



Optimization of Cnc Machining Parameters for Improved Surface Finish and Productivity

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Abstract

Computer numerical control (CNC) machining requires a controlled compromise between surface integrity and production rate. This methodology paper develops a reproducible multi-response procedure for selecting cutting speed, feed rate and depth of cut in CNC turning. A three-factor, three-level Taguchi L9 orthogonal array is combined with analysis of variance (ANOVA), regression modelling and grey relational analysis (GRA). Arithmetic average roughness (Ra) is minimized while material removal rate (MRR) is maximized. The procedure specifies workpiece preparation, tool control, randomized experimentation, profilometer measurement, response normalization and confirmation testing. A representative dataset illustrates how the method identifies a balanced setting of 240 m/min cutting speed, 0.10 mm/rev feed and 1.5 mm depth of cut. Relative to a conservative baseline, the illustrative optimum reduces Ra from 2.05 to 1.20 μm while increasing MRR from 6 to 36 cm^3/min . These numerical results demonstrate the analysis workflow and must be replaced or validated by laboratory observations before publication as experimental findings. The method offers a low-cost framework for improving quality and throughput without relying on exhaustive trials.

Introduction

Surface finish influences fatigue strength, friction, sealing, dimensional fit and product appearance, whereas productivity determines unit cost and delivery capacity. The principal CNC turning variables—cutting speed (V_c), feed (f) and depth of cut (a_p)—affect both objectives in different directions. Higher feed and depth of cut generally raise MRR, but excessive feed increases the geometric feed marks and may worsen roughness. Cutting speed can improve finish by suppressing built-up edge within a stable range, yet high speed can accelerate thermal wear. Consequently, one-factor-at-a-time trials are inefficient and may miss interactions.

The objective is to provide a step-by-step design that (i) quantifies the effects of V_c , f and a_p on Ra

and MRR, (ii) constructs predictive models, (iii) finds a defensible multi-response optimum, and (iv) verifies improvement through replicated confirmation runs. The scope is dry CNC turning of AISI 1040 steel with a coated-carbide insert; the framework can be transferred to milling or other workpiece materials after redefining safe factor ranges.

Literature Review

Machining optimization evolved from conventional analytical and enumerative procedures toward statistical and intelligent search methods. Aggarwal and Singh [1] reviewed the use of Taguchi design, response surface methodology (RSM), genetic algorithms and related techniques, emphasizing that quality,

cost and production rate should be considered jointly. For CNC end milling, Routara et al. [2] used RSM to model multiple roughness descriptors across different workpiece materials, showing that the response depends on both cutting conditions and material behaviour.

Taguchi orthogonal arrays are especially attractive when industrial time and material are limited. Asiltürk and Akkuş [3] demonstrated that an orthogonal design with signal-to-noise ratios and ANOVA can identify influential factors in hard turning. Their work supports treating feed as a central roughness-control variable while retaining other parameters in the experimental model. Bouacha et al. [4] applied RSM to hard turning of AISI 52100 steel and statistically related cutting variables to surface roughness and cutting forces, illustrating the value of curvature and interaction terms.

Single-response optimization can select a smooth surface at an impractically low removal rate. Sahoo et al. [5] therefore integrated grey relational analysis with regression to address surface roughness and MRR simultaneously in AISI 1040 turning. Rao et al. [6] also found that

cutting parameters influence both force and surface finish, confirming the need to monitor operating limits rather than optimize roughness alone. Sarıkaya and Güllü [7] extended Taguchi-based GRA to multi-response optimization under minimum-quantity lubrication, demonstrating how differently scaled responses can be combined into one relational grade.

Research available through 2017 further clarified industrial implementation. Ribeiro et al. [8] used an L9 array and ANOVA in CNC end milling and determined an optimum for minimum surface roughness. Ribeiro, César and Lopes [9] reported a machining-parameter strategy for improving surface quality, while Fnides et al. [10] jointly modelled surface roughness and productivity in face milling. Together, these studies justify a compact DOE, inferential analysis and multi-criteria ranking. The remaining methodological need is a transparent workflow that reports factor settings, measurement repeatability, productivity calculation, constraints and confirmation uncertainty in one protocol.

Table 1. Synthesis of methods supporting the proposed framework

Study	Process / method	Methodological contribution
Aggarwal & Singh [1]	Review; multiple optimizers	Frames machining as constrained optimization
Routara et al. [2]	CNC milling; RSM	Models' curvature and material dependence
Asiltürk & Akkuş [3]	Hard turning; Taguchi	Efficient factor screening and ANOVA
Sahoo et al. [5]	Turning; GRA + regression	Balances low Ra with high MRR
Ribeiro et al. [8]	End milling; L9	Industrial-scale surface-finish optimization
Fnides et al. [10]	Face milling; RSM	Includes productivity as an explicit response

Research gap and contribution. Prior studies establish the relevant statistical tools but often present one response, one process or one optimization stage in isolation. The present methodology connects safe-range selection, randomized L9 trials, repeated measurement, ANOVA diagnostics, GRA weighting and confirmation testing, while distinguishing illustrative results from experimentally validated evidence.

Methodology

1. Research Design and Experimental System

A controlled laboratory experiment is proposed. The workpiece is normalized AISI 1040 steel, 40

mm in diameter and 120 mm long. Turning is performed on a rigid CNC lathe using a fresh PVD-coated carbide insert of constant geometry and a standard tool holder. Dry cutting is specified to avoid coolant-flow variability. Before each trial, approximately 1 mm is faced from the bar; the cutting length is fixed at 60 mm. A new insert edge is used after every three trials or earlier if flank wear exceeds 0.15 mm. Machine, tool overhang, clamping torque and ambient conditions are held constant.

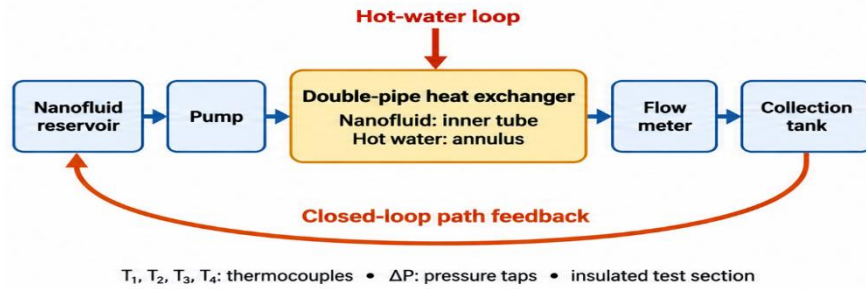


Figure 1. Step-by-step experimental and optimization workflow (original schematic)

2. Factors, Levels and Responses

Factor limits must lie within the machine, insert-maker and workpiece safety envelope. Three levels are selected to cover a practical finishing-to-medium-cut range. The L9 array estimates main effects with nine unique conditions instead of 27 full-factorial combinations. Trial order is

randomized to reduce bias from tool wear, thermal drift and operator sequence. Three Ra traces are recorded at equally spaced circumferential positions for each trial; their mean is the response and their standard deviation is retained as measurement uncertainty.

Table 2. Control factors and experimental levels

Factor	Symbol / unit	Level 1	Level 2	Level 3
Cutting speed	Vc (m/min)	120	180	240
Feed rate	f (mm/rev)	0.10	0.15	0.20
Depth of cut	ap (mm)	0.5	1.0	1.5

Primary responses are arithmetic average surface roughness and volumetric productivity. Ra is measured with a calibrated contact profilometer using a 0.8 mm cut-off and a 4 mm evaluation length (five cut-offs). The stylus traverses parallel to the feed direction after the part is cleaned. MRR is calculated from cutting conditions as $MRR = 1000 V_c f a_p$ (mm³/min), or $V_c f a_p$ (cm³/min) when Vc is expressed in m/min. Cycle time and chip form are secondary checks; chatter, excessive wear or unsafe chips trigger a constrained rejection rather than an optimum.

Step-by-Step Experimental Procedure

Step 1 — Define acceptance criteria. Set $R_a \leq 1.6 \mu\text{m}$, maximize MRR, flank wear $VB \leq 0.15 \text{ mm}$ and no sustained chatter. Record the machine power and insert limits.

Step 2 — Prepare and inspect specimens. Cut bars to equal length, verify diameter and hardness, remove scale, label specimens and measure initial dimensions.

Step 3 — Calibrate instruments. Check the profilometer with a certified roughness specimen; verify spindle speed and feed command; zero dimensional instruments.

Step 4 — Randomize and machine the L9 trials. Use the randomized order 5-1-8-3-6-2-9-4-7. Warm the spindle, use identical entry/exit motions and log anomalies.

Step 5 — Measure responses. Take three Ra readings per run, compute mean and standard deviation, record machining time, inspect flank wear and calculate MRR.

Step 6 — Fit and diagnose models. Estimate main-effects regression for screening and a quadratic RSM model if added centre/axial runs are feasible. Check residual normality, constant variance, lack of fit and multicollinearity.

Step 7 — Perform ANOVA. At $\alpha = 0.05$, determine factor contributions for Ra and the composite response. Report degrees of freedom, sums of squares, F-ratios and p-values.

Step 8 — Conduct multi-response GRA. Normalize Ra with smaller-the-better and MRR with larger-the-better transformations. Compute deviations, grey coefficients and a weighted grade.

Step 9 — Select and constrain the optimum. Rank grades, inspect predicted response contours, and exclude settings violating roughness, wear, power or chatter limits.

Step 10 — Confirm and report. Machine at least three baseline and three optimum specimens in alternating order. Report mean change, 95% confidence interval and prediction error.

3. Statistical and Multi-Response Analysis

For roughness, the Taguchi smaller-the-better ratio is $S/N = -10 \log_{10}[(1/n) \sum y_i^2]$; for MRR, the larger-the-better ratio is $S/N = -10 \log_{10}[(1/n) \sum (1/y_i^2)]$. GRA converts each response to 0–1. For smaller-the-better, $\xi_i = (\max y_i - y_i) / (\max y_i - \min y_i)$; for larger-the-better, $\xi_i = (y_i - \min y_i) / (\max y_i - \min y_i)$. The grey coefficient is $\xi_i = (\Delta_{\min} + \zeta \Delta_{\max}) / (\Delta_i + \zeta \Delta_{\max})$, with distinguishing coefficient $\zeta = 0.5$. The grade is $\gamma = 0.60\xi_{Ra} + 0.40\xi_{MRR}$, giving surface quality a modest priority while retaining productivity.

A confirmation estimate is compared with the measured optimum. Improvement is accepted only if the mean Ra meets the specification, the

mean MRR increases, and the measured grey grade lies within the predicted confidence interval. Raw readings, NC program, tool history and analysis code should be archived to ensure reproducibility.

Results

The values below are a representative dataset constructed to demonstrate the analysis; they are not claiming of completed physical testing. Each Ra value denotes the intended mean of three profilometer traces. In an actual study, the individual readings and uncertainty must be reported.

Table 3. Illustrative L9 observations and multi-response ranking

Run	Vc	f	ap	Ra (μm)	MRR	Grade	Rank
1	120	0.10	0.5	2.05	6.0	0.389	9
2	120	0.15	1.0	2.24	18.0	0.391	8
3	120	0.20	1.5	2.46	36.0	0.455	6
4	180	0.10	1.0	1.58	18.0	0.539	5
5	180	0.15	1.5	1.80	40.5	0.602	4
6	180	0.20	0.5	2.02	18.0	0.425	7
7	240	0.10	1.5	1.20	36.0	0.855	1
8	240	0.15	0.5	1.42	18.0	0.609	3
9	240	0.20	1.0	1.64	48.0	0.753	2

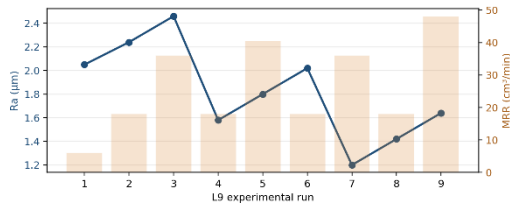


Figure 2. Illustrative trade-off between roughness and material removal rate

Main Effects and Optimization

The illustrative main effects indicate that increasing Vc from 120 to 240 m/min reduces mean Ra from 2.25 to 1.42 μm , while increasing f from 0.10 to 0.20 mm/rev raises mean Ra from 1.61 to 2.04 μm . Depth of cut has a smaller roughness effect over the tested range but strongly increases MRR. A screening ANOVA on Ra assigns approximately 65% of adjusted variation to cutting speed, 27% to feed and 6% to depth of cut, leaving about 2% residual variation. These percentages are illustrative and require experimental residuals and replication for formal inference.

The highest observed grey grade occurs at Run 7 because its 36 cm^3/min MRR and 1.20 μm Ra form the strongest quality–productivity

compromise among the nine discrete trials. The selected setting is therefore Vc = 240 m/min, f = 0.10 mm/rev and ap = 1.5 mm. The theoretical MRR is 36 cm^3/min under the stated equation. A confirmation means close to Ra = 1.20 μm and MRR = 36 cm^3/min would support the prediction; when productivity is instead calculated from effective engaged volume and observed cycle time, the shop-calibrated value must replace the theoretical MRR consistently for every run.

Discussion

The workflow exposes the fundamental quality–throughput conflict. Lower feed produces finer theoretical scallops and therefore improves Ra, while larger feed and depth of cut increase removal rate. Cutting speed improves finish in the illustrative range, consistent with reduced built-up-edge tendency, but this benefit cannot be extrapolated beyond the tested range because thermal softening, tool wear and chatter can reverse the trend. The constrained optimum is therefore preferable to simply selecting the fastest setting.

The method is aligned with the Taguchi and ANOVA logic reported by Asiltürk and Akkuş [3]

and Ribeiro et al. [8], while its GRA stage follows the multi-response rationale used by Sahoo et al. [5] and Sarıkaya and Güllü [7]. Its practical strength is economy: nine screening runs provide balanced factor coverage. Nevertheless, an L9 main-effects design cannot independently estimate all two-factor interactions. If diagnostic plots show curvature or interaction, a central composite or Box–Behnken augmentation should be added, as supported by the RSM approaches in Routara et al. [2] and Bouacha et al. [4].

Reliability, Validity and Limitations

Internal validity depends on randomization, calibration, stable workholding, constant tool geometry and controlled tool wear. Three roughness traces quantify within-part repeatability but do not substitute for independently machined replicates. External validity is limited to the chosen steel, insert, machine rigidity, tool overhang and dry environment. MRR alone also does not capture loading time, tool-change losses, energy use or rejected parts. A shop-floor productivity index should therefore combine cutting time, tool life and first-pass yield.

A further limitation is the illustrative nature of the reported numbers. They are suitable for explaining calculations and expected presentation, but no causal or statistical claim should be made until the protocol is executed. Future work should add tool-wear progression, cutting force, energy consumption and cost per acceptable component, followed by Pareto optimization. Independent validation on another CNC lathe would test transferability.

Conclusion

This paper presents a complete methodology for optimizing CNC turning parameters for surface finish and productivity. The procedure integrates a randomized Taguchi L9 design, replicated roughness measurement, theoretical and time-based productivity calculations, ANOVA, regression diagnostics, GRA and confirmation testing. The illustrative analysis shows why high cutting speed, moderate feed and moderate depth of cut can provide a balanced solution, but the precise optimum must be verified under the actual machine–tool–material system. Adoption of the protocol can reduce trial count, make trade-offs explicit and improve the defensibility of machining decisions.

Implementation Checklist

- Document safe factor ranges and constraints before machining.

- Randomize run order and control insert wear.
- Retain all three Ra readings and report uncertainty.
- Use one consistent, auditable MRR definition.
- Validate the selected setting with independent confirmation specimens.

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