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# Evaluation of Surface Roughness on MQL Turned Titanium (TI-6Al-4V) Alloy by RSM and Box - Cox Transformation

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ABSTRACT

The experiments has conducted to find the surface roughness ($R_a$, $R_q$ and $R_z$) optimization using Response surface methodology and Box - Cox transformation on the turning of Titanium (Ti-Al-4V) alloy with the insertion of minimum quality lubrication (MQL). It's been modeled that various machining parameters which includes feed rate, cutting velocity, and many others. Initially, a few tests has conducted and analyzed to determine the desired MQL parameters of oil flow rate, inlet pressure and compressed air flow rate. After obtaining the optimal MQL parameters, a desirability analysis can be used to evaluate the machining parameters for surface roughness values ($R_a$, $R_q$, and $R_z$) depends upon actual series of experiments within uncoated carbide tool. The outcomes state the feed rate posses a greater influence on the values of surface roughness as compared to cutting speed. The expected results are identical to the experimental values. So, these developed models using RSM and Box - Cox Transformation is used for evaluation of surface roughness values.


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## Introduction

Titanium alloys are the most advantageous materials for various industrial applications such as marine, aero space and bio medical industries. Because they have so many impressive characteristics like high strength to weight ratio, highly resistive to corrosion and fatigue, better fracture toughness, etc.. But, the machinability of titanium is quite less due to low thermal conductivity. This may leads to high temperature cutting zone and causes high tool wear as well as poor surface finish [1].At present days, surface finish has changed over into a prime performance parameter and has a large effect on various mechanical properties of machined parts such as resistance to corrosion, creep and fatigue. It also influences the functional aspects of work parts like friction, wear, light reflection, etc.. [2]. V. G. Sargade, S. R. Nipanikar and S. M. Meshram [3] analyzed surface roughness and cutting force for turning of Ti 6Al 4V ELI in dry environment. It was found that the feed rate is the most influencing factor on the surface roughness values'. Paulo Davim, V. N. Gaitonde, S. R. Karnik [4] investigated the effects of cutting conditions on surface roughness in turning of free machining steel by ANN(Artificial neural network) models. They observed that both the cutting speed and feed rate are the most influencing and sensitive parameters on the surface roughness. I. Shyha, S. Gariani, M. Bhatti investigated the effects of cutting tools and working conditions on cutting of Ti 6Al 4V using vegetable oil based cutting fluids. It was found that the tool flank wear increases as the cutting speed increases and also increase in depth of cut [5].Vikas Upadhyay, P. K. Jain, N. K. Mehta [6] developed a model on surface roughness in turning of Ti-6Al-4V alloy using cutting parameters and vibration signals. They presented that the models developed by In-process prediction has accurate output results on surface roughness. A prediction model of surface roughness on the hard turning of steel by ANOVA analysis has been determined as the feed rate and the cutting speed are the most influencing process parameters on the surface roughness [7].In a research, Response surface methodology [8] had been applied to find a cutting force model on turning of silicon metal matrix composite. This model has 95 percent of efficiency as compared to actual experimental values. And it has revealed that the cutting force is a most influencing factor on response variables. Sujan Debnath, Moola Mohan Reddy, Qua Sok Yi [9] studied various effects of cutting fluid levels and cutting parameters on surface roughness. It has been found that the feed rate is the most influencing factor on surface roughness, where the cutting speed has most effect on tool wear. But the cutting fluid can influence the surface roughness as well as tool wear. Ilhann asilturk, suleyman neseli, Mehmet Alper Ince [10] studied the models of optimization of parameters on surface roughness on CNC machining of Co28Cr6Mo medical material by using RSM and Taguchi methods. It has been found that the minimum combination of feed rate and speed gives minimum surface roughness. Grynal D'Mello, P. Srinivasa Pai, N. P. Puneeth [11] studied optimization of machining parameters on high speed turning of Ti 6Al 4V alloy. It has been observed that, For high speed machining, High cutting speed with minimum depth of cut and feed rate gives minimum surface roughness values as well as higher tool flank wear. A model on optimization of cutting parameters for cutting forces using response surface methodology was developed. it was mostly influenced in controlling of parameters for obtaining the desired cutting forces [12]. Vijay. S, Krishna raj. V [13] optimized machining parameters in end milling of Ti 6Al 4V. The most influencing parameters on surface roughness are speed per tooth as well as depth of cut and cutting speed.Dr. C J Rao, Dr. Nageswara Rao, P. Srihari [14] researched about the significance and influence of cutting parameters on cutting force and surface finish in turning operation. It has been concluded that the feed rate has large influence on surface roughness rather than the cutting speed and depth of cut. An Experimental study of

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cutting forces using response surface methodology explained the influence of cutting parameters. It has been resulted as the radial depth of cut has more influence on cutting forces rather than feed per tooth in balled end milling. Again, An analysis of cutting forces and optimization of cutting parameters in ball end milling using response surface methodology and genetic algorithm has been studied and concluded as the axial depth of cut can affects the radial and tangential cutting forces. And also the radial depth of cut has more influence in the axial and tangential cutting forces as well [15,16]. Supriya Sahu, B. B. Choudhury [17] optimized machining parameters based on surface roughness and tool wear using taguchi methodology. It has been observed that a necessary combination of low feed rate and high cutting speed should be maintained to achieve a minimized surface roughness value. Manish Gangil, M. K. Pradhan [18] developed a model for optimization of electrical discharge machining process using response surface methodology. It has been determined that the use of response surface methodology results in higher MRR as well as low TWR. And also improves surface quality. V. Prem ananth, D. Vasudevan [19] studied the effects of various cutting parameters on surface quality in turning operation. It has been found that the feed rate, depth of cut and cutting speed are the most influenced factors on the surface quality and cutting forces. Shakeel Ahmed. L, Pradeep Kumar. M [20] optimized reaming process parameters on titanium alloy using grey relational analysis. It has been revealed that the performance of reaming operation can be varied by the use of different cooling conditions' S Dureja, V K Gupta, V S Sharma; M Dogra [21] designed a model for optimization of cutting conditions and their effects on tool wear and surface roughness. It has been analyzed that Response surface methodology is an effective technique for optimization of parameters of surface roughness and tool wear. And also feed and work piece hardness are the most influencing factors on tool wear. An experiment and analysis for optimal decisions on turning Ti 6Al 4V conducted using Taguchi-Grey method. It has been observed that the feed rate, cutting speed and back rake angle are the main parameters influencing the minimization of surface roughness [22].

## Experimental

### Materials and Method

In this experiment (Fig. 1), the work material used was Titanium Grade 5 alloy (35 HRC) as round bar with the dimensions of 300 mm length and 31mm of diameter. The chemical composition of the work material is 90% of Titanium, 6% of Aluminum and 4% of Vanadium. Initially, the outer layer of 1mm was turned (Ø31 mm to Ø30 mm) to eliminate oxidized layer and to convert into exact size. Then, the actual series of turning tests were performed on a precision CNC Lathe named as ACE Microsmatic (JOBBER XL Model) with FANUC Control system. The uncoated Carbide Tools (CNMG 120404) having nose radius of 0.4 mm with a suitable tool holder were chosen. A new tool and 100mm of cutting length was used for each experiment to analyze the tool wear at each test for the given input parameters.

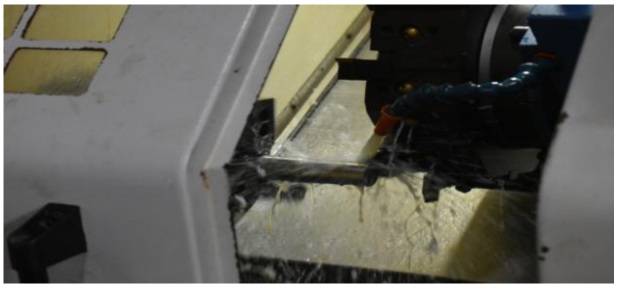


**Figure 1**: Experimental setup

### Cutting fluid and MQL Setup

The whole experiment was involved with three different conditions such as dry, Soluble oil MQL and Nano fluid based MQL. A vegetable oil based (soya bean) cutting fluid was used as soluble oil which has biodegradable in environment. In Nano fluid based MQL, Graphene Nano particles were mixed with soluble oil in a certain proportion by mechanical stirring. An MQL System made by TECHNO DROP ENGINEERS PVT. LTD. with 3 Liters of oil tank capacity was used.

### Surface roughness Measurement

Surface roughness is a result obtained by a machining action in the form of irregularities and peaks & valleys on the machined surface. The TR 200 surface roughness tester (TIME) has been used for taking three surface roughness values such as Ra, Rq and Rz. These values are taken at three different positions on the surface and the mean of them taken as the roughness value. This step was repeated for each experiment.

### Experimental Procedure

Table1: Minimum quantity lubrication parameters

| Parameters | Level 1 | Level 2 | Level 3 |
|---|---|---|---|
| Lubricants flow rate (ml/h) | 100 | 150 | 200 |
| Input pressure ,(bar) | 4 | 6 | 8 |
| Compressed air flow rate (l/min) | 40 | 60 | 80 |

The test has two stages which include pre machining stage and machining stage. Inside the first stage a few checks were carried out to assess the MQL parameters which are inlet air pressure, compressed air flow charge and lubricant go with the flow rates. The favored and highest quality values of MQL parameters were decided and decided on for machining (Table 1). The actual oil price acquired within the variety of 30 ml/hr to a 1000 ml/hr for the chosen MQL setup. A few machining experiments had been carried out with the aid of changing the oil go with the flow rate from minimal to maximum flow rate. a compressor (2 hp) as applied to offer compressed air at four bars to the MQL setup. A vegetable oil (soya bean) primarily based cutting fluid became used to go with the flow at 30 ml/hr from the go out of the nozzle.

### Design of experiment and its parameters

The selection of input machining parameters and their values were obtained with the use of software named as DESIGN OF EXPERT. Then those parameters were tabulated as a series of 29 experiments with different cooling conditions.

## Results and Discussion

The experimental results received (Table 2) have been used to set up models for Ra, Rq and Rz of Titanium (Grade-v) thru RSM (the use of design of expert software). The satisfaction becomes showed of generated models with the help of ANNOVA. This phase introduces the improvement of prediction version with and without transformation for Ra, Rq and Rz, evaluation of predictive models and impact of machining parameters on surface roughness values.

**Table 2**: Experimental design and their results

| Sl.no | Vc (m/min) | f (mm/rev) | ae (mm) | Ra (µm) | Rq (µm) | Rz (µm) |
|---|---|---|---|---|---|---|
| 1 | 150 | 0.15 | 0.4 | 0.798 | 0.953 | 3.896 |
| 2 | 150 | 0.2 | 0.2 | 1.566 | 1.78 | 6.627 |
| 3 | 100 | 0.2 | 0.4 | 1.756 | 1.783 | 6.207 |
| 4 | 100 | 0.1 | 0.4 | 0.473 | 0.56 | 2.391 |
| 5 | 150 | 0.15 | 0.4 | 0.799 | 0.954 | 3.897 |
| 6 | 200 | 0.15 | 0.6 | 0.991 | 1.124 | 4.052 |
| 7 | 200 | 0.15 | 0.2 | 1.023 | 1.158 | 4.267 |
| 8 | 200 | 0.1 | 0.4 | 0.361 | 0.451 | 2.052 |
| 9 | 150 | 0.1 | 0.2 | 0.448 | 0.552 | 2.55 |
| 10 | 150 | 0.1 | 0.6 | 0.575 | 0.696 | 3.063 |
| 11 | 100 | 0.15 | 0.6 | 0.873 | 1.06 | 4.647 |
| 12 | 150 | 0.15 | 0.4 | 0.796 | 0.955 | 3.898 |
| 13 | 150 | 0.15 | 0.4 | 0.78 | 0.92 | 3.912 |
| 14 | 200 | 0.2 | 0.4 | 1.95 | 2.238 | 8.411 |
| 15 | 100 | 0.15 | 0.2 | 0.756 | 0.92 | 3.258 |
| 16 | 150 | 0.2 | 0.6 | 1.394 | 1.612 | 5.747 |
| 17 | 150 | 0.15 | 0.4 | 0.792 | 0.936 | 3.874 |

### Prediction model without transformation for Ra, Rq and Rz

For Ra: The ANOVA was performed (shown in Table 3) and cutting speed, federate, second-order effect , feed rate and interaction effect of cutting speed and feed rate were significant model terms.

The F-value from reduced model 20.50 implies that the developed model is significant for Ra. The "Pred R2" of 0.4161 is in sensible concurrence with the "Adj R2" of 0.9164. Furthermore, the correlation coefficient R2 of 0.963 (close to unity) legitimizes the unwavering quality of proposed model. The Adeq Precision measures signal to noise ratio and greater than 4 i.e., 15.299 is desirable. The final regression eq. (1) without transformation for Ra is represented as:

*Ra=1.85600-0.017353vc-15.19750f+1.92000ap+0.030600vc*f-7.4750f*ae+0.000514vc2+85.40000f2-0.26875ae2* (1)

For Rq: the F-value of 29.87from table (4) construes the model is note worthy in this case cutting speed ,feed rate second order of depth of cut and interaction effect of cutting speed and feed are significant model terms .the pre R2 of 0.5975, is in sensible simultaneous with the adj R2 of 0.9420 the adeq precision "measures the signal to noise ratio and appropriation more prominent than 4 is desirable the ratio of 18.790 demonstrates a sufficient sign .the R"-squared of 0.9746 is near to unity ,which is significant . The final regression eq. (2) without transformation for Ra is represented as:

*Rq=2.16475-0.018294vc-16.98900f+1.63475ae+0.056400vc*f-7.8000f*ae+0.00004398vc2+81.7800f2-0.29875ae2* (2)

**Table 3**: ANOVA for the reduced quadratic model for Ra without transformation

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 3.24 | 9 | 0.36 | 20.50 | 0.0003 | Significant |
| A-speed | 0.027 | 1 | 0.027 | 1.55 | 0.2532 | |
| B-feed | 2.89 | 1 | 2.89 | 164.37 | < 0.0001 | |
| C-depth of cut | 2.000E-004 | 1 | 2.000E-004 | 0.011 | 0.9181 | |
| AB | 0.023 | 1 | 0.023 | 1.33 | 0.2865 | |
| AC | 5.550E-003 | 1 | 5.550E-003 | 0.32 | 0.5918 | |
| BC | 0.022 | 1 | 0.022 | 1.27 | 0.2968 | |
| $A^2$ | 0.070 | 1 | 0.070 | 3.95 | 0.0871 | |
| $B^2$ | 0.19 | 1 | 0.19 | 10.91 | 0.0131 | |
| $C^2$ | 4.866E-004 | 1 | 4.866E-004 | 0.028 | 0.8726 | |
| Residual | 0.12 | 7 | 0.018 | | | |
| Lack of Fit | 0.12 | 3 | 0.041 | 682.59 | < 0.0001 | Significant |
| Pure Error | 2.400E-004 | 4 | 6.000E-005 | | | |
| Cor Total | 3.37 | 16 | | | | |
| Std. Dev. | 0.13 | | R-Squared | 0.9634 | | |
| Mean | 0.95 | | Adj R-Squared | 0.9164 | | |
| C.V. % | 13.98 | | Pred R-Squared | 0.4161 | | |

**Table 4**: ANOVA for the reduced quadratic model for Rq without transformation

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 3.73 | 9 | 0.41 | 29.87 | < 0.0001 | Significant |
| A-speed | 0.052 | 1 | 0.052 | 3.79 | 0.0927 | |
| B-feed | 3.32 | 1 | 3.32 | 239.52 | < 0.0001 | |
| C-depth of cut | 8.405E-004 | 1 | 8.405E-004 | 0.061 | 0.8126 | |
| AB | 0.080 | 1 | 0.080 | 5.74 | 0.0478 | |
| AC | 7.569E-003 | 1 | 7.569E-003 | 0.55 | 0.4840 | |
| BC | 0.024 | 1 | 0.024 | 1.76 | 0.2268 | |
| $A^2$ | 0.051 | 1 | 0.051 | 3.67 | 0.0969 | |
| $B^2$ | 0.18 | 1 | 0.18 | 12.70 | 0.0092 | |
| $C^2$ | 6.013E-004 | 1 | 6.013E-004 | 0.043 | 0.8410 | |
| Residual | 0.097 | 7 | 0.014 | | | |
| Lack of Fit | 0.096 | 3 | 0.032 | 136.14 | 0.0002 | Significant |
| Pure Error | 9.412E-004 | 4 | 2.353E-004 | | | |
| Cor Total | 3.82 | 16 | | | | |
| Std. Dev. | 0.12 | | R-Squared | 0.9746 | | |
| Mean | 1.10 | | Adj R-Squared | 0.9420 | | |
| C.V. % | 10.73 | | Pred R-Squared | 0.5975 | | |
| PRESS | 1.54 | | Adeq Precision | 18.790 | | |

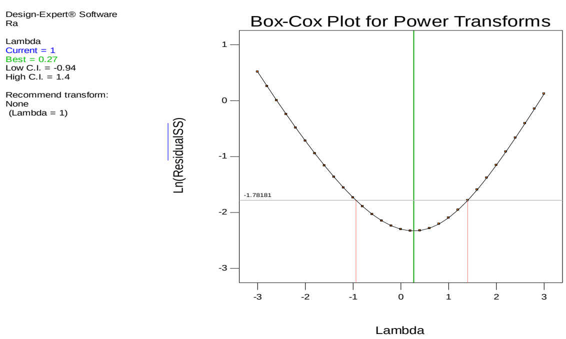
For Rz: In Table 5, only feed rate is the significant model term and also the F-value 23.20 connotes that the established model is significant at 95% confident interval. This empirical model was well fitted to experimental values, it could be seen that the value of "Pred R20.2567 and "Adj R2" 0.8938 gave a decent defense to the reliability of a regression model to Rz. The adequate precision ratio of developed model is 14.261 (ratio > 4 is desirable), which gives a satisfactory signal to use the proposed model. The eq. (3) shows final regression model without transformation for Rz.

**Table 5**: ANOVA for Rz without transformation

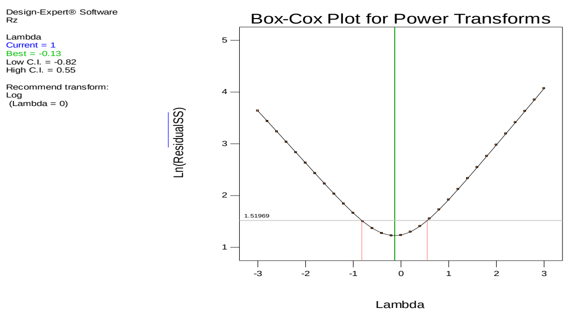
| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 41.40 | 9 | 4.60 | 15.96 | 0.0007 | Significant |
| A-speed | 0.65 | 1 | 0.65 | 2.25 | 0.1771 | |
| B-feed | 35.85 | 1 | 35.85 | 124.39 | < 0.0001 | |
| C-depth of cut | 0.081 | 1 | 0.081 | 0.28 | 0.6116 | |
| AB | 1.62 | 1 | 1.62 | 5.61 | 0.0497 | |
| AC | 0.64 | 1 | 0.64 | 2.23 | 0.1789 | |
| BC | 0.49 | 1 | 0.49 | 1.68 | 0.2356 | |
| $A^2$ | 0.19 | 1 | 0.19 | 0.67 | 0.4392 | |
| $B^2$ | 1.81 | 1 | 1.81 | 6.27 | 0.0407 | |
| $C^2$ | 0.012 | 1 | 0.012 | 0.043 | 0.8425 | |
| Residual | 2.02 | 7 | 0.29 | | | |
| Lack of Fit | 2.02 | 3 | 0.67 | 3618.47 | < 0.0001 | Significant |
| Pure Error | 7.432E-004 | 4 | 1.858E-004 | | | |
| Cor Total | 43.42 | 16 | | | | |
| Std. Dev. | 0.54 | | R-Squared | 0.9535 | | |
| Mean | 4.28 | | Adj R-Squared | 0.8938 | | |
| C.V. % | 12.55 | | Pred R-Squared | 0.2567 | | |
| PRESS | 32.27 | | Adeq Precision | 14.261 | | |

## Prediction model with transformation for Ra, Rq and Rz

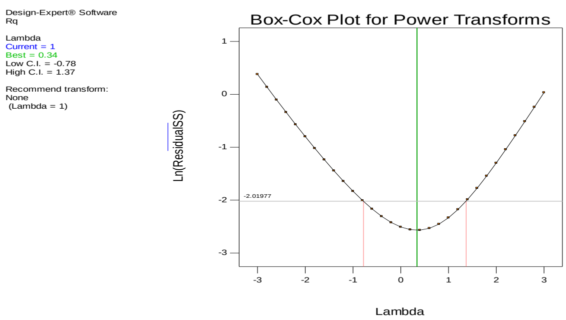
In order to better the results acquired from the above models, the Box–Cox transformation was been successfully employed. The Box–Cox transformation provides a family of transformations to normalize the data, which are not normally distributed by identifying an appropriate exponent (lambda, λ). The lambda value indicates the power to which all data should be raised. The Box and Cox originally envisioned this transformation as a panacea for simultaneously correcting normality, linearity and homogeneity. Figure 2(a) to 2(c) shows a Box–Cox plot for power transformation with respect to Ra, Rq and Rz. For all the models, the blue line indicates the current value of lambda for residuals as 1, which is lying outside the 95% confidence limits. But the best recommended value of lambda is approximately 0.27 for Ra, 0.34 for Rq and -0.13for Rz as shown by the green line. Thus, the square root transformation on the response is required to make the residuals normally distributed.




(a)



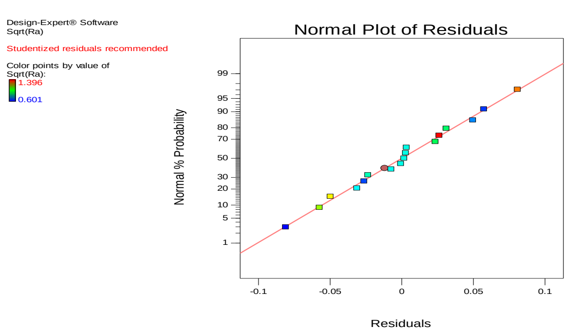

(b)



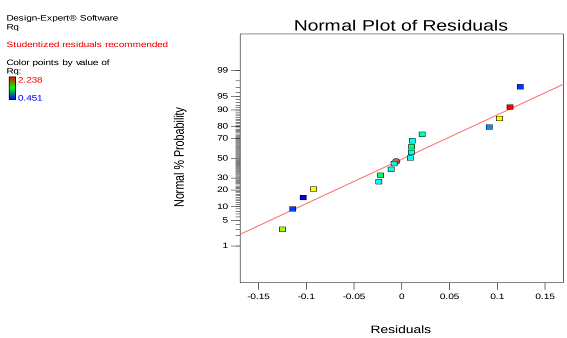

(c)

**Figure 2**: Box–Cox plot for power transformation (a) Ra, (b) Rq, (c) Rz

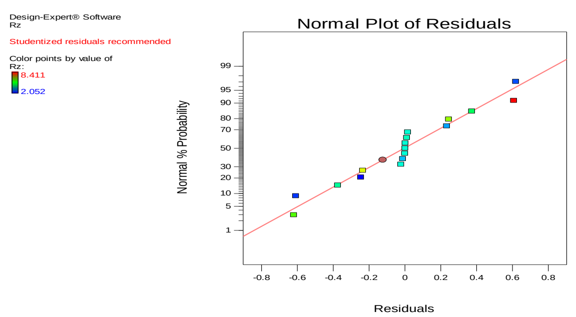
Figure 3(a) to 3(c) shows the normal distribution plot for residuals after he Box–Cox transformation. It infers that the residuals fall on a straight line implying that the residuals are distributed normally. Tables 6 to 8 show the ANOVA for the reduced quadratic model for Ra, Rq and Rz by selecting the forward elimination procedure to automatically reduce the terms that are not significant. These tables show that the models are still significant.




(a)




(b)




(c)

**Figure 3**: Normal probability plot after Box–Cox transformation (a) Ra, (b) Rq, (c) Rz

**Table 6**: ANOVA for reduced quadratic model with transformation for Ra

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 0.79 | 9 | 0.088 | 21.13 | 0.0003 | significant |
| A-speed | 4.393E-003 | 1 | 4.393E-003 | 1.06 | 0.3384 | |
| B-feed | 0.74 | 1 | 0.74 | 178.47 | < 0.0001 | |
| C-depth of cut | 5.637E-004 | 1 | 5.637E-004 | 0.14 | 0.7237 | |
| AB | 6.257E-003 | 1 | 6.257E-003 | 1.50 | 0.2598 | |
| AC | 1.632E-003 | 1 | 1.632E-003 | 0.39 | 0.5510 | |
| BC | 6.375E-003 | 1 | 6.375E-003 | 1.53 | 0.2557 | |
| A² | 0.010 | 1 | 0.010 | 2.52 | 0.1564 | |
| B² | 0.016 | 1 | 0.016 | 3.91 | 0.0886 | |
| C² | 6.358E-004 | 1 | 6.358E-004 | 0.15 | 0.7075 | |
| Residual | 0.029 | 7 | 4.161E-003 | | | |
| Lack of Fit | 0.029 | 3 | 9.684E-003 | 509.48 | < 0.0001 | significant |
| Pure Error | 7.603E-005 | 4 | 1.901E-005 | | | |
| Cor Total | 0.82 | 16 | | | | |
| Std. Dev. | 0.075 | | R-Squared | 0.9110 | | |
| Mean | 0.95 | | Adj R-Squared | 0.8905 | | |
| C.V. % | 7.90 | | Pred R-Squared | 0.8339 | | |
| PRESS | 0.14 | | Adeq Precision | 18.049 | | |

However in case of Ra, main effect of cutting speed, federate and the second-order effect of cutting speed, feed rate and depth of cut are the significant model terms. The main effect of depth of cut , two-level interaction of cutting speed and feed rate, feed rate and depth of cut , cutting speed and depth of cut, feed and nose radius were removed to support hierarchy. This scenario can be explained by the hierarchical principle, which indicates that if there is a high-order term in the model, it will contain all the lower order terms in the model. Similarly in Rq, cutting speed, feed rate, second order of depth of cut and interaction effect of cutting speed and feed rate are the significant terms. Whereas in case of Rz cutting speed, feed rate and second order of depth of cut are significant model terms. Moreover the percentage contribution of each cutting parameters are calculated and it was found that feed rate is the dominate factor affecting surface roughness values followed By cutting speed and depth of cut. There is very less effect of cutting speed and depth of cut on Ra, Rq and Rz. The percentage contribution of feed rate on Ra, Rq and Rz has foundtobe56.23%, 36.76% and 60.02%.

**Table 7**: ANOVA for reduced quadratic model with transformation for Rq

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 0.79 | 9 | 0.088 | 31.91 | < 0.0001 | Significant |
| A-speed | 6.699E-003 | 1 | 6.699E-003 | 2.42 | 0.1636 | |
| B-feed | 0.74 | 1 | 0.74 | 268.60 | < 0.0001 | |
| C-depth of cut | 8.254E-004 | 1 | 8.254E-004 | 0.30 | 0.6019 | |
| AB | 0.014 | 1 | 0.014 | 5.10 | 0.0585 | |
| AC | 1.862E-003 | 1 | 1.862E-003 | 0.67 | 0.4389 | |
| BC | 6.070E-003 | 1 | 6.070E-003 | 2.19 | 0.1821 | |
| A² | 6.310E-003 | 1 | 6.310E-003 | 2.28 | 0.1747 | |
| B² | 0.012 | 1 | 0.012 | 4.23 | 0.0787 | |
| C² | 1.888E-003 | 1 | 1.888E-003 | 0.68 | 0.4359 | |
| Residual | 0.019 | 7 | 2.766E-003 | | | |
| Lack of Fit | 0.019 | 3 | 6.371E-003 | 101.60 | 0.0003 | Significant |
| Pure Error | 2.508E-004 | 4 | 6.270E-005 | | | |
| Cor Total | 0.81 | 16 | | | | |
| Std. Dev. | 0.070 | | R-Squared | 0.9222 | | |
| Mean | 1.02 | | Adj R-Squared | 0.9043 | | |
| C.V. % | 6.81 | | Pred R-Squared | 0.8542 | | |
| PRESS | 0.12 | | Adeq Precision | 19.719 | | |

**Table 8**: ANOVA for reduced quadratic model with transformation for Rz

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 2.25 | 9 | 0.25 | 18.48 | 0.0004 | significant |
| A-speed | 0.021 | 1 | 0.021 | 1.58 | 0.2494 | |
| B-feed | 2.04 | 1 | 2.04 | 150.83 | < 0.0001 | |
| C-depth of cut | 9.402E-003 | 1 | 9.402E-003 | 0.70 | 0.4317 | |
| AB | 0.068 | 1 | 0.068 | 5.05 | 0.0594 | |
| AC | 0.041 | 1 | 0.041 | 3.01 | 0.1263 | |
| BC | 0.027 | 1 | 0.027 | 2.02 | 0.1984 | |
| A² | 2.536E-003 | 1 | 2.536E-003 | 0.19 | 0.6778 | |
| B² | 0.037 | 1 | 0.037 | 2.78 | 0.1397 | |
| C² | 5.677E-004 | 1 | 5.677E-004 | 0.042 | 0.8434 | |
| Residual | 0.095 | 7 | 0.014 | | | |
| Lack of Fit | 0.095 | 3 | 0.032 | 2639.74 | < 0.0001 | significant |
| Pure Error | 4.774E-005 | 4 | 1.194E-005 | | | |
| Cor Total | 2.34 | 16 | | | | |
| Std. Dev. | 0.15 | | R-Squared | 0.8833 | | |
| Mean | 2.04 | | Adj R-Squared | 0.8563 | | |
| C.V. % | 7.13 | | Pred R-Squared | 0.7634 | | |
| PRESS | 0.55 | | Adeq Precision | 15.817 | | |

The correlation coefficient ($R^2$ closes to unity) was tenacious to delineate the sufficiency of a fitted regression models and it was found that for all models $R^2$ closes to unity. The “Pred R-Squared” values for all responses are in plausible accidence with the “Adj R-Squared” values. The adequate precision ratio of all developed model (ratio > 4 is desirable) provides an adequate signal to use the proposed model. The final regression equations for Ra, Rq and Rz are represented in eq. (4) to eq. (6):

$\sqrt{Ra}$=0.94210-0.007084Vc-2.13909f+0.69803ap+0.015820Vc*f-0.00202Vc*ap3.99202f*ae+0.0000199Vc$^2$+24.85506f$^2$+0.30721ae$^2$ (4)

$\sqrt{Rq}$=1.02870-0.006765Vc-2.23512f+0.53522ae+0.023747Vc*f-0.002157Vc*ae3.89550f*ae+0.00001548Vc$^2$+21.0875f$^2$+21.08715f$^2$+0.5296ae$^2$ (5)

$\sqrt{Rz}$=0.2976+0.00103Vc+10.0934f+0.1714ae (6)

## Error analysis for prediction models

in order to know the predictability of models ,a comparison has been made on the basis of the statistical methods of percentage mean absolute error (%MAE),percentage mean square error (% MSE) and correlation coefficient ($R^2$ values ),these values are determined using eq. (7) and (8 ).

$$\%MAE = (1/n \sum e_i - p_i/e_i)*100 \quad (7)$$

$$\%MAE = (1/n \sum e_i - p_i/2)*100 \quad (8)$$

Where e is the experimental value, p is the predicted value and n is the number of treatments for experimentation. The tables for mean absolute and mean square errors are not shown here for space reasons. The analysis shows that the maximum percentage absolute error reduces from 28.31 to 6.53 for Ra, 20.82 to 8029 and 36.52 to 4.89 for Rz using a Box–Cox transformation. Furthermore, the maximum percent age square error reduces from 3.76 to 0.126 for Ra, 2.90 to 0.142 for Rq and 237.26 to 26.71for Rz. This indicates the improved prediction ability of the quadratic model using the Box–Cox transformation

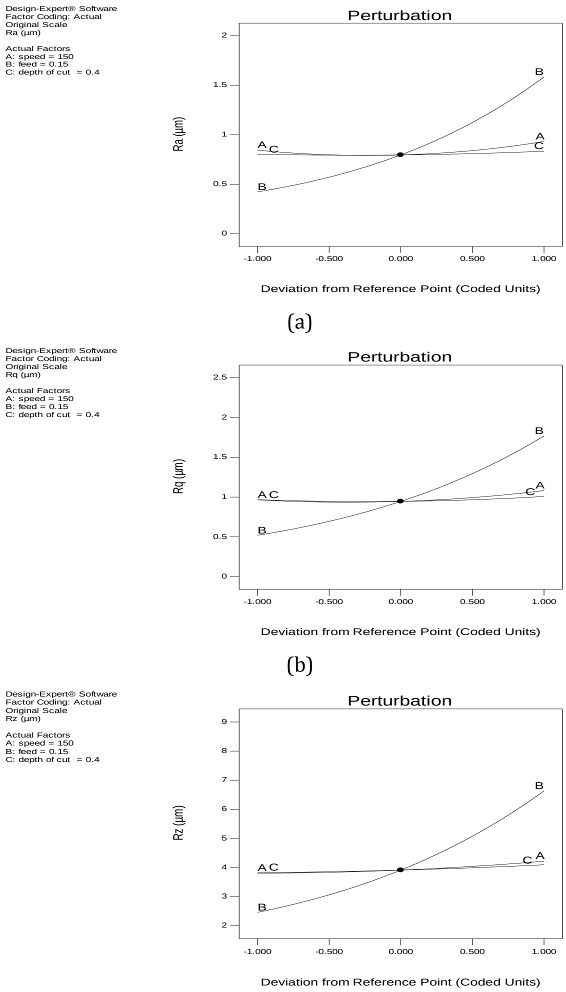
## Effect of machining parameters on surface roughness values

Effect of cutting speed on Ra, Rq and Rz: It was found that impact of cutting speed. Therefore, to study the effect of cutting speed in details three levels of cutting speed were considered. The examination of machined surface quality is conducted at the selected machining conditions. It has been observed that as in case of MQL turning during sticky material like titanium grade 5, the values of surface roughness moderately increasing due to rise in cutting speed. It is due to the, at  flows on the cutting edge of tool causes the high friction, which may leads to high surface roughness. In addition, this high friction generates the high temperature at  alloy thus making the surface rough. Also, high cutting speed creates the built up edge formation, thus lowering the surface finish.

Effect of feed rate on Ra, Rq and Rz: Due to the high ductility of titanium and its alloys, the built up edge are formed on tool rake face. When the effect of built up edge is considered negligible, the profile of cutting edge of the tool (pointed or curved) gets imprinted on the work surface and the surface roughness from this point depends on the feed rate. Moreover, it is well known fundamentals of metal cutting that feed rate influences pitch of the machined surface Profile (Ra = f2 32r), where f=feed rate and r = nose radius. That’s why surface roughness penetratingly increases due to rise in feed rate. This is due to the fact that at higher cutting speed and feed rate, tool traverses the work piece too fast, resulting in deteriorated surface quality and also the combination of high speed-feed combination increases the chatter and vibrations in machines, which leads to higher surface roughness.

## Desirability based multi response optimization

The ranges and goals of input parameters viz. cutting speed, feed rate and nozzle distance vs. output parameters viz. square root of surface roughness values are given in Table 9. The goal of optimization is to find a set of conditions that will meet all the goals. It is not necessary that the desirability value is 1.0 as the value is completely dependent on how closely the lower and upper limits are set relative to the actual optimum. A set of 4 optimal solutions are derived for the specific design space constraints for surface roughness values using Design Expert statistical software. The set of conditions possessing highest desirability value is selected as optimum condition for the desired responses. Once the optimal level of the process parameters is selected, the final step is to predict and verify the improvement of the performance characteristics using the optimal level of the machining parameters.




(a) (b) (c)

**Figure 4**: Effect of all cutting parameters after Box–Cox transformation (a) Ra, (b) Rq, (c) Rz

**Table 9**: Range of input parameters and responses for desirability optimization

| Parameters | Goal | Lower limit | Upper limit | Lower weight | Upper weight | Importan -ce |
|---|---|---|---|---|---|---|
| Vc | In range | 100 | 200 | 1 | 1 | 3 |
| f | In range | 0.1 | 0.2 | 1 | 1 | 3 |
| ae | In range | 0.2 | 0.6 | 1 | 1 | 3 |
| Sqrt Ra | minimize | 0.361 | 1.95 | 1 | 1 | 3 |
| Sqrt Rq | minimize | 0.451 | 2.238 | 1 | 1 | 3 |
| Sqrt Rz | minimize | 2.052 | 8.411 | 1 | 1 | 3 |

The ramp function and bar graph for desired objectives were selected as shown in Fig. 4. The dot on each ramp reflects the factor setting or response prediction for that response characteristic. The height of the dot shows how much desirable it is. A linear ramp function is created between low value and the goal or the high value and the goal. The value of desirability varies from 0 to 1 depending upon the closeness of the response toward target.
Figure 5 shows the overall desirability curve (all the three responses are given equal weight age) when input parameters such as cutting speed and feed were varied. The overall desirability value is less in the region of high cutting speed and feed rate, while this is close to 1 in the region where there was a low cutting speed and low cutting feed. This is owing to the fact that at higher cutting speeds and feed rates the surface roughness values will be high and rough surface is produced. Furthermore, to show the sensitivity of the results, contour plots for ramp overall desirability was drawn as shown in Fig. 6. The near optimal region was located close to the left hand bottom region of the plot, which had an overall desirability value greater than 0.986 that gradually reduced as we moved right and upwards. Sensitivities are obtained (and thus represented) using the shape of the contour lines in Fig. 6. The optimized value of the parameter is shown in Table 10. For confirmation of the experiments at optimization condition further experiments are done. The comparison of the initial and experimental optimized result is shown in Table 11. The predicted and experimental values are very close to each other, which show the significance of developed model.

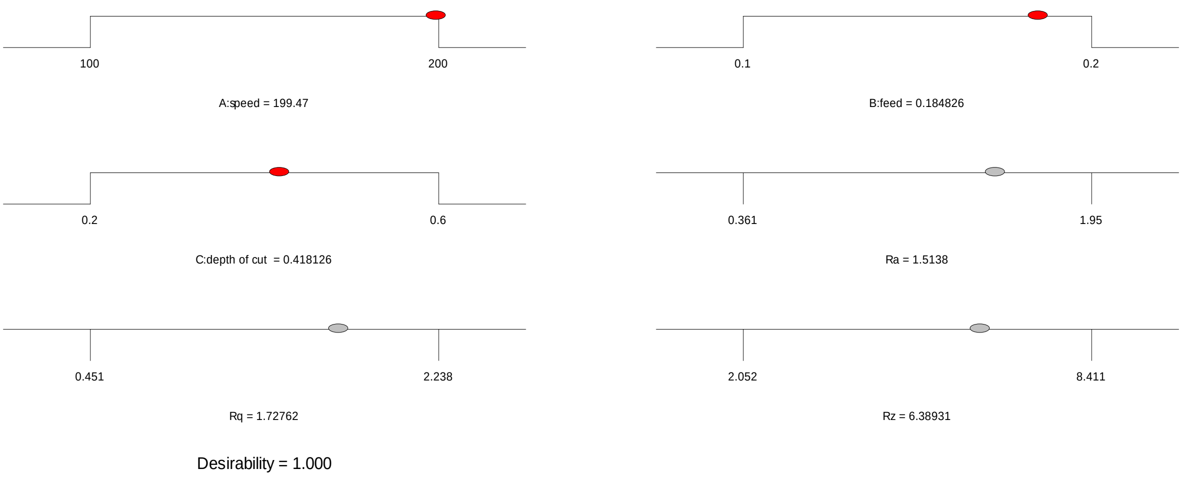



**Figure 5**: Ramp function graph of desirability optimization

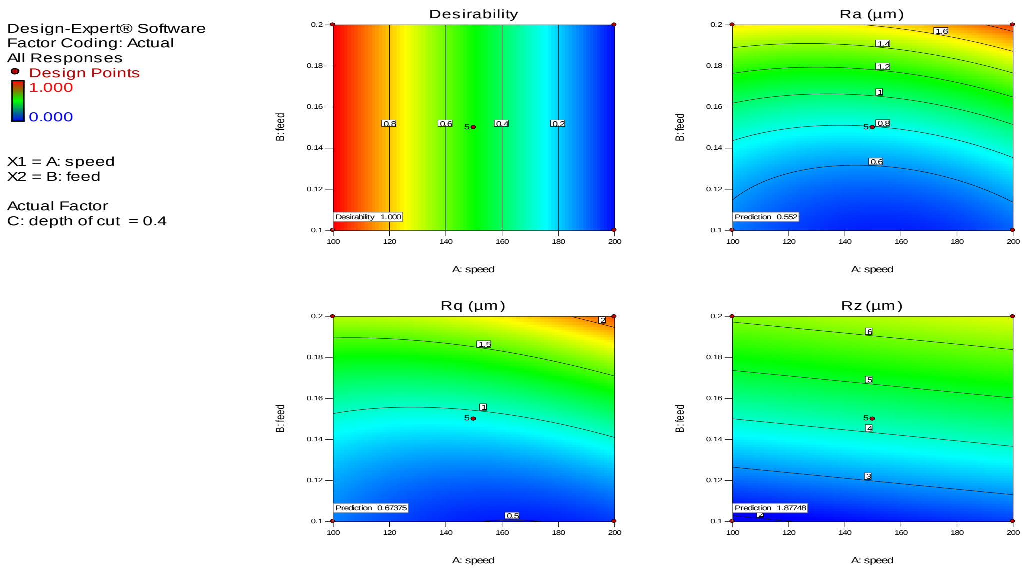



**Figure 6**: Contour plots for result of overall desirability function

**Table 10**: Optimization results

| Sl.no | Vcm/min | fmm/rev | ae mm | Sqrt Ra | Sqrt Rq | Sqrt Rz |
|---|---|---|---|---|---|---|
| 1 | 100 | 0.1 | 0.2 | 0.437 | 0.549 | 2.148 |
| 2 | 100 | 0.1 | 0.202 | 0.437 | 0.549 | 2.154 |
| 3 | 100.427 | 0.1 | 0.2 | 0.436 | 0.548 | 2.147 |
| 4 | 100 | 0.1 | 0.205 | 0.438 | 0.550 | 2.162 |

**Table 11**: Confirmation test for the optimization value

| Slno. | Parameters | Initial results at optimum value | Experimental results at optimum value |
|---|---|---|---|
| 1 | Vc | 100 | 100 |
| 2 | f | 0.1 | 0.1 |
| 3 | ae | 0.2 | 0.2 |
| 4 | Sqrt Ra | 0.436792 | 0.432631 |
| 5 | Sqrt Rq | 0.54884 | 0.546074 |
| 6 | Sqrt Rz | 2.14761 | 2.1341 |

## Conclusions

Within the present work, the effect of machining parameters (cutting speed, feed rate and depth of cut) on three surface roughness values in turning of titanium alloy beneath MQL parameters has been studied. first, a few experiments had been finished to discover the powerful premiere MQL parameters inclusive of lubricant flow rate of 300ml/h, input pressure of 4 bar and compressed air flow rate of 60 l/min. after reading the MQLparameters, the final experiments have been executed to optimize the machining parameters for surface roughness values i.e., Ra, Rq and Rz using desirability analysis. The experimental end result has led to the following

1. 1. The feed rate is the dominate component affecting surface roughness values followed by cutting speed and depth of cut . There is very less effect of cutting velocity and depth of cut on Ra, Rq and Rz. the percentage contribution of feed rate on Ra, Rq and Rz has located to be 47. 52%, 32.56% and 60.02%.
2. The RSM changed into determined to be powerful for the identity and improvement of sizeable relationships among machining parameters and given responses.
3. The utility of Box–Cox transformation has reduced the statistical errors in prediction of surface roughness, this is, reduces absolutely the mistakes from 28.31 to 6.53 for Ra, 20.82 to 8.29 for Rq and 36.52 to 4.89 for Rz. Furthermore, the maximum percentage square error reduces from 3.76 to 00.126 for Ra, 2.990 to 0.142 for Rq and 237.26 to 26.71 for Rz. This indicates the improved prediction ability of the quadratic model using the Box–Cox transformation.
4. The 3-D plots for standard desirability function discovered the desirability variety while responses are given identical weight age. as clean from the plots reducing pace of 100m/min, feed rate of 0.10mm/rev and depth of cut of 0.4mm are desirable for purchasing superior situations.

Those effects demonstrated that this optimization approach turned into efficient and greatly decreased the machining price and the design technique. The prediction models may be successfully carried out to determine the perfect cutting conditions, so one can obtain preferred floor roughness values the future empirical investigations will look into the impact of different parameters such as nose radius, tool materials, work materials etc. on the surface roughness values.

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