STADISTICAL MODELING OF SURFACE ROUGHNESS IN MACHINING OF TI 6AL 4V ALLOY

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Abstract: The objective of this work is to present a methodology to predict the roughness during the machining process of the Ti 6Al 4V, with a linear regression model, when multicollinearity is present in a set of the regression variables, the least square estimate of the regression coefficient tends to be unstable and it may lead to erroneous inference, in this paper generalized ridge estimate β(K) of the regression coefficient β to solve it problem; the surface of titanium alloy is easily damaged during machining operations due to their poor machinability, considering the parameters of speed rate, feed and depth as an input and compare the results. The data used for this paper was taken from conduce work in Faculty laboratories and determine the best parameters for the machining of titanium alloy 6AL-4V and considering optimize the roughness at the time of the machining of this material, using milling process in a rectangular pieces of titanium (Ti 6Al-4V), the tool was an endmill coated with Aluminum Titanium Nitride (AlTiN) with 4 cutting edge and 3/8" on a diameter of the tool. The milling was carried out over a length of 47 mm, using a design of experiment with 3 factors and 3 levels, giving a total of 27 experiments with 3 different tests. The roughness was measure with a ZEISS Perfilometers Surfcom 1500 SD2 with an automatic control. The model is useful to build a surface of the response of the machining process. This model can be used to predict the effect in roughness when the parameters are changed without risks and high costs; however, the model must be validated in order to be used as a predictor. The results indicate the ways to get a good model and established regression equation.

***Key words**: Linear Regression, Super alloy, Titanium, Machining parameters, Roughness, Ridge Regression*

1. INTRODUCTION

The key points for machining industry are productivity means material removed per time, tool´s wear, quality include increase precision and reduce roughness, environmental impact. Titanium alloys are extremely difficult to machine materials. The machinability of titanium and its alloys is generally considered to be poor because the several inherent properties of materials. Titanium alloys have low thermal conductivity because add to the temperature at the cutting edge of the tool and high chemical reactivity with many cutting tool materials. Consequently, on machining, the cutting tools wear off very rapidly due to high cutting temperature and strong adhesion between tool and workpiece material, it produces a bad quality in the workpiece. Additionally, the low modulus of elasticity of titanium alloys and its high strength at elevated temperature further impair its machinability. The most important surface quality requirement in machining process is surface roughness. The traditional way to monitor the surface quality of a machined part is to measure the surface roughness by using a surface gauge. The most used surface gauge is the stylus type surface gauge. It has a diamond stylus dragging along the test surface, of which, the up and down movement is recorded and calculated for the surface roughness. In quantifying surface roughness, average surface roughness definition, which is often represented with Ra symbol, is commonly used. Theoretically, Ra is the arithmetic average value of departure of the profile from the mean line throughout the sampling length (Sander, 1991). Ra is also an important factor in controlling machining performance. Surface roughness is influenced by tool geometry, feed, cutting conditions and the irregularities of machining operations such as tool wear, tool deflections, cutting fluid, and workpiece properties (Wang, 2004), (Suresh, 2002), (Oktem, 2006).

The surface finish of machined titanium parts is important in manufacturing engineering applications which have considerable effect on some properties such as wear resistance. While machining, quality of the parts can be achieved only through proper cutting conditions. In order to know the surface quality and dimensional properties in advance, it is necessary to employ theoretical models making it possible to do prediction in function of operation conditions (Sahin, 2004).

Pawadea (Pawadea, 2007) shows in his article entitled "Effect of machining and cutting edge geometry parameters on surface integrity of high-speed turned Inconel 718" high-speed cutting and low advance, as well as the moderate depth of cut coupled with the use little angles of court can ensure the generation of residual compression efforts in the face of machining. Krain (Krain, 2007) evaluated the effect of varying feed rate/chip thickness, immersion ratio (radial depth of cut), tool material and geometry on tool life, tool wear and productivity obtained when end milling Inconel 718. The study showed that no single tool material or geometry gave the best overall performance. Ramesh in his article "Modeling for prediction of surface roughness in machining of Ti64 alloy using response surface methodology" (Ramesh, 2007), made a prediction model which included parameters such as feed rate, cutting speed and depth of cut to see their effects turning the titanium and to obtain the quality parameters on surfaces response. It appears that a considerable amount of work is going on in the area of machining parameters optimization, based on different criteria such as tool wear, vibration, surface roughness, unit cost, etc (Pawadea, 2007), (Krain, 2007), (Kopac, 2002). Nowadays artificial intelligence (AI) based on modeling is a new trend in modeling for machining operations (Morales, 2007). It was found that the use of heuristic methods to model predictions of surface roughness was very limited, so emphasis was laid on the development of a surface roughness prediction model. New research using Neural Networks has appeared to improve and optimize the assembly and disassembly of products (Ramesh, 2007), on the other hand Rico (Rico, 2005), used the methodology Surface Response and neural networks to predict the roughness. Developing a model for predicted temperature and roughness of the cutting tool on the machining of the steel 1018.

El Gallab et al. (El-Gallab,1998) studied PCD tool performance during high-speed turning of 20% Al/SiC MMC and foun that PCD tools suffered excessive edge chipping and crater wear during the machining of the MMC. Palanikumar (Palanikumar,2007) developed a model for surface roughness through response surface method (RSM) while machining GFRP composites. Four factors five level central composite rotatable design matrix was employed to carry out the experimental investigation. Analysis of variance (ANOVA) was used to check the validity of the model. Jenn-Tsong Horng et al. (Horng J-T, 2008) made an attempt to model the machinability evaluation through the RSM while machining Hadfield steel. Results indicated that the flank wear was influenced principally by the cutting speed and the interaction effect of feed rate with nose radius of tool, the cutting speed and the tool corner radius had statistic significance on the surface roughness. Muthukrishnan et al. (Muthukrishnan N,2009) developed two modeling techniques used to predict the surface roughness namely ANOVA and ANN. In ANOVA, it is revealed that the feed rate has highest physical as well as statistical influence on the surface roughness (51%) right after the depth of cut (30%) and the cutting speed (12%). ANN methodology consumes lesser time giving higher accuracy. Hence, optimization using ANN is the most effective method compared with ANOVA. Oktem et al. (Oktem, 2006) developed an effective methodology to determine the optimum cutting conditions leading to minimum surface roughness while milling of mold surfaces by coupling RSM with a developed genetic algorithm (GA). Results showed that RSM model was further interfaced with the GA; the GA reduced the surface roughness value in the mold cavity from 0.412 to 0.375 μm corresponding to about 10% improvement. Choudhury et al. 20. (Choudhury IA,1998) developed the firstand second-order tool-life models at 95% confidence level for turning high strength steel. The tool-life models are developed in terms of cutting speed, feed rate, and depth of cut using response surface methodology and design of experiment. Authors found that the tool-life contours were useful in determining the optimum cutting conditions for agiven tool life.

Che-Haron (Che-Haron, 2005), worked in an investigation that determined the impact the machining of Ti64 has on the surface finish, checking metallographic alterations of material obtained in machining with a variety of types of tool used in the study. A. Molinari (Molinari, 2002) was devoted to comprehensive studies of chip produced at the milling Ti-6Al-4V, analyzing the process of cutting orthogonal produced at different speeds and the transformation of adiabatic shear banding. He found that the lower speeds chip becomes rougher; this is due to the limitation thermomechanical, which generates adiabatic shear banding, is different the conduct of high speeds. Kopac (Kopac, 2002) utilized a Taguchi experimental design to determine the optimal machining parameters for a desired surface roughness for traditional turning. The Taguchi designed method was used to identify the impact of various parameters on output and determine the combination of parameters for controlling them to reduce the variability in that output. They found that the surface roughness increased with an increase in cutting speed.

1.1 Lineal Regression

Regression analysis is a technique used for modeling and numerical data's analysis, consists of a number of independent and dependent variables. The model is a group of independent variables and one or more parameters. The parameters are adjusted to give more approximate value; it is using to obtain the best fit with the least-squares method, but also may use other criteria. In the dependent variable is assumed that this is a random variable with observation's errors.

The data consist of *r* values taken from *y* observations which are response or dependent`s variable. The dependent variable is subject to error. This error is assumed that a random variable with mean zero. The independent variable x, is called predictor o repressor's variable. In a simple linear regression model is described by the following equation (1). (Montgomery, 2004).

$$y_i = \beta_0 + \sum_{j=1}^{n} x_{ij}\beta_j + \varepsilon_i \qquad (1)$$

The constant`s coefficients are Xij or functions of the independent's variable, x. And this is under the following scenarios

• Residual ε_i is normal with mean zero and unknown common variance σ^2; addition, these residual are independent.
• The number variables that explain the problem (*m*) is lower than observations (*n*); this hypothesis is called full range.
• There is not exact linear relationship between the variables used to explain.

Using linear regression is to decide if the response variable *y* is really linear function of the *x* variable.

1.2 Ridge Regression

Ridge Regression is a variant of ordinary Multiple Linear Regression whose goal is to avoid the problem of collinearity predictors. It gives-up the Least Squares (LS) as a method for estimating the parameters of the model, and focuses instead of the X'X matrix which is highly conditioned or close to be singular. Ridge regression, based on adding a small quantity, k, to the diagonal of a correlation matrix of highly collinear independent variables, can reduce the error variance of estimators. For these conditions, the Ridge Regression Method is given by equation (2) (Piña, 2007)

$$\beta_R = (X^t X + kI)^{-1} X^t Y \mathrm{I}) \qquad (2)$$

that may be redefined to $\beta_R = Z\hat{\beta}$ where $\hat{\beta}$ is the ordinary estimator of ordinary least squares method (OLS) given by $\hat{\beta} = (X^t X)^{-1} X^t Y$ and $Z = (I + KI\ (X^t X)^{-1})^{-1}$ is the matrix that transforms $\hat{\beta}$ in β_R . The variance of β_R, is given by equation (3).

$$V(\beta_R) = \sigma^2 \sum \frac{\lambda_j}{(\lambda_j + k_j)^2} \qquad (3)$$

Where λ_j is the *jth* eigenvalue of ($X^t X$) that trends to zero when $R_{ij}^2 \rightarrow 1$. Therefore, when the constant *K* is added to the diagonal of ($X^t X$) by using the Ridge Regression method, the effect of the multicollinearity problem over the coefficients is minimized; because, accordingly to (4), *βR* is the solution to the optimization of the ellipsoid confidence region where the coefficients are obtained as reported by Piña, Rodríguez and Díaz, (Piña, 2006).

$$Min: (\beta_R - \hat{\beta}) X^t X (\beta_R - \hat{\beta}) \qquad subject\ to: \beta_R \beta_R \leq r^2 \qquad (4)$$

Unfortunately since the model given in (1), presents in inherent form the multicollinearity problem, then when its precision matrix $(X^t X)^{-1}$has variance inflator factors (VIF) greater than ten, their estimated $\boldsymbol{\beta_j}$ coefficients and their corresponding estimated eigenvalues, not represent the modeled system and as a consequence the final solution is a sub-optimal solution. (Praga-Alejo, 2007).

1.3 Surface Roughness

In everyday life as well as in industry, the degree of roughness of a surface is very important. Sometimes it is necessary to have very high values of roughness, other times this is undesirable because the surface of the product requires a better appearance, or it requires the lowest surface friction because it is in contact with another surface, in this manner minimizing the phenomenon of wear on materials. Surface roughness is the set of irregularities on the actual surface, conventionally defined within a section where the shape and undulation errors have been eliminated (González, 2005). To measure the roughness of the parts an electronic instrument sensitivity micrometer called roughness meter is used to quickly determine the roughness of surfaces. There are several parameters that reflect the measurement of roughness, such as Ra, Ry, Rz. The most common is that Ra is the arithmetic mean (González, 2005), of the absolute values of the distance profile roughness of the line of the length measurement see Figure 2, equation (4). The degree of roughness of a surface is very important. Sometimes it is necessary to have very high values of roughness, another is undesirable as the surface of the piece requires a better appearance, or because you need a low rate of friction in it to be in contact with another surface, thereby minimizing the phenomenon Wear of Materials

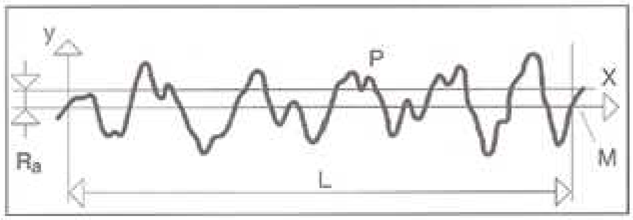

Figure 2 Graphic Ra for measuring the roughness

$$Ra = \frac{1}{N}\sum_{i=0}^{N}|Data| \tag{4}$$

2. EXPERIMENTAL DEVELOPMENT

First determine the parameters to be taken into account for the cut, ie the ranges for the depth of machining, the feed rate and speed, which would be the input of statistical analysis. The machining was done in a Vertical Machining Center Bridgeport VMC 760, figure 3 using rectangular pieces of titanium (Ti 6Al-4V) of size 125 x 47 x 22 mm, the tool was an endmill coated with Aluminum Titanium Nitride (AlTiN) with 4 cutting edge and 3/8" on a diameter of the tool, see figure 4. The milling was carried out over a length of 47 mm, using a design of experiment with 3 factors and 3 levels see Table 1, giving a total of 27 experiments with 3 runs. For roughness using a ZEISS Profilometers Surfcom 1500 SD2 with automatic control shows in the figure 5

Table 1 Machining parameter used for the test

Condition	Units	Level 1	Level 2	Level 3
Speed	m/min	70	80	90
Feed	mm/rev	0.11	0.13	0.15
Depth	mm	0.50	1.00	1.50


Figure 3. Vertical Machining Center Bridgeport VMC 760.

Figure 4. The material and the tool used in the test

Figure 5. Profilometer Surfcom 1500SD2.

In the past, some methods have been used to check the impact of machining parameters on the surface finish quality. Though the processes that previous researchers have utilized are similar, they all differ a little in their implementation. All of the relevant literature includes some kind of design of experiments that allows for an organized approach to quantifying the effects of a finite number of parameters. Some experiments were full-factorial designs with a small number of factors, while others were fractional factorial designs meant to screen factors for impact. In this test used a three-factor full factorial design to determine the effects of speed, feed and depth of cut on surface roughness in finish milling. They performed three replicates of each factor level combination in order to account for variability in the process. The table 2 shows some values of roughness of 27 combinations of parameters obtained in the tests, which were used to make the regression model that represents the machine under study. The main purpose of this study is to determine the best parameters for the machining of titanium alloy 6AL-4V and considering optimize the roughness at the time of the machining of this material.

Table 2. A sample of the results obtained in the test

test	Design of experiment			Replies		
	Speed	Feed	Depth	1 Roughness	2 Roughness	3 Roughness
1	1	1	1	0.8669	0.8472	0.8794
2	1	1	2	0.8442	0.8586	0.8644
3	1	1	3	0.9383	0.8520	0.9043
4	1	2	1	0.8188	0.8796	0.8265
5	1	2	2	0.9369	0.8541	0.8512

3. RESULTS AND DISCUSSIONS

3.1 Regression Model

After completing the experiments conducted an analysis of variance (ANOVA) to determine the differences in surface quality between various runs were statistically significant, using Minitab®. In addition to degrees of freedom (DF), mean square (MS) and F-ratio, p-values associated with each factor level and interactions were presented. It is important to observe the p-values in the tables 3. For the surface roughness generation, most of the factors are apparently significant only the p-value for feed and the interaction of feed and depth are statistically insignificance.

Table 3. ANOVA table for Ra surface roughness

Source	DF	MS	F	P-value
Speed	2	0.1547	266.390	0.000
Feed	2	0.0014	2.330	0.107
Depth	2	0.0021	3.570	0.035
speed*feed	4	0.0022	3.730	0.009
speed*depth	4	0.0024	4.120	0.006
feed*depth	4	0.0013	2.280	0.073
speed*feed*depth	8	0.0026	4.410	0.000
Error	54	0.0006		
Total	80			

The regression analysis technique using least squares estimation was applied to obtain the coefficients of the exponential model by using the experimental data and generated the next models. The equation (3) is the regression model only considering the variables without interaction between them. In the table 4 can see the model generate parameters, analyzing the VIF's values are apparently good but the R-Sq (adj) had a low value this means that the model fit is not satisfactory.

$$Ra = 1.35 - 0.000212\ speed + 0.065\ feed + 0.0026\ depth \qquad (3)$$

Table 4. Results of the regression model analyzing the Roughness versus speed, feed and depth using Minitab®

Predictor	Coef	SE Coef	T	P	VIF
Constant	1.35323	0.06219	21.76	0.000	
speed	-0.00021	0.00002	-11.43	0.000	1
feed	0.06490	0.29540	0.22	0.827	1
Depth	0.00260	0.01182	0.22	0.826	1
S = 0.0434111	R-Sq = 62.9%		R-Sq(adj) = 61.5%		

The next step was analyze the model using the interaction between the factors and generated the multiple lineal regression model suggested in the equation (4), however as in the Table 5, the parameters obtained with the model, the R-Sq(adj) improve but the VIF values are very problematic, that means the fit of the real data will be inefficient

$$Ra = -1.20 + 0.00244\ speed - 15.2\ feed - 1.00\ depth - 0.000001(speed^2) + 0.00320(speed)(feed) + 0.000475(speed)(depth) + 30.2\ (feed^2) + 10.4\ (feed)(depth) - 0.0600\ (depth^2) - 0.00436(speed)(feed)(depth) \qquad (4)$$

Table 5. Results of the regression model analyzing the Roughness versus speed, feed, depth and the interactions

Predictor	Coef	SE Coef	T	P	VIF
Constant	-1.2021000	0.85390000	-1.41	0.164	
speed	0.0024358	0.00043470	5.60	0.000	1217.80
feed	-15.2420000	6.82800000	-2.23	0.029	1185.10
depth	-1.0003000	0.62900000	-1.59	0.116	6284.30
speed*speed	-0.0000006	0.00000007	-8.61	0.000	768.20
speed*feed	0.0031960	0.00201800	1.58	0.118	1121.70
speed*depth	0.0004754	0.00024480	1.94	0.056	6622.50
feed*feed	30.1600000	17.18000000	1.76	0.083	508.00
feed*depth	10.4300000	4.78200000	2.18	0.033	6817.50
depth*depth	-0.0600300	0.02748000	-2.18	0.032	49.00
speed*feed*depth	-0.0043600	0.00186800	-2.33	0.022	7197.80
S = 0.0291520	R-Sq = 84.8%		R-Sq(adj) = 82.6%		

Using the real data in the generated models, the first model has a good fitting, however the second model that use interactions has a poor performance, so it is necessary to use other kind of interactions or inclusive to use ridge regression or robust regression.

3.2 Ridge Regression Model

The Quadratic model was hypothesized in obtaining the relationship between the surface roughness and the machining independent variables from the NCSS ® software. A general equation among feed rate, cutting speed and depth of cut is found out. The model of the second order ridge regression is given below in the equation (5).

Ra = 1.049368 + 8.270739E-06(Speed) + 1.301932E-02(Feed) + 6.577585E-02(Depth) - 3.413635E-08(Speed^2) + 2.748189(Feed^2) -1.437233E-02(Depth^2)-2.554128E-04(Speed)(Feed)-1.339853E-05(Speed)(Depth)-1.253528E-02(Feed)(Depth) (5)

Result of coefficient for the ridge regression function surface roughness for k = 0.02 is presented in Table 6 with this k value the VIFs were adjusted to values between 1 and 10. The table 7 present the ANOVA results for ridge regression this analysis is carried out for a level of significance of 5%, i.e., for a level of confidence of 95%. From the analysis of Table 7, it is apparent that, the F calculated value is greater than the F table value (F0.05,9,71=2.03) and hence the second order model function developed is quiet adequate.

Table 6 Ridge Regression Coefficient Section for k = 0.020000

Independent Variable	**Regression Coefficient**	**Standard Error**	**Standardized Regression Coefficient**	**VIF**
Intercept	1.049368			
C1	8.270739E-06	2.219569E-05	0.0309	1.3836
C2	1.301932E-02	0.4038507	0.0031	1.8062
C3	6.577585E-02	2.648658E-02	0.3862	4.8558
C5	-3.413635E-08	4.799018E-09	-0.6507	1.6801
C6	-2.554128E-04	2.064083E-04	-0.1975	5.1133
C7	-1.339853E-05	1.258049E-05	-0.2075	7.6214
C8	2.748189	1.804396	0.1680	2.4423
C9	-1.253528E-02	0.2560829	-0.0101	8.5183
C10	-1.437233E-02	1.791691E-02	-0.1705	9.0729

Table 7 Analysis of Variance Section for k = 0.020000

Source	**DF**	**Sum of Squares**	**Mean Square**	**F-Ratio**	**Prob Level**
Intercept	1	55.04634	55.04634		
Model	9	0.2530741	2.811935E-02	14.4171	0.000000
Error	71	0.1384799	1.950422E-03		
Total(Adjusted)	80	0.3915541	4.894426E-03		

4. CONCLUSIONS AND FUTURE WORK

This work has presented an approach to optimizing cutting condition in titanium machining process, considering speed, feed and depth cut. The objective of this study is the development a statistic model to titanium machining process considering three replicates of each factor level combination in order to account for variability in the process. Among the conclusions found in this paper is that the linear regression model by itself does not produce a close fit to reality, they need to process more complex analysis such as ridge regression or other means of making an analysis deeper. Continue working on experiment with regression to the square polynomial complete and the VIFs are higher than 10 and produce multicollineality, ridge regression is a technique to help optimizing these results. A second-order ridge regression surface model for surface roughness has been developed from the observed data, although ridge regression is biased, is widely used for the adjustment of the polynomial when there is multicollinearity. Once the proportionality constant K, the estimation of ridge regression can be treated as a least squares estimation and help to predict and measure values are fairly close. Which indicates that the developed model can be effectively used to predict the surface roughness on the machining of titanium alloys with 95% confidence intervals. Using such model, one can obtain are remarkable savings in time and cost. The results revealed that minimal surface roughness could be arrived significantly for titanium machining operations. Verification test results revealed that the determined optimal combination of machining parameters satisfy the real requirements of machining operation in the machining of titanium alloys. Search other material conditions affecting the machining of superalloys to evaluate most complete this process. Analyze machining process with other alloys with difficult machinability, materials such as Inconel, other titanium alloys, composites, or other expensive materials and actually being used in industry more frequently each time and it generate a lot time and economic waste.

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