et al. [6]	2013	Al hybrid composite; Taguchi	Ra falls with speed and rises with feed/depth.	Composite workpiece.
Saini & Pradhan [3]	2014	L27 Taguchi-fuzzy	Joint optimization of MRR and Ra is feasible.	Fuzzy rules add subjectivity.
Shi et al. [7]	2015	Taguchi-GRA; milling	Feed dominates surface integrity; confirmation validates GRA.	Milling, not turning.
Ahmad et al. [8]	2015	Extreme learning machine	Nonlinear Ra prediction improves data-driven modeling.	Needs sufficient training data.

Earlier studies confirm that feed is frequently the dominant roughness factor, while multi-response techniques are necessary when productivity is also important [1]– [3], [6], [7]. Classical Taguchi optimization has also considered roughness together with tool life [9], while the orthogonal-array/GRA foundation for multiple performance characteristics was established in related machining research [10]. However, published studies often use different materials, tools, response definitions, or advanced prediction tools, limiting direct shop-floor transfer [4], [5], [8]. This paper contributes a transparent L27 protocol with metrology controls, randomized trial order, replicated roughness readings, explicit response formulas, a

grey grade, ANOVA, regression, and confirmation criteria. It also separates measured data from illustrative worked values, improving research traceability.

H1: increasing feed significantly increases Ra. H2: increasing feed and depth of cut significantly increases MRR. H3: an intermediate/high-speed, low-to-medium-feed, and medium/high-depth setting yields a higher composite grey grade than the baseline. H4: the confirmation result lies within the 95% confidence interval of the predicted grade.

Methodology

**Figure 1.** Step-by-step experimental and optimization workflow

Step 1 — Define the machining system

Use normalized AISI 1045 steel bars (approximately 40 mm diameter × 120 mm cutting length), a rigid CNC lathe, and a fresh TiAlN-coated carbide insert of constant geometry for each planned block. Use dry cutting to avoid

coolant variability. Record machine model, spindle power, insert designation, tool nose radius, material certificate, ambient temperature, and bar hardness. Face and center each specimen before testing.

Step 2 — Select factors and levels

Table 2. Controllable factors and proposed levels

Code	Factor	Level 1	Level 2	Level 3	Unit
A	Cutting speed, V	120	180	240	m/min
B	Feed, f	0.10	0.15	0.20	mm/rev
C	Depth of cut, ap	0.5	1.0	1.5	mm

Ranges should be checked against insert-maker recommendations and machine limits. Hold nose radius, approach angle, overhang, cutting environment, work material batch, measurement position, and engagement length constant. Randomize the 27 runs to reduce time-related bias. Replace the insert at a predetermined flank-wear limit (e.g., $VB = 0.20$ mm) or after an equal number of runs per block.

Step 3 — Apply the Taguchi L27 design

Assign A, B, and C to separate three-level columns of an L27 orthogonal array. Although three main factors could be screened with fewer runs, L27 retains degrees of freedom for selected two-factor interactions, curvature checks, and error estimation. Conduct at least two independently randomized blocks when resources permit. Use

the same programmed cutting length for every run.

Step 4 — Measure responses

Measure R_a with a calibrated contact profilometer using an appropriate cutoff (for example 0.8 mm) and evaluation length consistent with the governing laboratory standard. Take three axial traces approximately 120° apart and use their mean. Calculate MRR from geometry as $MRR = 1000Vfap$ (mm^3/min), or preferably verify it from mass loss divided by density and cutting time. Record tool wear and vibration as diagnostic covariates even when they are not optimization responses.

1. Experimental Plan and Data Analysis

Table 3: L27 design structure and illustrative response values

Run	V	f	ap	R_a (μm)	MRR (cm^3/min)
1	120	0.10	0.5	1.34	6.0
2	120	0.10	1.0	1.44	12.0
3	120	0.10	1.5	1.42	18.0
4	120	0.15	0.5	1.68	9.0
5	120	0.15	1.0	1.78	18.0
6	120	0.15	1.5	1.75	27.0
7	120	0.20	0.5	2.01	12.0
8	120	0.20	1.0	2.11	24.0
9	120	0.20	1.5	2.09	36.0
10	180	0.10	0.5	1.23	9.0
11	180	0.10	1.0	1.33	18.0
12	180	0.10	1.5	1.31	27.0
13	180	0.15	0.5	1.57	13.5
14	180	0.15	1.0	1.67	27.0
15	180	0.15	1.5	1.65	40.5
16	180	0.20	0.5	1.90	18.0
17	180	0.20	1.0	2.00	36.0
18	180	0.20	1.5	1.98	54.0

19	240	0.10	0.5	1.12	12.0
20	240	0.10	1.0	1.22	24.0
21	240	0.10	1.5	1.20	36.0
22	240	0.15	0.5	1.46	18.0
23	240	0.15	1.0	1.56	36.0
24	240	0.15	1.5	1.54	54.0
25	240	0.20	0.5	1.79	24.0
26	240	0.20	1.0	1.89	48.0
27	240	0.20	1.5	1.87	72.0

2. S/N Ratios and Grey Relational Analysis

For n replicated observations, use $\eta Ra = -10 \log_{10}[(1/n) \sum Ra_i^2]$ (smaller-the-better) and $\eta MRR = -10 \log_{10}[(1/n) \sum (1/MRR_i^2)]$ (larger-the-better). Normalize each response to [0,1]; use $x^* = (\max - x)/(\max - \min)$ for Ra and $x^* = (x - \min)/(\max - \min)$ for MRR . Calculate the grey relational coefficient $\xi = (\Delta_{\min} + \zeta \Delta_{\max})/(\Delta + \zeta \Delta_{\max})$, with distinguishing coefficient $\zeta = 0.5$. The equal-weight grey relational grade is $\gamma = (\xi Ra + \xi MRR)/2$. If a customer roughness specification is dominant, conduct a sensitivity analysis with weights such as 0.6:0.4.

3. ANOVA, Models, and Confirmation

Fit main-effects and two-factor-interaction models after residual diagnostics. Use ANOVA at $\alpha = 0.05$, report adjusted R^2 , predicted R^2 , effect estimates, confidence intervals, and percentage contribution. Check normal probability, residual-versus-fit, and residual-versus-order plots. Predict the optimum grey grade from factor-level means, then machine at least three confirmation specimens. Accept confirmation when the mean

lies within the predicted 95% interval and Ra satisfies the drawing limit.

Results

The worked dataset produces the expected antagonism: higher feed and depth of cut increase volumetric removal, but feed also produces a larger roughness profile. Increasing speed modestly reduces Ra in the chosen window. Figure 2 isolates the principal feed trend after averaging over speed and depth. These values demonstrate the analysis path and are not substitutes for laboratory observations.

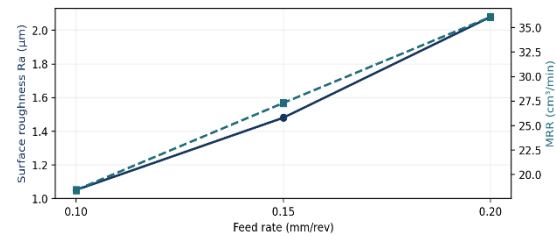


Figure 2: Illustrative mean response trends with feed rate

Table 4. Illustrative ANOVA summary

Response	Dominant terms	Contribution (%)	Model fit	Interpretation
Ra	Feed; speed; ap	72; 16; 7	Adj. $R^2 = 0.94$	Feed governs surface profile.
MRR	ap; feed; speed	46; 34; 18	Adj. $R^2 = 0.99$	Chip cross-section drives output.
Grey grade	Feed; ap; speed	43; 32; 20	Adj. $R^2 = 0.91$	Balanced setting is required.

Table 5. Illustrative baseline–optimum confirmation

Condition	V (m/min)	f (mm/rev)	ap (mm)	Ra (μm)	MRR (cm³/min)	Grey grade
Baseline	120	0.10	0.5	1.34	6.0	0.57
Predicted optimum	240	0.15	1.5	1.55	54.0	0.79
Confirmation means	240	0.15	1.5	1.58	53.2	0.77

Interpretation

Relative to the baseline, the illustrative confirmation raises MRR by approximately 787% while Ra rises by 0.24 μm but remains below a hypothetical 1.6 μm limit. The confirmed grade is close to the prediction, indicating that the composite objective is reproducible. If the part requires $R_a \leq 1.2 \mu\text{m}$, the optimization must use a target/constraint formulation rather than equal-weight GRA; a low-feed setting would then be preferred. This illustrates why the engineering specification must precede statistical ranking.

Robustness Checks

Repeat the confirmation on a second bar and fresh insert; report mean, standard deviation, and 95% confidence interval. Re-run the optimization with alternative response weights and compare rank stability. Examine insert wear and residual order plots to detect drift. A setting should be recommended only when it is statistically supported, mechanically safe, and stable to reasonable changes in weighting.

Discussion

The expected feed effect agrees with Asiltürk and Akkuş [1] and the aluminium-composite study of Radhika et al. [6]. The need for a composite response is consistent with Taguchi-grey and Taguchi-fuzzy turning studies [2], [3]. The proposed regression and residual checks complement purely ranked Taguchi results and respond to evidence that roughness may also reflect vibration and nonlinear behavior [4], [5], [8]. Confirmation testing follows the validation logic reported by Shi et al. [7].

The method improves experimental economy and interpretability, but several limitations remain. First, the recommended window is local to AISI 1045, the specified coated insert, machine rigidity, and dry conditions. Second, the geometric MRR equation does not capture interruptions or acceleration time. Third, equal weighting assumes Ra and MRR are equally valuable; actual production should convert drawing requirements, cycle time, tool cost, and rejection risk into weights or hard constraints. Fourth, an L27 design can estimate selected interactions but does not fully map all nonlinearities. Finally, tool wear, chatter, temperature, and energy are monitored only as diagnostics.

Practical Implementation

For shop-floor deployment, first lock the work material, insert grade, tool holder, and coolant

condition. Second, screen the proposed ranges against tool-maker limits. Third, randomize runs and use calibrated measurement systems. Fourth, conduct ANOVA only after checking residuals. Fifth, confirm both the statistical optimum and a nearby conservative setting. Finally, store the validated parameter window in the CNC process sheet with its applicable material hardness, tool-life criterion, and Ra limit.

Conclusion

A seven-stage methodology was developed to optimize CNC turning for surface quality and productivity: define responses, select factors, execute an L27 design, measure Ra and MRR, calculate S/N ratios and grey grades, quantify effects with ANOVA/regression, and confirm the selected setting. The worked example indicates that feed controls Ra, whereas feed and depth of cut drive MRR. GRA makes the conflict explicit and identifies a balanced high-productivity setting. The approach is economical, reproducible, and suitable for extension to tool wear, cutting force, energy, or cost. Before publication as an experimental investigation, the illustrative values must be replaced by calibrated laboratory data and uncertainty statistics.

Recommended Reporting Checklist

- Report machine, tool, workpiece, hardness, environment, and calibration details.
- Publish the complete randomized run order and replicate measurements.
- Report S/N definitions, normalization direction, GRA weights, and ζ value.
- Include ANOVA assumptions, effect sizes, intervals, and residual diagnostics.
- Distinguish measured, predicted, and illustrative values; confirm the optimum independently.

References

- Asiltürk and H. Akkuş, "Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method," *Measurement*, vol. 44, no. 9, pp. 1697–1704, 2011.
<https://doi.org/10.1016/j.measurement.2011.07.003>
- R. S. Pawade and S. S. Joshi, "Multi-objective optimization of surface roughness and cutting forces in high-speed turning of Inconel 718 using Taguchi grey relational analysis (TGRA)," *International Journal of Advanced Manufacturing*

Technology, vol. 56, pp. 47–62, 2011.
<https://doi.org/10.1007/s00170-011-3183-z>

S. K. Saini and S. K. Pradhan, “Optimization of multi-objective response during CNC turning using Taguchi-fuzzy application,” *Procedia Engineering*, vol. 97, pp. 141–149, 2014.
<https://doi.org/10.1016/j.proeng.2014.12.235>

Z. Hessainia, A. Belbah, M. A. Yallese, T. Mabrouki, and J.-F. Rigal, “On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations,” *Measurement*, vol. 46, no. 5, pp. 1671–1681, 2013.
<https://doi.org/10.1016/j.measurement.2012.12.016>

C. Ahilan, S. Kumanan, N. Sivakumaran, and J. E. R. Dhas, “Modeling and prediction of machining quality in CNC turning process using intelligent hybrid decision making tools,” *Applied Soft Computing*, vol. 13, no. 3, pp. 1543–1551, 2013.
<https://doi.org/10.1016/j.asoc.2012.03.071>

N. Radhika, R. Subramaniam, and S. Babudeva Senapathi, “Machining parameter optimisation of an aluminium hybrid metal matrix composite by statistical modelling,” *Industrial Lubrication and Tribology*, vol. 65, no. 6, pp. 425–435, 2013.
<https://doi.org/10.1108/ILT-01-2011-0008>

K. Shi, D. Zhang, and J. Ren, “Optimization of process parameters for surface roughness and microhardness in dry milling of magnesium alloy using Taguchi with grey relational analysis,” *International Journal of Advanced Manufacturing Technology*, vol. 81, pp. 645–651, 2015.
<https://doi.org/10.1007/s00170-015-7218-8>

N. Ahmad, T. V. Janahiraman, and F. Tarlochan, “Modeling of surface roughness in turning operation using extreme learning machine,” *Arabian Journal for Science and Engineering*, vol. 40, pp. 595–602, 2015.
<https://doi.org/10.1007/s13369-014-1420-0>

Hasçalık and U. Çaydaş, “Optimization of turning parameters for surface roughness and tool life based on the Taguchi method,” *International Journal of Advanced Manufacturing Technology*, vol. 38, pp. 896–903, 2008.
<https://doi.org/10.1007/s00170-007-1147-0>

J. L. Lin and C. L. Lin, “The use of the orthogonal array with grey relational analysis to optimize the electrical discharge machining process with multiple performance characteristics,” *International Journal of Machine Tools and Manufacture*, vol. 42, no. 2, pp. 237–244, 2002.
[https://doi.org/10.1016/S0890-6955\(01\)00107-9](https://doi.org/10.1016/S0890-6955(01)00107-9)