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Multi-Response Optimization of CNC Turning Conditions Using Central Composite Design and Response Surface Analysis

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Abstract

Efficient CNC turning requires a balanced selection of machining parameters because conditions that improve productivity may adversely affect surface quality. This study presents a statistically structured methodology for multi-response optimization of CNC turning conditions using a central composite design and response surface analysis. Cutting speed, feed rate, and depth of cut are treated as controllable factors, while average surface roughness and material removal rate are considered as the principal quality and productivity responses. A three-factor, 20-run central composite design is employed to estimate linear, interaction, and quadratic effects over a practical machining region. The proposed procedure is demonstrated for dry longitudinal turning of AISI 1045 steel using a coated carbide insert under controlled tool and workpiece conditions. Experimental responses are analyzed using second-order regression models, analysis of variance, lack-of-fit testing, residual diagnostics, and multi-response desirability optimization. The representative statistical analysis indicates that feed rate is the dominant contributor to surface roughness, while cutting speed and depth of cut provide secondary but significant effects. A balanced desirability solution is obtained near a cutting speed of 190 m/min, feed rate of 0.14 mm/rev, and depth of cut of 1.10 mm, with predicted surface roughness of approximately 0.82 µm and material removal rate of about 29,260 mm^3/min. Representative confirmation values show prediction errors of approximately 3.5% for surface roughness and 1.2% for material removal rate. The methodology provides a reproducible framework for identifying CNC turning conditions that achieve an effective compromise between surface finish and machining productivity while reducing dependence on trial-and-error parameter selection.

Introduction

CNC turning is a fundamental subtractive manufacturing process for producing rotational parts with controlled dimensional accuracy and surface integrity. Its performance is governed by an interacting set of variables, among which cutting speed, feed rate and depth of cut are the most readily programmable. Selecting these variables independently is inefficient because a condition that improves productivity may worsen surface finish, increase cutting force, accelerate tool wear, or create thermal damage. Consequently, machining optimization is best treated as a multivariable problem rather than a sequence of one-factor-at-a-time trials.

Response Surface Methodology combines designed experiments, regression modeling and

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optimization. In turning research, RSM has been applied to model Ra, cutting forces, temperature and MRR and to quantify both main and interaction effects [1–6]. Asiltürk and Neşeli [1] combined a structured design with response-surface analysis for CNC turning of AISI 304 and reported that feed rate strongly controlled roughness. Routara et al. [2] similarly used RSM in CNC turning of EN-8 steel and validated quadratic models through ANOVA.

The statistical advantage of RSM is that it can describe curvature in a process response using fewer experiments than a dense full-factorial study. Makadia and Nanavati [3] demonstrated this for AISI 410 steel and showed that response contours can guide the selection of conditions for a required surface finish. Later work on stainless steels and aluminium-based materials further demonstrated the usefulness of quadratic models, desirability functions and ANOVA for turning optimization [4–9]. These studies establish a practical basis for a methodology in which the experimental region is deliberately selected, the model is checked for significance and lack of fit, and the predicted optimum is verified by confirmation runs.

The objective of the present paper is therefore to define a reproducible RSM-based methodology for CNC turning. The specific goals are: (i) to develop a CCD for three controllable machining factors, (ii) to fit a second-order equation for Ra and a productivity response, (iii) to identify statistically significant factors and interactions through ANOVA, and (iv) to determine a compromise parameter setting using desirability optimization. The scope is intentionally limited to dry longitudinal turning with a constant tool geometry and workpiece material so that the influence of the selected process parameters can be isolated.

Literature Review

RSM has a long record in machining because it converts experimental observations into an explicit mathematical relationship between inputs and outputs. In CNC turning of AISI 304, Asiltürk and Neşeli [1] modeled Ra and Rz and found that the predicted and experimental roughness values were closely aligned. Routara et al. [2] applied RSM and a genetic algorithm to EN-8 steel and used F-tests and ANOVA to establish the adequacy of the roughness model. Makadia and Nanavati [3] analyzed speed, feed, depth of cut and tool nose radius for AISI 410; their results identified feed as the leading factor for roughness, followed by tool nose radius, while the verification error remained small.

For martensitic stainless steel, response-surface studies have also considered a broader set of surface and force responses. Bouzid et al. [4] used a full-factorial design with ANOVA and RSM for AISI 420 and demonstrated that quadratic regression can represent the relationship between cutting conditions, force components and Ra. A related optimization study on AISI 420 also reported strong sensitivity of roughness to feed and used desirability-based optimization [5]. Khidhir et al. [6] developed RSM prediction models for AISI 1020 mild steel under dry turning and again found feed rate to be the most important factor affecting surface roughness, followed by cutting speed.

The method is not limited to steels. Gangil et al. [7] used RSM to study Al-7075 turning and modeled MRR and roughness, while Nataraj et al. [8] adopted a central composite rotatable design for an aluminium metal-matrix composite and optimized both surface finish and interface temperature. These studies indicate that CCD-type RSM designs are suitable when curvature is expected and when multiple responses must be balanced.

More recent studies before and during 2020 reinforced the industrial relevance of systematic turning optimization. Beemaraj and Mohan [9] optimized CNC turning parameters for IS2062 E250 steel using designed experiments and ANOVA, and Pandiyan and Prabaharan [10] applied CCD-based RSM to AA6351 turning with surface roughness as the principal quality response. Taken together, the literature supports three methodological choices used here: a three-factor design space, quadratic response equations, and confirmation of the predicted optimum through an independent test.

Methodology

1. Experimental system and factors

A methodology-oriented experiment is proposed for longitudinal dry turning of AISI 1045 medium-carbon steel bars, 40 mm in diameter and 120 mm in length, on a rigid CNC lathe. A TiN/TiCN-coated carbide insert with fixed nose radius is assumed throughout the experiment. Tool overhang, work holding, insert geometry and measurement procedure are maintained constant to minimize nuisance variation. The three controllable factors are cutting speed (V), feed rate (f) and depth of cut (d). Surface roughness Ra is selected as the primary quality response; MRR is retained as a productivity response so that the final optimum does not simply select the lowest material-removal condition.

Table 1. RSM factor levels for the proposed CNC turning experiment

Factor	Symbol	−α	−1	0	+1	+α	Unit
Cutting speed	V	100	120	150	180	200	m/min
Feed rate	f	0.10	0.14	0.20	0.26	0.30	mm/rev
Depth of cut	d	0.50	0.70	1.00	1.30	1.50	mm

The axial distance α is approximately 1.682 for a rotatable three-factor CCD. The actual values are rounded to practical CNC settings while preserving a symmetric experimental region.

2. Central composite design

For three factors, the CCD contains eight factorial points (±1), six axial points (±α) and six replicated center points, giving 20 runs. Center replication provides an estimate of pure error and improves the ability to detect lack of fit. Run order should be randomized to reduce bias from tool temperature, insert wear or machine drift. A fresh cutting edge should be used according to a predefined replacement rule, and the workpiece surface should be cleaned before roughness measurement.

3. Responses and measurements

After each pass, Ra should be measured using a calibrated contact profilometer at three equally spaced circumferential locations. The arithmetic mean of the three readings is used as the run response. MRR is calculated from the turning variables as MRR = 1000Vfd (mm^3/min), where V is expressed in m/min. When actual diameter reduction is available, the calculated value can be cross-checked from removed volume and machining time. Environmental and machine conditions should be documented because vibration and built-up edge can influence the measured roughness.

4. Statistical model

Each response is fitted to a second-order polynomial in coded variables: $Y = \beta_0 + \Sigma\beta_i x_i + \Sigma\beta_{ii} x_i^2 + \Sigma\beta_{ij} x_i x_j + \varepsilon$. Model significance is assessed using ANOVA at $\alpha = 0.05$. Adequacy criteria include a significant regression, non-significant lack of fit where replicated pure error is available, high adjusted and predicted R^2 values, and residuals that are approximately normal and structure-free. Terms with $p > 0.05$ may be removed hierarchically only if model heredity is preserved.

5. Optimization and confirmation sequence

The analysis is performed in seven linked stages, shown in Figure 1. First, the practical factor ranges are fixed from tooling recommendations and preliminary trials. Second, the CCD run matrix is generated and randomized. Third, the turning experiments are executed under controlled conditions. Fourth, Ra and MRR are obtained for every run. Fifth, quadratic RSM models are fitted. Sixth, ANOVA and residual diagnostics are used to decide whether the models are statistically credible. Finally, a numerical desirability function is used to minimize Ra while maximizing MRR inside the experimental region.

Figure 1. Proposed RSM-based workflow for optimizing CNC turning parameters.

6. Desirability formulation

For multi-response optimization, individual desirability values are assigned to Ra and MRR. The roughness desirability decreases from 1 toward 0 as Ra moves from the target minimum to an unacceptable upper limit. In contrast, MRR desirability increases with productivity. The overall desirability D is the geometric mean of the individual desirabilities. Equal response weights are appropriate for a balanced study; however, a production environment may assign greater importance to Ra for finish turning or to MRR for roughing.

7. Confirmation test

The predicted optimum is not accepted directly from the software. At least three confirmation runs should be performed at the optimized setting using the same tool-workpiece system. Prediction error is computed as |experimental − predicted|/experimental × 100. A prediction error below about 5–10%, together with stable repeated measurements, is considered evidence

that the fitted response surface is useful inside the studied region. The confirmation procedure is essential because a high R^2 alone does not guarantee reliable optimization.

8. Reproducibility controls

To improve reproducibility, the same insert grade and tool holder should be used throughout the design, run order should be recorded, the profilometer cutoff and evaluation length should remain fixed, and at least one center-point specimen should be rechecked at the end of the test sequence. These controls are consistent with the experimental discipline used in prior RSM turning studies [2–4,8,10].

Results

The following results are included to demonstrate how the proposed RSM workflow is interpreted. They are representative model-based values, not claims of completed physical experiments. In an implemented study, this section should be regenerated from measured CCD data.

Representative response model

Using coded variables x_1 (cutting speed), x_2 (feed) and x_3 (depth of cut), a representative roughness equation can be written as $Ra = 1.32 - 0.18x_1 + 0.71x_2 + 0.10x_3 + 0.08x_1x_2 + 0.05x_2x_3 + 0.07x_1^2 + 0.16x_2^2 + 0.04x_3^2$. The coefficient signs indicate that increasing feed raises Ra strongly, while increasing cutting speed over the selected range tends to reduce Ra. Curvature in the feed term indicates that the deterioration in finish accelerates at the upper feed levels.

Table 2. Representative ANOVA summary for surface roughness model

Source	df	F-value	p-value	Interpretation
Model	9	34.8	<0.001	Significant
Cutting speed, V	1	18.6	0.0015	Significant
Feed rate, f	1	164.2	<0.001	Dominant
Depth of cut, d	1	6.9	0.025	Significant
Two-factor interactions	3	3.4	0.062	Weak/moderate
Quadratic terms	3	8.1	0.004	Curvature present
Lack of fit	5	1.7	0.27	Not significant

The representative ANOVA pattern is consistent with the literature: feed is expected to exert the largest effect on Ra, while speed often has a secondary but meaningful influence [1,3,4,6]. A non-significant lack-of-fit result supports use of the quadratic model for interpolation within the selected factor ranges.

Optimization result

A balanced desirability search gives a representative compromise near V = 190 m/min, f = 0.14 mm/rev and d = 1.10 mm. The model predicts Ra ≈ 0.82 µm and MRR ≈ 29,260 mm^3/min, with an overall desirability of approximately 0.86. Selecting the absolute minimum feed could reduce Ra further, but would also lower productivity; the desirability solution therefore represents a more useful production compromise.

Table 3. Representative predicted and confirmation-style values

Response	Predicted	Representative confirmation	Error
Ra (µm)	0.82	0.85	3.5 %
MRR (mm^3/min)	29,260	28,900	1.2 %

Interpretation of response trends

At low-to-moderate feed, the theoretical feed marks produced by the tool nose are smaller, so Ra decreases. At excessive feed, deeper feed marks and greater cutting load degrade the surface. Higher speed can reduce built-up edge and improve finish, but this benefit may eventually be offset by thermal effects or accelerated tool wear. Increasing depth of cut primarily increases material removal and cutting load, so its influence on Ra is generally weaker than feed within a stable cutting region. These patterns agree with RSM turning studies on steels and metal-matrix materials [3,4,8,10].

Discussion

The principal advantage of the proposed methodology is that it treats CNC turning as an interacting system. One-factor-at-a-time testing can identify simple trends, but it cannot estimate curvature or interaction effects efficiently. CCD-based RSM resolves this limitation by combining factorial, axial and center points in a design that

supports a full quadratic model. This is especially useful in turning because feed, speed and depth of cut affect not only the magnitude of a response but also the physical cutting mechanism that produces it.

The literature reviewed in this paper shows a strong recurring result: feed rate is frequently the most influential variable for surface roughness [1,3,4,6]. That result has a physical basis because feed directly determines the spacing of successive tool marks, while nose radius and cutting stability determine how strongly those marks appear on the finished surface. Speed can improve finish by suppressing built-up edge in some materials, although the response is material- and tool-dependent. Depth of cut often contributes more strongly to MRR and cutting force than to Ra, but it should remain in the model because its interaction with feed and speed can become important at higher removal rates.

A second benefit of the RSM framework is the ability to balance quality and productivity rather than optimize Ra alone. For finish turning, a low feed may appear optimal if only roughness is considered. In practice, an extremely low feed lengthens cycle time. Desirability optimization allows a compromise by assigning simultaneous goals to Ra and MRR. This approach is consistent with turning investigations that considered multiple responses or combined response-surface models with additional optimization tools [2,7,8].

The methodology nevertheless has limitations. A quadratic surface is an approximation and should not be extrapolated outside the tested ranges. Tool wear, coolant strategy, chatter, material hardness variation and insert geometry are intentionally controlled rather than modeled. If these factors are important to the intended application, they should be introduced in a larger design or handled through blocking. The representative numerical results included here demonstrate the calculation sequence only; a publishable experimental paper must replace them with measured observations and report raw-run uncertainty.

Conclusion

A structured methodology has been developed for optimizing CNC turning parameters using Response Surface Methodology. The procedure uses a 20-run three-factor central composite design, quadratic regression, ANOVA, residual diagnostics, desirability optimization and confirmation testing. Cutting speed, feed rate and depth of cut are treated as controllable inputs, while Ra and MRR represent quality and productivity. Based on prior research and the representative analysis, feed rate is expected to dominate surface roughness, cutting speed to provide a secondary improvement over a practical range, and depth of cut to contribute strongly to productivity. The proposed framework reduces reliance on trial-and-error parameter selection and provides an auditable statistical basis for choosing operating conditions. For laboratory implementation, the key final step is to perform randomized CNC experiments and replace the representative result tables with measured values before drawing empirical claims.

References

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

Makadia, A. J., & Nanavati, J. I. (2013). Optimisation of machining parameters for turning operations based on response surface methodology. Measurement, 46(4), 1521–1529. https://doi.org/10.1016/j.measurement.2012.11.026

Bouzid, L., Yallese, M. A., Chaoui, K., Mabrouki, T., & Boulanouar, L. (2015). Mathematical modeling for turning on AISI 420 stainless steel using surface response methodology. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 229(1), 45–61. https://doi.org/10.1177/0954405414526385

Bouzid, L., Yallese, M. A., Belhadi, S., Mabrouki, T., & Boulanouar, L. (2014). RMS-based optimisation of surface roughness when turning AISI 420 stainless steel. International Journal of Materials and Product Technology, 49(4), 224–251. https://doi.org/10.1504/IJMPT.2014.064934

Khidhir, B. A., Al-Oqaiel, W., & Kareem, P. M. (2015). Prediction models by response surface

methodology for turning operation. American Journal of Modeling and Optimization, 3(1), 1–6. https://doi.org/10.12691/ajmo-3-1-1

Gangil, B., Kothiyal, P., & Kumar, S. (2016). Experimental investigation of machining process parameters in conventional turning of Al-7075 on MRR using response surface methodology. AIP Conference Proceedings, 1728, 020631. https://doi.org/10.1063/1.4946682

Nataraj, M., Balasubramanian, K., & Palanisamy, D. (2018). Optimization of machining parameters for CNC turning of Al/Al2O3 MMC using RSM approach. Materials Today: Proceedings, 5(6), 14265–14272. https://doi.org/10.1016/j.matpr.2018.03.008

Radha Krishnan, B., & Ramesh, M. (2020). Optimization of machining process parameters in CNC turning process of IS2062 E250 steel using coated carbide cutting tool. Materials Today: Proceedings, 21, 346–350. https://doi.org/10.1016/j.matpr.2019.05.460

Pandiyan, G. K., & Prabaharan, T. (2020). Optimization of machining parameters on AA6351 alloy steel using Response Surface Methodology (RSM). Materials Today: Proceedings, 33, 2686–2689. https://doi.org/10.1016/j.matpr.2020.01.369