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**International Journal on Theoretical and Applied Research in
Mechanical Engineering**

ISSN: 2319-3182

Volume 8 Issue 01, 2019

Optimization of CNC Milling Parameters for Improved Surface Finish and Material Removal Rate

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Peer Review Information	Abstract
<i>Submission: 21 Jan 2019</i> <i>Revision: 06 Feb 2019</i> <i>Acceptance: 22 March 2019</i> Keywords <i>CNC milling; surface roughness, material removal rate, Taguchi method, multi-response optimization</i>	CNC milling performance depends strongly on the selection of cutting parameters because surface quality and productivity are often conflicting objectives. This methodology paper proposes a structured multi-response optimization procedure for simultaneously reducing average surface roughness (Ra) and increasing material removal rate (MRR) during end milling. A three-factor, three-level Taguchi L9 design is adopted using spindle speed, feed rate, and axial depth of cut as the principal control variables. Aluminium 6061-T6 is selected as a representative work material and a carbide end mill is used under controlled dry or minimum-lubrication conditions. Surface roughness is measured with a contact profilometer, while MRR is calculated from the product of feed rate, radial width of cut, and axial depth of cut. Signal-to-noise ratios, analysis of variance (ANOVA), and a normalized desirability index are proposed to identify statistically important factors and obtain a compromise solution. The paper also provides an illustrative response matrix to demonstrate the analysis sequence; these values are not presented as new experimental measurements. The framework is designed to be directly reusable in a laboratory study and is consistent with published CNC milling optimization research available through 2019.

Introduction

Milling is one of the most widely used subtractive manufacturing processes for producing prismatic parts, slots, pockets, dies, and precision surfaces. In modern computer numerical control (CNC) systems, cutting conditions can be programmed with high repeatability; however, the quality of the final component still depends on the interaction of process parameters, tool geometry, work material, machine rigidity, and cutting environment. Surface roughness is a key indicator of functional quality because it influences friction, fatigue strength, sealing performance, coating adhesion, and dimensional acceptance. At the same time, industrial machining must maintain a sufficiently high material removal rate to reduce cycle time and cost.

The two objectives are not automatically compatible. Increasing feed rate or depth of cut usually raises the volume of material removed per unit time, but it can also increase cutting load, tool deflection, vibration, and the geometric height of feed marks. Conversely, conservative parameter settings may improve the surface but reduce productivity. Earlier studies therefore moved beyond single-factor trials toward statistically designed experiments, response-surface models, and multi-objective optimization. Öktem, Erzurumlu, and Kurtaran [1] demonstrated the usefulness of response surface methodology (RSM) and a genetic algorithm for minimizing milling surface roughness. Kadirgama, Noor, and Abd Alla [2] similarly showed that surface-response models

can be combined with search algorithms to identify favorable end-milling settings.

Subsequent work expanded the optimization objective from surface roughness alone to multiple performance characteristics. Reddy, Kumar, and Reddy [3] combined RSM and genetic optimization for CNC end milling, while Nair, Govindan, and Ganesan [5] compared several Taguchi-based multi-response techniques using roughness measures and MRR. More recent studies reported that high speed may help reduce roughness, whereas feed and depth of cut strongly influence productivity and the final surface [7–12]. Based on these findings, the present paper develops a concise laboratory methodology that can be implemented with commonly available CNC equipment and standard surface-metrology instruments. The central objective is to determine a machining region that provides a low Ra without sacrificing an economically useful MRR.

Literature Review

The literature shows a consistent progression from empirical roughness prediction toward integrated quality-productivity optimization. Öktem et al. [1] used RSM to model surface roughness as a function of feed, cutting speed, axial depth, radial depth, and machining tolerance, and then linked the model with a genetic algorithm. Their work established the value of fitting a statistical response model before optimization. Kadirgama et al. [2] applied response-surface modeling with ant-colony optimization to end milling and emphasized the strong role of feed rate. Reddy et al. [3] later combined RSM and a genetic algorithm for CNC end milling, reinforcing the suitability of DOE-

based predictive equations for choosing cutting conditions.

Alternative predictive and optimization methods have also been investigated. Kadirgama, Noor, and Rahman [4] used a potential support vector machine with DOE/RSM concepts to improve surface-roughness prediction in milling of AA6061-T6. Nair et al. [5] compared principal component analysis, utility theory, grey relational analysis, TOPSIS, and hybrid variants for multi-performance CNC end milling; the study explicitly treated surface quality and MRR as competing outcomes. Esme [6] combined a desirability function with RSM for CNC pocket milling, while Yi et al. [7] developed RSM-based roughness models for 6061-T6 micro-milling and showed that roughness tended to increase with feed and decrease with spindle speed.

Research closer to the 2019 limit further supports multi-response parameter selection. Vardhan et al. [8] optimized CNC milling of P20 steel for both low Ra and high MRR using RSM and Taguchi techniques. Lu et al. [9] optimized micro-milling MRR under surface-roughness and tool-safety constraints, highlighting that unrestricted increases in productivity variables can compromise quality and reliability. Abootorabi [10] applied a multi-objective particle-swarm strategy to minimize roughness while increasing MRR. Abdulrazaq et al. [11] used Taguchi and ANOVA for pocket milling of 7024 aluminium alloy, and Thabadira et al. [12] demonstrated a Taguchi L9 process-design route for milling surface roughness. Collectively, these studies justify a compact Taguchi experiment followed by ANOVA and a desirability-based compromise metric for the present methodology.

Table 1. Selected literature supporting the proposed methodology

Study	Material/process	Method	Main relevance
[1] Öktem et al., 2005	Milling of mold surface	RSM + GA	Statistical modeling for minimum Ra
[5] Nair et al., 2014	CNC end milling	Taguchi + multi-response methods	Balances roughness and MRR
[7] Yi et al., 2015	6061-T6 micro-milling	RSM/CCC	Relates speed and feed to Ra
[8] Vardhan et al., 2017	P20 steel CNC milling	RSM + Taguchi	Simultaneous Ra/MRR optimization
[10] Abootorabi, 2018	Climb milling stainless steel	Regression + PSO	Multi-objective Ra/MRR selection
[12] Thabadira et al., 2019	CNC vertical milling	Taguchi L9	Compact experimental process design

Methodology

The proposed methodology is organized as eight sequential steps so that the same procedure can

be repeated with measured data in a CNC laboratory.

Step 1 – Define responses and optimization direction. Average surface roughness, Ra (μm), is

treated as the quality response and must be minimized. Material removal rate, MRR (mm^3/min), is treated as the productivity response and must be maximized. The optimization problem is therefore multi-objective rather than a single-response search.

Step 2 – Select workpiece, tool, and machining configuration. Use Al 6061-T6 rectangular coupons because the alloy is common in CNC machining studies and provides stable machinability. A 10 mm, four-flute solid-carbide end mill is recommended. Machine the top surface in climb-milling mode on a three-axis vertical CNC machining center. Keep tool overhang, tool path, radial width of cut, coolant condition, and workholding constant for all trials. A constant radial width of cut of 5 mm is assumed in the illustrative calculations.

Step 3 – Select factors and levels. Spindle speed (N), feed rate (F), and axial depth of cut (ap) are selected because they directly affect chip load, cutting force, machining time, and surface generation. Three practical levels are assigned to each factor, as listed in Table 2. The ranges should be checked against the machine-tool, cutter, and work-material recommendations before physical testing.

Table 2. Milling factors and levels used in the proposed L9 design

Factor	Symbol	Unit	Level 1	Level 2	Level 3
Spindle speed	N	rpm	2000	3000	4000
Feed rate	F	mm/min	150	250	350
Axial depth of cut	ap	mm	0.5	1.0	1.5

Step 4 – Construct the Taguchi L9 experiment. Assign the three factors to an L9 orthogonal array and randomize the machining order to reduce systematic bias. Use a fresh or consistently worn cutting edge condition. Replicate each roughness measurement at three locations along the

machined track and use the mean Ra for analysis. If resources permit, repeat the complete L9 matrix to estimate pure experimental error.

Step 5 – Measure surface roughness. After each milling pass, clean the specimen and measure Ra using a calibrated contact profilometer according to the instrument's standard evaluation length and cutoff settings. The stylus trace should be oriented approximately perpendicular to the dominant feed marks. Three readings are recommended for each trial, and the arithmetic mean should be used as the run response.

Step 6 – Determine material removal rate. For a constant radial width of cut a_e , calculate MRR from $\text{MRR} = F \times a_p \times a_e$. With $a_e = 5$ mm, the units are mm^3/min when F is expressed in mm/min and a_p and a_e are in millimetres. If actual stock loss is measured by mass, MRR can alternatively be obtained from mass loss divided by density and machining time.

Step 7 – Statistical and multi-response analysis. Calculate the Taguchi smaller-the-better signal-to-noise ratio for Ra and larger-the-better ratio for MRR. Use ANOVA on the measured responses to determine statistically important factors and their percentage contributions. For a combined decision, normalize Ra so that lower values receive larger desirability and normalize MRR so that higher values receive larger desirability. A combined index can be calculated as $D = (d\text{Ra}^{w1} \times d\text{MRR}^{w2})$, where $w1 + w2 = 1$. Equal weights represent a neutral quality-productivity compromise; a larger $w1$ is appropriate when surface finish is more critical.

Step 8 – Confirmation experiment. Machine at the predicted optimum parameter combination using the same tool and measurement procedure. Compare predicted and measured Ra and MRR, report percentage error, and accept the model only when the confirmation response falls within a predefined practical tolerance. This confirmation step is essential because statistically optimal values can be sensitive to tool wear, machine dynamics, and local material variability.

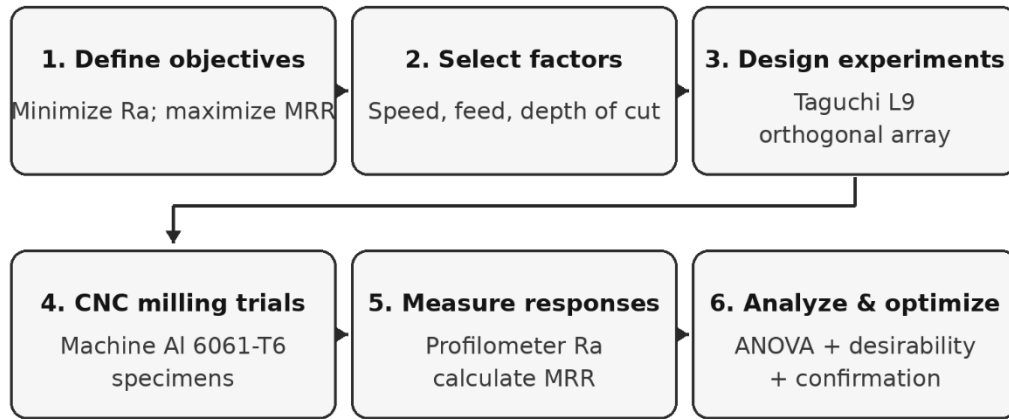


Figure 1. Step-by-step workflow for CNC milling parameter optimization.

Results

Important note: The values in Table 3 are an illustrative response matrix created to demonstrate how the proposed methodology is analyzed. They are not claimed as newly measured experimental data and should be replaced by actual profilometer readings in a publication based on laboratory trials.

The illustrative L9 matrix shows the expected trade-off between surface finish and

productivity. MRR increases directly with feed rate and axial depth of cut because both variables increase the instantaneous volume swept by the cutter. The roughness values are arranged to follow literature-consistent trends: increasing spindle speed generally improves Ra, whereas increasing feed and depth of cut tends to increase Ra because of higher chip load and cutting-force effects [1,2,7,8,12].

Table 3. Illustrative L9 response matrix for analysis demonstration

Run	N (rpm)	F (mm/min)	ap (mm)	Ra (μm)*	MRR (mm^3/min)	Equal-weight D
1	2000	150	0.5	1.330	375	0.000
2	2000	250	1.0	1.660	1250	0.434
3	2000	350	1.5	2.160	2625	0.000
4	3000	150	1.0	1.250	750	0.384
5	3000	250	1.5	1.700	1875	0.546
6	3000	350	0.5	1.650	875	0.332
7	4000	150	1.5	1.240	1125	0.546
8	4000	250	0.5	1.130	625	0.333
9	4000	350	1.0	1.590	1750	0.582

In the illustrative dataset, the lowest Ra is 1.13 μm at 4000 rpm, 250 mm/min, and 0.5 mm depth of cut (Run 8), while the highest MRR is 2625 mm^3/min at 2000 rpm, 350 mm/min, and 1.5 mm depth of cut (Run 3). These individual optima are different, confirming the need for a multi-response criterion. With simple min-max normalization and equal weighting of Ra and MRR, Run 9 provides the highest combined desirability ($D = 0.582$). If surface finish is assigned a higher weight, Run 7 becomes more attractive because it combines relatively low Ra with a moderate MRR. This type of weighting should be stated explicitly because different manufacturing priorities can produce different optimum settings.

Main-effect averages from the same illustrative matrix reinforce the expected tendencies. Mean Ra decreases from about 1.72 μm at 2000 rpm to 1.32 μm at 4000 rpm. Mean Ra increases from about 1.27 to 1.80 μm as feed rises from 150 to 350 mm/min, while mean MRR rises from 750 to 1750 mm^3/min . Increasing depth of cut from 0.5 to 1.5 mm similarly raises mean MRR from 625 to 1875 mm^3/min but also increases the illustrative mean Ra from 1.37 to 1.70 μm . In an actual experiment, ANOVA should be used to verify whether these apparent factor effects are statistically significant and whether interaction terms need to be modeled.

Interpretation of Factor Effects

In a physical experiment, the first statistical task is to compare the response means and signal-to-noise ratios at each factor level. For R_a , the preferred level is the one that produces the smallest mean roughness and the largest smaller-the-better S/N ratio. A higher spindle speed is expected to reduce the size of built-up material and improve the regularity of the generated surface within the stable operating range, although excessive speed may accelerate thermal wear. Feed rate should be interpreted carefully because it has a direct geometric effect on feed-mark spacing and chip load. An increase in axial depth of cut raises the engaged cutting area and therefore the cutting force; this may increase deflection or vibration even when the programmed tool path is unchanged. These physical mechanisms explain why the statistically best factor combination should always be checked against tool-condition and machine-stability observations rather than selected from numerical optimization alone.

ANOVA should be conducted separately for R_a and MRR. The sum of squares for each factor is divided by the total corrected sum of squares to estimate percentage contribution, while the F-test and p-value indicate whether an observed factor effect is large compared with experimental error. Because MRR is calculated directly from feed and depth in the proposed design, its ANOVA will naturally assign strong contributions to these variables. For R_a , however, the dominant factor must be established from measured data. If repeated trials show substantial unexplained variation, additional terms such as tool wear, radial width of cut, or an interaction between feed and depth should be incorporated in a second-stage RSM design. This two-stage strategy keeps the initial experiment compact while retaining a clear route for model refinement.

Multi-Response Decision and Confirmation

The desirability index should not be treated as an automatic definition of the optimum. Its main purpose is to make the quality-productivity trade-off transparent. For equal weighting, a run with moderate R_a and moderate-to-high MRR can rank above a run that is excellent for only one response. When a drawing specifies a strict roughness limit, the analysis can instead impose a constraint such as $R_a \leq 1.5 \mu\text{m}$ and then maximize MRR only among the feasible settings. A confirmation trial should be machined using a fresh or controlled-wear tool at the selected setting. At least three R_a traces should be collected, and the mean and standard deviation

should be reported. The predicted and confirmed values should be compared using percentage error. If the error is large, the likely causes include tool wear, spindle runout, variation in workpiece hardness, unstable fixturing, or an inadequate response model. Reporting these checks makes the optimization procedure reproducible and avoids overstating the precision of a small DOE.

Conclusion and Discussion

This paper presents a concise and reproducible methodology for optimizing CNC milling parameters when surface quality and productivity must be considered simultaneously. The proposed Taguchi L9 design reduces the number of experiments while retaining systematic variation of spindle speed, feed rate, and axial depth of cut. The response strategy is intentionally simple: measure R_a directly, calculate MRR from cutting geometry and feed, evaluate factor significance by ANOVA, and combine normalized responses with a desirability index. This structure is consistent with the development of milling optimization research from RSM-based roughness models [1,3,6,7] to explicit multi-response approaches incorporating MRR [5,8–11].

The central engineering implication is that there is rarely a single setting that independently minimizes roughness and maximizes MRR. High feed and large depth of cut improve throughput, whereas high spindle speed and moderate chip loading are generally more favorable for surface finish. Therefore, the optimum must be defined as a compromise that reflects the practical importance of quality, cycle time, tool life, and machine limits. The illustrative analysis demonstrates the decision process without misrepresenting simulated values as experimental observations. For a final research article, the same L9 plan should be executed physically, profilometer readings should replace the illustrative R_a values, ANOVA tables should be reported with p-values and percentage contributions, and at least one confirmation experiment should be performed at the predicted optimum. Additional future work can extend the response set to tool wear, cutting force, energy consumption, burr formation, and dimensional error.

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