

Performance of Coated Carbide Tools when Turning Inconel Alloy 718 under Cryogenic Condition using RSM

N. Badroush^{*1,2}, C. H. Che Haron¹, J. A. Ghani¹,
M. F. Azhar¹, Nurul Hayati Abdul Halim^{1,3}

¹Department of Mechanical & Materials Engineering,
Faculty of Engineering and Built Environment,
Universiti Kebangsaan Malaysia, 43600, Bangi, Selangor

²Center of Human Resource Development & Quality,
Academy of Maritime Studies, Tripoli, Libya

³Faculty of Mechanical Engineering,
Universiti Teknologi MARA, Shah Alam, Selangor

*nordinbadroush@yahoo.com

ABSTRACT

This paper investigates the influence of cutting parameters on different responses variables and the performance of PVD coated carbide cutting tool when turning Inconel 718 under cryogenic condition. The factors and range of parameters investigated are; cutting speed (90-150 m/min), feed rate (0.05-0.2mm/rev) and depth of cut (0.25-0.75mm). The experimental runs were established using Box-Behnken design experiment. For the responses, 2 variables were evaluated which are surface roughness (Ra) of the machined surface and tool life (TL) of the insert. Analysis of Variance (ANOVA) was used to identify factors which significantly affect the response variables. From the analysis, the cutting speed and feed rate are the most significant factors affecting the TL followed by the depth of cut. While for the Ra, the interaction of feed rate and depth of cut are the most significant, followed by the depth of cut. The prediction Ra and TL models were developed with 95% of prediction interval between the predicted and actual experiments using the optimal parameters.

Keywords: Cryogenic; Coated carbide; RSM; Surface roughness; Tool life

Introduction

Maximum heat is generated at the cutting zone during machining process. This condition causes high cutting temperatures at the area resulted with decreases tool life and dimensional accuracy of work material as well as higher surface roughness. The situation is getting worst for nickel alloys such as Inconel 718 that has poor thermal conductivity. During the cutting process, more heat would be generated that could increases the temperature particularly at the tool and workpiece interface, thus, accelerates the tool wear and results in reducing cutting tool life. Inconel 718 is also a heat-resistant alloy and able to retain high mechanical and chemical properties at high temperatures. These characters make these superalloys suit to be used in aero-engine components [2]. Conventional cooling method of flooded cutting fluids cannot penetrate and reach the highest temperature at the cutting zone, especially at high cutting speeds. To end this problems, cryogenic machining was used as an alternative to the conventional cooling method. Many researchers have reported that the machinability of nickel alloys with cryogenic cooling has been improved and reduced machining cost significantly [3].

Design of experiment is widely used in investigating machinability. This method helps to properly plan the experiment so the proper information can be analyzed with valid results and conclusions [4]. Presently, methods such as Response Surface Methodology (RSM), Central Composite Design (CCD), factorial design, and Taguchi are widely used in order to reduce the investigation time and cost [5]. For the RSM, it is use mathematical and statistical techniques for modeling and analysis of problems in which a response of interest is influenced by some variables. The main objective is to optimize the response. For instance, Ranganath and Vipin [7] applied the RSM to analyze the impact of process parameters on the surface roughness. Menwhile, Shihab et al [8] applied the CCD to collect and analyze experimental data for surface roughness and microhardness. Yang and Tang [9] applied the Taguchi method in order to determine the optimal cutting parameters for turning operations. They also employed orthogonal array, signal-to-noise (S/N) ratio, and analysis of variance (ANOVA) to investigate the cutting characteristics. Another case study is by Arbizu and Perez [11] that deployed a 2^3 factorial design to generate a first-order model to predict the surface roughness in a turning process. In the same way, Aruna and Dhanalakshmi [12] used the RSM to validate the results of surface finish measurement in turning of Inconel 718. They also applied ANOVA to prove the adequacy of the developed mathematical model.

In this study, the version 10 of the Design Expert software is used to develop the experimental plan for RSM and to identify the factors which influence the surface roughness and the machining time.

Experimental details

Cutting insert

KC5510 PVD coated carbide insert as shown in Figure 1 was used in the experiments. The insert is a PVD coated carbide and was manufactured by Kennametal Inc. specifically for machining high-temperature alloys. The geometry of cutting tool has been selected based on some important aspect such as reducing the cutting force and temperature which can be obtained by choosing a positive rake angle (see Table 1).

Table 1: Tool Specifications

Material	Carbide
Coating	TiAlN
Material Grade	C3/C4
Coating Process	PVD
ISO-No.	CNMG 120408
Insert Thickness, S	04
Corner radius, r	08
Length (mm)	12.90
Hole Diameter (mm)	5.16
Rake	Positive
Included Angle (Degree)	80
Insert Hand	Neutral

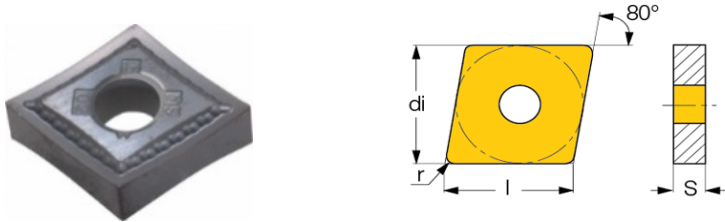


Figure 1: The cutting insert

Workpiece

The experiments were carried out using a bar of Inconel alloy 718 as the workpiece. Table 2 presents the chemical composition of the workpiece. Its hardness is 43.15HRC with the dimension of 150 mm in length and 100 mm in diameter.

Table 2: The chemical composition of Inconel 718 (Source: Haynes International 2009)

Elements	Ni	B	C	Nb+Ta	Co	Cr	Mn	Fe
[% wt.]	53	0.004	0.051	5.05	0.3	18.3	0.23	18.7
Elements	Al	P	S	Si	Ti	Cu	Mo	
[% wt.]	0.49	<0.005	<0.002	0.08	1.05	0.04	3.05	

Design of experiments

Box-Behnken method was applied to design the experiments with factors and their design levels as shown in Table 3. A total of 15 experiments were conducted according to experimental designs in Table 4. The responses variables which are surface roughness (Ra) and tool life (TL) were measured. Analysis of variance (ANOVA) was performed to identify factors which significantly affect the response variables.

Table 3: The factors and their design levels

Factors	Levels		
	Low	Intermediate	High
Cutting speed, V(m/min)	90	120	150
Feed, f (mm/rev)	0.05	0.12	0.2
Depth of cut, a (mm)	0.25	0.5	0.75

Table 4: The experimental designs

Run No	Factor Levels		
	Cutting speed, V (m/min)	Feed, f (mm/rev)	Depth of cut, a (mm)
1	90	0.05	0.5
2	150	0.05	0.5
3	90	0.2	0.5
4	150	0.2	0.5
5	90	0.12	0.25
6	150	0.12	0.25
7	90	0.12	0.75
8	150	0.12	0.75
9	120	0.05	0.25
10	120	0.2	0.25
11	120	0.05	0.75
12	120	0.2	0.75
13	120	0.12	0.5
14	120	0.12	0.5
15	120	0.12	0.5

Result and discussion

Table 5 shows the measured values of surface roughness (Ra) and tool life (TL). The Fit Summary output affirmed that the quadratic model is statistically significant for the Ra and TL. Thus, it can be used for next analysis. Table 6 shows the output from ANOVA for TL. As can be seen, the factor A (cutting speed) and B (feed rate) are the most significant factors affecting the TL with 99.98%. This is followed by factor C (depth of cut) with 99.97%. The interaction between AC is also significant with 99.23%. The R² value of 0.9841 is desirable while the predicted R² is in reasonable agreement with the adjusted R². With the Ratios greater than 4, it indicates adequate model discrimination.

Table 7 shows the ANOVA table for surface roughness (Ra). The most significant factor is the interaction of feed rate and depth of cut (BC) followed by the depth of cut (C) and the interaction of cutting speed and depth of cut (AC). The lack-of-fit is not significant. However, the R² value is high, close to 1, which is desirable. The predicted R² of 0.8056 is in reasonable agreement with the adjusted R² of 0.9128. The ratios is also indicates adequate model discrimination for the Ra. The final empirical models in terms of coded factors are shown below:

$$i. TL = +1.089 - 0.642 x A - 0.644 x B - 0.601 x C + 0.197 x AB + 0.408x AC + 0.128 x BC + 0.338x A^2 + 0.373x B^2 + 0.221x C^2 \quad (1)$$

$$ii. Ra = +1.625 - 0.054x A - 0.175 x B + 0.233 x C + 0.114 x AB - 0.297 x AC - 0.678 x BC - 0.295 x A^2 + 0.203 x B^2 \quad (2)$$

While, the following equations are for the actual factors:

$$i. TL = +18.263 - 0.150 x Vc - 39.068 x f - 13.310 x da + 0.087 x Vc x f + 0.054 x Vc x da + 6.829 x f x da + 3.759 E-004 x Vc^2 + 66.295 x f^2 + 3.533 x da^2 \quad (3)$$

$$ii. Ra = - 6.353 + 0.0902 x Vc + 0.588 x f + 10.202 x da + 0.051 x Vc x f - 0.040 x Vc x da - 36.137 x f x da - 3.274 E-004 x Vc^2 + 36.163 x f^2 \quad (4)$$

Table 5: Experimental results

Std. run No	Response TL(min)	Response Ra(μm)
1	3.3	1.909
2	1.52	1.603
3	1.68	1.192
4	0.7	1.34
5	3.41	0.888
6	1.37	1.328
7	1.2	1.996
8	0.8	1.248
9	3	1.022
10	1.4	2.17
11	1.72	2.889
12	0.61	1.321
13	0.9	1.814
14	1.2	1.603
15	1.3	1.405

Figure 2 and Figure 4 present the normal probability plot of the residuals of Ra and TL. Since the residuals are fall close to the line, it means that the errors are distributed normally. Figure 3 and Figure 5 show the standardized residuals with respect to the predicted values of Ra and TL. The residuals are fall in both positive and negative directions. This indicates that the models proposed are satisfactory. The 3D surface graph for the TL is shown in Figure 7. It has a curvilinear profile in accordance with the quadratic model fitted. Accordance to the model fitted, the TL increases at cutting speed of 90 m/min and feed rate of 0.12 mm/rev. While for the contour plot of TL as shown in Figure 9, it shows the effects of different cutting speed (A) and feed rate (B) on TL. Higher TL can be generated from lower cutting speed and low to medium feed rate.

Table 6: ANOVA table for TL

Source	Sum of squares	df	Mean Square	F-Value	P-value	Prob. >
Model	11.18	9	1.24	34.29	0.0006	significant
A-cutting speed	3.30	1	3.30	91.24	0.0002	
B-feedrate	3.21	1	3.21	88.71	0.0002	
C-depth of cut	2.80	1	2.80	77.40	0.0003	
AB	0.16	1	0.16	4.29	0.0931	
AC	0.67	1	0.67	18.56	0.0077	
BC	0.047	1	0.047	1.31	0.3040	
A ²	0.45	1	0.45	12.46	0.0167	
B ²	0.48	1	0.48	13.14	0.0152	
C ²	0.17	1	0.17	4.59	0.0852	
Residual	0.18	5	0.036			
Lack of Fit	0.094	3	0.031	0.73	0.6234	not significant
Pure Error	0.087	2	0.043			
Cor Total	11.36	14				
Std. Dev.	0.19	R-Squared			0.9841	
Mean	1.60	Adj R-Squared			0.9554	
C.V. %	11.88	Pred R-Squared			0.8499	
PRESS	1.71	Adeq Precision			18.124	

Table 7: ANOVA table for Ra

Source	Sum of Squares	df	Mean Square	F-Value	p-value	Prob. > F
Model	3.53	8	0.44	19.33	0.0010	significant
A-cutting speed	0.024	1	0.024	1.04	0.3481	
B-feedrate	0.25	1	0.25	10.73	0.0169	
C-depth of cut	0.43	1	0.43	19.00	0.0048	
AB	0.053	1	0.053	2.30	0.1801	
AC	0.35	1	0.35	15.45	0.0077	
BC	1.84	1	1.84	80.59	0.0001	
A ²	0.32	1	0.32	14.12	0.0094	
B ²	0.15	1	0.15	6.66	0.0418	
Residual	0.14	6	0.023			
Lack of Fit	0.053	4	0.013	0.32	0.8484	not significant
Pure Error	0.084	2	0.042			
Cor Total	3.67	14				
Std. Dev.	0.15	R-Squared	0.9626			
Mean	1.58	Adj R-Squared	0.9128			
C.V. %	9.55	Pred R-Squared	0.8056			
PRESS	0.71	Adeq Precision	17.808			

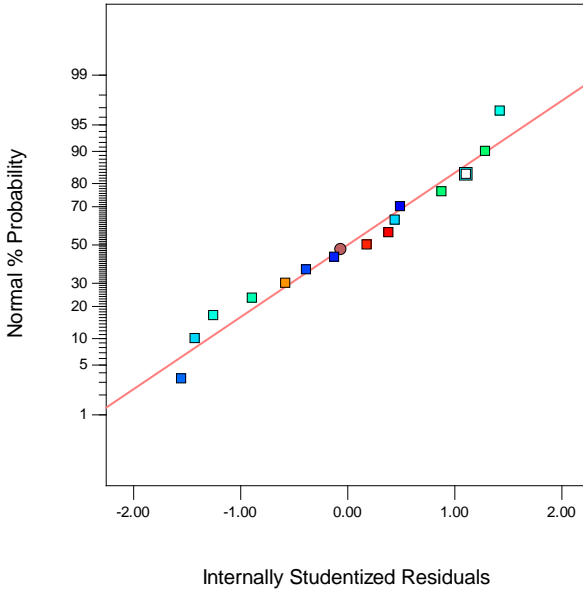


Figure 2: Normal probability plot of residuals for TL

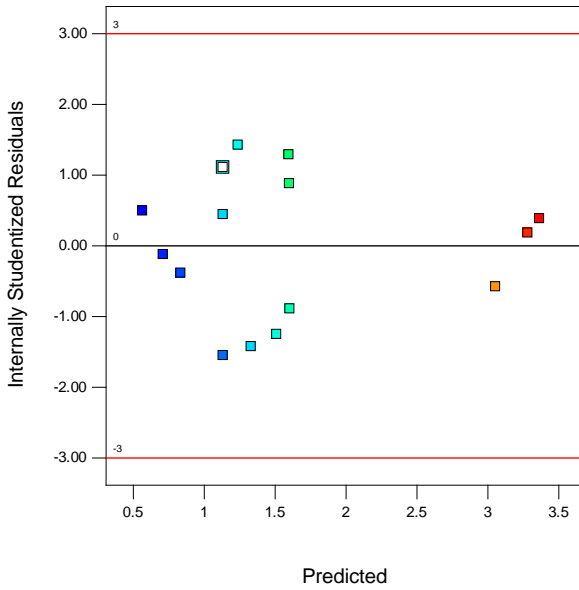


Figure 3: Residuals vs. predicted response for TL

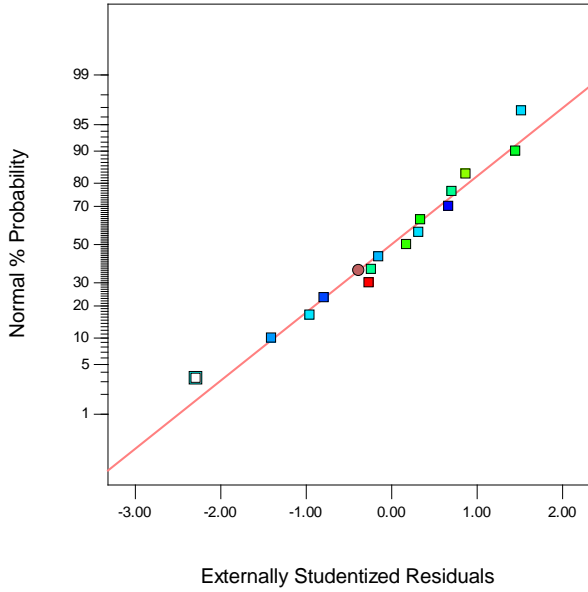


Figure 4: Normal probability plot of residuals for Ra

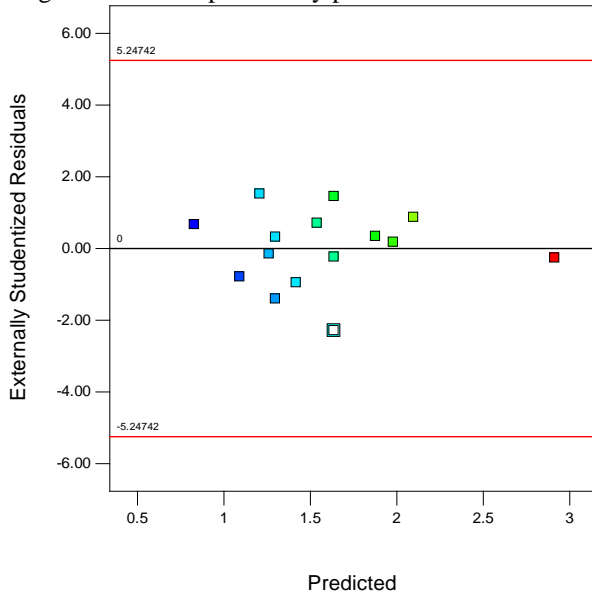


Figure 5: residuals vs. predicted response for Ra

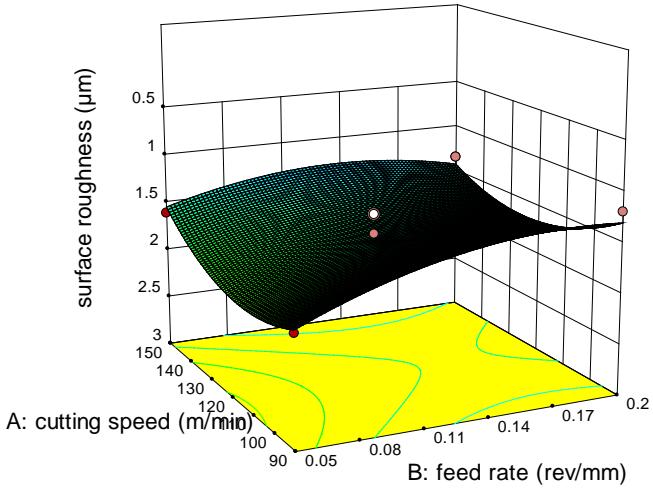


Figure 6: 3D Surface graph for Ra

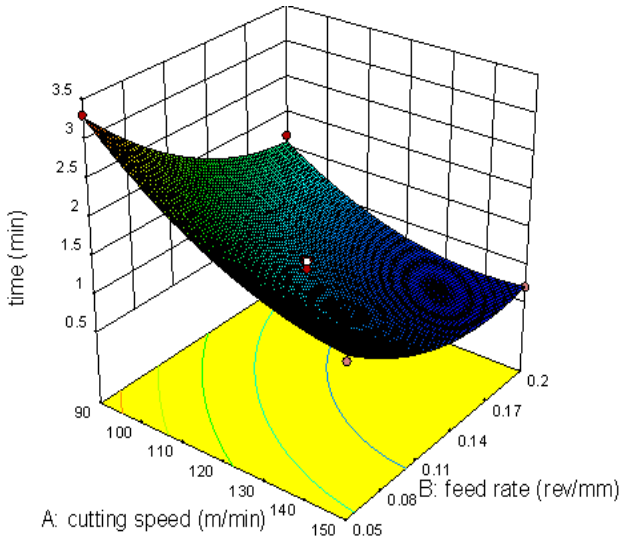


Figure 7: 3D surface graph for TL

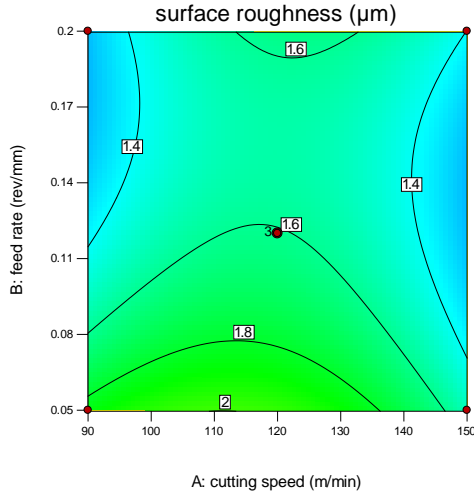


Figure 8: Ra contour plot of cutting speed against feed rate

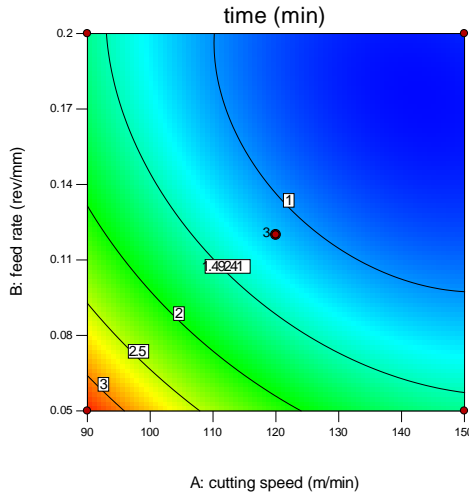


Figure 9: TL contour plot of cutting speed against feed rate

Figure 6 shows the 3D surface graph for the Ra. It can be observed that the minimum Ra is produced when the feed rate is 0.05 mm/rev and cutting speed is 90 to 120 m/min. But when the feed rate and cutting speed increase from 0.05 to 0.2 mm/rev and 120 to 150 m/min respectively, the Ra

increases. Figure 8 illustrates the effect of feed rate and cutting speed on the Ra. As shown, lower Ra values were obtained at both lower and medium cutting speeds accompanied with medium feed rate. Numerically, the smallest Ra (0.888 μm) occurred at cutting speeds 90 m/min with depth of cut of 0.5 mm and feed rate of 0.12 rev/mm.

Response Optimization

To optimize the responses, Figure 10 shows the ramp function graph for the optimum value of the cutting parameters to obtain minimum Ra and maximum TL. It can be seen that the minimum Ra is 0.826678 μm and the longest TL is 3.4083 min which happened at cutting speed 90.1444 m/min, feed rate 0.11084 mm/rev, and depth of cut 0.26.2943 mm. It is also found that the value to maximize the desirability is 1 as shown in Figure 11. This indicates that the method is highly strong.

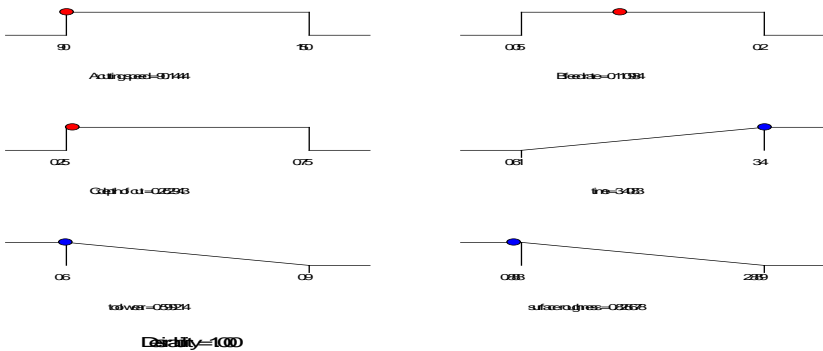


Figure 10: Ramp function of cutting parameters for Ra and TL

Validation of optimized factors

To validate the optimized factors, an experiment was conducted with the cutting speed, feed rate and depth of cut were set at 90.14 m/min, 0.11 mm/rev, and 0.26 mm respectively. The Ra and TL values were recorded to be 1.104 μm and 3.46 min. Table 8 shows the difference between the predicted and the actual results. To calculate the percent residual value, Eq. 5 was used:

$$\text{Percent residual} = \frac{\text{predicted result} - \text{observed result}}{\text{predicted result}} \quad (5)$$

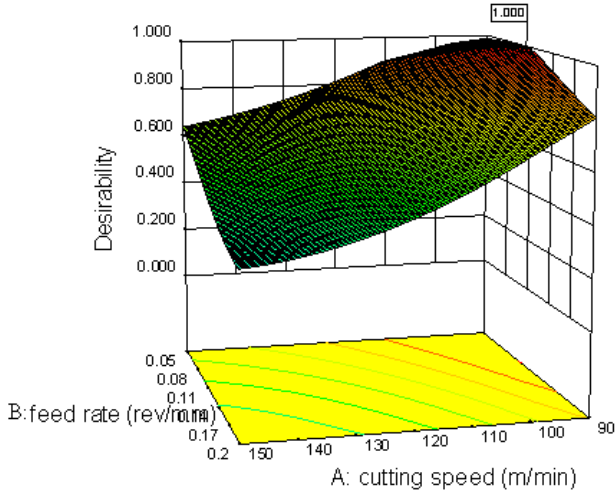


Figure 11: The 3D surface response plot of desirability for optimization of factors

Table 8: Validation of optimized factors

Response	Predicted results	Observed results	Residual values
TL	3.4083 min	3.46	-1.517
Ra	0.826678 μm	1.10	-33.54

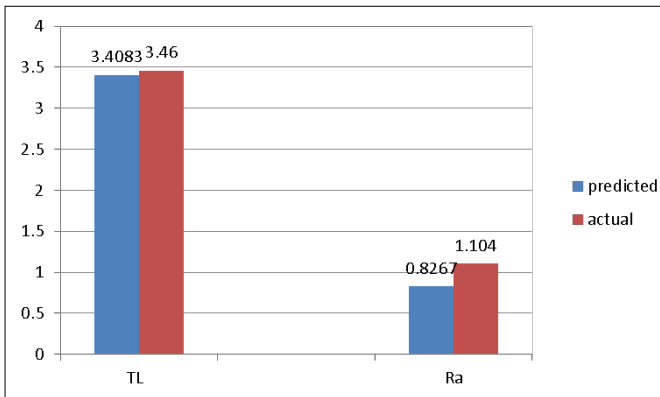


Figure 12: Comparison of TL and Ra between predicted and experimental values

From Figure 12, it can be concluded that the empirical models developed were reasonably accurate, notably for TL. With 95% of prediction interval, it is within permissible limits of error percentage. Thus, the mathematical models generated in this study can be applied to predict the Ra and TL for any within the range of parameters combination.

Conclusion

Through this study, the two methods which are Response Surface Methodology (RSM) and ANOVA have proved to be suitable and practical techniques that can be used to properly design the experiments, identify factors that significantly affect the responses as well as predict the responses value under the optimal parameters. With the application of cryogenic condition (LN₂) in this turning process, results from the experiments show that the minimum value of Ra was achieved at as low as 0.888 μm. The RSM models reveal that the interaction of feed rate and depth of cut are the most significant factors for this response. While for the tool life, the longest TL was achieved at 3.41 min with the cutting speed and the feed rate are the most dominant factors. In general, the TL decreases with the increase of both cutting speed and feed rate. The prediction Ra and TL models were developed with 95% of prediction interval between the predicted and actual experiments.

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