



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

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Peer Review Information	Abstract
<i>Submission: 20 Jan 2017</i> <i>Revision: 05 Feb 2017</i> <i>Acceptance: 17 March 2017</i> Keywords <i>CNC turning, Surface roughness, Material removal rate, Taguchi method, Grey relational analysis</i>	This paper presents a structured experimental methodology for optimizing computer numerical control (CNC) turning parameters to obtain a low surface roughness while maintaining a high material removal rate (MRR). The proposed framework considers cutting speed, feed rate and depth of cut as controllable factors and uses a Taguchi L9 orthogonal array to reduce the number of machining trials. Surface roughness (Ra) is treated as a smaller-the-better response, whereas MRR is treated as a larger-the-better response. Signal-to-noise ratios and analysis of variance (ANOVA) are used to identify factor influence, and Grey Relational Analysis (GRA) combines the two conflicting responses into a single optimization index. A representative L9 dataset is included to demonstrate the analysis sequence; these values are illustrative and should be replaced by measured values when the proposed experiment is implemented. The demonstration identifies a high cutting speed, low feed and high depth of cut as a favorable compromise, with the highest Grey Relational Grade occurring at 200 m/min, 0.10 mm/rev and 1.5 mm depth of cut. The methodology provides a reproducible basis for selecting CNC turning conditions where both product quality and machining productivity are important.

Introduction

CNC turning is one of the most widely used material-removal processes for producing cylindrical components in automotive, aerospace, tooling and general engineering applications. The quality and cost of a turned component depend strongly on the selection of cutting parameters. Surface finish affects dimensional fit, fatigue behavior, friction, sealing and appearance, whereas material removal rate governs cycle time and productivity. These objectives are usually conflicting because an increase in feed or depth of cut can raise productivity but may also deteriorate the machined surface. Therefore, parameter selection should not be based only on a handbook value or operator experience; it should be supported by a systematic design of experiments and multi-response optimization.

Taguchi parameter design has been extensively used in turning because orthogonal arrays provide useful information with a limited number of trials. Yang and Tarng (1998) demonstrated that cutting speed, feed and depth of cut can be optimized through orthogonal arrays, signal-to-noise ratios and ANOVA. Nian et al. (1999) extended the approach to multiple turning performance characteristics, showing that a single optimum setting may require balancing several responses rather than optimizing each response independently. Later work also established that statistical response models and evolutionary methods can predict and optimize surface roughness (Suresh et al., 2002), while Taguchi-based studies on difficult and hardened materials confirmed the practical value of structured factor selection and

confirmation experiments (Davim, 2003; Aslan et al., 2007).

For the present study, the machining problem is formulated around three easily controllable variables: cutting speed (V_c), feed rate (f), and depth of cut (a_p). The main response for quality is arithmetic average surface roughness, R_a , and the productivity response is MRR. Because R_a should be minimized and MRR should be maximized, a multi-objective treatment is required. Grey Relational Analysis is suitable because it normalizes responses with different units and transforms them into one grade that can be ranked. This methodology paper therefore integrates Taguchi design, R_a measurement, MRR calculation, S/N analysis, ANOVA, GRA and a final confirmation test in a single workflow that can be implemented on a standard CNC lathe.

Literature Review

Early optimization research in turning established the statistical basis for selecting machining conditions. Yang and Tarng (1998) used Taguchi design to identify influential turning parameters and to obtain optimum cutting conditions for S45C steel. Their work showed that orthogonal arrays can efficiently screen process parameters and that ANOVA can quantify the relative contribution of each factor. Nian et al. (1999) addressed a more realistic multi-performance situation involving tool life, cutting force and surface finish, and demonstrated that Taguchi analysis can be extended beyond a single quality characteristic.

Surface roughness prediction has also been treated through mathematical modelling. Suresh et al. (2002) developed a second-order response surface model for surface roughness in turning mild steel and coupled the model with a genetic algorithm. Their study highlighted the importance of feed, cutting speed, depth of cut and tool nose radius, and showed that an empirical model can be used to search for optimum operating conditions. Davim (2003) applied Taguchi techniques, ANOVA and regression to turning a particle-reinforced metal-matrix composite, confirming the usefulness of statistically designed experiments for relating cutting conditions to surface roughness, tool wear and power.

The effect of turning parameters on hardened steels has been investigated in several studies. Aslan et al. (2007) optimized the turning of hardened AISI 4140 steels using a mixed ceramic tool and concluded that cutting speed, feed and depth of cut significantly influence flank wear and surface roughness. Asiltürk and Akkuş

(2011) used an L9 array in CNC hard turning of AISI 4140 and reported that feed rate was the most important factor for R_a and R_z . This observation is consistent with turning geometry: increasing feed increases the spacing and height of feed marks, causing a direct rise in theoretical and measured roughness.

A direct foundation for simultaneous R_a -MRR optimization was provided by Sahoo et al. (2012). They investigated AISI 1040 steel using a coated carbide insert, developed regression models for surface roughness and MRR, and then combined the responses through a Grey-based Taguchi procedure. Kaladhar et al. (2014) similarly used Grey Relational Analysis for CNC turning of AISI 304 stainless steel to optimize surface roughness, flank wear, tool vibration and MRR simultaneously. These studies show that GRA is especially useful when high productivity and high surface quality must be achieved together.

Research closer to the 2017 cutoff further strengthened the multi-response approach. Senthilkumar et al. (2015) combined grey analysis and fuzzy logic to optimize surface roughness, flank wear and MRR during turning of AISI 1045 steel. Debnath et al. (2016) used Taguchi design to study cutting-fluid conditions and cutting parameters and found feed rate to be a dominant contributor to surface roughness. Rao and Venkatasubbaiah (2016) also reported successful L9-based optimization of surface roughness in CNC turning. Finally, Surya et al. (2017) optimized MRR and surface roughness during dry and wet machining of EN19 steel using Grey Relational Analysis. Collectively, the literature supports a methodology in which feed is carefully controlled for finish, while cutting speed and depth of cut are adjusted to recover productivity.

Methodology

1. Workpiece, cutting tool and machine

The proposed experiment uses AISI 1040 medium-carbon steel bars of approximately 40 mm diameter and 150 mm machining length. A coated carbide CNMG insert with a nominal nose radius of 0.8 mm is mounted in a rigid tool holder. The experiments are performed on a CNC turning center under dry cutting conditions so that the influence of the primary machining parameters can be studied without introducing an additional coolant factor. Before every trial, the workpiece surface is cleaned by a light preparatory cut. A fresh cutting edge is used whenever visible edge damage is observed.

2. Selection of factors and levels

Three controllable factors are selected from the turning literature: cutting speed, feed rate and depth of cut. Each factor is set at three levels: $V_c = 100, 150$ and 200 m/min; $f = 0.10, 0.15$ and 0.20 mm/rev; and $a_p = 0.5, 1.0$ and 1.5 mm. These

ranges create sufficient variation to observe the quality-productivity trade-off without imposing extremely aggressive cutting conditions. A Taguchi L9 orthogonal array is used, reducing the full 3^3 factorial requirement from 27 runs to nine principal trials.

Table 1. Proposed CNC turning factors and levels

Factor	Symbol	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	a_p (mm)	0.5	1.0	1.5

3. Experimental sequence and surface roughness measurement

The nine L9 combinations are machined in randomized order to reduce the effect of time-dependent disturbances such as machine warm-up and gradual tool condition changes. After each turning pass, R_a is measured using a portable contact-type surface roughness tester. Three

readings are taken at different circumferential positions over the machined length and averaged. The cut-off length, traversing length and stylus settings are kept constant for all runs. This measurement strategy follows the repeated-measurement logic commonly used in CNC turning studies (Asiltürk & Akkuş, 2011; Debnath et al., 2016).

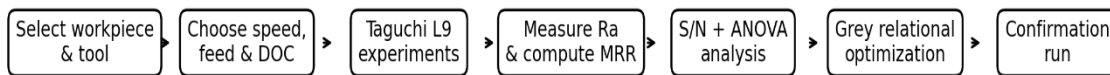


Figure 1. Proposed experimental and multi-response optimization workflow

4. Material removal rate

For turning, MRR is calculated from the product of cutting speed, feed and depth of cut. With V_c expressed in m/min, f in mm/rev and a_p in mm, the approximate volumetric material removal rate is: $MRR = 1000 \times V_c \times f \times a_p$ (mm³/min). This expression is suitable when the depth of cut is small relative to workpiece diameter and the programmed cutting speed represents the effective cutting velocity. MRR is treated as a larger-the-better response.

5. Taguchi signal-to-noise ratio and ANOVA

The S/N ratio for surface roughness is calculated using the smaller-the-better form, $S/N = -10 \log_{10}[(1/n)\Sigma(y_i^2)]$, whereas the larger-the-better form, $S/N = -10 \log_{10}[(1/n)\Sigma(1/y_i^2)]$, is used for MRR. Mean S/N values are computed at each factor level to identify the parameter setting that improves robustness. ANOVA is then applied to R_a , MRR and the final Grey Relational Grade to quantify the percentage contribution of cutting speed, feed and depth of cut. Statistical significance can be tested at a 95% confidence level.

6. Grey Relational Analysis

Because the two responses have different units and opposite optimization directions,

experimental results are first normalized to a 0–1 scale. For R_a , smaller-the-better normalization is used; for MRR, larger-the-better normalization is used. A Grey Relational Coefficient is then calculated from the deviation of each normalized result from the ideal value of 1, using a distinguishing coefficient of 0.5. Equal weights of 0.5 are assigned to R_a and MRR in the base methodology. The average of the two coefficients is the Grey Relational Grade (GRG). The run with the largest GRG is the best simultaneous compromise. If a production application values surface quality more strongly than productivity, unequal weights such as 0.6 for R_a and 0.4 for MRR can be adopted.

7. Confirmation and repeatability

After identifying the optimum factor levels from the GRG response table, a confirmation experiment is performed at the predicted optimum combination. At least three replicate confirmation cuts are recommended. The measured mean R_a , MRR and GRG are compared with the predicted values. A practical improvement is confirmed when the GRG exceeds that of the initial or middle-level parameter setting and the variation among replicate R_a measurements remains small.

Results

Because this is a methodology paper rather than a report of a completed laboratory campaign, Table 2 provides a representative L9 dataset only to demonstrate the calculation and decision

sequence. The Ra values are physically plausible for carbide turning in the selected range, while MRR is calculated directly from the programmed parameters. These demonstration values must not be presented as measured experimental data in a final empirical study.

Table 2. Representative L9 response data used to demonstrate the optimization procedure

Run	Vc (m/min)	f (mm/rev)	ap (mm)	Ra (μm)	MRR (mm^3/min)	GRG	Rank
1	100	0.10	0.5	0.68	5,000	0.600	5
2	100	0.15	1.0	1.12	15,000	0.479	8
3	100	0.20	1.5	1.88	30,000	0.485	7
4	150	0.10	1.0	0.60	15,000	0.691	2
5	150	0.15	1.5	1.15	33,750	0.635	4
6	150	0.20	0.5	1.71	15,000	0.388	9
7	200	0.10	1.5	0.58	30,000	0.818	1
8	200	0.15	0.5	0.98	15,000	0.515	6
9	200	0.20	1.0	1.68	40,000	0.686	3

The representative results show the expected trade-off between surface quality and productivity. The lowest Ra is obtained at run 7 (0.58 μm), where the cutting speed is high and feed is low. The largest MRR occurs at run 9 (40,000 mm^3/min), where cutting speed and

feed are both at their highest levels. However, run 9 does not provide the best surface finish. Grey Relational Analysis resolves this conflict by favoring a combination that is reasonably productive without sacrificing surface quality.

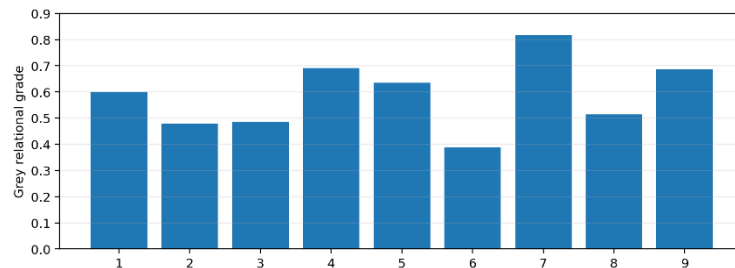


Figure 2. Grey Relational Grade for the representative L9 experiments

Run 7 produces the highest GRG of 0.818 and is therefore ranked first. Its setting is Vc = 200 m/min, f = 0.10 mm/rev and ap = 1.5 mm. The factor-level means of GRG indicate that the best levels are also high cutting speed, low feed and high depth of cut. A simple main-effect sum-of-squares calculation for the demonstration data assigns approximately 41.8% of GRG variation to feed, 25.1% to cutting speed and 24.8% to depth of cut, leaving about 8.4% as residual/interaction variation. This ranking is consistent with the literature: feed commonly dominates surface roughness, while speed and depth of cut help increase MRR (Sahoo et al., 2012; Senthilkumar et al., 2015; Surya et al., 2017).

For implementation, the confirmation run should be performed at the predicted optimum and compared against a baseline such as the middle-level combination. If the measured Ra remains

close to the predicted low value while MRR remains near 30,000 mm^3/min , the parameter set can be accepted. If chatter, excessive tool wear or thermal instability occurs, the process window should be narrowed and the L9 design repeated around the safe operating region.

Conclusion and Discussion

The proposed methodology provides a compact and reproducible route for optimizing CNC turning when the objectives are improved surface finish and increased material removal rate. The approach uses three primary machining variables—cutting speed, feed rate and depth of cut—and combines Taguchi L9 experimental design with surface roughness measurement, MRR calculation, S/N analysis, ANOVA and Grey Relational Analysis. This structure is supported by the turning literature published up to 2017,

which repeatedly shows that feed has a strong influence on surface roughness and that multi-response optimization is preferable when quality and productivity must be considered simultaneously (Yang & Tarng, 1998; Nian et al., 1999; Asiltürk & Akkuş, 2011; Kaladhar et al., 2014). Using the representative dataset, the best simultaneous setting is a high cutting speed of 200 m/min, a low feed of 0.10 mm/rev and a high depth of cut of 1.5 mm. This combination achieves the highest demonstration GRG because it preserves a fine surface while maintaining a comparatively high MRR. The result should be interpreted as a worked example rather than laboratory evidence. In an actual study, measured Ra values, replicated trials, tool wear observations and confirmation data must replace the illustrative values. Future extensions can include tool nose radius, coolant condition, cutting force, energy consumption and tool wear as additional responses. Nevertheless, the method is sufficiently simple for a university or industrial CNC laboratory and provides a clear statistical basis for process-parameter selection.

Practical limitations and implementation considerations

The method also has practical limitations that should be controlled during implementation. A Taguchi L9 array efficiently estimates main effects, but it does not fully resolve every interaction among cutting speed, feed and depth of cut. If the confirmation trial differs substantially from the predicted response, a second-stage response-surface design can be applied around the best L9 region. Tool wear should also be monitored because a worn edge may increase Ra even when the programmed cutting parameters are unchanged. Workpiece hardness, tool nose radius, machine rigidity, workholding, runout and ambient thermal conditions should therefore be maintained as consistently as possible. When comparing dry and wet turning, coolant condition should be treated as an additional factor rather than changed informally between trials.

For industrial use, the selected optimum must be checked against machine power, spindle-speed limits, insert recommendations, vibration and dimensional tolerance. The highest MRR is not automatically the most economical setting if it produces chatter or accelerates tool wear. Similarly, the lowest Ra may require a feed so small that cycle time becomes excessive. The Grey Relational Grade provides a transparent compromise, but its weighting should reflect production priorities. Equal weighting is suitable for a balanced study; a finish-critical component

may assign a larger weight to Ra, whereas a roughing operation may give more weight to MRR. Replicate confirmation tests and reporting of mean, standard deviation and percentage improvement are recommended before releasing the parameter set for routine production.

References

- Yang, W. H., & Tarng, Y. S. (1998). Design optimization of cutting parameters for turning operations based on the Taguchi method. *Journal of Materials Processing Technology*, 84(1-3), 122-129. [https://doi.org/10.1016/S0924-0136\(98\)00079-X](https://doi.org/10.1016/S0924-0136(98)00079-X)
- Nian, C. Y., Yang, W. H., & Tarng, Y. S. (1999). Optimization of turning operations with multiple performance characteristics. *Journal of Materials Processing Technology*, 95(1-3), 90-96. [https://doi.org/10.1016/S0924-0136\(99\)00271-X](https://doi.org/10.1016/S0924-0136(99)00271-X)
- Suresh, P. V. S., Venkateswara Rao, P., & Deshmukh, S. G. (2002). A genetic algorithmic approach for optimization of surface roughness prediction model. *International Journal of Machine Tools and Manufacture*, 42(6), 675-680. [https://doi.org/10.1016/S0890-6955\(02\)00005-6](https://doi.org/10.1016/S0890-6955(02)00005-6)
- Davim, J. P. (2003). Design of optimisation of cutting parameters for turning metal matrix composites based on the orthogonal arrays. *Journal of Materials Processing Technology*, 132(1-3), 340-344. [https://doi.org/10.1016/S0924-0136\(02\)00946-9](https://doi.org/10.1016/S0924-0136(02)00946-9)
- Aslan, E., Camuşcu, N., & Birgören, B. (2007). Design optimization of cutting parameters when turning hardened AISI 4140 steel (63 HRC) with Al₂O₃ + TiCN mixed ceramic tool. *Materials & Design*, 28(5), 1618-1622. <https://doi.org/10.1016/j.matdes.2006.02.006>
- 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>
- Sahoo, A. K., Baral, A. N., Rout, A. K., & Routra, B. C. (2012). Multi-objective optimization and predictive modeling of surface roughness and material removal rate in turning using Grey relational and regression analysis. *Procedia*

Engineering, 38, 1606–1627.
<https://doi.org/10.1016/j.proeng.2012.06.197>

Kaladhar, M., Venkata Subbaiah, K., & Srinivasa Rao, C. (2014). Simultaneous optimization of multiple responses in turning operations. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 228(7), 882–892.
<https://doi.org/10.1177/0954405413510915>

Senthilkumar, N., Sudha, J., & Muthukumar, V. (2015). A grey-fuzzy approach for optimizing machining parameters and the approach angle in turning AISI 1045 steel. *Advances in Production Engineering & Management*, 10(4), 195–208.
<https://doi.org/10.14743/apem2015.4.202>

Debnath, S., Reddy, M. M., & Yi, Q. S. (2016). Influence of cutting fluid conditions and cutting

parameters on surface roughness and tool wear in turning process using Taguchi method. *Measurement*, 78, 111–119.
<https://doi.org/10.1016/j.measurement.2015.09.011>

Rao, Ch. M., & Venkatasubbaiah, K. (2016). Optimization of surface roughness in CNC turning using Taguchi method and ANOVA. *International Journal of Advanced Science and Technology*, 93, 1–14.
<https://doi.org/10.14257/ijast.2016.93.01>

Surya, M. S., Shalini, M., & Sridhar, A. (2017). Multi-response optimization on EN19 steel using Grey relational analysis through dry & wet machining. *Materials Today: Proceedings*, 4(2), 2157–2166.
<https://doi.org/10.1016/j.matpr.2017.02.062>