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Process Design for Optimal Minimization of Resultant Cutting Force during the Machining of Ti-6Al-4V: Response Surface Method and Desirability Function Analysis

Daramola, O.O.[a,c]*, Tlhabadira, I.[b], Olajide, J.L.[c], Daniyan, I.A[b]., Sadiku, E.R[c]., Masu, L.[d], VanStaden L.R.[e].

[a]*Department of Metallurgical and Materials Engineering, Federal University of Technology, Akure, PMB 704, Akure Nigeria*
[b]*Department of Mechanical & Mechatronics Engineering, Tshwane University of Technology, Pretoria, South Africa*
[c]*Institute of NanoEngineering Research (INER), Department of Chemical, Metallurgical and Materials (Polymer Division Technology) and the Tooling Center, Soshanguve Campus, Tshwane University of Technology, Pretoria, 117, Republic of South Africa*
[d]*Department of Mechanical Engineering, Vaal University of Technology, Vanderbijlpark, South Africa.*
[e]*Office of the VC, Tshwane University of Technology, Pretoria, South Africa*

* Corresponding author. Tel.: +2-764-031-1197; Tel.: +234-816-681-4002. *E-mail address:* daramolaoo@tut.ac.za, oodaramola@futa.edu.ng

Abstract

Cutting Forces are very essential during machining process as they determined the surface finish, power consumption, machining precision and working temperature of the process. Therefore, it is paramount to have a thorough understanding of how cutting parameters influence the resultant cutting force during machining operations. In the present study, the optimal RCF required to machine Ti-6Al-4V alloy using carbide insert on a DMC 635V DMG CNC vertical milling machine attached with a Kisler dynamometer has been investigated; the influence of four machining parameters namely cutting speed, feed rate, feed/tooth and depth of cut was considered. Data sets generated from the dynamometer were used as building blocks for the RSM design matrix which was developed and analyzed with the aid of Design Expert Software. Design data for optimum cutting force during milling process were generated. The validity and reliability of the developed models were established with ANOVA and experimental results. It was found that a significant second-order model best suited the prediction of RCF at 95% confidence level.

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Keywords: Titanium alloys; Design of experiment; Statistical modeling; Manufacturing technology; Cutting force

1. Introduction

Ti-6Al-4V (Grade 5) alloy is a unique and high-performance material that ranks very high when it comes to diverse areas of applications. Its applications are notably seen in several industries such as aerospace, marine, power generation, offshore and biomedical industries [1-3]. This is attributed to its large array of attractive properties which include but not limited to high strength-to-weight ratio, excellent corrosion resistance, excellent fatigue performance, outstanding biocompatibility and appreciable creep resistance [1-3]. However, to meet targeted end-use(s), this alloy requires machining to desired geometries and quality which is not easily achievable owing to the poor machinability associated with titanium-based materials [1].

Generally, titanium-based materials are difficult-to-machine materials. This is due to their low stiffness, high work hardening potential, high chemical reactivity and low thermal conductivity [1-3]. The downside to this is that, high cutting

Nomenclature

RSM	Response Surface Methodology
RCF	Resultant Cutting Force
ANN	Artificial Neural Network
DFA	Desirability Function Analysis
DOE	Design of Experiment
ANOVA	Analysis of Variance

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forces are usually required which in turn may rapidly wear out cutting tools, impart low quality to surface finish, increase power consumption, increase operating temperature and overall increase machining cost [1]. Therefore, it is paramount for the machinist to establish a predicted range of cutting forces that would be beneficial in terms of economic viability and machine surface quality. This is usually achieved either through experimental design or theoretical means and at times through both means [3].

Previous studies have shown the capability and reliability of statistical Design of Experiments (DOE) in helping the machinist to achieve the above-mentioned objectives [4]. In this context, design matrices for required experimental runs for predictive model development are first determined theoretically by hand or automatically by specific software packages prior to the destructive machining test. Of late, the latter has become prevalent amid design engineers and researchers as it saves time and cost and also rapidly generates multiple models for further predictions of preferred machining responses [4]. The predominant DOE methods that have proven effective in this regard are RSM, Artificial Neural Network (ANN) and Taguchi [2-4]. However, of interest to the present study is the prediction and minimization of required Resultant Cutting Force (RCF) to machine Ti-6Al-4V using RSM and Desirability Function Analysis (DFA).

As obtainable from the literature, RSM is a convenient numerical tool for generating reliable DOE models that can accurately predict machining responses such as cutting forces and surface roughness of Ti-6Al-4V from design matrix-dependent experimental results. Chauhan and Dass showed that RSM-derived quadratic models accurately predicted the surface roughness and tangential cutting force of Ti-6Al-4V in comparison with experimental results [5]. A similar result was reported by Ribeiro Filho et al when they used RSM and DFA to study the influence of cutting parameters on the surface roughness, cutting forces and biocompatibility of Ti-6Al-4V and Ti-6AL-7Nb alloys [6]. According to Mia et al, a comparative study between RSM and ANN predictions of cutting forces in turning Ti-6Al-4V also indicated that RSM has greater accuracy than ANN [2]. Another detailed work conducted by Sahu and Andhare on multi-objective optimization for improving the machinability of Ti-6Al-4V using RSM and advanced algorithms revealed a parallel result between RSM predictions and that of the best algorithm developed [7].

It is evident that there exists an impressive number of interesting research findings associated with this subject matter. However, literature references on varying cutting speed, feed rate, feed/tooth and depth of cut during machining of Ti-6Al-4V with carbide insert for RCF prediction and its optimal minimization using RSM-DFA approach are limited. In the present study, RSM based on a three-level four-factor Box Behnken design was used to evaluate the individual and interactive effects of cutting speed, feed rate, feed/tooth and depth of cut on the RCF required to machine Ti-6Al-4V. For the predictive models' development, the above-mentioned machining parameters were set as the independent/input variables while RCF (obtained from Kitsler Dynamometer) was set as the dependent/output variable. The DFA study (smaller is better) for RCF optimization was also carried out in Design Expert DOE software environment. However, it should be noted that RCF must not be drastically minimized as this could somewhat aggravate poor machinability of Ti-6Al-4V with certain poor machine surface quality and undesirable chip morphologies as consequences [8]. In light of this, this study considered a suitable range of RCFs deficient of the foregoing shortcomings for the DFA study.

2. Experimental

2.1. Materials

Commercial grade Ti-6Al-4V (Grade 5) sourced for and procured from SAETRA (Pty) Ltd., Republic of South Africa was the primary material used as the workpiece/test specimen in this study. The test specimens were rectangular blocks of 172mm x 78mm x 67mm. The chemical composition and properties of the alloy are given in Table 1.

Table 1. Chemical composition and properties of Ti-6Al-4V.

Element	Comp (wt.%)	Property	Value
Ti	89.900	Tensile Strength	862 MPa
Al	5.500	Young Modulus	110 GPa
V	4.000	Hardness	3370 MPa
C	0.100	Fracture Toughness	84 MPa
O	0.200	Thermal Conductivity	07.1 W/mk
N	0.050	Property	Value
H	0.013	Tensile Strength	862 MPa
Fe	0.240	Young Modulus	110 GPa

The cutting tool/insert material selected for the Ti-6Al-4V was carbide tool with a nose radius of 0.8 mm.

2.2. Methods

The milling operation of the Ti-6Al-4V alloy was performed using a DMC 635 V DMG ECOLINE, Deckel Maho Germany, Siemens 810D, 3- Axis, CNC vertical milling machine The orthogonal cutting forces (f_x, f_y, and f_z) were automatically measured with the aid of a Kistler brand 9257 B-type three component piezoelectric dynamometer in conjunction with XFC software and a PC. The RCF was calculated according to Equation 1. The milling operation was carried out with varying values of the machining parameters where cutting speeds C_s range between 260 and 275 m/min, feed rates between 828 and 2188 mm/rev, feed/teeth between 0.08 and 0.2 mm/tooth and depths of cut between 0.5 and 1.5 mm.

$$RCF = (f_x^{\,2} + f_y^{\,2} + f_z^{\,2})^{1/2} \quad (1)$$

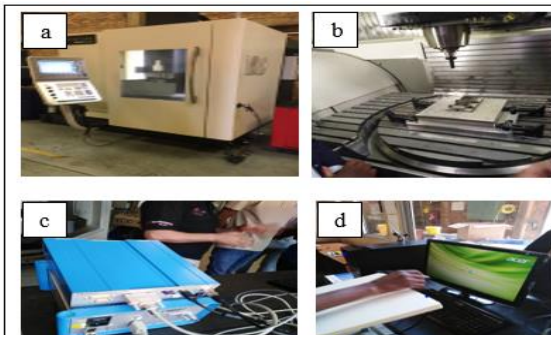

Fig.1. Design of physical experiment for the milling operation showing (a) vertical CNC milling machine (b) milling of the Ti-6Al-4V (c) Kistler dynamometer (d) Visualization of the Kistler dynamometer results

RSM and DFA

RSM is a numerical/statistical tool that fits a polynomial regression model with cross-product terms of variables that may be raised up to the third power. It calculates the minimum and maximum of the surface. In industrial process, RSM is usually employed for formulation of problems and process optimization [4-8]. The concept of RSM involves dependent variables (y_1, y_2, y_3….y_n) also known as the response variables and several independent variables (x_1, x_2, x_3…….x_k). If all these variables are measurable, the response surface for a single response can be expressed as:

$$y = f(x_1, x_2, x_3, \ldots x_k) + \varepsilon \qquad (2)$$

Where "ε" is the error/noise which is normally distributed with zero mean according to the observed response. One of the main goals of RSM is to find a polynomial approximation of the true nonlinear model that works well in a specified region. In a very small region, linear (first-order) approximation may be adequate (when there is no curvature) as shown in Equation 3.

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_n x_n + \varepsilon \quad (3)$$

A larger region may require a quadratic (second-order) approximation or higher-order approximation (when there is curvature) as shown in Equation 4.

$$y = \beta_0 x_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \sum\sum_{i<j}^{n} \beta_{ij} x_i x_j + \varepsilon \quad (4)$$

Where β_0 is the fixed term and β_i, β_{ii} and β_{ij} are the coefficients of linear, quadratic and cross-product terms, respectively.

In this research a second-order model is used to predict the RCF (Equation 4). Design Expert DOE software (version 11.1.0.1) was employed for the RSM and DFA. The RSM in this study was based on a four-factor three-level Box-Behnken design having 1 block and 6 center points. Previous studies have shown this design to be effective in cases like this [9,10]. The design matrix-layout (randomized) for the 30 experimental runs used is given in Table 2.

Table 2: Box-Behnken Design Matrix Layout

Run	Factor A	Factor B	Factor C	Factor D	Response
1	260	1508	0.2	1	10.3455
2	260	2188	0.14	1	12.9443
3	267.5	828	0.2	1	12.3454
4	267.5	1508	0.14	1	12.3451
5	260	828	0.14	1	9.94843
6	267.5	1508	0.14	1	12.3454
7	267.5	2188	0.14	0.5	18.0344
8	267.5	1508	0.2	1.5	16.345
9	275	828	0.14	1	3.4574
10	267.5	1508	0.14	1	12.3454
11	260	1508	0.08	1	8.9034
12	267.5	1508	0.08	0.5	12.1454
13	267.5	828	0.14	1.5	10.3454
14	267.5	2188	0.2	1	16.8393
15	267.5	1508	0.14	1	12.3454
16	267.5	828	0.14	0.5	10.2454
17	275	2188	0.14	1	15.6843
18	267.5	828	0.08	1	6.1881
19	275	1508	0.14	0.5	6.9533
20	267.5	1508	0.2	0.5	12.3454
21	275	1508	0.08	1	6.3454
22	275	1508	0.2	1	8.3104
23	267.5	1508	0.14	1	18.3454
24	275	1508	0.14	1.5	9.9346
25	260	1508	0.14	0.5	10.4566
26	267.5	1508	0.08	1.5	16.0434
27	267.5	1508	0.14	1	18.3454
28	260	1508	0.14	1.5	9.9454
29	267.5	2188	0.14	1.5	18.0394
30	267.5	2188	0.08	1	16.0455

Where Factors A, B, C and D are Cutting Speed (mm/min), Feed Rate (mm/rev), Feed/Tooth (mm/tooth) and Depth of Cut (mm), respectively. The codes -1, 0, 1 are the corresponding levels of each independent variable, that is, form high to low levels where -1 is low level, 0 is medium level and 1 is high level. The Response is the RCF.

Optimization (minimization or maximization) by DFA includes the use of a desirability function D(x) which comprises multiple desirability values (i.e., d_i). Each desirability ranges from the lowest to the highest which in turn possesses the numerical value 0 to 1. Presumably, the highest combined desirability, which is computed by taking the geometric means of all the desirability functions, represents the optimum responses for an optimum parameter setting. The combined objective function is presented in Equation 5,

$$D = (d_1 \times d_2 \times \ldots\ldots d_n)^{1/n} = \left(\prod_{i=1}^{n} d_i\right)^{1/n} \qquad (5)$$

3. Results and Discussion

Automatic fitting of the experimental data to various models available in Design Expert ensued by their ANOVA indicated that influence of cutting parameters on the RCF is best captured by the quadratic model .The generated quadratic model is given in Equation 6.

$$\begin{aligned} RCF = {} & 14.35 - 0.9882A + 3.75B + 0.9050C + 0.8727D \\ & + 2.31AB + 0.1307AC + 0.8731AD \\ & - 1.34BC - 0.0238BD + 0.0254CD \\ & - 4.61A^2 + 0.0007B^2 - 0.9887C^2 \\ & + 0.0902D^2 \end{aligned} \qquad (6)$$

Table 3: ANOVA for the Quadratic Model

Source	SS	DF	MS	F-Val	p-Val	R
Model	385.14	14	27.51	5.99	0.0007	Sig
A-Cs	11.72	1	11.72	2.55	0.0311	Sig
B	169.18	1	169.18	36.82	<0.0001	Sig
C	9.83	1	9.83	2.14	0.1642	~~Sig~~
D	9.14	1	9.14	1.99	0.1008	~~Sig~~
AB	21.30	1	21.30	4.64	0.0410	Sig
AC	0.0684	1	0.0684	0.0149	0.0045	Sig
AD	3.05	1	3.05	0.6637	0.0280	Sig
BC	7.19	1	7.19	1.57	0.2301	~~Sig~~
BD	0.0023	1	0.0023	0.0005	0.0826	~~Sig~~
CD	0.0026	1	0.0026	0.0006	0.0014	Sig
A^2	145.75	1	145.75	31.72	<0.0001	Sig
B^2	3.3E-6	1	3.3E-6	7.2E-7	0.0993	~~Sig~~
C^2	6.70	1	6.70	1.46	0.2458	~~Sig~~
D^2	0.0558	1	0.0058	0.0122	0.0137	Sig
Res	68.92	15	4.59			
LOF	20.92	10	2.09	0.2179	0.981	~~Sig~~
P.Err	48.00	5	9.60			
Cor.T	454.06	29				
Where Sig -Significant, ~~Sig~~ -Insignificant and R -Remark						

The Fit statistics report for the quadratic model indicated R^2, Adjusted R^2, Predicted R^2, Adequate Precision, Standard Deviation, Mean and C.V % values of 0.8482, 0.7065, 0.5824, 10.7904, 2.14, 12.14 and 17.65, respectively.

From the results, the Model F-Val implies the model is significant at 95 % confidence level. There is only a 0.07% chance that an F-Val this large could occur. P-Val less than 0.0500 indicate model terms are significant and values greater than 0.1000 indicate the model terms are not significant. The LOF value of 0.22 implies the LOF is not significant relative to the P.Err. There is a 95.05 % chance that a LOF F-Val this large could occur due to noise. Non-significant LOF is a good attribute of a reliable model. It shows that the predicted values correlate with the actual values. The Predicted R^2 of 0.8824 is in reasonable agreement with the Adjusted R^2 of 0.7965; i.e. the difference is less than 0.2. The value of the adjusted R^2 which increases with number of terms in the model observed shows the model can be adequately used to represent the actual relationship between the cutting parameters and the RCF. R^2 values below 0.75 are considered inadequate for reliable predictions [11]. Adequate Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The ratio of 10.790 observed in this study indicates an adequate signal. Thus, this model can be used to navigate the design space. The plot of actual RCF values from the experiment versus predicted RCF values from the model is shown in Fig. 2. The maximum residual observed between the predicted and actual values is < 5 and this is in reasonable agreement with the findings of [5-8].

From the quadratic model equation (Equation 5), it was observed the coefficients of cross-product terms BC and BD are negative. This is an indication that the mutual effects of these factors would be negative on the RCF once the optimum region is exceeded. However, it is important to note that these two model terms are not significant as reflected in the ANOVA outcome (Table 3). Therefore, little emphasis would be laid on their interactive effect on the RCF. From the ANOVA outcome, the most significant factor is feed rate, followed by the interaction between feed rate and cutting speed.

Fig. 2 shows the plot of actual RCF values versus predicted RCF values. The trend of the result shows good correlation between the experimental and theoretical outputs. Therefore, the model can be used to predict the RCF within the limits of factors studied with good degree of approximation.

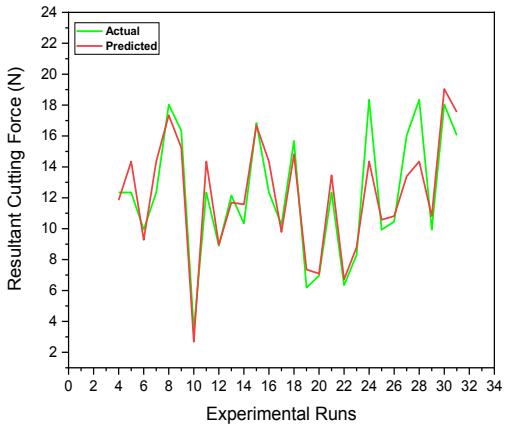

Fig. 2. Plot of actual RCF values versus predicted RCF values

Interactive Effects of Cutting Parameters on the RCF

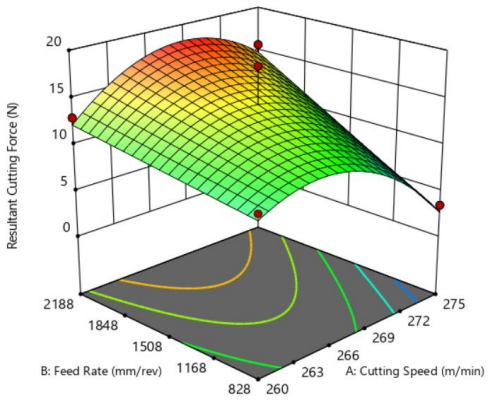

Fig. 3. Response surface plot showing the effect of feed rate, cutting speed and their mutual effect on the RCF required to machine Ti-6Al-4V. Other variables are constant: feed/tooth, 0.14 mm/tooth and depth of cut, 1 mm

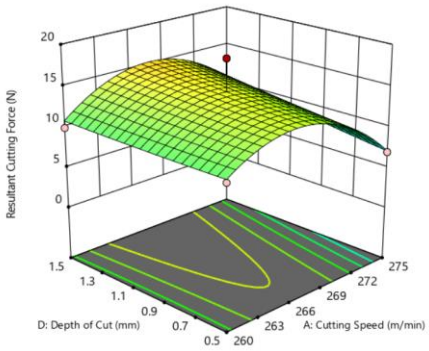

Fig. 4. Response surface plot showing the effect of depth of cut, cutting speed and their mutual effect on the RCF required to machine Ti-6Al-4V. Other variables are constant: feed rate, 1508 mm/rev and feed/tooth, 0.14 mm/tooth

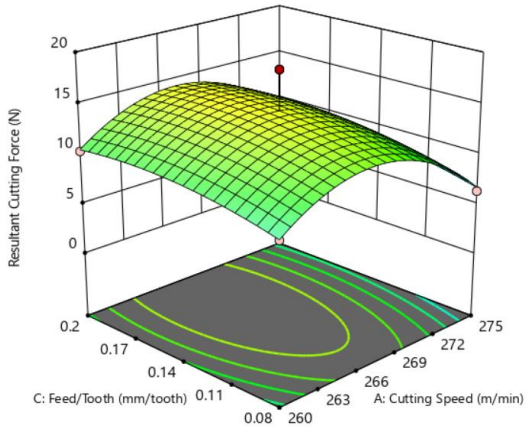

Fig. 5. Response surface plot showing the effect of feed/tooth, cutting speed and their mutual effect on the RCF required to machine Ti-6Al-4V. Other variables are constant: feed rate, 1508 mm/rev and depth of cut 1 mm

Fig. 3 shows the effect of feed rate and cutting speed at a constant feed/tooth of 0.14 mm/tooth and depth of cut of 1 mm. It was found that RCF initially increases with increase in both factors until a critical cutting speed value was reached. This was ensued by continuous decrease in RCF as cutting speed increases (negative effect). This is supported by the ANOVA report wherein the estimated coefficients of A (cutting speed) and A^2 are negative. In fact, it is expected that the effect of the combination of A with any other factor would be negative beyond a critical value. The maximum RCF of 18.3454 N was observed at highest feed rate (2188 mm/rev) and intermediate cutting speed (267.5 m/min). According to Hou et al, this is due to the effect of thermal softening and chip thickness reduction which predominates over the effect of strain hardening on the alloy in the given condition [12]. Also, Polishetty et al explained the linear relationship between feed rate and RCF as a function of effort required to remove chip [13]. According to their findings, as feed rate increases, section area of sheared chip also increases due to extensive plastic deformation exhibited by titanium alloys at high temperature. Thus, large effort is required for chip removal.

Fig. 4 shows the effect of depth of cut and cutting speed at a constant feed rate of 1508 mm/rev and feed/tooth of 0.14 mm/tooth). Similarly, Fig. 5 shows the effect of feed/tooth and cutting speed at a constant feed rate of 1508 mm/rev and depth of cut of 1 mm. Observations from both results, also showed the negative effect of cutting speed on RCF after the critical value was exceeded. However, the lowest RCF values (Fig 4, 6.3454 N and Fig 5, 6.9533 N) observed for both cases were not as low as that observed for Fig. 2 (3.4574 N). The maximum RCFs for the factors AD and AB interactions are 15.0066 N and 14.4772 N, respectively. For AD interaction, this value of RCF w obtained at cutting speed of 267.5 m/min and depth of cut of 1.5 mm and for AC interaction, it was observed at the same cutting speed and feed/tooth of 0.16 mm/tooth. Going by the ANOVA report, both model terms (AB and AD) are also significant, therefore should be put into substantial consideration for optimal minimization of RCF. From Fig. 4, the depth of cut remained constant with respect to RCF, it was only influential on RCF when combined with the cutting speed. A little deviation from this trend was observed in Fig. 5 with respect to effect of AC interaction on RCF. RCF slightly increased till a critical feed/tooth value (0.16 mm/tooth) was reached, beyond which RCF began to decrease slightly. Indications from both results show that unless depth off cut and feed/tooth are combined with either feed rate or cutting speed, they have little impact on the RCF. This is fully corroborated by the ANOVA report, where both factors are insignificant model terms in their linear forms. In most machining operations, these two factors are usually used to measure surface roughness and hardness as they are directly related to these responses [14]. However, this study investigated them as function of RCF because reports in this context are difficult to come by in the existing literature.

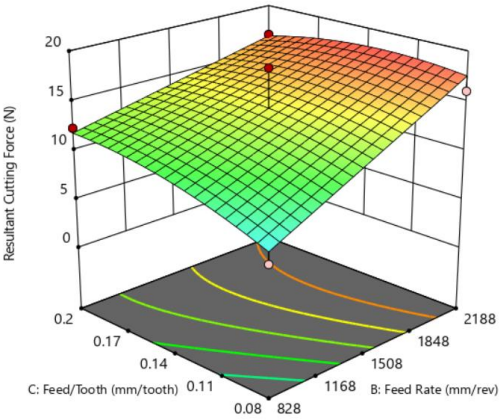

Fig. 6. Response surface plot showing the effect of feed/tooth, feed rate and their mutual effect on the RCF required to machine Ti-6Al-4V. Other variables are constant: cutting speed, 267.5 m/min and depth of cut 1 mm

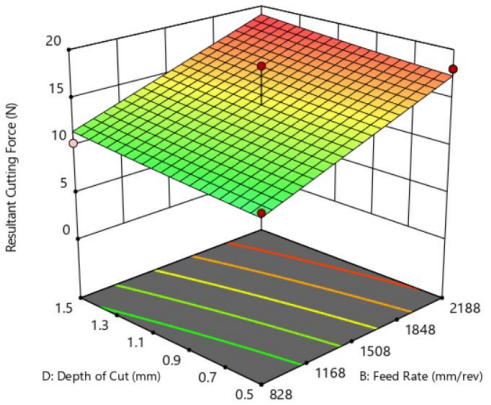

Fig. 7. Response surface plot showing the effect of depth of cut, feed rate and their mutual effect on the RCF required to machine Ti-Al-4V. Other variables are constant: cutting speed, 267.5 m/min and feed/tooth, 0.14 mm/tooth

Fig. 6 presents the effect of feed/tooth and feed rate at a constant cutting speed of 267.5 m/min and depth of cut of 1 mm. Fig. 7 presents the effect of depth of cut and feed rate at a constant cutting speed of 267.5 m/min and feed/tooth of 0.14 mm/tooth. Both results confirmed what was previously discussed in the preceding sections. In Fig. 6 the plot of RCF versus feeding rate shows a linear relationship which explains why the F-value (36.82, most significant value observed) and p-value (<0.0001) of the model term B are highly significant in the linear form. This is expected because the estimated coefficient of factor B (feed rate) from the model equation is the highest positive value (+3.75) observed. Thus, its notable

positive effect on RCF. Similarly, the plot of RCF versus feed/tooth also shows a pseudolinear relationship. Similarly, the coefficient of factor C (feed/tooth) is positive (+0.9050). This is an indication that the mutual effect of feed rate and feed/tooth on RCF would be positive if it is possible to establish a linear relationship between this mutual effect and RCF. This might actually be difficult to achieve in real life as other factors such as temperature, friction, abrasion and material type would influence the operation [15].

In Fig. 7, contrary to the pseudolinear relationship observed between feed/tooth and RCF, variation in depth of cut seemingly has little or no influence on RCF at a constant of 267.5 m/min and feed/tooth of 0.14 mm/tooth Similarly, in one work presented by [16] on dry turning of Ti-6Al-4V alloy, no significant change occurred in the frequency of depth of cut, even though the amplitude increased linearly with increase in cutting force. As for the feed rate in this study, it still exhibited a linear increase relationship with RCF regardless of the magnitude of depth of cut. That is, the mutual effect of depth of cut and feed rate on RCF is equivalent to the singular effect of feed rate on RCF.

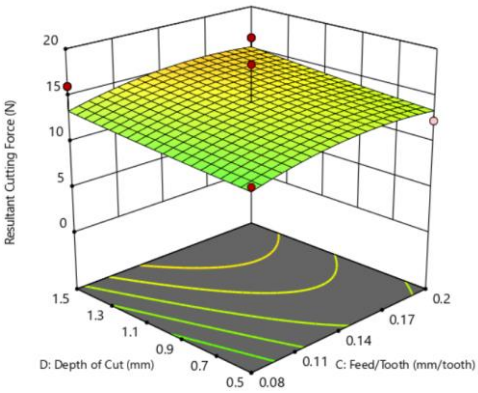

Fig. 8. Response surface plot showing the effect of depth of cut, feed/tooth and their mutual effect on the RCF required to machine Ti-6Al-4V. Other variables are constant: cutting speed, 267.5 m/min and feed rate 1508 mm/rev

In Fig. 8, the effect of depth of cut and feed/tooth on RCF at constant cutting speed of 267.5 m/min and feed rate of 1508 mm/rev is presented. The surface plot is a pseudo-flat surface which translates to very little impact of both factors on RCF irrespective of their variation and combination. The ANOVA report also showed that both factors are insignificant model terms in the prediction of RCF which is evident in this observation.

Optimal Minimization of RCF using DFA

Titanium alloys are very expensive and difficult-to-machine materials with most machining cases resulting in 90 % removal of the material as chip before the desired shape and surface finish are achieved [1]. Therefore, it is very essential to establish an optimum machining condition that would be favourable to economic viability in terms of minimal material removal, tolerable surface roughness, minimal tool wear rate and optimal RCF minimization. As obtainable from the literature, the machining of Ti-6Al-4V alloy (Grade 5) should be performed at maximized feed rate, minimized cutting speed using low-moderate RCF. These factors coupled with the observations from the RSM observations are taken into consideration to set the desirability constraints for machining Ti-6Al-4V in this study. The results obtained using Design Expert are presented in Table 4 and Fig. 9. As excessive minimization should be avoided due to reasons given in section 1, the optimal RCF was set to 10.6199 N which also happens to be the value with highest desirability within the given constraints.

Table 4. Desirability Constraints

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Limit
A-Cs	Minimize	260	275	1	1
B-FR	Maximize	828	2188	1	1
C-FT	in range	0.08	0.02	1	1
D-DC	in range	0.5	1.5	1	1
RCF	Minimize	3.4574	18.3454	1	1

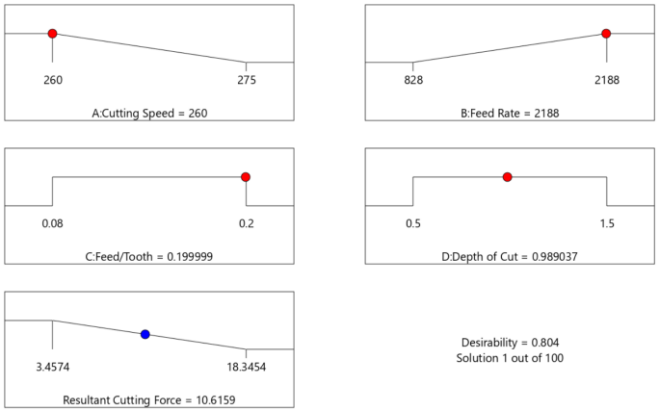

Fig.9. Optimization Ramps for Desirability Function Analysis

Conclusions

The influence of cutting parameters namely cutting speed, feed rate, feed/tooth and depth of cut on the RCF required to machine Ti-6AAl-4V was investigated and reported. In addition, RSM-ANOVA-DFA approach was used to establish the optimal RCF to machine the alloy. From the experimental and numerical results, designs data were generated the following conclusions can be drawn:

- The optimum cutting force (smaller is better) was found to be 10.6159 N with a desirability of 0.804 at feed rate, feed/tooth, cutting speed and depth of cut values of 2188 mm/rev, 0.1999 mm/tooth, 260 m/min and 0.9890 mm, respectively.
- Feed rate has the greatest influence on RCF, followed by cutting speed. Both feed/tooth and depth of cut has little to no influence on RCF. However, the feed/tooth slightly edged depth of cut in terms of little influence on RCF.
- RCF increased with increasing cutting speed till a critical cutting speed value was reached at 267.5 m/min. This was ensued by decrease in RCF at cutting speed above 267.5 m/min which is explained by predominance of chip shearing over plastic flow.

- RCF increased linearly with increasing feed rate irrespective of variations in depth of cut and feed/tooth.
- At 95 % confidence level, the developed quadratic model accurately predicts the RCF within the experiment's domain. The most significant model term is feed rate which is in agreement with the experimental results.
- RSM surface plots fully describe the actual relationship between the RCF and the interactive effects of the cutting parameters.
- From the DFA results, optimal minimization of RCF for machining Ti-6Al-4V can be achieved at high feed rate, low speed, high-low feed/tooth and high-low depth of cut. .

Further studies are encouraged in the optimal minimization of RCF required to machine Ti-6Al-4V at different temperatures and dry-wet machining conditions with huge emphasis on depth of cut and feed/tooth. This is expected to give more insight into the actual effect of these cutting parameters on RCF

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