IMPROVING SURFACE ROUGHNESS PREDICTION RELIABILITY USING TOOL WEAR-BASED MODELING

Van-Canh Nguyen[1], Dung Hoang Tien[1], Quang-Tu Ngo[1], Nguyen Chi Bao[1], Nguyen Thanh Cong[2], Nguyen Dang Kham[3]

DOI: https://doi.org/10.57001/huih5804.2026.119

ABSTRACT

Surface roughness prediction in turning is typically formulated as a function of cutting parameters, while progressive tool wear is often neglected. In machining of difficult-to-cut alloys, however, flank wear modifies effective cutting geometry and may reduce predictive reliability. This study evaluates the effect of incorporating flank wear (V_b) into surface roughness (R_a) prediction using a quadratic Response Surface Methodology (RSM) model. A Central Composite Design with 20 dry turning experiments was conducted. Two formulations were compared: a parameter-based model $R_a = f(V_c, f, a_p)$ and a wear-integrated model $R_a = f(V_c, f, a_p, V_b)$. Model performance was assessed using R^2 and Leave-One-Out Cross-Validation (LOOCV). The baseline model achieved $R^2 = 0.69$, whereas incorporating V_b increased R^2 to 0.95 and reduced LOOCV error by approximately 40%. The results demonstrate that tool wear significantly enhances prediction reliability and should be considered a state variable in surface roughness modeling.

Keywords: *Surface roughness; Tool wear integration; CNC turning; Inconel 718; Predictive reliability.*

[1]Hanoi University of Industry, Vietnam

[2]Department of Mechanical Engineering, National Kaohsiung University of Science and Technology, Taiwan

[3]Faculty of Mechanical Engineering, East Asia University of Technology, Vietnam

*Email: nguyenvancanh@haui.edu.vn

Received: 10/3/2026

Revised: 12/5/2026

Accepted: 25/5/2026

1. INTRODUCTION

Inconel 718 is widely used in aerospace applications due to its high strength and thermal stability, but its low thermal conductivity and strong strain hardening make it difficult to machine [1]. During turning, severe heat concentration and rapid tool wear frequently occur, significantly influencing surface integrity [2].

Surface roughness (R_a) is a key quality indicator affecting fatigue life and functional performance [3, 4]. Conventional predictive models typically describe roughness as a function of cutting parameters: model $R_a = f(V_c, f, a_p)$, where V_c, f, and a_p represent cutting speed, feed rate, and depth of cut. Such formulations are based on geometric surface generation theory and assume constant tool condition. However, in machining of superalloys, progressive flank wear (V_b) modifies the effective cutting edge geometry and increases tool-workpiece contact length. These changes intensify ploughing and frictional effects, causing deviations from purely kinematic predictions.

Neglecting tool wear may therefore reduce predictive reliability, particularly under extended cutting conditions. While many studies focus on parameter optimization, limited attention has been given to quantitatively evaluating the improvement in prediction accuracy when tool wear is incorporated into the model.

This study investigates whether integrating flank wear into a quadratic Response Surface Methodology (RSM) model significantly enhances surface roughness prediction [5]. Two formulations are compared: a parameter-based model $R_a = f(V_c, f, a_p)$, and a wear-integrated model $R_a = f(V_c, f, a_p, V_b)$. Model reliability is assessed using goodness-of-fit indicators and Leave-One-Out Cross-Validation (LOOCV) [6]. The objective is to determine whether tool wear acts as a necessary state variable for reliable roughness prediction in superalloy turning.

2. EXPERIMENTAL PROCEDURE

Turning experiments were performed on cylindrical Inconel 718 workpieces using a CNC lathe under dry cutting conditions. The experimental setup is illustrated in Figure 1. A CBN insert with a nose radius of 0.4mm was employed to ensure adequate thermal stability and wear resistance during machining of the superalloy. The workpiece was rigidly clamped using a hydraulic chuck to minimize vibration and maintain consistent cutting stability throughout the tests.

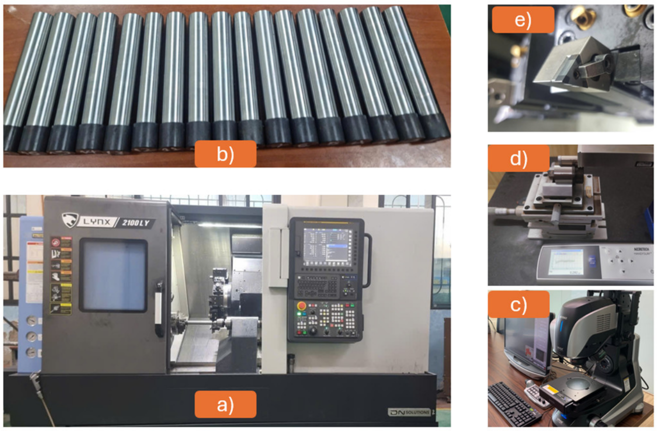


Figure 1. Experimental setup and measurement instruments used in the turning tests: (a) Doosan Lynx 2100LY CNC lathe; (b) Inconel 718 cylindrical workpieces; (c) Keyence VHX-7000 digital optical microscope for flank wear (VB) measurement; (d) Surface roughness tester; (e) CBN cutting insert used in the experiments.

A rotatable Central Composite Design (CCD) with 20 runs was adopted to investigate the effects of cutting speed (V_c), feed rate (f), and depth of cut (a_p). The investigated ranges were 60 - 160m/min for V_c, 0.05 - 0.15mm/rev for f, and 0.10 - 0.30mm for a_p. Surface roughness (R_a) was measured using a contact profilometer, and the average of three measurements per specimen was recorded. Flank wear (V_b) was quantified after each run using a digital optical microscope by measuring the average wear land width.

The complete experimental matrix and corresponding measured responses are summarized in Table 1. The dataset comprises 20 observations including cutting parameters, flank wear, and surface roughness, forming the basis for subsequent predictive modeling and reliability comparison.

Table 1. Experimental design matrix and measured responses

STD	Run	V_c (m/min)	f_z (mm/rev)	a_p (mm)	R_a (µm)	V_b (µm)
4	1	120	0.12	0.05	0.64	92.53
5	2	60	0.05	0.15	0.36	115.4
18	3	90	0.085	0.1	0.35	180.64
2	4	120	0.05	0.05	0.47	136.68
9	5	39.5462	0.085	0.1	0.46	67.51
14	6	90	0.085	0.18409	0.38	107.7
8	7	120	0.12	0.15	0.48	81.27
15	8	90	0.085	0.1	0.34	184.87
13	9	90	0.085	0.01591	0.44	101.96
10	10	140.454	0.085	0.1	0.27	215.8
1	11	60	0.05	0.05	0.22	110.22
3	12	60	0.12	0.05	0.59	45.41
16	13	90	0.085	0.1	0.31	180.14
12	14	90	0.14386	0.1	0.51	99.3
7	15	60	0.12	0.15	0.47	73.98
6	16	120	0.05	0.15	1.6	133.1
11	17	90	0.02614	0.1	0.59	112.8
19	18	90	0.085	0.1	0.32	194.06
20	19	90	0.085	0.1	0.32	184.89
17	20	90	0.085	0.1	0.3	174.34

3. MODELING STRATEGY

The objective of the modeling framework is to quantitatively evaluate whether incorporating tool wear (V_b) improves the predictive reliability of surface roughness (Ra). Two modeling strategies were therefore constructed and compared using the same experimental dataset.

3.1. Baseline Model (Parameter-Based)

The baseline formulation assumes that surface roughness is governed solely by cutting parameters: $R_a = f(V_c, f, a_p)$, where V_c is cutting speed, f is feed rate, and a_p is depth of cut. This formulation reflects classical kinematic surface generation theory, in which roughness is primarily determined by feed marks and tool nose geometry under the assumption of constant tool condition. In this approach, progressive tool wear is not explicitly considered, and the cutting edge is assumed to remain geometrically stable throughout the process.

3.2. Wear-Integrated Model

To account for tool degradation effects, an extended formulation was introduced: $R_a = f(V_c, f, a_p, V_b)$, where V_b represents flank wear.

The inclusion of V_b enables the model to capture the influence of evolving tool geometry and tribological conditions at the tool-workpiece interface. Since flank wear modifies effective edge radius, clearance angle, and contact length, it may explain part of the variability in surface roughness not captured by cutting parameters alone. The comparison between Sections 3.1 and 3.2 therefore allows direct quantification of the contribution of wear information to prediction performance.

3.3. Modeling Methods

In this study, surface roughness prediction was performed using Quadratic Response Surface Methodology (RSM). A second-order polynomial regression model was constructed to approximate nonlinear relationships within the experimental domain.

For the baseline formulation, the model was expressed as: $R_a = f(V_c, f, a_p)$, including linear, interaction, and quadratic terms of cutting speed (V_c), feed rate (f), and depth of cut (a_p).

To evaluate the contribution of tool wear, an extended formulation was developed: $R_a = f(V_c, f, a_p, V_b)$, where flank wear ($V_b$) was incorporated as an additional independent variable with corresponding linear, interaction, and squared terms.

The quadratic RSM framework enables explicit regression equations and statistical interpretability, allowing direct assessment of the incremental explanatory power introduced by V_b. The comparison between the baseline and wear-integrated models was conducted under identical experimental conditions to ensure fair evaluation of improvement.

3.4. Reliability Evaluation Metrics

Model performance was evaluated using both fitting accuracy and generalization indicators. The coefficient of determination (R^2) and adjusted R^2 were used to quantify explained variance while accounting for model complexity. The Root Mean Square Error (RMSE) was employed to measure average prediction deviation.

To assess predictive reliability, Leave-One-Out Cross-Validation (LOOCV) was adopted due to the limited dataset (20 experiments). In each iteration, one observation was excluded from model calibration and predicted using the remaining data. The mean squared prediction error was then computed.

Compared with training R^2 alone, LOOCV provides a more robust estimate of generalization capability. Therefore, reduction in LOOCV error when incorporating V_b is considered the primary indicator of reliability improvement.

4. RESULTS AND COMPARISON

This section quantitatively compares the predictive performance of the parameter-based RSM model and the wear-integrated RSM model. The objective is to determine whether incorporating flank wear (V_b) significantly enhances surface roughness prediction accuracy and reliability.

4.1. Baseline Model Performance (Without V_b)

The baseline RSM model formulated as: $R_a = f(V_c, f, a_p)$, yielded a coefficient of determination $R^2 = 0.6926$ with an adjusted $R^2 = 0.416$. The corresponding RMSE was 0.156 µm.

Although the model captured general roughness trends, residual dispersion was relatively large, particularly at higher Ra values. The low adjusted R^2indicates that the quadratic polynomial structure based solely on cutting parameters was insufficient to fully explain surface variability.

More importantly, Leave-One-Out Cross-Validation (LOOCV) revealed limited generalization capability. The cross-validation error remained high (≈ 0.25µm), indicating noticeable performance degradation when predicting unseen samples. This suggests that part of the surface roughness variability cannot be attributed solely to V_c, f, and a_p.

Overall, the baseline results demonstrate moderate fitting performance but limited predictive reliability when tool wear is not considered.

4.2. Wear-Integrated Model Performance

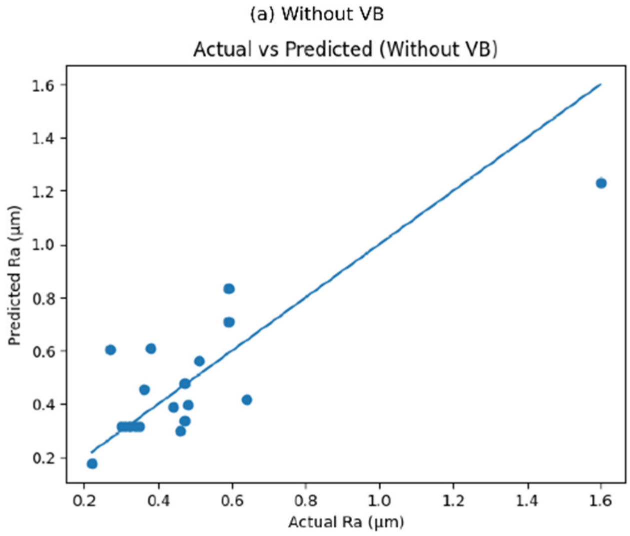
When flank wear was incorporated: $R_a = f(V_c, f, a_p, V_b)$, a substantial improvement in predictive capability was observed.

The wear-integrated RSM model achieved $R^2 = 0.954$ with adjusted $R^2 \approx 0.90$, representing an improvement of approximately 37% in explained variance compared to the baseline model. Residual dispersion was significantly reduced, and predicted values aligned more closely with experimental data across the entire roughness range.

More importantly, LOOCV error decreased from approximately 0.25µm to about 0.15µm, corresponding to nearly a 40% reduction in cross-validation error. This reduction confirms that V_b explains a considerable portion of previously unmodeled variability and enhances model generalization capability.

The inclusion of flank wear therefore stabilizes prediction behavior and reduces variance under evolving tool conditions.

The comparison between the two formulations is illustrated in Figure 2. The wear-integrated model shows significantly improved alignment with the 45° reference line, indicating enhanced predictive accuracy and stability.



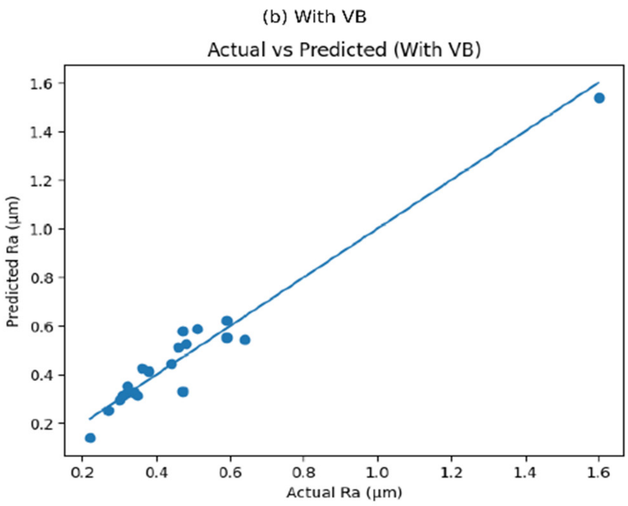


Figure 2. Comparison of actual and predicted surface roughness using RSM: (a) without flank wear (V_b); (b) with flank wear (V_b)

4.3. Comparative Summary

The improvement is not limited to goodness-of-fit indicators. The most significant enhancement appears in cross-validation performance, which reflects true predictive reliability. The substantial reduction in LOOCV error demonstrates that incorporating VB mitigates systematic bias associated with progressive tool degradation and improves robustness.

Table 2. Summarizes the key performance metrics

Model	R^2	Adjusted R^2	RMSE (µm)	LOOCV Error (µm)
RSM (without V_b)	0.69	0.42	0.156	0.25
RSM (with V_b)	0.95	0.9	↓	0.15

These results confirm that tool wear is a critical state variable for reliable surface roughness prediction rather than merely an auxiliary parameter.

4.4. Residual and Stability Analysis

The baseline model (without V_b) exhibited larger and unevenly distributed residuals, particularly at higher roughness values. Error magnitude increased with flank wear, indicating reduced stability under evolving tool conditions.

In contrast, the wear-integrated model produced more uniformly distributed residuals around zero with noticeably reduced variance. The decrease in LOOCV error confirms improved generalization capability. These results indicate that excluding VB leads to systematic prediction bias as tool wear progresses.

4.5. Interpretation of Improvement Mechanism

The observed improvement has a clear physical basis. Cutting parameters determine thermo-mechanical load, which drives flank wear progression. Flank wear subsequently modifies effective cutting edge geometry and tool-workpiece contact conditions, directly influencing surface formation.

Thus, surface roughness follows a state-dependent relationship:

$$V_c, f, a_p \rightarrow V_b \rightarrow R_a$$

By incorporating V_b, the model captures both geometric and tribological effects, reducing unexplained variance and enhancing predictive reliability.

5. CONCLUSIONS

This study examined the effect of incorporating flank wear (V_b) into surface roughness prediction for turning using a quadratic Response Surface Methodology (RSM) model. Two formulations were compared: a conventional parameter-based model $R_a = f(V_c, f, a_p)$ and a wear-integrated model $R_a = f(V_c, f, a_p, V_b)$.

Results show that excluding tool wear limits predictive reliability. The baseline model achieved moderate explanatory power ($R^2 = 0.69$) with relatively high cross-validation error. After incorporating V_b, R^2 increased to 0.95 and LOOCV error decreased by approximately 40%, demonstrating substantial improvement in generalization capability.

Residual analysis confirmed reduced prediction variance and elimination of systematic drift associated with progressive tool wear. These findings indicate that surface roughness in superalloy machining is strongly influenced by the evolving wear state rather than solely by cutting parameters.

Overall, integrating tool wear into the RSM framework significantly enhances prediction stability and reliability, supporting V_b as a necessary state variable for robust surface roughness modeling.

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