



Optimization of CNC Turning Parameters for Improved Surface Roughness and Material Removal Rate

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Abstract

This methodology paper presents a systematic multi-response framework for optimizing computer numerical control (CNC) turning parameters to obtain low surface roughness and high material removal rate (MRR). The proposed procedure combines a Taguchi L9 orthogonal array with signal-to-noise analysis, Grey Relational Analysis (GRA), analysis of variance (ANOVA), and a confirmation experiment. Cutting speed, feed rate, and depth of cut are treated as controllable factors, while average surface roughness (Ra) and MRR are selected as performance responses. The method is intended for medium-carbon-steel turning with a carbide insert under dry cutting, but it can be transferred to other workpiece-tool combinations by redefining factor ranges. Literature up to 2016 shows that feed rate commonly exerts a strong influence on surface finish, whereas MRR increases with speed, feed, and depth of cut; therefore, simultaneous optimization is necessary. A representative L9 dataset is used to demonstrate the calculations because raw laboratory measurements were not supplied. The Grey grade identifies the best compromise parameter combination, and ANOVA quantifies the relative influence of factors. The proposed workflow reduces the number of trials while providing a statistically interpretable basis for balancing machining quality and productivity.

Introduction

Turning is one of the most widely used subtractive manufacturing processes for producing cylindrical and rotational components. In CNC turning, the workpiece rotates while a single-point cutting tool is fed along a programmed path. The process is capable of high dimensional repeatability, but final component quality and productivity depend strongly on the selected cutting conditions. Cutting speed, feed rate, and depth of cut affect chip formation, cutting temperature, cutting forces, tool wear, dimensional stability, surface texture, cycle time, and the volume of material removed per unit time. Consequently, parameter selection is not merely a machine-setting task; it

is a multi-objective engineering decision in which quality, productivity, and tool reliability must be considered simultaneously.

Surface roughness is a key indicator of functional surface quality because it influences friction, fatigue performance, wear, sealing, coating adherence, and assembly behavior. Average roughness, Ra, is frequently used as a practical response because it is readily measured with a stylus profilometer and can be compared across cutting conditions. Conventional shop-floor practice often favors low feed and moderate cutting conditions when a fine surface is required. However, such settings may reduce throughput. In contrast, increasing feed and

depth of cut generally increases the amount of material removed in a given time, which improves productivity but can deteriorate surface finish or accelerate tool wear. This inherent conflict makes simultaneous optimization of Ra and MRR particularly important.

The Taguchi method provides an efficient design-of-experiments structure for studying several factors using fewer experiments than a full factorial design. Yang and Tarng (1998) demonstrated the use of orthogonal arrays, signal-to-noise ratios, and ANOVA to identify influential turning parameters and verify optimum settings. Davim (2001) similarly used Taguchi-based experimental planning and regression to relate cutting velocity, feed, and depth of cut to surface-finish parameters. Later studies consistently showed that statistical design and confirmation testing provide a more reliable basis for parameter selection than trial-and-error approaches (Nalbant et al., 2007; Asilturk & Akkus, 2011).

A single-response optimization, however, may be inadequate when the objective is to minimize roughness and maximize MRR at the same time. Sahoo et al. (2012) combined Taguchi design, regression, and Grey Relational Analysis to treat surface roughness and MRR as a multi-objective turning problem. Jayaraman and Mahesh Kumar (2014) and Puh et al. (2016) further demonstrated that Grey-based Taguchi methods can convert multiple normalized responses into a single Grey relational grade that is suitable for ranking experiments and performing ANOVA. On this basis, the present paper develops a concise methodology that can be implemented with common CNC turning and metrology facilities.

The objective is therefore to establish a reproducible procedure for selecting cutting speed, feed rate, and depth of cut that yields the best compromise between minimum Ra and maximum MRR. The methodology uses three levels for each factor and an L9 orthogonal array, followed by response normalization, Grey relational coefficients, Grey relational grade, factor-effect analysis, ANOVA, and a confirmation run. Because the user did not provide raw experimental measurements, the numerical results included later are an illustrative, internally consistent demonstration of the proposed calculation route and should be replaced by laboratory measurements before submission as an original experimental research paper.

Literature Review

Yang and Tarng (1998) optimized turning parameters using the Taguchi method for S45C steel and showed how orthogonal arrays, signal-to-noise ratios, and ANOVA can identify the settings that control turning performance. Their work established an influential template for machining optimization: design a compact experiment, quantify factor effects, select optimum levels, and perform confirmation tests. The study is particularly relevant because it treats optimization as a structured quality-engineering problem rather than as isolated machining trials.

Davim (2001) investigated the influence of cutting velocity, feed, and depth of cut on surface finish and developed correlations for Ra and Rt using multiple linear regression. The work emphasized that surface roughness is affected by a combination of cutting variables and that statistical models can support prediction within the tested region. This is important for CNC turning because a predictive equation allows engineers to estimate the likely surface response before committing to additional production trials.

Nalbant et al. (2007) applied a Taguchi approach to AISI 1030 steel with TiN-coated tools and examined insert radius, feed rate, and depth of cut with surface roughness as the performance characteristic. The authors demonstrated the usefulness of the orthogonal-array/S-N/ANOVA sequence for selecting robust conditions. Hascalik and Caydas (2008) extended Taguchi optimization to Ti-6Al-4V turning and evaluated both surface roughness and tool life, illustrating that a factor setting favorable for one machining response may not be favorable for another.

Asilturk and Akkus (2011) studied hard turning of AISI 4140 using an L9 orthogonal array and coated carbide tools. Their ANOVA results showed that feed rate was the most significant factor affecting Ra and Rz, while interactions with cutting speed were also relevant. This finding supports the need to control feed carefully when the main quality objective is surface finish, and it also explains why a productivity objective such as MRR can create a conflict, since MRR benefits from increased feed.

Sahoo et al. (2012) directly addressed this conflict by optimizing surface roughness and MRR in turning AISI 1040 steel. They used Taguchi design, regression, and Grey Relational Analysis, demonstrating that individual optima for Ra and MRR differ and that Grey analysis can provide a simultaneous compromise. Their work

is the central methodological basis for the present study because it integrates experimental design with a scalar multi-response grade.

Jayaraman and Mahesh Kumar (2014) used Grey Relational Analysis with a Taguchi orthogonal array for turning AA6063-T6, considering surface roughness, roundness, and MRR. Their procedure normalized responses according to whether a smaller or larger value was preferred, calculated Grey coefficients and a combined grade, and used ANOVA to identify significant factors. Puh et al. (2016) used a similar Grey-based Taguchi framework to obtain minimum Ra and maximum MRR simultaneously and validated the identified parameter settings through confirmation experiments.

Deepak and Rajendra (2016) applied robust design principles to turning Al6061 and found feed rate to be the most influential parameter on surface roughness, followed by cutting speed and depth of cut. Ram Kumar (2016) also investigated CNC turning of EN8 with Taguchi methods and considered surface roughness together with other machining outputs. Collectively, these studies indicate that parameter significance depends on material-tool conditions, but they consistently support statistically designed experiments and confirm the strong role of feed in surface finish. The research gap addressed here is therefore not the creation of a new optimization theory, but the formulation of a concise, transferable methodology focused specifically on the competing objectives of surface roughness and MRR using evidence available up to 2016.

Methodology

The proposed experiment considers dry external turning of EN8 medium-carbon steel with a coated carbide insert on a CNC lathe. EN8 is selected as a representative engineering steel because it is widely used for shafts, pins, studs, gears, and general machine parts. The precise workpiece diameter, insert grade, nose radius, tool holder, and machine power should be recorded during actual experimentation. A fresh or equivalently worn insert should be used according to a fixed protocol so that tool wear does not become an uncontrolled source of variation.

Step 1 - Selection of factors and levels. Three controllable factors are selected: cutting speed V_c , feed rate f , and depth of cut d . For a compact demonstration, the factor levels are $V_c = 100, 150, \text{ and } 200 \text{ m/min}$; $f = 0.10, 0.15, \text{ and } 0.20 \text{ mm/rev}$; and $d = 0.5, 1.0, \text{ and } 1.5 \text{ mm}$. These levels are sufficiently separated to reveal

response trends while remaining plausible for carbide turning of medium-carbon steel. In an actual study, the levels should be checked against the insert manufacturer's recommendations, machine-tool limits, workpiece rigidity, and required surface specification.

Step 2 - Taguchi experimental design. A three-factor, three-level problem would require 27 runs in a full factorial experiment. The Taguchi L9 orthogonal array reduces this to nine principal trials while preserving balanced representation of the factor levels. The nine combinations are randomized before machining to reduce the influence of time-dependent disturbances such as progressive tool wear, ambient temperature, or machine warm-up. If resources allow, each run should be replicated at least twice and the mean response should be used for analysis.

Step 3 - Measurement of surface roughness. After each turning run, Ra is measured using a calibrated stylus-type surface roughness tester. Measurements should be taken at three equally spaced circumferential or axial locations within the machined region, avoiding start/stop marks. The arithmetic mean of the three readings is reported as the Ra for that run. The cutoff length, evaluation length, filter, and instrument standard should be kept constant for all specimens.

Step 4 - Calculation of material removal rate. MRR is calculated from the machining variables. For turning, an approximate expression is $MRR = 1000 V_c f d \text{ in mm}^3/\text{min}$ when V_c is in m/min and f and d are in mm/rev and mm, respectively. Dividing by 1000 gives MRR in cm^3/min . Alternatively, MRR may be determined by the actual removed volume divided by cutting time if diameters and machining time are measured directly.

Step 5 - Signal-to-noise analysis. For Ra, the smaller-the-better S/N ratio is used: $S/N = -10 \log_{10}[(1/n) \sum(y_i^2)]$. For MRR, the larger-the-better form is used: $S/N = -10 \log_{10}[(1/n) \sum(1/y_i^2)]$. Higher S/N values are preferred because they indicate a response closer to the desired objective with lower sensitivity to noise. The S/N analysis can be used for single-response interpretation before the multi-response calculation.

Step 6 - Grey Relational Analysis. Because Ra and MRR have different units and opposite desired directions, they are first normalized to a 0-1 scale. Ra is normalized using the smaller-the-better transformation, whereas MRR uses the larger-the-better transformation. The Grey relational coefficient is then calculated from the

deviation of each normalized response from the ideal sequence, using a distinguishing coefficient of 0.5. The Grey relational grade (GRG) is the arithmetic mean of the two coefficients; equal weights are used here so that surface quality and productivity have the same importance. A higher GRG represents a better overall compromise.

Step 7 - ANOVA and optimum selection. The mean GRG at each level of each factor is calculated. The factor level with the highest mean grade is selected as optimum. ANOVA is then applied to the GRG to estimate the contribution of cutting speed, feed rate, and depth of cut to the combined response. Residual error provides an indication of the variation not explained by the main effects.

Step 8 - Confirmation experiment. A final turning test is conducted at the predicted optimum combination using a controlled insert condition. The measured R_a and MRR are compared with

the predicted values and with a baseline parameter combination. A successful optimization should demonstrate a higher Grey grade and a practically meaningful improvement in at least one response without an unacceptable loss in the other. The confirmation run is essential because Taguchi level effects and Grey analysis identify an expected optimum but do not substitute for physical verification.

Table 1. Control factors and levels used in the proposed L9 design

Factor	Level 1	Level 2	Level 3
Cutting speed, V_c (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



Figure 1. CNC turning multi-response optimization workflow

Results

Table 2 presents a representative L9 dataset to demonstrate the proposed calculations. These values are not claimed as laboratory observations; they are included so that the optimization route is complete and reproducible.

The roughness values follow the expected tendency of increasing with feed and decreasing moderately with cutting speed, while MRR follows the turning relation $V_c \times f \times d$. The Grey relational grade combines both responses after normalization and coefficient calculation.

Table 2. Representative Taguchi L9 responses and Grey relational grade

Run	V_c (m/min)	f (mm/rev)	d (mm)	R_a (μm)	MRR (cm^3/min)	GRG	Rank
1	100	0.10	0.5	1.805	5.00	0.553	6
2	100	0.15	1.0	2.387	15.00	0.449	8
3	100	0.20	1.5	3.102	30.00	0.485	7
4	150	0.10	1.0	1.670	15.00	0.653	3
5	150	0.15	1.5	2.301	33.75	0.625	4
6	150	0.20	0.5	2.760	15.00	0.402	9
7	200	0.10	1.5	1.580	30.00	0.818	1
8	200	0.15	0.5	1.912	15.00	0.554	5
9	200	0.20	1.0	2.741	40.00	0.698	2

The highest GRG is obtained for Run 7, corresponding to $V_c = 200$ m/min, $f = 0.10$ mm/rev, and $d = 1.5$ mm. This setting provides a low illustrative R_a of 1.580 μm while maintaining an MRR of 30.00 cm^3/min . Run 9 produces the highest MRR, 40.00 cm^3/min , but its higher feed increases R_a to 2.741 μm ; therefore, its combined

grade is lower than Run 7. This comparison shows why maximizing MRR alone does not satisfy a multi-response quality objective.

The mean GRG values by factor level are 0.495, 0.560, and 0.690 for cutting-speed levels 1 to 3; 0.675, 0.543, and 0.528 for feed levels 1 to 3; and 0.503, 0.600, and 0.643 for depth-of-cut levels 1

to 3. The optimum level combination is therefore V3-f1-d3. An ANOVA of the illustrative GRG assigns approximately 42.9% of the total variation to cutting speed, 28.4% to feed rate, 22.4% to depth of cut, and 6.2% to residual variation. These percentages should not be generalized beyond the illustrative dataset, but the calculation demonstrates how factor importance can be quantified.

The direction of the effects is consistent with the literature. Asilturk and Akkus (2011) and Deepak and Rajendra (2016) reported the strong influence of feed on surface roughness, whereas Sahoo et al. (2012) showed that the parameter combination that minimizes Ra differs from the one that maximizes MRR. Grey-based optimization resolves this conflict by ranking each trial according to simultaneous closeness to the desired quality and productivity targets. Puh et al. (2016) likewise demonstrated that Grey Relational Analysis can be coupled with Taguchi design and ANOVA to obtain an experimentally verifiable compromise between low roughness and high MRR.

For an actual validation experiment, the V3-f1-d3 combination should be machined with the same workpiece batch, tool geometry, cooling condition, measurement method, and randomization controls used for the L9 tests. The observed GRG should then be compared with the predicted grade. If the confirmation result is substantially lower than expected, potential causes include insert wear, chatter, built-up edge, inconsistent workpiece hardness, measurement scatter, or interaction effects not captured by the main-effect L9 model. Replication and residual checks are therefore recommended when the study is intended for journal publication or production qualification.

Conclusion and Discussion

This paper has developed a concise methodology for optimizing CNC turning parameters when the two principal objectives are improved surface finish and increased material removal rate. The method combines a Taguchi L9 orthogonal array with surface-roughness measurement, MRR calculation, S/N analysis, Grey Relational Analysis, ANOVA, and a confirmation test. The literature available up to 2016 supports this sequence: feed rate is repeatedly identified as a major determinant of surface roughness, while productivity rises as cutting speed, feed, and depth of cut increase. These opposing tendencies justify a multi-response method rather than independent single-response optimization. In the representative demonstration, the highest Grey

grade occurs at high cutting speed, low feed, and high depth of cut, providing a practical compromise between Ra and MRR. The methodology reduces experimental effort from 27 full-factorial combinations to nine principal trials and yields an interpretable ranking of factor effects. For final experimental publication, the illustrative values in this paper must be replaced with measured data and the predicted optimum must be validated physically. Additional work may include tool wear, cutting force, energy consumption, coolant strategy, interaction effects, response-surface modeling, and weighted Grey grades when surface quality and productivity do not have equal industrial importance. From an engineering perspective, the optimum should not be interpreted as a universal machine setting. It is an optimum only within the selected material, tool, machine, factor ranges, response definitions, and weighting assumptions. A production engineer may deliberately select a nearby setting if tool life, spindle-power limits, dimensional tolerance, or chip control is more critical than the equal-weighted Ra-MRR compromise used here. The value of the methodology is that such a choice can be made from quantified evidence. If surface integrity is dominant, a larger weight may be assigned to Ra; if throughput dominates, a larger weight may be assigned to MRR. The same Grey-analysis sequence can then be repeated without changing the experimental design. The main limitation of an L9 main-effect design is its restricted ability to estimate all two-factor interactions and curvature. If preliminary experiments show chatter, severe built-up edge, rapid tool wear, or non-linear response behavior, the study should be extended with replication, interaction columns, or a response-surface design. Measurement uncertainty should also be reported because a small numerical improvement in Ra may not be practically meaningful if it is comparable with profilometer repeatability. Thus, the recommended implementation is to use the L9-GRA method as an efficient screening and optimization stage, verify the selected condition with confirmation trials, and then refine the operating window when industrial qualification demands higher statistical confidence.

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