PREDICTION AND OPTIMIZATION OF THE ROUGHNESS IN THE MILLING PROCESS USING RESPONSE SURFACE METHODOLOGY

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ABSTRACT*: The purpose of this research is to apply response surface methodology to the machining process with milling, with the aim of evaluating, predicting, and optimizing the roughness of machined surfaces. Based on an experimental database, a model was been constructed using the RSM approach, the inputs of the RSM model were three factors: the cutting speed, cutting depth and the feed, while the response was the roughness. The results of ANOVA reveal that cutting speed then the feed are the most influential factors affecting the roughness. An empirical mathematical model was created to represent the relationship between the cutting parameters and the roughness, the predicted values aligned well with the experimental results, with an average error rate of 3.29%. Response surface optimization has been used to get the optimal values (cutting speed 120 m/min, feed 0.05 mm/tooth, and cutting depth 1.234 mm have been achieved for minimum roughness of 0,771 µm).*

KEYWORDS*: RSM, milling, cutting parameters, optimization, roughness.*

1 INTRODUCTION

The roughness is considered one of the most essential aspects of the surface integrity, particularly for its effect on fatigue life of the machined workpiece. In recent years, a large number of experiments have been performed with the objective of investigating the ways in which the milling conditions influence the roughness. And here are some researches that have investigated the roughness of machined surface by milling process:

(Davis & Singh, 2020) in their work they studied the surface integrity in the end milling of Mg Alloy AZ31B under different machining conditions (cryogenic, wet and hybrid) using cryogenic treated and non-treated coated carbide end mill. They obtained the best surface finish (roughness and micro-hardness) using untreated end mill tool in milling with cryogenic condition under higher spindle speed and lower cutting depth and feed rate.

(Hassanpour et al., 2016) investigated the influence of the cutting conditions on the surface integrity in the hard milling of 4340 alloy steel under MQL. After using RSM, the statistical analysis shows the contribution of every parameter, the feed rate has a 49.2% impact, cutting speed has a 23.1% impact, radial cutting depth has a 14.1% impact, and axial cutting depth has a 4% impact on surface roughness. Additionally, there is a similar pattern in the effects of axial and radial cutting depths on surface roughness.

(Oosthuizen et al., 2016) According to their research on the impact of cutting conditions on the surface roughness of milled Ti6Al4V, at stable cutting speeds, a progressive rise in the roughness is seen when milling with a greater feed rate. while variation in feed rate will have less impact on the roughness as cutting speed start to become higher. Furthermore, roughness values decrease as the cutting speed is increased. The increased tool wear observed with higher feeds has an impact on the roughness of the milled surface.

(Yi et al., 2015) used RSM with the objective to estimate the roughness of machined aluminum alloy with micro milling process. Then they used the model to examine the impact of the cutting conditions on the roughness of the milled surface, the results show that the model performs well and it can be used before the machining process in order to estimate and control the surface roughness by choosing the appropriate cutting settings. They found also from the analysis of the results that with increased feed rate and decreased spindle speed, the surface roughness increases.

(Santhakumar & Mohammed Iqbal, 2019) used RSM with the objective to analyze and estimate the roughness of machined steel with end milling process, the estimated values aligned well with experimental results, with an error rate of 6.10 %.

The ANOVA studies shows that the roughness is influenced by the feed rate more than any other factor. In order to find the best solution for optimizing the end milling, a desirability multi-objective optimization strategy based on RSM was used.

(Karkalos et al., 2016) in their work used both ANN and RSM methods with the objective of estimating and optimizing the roughness in the machining with milling. They found that the ANN modeling gives a better estimation of the roughness compared to the RSM technique, but the RSM found to be better on the optimization and the analyze in order to find the major parameters that have influence on the machining process. They also reported that the feed rate is the principal parameter influencing the roughness.

(Kasim et al., 2019) in their research they investigated the roughness of inconel 718 in the process of end ball milling, the roughness was found to be infected by the flank wear during the cutting. the grooved mark of the rear surface of the chip shows that the cutting-edge notch wear had no effect on the surface quality of the machined workpiece.

(Bhopale & Joshi & Pawade, 2015) found that the produced surface in dry condition is generally smoother than the produced in cooled air, and double passes produce surface with high roughness value than the single pass cutting, they found also, that the path of the cutter has big impact on the generated surface roughness.

(Akhtar & Sun & Chen, 2016) in their work used two types of inserts, SiC whisker reinforced coated ceramic and PVD-TiAlN coated cemented carbide inserts. they reported that despite the fact that the two types of inserts had a different range of cutting parameters, the lowest surface roughness was reached at medium value of cutting speed and the lowest value of feed, and the medium value of cutting depth. This result appeared to show that the two different cutting inserts types produced similar value of roughness, but this was not the case, in reality, the surface roughness generated by the two types of tools was similar at the beginning of the cutting then while cutting went past the cutting length of 50 mm, ceramic tools generate a very poor surface quality.

(Molaiekiya et al., 2021) in their study the surface integrity in high-speed dry milling of inconel 718, compared between the wet conventional milling using the coated cemented carbide tools of an industrial benchmark and machined surfaces produced in dry high-speed milling with SiAlON ceramic tools with identical geometry. they concluded that when conducting cutting at high speeds, the new ceramics tools generate a better surface roughness than the conventional tools. They found also that at their end of tool life ceramic tools generate a rougher surface (Ra = 4.5 m) compared to cemented carbide tools at their end of tool life (Ra = 2.19 m).

(Najiha & Rahman, 2015) used TiAlN + TiN-coated carbide and uncoated tungsten carbide inserts in the end milling process to study the machining performance of AA6061-T6, using the MQL by injecting TiO2 nanofluid into the cutting zone. The results showed that the coated insert having two-layer was superior than a single-layer coated tungsten carbide in terms of producing a good surface quality.

Because of their capacity to model many processes, prediction techniques have been utilized to solve the problems of variation in the surface integrity.

However, the utilization of the numerical Approaches to examine, estimate and optimize the roughness in the milling process need more contribution in the industry.

Therefore, the purpose of this research is to apply response surface methodology to the machining process with milling with the aim of evaluating, predicting, and optimizing the surface roughness of the machined workpieces of titanium alloy Ti-6Al-4V which is influenced by the cutting conditions.

2 EXPERIMENTAL DATABASE

The aim of this research is to examine and predict the roughness of milled surfaces, a model was constructed with response surface methodology using an experimental database that includes the roughness variation according to the variation in cutting conditions (cutting speed, feed and cutting depth). The model was constructed using Design-Expert software.

The milling machine FB4MB was used for cutting blocks of the titanium alloy Ti-6Al-4V, the blocks had the following dimensions: 300 mm in length, 80 mm in width, and 120 mm in height. The six inserts cutter that was used had a diameter of 40 mm. The type of inserts was the SANDVIC R390-1806 12M-PM. The Taylor Hobson Surftronic + 3 was used to determine the roughness value of the milled workpiece (Mahdavinejad et al., 2012).

Twenty-seven milling tests were done using three input (factor) parameters each of these parameters varies to different level.

The table 1 show the variation of the experimental surface roughness value according to the variation in cutting conditions.

Table 1. Exp. data (Mahdavinejad et al., 2012)

$f_z(mm/tooth)$		0.05	0.15	0.25
$a_p(mm)$	$V_c(m/\min)$	The Roughness (μm)		
0.3	60	1.96	2.4	2.46
	90	1.39	1.71	1.85
	120	0.93	1.14	1.53
0.9	60	1.78	2.23	2.31
	90	1.11	1.52	1.68
	120	0.86	0.93	1.27
0.15	60	1.76	2.22	2.3
	90	1.12	1.5	1.65
	120	0.81	0.95	1.29

3 RESPONSE SURFACE METHODOLOGY

3.1 Response surface methodology

In this work response surface methodology will be employed, because it is a combination of mathematical and statistical optimization technique very powerful, used to exploring the relationship between multiple independent factors with a particular response and allows to analyze the effect of these factors on the response and their interactive effects as shown in figure 1.

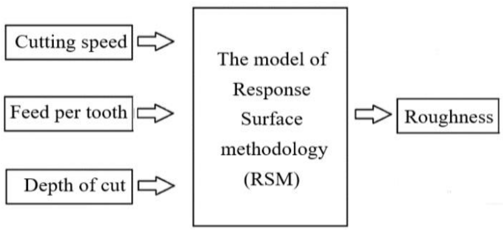

Fig. 1 Response Surface Method System

3.2 Developing Mathematical Relationships and Regression Analysis

Design expert software was used to determine the coefficients of response surface regression model in an empirical form. ANOVA was utilized to figure out the influence and the significance of the provided input factors from the experimental tests using the design of experiments method in the milling processes, and it allows also to figure out the interactive effects of those factors.

Table 2 shows the results of ANOVA of the reduced cubic model for the roughness. the Model F-value of 633.99 mean that the model is very significant. The P-values < 0.0001 mean that the terms of the model are significant.

The R^2 is 0.9966, and the predicted R^2 is 0.9951 and it is very close to the adjusted R^2 of 0.9925.

The signal to noise ratio is measured by Adeq Precision. A ratio of at least 4 is preferred. The ratio of 81.5928 mean an adequate signal.

According to the ANOVA results, the most significant parameters were determined, the results show that the cutting speed followed by the feed per tooth are the most critical factors on roughness. Also, the most critical interaction factor is cutting speed × feed peer tooth × feed peer tooth, and these results have been integrated into the mathematical model.

The obtained mathematical empirical model relationship between the cutting parameters and the roughness is as flow:

$$R_a = 3.22417 - 0.032819 \times V_c + 18.01667 \times F_z - 0.605556 \times a_p - 0.150556 \times V_c \times F_z + 0.000128 \times V_c{}^2 - 50.83333 \times F_z{}^2 + 0.24537 \times a_p{}^2 + 0.494444 \times V_c \times F_z{}^2$$

Table 2. ANOVA for reduced cubic model of roughness

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	6.84	8	0.8546	663.99	< 0.0001	significant
A-Vc	2.44	1	2.44	1899.57	< 0.0001	
B-Fz	1.19	1	1.19	921.34	< 0.0001	
C-ap	0.1741	1	0.1741	135.23	< 0.0001	
AB	0.0005	1	0.0005	0.4144	0.5279	
A^2	0.0793	1	0.0793	61.65	< 0.0001	
B^2	0.0241	1	0.0241	18.70	0.0004	
C^2	0.0468	1	0.0468	36.38	< 0.0001	
AB^2	0.0880	1	0.0880	68.38	< 0.0001	

Residual	0.0232	18	0.0013
Cor Total	6.86	26	

Std. Dev.	0.0359	R^2	0.9966
Mean	1.58	Adjusted R^2	0.9951
C.V. %	2.27	Predicted R^2	0.9925
		Adeq Precision	81.5928

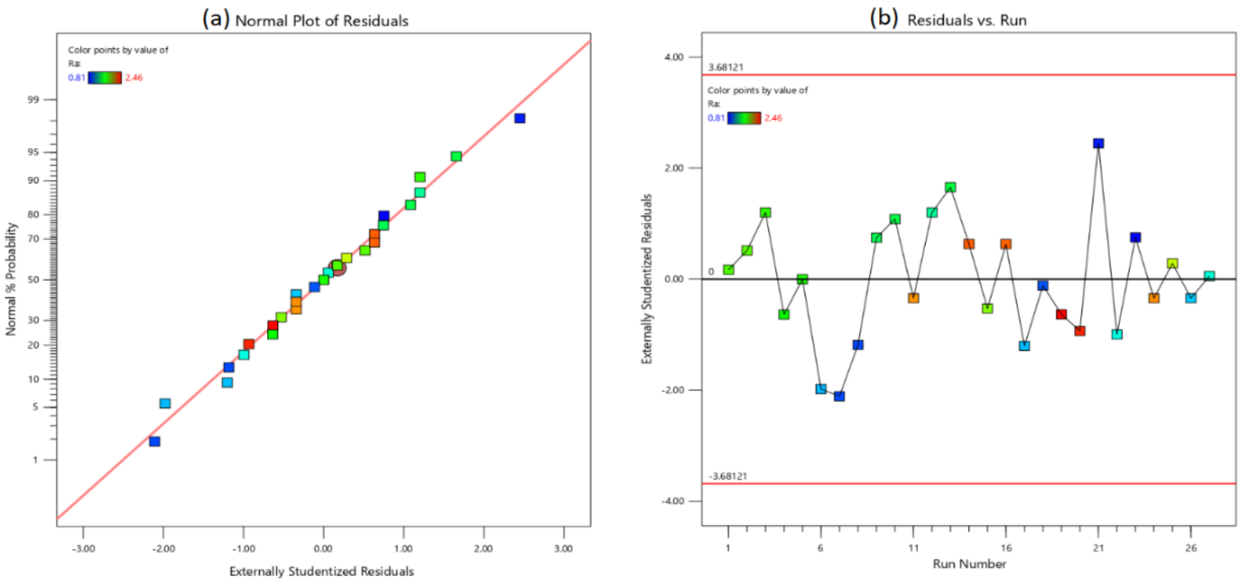

Fig. 2 The Residual graph for roughness model: (a) normal plot of residuals, (b) residual versus run

Figure 2 illustrates the normal plot of residuals and residuals versus run for roughness, the residual normal plot results in figure 2 (a) show that all dots are near to the straight line, Furthermore, in the figure 2 (b) residuals versus run number there is no special pattern or unused structure that is observed, the above results indicate that the model is acceptable since these are two conditions essential for proving the adequacy of the model.

4 RESULTS AND DISCUSSION

4.1 Results

For the verification of the model which was constructed using twenty-seven experimental tests, it will be tested by comparing the twenty-seven experimental values with the predicted value by the regression model.

Figure 3 illustrates the superposition of the experimental versus the estimated values of the surface roughness by the regression model. A similarity is noticed between the experimental values and the predicted values of the surface roughness, that demonstrates that the model work well and that it can be applied to examine the results.

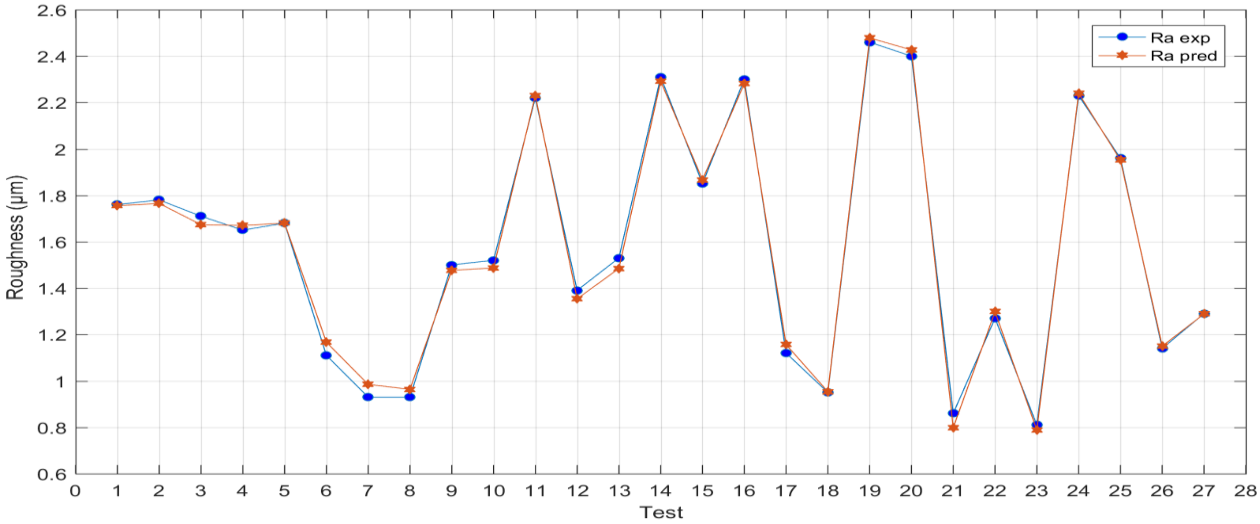

Fig. 3 Experimental versus predicted values of the roughness

4.2 Validation of the model

To validate the model twenty experimental tests are used that are not included in the model's construction. Table 3 shows the error and the accuracy of the model that have been investigated using the mathematical model of the roughness that connects the inputs and outputs parameters modeled by regression.

Formula 1 is used to determine error rate of the 20 tests:

$$e_i = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\left|Ra_{\exp} - Ra_{pred}\right|}{Ra_{\exp}}\right]\times 100 \quad (1)$$

$Ra_{\exp}$: Experimental roughness (µm).

Ra_{pred} : Predicted roughness (µm).

N : The numbers of tests (20).

e_i : Error rate

Formula 2 is used to determine the accuracy of the 20 tests:

$$A = \frac{1}{N}\sum_{i=1}^{N}\left[1 - \frac{\left|Ra_{\exp} - Ra_{pred}\right|}{Ra_{\exp}}\right]\times 100 \quad (2)$$

$Ra_{\exp}$: Experimental roughness (µm).

Ra_{pred} : Predicted roughness (µm).

N = The numbers of tests (20).

A : Accuracy

The table 3 show the results of the experimental versus the predicted value of the roughness.

The average error rate is 3.29 %, that's means that the RSM model developed in this research allows for roughness prediction of the milled surface of Ti-6Al-4V and can be utilized as a means to anticipate roughness prior to initiating the machining process.

4.3 Graphical representation of results

Figure 4 represents the surfaces provided using RSM, it shows how the milling operations are carried out by showing the effect that cutting conditions have on the milled surfaces roughness as follows:

- The surface (a) illustrates the impact of the feed and cutting speed and on the roughness for a cutting depth of 0.3 mm.
- The surface (b) illustrates the impact of the feed and cutting speed on the roughness for a cutting depth of 0.9 mm.
- The surface (c) illustrates the impact of the feed and cutting speed on the roughness for a cutting depth of 1.5 mm.

As can be observed, a decrease in cutting speed results in a rise in roughness, and vice versa; nevertheless, a rise in the feed per tooth results in a rise in roughness, and vice versa. However, the cutting depth has almost no effect on the roughness.

Table 3. The results of the experimental versus predicted roughness value

Tests	Cutting conditions			The roughness results			
	V_c	f_z	a_p	$Ra_{\exp}$	Ra_{pred}	**Error %**	**Accuracy %**
1	90	0.2	0.3	1.78	1.79	0.33	99.67
2	90	0.05	0.6	1.24	1.24	0.17	99.83
3	120	0.25	1.2	1.24	1.27	2.52	97.48

4	75	0.2	0.3	2.19	2.12	3.34	96.66
5	120	0.15	0.6	1.04	1.03	0.52	99.48
6	90	0.25	0.6	1.75	1.75	0.07	99.93
7	60	0.25	1.2	2.27	2.26	0.24	99.76
8	90	0.15	0.6	1.61	1.56	3.23	96.77
9	75	0.1	1.2	1.77	1.64	7.17	92.83
10	105	0.05	0.3	1.04	1.14	9.66	90.34
11	120	0.1	0.6	0.94	0.93	0.97	99.03
12	120	0.1	0.9	0.91	0.86	5.54	94.46
13	75	0.2	1.5	1.98	1.92	3.02	96.98
14	75	0.2	1.2	1.94	1.90	1.90	98.10
15	60	0.05	0.6	1.86	1.84	1.28	98.72
16	75	0.2	0.9	2	1.93	3.49	96.51
17	105	0.05	0.6	0.94	1.03	9.04	90.96
18	75	0.2	0.6	2.12	2.00	5.59	94.41
19	60	0.15	1.2	2.17	2.21	1.98	98.02
20	120	0.1	0.3	0.99	1.05	5.68	94.32
The average						3.29 %	96.71 %

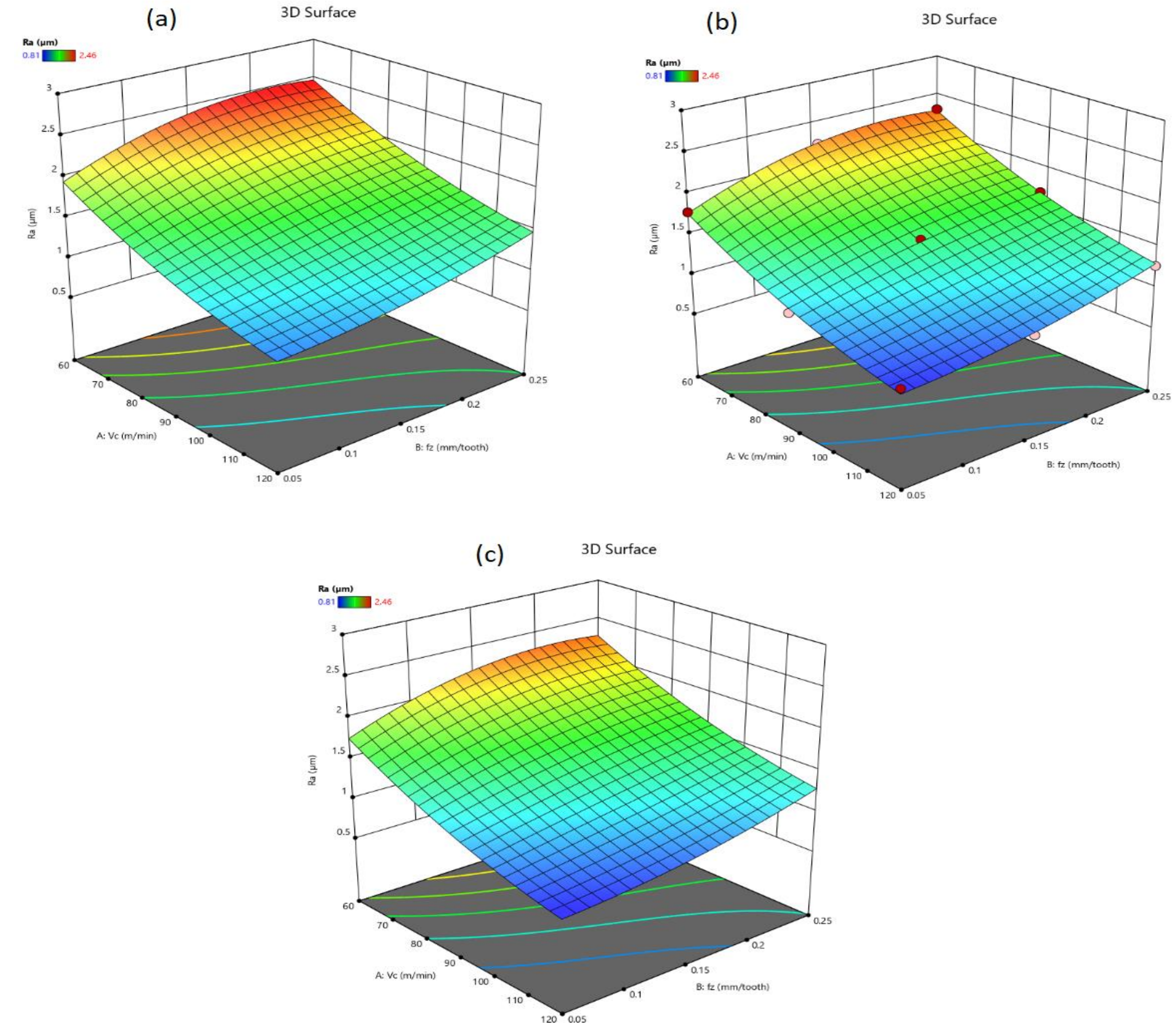

Fig. 4 Variation of the roughness predicted with the RSM according to the variation in the cutting conditions

5 OPTIMIZATION

In this part. response surface optimization has been used to get the optimal values of the inputs of cutting conditions with the objective of minimizing the roughness in the milling of the Ti-6Al-4V.

The constraints for optimizing the cutting conditions are shown in the table 4

Table 4. The cutting conditions constraints

Inputs	Lower limit	Higher limit
$V_c\,(m/\min)$	60	120
$f_z\,(mm/tooth)$	0.05	0.25
$a_p\,(mm)$	0.3	1.5

In the table 5 is represented the optimal value for the cutting conditions for the minimized roughness value. It is clearly seen that the optimal value is 0.771 for the respective values of cutting conditions (V_c = 120 m/min, f_z = 0.05 mm/tooth and a_p = 1.234 mm).

Table 5. Optimization Results

$V_c\,(m/\min)$	$f_z\,(mm/tooth)$	$a_p\,(mm)$	$R_a\,(\mu m)$
120	0.05	1.234	0.771

6 CONCLUSION

The purpose of this research is to apply response surface methodology to the machining process with milling with the aim of evaluating. predicting. and optimizing the surface roughness of machined titanium alloy Ti-6Al-4V which is influenced by the cutting conditions. The main findings of this study are as follows:

- The error/accuracy analysis confirmed the validation of the mathematical model.
- The predicted values aligned well with experimental results; the average error rate is 3.29% for the roughness calculations.
- The RSM model developed in this research allows for roughness prediction of the milled surface of Ti-6Al-4V.

- Optimized values of cutting parameters (V_c = 120 m/min, f_z = 0.05 mm/tooth and a_p = 1.234 mm) have been achieved for minimum roughness (0.771 µm).
- Roughness values decrease as the cutting speed is increased while a rise in the roughness value is caused by a higher value of feed per tooth.
- Analysis of Variance revealed that the two variables that affect the roughness were the cutting speed and feed per tooth.
- The roughness is not greatly influenced by the cutting depth.

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