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Optimization of Surface Roughness in Turning AISI 1045 Steel Using Taguchi L9 Design, ANOVA and Regression Modelling

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ABSTRACT: This paper optimizes surface roughness (Ra) of a workpiece AISI1045 machined on a lathe using the Taguchi methodology. Experiments followed an L9 (3^3) orthogonal array with three control factors at three levels each: cutting speed Vc (12.35, 19.42 and 28.27 m/min), depth of cut DOC (0.9, 1.6 and 2.0 mm) and feed rate F (0.15, 0.18 and 0.24 mm/rev). Ra was measured three times in every run. Smaller-the-better signal-to-noise (S/N) ratios, analysis of variance (ANOVA) and multiple linear regression were applied. Measured Ra ranged from 3.96 to 7.96 µm. DOC was the dominant factor (69.5% contribution), followed by Vc (18.2%) and F (10.8%), and increasing any of the three factors increased Ra. The best conditions at the optimum Vc = 12.35 m/min, DOC = 0.9 mm and F = 0.15 mm/rev gave a predicted Ra of 4.00 µm which was close to the measured Ra = 3.96 µm. However, the Ra of the worst run and mean of all runs were about 50% and 37% higher respectively. The regression model obtained excellent results; with R^2 = 98.02%, R^2(adj) = 96.83% and R^2(pred) = 92.75%; the residuals appeared to be a random pattern. All best settings were just under the edge of feasible region.

Keywords: **Taguchi method, surface roughness, turning, ANOVA, signal-to-noise ratio, regression model and depth of cut**

الملخص: تهدف هذه الورقة البحثية الى تحسين خشونة السطح (Ra) لقطعة فولاذ AISI1045 مشغلة على المخرطة تقليدية باستخدام منهجية تاقوتشي. حيث صممت التجارب وفق المصفوفة المتعامدة (3^3) L9 بثلاثة عوامل ضابطة وثلاثة مستويات لكل منها : سرعة القطع Vc (12.35 و19.42 و28.27 م/د)، وعمق القطع DOC (0.9 و1.6 و2.0 مم)، ومعدل التغذية F (0.15 و0.18 و0.24 مم/دورة)، وقيست Ra ثلاث مرات لكل تجربة. وتم اعتماد نسبة الاشارة إلى الضجيج من نوع (الأصغر هو الأفضل)، واجري تحليل التباين (ANOVA) لتحديد أي مستويات عوامل التشغيل اكثر تاثير على خشونة السطح ونسب مشاركة كل عامل في ذلك التاثير، ومن تم استنتج نموذج انحدار خطي متعدد لتنبؤ بقيم الخشونة وفق المدى المدروس. تراوحت القيم المقاسة لـ Ra بين 3.96 و7.96 µm واظهرت النتائج أن عمق القطع هو العامل الاشد تأثيراً (بمساهمة 69.5%) يليه سرعة القطع (18.2%) ثم معدل التغذية (10.8%)، وأن رفع أي من العوامل الثلاثة يزيد الخشونة. وتبين أن التوليفة المثلى Vc = 12.35 م/د و DOC = 0.9 مم و F = 0.15 مم/دورة تعطي Ra متوقعة قدرها 4.00 µm مقابل 3.96 µm مقاسة، أي انخفاضاً بنحو 50% قياساً بأسوء تجربة و37% قياساً بمتوسط التجارب. وسجل نموذج الانحدار R^2 = 98.02% و R^2(adj) = 96.83% و R^2(pred) = 92.75% دون انحراف ملحوظ في البواقي عن التوزيع الطبيعي. وتبين الدراسة أن المستويات المثلى تقع جميعها عند الحد الأدنى للمجال المدروس.

الكلمات المفتاحية **:طريقة تاقوتشي؛ خشونة السطح؛ الخراطة؛ تحليل التباين؛ نموذج الانحدار؛ عمق القطع.**

I. INTRODUCTION

Surfaces with different roughness levels directly influence factors such as wear and fatigue resistance, friction, sealing, assembling and service life, thus making it one of the most important

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quality indicators of machining parts [1]. In the context of machining, the roughness of a surfaced is a physical property quantifying how uneven the surface is, and is usually given as Ra, a metric standard established in the ISO 4287 [2]. Roughness of surfaces is an outcome of various factors and phenomena related to the cutting process, such as a cutting tool, a workpiece, and the machine tool, as well as cutting speed, feed rate and depth of cut, built-up edge, chatter, and tool ware [3]. A review article cited approximately twenty-five elements that were found to affect roughness in this paper. To predict roughness solely with the use of geometrical models remains a difficult task. As a result, well-thought experimental studies and testing remain crucial in order to determine and optimize cutting conditions in the field of machining.

Taguchi method [1,4] is an elegant way of achieving what we want by using orthogonal arrays that significantly decreases the number of experiments from twenty-seven to nine in case of three factors with three levels, the signal-to-noise (S/N) ratio is used as a quality measure which reflects the level of the response and the dispersion simultaneously, besides this it is also very useful to apply ANOVA to estimate the percentage of the contribution of each factor. It is very popularly being used in turning due to its ease of understanding and low costs [5–6].

The aims of the present study are: (a) to reveal the interaction or effect of Vc, DOC and F on Ra of the component turned on lathe; (b) to order the three variables according to the level of their statistical contribution; (c) to find out the machine setting resulting in the minimum Ra; (d) to develop a regression model based on experiments for surface roughness prediction and test its validity; (e) to compare these results with those of other researchers and put together a set of practical conclusions.

II. Literature Review

Taguchi L9 applications in turning. Several studies have optimized Ra with an L9 array. For AISI 4340 steel, Aydemir et al. [5] combined an L9 design with multiple linear regression and obtained R^2 = 98.05%, R^2(adj) = 96.10% and R^2(pred) = 90.09%, figures close to those of the present study. Putra et al. [7] built a similar linear model for aluminium 6063 (R^2 = 0.9115), and Zhujani et al. [8] used a Taguchi–grey relational approach to optimize several responses in turning Inconel 718.

Low-carbon steels and the dominance of depth of cut. For AISI 1045, Kriswanto et al. [6] reported that depth of cut was the most influential factor on Ra (45.21%). For AISI 4340, Juraev et al. [9] found depth of cut to be the most significant factor (48.2% of the variation in Ra) and observed that surface quality deteriorated sharply beyond about 0.7 mm owing to the onset of regenerative chatter.

Dominance of feed rate. Conversely, many studies report feed rate as the most influential factor, particularly in CNC finish turning: its contribution was 53.73% in [10], it ranked first in [11], it was about 50.4–54.5% in [12], and 90.35% in a study on C45 steel [13]. Çaydaş et al. [14] found cutting speed to be the most influential factor in AISI 1050 and depth of cut to be insignificant. This divergence shows that the ranking of factors depends on the material, the tool, the range of each factor and the stiffness of the system.

Conventional lathes and vibration. On a conventional lathe with an HSS tool and low-carbon steel, Fahrizal et al. [15] recorded a lowest Ra of 2.968 µm, much higher than the 0.46 and 0.713 µm recorded on CNC lathes in [10,12]. Machfuroh et al. [16] showed on a conventional lathe that Ra ranged from 2 to 6 µm under acceptable vibration but exceeded 10 µm under some conditions when vibration moved to a higher ISO 10816 zone, with evidence of mild regenerative chatter. Aktaş [17] observed in internal turning that the onset of chatter is governed mainly by cutting speed and that chatter alters the roughness profile; higher vibration has been reported to accompany rougher surfaces [18]; and a tool-holder overhang beyond a critical length sharply increases roughness [19]. In contrast, Nour Eldeen et al. [20] reported lower Ra for mild steel with higher spindle speed and smaller depth of cut and feed.

III. METHODOLOGY

A) Design of experiments

Three control factors at three levels each were selected (Table 1), and the experiments followed the L9 (3^3) orthogonal array, which needs nine runs and is balanced (each level appears three times in each column). Figure 1 shows the workflow from factor definition to verification of the optimum.

TABLE 1. CONTROL FACTORS AND THEIR LEVELS

Factor	Symbol	Unit	Level 1	Level 2	Level 3
Cutting speed	Vc	m/min	12.35	19.42	28.27
Depth of cut	DOC	mm	0.9	1.6	2.0
Feed rate	F	mm/rev	0.15	0.18	0.24

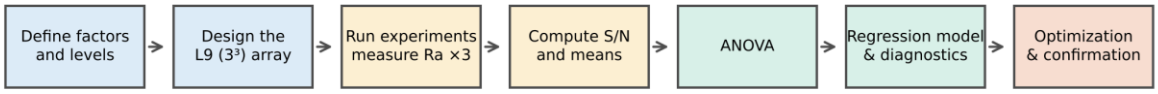


Figure 1. Methodological workflow

B) Experimental conditions and measurement

The experiments were carried out on an AL-PIN 180 N conventional centre lathe (Italy) with a power of 5.5 kW, machining an AISI 1045 steel bar of 15 mm diameter and 70 mm length with a carbide cutting tool in the presence of coolant. For the nominal 15 mm diameter, the three Vc levels correspond to spindle speeds of approximately 262, 412 and 600 rpm. Surface roughness Ra was measured with a Taylor Hobson Surtronic 3+ stylus profilometer according to ISO 4287 and ISO 4288 [2,21], taking three readings (R1, R2, R3) per run; their mean was used as the response. The instrument manual lists cut-off values of 0.8 and 2.5 mm as suitable for turning (Ra ≈ 0.4–6.3 µm), and ISO 4288 recommends a cut-off of 2.5 mm when Ra lies between 2 and 10 µm, as in this study (3.96–7.96 µm).

C) Analysis methods

Data were analyzed with Minitab 22 (Taguchi analysis and regression), and all results were independently recomputed in code to verify agreement. The smaller-the-better S/N ratio was used because the aim is to minimize Ra:

$$\eta = -10 \cdot \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} {y_i}^2\right) \quad (1)$$

where y are the Ra readings and n is the number of readings in a run (3). A higher (less negative) η indicates better performance. The percentage contribution of each factor to the total variation was computed as:

$$PCR_i = \frac{SS_i}{SS_T} \times 100\% \quad (2)$$

A multiple linear regression model was fitted by least squares:

$$Ra = \beta_0 + \beta_1 \cdot Vc + \beta_2 \cdot DOC + \beta_3 \cdot F + \varepsilon \quad (3)$$

Model adequacy was assessed with R^2, R^2(adj) and R^2(pred), F test, and residual diagnostics [21]. The predicted S/N ratio at the optimum was estimated from:

$$\eta_{opt} = \eta_m + \sum_{i=1}^{3}(\eta_{i,opt} - \eta_m) \quad (4)$$

To assess the productivity cost of quality, the material removal rate (MRR) was computed approximately as:

$$MRR = 1000 \cdot Vc \cdot DOC \cdot F \ (mm^3/min) \quad (5)$$

IV. RESULTS AND DISCUSSION

A) Experimental results

TABLE 2. L9 ARRAY, MEASURED RA AND S/N RATIO FOR EACH RUN

Run	Vc (m/min)	DOC (mm)	F (mm/rev)	R1 (µm)	R2 (µm)	R3 (µm)	Mean Ra (µm)	S/N (dB)
1	12.35	0.9	0.15	3.91	3.96	4.01	3.960	-11.95
2	12.35	1.6	0.18	5.98	6.05	6.12	6.050	-15.64
3	12.35	2.0	0.24	6.89	6.95	7.01	6.950	-16.84
4	19.42	0.9	0.18	4.65	4.70	4.75	4.700	-13.44
5	19.42	1.6	0.24	6.99	7.06	7.13	7.060	-16.98
6	19.42	2.0	0.15	6.82	6.88	6.94	6.880	-16.75
7	28.27	0.9	0.24	6.09	6.15	6.21	6.150	-15.78
8	28.27	1.6	0.15	6.43	6.50	6.57	6.500	-16.26
9	28.27	2.0	0.18	7.89	7.96	8.03	7.960	-18.02
						Total mean	**6.25**	**-15.74**

Table 2 and Figure 2 shows raw results. Ra ranged from 3.96 µm (run 1: lowest level of all three factors) to 7.96 µm (run 9: Vc = 28.27, DOC = 2.0, F = 0.18), so changing the cutting conditions doubled the roughness (ratio 2.01). The scatter among the three readings at the same location is small (standard deviation 0.05–0.07 µm, below 1.3% of the mean), showing good repeatability of the measurement itself, while the differences between runs exceed this scatter many times over,

which strengthens confidence in the conclusions on factor effects. All runs with DOC = 2.0 mm (3, 6 and 9) lie between 6.88 and 7.96 µm, whereas runs with DOC = 0.9 mm (1, 4 and 7) lie between 3.96 and 6.15 µm.

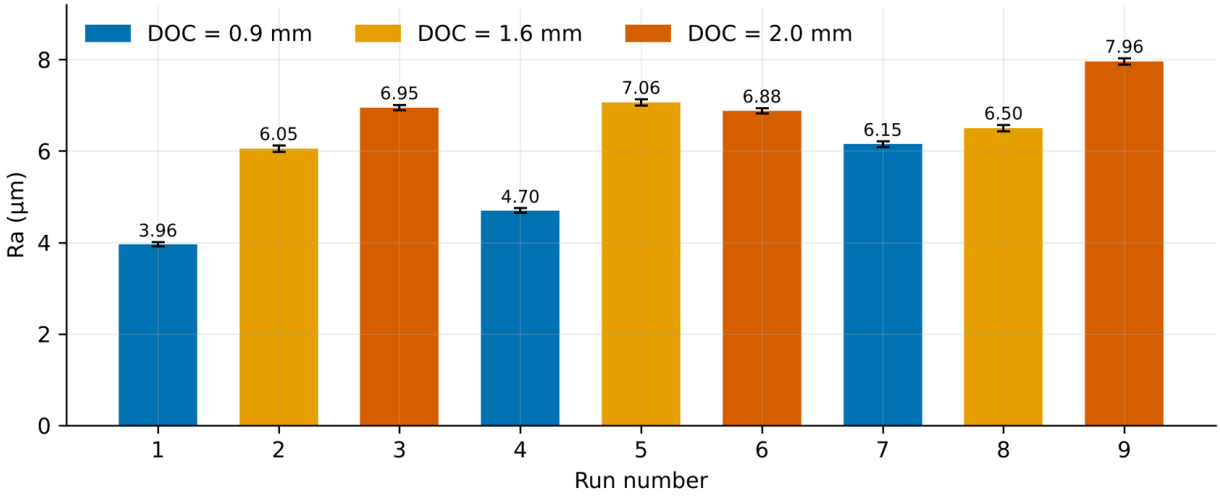


Figure 2. Measured Ra for each run

B) Signal-to-noise ratio analysis

TABLE 3. RESPONSE TABLE FOR S/N RATIOS (DB), SMALLER IS BETTER

Level	Vc	DOC	F
1	-14.81	-13.72	-14.99
2	-15.72	-16.29	-15.70
3	-16.68	-17.20	-16.53
Delta (Δ)	1.88	3.48	1.54
Rank	2	1	3

Table 3 and Figure 3 show that DOC has the largest range (Δ = 3.48 dB) and is ranked first, followed by Vc (1.88 dB) and F (1.54 dB). The S/N ratio decreases steadily as the level of each factor rises, so the best performance occurs at the first level of all three factors (Vc1 DOC1 F1): Vc = 12.35 m/min, DOC = 0.9 mm and F = 0.15 mm/rev. The drop between DOC = 0.9 and 1.6 mm (2.57 dB, about 3.7 dB per mm) is larger than that between 1.6 and 2.0 mm (0.91 dB, about 2.3 dB per mm).

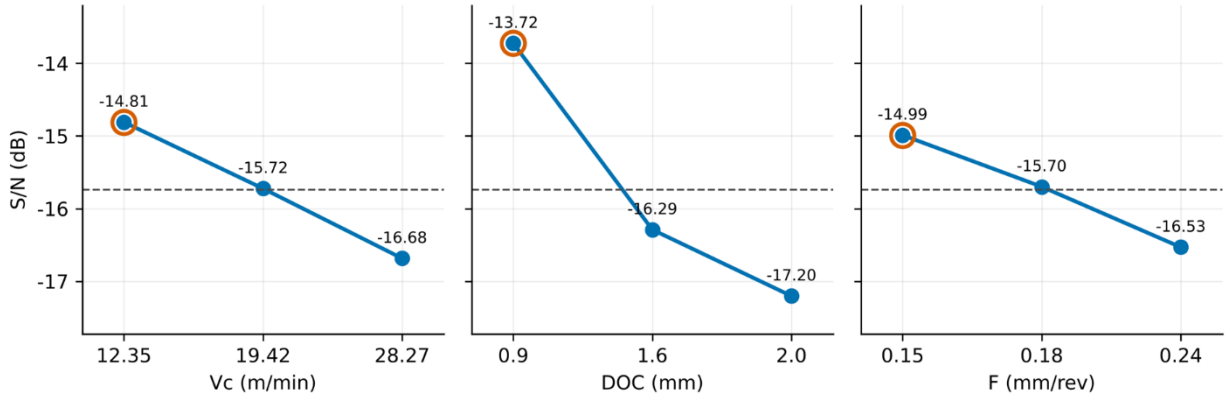


Figure 3. Main effects plot for S/N ratios (dashed line: total mean −15.74 dB).

4.3 Analysis of mean Ra

Table 4. Response table for mean Ra (µm)

Level	Vc	DOC	F
1	5.653	4.937	5.780
2	6.213	6.537	6.237
3	6.870	7.263	6.720
Delta (Δ)	1.217	2.327	0.940
Rank	2	1	3

The ranking of factors in the means table (Table 4, Figure 4) matches the S/N ranking. Raising DOC from 0.9 to 2.0 mm increases mean Ra by 2.33 µm (+47%), raising Vc from 12.35 to 28.27 m/min increases it by 1.22 µm (+22%), and raising F from 0.15 to 0.24 mm/rev increases it by 0.94 µm (+16%).

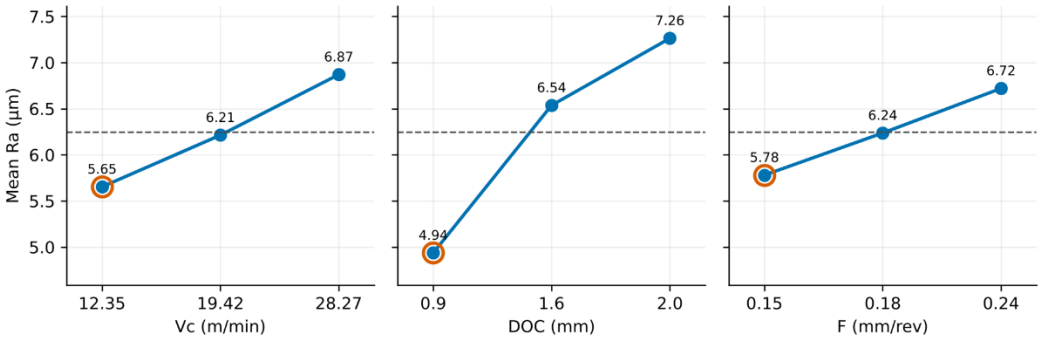


Figure 4. Main effects plot for mean Ra (dashed line: total mean 6.25 µm).

4.4 Analysis of variance (ANOVA)

Table 5. ANOVA for mean Ra (three-level factors)

Source	DF	Sum of squares	Mean square	F	P-value	Contribution %
Vc	2	2.2251	1.1125	12.81	0.072	18.20
DOC	2	8.5014	4.2507	48.93	0.020	69.54
F	2	1.3258	0.6629	7.63	0.116	10.84
Error	2	0.1738	0.0869	—	—	1.42
Total	8	12.2260				100.00

Table 5 shows that DOC accounts for about 69.54% of the total variation and is the only statistically significant factor at the 5% level (P = 0.020) in this analysis with two error degrees of freedom (DOF), while Vc approaches significance (P = 0.072). In the regression model (Table 6) all three factors become significant (P ≤ 0.004) because the linear model uses a single degree of freedom per factor and leaves five for error, which raises test power; this is acceptable here because the response is close to linear, as the main effects plots show. Both analyses agree on the ranking and on an error share of no more than about 2%, meaning that the three factors explain almost all of the variation and that interaction effects within the tested region are small.

Table 6. ANOVA of the regression model

Source	DF	Seq SS	Contribution	Adj MS	F-value	P-value
Regression	3	11.9841	98.02%	3.99468	82.55	<0.001
Vc	1	2.2243	18.19%	2.22432	45.96	0.001
DOC	1	8.4736	69.31%	8.47360	175.10	<0.001
F	1	1.2861	10.52%	1.28613	26.58	0.004
Error	5	0.2420	1.98%	0.04839		
Total	8	12.2260	100.00%			

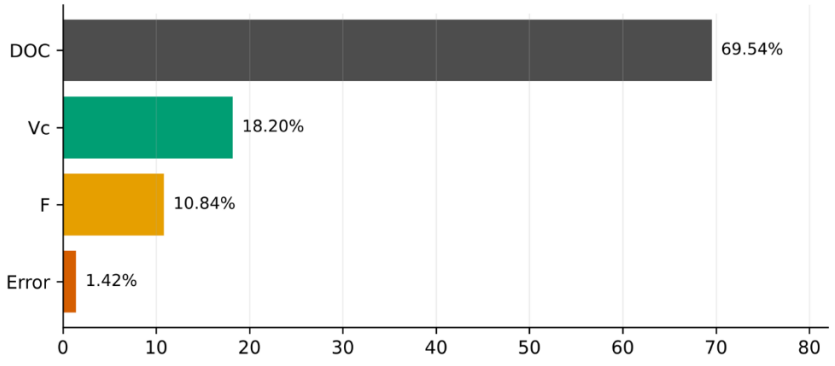


Figure 5. Contribution of each factor to the variance of Ra

4.5 Regression model and adequacy checks

Multiple linear regression on the mean Ra values gave the following equation ($R^2 = 98.02\%$):

$$Ra = -0.403 + 0.0763 \cdot Vc + 2.134 \cdot DOC + 10.10 \cdot F \quad (6)$$

Table 7. Regression coefficients

Term	Coefficient	Std. error	t-value	P-value
Constant	-0.403	0.503	-0.80	0.459
Vc (m/min)	0.0763	0.0113	6.78	0.001
DOC (mm)	2.134	0.161	13.23	<0.001
F (mm/rev)	10.10	1.96	5.16	0.004

The coefficients mean that Ra rises by 0.0763 µm per 1 m/min increase in Vc, by 2.13 µm per 1 mm increase in DOC and by 0.101 µm per 0.01 mm/rev increase in F. Over the tested ranges these correspond to changes of 1.21 µm for Vc, 2.35 µm for DOC and 0.91 µm for F, in line with the response tables. The constant is not significant (P = 0.459), as expected since it results from extrapolation to the origin, outside the experimental region. The high R^2(pred) of 92.75% indicates that the model does not suffer from obvious over-fitting despite the small number of observations (9 observations and 4 coefficients).

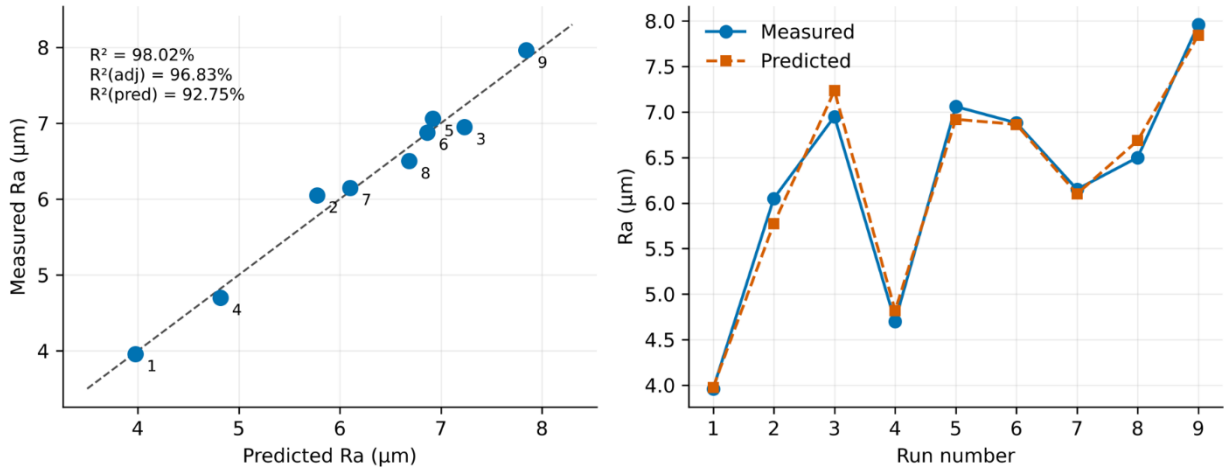


Figure 7. Model fit: (left) measured versus predicted Ra; (right) run-by-run comparison.

Normality plots (Figure 8) illustrate that the error values closely approximate the normal line (Shapiro, Wilk W=0.986, P=0.989), with no apparent pattern in the residuals against fitted values or by experimental run order. The highest value was only 0.68. The biggest standardized residual was 2.03 (run 3: predicted 7.23, measured 6.95).

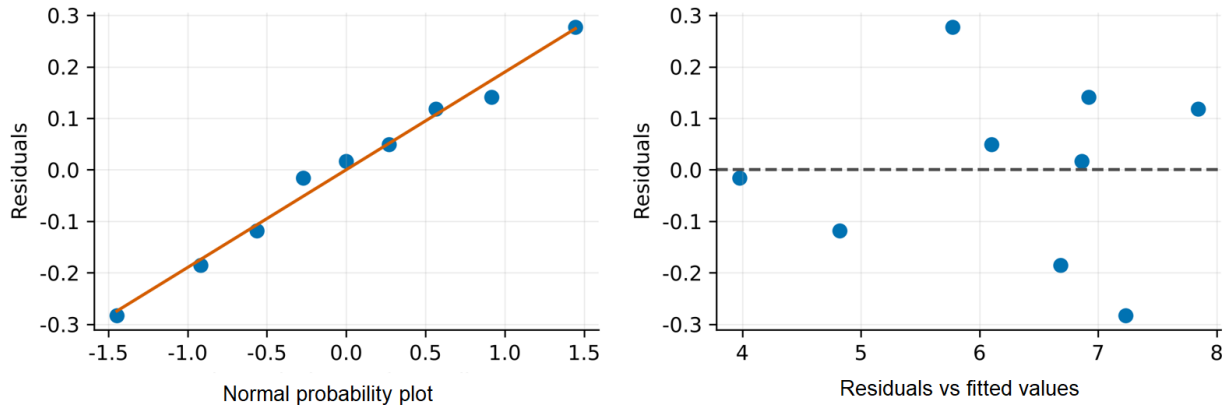


Figure 8. Residual diagnostic plots for the regression model.

4.6 Interpretation of factor effects

Depth of cut. This is the dominant factor (69.54%). Increasing DOC enlarges the chip cross-section and therefore the cutting forces (main and radial), which increases deflection of the workpiece and tool and favours self-excited vibration; this explains why the surface deteriorates as depth increases. It agrees with [6,9], which place DOC first, and with the sharp deterioration beyond about 0.7 mm caused by regenerative chatter reported in [9]. The DOC levels studied here start at 0.9 mm, above that threshold reported for a different material and tool, so an optimum at the lowest level is to be expected. The effect is probably aggravated by the relative slenderness of the workpiece (length-to-diameter ratio 70/15 ≈ 4.7), which makes it prone to bending under the cutting force unless supported by a tailstock centre; moreover, the workpiece diameter decreases by 2×DOC (up to 4 mm at DOC = 2.0 mm), so its stiffness falls progressively during the pass.

Cutting speed. Ra increased with Vc (from 5.65 to 6.87 µm). This is different from the conventional wisdom which connects higher cutting speed with smaller built-up edge and better surface [3,20], but in agreement with results that attribute to cutting speed a role in the initiation of chatter [17] and the caution of Yonicode et al. that excessive speeds might cause vibration [18]. The Vc range studied (12–28 m/min) is low in absolute terms.

Feed rate. This was the weakest factor (10.8%), contrary to many studies [10–13]. The most likely reason is that F varied over a relatively narrow range (0.15–0.24 mm/rev, i.e. 60%), whereas DOC varied by 122% and Vc by 129%; a factor's contribution depends on the width of the range studied. Moreover, the theoretical roughness produced by the tool geometry, $Ra \approx f^2/(32 \cdot r\varepsilon)$ [22], i s about 0.88–2.25 µm for an assumed nose radius $r\varepsilon = 0.8$ mm (the actual value was not recorded) (and 1.76–4.50 µm for $r\varepsilon = 0.4$ mm) over the F range studied, which is below the measured Ra (3.96–7.96 µm) in every run. The Hence, the roughness seen can be explained mostly to the dynamics at play and not just geometry which accounts also for the small contribution of F and confirms with literature that associate roughness and vibration in a conventional lathe [16,18].

4.7 Optimum setting and verification

The optimum combination Vc1 DOC1 F1 is part of the L9 array (run 1). According to Eq. (4), the predicted S/N ratio is $\eta = -15.74 + 0.93 + 2.01 + 0.75 = -12.04$ dB, i.e. a predicted Ra of 4.00 µm, whereas the measured S/N was −11.95 dB and the measured Ra 3.96 µm (error 1.0%). The regression model predicts 3.98 µm with a 95% confidence interval for the mean of [3.54, 4.41] µm and a 95% prediction interval of [3.26, 4.69] µm; the measured value falls inside both.

Table 8. Comparison of the optimum with reference values

Case	Vc	DOC	F	Ra (µm)	Difference from optimum
Optimum (run 1) – measured	12.35	0.9	0.15	3.96	—
Optimum – predicted (S/N)	12.35	0.9	0.15	4.00	+1.0%
Optimum – predicted (regression)	12.35	0.9	0.15	3.98	+0.4%
Worst run (9) – measured	28.27	2.0	0.18	7.96	+101%
Mean of the nine runs	—	—	—	6.25	+58%

Whereas the optimum was one of the L9 runs, the agreement between measured and predicted values is not an independent confirmation experiment, and a new confirmation run with randomized replicates is required. Also, because the optimal levels lie at the lower boundary of the region, the true optimum may lie outside it (most likely at lower DOC); what is called optimal here holds only within the tested region.

4.8 Trade-off between surface quality and productivity

For the optimal setting, the roughness (Ra) is reduced the most with the lowest value of material removal rate (MRR). This is represented for example by MRR of about 1667 mm^3/min which is 84% lower than run 9 at 10177 mm^3/min. Figure 9 compares the predicted Ra over MRR of all 27 combinations, the Pareto front shows that Ra is expected to always remain above 3.98 µm in this region, a gain in productivity always leads to a raise in roughness. The 4th run (Vc = 19.42, DOC = 0.9, F = 0.18) is a suitable example of a compromise: the measured Ra goes up by about 19% (4.70 µm), but the MRR is practically doubled (3146 mm^3/min, ×1.89) as this run still keeps the low DOC as the major governing factor for roughness and makes its gain in productivity through F and Vc which affect the final result to a very little degree. At last, the decision lies with the workshop aim: to have the best possible quality (run1) or a balanced solution (run4).

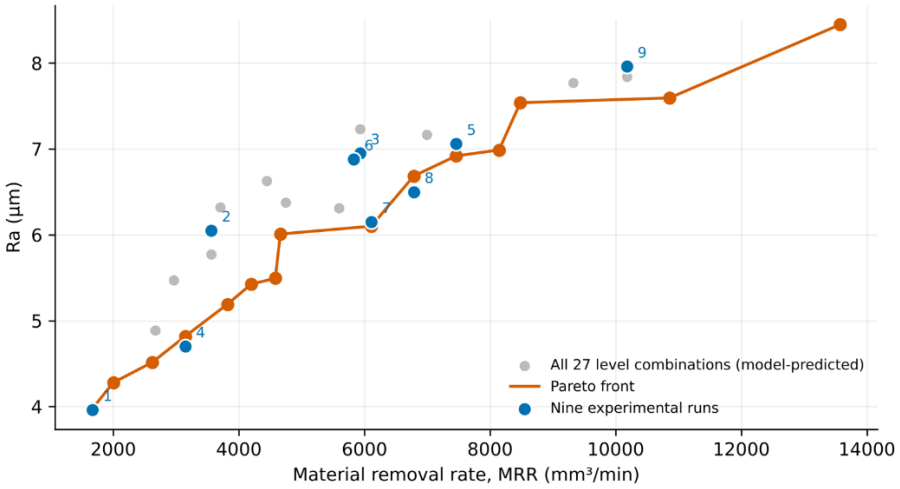


Figure 9. Trade-off between predicted Ra and calculated material removal rate (MRR).

4.9 Comparison with the literature

Table 9. Comparison of the present results with selected recent studies

Study	Material / tool	Most influential factor (contribution)	Remark
Present study	AISI 1045 / carbide / conventional lathe	DOC (69.5%), then Vc, then F	Ra 3.96–7.96 µm; R^2(pred) = 92.75%
Kriswanto et al. [6], 2025	AISI 1045 / CNC	DOC (45.21%)	L9 + ANOVA
Juraev et al. [9], 2026	AISI 4340 / TiAlN	DOC (48.2%)	Sharp deterioration beyond ≈0.7 mm (chatter)
Fahrizal et al. [15], 2022	Low-carbon steel / HSS / conventional lathe	Spindle speed (42.2%); F 20.3%; DOC 10%	Lowest Ra = 2.968 µm
Rifelino et al. [10], 2021	AISI 1045 / carbide	F (53.73%)	Lowest Ra = 0.46 µm
Huynh et al. [11], 2025	C45 / carbide	F, then Vc, then DOC	R^2 = 0.9985
Pham et al. [12], 2026	SAE 1215	F (50.4–54.5%)	Lowest Ra = 0.713 µm
Aydemir et al. [5], 2026	AISI 4340 / CNC	F (significant, P<0.001)	R^2(pred) = 90.09%

Table 9 shows that the present results agree with studies that place DOC first [6,9], where Juraev et al. attribute the effect to regenerative chatter at greater depths [9], and differ from studies in which F stood out [10–13], including CNC studies that recorded Ra below 1 μm [10,12]. The Ra level here (4–8 μm) is also closer to that observed on conventional lathes [15,16] than on CNC centres. The statistical quality of the model is comparable with that published in [5]. The comparison thus supports the interpretation that rough turning on a system with limited stiffness makes DOC and vibration the decisive factors.

5. Conclusions

1. Measured roughness, Ra, ranged between 3.96 to 7.96 micrometer. A high level of measurement repeatability was also observed (standard deviation between readings was 0.05–0.07 μm).
2. The effect of each factor can be ranked by the contribution: the depth of the cut DOC has the highest effect (69.5%), the cutting speed Vc the second (18.2%) and the feed rate Fr the last one (10.8%). Any increasing of this factor causes rising of the Ra value. The residual variability, or what's often called the statistical error varies approximately from 1.4% to 2%.
3. One optimal combination of parameters in the tested region is Vc = 12.35 m/min, DOC = 0.9 mm and F = 0.15 mm/rev, resulting in a measured Ra of 3.96 μm (4.00 obtained via S/N method and 3.98 from regression), a difference of about 50% from the worst result and 37% from the overall average.
4. The regression model $Ra = -0.403 + 0.0763 \cdot Vc + 2.134 \cdot DOC + 10.10 \cdot F$ is statistically sound ($R^2 = 98.02\%$; $R^2(pred) = 92.75\%$) with acceptable residuals.
5. There's an inverse relation between lower Ra at optimum and the MRR falling to around 1667 mm^3/min. With run no 4 you'd get both Ra and MRR (which will be Ra +19%, MRR ×1.89).

6. Recommendations

- Use DOC to its least extent (0.9 mm or less) in the finish passes to get the finest surface roughness and split up the material removal into several passes if there is any necessity rather than going for a single deep cut.
- The recommended setting with Vc = 12.35 m/min and F = 0.15 mm/rev will be optimal. In case of higher productivity requirement, you can use the combination of run 4 (Vc = 19.42, DOC = 0.9, F = 0.18) as a compromise.
- Increasing the stiffness of the system by reducing tool and workpiece overhang, using a tailstock center for support and double checking bearing and tool-post clearances, given the observed roughness is much higher than the theoretical geometric value.
- Vibration and cutting-force monitoring via a measure tool/machine (accelerometer) along with recording the surface roughness values (Ra) will be used for explaining the reason of increasing Ra with Vc. Moreover, tool wear status of the tools will be examined for each run by the use of tool wear microscope to ensure that it was changed from one run to the other

- Add further responses as (tool wear, power consumption) and also carry out multi-objective optimization using (GRA, TOPSIS).

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