Prediction of surface roughness of Ti6Al4V and optimization of cutting parameters based on experimental design

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ABSTRACT

The effect of machining parameters on the surface roughness in dry-turning Ti6Al4V alloy using an experimental design method was investigated. A mathematical equation based on the response surface methodology was established to fully understand the influence of machining parameters (cutting speed, feed rate, and depth of cut) on the surface roughness. A set of experiments based on a three-level statistical full factorial design of the experimental method was performed to collect the mean of surface roughness data. The model of R^2 = 0.9656 shows a good correlation between the experimental results and predicted values. The analysis results from the model revealed that the feed rate is the dominant factor affecting surface roughness, followed by cutting speed, and depth of cut. The surface roughness was minimized when the feed rate and depth of cut are set to the lowest, and the cutting speed was set to the highest level. Verification of the experimental results indicated that the surface roughness of 0.832 µm at cutting speed of 200 m/min, feed rate of 0.1 mm/rev, and depth of cut of 0.1 mm were achieved under the optimal conditions

Keywords: Ti-6Al-4V alloy; Cutting parameters; Surface roughness; ANOVA.

1. INTRODUCTION

Titanium alloys are widely used in automotive, aviation, medical, military, and other industries due to their outstanding properties such as lightweight strength, anti-cracking properties, and great resistance to corrosion [1]. However, the machinability of titanium alloys is limited because of some of the inherent properties of the materials. Studying the machinability of titanium alloy is imperative. Turning is the primary operation in most of the production processes in the machining operations. The surface roughness of turned process has a greater influence on the surface quality of the product, achieving the desired surface quality is critical for extending the service life of a machine part [2].

Various factors affect surface quality, but it is difficult to fully quantify [3]. Rigidity is a significant factor affecting surface roughness. The surface roughness increases accompanying a decrease in material rigidity. Therefore, low-rigidity materials like titan alloys produce high surface roughness. In many of the turning parameters, the surface roughness is major affected by cutting speed, feed rate, depth of cut, tool nose radius, etc. Exploring the effect of machining parameters, predicting surface roughness, and optimizing multiple independent variables in the machining process through experimental methods is labor-intensive because of requires carrying out many experiments to optimize the process, resulting in increased costs in time and manpower [4]. Besides, it is difficult to keep all the factors under control necessary to obtain reproducible results [5]. Furthermore, there is a complex relationship between surface quality and machining parameters. The interactions between the different input parameters that affect the surface roughness would be unexplained variability due to extraneous factors. Therefore, a model and quantifying the relationship between surface roughness and the parameters affecting its value is required for improving the stable machining process. Response surface methodology (RSM) is a widely used technique in solving many complex engineering problems [6]. It is one of the most efficient and economical solutions for the pre-production industrial process. RSM method is commonly used o model, analyzed, and optimize processes, which are required fewer experiments and are less time-consuming in contrast to real experimental study. Furthermore, RSM can establish the nonlinear correlation between input parameters and output results that represents the interactive effects of multiple independent variables and their effects on response variables [7].

This work investigates the dry-turning process of Ti6Al4V alloy using a polycrystalline diamond (PCD) tool insert. The effects of various machining parameters (i.e., cutting speed, feed, depth of cut) and their mutual influence on the response variables (i.e., surface roughness) were investigated using RSM. With the minimum number of experiment data, a mathematical surface model was built. An analysis of variance (ANOVA) was carried out to understand significant differences and interactions between these variables. Besides, optimization of cutting parameters has been performed to achieve minimum surface roughness.

2. MATERIALS AND METHODOLOGY

2.1. Experimental methodology

This study used an experimental design method based on RSM. The experimental data collected from the experiments according to the design of experiments (DoE) were utilized to build mathematical surface model by RSM. Herein, mathematical regression model was establish the relationship between the input factors of cutting speed (X_1), feed rate (X_2), and depth of cut (X_3), and output variable, such as surface roughness (Y).

Table 1. *Experimental factors and levels of the input parameters.*

Experimental factors	Symbols		Levels			Step change value (ΔX_i)
	Un-coded	Codified	Low (-1)	Middle (0)	High (+1)	
Cutting speed (m/min)	X_1	x_1	100	150	200	50
Feed rate (mm/rev)	X_2	x_2	0.1	0.2	0.3	0.1
Depth of cut (mm)	X_3	x_3	0.1	0.15	0.2	0.05

For the experimental plan, a design of experimental (DoE) for three levels full factorial was used. Table 1 indicates the experimental factors and the assignment of coded and un-coded levels, respectively. A central composite design (CCD) and quadratic model with three variables were used to study the influence of independent variables and to determine the optimum combination of variables [6]. Each independent variable contains three levels as shown in table 1. Based CCD design, total of 20 experiments, including six axial points, eight fractional points, and six replicates at the center point was selected randomly. The variables were coded following equation.

$$x_i = \frac{X_i - \overline{X_\iota}}{\Delta X_i} \quad (1)$$

where x_i indicates the dimensionless value of an independent variable, X_i represents the real value of an independent variable, $\overline{X_\iota}$ shows the actual value of an independent variable at the center point, and ΔX_i is step change content of un-coded variable.

A quadratic polynomial equation is used to build the relationship between the predicted responses (surface roughness) and the independent variable. The equation proposed for the response variable is given using Eq. (2):

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} \beta_{ij} x_i x_j \quad (2)$$

where Y represents response values; x_i, x_j,…, x_k indicates input variables; x_i^2, x_j^2,..., x_k^2 are the square effects; $x_i x_j, x_i x_k, \dots, x_j x_k$ are the interaction effects; β0 is a constant coefficient; βi, βii, βij are estimated the values of linear, quadratic and interaction coefficients, respectively [9].

The regression models can be checked through the coefficient of determination (R^2) and adjusted coefficient of determination (R^2_{adj}). Analysis of variance (ANOVA) are used to assess the suitability of the regression model. The significance of coefficients of mathematical equation was determined via F-value and p-value. The RSM method was performed with the help of computer software to build the mathematical model equation. The Design-Expert software version 12 (DoE, Stat-Ease Inc., USA) was employed for the design of experiments, analyzing data, building a nonlinear relationship between input variables and output variables, and optimizing response variables.

2.2. Experimental setup

The experimental data is performed to establish a relationship between the cutting parameters and surface roughness through mathematical model. The experiments were carried out under dry turning conditions on a CNC lathe Mitsubishi MALC-12A ANBE-047-02. The experiments were performed according to the combination of input variables based on RSM. The experimental setup is illustrated in Fig.1.

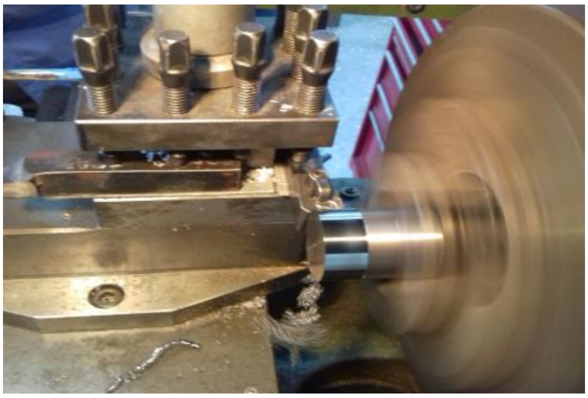

Figure 1. *The arrangement of experimental setup.*

The experiments used a ISO standards cutting tool. The cutting tool consists of two parts: the tool body and tool insert. The tool body is made of CD70 tool carbon steel, and the tool insert is a piece of polycrystalline diamond (PCD-ISO Standard PCD cutting Tool, type of CCGW09T308) with a nose radius of 0.8 mm. The experimental material was Ti6Al4V alloy rods, length of 150 mm, and a diameter of 60 mm.

Table 2. *Experimental design matrix, and surface roughness data.*

Run order	Codes values (X)			Experimental data responses (Y)	Predicted value
	X_1(m/min)	X_2(mm/rev)	X_3(mm)	Y (Ra(μm))	Y' (Ra(μm))
1	150	0.2	0.15	1.25	1.21
2	150	0.2	0.1	1.13	1.18
3	200	0.2	0.15	1.03	1.07
4	150	0.2	0.15	1.23	1.21
5	200	0.3	0.1	1.15	1.13
6	100	0.3	0.2	1.47	1.48
7	150	0.2	0.15	1.21	1.21
8	100	0.3	0.1	1.39	1.38
9	100	0.1	0.1	0.95	0.94
10	150	0.2	0.15	1.21	1.21
11	100	0.1	0.2	1.04	1.05
12	200	0.3	0.2	1.2	1.2
13	150	0.2	0.15	1.28	1.21
14	150	0.2	0.2	1.28	1.27
15	150	0.1	0.15	0.93	0.95
16	200	0.1	0.1	0.85	0.83
17	100	0.2	0.15	1.27	1.27
18	150	0.3	0.15	1.29	1.31
19	200	0.1	0.2	0.91	0.91
20	150	0.2	0.15	1.15	1.21

The surface roughness was measured by using a surface roughness tester (TR-200). The probe is placed at a position on the work-piece surface, then moves the probe along a parallel line of the work-piece center axis.

3. RESULTS AND DISCUSSION

3.1. Regression models and data analysis

The design matrix (actual values) based on the CCD method, actual results of surface roughness, and predicted values are shown in table 2.The results revealed that there was no significant difference between the actual and predicted values. It can be observed that the experimental values are in a reasonable correlation with the predicted values from the RSM model. A multivariate regression empirical equation between machining parameters and surface roughness was established using the polynomial equation (2). The coefficients of the polynomial equation were calculated from experimental data through analysis of variance (ANOVA). The best-fit model of the surface roughness in terms of coded factors is given in Eq. (3). This equation can be used to make predictions about surface roughness for random combinations of each factor.

$$\left(\text{Ra}(\mu\text{m})\right) = 1.21 - 0.098x_1 + 0.182x_2 + 0.043x_3 - 0.035x_1x_2 - 0{,}0075x_1x_3 - 0.0025x_2x_3 - 0.0359x_1^2 - 0.0759x_2^2 + 0.0191x_3^2 \quad (3)$$

Table 3. *ANOVA analysis for the surface roughness quadratic model.*

Response	Model terms	Sum of square	Degree of freedom	Mean square	F-value	p-value (Prob. >F)	
Surface roughness	Mode	0.4967	9	0.0552	31.21	< 0.0001	significant
	X_1-Cutting speed	0.096	1	0.096	54.31	<0.0001	
	X_2-Feed rate	0.3312	1	0.3312	187.32	< 0.0001	
	X_3-Depth of cut	0.0185	1	0.0185	10.46	0.009	
	X_1X_2	0.0098	1	0.0098	5.54	0.0404	
	X_1X_3	0.0005	1	0.0005	0.2545	0.6249	
	X_2X_3	0	1	0	0.0283	0.8698	
	X_1^2	0.0035	1	0.0035	2.01	0.1871	
	X_2^2	0.0158	1	0.0158	8.96	0.0135	
	X_3^2	0.001	1	0.001	0.5668	0.4689	
	Residual	0.0177	10	0.0018			
	Total	0.5144	19				
	Lack of fit	0.008	5	0.0016	0.8261	0.5805	
	Pure error	0.0097	5	0.0019			
	R^2 = 0.9656, Adj. R^2 = 0.9347, AP = 21.7257, C.V. = 3.62%						

ANOVA analysis was performed to check the adequacy of the regression model. The results in table 3 revealed that the experimental data can be well represented by a quadratic polynomial model. The coefficient of determination (R^2) values for surface roughness (Y) was 0.9656, indicating at least 96.56% for response values can be attributed to the defined independent variables. Furthermore, the value of R^2 proximity to unity indicates that the influence of cutting parameters on response variables could be fully described through a quadratic polynomial model, and the data show a better fit of the model with the experimental results.

A smaller P value and a larger F value also show a significant effect on the response variable [9]. In our work, the model F-value of 31.21 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise factors. The P-values are less than the level of significance (≤0.05) relative to pure error for all variables, which indicates that our model is statistically accurate. Furthermore, the signal-to-noise ratio of the models is characterized by adequate precision (AP). The AP values in this work are 21.7257, which is higher than 4 for all the responses, indicating an adequate intensity of the signals. The Lack of Fit F-value of 0.83 implies the Lack of Fit is not significant relative to the pure error. Herein, there is a 58.05% chance that a Lack of Fit F-value. This large could occur due to noise. Notably, a non-significant lack of fit is good [10]. The results obtained conclude that RSM model is reliable.

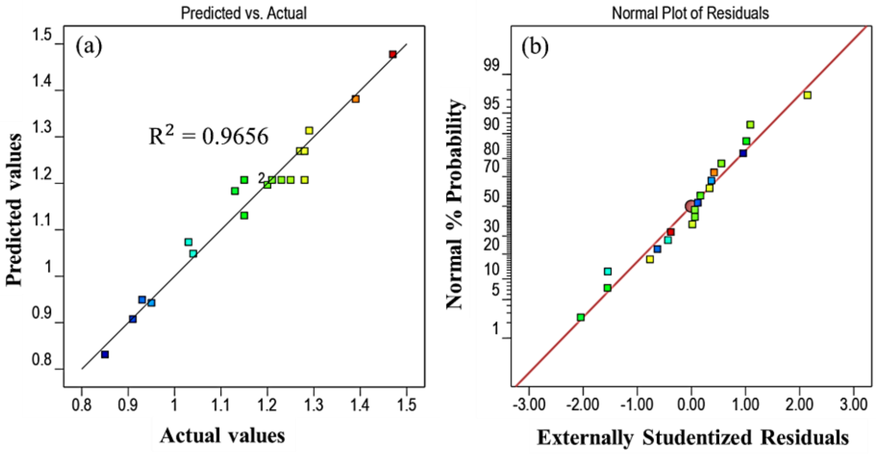

Figure 2. *The plot of predicted value versus real values for surface roughness.*

Fig. 2 presents a reasonable correlation between the actual measured values of surface roughness and the predicted response values from the model. Indeed, the results observed in Fig. 2 showed that the actual values were distributed relatively close to the straight line, indicating that the predicted values from the quadratic model equation are in good agreement with the experimental results within an acceptable variance range (Fig. 2a). The normal probability plots of the residuals and the plots of the residuals versus the predicted response variables are depicted in Fig. 2b. The residuals lie on a straight line, implying that the errors are normally distributed. These results show that the proposed models are valid and there is no reason to suspect any violation of independence or constant variance assumption.

3.2. Effect of independent variables on response variables

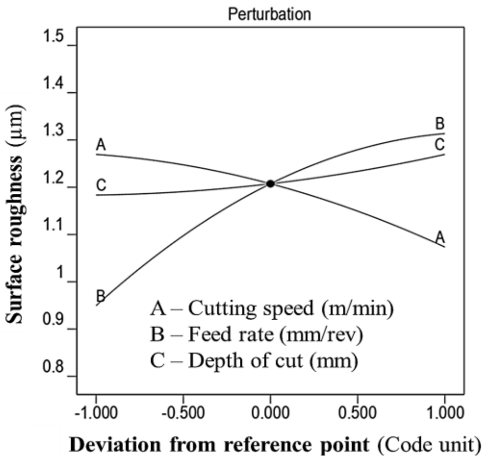

Figure 3. *The influence of each machining parameter on surface roughness.*

From the analysis of variance (ANOVA) (table 3) and response surface Eq. (3), the interactive influence of independent variables at different levels such as cutting speed, feed rate, and depth of cut on the surface roughness was identified. Eq. (3) gives the prediction model for the surface roughness based on experimental results. It reveals that feed rate is the most significant factor on the surface roughness, followed cutting speed and depth of cut. Fig. 3 indicates the influence of each machining parameter on surface roughness for the given range of parameters. It was observed that the feed rate is the most important factor affecting the surface roughness, followed by cutting speed and depth of cut. Herein, the depth of cut is a negligible effect on the surface roughness. One of the reasons for that might be related to the chosen range of the depth of cut in this work. On the other hand, the experimental results of table 2 showed that the minimum surface (0.83 µm) was obtained at a low feed rate (0.1 mm/rev) while the maximum surface roughness (1.48 µm) was observed at a high feed rate (0.3 mm/rev) and cutting speed of 200 m/min.

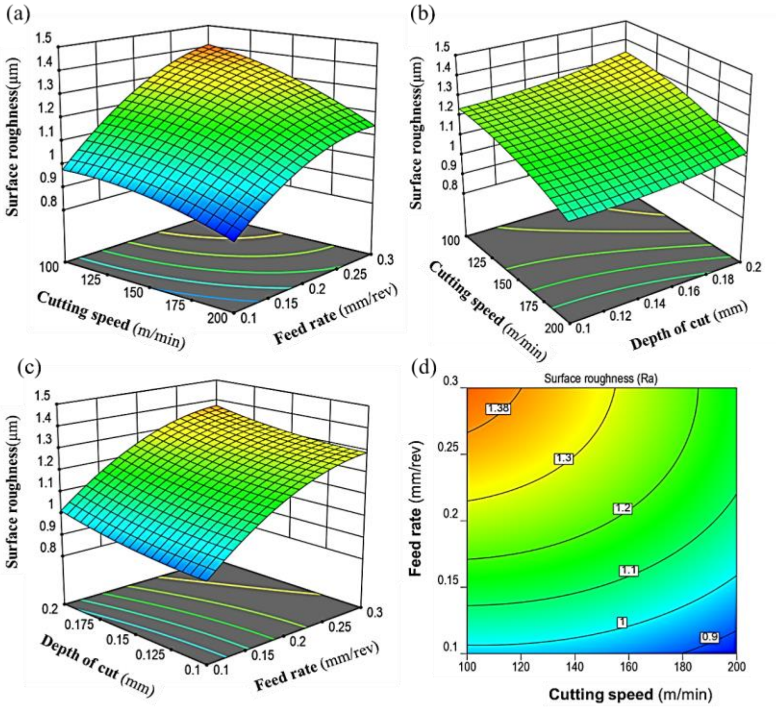

Figure 4. *3D plot of the cutting parameters against the surface roughness.*

The response surfaces based on a quadratic polynomial regression model illustrated complex interaction among independent variables as shown in Fig. 4. These plots are created by varying two independent variables in the experimental range while the third variable is kept at the center point. Fig. 4a presents the influence of cutting speed and feed rate on surface roughness, which showed that the increasing feed rate has a negative effect on surface quality. However, the overall observation showed that both independent variables have a strong influence on surface roughness, in which, the feed rate is the dominant factor affecting surface roughness in the selected range of cutting parameters, followed by cutting speed. Increasing cutting speed lead to a decrease in the surface roughness. This result can be attributed to the presence of built-up-edge at the lower cutting speeds and large cutting forces [11]. The interaction effect of cutting speed and depth of cut is clearly observed in Fig. 4b. Good surface quality can be obtained for a higher cutting speed, and depth of cut has negligible on the surface roughness. Fig. 4c shows the interactive effect of feed rate and depth of cut on surface roughness. This plot was obtained by varying the feed rate and depth of cut over the test range while the cutting speed is kept at the center point. The result in Fig. 4c shows that the surface roughness changes slightly with increasing the depth of cut from 0.1 to 0.2 mm. Fig. 4d presents the contour plot as an estimate of the surface roughness as a function of two key parameters, feed rate and cutting speed. The lowest surface roughness is obtained at the minimum feed rate and the maximum cutting speed. In summary, the use of response surface methodology indicates that the predicted surface roughness is strongly dependent on the feed rate, followed by the cutting speed and the depth of cut in the range survey of this work.

3.3. Optimization of independent variables

Achieving the desired surface roughness of optimal cutting parameters is one of the most important goals of experiments related to manufacturing. The optimization of the response variable was carried out using expert design software to find the best combination of cutting parameters that could lead to minimum surface roughness.

The minimum of surface roughness was 0.832 µm, which achieved under the machining conditions of cutting speed (200 m/min), feed rate (0.1 mm/rev), and depth of cut (0.1 mm). There is a small difference between the optimized value and the experimental value.

4. CONCLUSIONS

This work investigated the influence of machining parameters on the surface roughness in dry-turning Ti6Al4V alloy. A mathematical regression model based on RSM has been developed to understand the combined effect of cutting parameters on the surface roughness (R_a (µm)), and to facilitate the optimization of the machining process. The results reported that the quadratic model was sufficient to describe and predict the responses of surface roughness with the change of independent variables. The experimental values were very close to the predicted values of surface roughness. The feed rate and cutting speed have a significant effect on the surface quality, in which, the feed rate is a dominant factor affecting surface roughness in the selected range of cutting parameters. The depth of cut has a negligible effect on the surface roughness in the specified range. The optimum condition was obtained for a minimum surface roughness value of 0.832 µm corresponding to optimum machining parameters of 200 m/min cutting speed, 0.1 mm/rev of feed rate, and 0.1 mm of the depth of cut. Experimental results demonstrate that the machining model is suitable and satisfies the practical requirements.

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TÓM TẮT

Dự đoán nhám bề mặt hợp kim Ti6Al4V và tối ưu hóa tham số công nghệ dựa trên phương pháp thiết kế thí nghiệm

Ảnh hưởng của các tham số công nghệ trong quá trình tiện khô hợp kim Ti6Al4V sử dụng một phương pháp thiết kế thí nghiệm đã được nghiên cứu. Một phương trình toán học dựa trên phương pháp bề mặt đáp ứng đã được thiết lập để hiểu đầy đủ sự ảnh hưởng của các tham số công nghệ (tốc độ cắt, lượng tiến dao, và chiều sâu lớp cắt) lên độ nhám bề mặt Ra (µm). Một tập hợp các thí nghiệm dựa trên thiết kế giai thừa đầy đủ thống kê ba cấp của phương pháp thí nghiệm đã được thực hiện để thu thập giá trị trung bình của dữ liệu độ nhám bề mặt. Giá trị của mô hình R^2 = 0,9656 cho thấy mối tương quan tốt giữa kết quả thực nghiệm và giá trị dự đoán. Kết quả phân tích từ mô hình cho thấy tốc độ chạy dao là yếu tố có ảnh hưởng mạnh nhất đến độ nhám bề mặt, tiếp đến là tốc độ cắt và chiều sâu cắt. Độ nhám bề mặt nhỏ nhất khi lượng tiến dao và chiều sâu cắt được đặt ở mức thấp nhất và tốc độ cắt được đặt ở mức cao nhất. Xác minh kết quả thực nghiệm cho thấy điều kiện tối ưu của độ nhám bề mặt 0,832 µm đã đạt được ở tốc độ cắt 200 m/phút, lượng tiến dao 0,1 mm/vòng và chiều sâu cắt 0,1 mm.

Từ khoá: Hợp kim Ti-6Al-4V; Tham số công nghệ; Độ nhám bề mặt; ANOVA.