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Performance Evaluation in Dry and Wet Cutting Conditions on Inconel 718 Using a Lathe CNC Machine

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ABSTRACT

This study compared the performance of dry and wet machining on Inconel 718, then optimised the wet machining parameters by examining tool wear and surface roughness. Inconel 718 is renowned for its exceptional hardness and high heat resistance, which makes machining challenging. This research aims to analyse the machining performance in dry and wet cutting, then optimise the machining parameters to achieve lower tool wear and surface roughness. The experiment was conducted using coated carbide inserts while studying three independent variables: cutting speed (*Vc*) varying from 30 to 100 m/min, feed rate (*fz)* from 0.03 to 0.07 mm/rev, and depth of cut maintained constant at 1 mm. Experimental results demonstrate that wet cutting achieved a 57.14% superior surface finish compared to dry cutting. However, the minimum tool wear rate was achieved with both cutting methods at different cutting speeds (wet at 30 m/min and dry at 100 m/min). The optimisation results showed that wet cutting conditions utilise a low *Vc* (30 m/min) but differ in *fz*, where a low *fz* (0.03 mm/rev) is optimal for achieving the best surface quality. In comparison, a high *fz* (0.07 mm/rev) is suitable for maximising productivity with better tool life. Findings show that wet cutting conditions produce low surface roughness (*Ra*) through low *Vc* and *fz*, while high *fz* is suitable for long cutting tool life.

INTRODUCTION

Inconel 718 is a nickel-based superalloy extensively employed across aerospace, nuclear, and oil & gas sectors due to its outstanding mechanical properties, exceptional corrosion resistance, and remarkable

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dimensional stability at elevated temperatures. These properties make Inconel 718 a prime choice in components such as turbine blades, aircraft brake discs, and high-pressure moulds (Shard et al., 2021). Inconel 718, with its high hardness and exceptional heat resistance, is a very challenging material to machine. These characteristics have led it to be categorised as a “difficult to machine” material (Gong et al., 2023; Darsin et al., 2025). Due to these challenges, even the use of modern machining methods, such as computer numerical control (CNC) lathes, often results in severe and rapid tool wear (*VB*) if the correct parameters are not employed. The high temperatures generated in the cutting zone accelerate this wear, drastically reducing tool life. In machining operations, the elevated temperatures within the cutting zone typically surpass 800–1000°C due to frictional heat generation, intensifying tool wear mechanisms such as adhesive, abrasive, and diffusive processes, thereby substantially diminishing the durability and overall service life of cutting tools (Azhar et al., 2020). As a result, machining Inconel 718 without optimal machining parameters can result in poor surface quality and compromise the integrity of the resulting component.

The main challenges in machining Inconel 718 are rapid wear on the cutting tool, high cutting temperatures due to friction between the cutting tool and the material, and poor surface finish quality when machining parameters are not correctly optimised. To mitigate these machining issues, various cooling systems have been introduced, including flood cooling, minimum quantity lubrication (MQL), and cryogenic cooling (Darsin et al., 2025). Among the most common approaches is the wet machine, which utilises water, oil-based coolants that can absorb heat and reduce friction between the tool and the workpiece (Ogedengbe et al., 2019; Lei et al., 2023). This method has proven to increase tool life and produce better surface quality. However, excessive use of coolants raises concerns, including environmental pollution, high costs associated with chemical waste disposal, and health risks to machine operators (Kumar et al., 2022; Radchenko et al., 2024). Although several studies have been conducted on the machining performance of Inconel 718 using various cooling strategies, a direct comparison between dry and wet cutting performance in terms of critical parameters such as *Ra* and *VB* has not yet been thoroughly studied, especially in the context of machining using CNC turning. In addition, analysis based on response surface methodology (RSM) through central composite design (CCD) also needs to be explored and analysed, and the results can be shared with the industry to guide machining operators. This knowledge gap is crucial to fill, given the urgent need in the manufacturing industry to optimise machining processes.

The objective of this study is to compare cutting conditions between dry and wet conditions with various combinations of machining parameters, including *Vc* and *fz*, on Inconel 718. In addition, this study aims to evaluate the effects of various machining parameters on the surface quality of the workpiece to achieve minimal *VB* and uniform *Ra*. This study uses Response Surface Methodology (RSM) as an effective statistical tool to model and analyse the relationship between machining parameters and response variables, namely, *VB* and *Ra*. This approach enables researchers to understand how the simultaneous combination of factors, such as Vc and *fz*, affects machining results. Through RSM, mathematical equations can be constructed to predict machining performance within the range of parameters studied. Additionally, RSM minimises the number of experiments required, making it a more cost- and time-efficient approach compared to other methods. Ultimately, this method helps identify the optimum point where tool life is maximised and the desired surface quality can be achieved (Reji & Kumar, 2022; Suhaimey et al., 2025). The use of RSM is crucial because it not only allows for the simultaneous optimisation of parameters but also facilitates an understanding of the interactions between different factors, thereby providing a systematic and efficient approach to achieving the study’s objectives (Manoj et al., 2022; Sai et al., 2023).

Future studies could broaden the scope of the variables by investigating the effects of using different coolants, such as minimum quantity lubrication (MQL) and cryogenic, on tool life and surface quality. To improve accuracy and efficiency, IoT integration is proposed to enable real-time monitoring of machining parameters such as tool tip temperature, vibration, and cutting force (Marwal et al., 2024; Kasiviswanathan et al., 2024). Data from these sensors will be used to analyse the direct correlation between machining parameters, *VB* rates, and surface quality outcomes such as *Ra*. This analysis, when combined with artificial

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intelligence (AI) methods, will enable the prediction and automatic identification of the optimal machining parameters. This will enable the system to respond adaptively to changing machining conditions, thereby providing a more comprehensive, sophisticated, and automated model for optimising the Inconel 718 machining process.

EXPERIMENTAL PROCEDURE

The study began by comparing dry and wet cutting conditions for Inconel 718, with *VB* and *Ra* measured. Statistical analysis was then applied to the wet cutting data to identify optimal machining parameters. These parameters were later verified to confirm their effectiveness. The overall process is illustrated in Fig. 1.

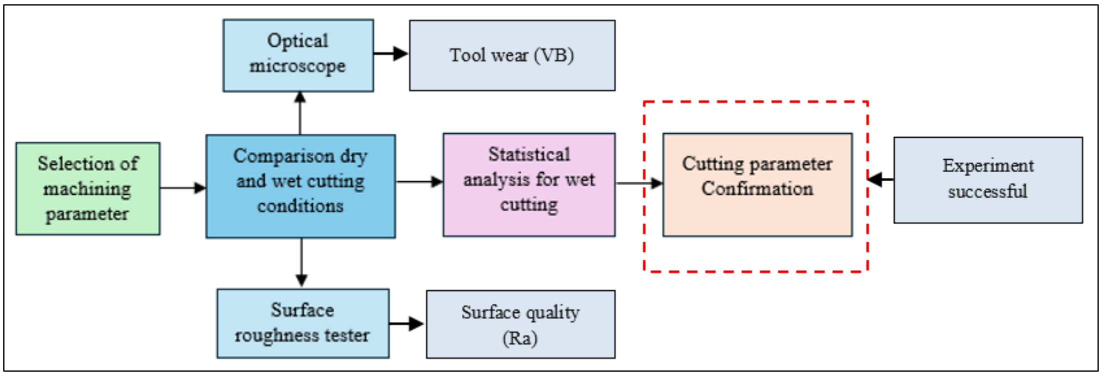

Fig. 1. Flow diagram of research methodology.

Material

Inconel 718, a Ni-Cr-Fe superalloy commonly used in aerospace applications, was selected for this study due to its high strength, corrosion resistance, and high-temperature performance. However, it is difficult to machine due to its low thermal conductivity, high work-hardening rate, and high cutting forces. The experiment used a cylindrical workpiece measuring 50 mm in diameter and 220 mm in length, with a density of 8.19 g/cm^3 and a hardness of about 45 HRC. Table 1 presents the detailed physical properties of Inconel 718 used in this research.

Table 1. Inconel 718 properties

Hardness (HRc)	Melting point (°C)	Yield strength (MPa)	Tension strength (MPa)
48	1350	490	820

This study used a Doosan 3-axis CNC Turning Centre with a Fanuc 10i controller to ensure high accuracy, repeatability, and consistent machining conditions. Wet machining was performed with an 8% water-emulsion coolant at 4 bars, while dry machining was performed without coolant. Cutting parameters, including *Vc*, *fz*, and a constant ap, were applied, as listed in Table 2.

Cutting tool and machine parameters

Fig. 2(a) shows the TiAlN-coated carbide inserts (CNMG120408) on ISO-standard tool holders, which were selected for their heat and wear resistance, making them suitable for machining Inconel 718. A total

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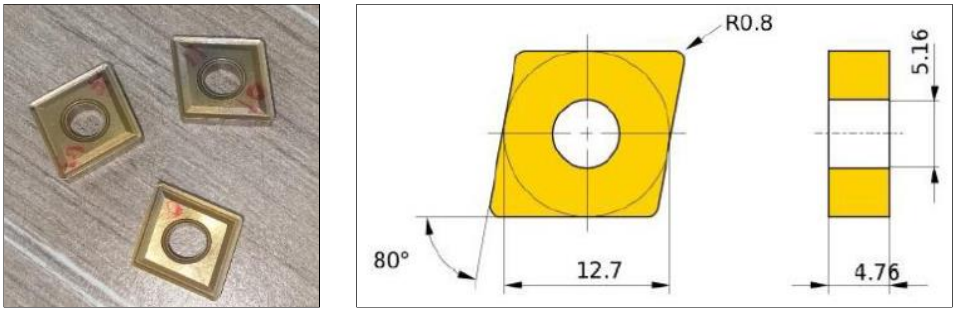
of three cutting tools were available, each capable of performing 11 machining tests. The detailed tool specifications are provided in Fig. 2(b).

Table 2. Machining parameters for comparing dry and wet cutting conditions

Parameters	Values
Vc	30, 65, 100 m/min
fz	0.05 mm/rev
ap	1 mm
Cutting length	220 mm
Machining conditions	Wet and dry



(a) (b)

Fig. 2. (a) Carbide cutting tool and (b) specification of CNMG120408.

Ra was measured using a Mitutoyo SJ-210 profilometer in accordance with ISO 4287 and 4288, while *VB* was recorded at 220 mm intervals using a Dino-Lite microscope in accordance with ISO 3685. Basic statistical analyses and comparative evaluations were performed, and optimal wet-machining parameters were determined using Design-Expert 13 via response surface methodology (RSM) on a central composite design (CCD). The parameter ranges used were 30–100 m/min for *Vc*, 0.03–0.07 mm/rev for *fz*, and a constant ap of 1 mm, with the generated RSM parameters shown in Table 3.

Table 3. The parameters suggested by RSM are based on the range

Run	*Vc* (m/min)	*fz* (mm/rev)	*ap* (mm)
1	65	0.05	1
2	30	0.07	
3	65	0.03	
4	30	0.03	
5	65	0.05	
6	30	0.05	
7	100	0.05	
8	100	0.03	
9	65	0.05	
10	65	0.07	
11	100	0.07	

RESULTS AND DISCUSSION

This section details the experimental findings from the machining of Inconel 718 carried out under dry and wet cutting conditions. The primary evaluation focuses on two critical metrics: Ra and average *VB*. The study begins by comparing the machining performance under both conditions. Initial comparative analysis shows that wet machining significantly reduces *VB* and produces lower Ra compared to dry machining. Based on these findings, the subsequent study focuses entirely on wet machining using Response Surface Methodology (RSM) to optimise machining parameters and achieve the lowest values of *VB* and Ra.

VB **and** ***Ra*** **comparison in wet and dry conditions**

Fig. 3(a) shows a comparison of Ra values for dry and wet machining, with changes in *Vc* (30, 65, and 100 m/min), while *fz* and depth of cut are kept constant at 0.05 mm/rev and 1 mm, respectively. Generally, wet machining consistently produces lower Ra values. This is particularly evident at low *Vc* (30 m/min), where the Ra reduction can reach up to 57.14%. This phenomenon highlights the crucial role of coolant in reducing friction and preventing the formation of microcracks on the material's surface. However, at higher *Vc* (100 m/min), it is found that Ra values for dry machining are better. This improvement is attributed to the formation of a stable built-up edge (BUE), which effectively enhances Ra quality in dry cutting conditions. This situation emphasises that no single cutting method is universally superior; rather, the performance is highly dependent on the combination of machining parameters used. Therefore, a deep understanding of the interaction between machining parameters and cutting conditions is essential to achieve optimal results (Redhwan et al., 2024). Supporting this, an experimental study on dry turning of mild carbon steel found that increasing *Vc* reduces built-up edge (BUE) formation, leading to improved Ra (Jomaa et al., 2014; Faiz et al., 2019; Mohd Ghazali & Rahiman, 2021). Additionally, higher *Vc* in dry machining can lead to thermal softening of the workpiece material, resulting in smoother chip flow and reduced Ra (Song et al., 2019). However, while high *Vc* in dry machining can accelerate the process, it also has the potential to impact the surface quality and dimensional accuracy of the produced components. Therefore, a careful balance between *Vc* and other parameters is essential to avoid these risks.

Fig. 3(b) shows the significant difference in wear patterns observed between wet and dry machining for all three *Vc* tested. Specifically, at low speed (30 m/min), dry machining recorded higher *VB* values (0.22 mm) compared to wet machining (0.16 mm). This proves that the presence of cutting fluid provides effective cooling and lubrication, thereby reducing friction and temperature in the cutting zone. The use of water-soluble cutting fluid can extend the life of the cutting tool compared to dry machining due to the better lubrication and cooling effects (Pawanr & Gupta, 2024). At a medium speed of 65 m/min, both machining methods showed an increase in *VB* values, with dry machining reaching a maximum value of 0.26 mm while wet machining increased to 0.19 mm. However, at a high speed of 100 m/min, *Vc*, the opposite pattern was observed, with both machining methods showing a decrease in *VB* values. Dry machining recorded 0.16 mm, a significant reduction of 61.5% compared to wet machining, which only decreased to 0.20 mm. This phenomenon was attributed to the high thermal effects at extreme *Vc*, which caused thermal softening of the Inconel 718 chip. These conditions are consistent with the theory that optimal selection of cutting parameters is critical in machining superalloys (Basmacı, 2023; Liu et al., 2024).

Higher *Vc* consistently increases *VB* under wet cutting conditions due to elevated temperatures in the cutting zone, which accelerate *VB* through thermal softening of the cutting edge. At high *Vc*, the friction between the tool and the raw material becomes more intense, thus accelerating wear mechanisms such as abrasion and diffusion, as reported in various modern machining studies (Azhar et al., 2024). A comparison of these two conditions found that dry machining dominated with high *VB*; this was due to a combination of excessive friction and extreme cutting zone temperatures (up to 288 °C) (Zhang et al., 2023), and metal workpiece interactions at high temperatures, resulting in adhesive wear, diffusion wear, and in some

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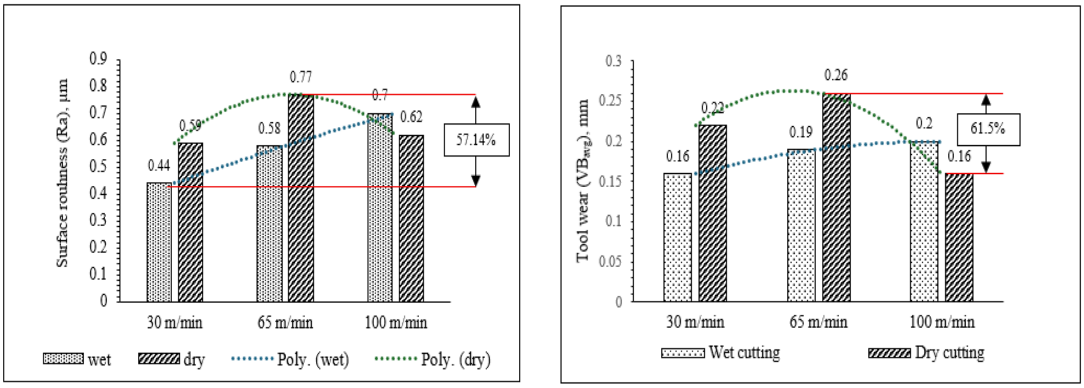
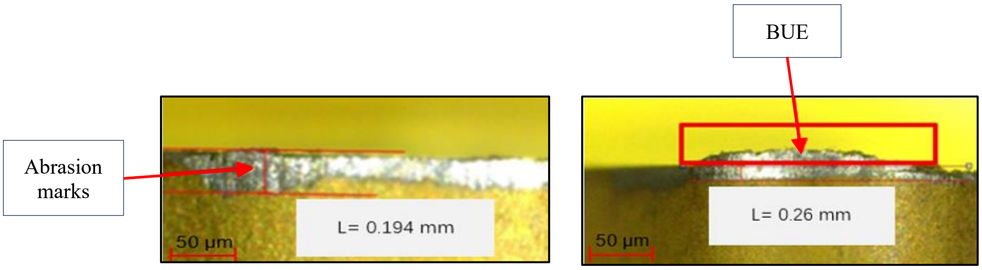
instances, the occurrence of oxidation wear (Xu et al., 2021; Aniołek et al., 2021). Fig 4(a) shows uniform abrasion marks in wet machining. Flank wear in turning cutting tools is predominantly governed by abrasive mechanisms, whereby hard asperities and inclusions within the workpiece material progressively remove tool material along the flank face, leading to measurable wear land formation as observed through image processing techniques (Junior et al., 2020). Whereas Fig. 4(b) displays built-up edge (BUE) with a cutting tool in dry conditions. This phenomenon occurs because in Inconel 718 machining, high cutting temperatures accelerate the diffusion of metal elements from the cutting tool to the workpiece, thereby compromising the cutting tool's integrity.



(a) (b)

Fig. 3. Comparison of dry and wet cutting conditions at 0.05 mm/rev *fz* for (a) *Ra* and (b) *VB*.



(a) (b)

Fig. 4. Wear characteristics between (a) wet and (b) dry cutting conditions at 100 m/min Vc.

The comparison between wet and dry machining clearly shows that wet machining dominates with the lowest Ra. However, dry machining is comparable to wet cutting at different *Vc*: 30 m/min for wet cutting and 100 m/min for dry cutting. This indicates that although wet machining consistently yields a superior surface finish, dry machining can achieve a comparable *VB* when operated at a much higher cutting speed.

Optimisation of wet cutting conditions

Table 4 shows the results of experiments conducted with cutting parameters generated by the RSM method. Each combination of parameters, including *Vc*, *fz*, and *ap*, was tested to evaluate its effect on the two main responses, namely *VB* and *Ra*. The data obtained showed apparent variations in *VB* and *Ra*, reflecting the machining process's sensitivity to changes in cutting parameters. Overall, this table provides an initial insight into the relationship between parameter changes and cutting performance, serving as an essential basis for subsequent optimisation analysis.

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Table 4. Results of experiments conducted based on parameters generated by RSM

Run	*Vc* (m/min)	*fz* (mm/rev)	*ap* (mm)	*VB* (mm)	*Ra* (µm)
1	65	0.05	1	0.194	0.59
2	30	0.07		0.107	0.48
3	65	0.03		0.213	0.51
4	30	0.03		0.197	0.38
5	65	0.05		0.189	0.56
6	30	0.05		0.159	0.44
7	100	0.05		0.199	0.7
8	100	0.03		0.184	0.61
9	65	0.05		0.188	0.58
10	65	0.07		0.188	0.64
11	100	0.07		0.223	0.77

VB lowest

Ra lowest

Fig. 5(a) presents the Ra test results obtained from the experiments designed by RSM. Data analysis reveals that the lowest Ra value is achieved when machining is conducted at a *Vc* of 30 m/min and an *fz* of 0.03 mm/rev, resulting in an Ra value of only 0.38 µm. This optimum value represents a significant improvement of 50.64% compared to the results obtained at a *Vc* of 100 m/min and a *fz* of 0.07 mm/rev. In general, these findings suggest that machining Inconel 718 with low *Vc* and *fz* tends to produce better surface quality, whereas higher parameters tend to produce rougher surfaces. The low *Vc* and *fz* are due to the reduction of energy and frictional heat during cutting, which in turn reduces vibration and micro-defects on the workpiece surface (Deng et al., 2023). Therefore, the combination of machining parameters at low *Vc* and *fz* is the most optimal to achieve the best surface quality. This finding reinforces that for Inconel 718, cutting strategies that reduce friction and heat are the primary keys to improving surface quality.

Fig. 5(b) depicts the *VB* measurements obtained using RSM-optimised machining parameters within the designated range. Results indicate that lower *Vc* produces *VB* reductions to 108% compared to higher *Vc* when *fz* remains constant at 0.07 mm/rev. On the other hand, when machining is carried out at a high *Vc* of 100 m/min, the heat generated by friction between the tool and the workpiece increases dramatically. This extreme temperature increase accelerates several critical *VB* mechanisms, including abrasion, diffusion, and oxidation. These processes collectively cause a rapid increase in the VB_{avg} value, which in turn significantly reduces the tool's life. This explains why machining at high parameters is not suitable for obtaining low *VB*. This is because the temperature in the cutting zone is more controlled, which in turn reduces friction and thermal reaction between the tool and the workpiece, thus slowing down the *VB* rate (Osman et al., 2018; Shang et al., 2023). Besides, the physical integrity and structural density of the tool material dictate its ability to withstand the extreme thermo-mechanical stresses of CNC turning, directly determining the progression of edge degradation and the resulting surface quality (Faiz et al., 2019).

Analysis of variance

Table 5 shows that the p-value for the Ra model is < 0.0001, proving that the model is highly significant. Factors A (*Vc*) and B (*fz*), and the AB interaction, each show a low p-value, indicating a significant effect on Ra. The Lack of Fit value is not significant (p = 0.7739), indicating that the model fits the experimental data. In Table 6, the *VB* model is also significant (p-value < 0.0001), further supporting the suitability of the quadratic model. The Lack of Fit value for the *VB* model is also not significant (p = 0.2047), confirming that the model is reliable for predicting *VB*. In addition, both tables show high R^2, Adjusted R^2, and Predicted R^2 values, indicating that the model has good predictive performance. Overall, the results of this ANOVA confirm that the quadratic model used is stable, significant, and suitable for the analysis and optimisation of cutting parameters.

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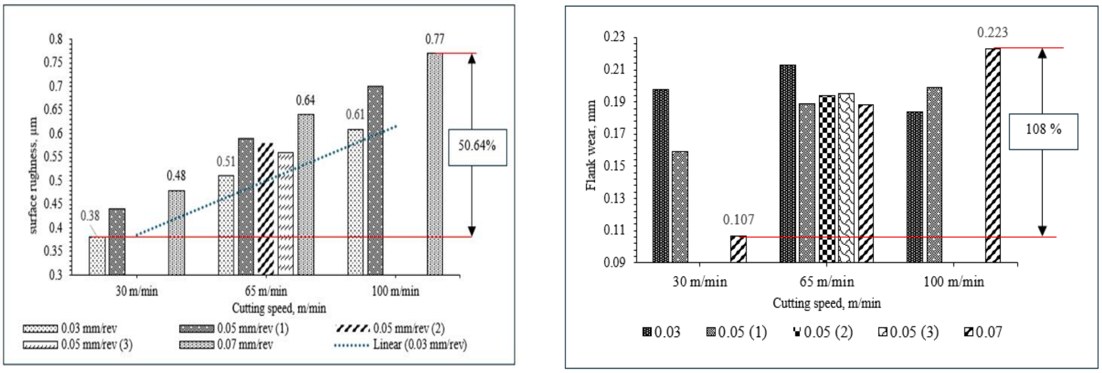

(a) (b)

Fig. 5. Parameter range results from RSM involving (a) *Ra* and (b) *VB*.

Table 5. ANOVA for the Ra - quadratic model

Source	Sum of Squares	df	Mean square	F-value	P-value	Contribution %
Model	0.1282	3	0.0256	251.07	< 0.0001	significant
Cutting speed	0.1014	1	0.1014	993.09	< 0.0001	
Feed rate	0.0254	1	0.0254	248.27	< 0.0001	
AB	0.0009	1	0.0009	8.81	0.0312	
A^2	0.0003	1	0.0003	3.03	0.1422	
B^2	0.0001	1	0.0001	0.9089	0.3842	
Residual	0.0005	7	0.0005			
Lack of fit	0.0000	5	0.0001	0.4922	0.7739	Not significant
Pure Error	0.0005	2	0.0002			
Cor Total	0.1287	10				
R^2						
Adjusted R^2						0.9921
Predicted R^2						0.9910
Adeq. Precision						52.2590

The Model p-value of <0.0001 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

Removed: the p-value is greater than 0.1000

There is a 77.39% chance that a Lack of Fit F-value this large could occur due to noise. Non-significant lack of fit is good could occur due to noise. Non-significant lack of fit is good.

Regression mathematical model

Equations 1 and 3 present the RSM-based mathematical model used to predict response Y as a function of two process variables, A (*Vc*) and B (*fz*). The use of these coded equations is very convenient, as it allows accurate prediction of the results Ra (Equation 1) and *VB* (Equation 3) based on different combinations of input factors. Equations 2 and 4 represent the mathematical model coefficients for Ra and *VB*, respectively.

$$Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_{12} AB + \beta_{11} A^2 + \beta_{22} B^2 \tag{1}$$

$$Ra = +\,0.5833 + 0.1301\mathrm{A} + 0.0639\mathrm{B} + 0.0138\mathrm{AB} - 0.0143\mathrm{A}^2 - 0.0086\mathrm{B}^2 \tag{2}$$

$$Y = \beta_0 + \beta_1 \mathrm{A} + \beta_2 \mathrm{B} + \beta_{12} \mathrm{AB} + \beta_{11} \mathrm{A}^2 \tag{3}$$

$$VB = +\,0.1957 + 0.0240A - 0.0127B + 0.0321AB - 0.0175A^2 \tag{4}$$

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Table 6. ANOVA for the *VB* – quadratic model

Source	Sum of Squares	df	Mean square	F-value	P-value	Contribution %
Model	0.0092	4	0.0023	72.66	<0.0001	significant
Cutting speed	0.0034	1	0.0034	107.09	<0.0001	
Feed rate	0.0010	1	0.0010	30.25	0.0015	
AB	0.0042	1	0.0042	130.72	<0.0001	
A^2	0.0007	1	0.0007	22.58	0.0032	
Residual	0.0002	6	0.0000			
Lack of fit	0.0002	4	0.0000	4.12	0.2047	Not significant
Pure Error	0.0000	2	0.0000			
Cor Total	0.0094	10				
R^2						0.9798
Adjusted R^2						0.9663
Predicted R^2						0.9352
Adeq. Precision						29.4911

The Model p-value of <0.0001 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

There is a 20.47% chance that a Lack of Fit F-value this large could occur due to noise. Non-significant lack of fit is good. There is only a 0.01% chance that an F-value this large could occur due to noise.

To enable accurate predictions, the regression coefficients in the equation model were modified to correspond to the values of the machining parameters in the original units. This approach allows for the direct prediction of Ra and *VB* responses using Equations 5 and 6, respectively, by substituting the actual factor values. In other words, this model offers a practical tool for estimating machining performance based on specified parameters, eliminating the need for additional experiments.

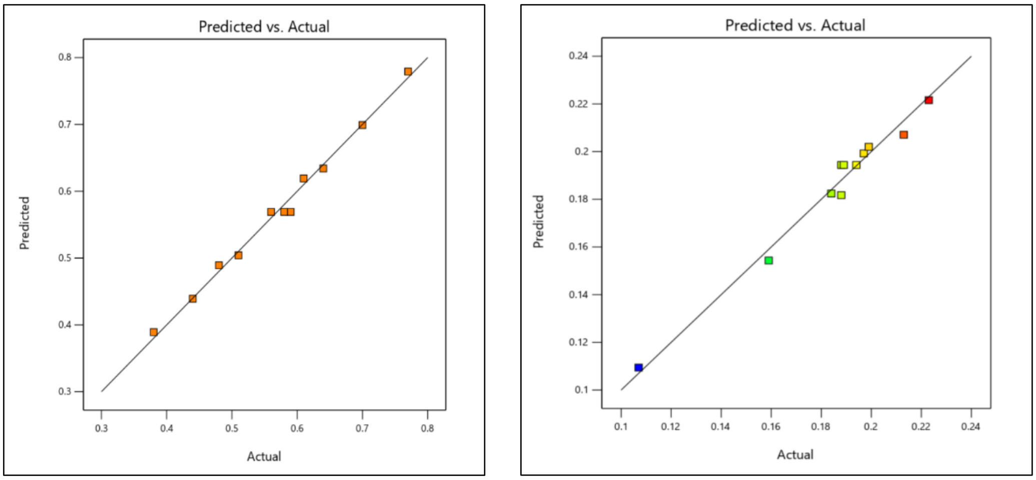
$$Ra = +\,0.1431 + 0.004251Vc + 4.055fz + 0.01971Vcfz - 0.000012Vc^2 - 21.4276fz^2 \tag{5}$$

$$VB = +0.271615 + 0.000245Vc - 3.61405fz + 0.45857Vcfz - 0.00014Vc^2 \tag{6}$$

Predicted vs. actual

Fig. 6(a) shows a plot of the comparison between the Ra values predicted by the model and the actual values from the experiment. This graphical analysis shows that almost all the data points are located very close to and parallel to the identity line (y = x). This situation, reflected by the minimal deviation, proves the reliability and accuracy of the developed statistical model. Therefore, the model can be considered feasible and very useful in industrial applications for the purpose of controlling and optimising the surface quality of the manufactured components more accurately. This shows that the RSM model effectively captures the relationship between the process variables (*Vc* and *fz*) and the Ra value.

Fig. 6(b) shows the opposite result of the prediction model for *VB*avg. Although most of the data points are also close to the identity line, there is a more significant spread and deviation compared to the Ra model. This slightly lower prediction accuracy is due to the inherent nature of the *VB* of the cutting tool, which is a more complex phenomenon and is influenced by various external factors that are difficult to model linearly. Therefore, this explains why the RSM model provides better prediction accuracy for Ra than VB_{avg}. Nevertheless, the model is still considered to provide acceptable and useful performance for both parameters in the context of Inconel 718 machining applications.



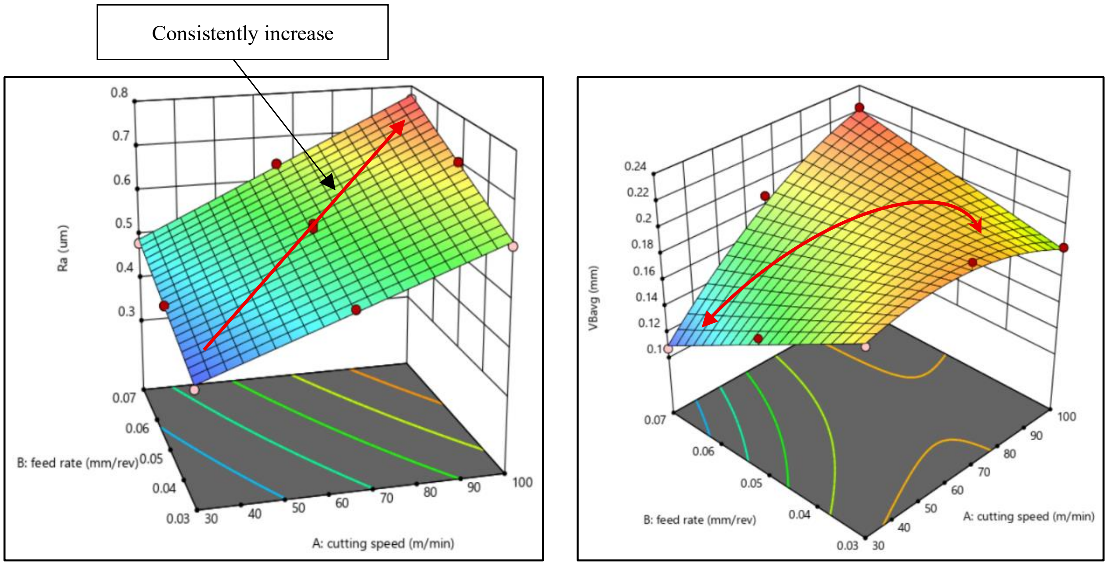
(a) (b)

Fig. 6. Prediction versus actual results on (a) Ra and (b) *VB*.

3D surface model analysis

Fig. 7(a) shows the three-dimensional surface model generated by RSM, illustrating the interactive relationship between *Vc* and *fz* on Ra. The curved surface is coloured to scale, with the blue area indicating the lowest Ra value (smooth surface) and the red area indicating the highest Ra value (rough surface). Visually, this analysis reveals two main trends: increasing *Vc* generally contributes to a decrease in Ra, while increasing *fz* causes an increase in Ra. revealing that feed rate has the strongest influence on roughness, followed by cutting speed and depth of cut (Marsool & Radhi, 2022; Saha et al., 2024). Therefore, this model serves as a valuable tool for predicting and determining the optimal combination of machining parameters to achieve the desired surface quality.

The use of RSM allows researchers to identify the optimal machining conditions for minimum Ra (Shard et al., 2021). While Fig. 7(b) shows the effect of machining parameters (*Vc* and *fz*) and analysis on *VB*. The coloured surface indicates the increase in *VB*, ranging from blue (low) to red (high). Analysis shows that high *fz* is the main factor contributing to significant *VB*. Meanwhile, the selection of appropriate *Vc* is critical and depends on the type of workpiece. For machining hard materials, such as Inconel 718, using low *fz* is highly recommended. This is because the high *Vc* will generate excessive cutting heat, which is the leading cause of *VB* (Raghavendra et al., 2020). In conclusion, reducing the *fz* and *Vc* is an important strategy to minimise *VB* when machining hard materials. The optimum *Vc* requires careful consideration of the tool and workpiece materials; harder materials require slower speeds to reduce *VB* (Gong et al., 2023). Optimising machining parameters requires regular monitoring, adjustments tailored to the material, and adherence to manufacturer guidelines (Darsin et al., 2025).



(a) (b)

Fig. 7. The effect of interaction (a) between *Vc* and *fz* on Ra and (b) Vc and *fz* on *VB*.

Model confirmation

Table 7 shows the validation results of the developed Ra model. This validation process was carried out by retesting the machining process at the optimum parameter values and comparing the actual average Ra value with the value predicted by the model. The validation test, conducted three times, showed that the measured Ra value was within the optimum range with a confidence level of 94%. The overall experimental error percentage was minimised at the parameters of 30 m/min *Vc* and 0.03 mm/rev *fz*, with an error value of 5.26%. Meanwhile, Table 8 presents the validation results of the VB_{avg} model. The validation test for *VB* showed that the measured values varied within the optimum range with a confidence level exceeding 92%. The overall experimental error percentage for this model is based on the minimum *VB*avg value tested at the parameters of 30 m/min *Vc* and 0.07 mm/rev *fz*, which recorded an error of 8%. Non-uniform *VB* measurement positions can cause high percentage errors, as *VB* occurs unevenly along the cutting edge, and the gauge may take readings at different locations (Śmigielski et al., 2025). Uneven *VB* refers to non-uniform degradation along the cutting edge or flank of a turning tool, resulting in irregularities on the machined workpiece.

Table 7. *Ra* verification results

Machining parameter		Actual value, µm	Experimental value			Mean	Error
Vc	*fz*		1	2	3		
30	0.03	0.38	0.40	0.39	0.42	0.40	5.26

Table 8. *VB* verification results

Machining parameter		Actual value, mm	Experimental value			Mean	Error
Vc	*fz*		1	2	3		
30	0.07	0.107	0.115	0.110	0.122	0.116	8.00

CONCLUSIONS

The study showed that wet machining significantly improved the surface quality of Inconel 718 by up to 57.14% compared to dry machining. Wet machining revealed clear abrasion marks along the tool's cutting edge, indicating rough wear from debris sliding along the surface. Meanwhile, dry-cutting conditions produced a BUE, which adversely affected surface quality. However, *VB* measurements at different *Vc* showed comparable performance between dry and wet machining. Parameter optimisation of wet machining identified 30 m/min *Vc* (the lowest) as crucial for reducing both *Ra* and *VB*. Observations on feed rates found that 0.03 mm/rev fz produced minimum Ra, and 0.07 mm/rev fz could maximise cutting tool utilisation. This study can guide the industry in selecting optimal parameters, which, in turn, affect machining efficiency. It is also an innovative study that integrates controlled experiments with RSM-based optimisation via CCD to generate practical, validated parameter guidelines for machining applications of Inconel 718 superalloy. However, this study is limited in its focus, focusing on only one type of cutting tool and a fixed depth of cut, which may not cover all industry variations. Overall, these findings highlight the need to balance surface quality and cutting tool life when selecting machining parameters for Inconel 718, depending on industry priorities.

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CONFLICT OF INTEREST STATEMENT

All authors declare that they have no conflicts of interest.

AUTHORS' CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: study conception and design: Norfauzi Tamin, Kahirol Mohd Salleh; data collection: Ahmad Arif Hakimi; analysis and interpretation of results: Norfauzi Tamin, Ahmad Arif Hakimi, Debie Dedvise Gerijih; resources: Raja Izamshah Raja Abdullah, Kamaruddin Kamdani, Tun Danish Tun Mohammed Kamarul; draft manuscript preparation: Norfauzi Tamin. All authors reviewed the results and approved the final version of the manuscript.

DATA AVAILABILITY/ SUPPLEMENTARY MATERIALS

Available upon request:

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Data included in the article:

All data generated or analysed during this study are included in this published article

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ETHICS STATEMENT

The authors declare that this research did not involve human or animal subjects.

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