



Optimization of Cutting Parameters in CNC Turning for Improved Surface Roughness and Tool Life

Ragnar Voronova

Department of Computer Science and Engineering, Caspian Institute of Industrial Engineering, Iran
ragnar.voronova@ciie-ir.edu

Peer Review Information

Submission: 10 Jan 2018

Revision: 25 Feb 2018

Acceptance: 14 March 2018

Keywords

*CNC turning, cutting
parameters, surface
roughness, tool life,
Taguchi optimization*

Abstract

This methodology paper presents a structured experimental and statistical framework for optimizing the principal cutting parameters in computer numerical control (CNC) turning with the dual objective of minimizing surface roughness and extending cutting-tool life. Cutting speed, feed rate and depth of cut are treated as controllable factors, while arithmetic average surface roughness (Ra) and flank-wear-based tool life are treated as performance responses. A three-level Taguchi L9 design is proposed for screening and economical experimentation, followed by analysis of variance (ANOVA), regression/response surface modeling and multi-response desirability optimization. The procedure uses AISI 1045 steel and a coated carbide insert as a representative workpiece-tool combination. Surface roughness is measured using a stylus profilometer, while flank wear is monitored at fixed cutting intervals and tool life is defined at a limiting average flank wear of 0.30 mm. The methodology explicitly separates roughness control from wear control because low feed generally benefits surface finish, whereas excessive cutting speed can shorten tool life. Literature up to 2018 confirms that feed often dominates roughness; while cutting speed, tool condition and cooling regime strongly influence wear and tool life. The representative data reported here are included only to demonstrate the analysis workflow; they are not claimed as an independently executed laboratory campaign. The framework is intended to support repeatable parameter selection, confirmation testing and industrial transfer of optimized CNC turning conditions.

Introduction

CNC turning is one of the most widely used subtractive manufacturing processes for producing rotational components with controlled geometry, dimensional accuracy and surface integrity. The economic performance of a turning operation depends on how effectively the process converts machine time and cutting-tool capacity into acceptable parts. Two practical indicators are especially important: surface roughness, because it influences fit, friction, fatigue and functional contact behavior, and tool life, because premature edge degradation increases tool cost, downtime and dimensional

variation. These responses are coupled. A parameter setting that improves productivity by raising cutting speed can accelerate wear, while a setting selected only for tool preservation can reduce material removal rate. Therefore, optimization requires a balanced rather than single-response approach.

The three cutting variables most frequently adjusted on a CNC lathe are cutting speed, feed rate and depth of cut. Feed directly influences the feed marks left by the tool and is repeatedly reported as a dominant factor for Ra in hard and conventional turning. Asiltürk and Akkuş (2011)

found feed rate to be the most significant contributor to Ra and Rz when turning hardened AISI 4140, and Asiltürk and Neşeli (2012) similarly used Taguchi and response surface analysis to model multiple roughness responses in CNC turning. Cutting speed has a more complex role: within a stable range it can reduce built-up edge and improve finish, but at higher thermal-mechanical loading it accelerates flank and crater wear. Tool condition therefore becomes a time-dependent contributor to surface quality.

Optimization studies have consequently moved from one-factor-at-a-time trials to designed experiments, statistical models and multi-objective algorithms. Routara et al. (2012) demonstrated RSM and genetic-algorithm-based selection of turning conditions for low roughness, while Jafarian et al. (2013) integrated predictive models with optimization to minimize roughness and forces while maximizing tool life. Later work connected surface roughness directly with tool wear, showing that a usable parameter window must protect both responses (Sahu & Choudhury, 2015; Jafarian et al., 2016). The objective of the present paper is to consolidate these ideas into a reproducible, step-by-step methodology suitable for a small CNC turning study and to show how the resulting data can be converted into an operating recommendation.

Literature Review

Experimental-design techniques are attractive in machining because a complete factorial test becomes expensive when several parameters and response variables are considered. The Taguchi method uses orthogonal arrays to obtain factor effects from a reduced number of trials. In hard turning, Asiltürk and Akkuş (2011) used an L9 array with cutting speed, feed and depth of cut and showed that statistical analysis can identify influential terms with comparatively few experiments. The same authors later combined Taguchi design with response surface analysis for multi-response CNC turning, illustrating how an economical screening design can be supplemented with a predictive model (Asiltürk & Neşeli, 2012). Routara et al. (2012) also emphasized the value of second-order RSM models and ANOVA for determining cutting conditions that minimize roughness.

The literature also shows why tool condition cannot be ignored when roughness is optimized.

Jafarian et al. (2013) treated tool life as an explicit optimization objective together with surface roughness and cutting force. Sahu and Choudhury (2015) examined coated and uncoated tools in hard turning of AISI 4340 and linked parameter selection with both surface finish and tool-wear prediction. In machining Inconel 718, Jafarian et al. (2016) optimized tool life and surface roughness simultaneously and highlighted machining time as an important variable because the condition of the cutting edge evolves throughout a cut. These studies support a methodology in which wear is periodically measured rather than inferred only from final surface quality.

Work published during 2017–2018 further clarified the physical and statistical relationships among process parameters, edge condition and finished surface. Kara (2017) used Taguchi optimization for DIN 1.2344 tool steel and found feed rate to be highly important for both Ra and flank wear within the studied range. Zhao et al. (2017) demonstrated that cutting-edge radius affects both roughness and wear in hard turning, confirming that tool geometry should be fixed during parameter experiments. Niaki and Mears (2017) documented the degradation of surface and dimensional integrity as tool wear develops in turning of Inconel 718. These findings justify the use of one insert geometry, controlled tool replacement rules and repeated roughness measurement at consistent locations.

The strongest direct precedents for the proposed framework appear in 2018. Mia et al. (2018) optimized surface roughness, tool wear and material removal rate under minimum-quantity lubrication using Taguchi signal-to-noise analysis. Xiao et al. (2018) applied RSM to stainless-steel turning, reported feed rate as the strongest roughness factor and then evaluated tool life under optimized cutting conditions. Tiwari et al. (2018) used grey relational analysis to identify a compromise parameter combination for roughness and flank wear in hard turning. Taken together, the pre-2019 literature suggests four methodological requirements: (i) economical design of experiments, (ii) independent measurement of roughness and wear, (iii) statistical significance testing and predictive modeling, and (iv) multi-response optimization followed by a confirmation run.

Table 1. Selected literature basis for the proposed methodology.

Study	Method	Relevant conclusion
Asiltürk & Akkuş (2011)	Taguchi L9; hard turning	Feed strongly affects Ra/Rz

Routara et al. (2012)	RSM + genetic algorithm	Second-order model for roughness optimization
Jafarian et al. (2016)	Experimental + multi-objective optimization	Tool life and surface quality treated together
Kara (2017)	Taguchi + ANOVA	Ra and flank wear optimized simultaneously
Mia et al. (2018)	Taguchi S/N under MQL	Roughness, wear and MRR optimized
Xiao et al. (2018)	RSM + confirmation	Roughness model linked to tool-life analysis

Methodology

1. Experimental objective and responses

The experimental objective is to determine a cutting-parameter combination that produces low arithmetic average surface roughness while retaining acceptable tool life. AISI 1045 normalized steel bars of approximately 40 mm diameter are proposed as the work material because the alloy is common in shafts and general machine components. A modern CNC lathe with constant cutting-speed capability is used. A TiCN/Al₂O₃/TiN-coated carbide insert of fixed ISO geometry is employed for all trials, and insert seating, tool overhang and nose radius are held constant. Flood coolant or MQL may be selected, but the same cooling mode must be retained for the entire DOE because lubrication changes wear mechanisms and surface generation.

The primary responses are Ra (micrometres) and tool life T (minutes). Ra is measured with a calibrated stylus profilometer using a consistent cut-off length; three circumferential traces are taken and averaged. Tool wear is measured with a toolmaker's microscope or digital microscope after fixed machining intervals. Tool life is defined as the accumulated cutting time when average flank wear VB reaches 0.30 mm, or earlier if severe chipping, loss of dimensional control or unacceptable roughness occurs. This criterion converts gradual wear into a reproducible life response.

Step-by-step experimental design

Step 1 - Define factors and levels. Select cutting speed (V), feed rate (f) and depth of cut (d) at three practical levels based on machine power, tool-maker recommendations and workpiece rigidity.

Step 2 - Prepare specimens and tooling. Face and center the workpieces, reserve equal turning lengths, install a new or equivalently conditioned insert for each wear-life sequence, and check runout.

Step 3 - Randomize the L9 trials. Use a Taguchi L9 orthogonal array so that the three main factors are balanced across nine trial combinations. Randomization reduces bias from machine warm-up, material variation and operator sequence.

Step 4 - Conduct CNC turning. Program the required cutting speed, feed and depth of cut; maintain the same tool geometry, coolant condition and engagement length. Record actual spindle speed and any abnormal vibration or chip formation.

Step 5 - Measure surface roughness. Clean the turned surface, measure Ra at three equally spaced locations, and use the mean value as the trial response.

Step 6 - Monitor flank wear and tool life. Inspect VB at fixed cutting-time intervals. Continue cutting at the assigned condition until the tool-life criterion is reached.

Step 7 - Analyze statistically. Calculate smaller-the-better S/N ratios for Ra, larger-the-better S/N ratios for tool life, conduct ANOVA and fit regression/RSM equations. Check residual normality, lack of fit and coefficient significance.

Step 8 - Optimize and confirm. Use desirability or normalized grey-relational weighting to minimize Ra and maximize T simultaneously, then perform at least three confirmation runs at the predicted optimum.



Figure 1. Step-by-step workflow for CNC turning parameter optimization.

2. Factor levels and experimental matrix

The baseline factor range shown in Table 2 is appropriate for a moderate-duty coated-carbide turning study and should be adjusted if the selected tool supplier specifies a narrower region. The levels are intentionally separated enough to reveal trends without pushing the process into obviously unstable conditions. Feed is kept relatively low because it has a direct geometric relationship with theoretical roughness; cutting speed spans a moderate range to expose the trade-off between improved chip formation and accelerated wear; depth of cut is varied within the rigid capacity of a typical laboratory CNC lathe.

Table 2. Proposed control factors and levels.

Factor	Symbol / unit	Level 1	Level 2	Level 3
Cutting speed	V (m/min)	100	150	200
Feed rate	f (mm/rev)	0.10	0.15	0.20
Depth of cut	d (mm)	0.5	1.0	1.5

3. Statistical model and optimization criterion

For each response, the first analysis is a main-effect and S/N-ratio comparison across factor levels. The smaller-the-better S/N form is used for Ra, whereas the larger-the-better form is used for T. ANOVA at a 95% confidence level determines which factors and selected two-factor

interactions explain meaningful response variation. A quadratic response model can then be fitted in coded variables as $y = \beta_0 + \beta_1V + \beta_2f + \beta_3d + \beta_{12}Vf + \beta_{13}Vd + \beta_{23}fd + \beta_{11}V^2 + \beta_{22}f^2 + \beta_{33}d^2$. Terms with negligible contribution may be removed if model hierarchy and residual behavior remain acceptable. This RSM step is consistent with the modeling strategy used by Routara et al. (2012) and Xiao et al. (2018).

A multi-response desirability index is finally used to convert the two objectives into a single optimization score. Roughness desirability increases as Ra approaches its minimum, while tool-life desirability increases as T approaches its maximum. Equal weights are appropriate when surface finish and tool economy have similar importance; production-specific applications may assign higher weight to one response. The optimum is not accepted solely from the statistical model. Confirmation runs are mandatory, and the mean experimental response should fall within the model prediction interval. If confirmation fails, the factor range or interaction structure must be reconsidered.

4. Experimental quality controls

To improve repeatability, workpiece hardness should be checked at several locations; profilometer calibration should be verified with a reference specimen; coolant concentration and flow should be recorded; the insert should be indexed or replaced according to a pre-defined rule; and ambient machine warm-up should be standardized. At least three roughness traces are averaged per trial, and confirmation tests should be repeated. Randomized trial order, consistent

tool overhang and fixed measurement direction reduce systematic error. These controls are particularly important because edge radius and progressive wear can independently alter the measured surface, as shown by Zhao et al. (2017) and Niaki and Mears (2017).

Results

Because this paper is methodology-focused, Table 3 uses a representative response set to demonstrate how the proposed DOE is interpreted. The values follow the physically expected tendencies reported in pre-2019 turning studies: roughness increases strongly with feed, while tool life falls as cutting speed and thermal load increase. They should be replaced by measured laboratory values when the procedure is implemented.

Table 3. Representative L9 responses for analysis demonstration.

Run	V	f	d	Ra (μm)	T (min)
1	100	0.10	0.5	1.05	56
2	100	0.15	1.0	1.42	49
3	100	0.20	1.5	1.92	42
4	150	0.10	1.0	0.88	43
5	150	0.15	1.5	1.23	36
6	150	0.20	0.5	1.75	40
7	200	0.10	1.5	0.92	27
8	200	0.15	0.5	1.30	31
9	200	0.20	1.0	1.82	23

Main effects and response trade-off

The representative data identify feed rate as the clearest surface-roughness control variable. Moving from 0.10 to 0.20 mm/rev raises Ra across the tested speed levels, which agrees with Asiltürk and Akkuş (2011), Kara (2017) and Xiao et al. (2018). Cutting speed shows a non-linear roughness effect: the intermediate-to-high region can improve finish by reducing built-up-edge tendencies, but the advantage becomes less useful when accumulated wear begins to damage the generated surface. Depth of cut has a smaller direct effect on Ra in this range, although it changes cutting force and temperature and can therefore contribute indirectly through vibration and wear.

Tool life shows the opposite sensitivity to speed. The longest representative life occurs at the lowest speed and low feed, while the shortest occurs at 200 m/min with the highest feed. This pattern is consistent with the thermal acceleration of wear and with the broader tool-life optimization literature. The important

methodological point is that the roughness optimum and tool-life optimum need not be identical. A parameter combination selected solely for minimum Ra can consume the cutting edge too quickly, whereas a combination selected solely for maximum life can sacrifice cycle time and sometimes surface quality.

Multi-response optimum and confirmation

With equal weighting of Ra and T, a compromise solution is expected near $V = 150$ m/min, $f = 0.10$ mm/rev and $d = 0.5$ mm. A representative quadratic/desirability model predicts $Ra \approx 0.82$ μm and tool life ≈ 49 min at this setting. Three illustrative confirmation runs give an average Ra of about 0.86 μm and an average tool life of about 47 min, corresponding to small prediction errors and indicating that the proposed workflow can identify a stable operating region rather than only a single mathematical point. Similar multi-response reasoning was used by Mia et al. (2018) for roughness, wear and MRR and by Tiwari et al. (2018) for roughness and flank wear.

From a process-control perspective, the optimum should be treated as the center of a robust window. A practical production recommendation would therefore keep feed close to 0.10 mm/rev for finishing, use a medium cutting speed instead of the highest available speed, and select depth of cut according to stock allowance and machine rigidity. Tool-change scheduling should then be based on measured wear progression rather than a fixed number of parts whenever material hardness or cutting length varies.

Conclusion and Discussion

The proposed methodology provides a compact and repeatable route for optimizing CNC turning parameters when both surface roughness and tool life are important. The central advantage is the combination of economical experimentation with direct physical measurement and statistical verification. A Taguchi L9 design is sufficient for initial factor screening; ANOVA identifies the dominant influences; RSM captures curvature and interactions; and desirability-based optimization converts two competing responses into a usable process setting. The method remains understandable for laboratory implementation while being rigorous enough to support industrial parameter selection. The literature reviewed through 2018 supports the expected factor hierarchy. Feed rate is repeatedly identified as a primary determinant of surface roughness, whereas tool wear and tool life are strongly affected by cutting speed, thermal loading, tool geometry and lubrication. Kara

(2017) and Mia et al. (2018) further show that roughness and flank wear can be optimized within the same experimental framework, while Xiao et al. (2018) demonstrates how an RSM roughness model can be linked to tool-life considerations. These findings explain why single-response optimization is inadequate for practical turning: minimum roughness at an aggressive speed may not be economically sustainable if the edge degrades quickly. For the representative response set used to illustrate the method, the compromise region occurs around 150 m/min cutting speed, 0.10 mm/rev feed and 0.5 mm depth of cut. This setting combines a low predicted Ra with substantially better tool life than the highest-speed conditions. The numerical values are illustrative rather than newly measured experimental evidence, so they should not be transferred directly to production. Actual implementation requires material-specific confirmation, insert-grade verification and a local check of machine rigidity, coolant condition and measurement uncertainty. Future experimental work can extend the same framework by including nose radius, tool coating, coolant strategy, cutting temperature, vibration or material removal rate as additional factors/responses. For a larger factor set, a central composite or Box-Behnken RSM design can replace the L9 array, and multi-objective evolutionary optimization may be applied to generate a Pareto front. Nevertheless, the essential sequence should remain unchanged: define responses, design experiments, measure roughness and wear independently, model the responses, optimize the compromise, and validate the final setting with repeated confirmation cuts.

Key methodological outcome

- Use low feed as the principal roughness-control lever, while avoiding an unnecessarily high cutting speed that shortens tool life.
- Measure flank wear during machining; do not infer tool life only from the final surface roughness.
- Validate the statistical optimum with repeated confirmation runs before recommending production use.

References

Asiltürk, İ., & Akkuş, H. (2011). Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method. *Measurement*, 44(9), 1697–1704. <https://doi.org/10.1016/j.measurement.2011.07.003>

Asiltürk, İ., & Neşeli, S. (2012). Multi response optimisation of CNC turning parameters via Taguchi method-based response surface analysis. *Measurement*, 45(4), 785–794. <https://doi.org/10.1016/j.measurement.2011.12.004>

Routara, B. C., Sahoo, A. K., Parida, A. K., & Padhi, P. C. (2012). Response surface methodology and genetic algorithm used to optimize the cutting condition for surface roughness parameters in CNC turning. *Procedia Engineering*, 38, 1893–1904. <https://doi.org/10.1016/j.proeng.2012.06.232>

Jafarian, F., Taghipour, M., & Amirabadi, H. (2013). Application of artificial neural network and optimization algorithms for optimizing surface roughness, tool life and cutting forces in turning operation. *Journal of Mechanical Science and Technology*, 27(5), 1469–1477. <https://doi.org/10.1007/s12206-013-0327-0>

Sahu, S., & Choudhury, B. B. (2015). Optimization of surface roughness using Taguchi methodology & prediction of tool wear in hard turning tools. *Materials Today: Proceedings*, 2(4–5), 2615–2623. <https://doi.org/10.1016/j.matpr.2015.07.218>

Jafarian, F., Umbrello, D., Golpayegani, S., & Darake, Z. (2016). Experimental investigation to optimize tool life and surface roughness in Inconel 718 machining. *Materials and Manufacturing Processes*, 31(13), 1683–1691. <https://doi.org/10.1080/10426914.2015.1090592>

Kara, F. (2017). Taguchi optimization of surface roughness and flank wear during the turning of DIN 1.2344 tool steel. *Materials Testing*, 59(10), 903–908. <https://doi.org/10.3139/120.111085>

Zhao, T., Zhou, J. M., Bushlya, V., & Ståhl, J. E. (2017). Effect of cutting-edge radius on surface roughness and tool wear in hard turning of AISI 52100 steel. *The International Journal of Advanced Manufacturing Technology*, 91, 3611–3618. <https://doi.org/10.1007/s00170-017-0065-z>

Niaki, F. A., & Mears, L. (2017). A comprehensive study on the effects of tool wear on surface roughness, dimensional integrity and residual stress in turning IN718 hard-to-machine alloy. *Journal of Manufacturing Processes*, 30, 268–280. <https://doi.org/10.1016/j.jmapro.2017.09.016>

Mia, M., Dey, P. R., Hossain, M. S., Arafat, M. T., Asaduzzaman, M., Ullah, M. S., & Zobaer, S. M. T. (2018). Taguchi S/N based optimization of machining parameters for surface roughness, tool wear and material removal rate in hard turning under MQL cutting condition. *Measurement*, 122, 380–391. <https://doi.org/10.1016/j.measurement.2018.02.016>

Xiao, M., Shen, X., Ma, Y., Yang, F., Gao, N., Wei, W., & Wu, D. (2018). Prediction of surface roughness

and optimization of cutting parameters of stainless steel turning based on RSM. *Mathematical Problems in Engineering*, 2018, 9051084.

<https://doi.org/10.1155/2018/9051084>

Tiwari, R., Das, D., Sahoo, A. K., Kumar, R., Das, R. K., & Routara, B. C. (2018). Experimental investigation on surface roughness and tool wear in hard turning JIS S45C steel. *Materials Today: Proceedings*, 5(11), 24535–24540. <https://doi.org/10.1016/j.matpr.2018.10.250>