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Development of Surface Roughness Models in End Milling Titanium Alloy Ti-6Al-4V Using Uncoated Tungsten Carbide Inserts

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Abstract

This paper focuses on developing an effective methodology to determine the performance of uncoated WC-Co inserts in predicting minimum surface roughness in end milling of titanium alloys Ti-6Al-4V under dry conditions. Central composite design of response surface methodology is employed to create an efficient analytical model for surface roughness in terms of cutting parameters: cutting speed, axial depth of cut, and feed per tooth. Surface roughness values were measured using a surface roughness measuring instrument- Mitutoyo Surftest model SV-500. Design of expert package was applied to establish the first order and the second order model and develop the contours. The adequacy of the predictive model was verified using analysis of variance.

Keywords: Surface roughness, Response surface, Ti-6Al-4V, Uncoated WC-Co

1. Introduction

Metal cutting is one of the important and widely used manufacturing processes in engineering industries. The study of metal cutting focuses, among others, on the features of tools, input work materials, and the machine parameter settings influencing process efficiency and output quality characteristics (or responses) [Mukherje and Ray, 2006]. Metal cutting technology has grown rapidly over time owing to the contribution from many branches of engineering with a common goal of achieving higher machining process efficiency. Selection of optimal machining condition(s) is a key factor in achieving this condition [Lopez et.al, 2000]. With time, as complexity in dynamics of cutting processes increased substantially, researchers and practitioners have focused on mathematical modeling techniques to determine the optimal or near-optimal cutting condition(s) with respect to various objective criteria. Despite numerous studies on process optimization problems, there exists no universal input – output and in-process parameters relationship model, which is applicable to all kinds of metal cutting processes [Hassan and Suliman, 1998].

Many researchers and practitioners use response surface methodology in achieving the optimum cutting parameters. Taramen [1974] used a contour plot technique to simultaneously optimize tool wear, surface finish, and tool force for finished turning operations. Fuh and Chang [1997] analyses the effect change in workpiece material and each cutting parameters in various peripheral milling operations, and model the dimensional accuracy by a second order response surface design. Kaye et al. [1995] used response surface methodology in predicting tool flank wear using spindle speed change. A unique model has been developed which predicts tool flank wear, based on the spindle speed change, provided the initial flank wear at the beginning of the normal cutting stage is known. Alauddin et al. [1996] applied response surface methodology to optimize the surface finish in end milling Inconel 718. They suggested that it is possible to select a combination of cutting speed and feed that reduces machining times without increasing the surface roughness. Fuh and Wang [1997] studied a predicted milling force model for end milling operation. They found that the proposed predicted milling force had a good correlation with experimental values and is suitable for practical engineering application, since the milling force analyzed in the model has already encompassed the structural characteristics of the milling machine and the real conditions of the tool and workpiece. Choudhury and el-Baradie [1998] found that response surface methodology combined with the factorial design of experiments were useful techniques for tool life testing. Relatively, a small number of designed experiments are required to generate much useful information that is used to develop the predicting equation for tool life. Choudhury and El-Baradie [1999] used response surface methodology for assessing machinability of inconel 718. They found that the dual response contours of tool life and surface roughness are very useful in assessing the maximum attainable tool life for the same surface finish. Mansour and Abdalla [2002] developed a surface roughness model for end milling of a semi-free cutting carbon casehardened steel. They investigated a first-order equation covering the speed range 30 – 35 m/min and a second order generation equation covering the speed range 24 – 38 m/min. They suggest that an increase in either the feed or the axial depth of cut increases the surface roughness, whilst an increase in the cutting speed decreases the surface roughness. Oktem et al [2005] used response surface methodology with a developed genetic algorithm (GA) in the optimization of cutting conditions for surface roughness. S. Sharif et al [2006] used factorial design coupled with response surface methodology in developing the surface roughness model in relation to the primary machining variables such as cutting speed, feed, and radial rake angle.

Meanwhile, the main objective of this work was to develop a model for surface roughness based on cutting speed, depth of cut and feed using response surface methodology. Design Expert 6.0 package was used to analyze and the data and develop the model. Surface roughness contours in cutting speed - depth of cut planes were develop to describe the surface roughness values resulting from the cutting parameters selected.

2. Mathematical models

The multiplicative model for the predicted surface roughness (response surface) in end milling in terms of the independent variable investigated can be expressed as:

$$R_a = C\,V^k\,f_z^l\,a^m \tag{1}$$

Where R_a is the predicted surface roughness (µm), V is the cutting speed (m/min), f_z is the feed per tooth (mm/tooth), and a is the axial depth of cut (mm). C, k, l, and m are model parameters to be estimated from experimental results. To determine the constants and exponents, this mathematical model can be linearized by employing a logarithmic transformation, and Eq. (1) can be re-expressed as:

$$\ln R_a = \ln C + k \ln V + l \ln f_z + m \ln a \tag{2}$$

The linear model of Equation (2) is :

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \tag{3}$$

where y is the true response of surface roughness on a logarithmic scale $x_0 = 1$ (dummy variable), x_1,x_2, x_3 are logarithmic transformations of speed, feed, and depth of cut, respectively, while β_0, β_1, β_2, and β_3 are the parameters to be estimated. Eq (3) can be expressed as :

$$\hat{y}_1 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 \tag{4}$$

where $\hat{y}$ is the estimated response and y the measured surface roughness on a logarithmic scale, ε the experimental error and the b values are estimates of the β parameters.

The second-order model can be extended from the first-order model's equation as:

$$\hat{y}_2 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_{11} x_1^2 + b_{22} x_2^2 + b_{33} x_3^2 + b_{12} x_1 x_2 + b_{13} x_1 x_3 + b_{23} x_2 x_3 \tag{5}$$

where $\hat{y}_2$ is the estimated response based on the second order model.

3. Experimental Details

3.1. Machining Tests

End milling tests were conducted on Vertical Machining Center (VMC ZPS, Model: MLR 542 with full immersion cutting and under dry condition. Machining was performed with a 20 mm diameter end-mill tool holder fitted with one uncoated WC-Co insert. Mitutoyo SURFTEST SV-500 was used to measure the surface roughness.

3.2. Coding of the Independent Variables

The independent variables were coded taking into consideration the limitation and capacity of the milling machine. Levels of independent and coding identification are presented in Table 1.

Table 1: Level of Independent variables and Coding Identification

Levels	**Lowest**	**Low**	**Centre**	**High**	**Highest**
Coding	$-\sqrt{2}$	-1	0	+1	$+\sqrt{2}$
X_1, cutting speed, *V* (m/min)	30.59	39	70.1	126	160.6
X_2, axial depth of cut, *a* (mm/tooth)	0.5	0.61	1	1.65	2.03
x_3, feed, f_z (mm)	0.05	0.06	0.088	0.128	0.15

The transforming equations for each of the independent variables are:

$$x_1 = \frac{\ln V - \ln 70.1}{\ln 126 - \ln 70.1} \quad x_2 = \frac{\ln a - \ln 1}{\ln 1.65 - \ln 1} \quad x_3 = \frac{\ln f_z - \ln 0.088}{\ln 0.128 - \ln 0.088} \tag{6}$$

3.3. Experimental Design

Design of experiments has an effect on the number of experiment required. Therefore, it is important to have a well-designed experiment to minimize the number of experiments often carried out randomly. In the experiments, small central composite design (CCD) was used to develop the first order and second order model. The analysis of variance (ANOVA) was carried out using Design Expert 6.0 package for both the first order and second order models at 95% confidence level. Cutting condition and the surface roughness values obtained is presented in Table 2.

Table 2: Surface Roughness Results and Cutting Conditions in Coded factors

Standard Order	Type	Coding of Level			R_a, Surface Roughness (µm)
		x_1	x_2	x_3	
1	Factorial	1	1	-1	0.33
2	Factorial	1	-1	1	0.41
3	Factorial	-1	-1	-1	0.17
4	Factorial	-1	1	1	0.37
5	Centre	0	0	0	0.22
6	Centre	0	0	0	0.24
7	Centre	0	0	0	0.23
8	Centre	0	0	0	0.23
9	Axial	0	-1.414	0	0.20
10	Axial	-1.414	0	0	0.23
11	Axial	0	0	1.414	0.50
12	Axial	0	0	-1.414	0.17
13	Axial	1.414	0	0	0.61
14	Axial	0	1.414	0	0.23

4. Results and Discussion

4.1. Development First Order Model

From the experimental results, empirical equations were developed to predict the surface roughness and the significant parameters involved. The first order model obtained from the experiments data in Table 2 is as follows:

$$\hat{y}_1 = -1.30 + 0.27x_1 + 0.095x_2 + 0.32x_3 \quad (7)$$

By substituting Eq. 6 in Eq.7, the transformed equation of surface roughness prediction is as follows:

$$R_a = 0.305\, V^{0.46}\, a^{0.19}\, f_z^{0.85} \quad (8)$$

The analysis of variance (ANOVA) of linear CCD is as follows:

Table 3: ANOVA of Linear CCD Model

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Model	1.4412	3	0.4804	7.79171	0.0057	significant
A	0.5753	1	0.5753	9.33070	0.0122	
B	0.0718	1	0.0718	1.16572	0.3056	
C	0.7940	1	0.7940	12.8787	0.0049	
Residual	0.6165	10	0.0616			
Lack of Fit	0.5913	7	0.0844	10.04	0.0423	significant
Pure Error	0.0252	3	0.0084			
Cor Total	2.0578	13				

From the ANOVA, the “Model F-Value” of 7.79 implies the model is significant. There is only a 0.57% chance that a “Model F-Value” this large could occur due to noise. The lack of fit value of 10.04 implies the LOF is significant. There is only a 4.23% change that a “Lack of Fit F-value” this large occur due to noise. Therefore, the model can not be used to predict surface roughness values. Fig.1 and Fig. 2 present the surface roughness contours in cutting speed – depth of cut planes. The two graphs imply that an increase in feed values resulting in an increase in surface roughness values. Fig. 3

and Fig. 4 develop the surface roughness contours in depth of cut – feed planes. The two graphs imply that an increase in cutting speed, will give an increase in surface roughness values.

Figure 1: Surface Roughness Contours in Cutting Speed – Depth of Cut Planes (x_3 = -0.5)

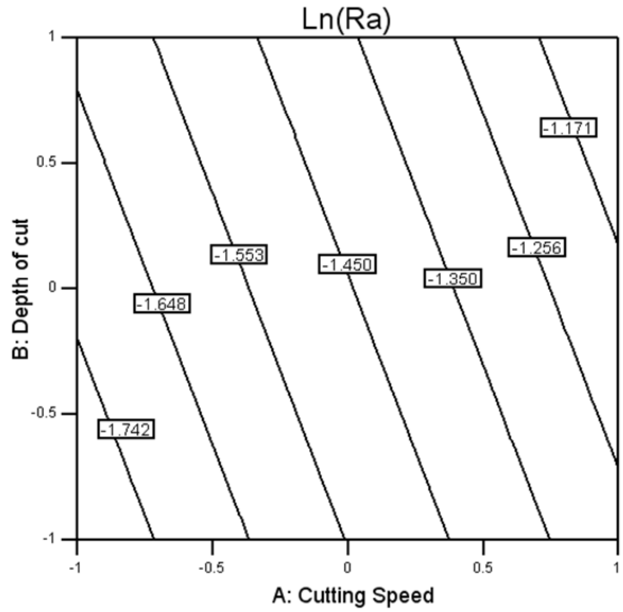


Figure 2: Surface Roughness Contours in Cutting Speed – Depth of Cut Planes (x_3 = 0.5)

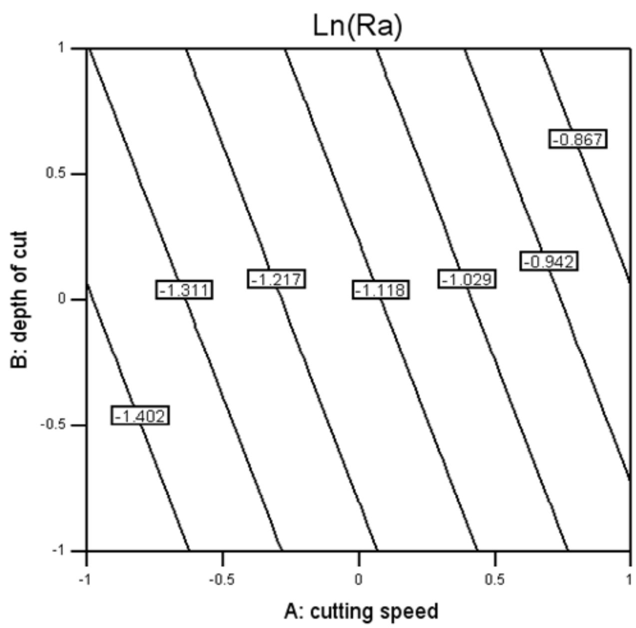


Figure 3: Surface Roughness Contours in Depth of Cut – Feed Planes (x_1 = -0.5)

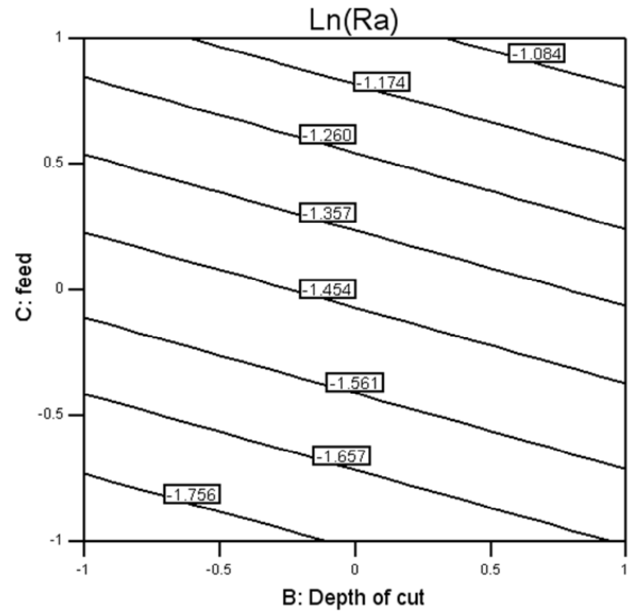
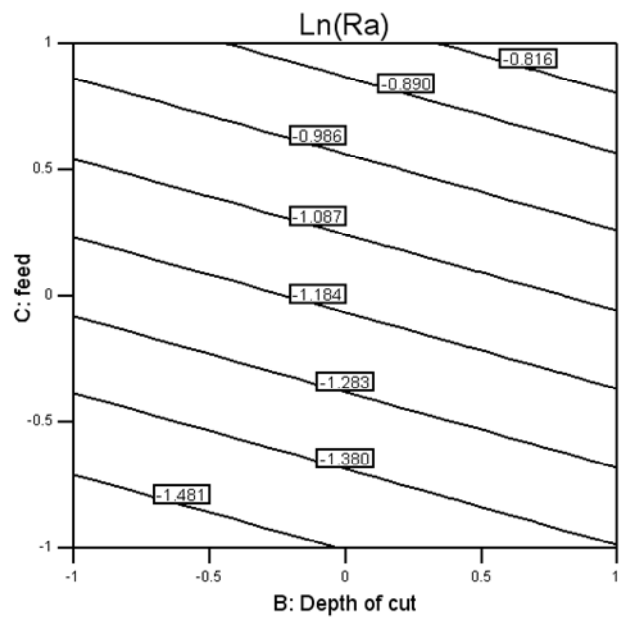


Figure 4: Surface Roughness Contours in Depth of Cut – Feed Planes (x_1 = 0.5)



4.2. Development Second Order Model

Fit and summary test in Table 4 summarizes that the quadratic model CCD model was more significant than that of linear model and it also proved that linear model has a significant lack of fit (LOF). Therefore, the quadratic model was chosen in order to develop the CCD model. The second order model in coded forms, which was obtained using the experimental data in Table 2 is given as:

$$\begin{aligned}\hat{y}_2 &= -1.46 + 0.34x_1 + 0.049x_2 + 0.38x_3 + 0.23x_1^2 - 0.047x_2^2 + 0.111x_3^2 \\ &\quad + 0.13x_1x_2 - 0.091x_1x_3 + 0.15x_2x_3\end{aligned} \tag{9}$$

Table 4: Fit and Summary Test of the Second Order CCD Model

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	Square
Mean	23.572	1	23.5721			
Linear	1.44126	3	0.4804	7.7917	0.0057	
2FI	0.09874	3	0.0329	0.4449	0.7285	
Quadratic	0.48881	3	0.1629	22.4532	0.0058	Suggested
Cubic	0.00378	1	0.0037	0.4498	0.5504	Aliased
Residual	0.02524	3	0.0084			
Total	25.6300	14	1.8307			

To verify the adequacy of the proposed second order CCD model, ANOVA was used and the results are shown in Table 5. The Model F-Value of 31.06 implies the model is significant. There is only a 0.24% chance that a "Model F-Value" this large could occur due to noise. The "lack of Fit F-value" of 0.45 implies that the Lack of Fit is not significant relative to the pure error. There is a 55.04% chance that a "Lack of Fit F-Value" this large could occur due to noise. Non-significant lack of fit is good. Therefore, we can use the model to navigate the response surface.

The quadratic CCD model (Eq. 9) shows that feed will give the highest effect on surface roughness, followed by cutting speed and depth of cut. The interaction effects between cutting speed and depth of cut and between depth of cut and feed will also give significant effects on surface roughness values. The range of the cutting speed V, axial depth of cut a, and feed f_z are: $30.59 \leq V \leq 126$, $0.5 \leq a \leq 2.03$, and $0.05 \leq f_z \leq 0.15$ respectively.

Table 5: ANOVA for Second Order CCD Model

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Model	2.0288	9	0.2254	31.0641	0.0024	significant
A	0.4756	1	0.4756	65.5506	0.0013	
B	0.0097	1	0.0097	1.3458	0.3105	
C	0.5819	1	0.5819	80.1897	0.0009	
A^2	0.3931	1	0.3931	54.1746	0.0018	
B^2	0.0163	1	0.0163	2.2561	0.2075	
C^2	0.0827	1	0.0827	11.4088	0.0278	
AB	0.0352	1	0.0352	4.8550	0.0923	
AC	0.0164	1	0.0164	2.2696	0.2064	
BC	0.0470	1	0.0470	6.4822	0.0636	
Residual	0.0290	4	0.0072			
Lack of Fit	0.0037	1	0.0037	0.4498	0.5504	not significant
Pure Error	0.0252	3	0.0084			
Cor Total	2.057843	13				

Figure 5: Surface Roughness Contours in Cutting Speed – Feed Planes (x_2 = -0.5)

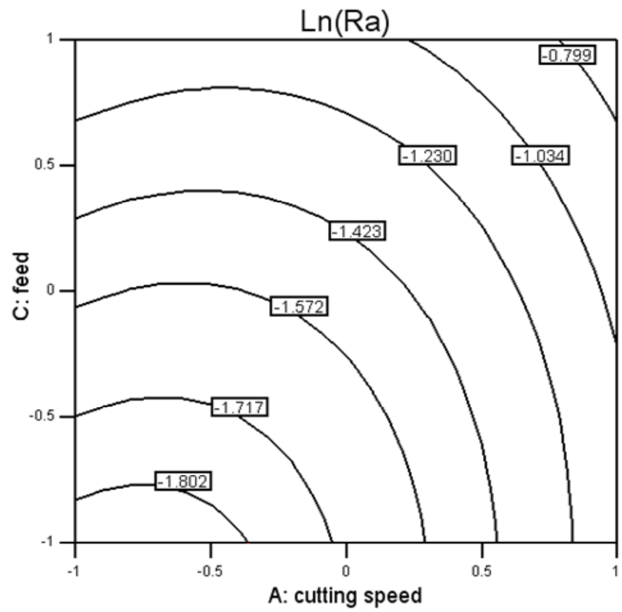


Figure 6: Surface Roughness Contours in Cutting Speed – Feed Planes (x_2 = 0.5)

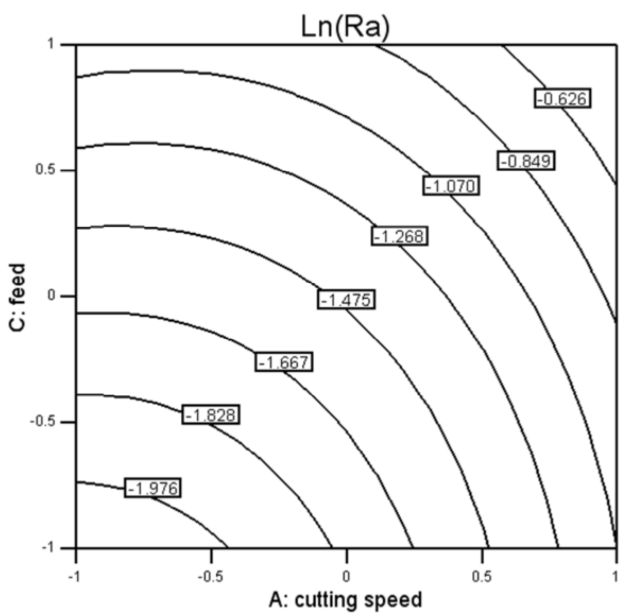


Fig. 5 and Fig. 6 show the surface roughness contours in cutting speed – feed planes at different depth of cut values (in coded forms). The two graphs imply that an increase in depth of cut, resulting in an increase in surface roughness values.

Fig. 7 and Fig. 8 show the surface roughness contours in feed – depth of cut at different cutting speed values (in coded forms). The graph indicates that an increase in cutting speed, resulting in an increase in surface roughness values.

Figure 7: Surface Roughness Contours in Feed - Depth of Cut Planes (x_2 = -0.5)

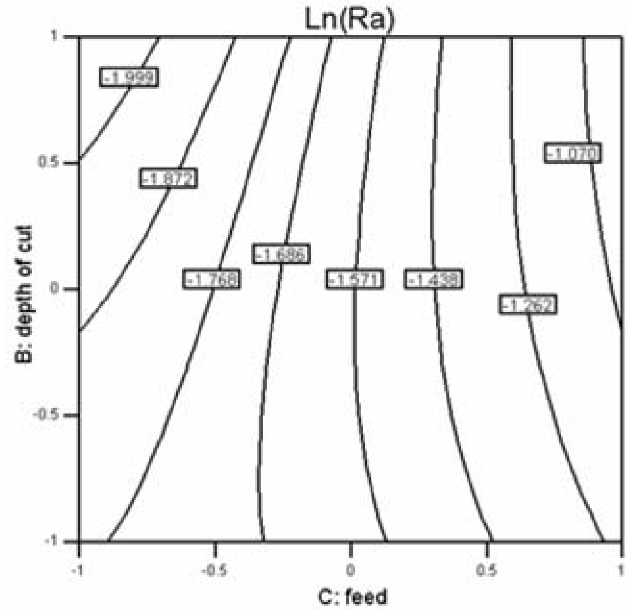
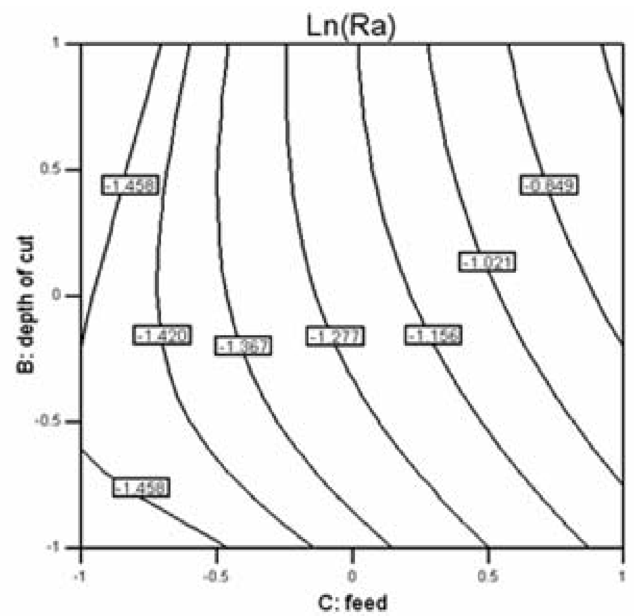


Figure 8: Surface Roughness Contours in Feed - Depth of Cut Planes (x_2 = -0.5)



5. Conclusions

The following conclusion can be withdrawn from this study:

1. Small central composite design has proved to be a successful technique to predict the surface roughness produced in end-milling of titanium alloy Ti-6Al-4V using uncoated inserts under dry conditions.
2. Linear CCD model is inadequate to predict surface roughness values.
3. Quadratic CCD model developed by RSM using Design-expert package is able to provide accurately predicted values of surface roughness close to experimental values. The equations are checked for their adequacy with a confidence interval of 95%.

4. The two equations indicate that the feed was the most dominant cutting condition on surface roughness, followed by cutting speed and axial depth of cut. Interaction effect between cutting speed and feed will also give a high effect on surface roughness values.

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