

# Prediction of surface roughness in turning of Ti-6Al-4V using cutting parameters, forces and tool vibration

Neelesh Kumar Sahu<sup>1</sup> Atul B. Andhare<sup>2</sup> Sandip Andhale<sup>3</sup> Roja Raju Abraham<sup>4</sup>

<sup>1</sup>Assistant Professor, Shri Ramdeobaba College of Engineering and Management, Nagpur India

<sup>2</sup>Associate Professor, Visvesvaraya National Institute of Technology, Nagpur, India

<sup>3</sup>M.Tech, Visvesvaraya National Institute of Technology, Nagpur, India

<sup>4</sup>Research Scholar, Visvesvaraya National Institute of Technology, Nagpur India

sahunk1@rknc.edu

**Abstract.** Present work deals with prediction of surface roughness using cutting parameters along with in-process measured cutting force and tool vibration (acceleration) during turning of Ti-6Al-4V with cubic boron nitride (CBN) inserts. Full factorial design is used for design of experiments using cutting speed, feed rate and depth of cut as design variables. Prediction model for surface roughness is developed using response surface methodology with cutting speed, feed rate, depth of cut, resultant cutting force and acceleration as control variables. Analysis of variance (ANOVA) is performed to find out significant terms in the model. Insignificant terms are removed after performing statistical test using backward elimination approach. Effect of each control variables on surface roughness is also studied. Correlation coefficient ( $R^2_{pred}$ ) of 99.4% shows that model correctly explains the experiment results and it behaves well even when adjustment is made in factors or new factors are added or eliminated. Validation of model is done with five fresh experiments and measured forces and acceleration values. Average absolute error between RSM model and experimental measured surface roughness is found to be 10.2%. Additionally, an artificial neural network model is also developed for prediction of surface roughness. The prediction results of modified regression model are compared with ANN. It is found that RSM model and ANN (average absolute error 7.5%) are predicting roughness with more than 90% accuracy. From the results obtained it is found that including cutting force and vibration for prediction of surface roughness gives better prediction than considering only cutting parameters. Also, ANN gives better prediction over RSM models.

## 1. Introduction

Titanium and its alloys are widely used in applications where components are subjected to extreme conditions of temperature, stress, corrosion, etc. This is because; these alloys are having exceptional properties such as high strength at elevated temperature, low density, high corrosion, creep resistance and biocompatible [1-3]. Unlike other engineering materials, Titanium alloys are difficult to cut due to their high temperature strength, very low thermal conductivity, relatively low modulus of elasticity

and high chemical reactivity [4-6]. In order to have high reliability of machined surface of Titanium alloys, its surface integrity is one of the most important parameters to evaluate the quality of surface produced [1].

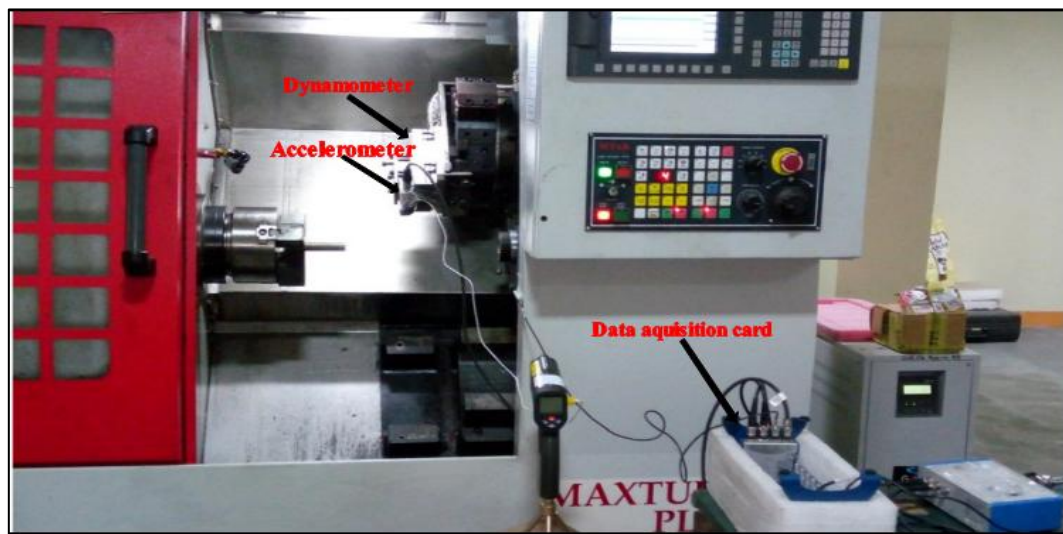
Surface roughness is an important parameter to characterize surface integrity. It gives primary indication of quality of machined surface. Surface roughness requirements are decided prior to machining of components to gain desired fatigue strength, corrosion resistance tribological and aesthetical requirement. The general model used to predict surface roughness in turning operation is  $R_a = f^2/32r$  where  $f$  is feed rate and  $r$  is nose radius tool insert [7]. Although it is well known that feed rate and nose radius affects surface roughness but in actual machining, it is not possible to predict accurate surface roughness. The main reason is because of effect of tool vibration, tool wear, cutting forces generated and other cutting parameters are not considered in the above model. In the literature it is found that Surface roughness is influenced by several factors such as - cutting speed, feed, depth of cut, tool geometry, tool wear, etc. [8-11]. Upadhyay et al. [12] predicted surface roughness using vibration in terms of acceleration in three directions as well as cutting parameters. They found that effective parameters to predict surface roughness are feed rate followed by acceleration in radial direction then depth of cut and acceleration in tangential direction. They have also validated the adequacy of developed model using Artificial Neural Network (ANN). Marek et al. [13] Predicted the surface roughness using artificial intelligence approach(ANN) for nickel based super alloy UDIMET 720 by considering the effects of cutting conditions, tool wear and monitoring parameters for the drilling process. Tugrul Ozel, et al. [14] has used the artificial neural network (ANN) to predict the surface roughness and tool flank wear over the machining parameters in finish hard turning using cubic boron nitride (CBN) tool. The workpiece material used for performing the experiments is AISI 52100 steel. Regression technique was used to develop the model of surface roughness and tool flank wear. Artificial neural network was then used to train the experimental data for obtaining the suitable neural network models. ANOVA is then used to show the interaction between hardness and edge geometry, hardness and feed rate.

Usually surface roughness is measured after machining during which component may be rejected or rework for not getting desired surface roughness. This strategy is not cost effective for super alloys like titanium alloys which are used in critical component of aircraft as well as biomedical implants. Therefore the quality of components after machining cannot be compromised. Although lot of work has been done to predict surface roughness of machined components, still there are few literatures are found in the machining of titanium alloys especially considering the effects of dynamic behaviour of tool movement. Therefore in the present work, apart from cutting parameters, additionally dynamic effects such as cutting force and tool vibration are considered to predict the surface roughness

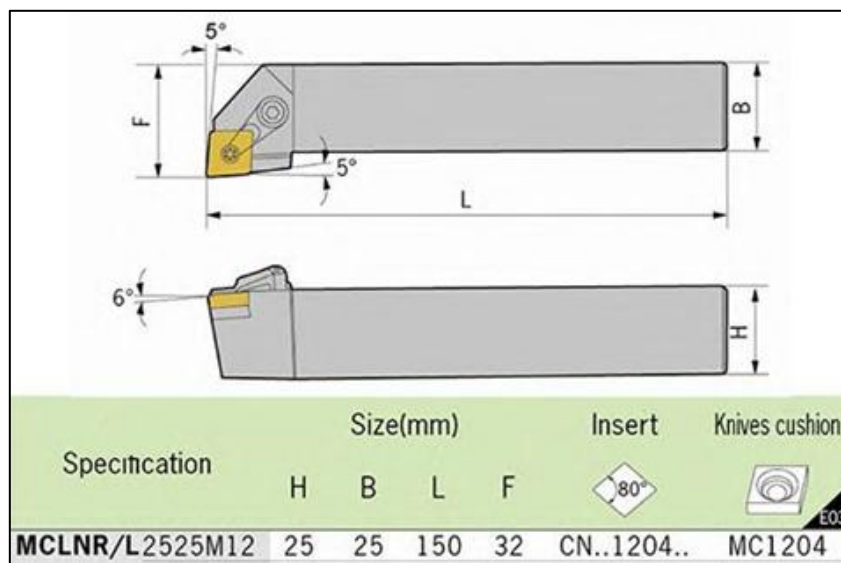
## 2. Experimental Details

### 2.1 machine tool, cutting tool and workpiece material

Machine tool used for turning operation was MTAB CNC lathe machine (Maxturn++) with power capacity of 5.5 kW as shown in figure1. Machine is equipped with Sinumeric 828D controller for precise motion and spindle speed control with  $\pm 0.005$  mm position accuracy and  $\pm 0.004$  mm repeatability during the cutting process; when operated with a NC program. CBN Cutting inserts with specification CNMA120408 are used for turning operations. CBN inserts were mounted over tool holder with specification MCLNL 2525 M12 as shown in figure 2. This type of tool holder can be used for the tools of specification CNMG120408/CNMA120408. For the present work Ti-6Al-4V (titanium grade 5 alloys) which is widely used among all the titanium alloys is considered as workpiece material. Table 1 and 2 show the composition and physical properties of Ti-6Al-4V respectively. The diameter of the workpiece was 25 mm and total length was 100 mm. The cutting length was 20 mm for each experiment as shown in figure 3.



**Figure 1** Experimental set up



**Figure 2** Tool holder specifications



**Figure 3** Workpiece sample

**Table 1** Material composition of Ti-6Al-4V

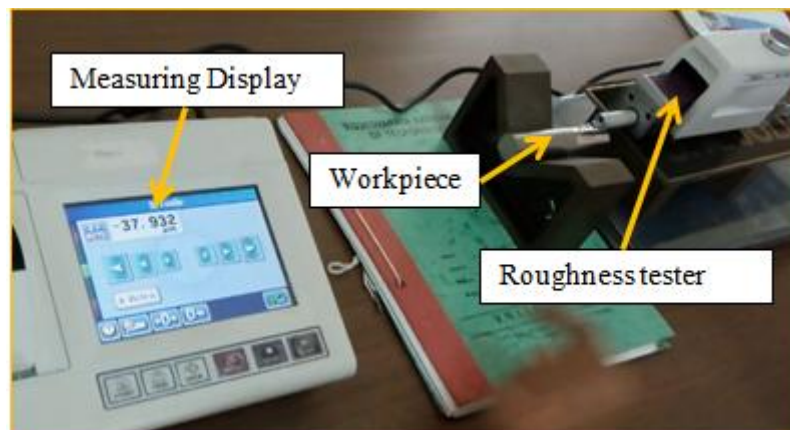
Element	Carbon	Aluminium	Oxygen	Vanadium	Iron	Hydrogen	Nitrogen	Titanium
Weight (%)	0.1 (Max.)	5.50 to 6.75	0.02 (Max.)	3.50 to 4.50	0.4 (Max.)	0.015 (Max.)	0.05	Balance

**Table 2** Physical properties of Ti-6Al-4V

Density, g/cm <sup>3</sup>	Melting Range, °C±15°C	Specific Heat, J/kg.°C	Thermal Conductivity, W/m.K	Elastic Modulus, Gpa	Hardness Rockwell, HRC	Tensile Strength, Mpa
4.42	1649	560	7.2	114	36	897

## 2.2 measuring instruments

Cutting force measurement during turning operations was done using Kistler dynamometer of type 9257BA. It is quartz based three-component dynamometer for measuring the three orthogonal components of a force. It has measuring range -5kN to 10 kN sensitivity 5 pC/N Output of dynamometer is given to NI cDAQ-9178 (Data acquisition card) shown in figure 1. Present work uses Accelerometer sensor IMI Sensors model 603C11 is also shown in figure 1. It has sensitivity of 100mV/g, measurement range is ±50g, and operating frequency is 0.5-25 kHz. Surface roughness of machined surface was measured using Mitutoyo surfest SJ-410 which is portable surface roughness tester as shown in figure 4. It has a measuring range 50 mm and backward transverse direction. Length of measurement for roughness testing of work piece is 4.8 mm and measuring speed is 0.5 mm/s.

**Figure 4** Surface roughness measurement

In this work, full factorial design has been used to create list of experiments using cutting speed, feed rate and depth of cut as design variables. Table 3 shows the levels of cutting parameters used for turning operation on Ti-6Al-4V using CBN inserts. After the work piece material, machine and tooling and measuring devices were selected and prepared, turning experiments were conducted as per the scheme of runs determined by full factorial design for design of experiments and various parameters were measured such as cutting forces, acceleration and surface roughness as shown in table 4. The design of experiments was performed using MINITAB 17 statistical software.

**Table 3** Cutting parameters and their levels

S. No.	Factors	Nomenclature	Low	Medium	High
1	Cutting Speed (m/min)	$V_c$	120	180	240
2	Feed (mm/rev)	$f$	0.1	0.15	0.2
3	Depth of cut (mm)	$a_p$	0.5	0.75	1

**Table 4** Sequence of experiments and measured responses

Exp. No.	Speed $V_c$ (m/min)	Feed $f$ (mm/rev)	Depth of cut $a_p$ (mm)	Feed Force $F_x$ (N)	Cutting Force $F_z$ (N)	Resultant Force $F$ (N)	Acceleration $A$ (m/s <sup>2</sup> )	Surface Roughness $R_a$ ( $\mu$ m)
1	180	0.15	1	234.6	256.3	347.4	1.757	2.229
2	180	0.1	0.75	101.9	146.1	178.1	3.377	2.106
3	120	0.2	1	296.5	336.4	448.4	1.149	2.596
4	180	0.2	0.75	214.6	375.7	432.7	2.105	2.186
5	120	0.1	1	148.0	139.4	203.3	1.653	2.599
6	240	0.1	0.75	117.0	156.3	195.2	5.049	1.736
7	120	0.2	0.5	196.0	365.1	414.4	0.301	2.425
8	180	0.2	1	323.0	379.8	498.6	2.327	2.224
9	180	0.1	1	169.4	145.7	223.0	2.62	2.210
10	180	0.15	0.75	156.2	264.3	307.0	3.306	2.194
11	18	0.1	0.5	90.2	182.3	203.4	1.261	1.962
12	120	0.2	0.75	215.4	328.2	392.6	1.392	2.524
13	240	0.15	0.5	135.8	333.3	359.9	4.168	1.645
14	180	0.15	0.5	132.4	306.1	333.5	1.952	2.019
15	120	0.15	0.75	155.7	234.6	281.5	2.777	2.481
16	240	0.2	0.5	157.6	438.1	465.6	3.909	1.704
17	120	0.15	1	229.2	245.7	336.0	2.516	2.573
18	240	0.15	1	270.3	299.0	403.0	5.2	1.848
19	240	0.2	0.75	210.8	445.8	493.2	4.472	1.866
20	120	0.15	0.5	137.7	272.6	305.4	0.863	2.371
21	180	0.2	0.5	189.6	415	456.2	2.288	2.012
22	120	0.1	0.75	91.2	166.8	190.1	3.092	2.476
23	120	0.1	0.5	101.4	165.2	193.9	0.935	2.334
24	240	0.2	1	332.7	456.1	564.6	3.479	1.908
25	240	0.1	0.5	87.8	186.3	206.0	1.93	1.598
26	240	0.15	0.75	156.4	287.1	326.9	4.302	1.837
27	240	0.1	1	183.6	169.0	249.5	3.314	1.826



### 3. Results and discussions

#### 3.1 Prediction model for surface roughness using response surface methodology

Response Surface Methodology (RSM) is a significant tool on the statistical analysis. This technique was initially presented by G. E. P. Box and K. B. Wilson in 1951. It is useful for the modelling and analysis of response which is influenced by several variables [15-17]. If there is curvature in the system, then a polynomial of higher degree must be used. Most of the industrial problems can be modelled with sufficient accuracy by using a second-degree polynomial, which yields the following second order model as equation 1

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

Second order model is developed for surface roughness using cutting speed, feed rate, depth of cut, resultant force, and tool vibration (acceleration) as variables. Initially the model is developed for full quadratic terms including all variables. Analysis of variance (ANOVA) was performed to see the significant and insignificant parameters of the predicted model. This procedure involves checking individually variability of variable over the response. In this test procedure, sums of square of regression and errors are calculated. To check the significance of variables, F value is calculated as ratio of mean of square (regression) to mean of square (error) is calculated. Larger values of F suggest that model is significant. Alternatively, p value is the probability of the predicted model shows its significance in terms of statistics. If p value is less than 0.05 model terms are significant and p value greater than 0.05 indicates that model terms are not significant. Similarly the value of  $R^2$  (correlation coefficient) is calculated as ratio of sum of square of regression to the total sum of square. The correlation coefficient ( $R^2$ ) value suggests a satisfactory representation of process by model and good correlation between experimental and theoretical values provided by the model equation. In order to avoid insignificant terms in the model such that modified model clarifies the response, the backward regression elimination method (also known as stepwise deletion) is used. In the stepwise deletion method, t test or F test for significance of design variable is performed with sequence begin with full model. Insignificant variables with the highest p value (e.g.  $p > 0.05$ ) are removed from the full model. Table 5 shows the estimated regression coefficients corresponding to variables and their T test and p value to check significance of variables. Equation 2 represents modified prediction model for surface roughness after removing insignificant terms using backward elimination approach.

**Table 5** Estimated regression coefficients of input variables

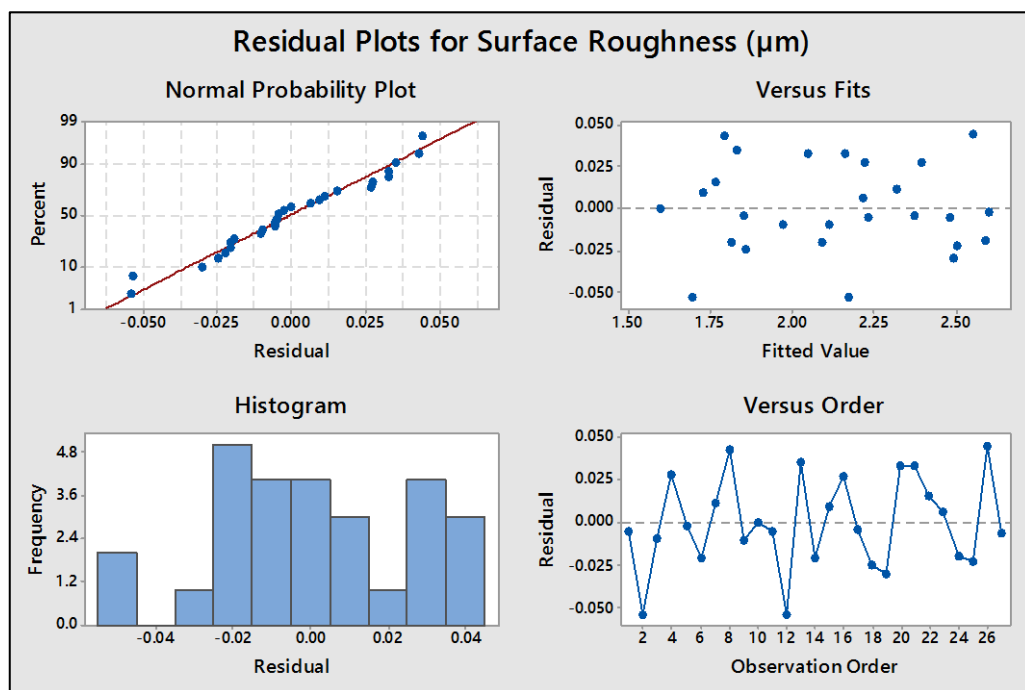
Term	Coefficient	SE Coefficient	T	P	P<0.05 (Significant)
Constant	2.2137	0.0349	63.36	0.000	Yes
Cutting speed ( $V_c$ )	-0.3291	0.0143	-22.99	0.000	Yes
Feed rate (f)	-0.0525	0.0644	-0.81	0.042	Yes
Depth of cut ( $a_p$ )	0.1089	0.00862	12.65	0.000	Yes
Resultant Force(F)	0.1158	0.0959	0.00	0.246	No
Acceleration (A)	-0.0825	0.0200	1.21	0.001	Yes
$f^2$	-0.02171	0.00797	-4.13	0.016	Yes
$a_p^2$	-0.0963	0.0236	-2.72	0.001	Yes
$V_c \times a_p$	-0.01843	0.00726	-2.54	0.023	Yes
$V_c \times F$	0.0258	0.0130	1.98	0.066	No
$V_c \times A$	0.0355	0.0111	3.20	0.006	Yes
$f \times a_p$	-0.02443	0.00712	-3.43	0.004	Yes

$$R_a = 1.722 - .000605 \times V_c + 3.02 \times f + 3.263 \times a_p - 0.0771A - 8.68 \times f^2 - 1.542 \times a_p^2 - 0.000123 \times V_c \times a_p + 0.000024 \times V_c \times A - 1.954 \times f \times a_p \quad (2)$$

Correlation coefficient  $R^2_{(adjusted)} = 99.43\%$  this value shows that the model well explained experimental values, so, model behaves well when adjustment is made in factor or new factor are added or eliminated.

### 3.2 validation of prediction model

Residual graphs are useful to adequacy of developed model for the response. Figure 5 shows the residual plots for surface roughness in turning operation. Distributions of data along straight line in normal plot of residual suggest that the data meet the sample size guidelines and confidence intervals and also p values are accurate. Random distribution of all points on both the side of zero in residual versus fitted plot shows that there is no any non-constant variance or outlier is observed. The residual versus order plot shows the order in which data are collected and displays the observation in order and patterns in the points. From figure 5, it is clear that residuals near each other are correlated and thus not independent.



**Figure 5** Residual plot for Prediction model for surface roughness

**Table 6** Validation experiments and compare with RSM results

$V_c$ (m/min)	$F$ (mm/rev)	$a_p$ (mm)	$F$ (N)	$A$ (m/sec <sup>2</sup> )	$R_a$ (Regression)	$R_a$ (Exp.)	%Error
130	0.15	0.95	318.3	2.396	2.425	2.705	-11.57
130	0.19	0.75	379.7	2.041	2.563	2.305	10.07
180	0.19	0.55	413.1	2.168	1.976	2.213	-11.41
230	0.11	0.75	219.3	4.160	1.829	1.973	-7.895
230	0.15	0.55	334.6	3.784	1.803	1.622	10.032

In order to validate the prediction model developed, turning experiment was carried out by using the five reserved values of cutting speed, feed rate and depth of cut as shown in table 6 and the obtained responses were recorded. After experimentation surface roughness is measured by surface roughness tester for validation. The average absolute error between RSM and experimental results are found to be 10.2 % which is acceptable.

### 3.3 main effect plots

Figure 6 shows the influence of main cutting parameters (cutting speed, feed rate and depth of cut) in dry condition, on the turning of Ti-6Al-4V. Main effect was plotted for each parameter by keeping other input parameters constant and at the center value. It is found that roughness of machined surfaces decreases with increase in cutting speed. Same kind of trends were found for surface roughness with the earlier work by Che-Haron et al.[11] ;shokrani et al.[18] and S. Ramesh et al. [19] in machining of Ti-6Al-4V alloys. The conceivable reason for the above tendency is that as cutting speed increases, due to low thermal conductivity, high heat is accumulated in workpiece surface. Further due to thermal softening of workpiece and therefore results in elastically deformation of workpiece surface. This outcomes in lesser cutting forces together with a lesser amount of vibration, produces better surface finish [20]. It is clear from the figure 5 that as feed rate is increasing; roughness of machined surface is increasing. At higher feed rate, due to high friction between tool and workpiece high temperature is generated in the cutting zone. As a result, removed bits of chips are fused to the cutting edge of the tool known as built-up edge. At higher feed rate, due to higher feed forces along with, formation of the built-up edge on cutting edge of tool damages workpiece surface and roughens it. Similarly while increasing depth of cut, cutting forces and tool wear increases which results in roughened surfaces.

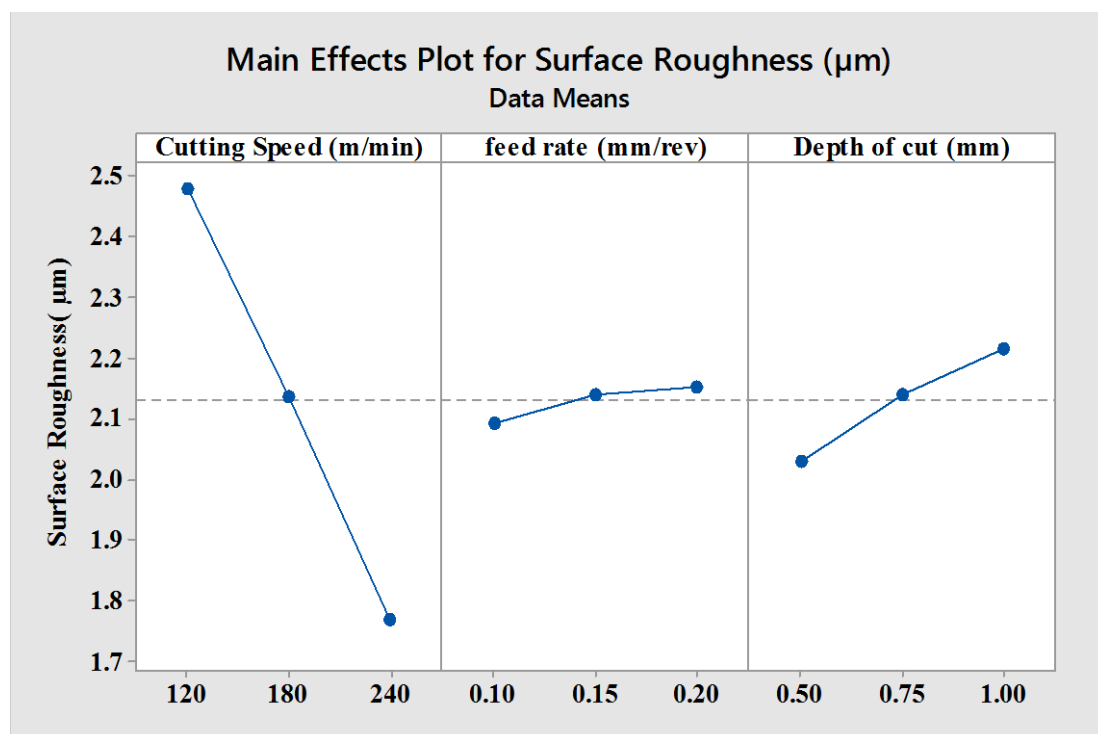
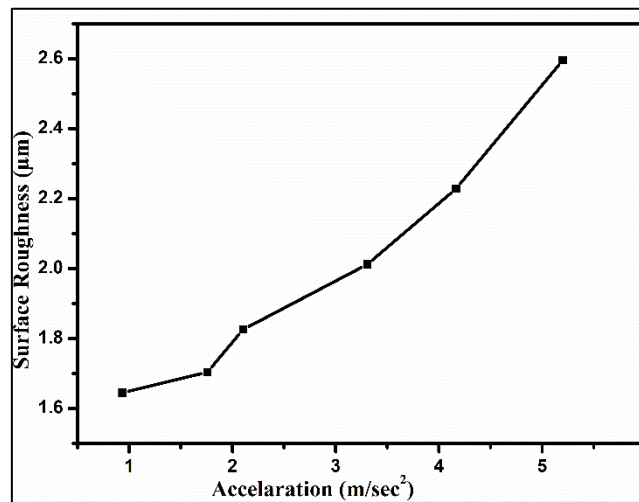


Figure 6 Main effect for surface roughness





**Figure 7** Variation of surface roughness with tool vibrations

Figure 7 shows the variation of acceleration with tool vibrations in which tool vibrations (accelerations m/sec<sup>2</sup>) was measured using accelerometer mounted over tool holder. Tool vibration occurs due to self-excitation vibration of machine tools due to chip thickness variation during machining of Ti-6Al-4V as well as due to rigidity of machine tools. Due to increase in vibrations chatter marks appear over the workpiece and results in poor surface finish.

#### 4. Prediction of surface roughness using Artificial Neural Network

Surface Roughness is predicted by considering variables cutting speed, feed, depth of cut, resultant force and acceleration as a control parameters using artificial neural network (ANN). ANN was performed using ANN toolbox in matlab 2014a software. The appropriate architecture for the artificial neural network was selected through an exhaustive examination of a number of network configurations. This was accomplished by changing the number of hidden layers and number of neurons in the hidden layer. Networks with different architecture were trained for a fixed number of cycles and were tested using a set of input and output parameters. According to Zhang et al. (21), the recommended number of neurons in the hidden layer are ‘n/2’, ‘1n’, ‘2n’, and ‘2n + 1’ where n is the number of input nodes. Therefore, this study was applied to six different architecture, which are 5–10–1, 5–11–1, 5–12–1, 5–10–10–1, 5–11–11–1 and 5–12–12–1 apart from other configurations.

In this present work, ‘learngdm’ was considered as the learning function and ‘trainlm’ as the training function. The transfer function of the ANN model was considered as “tansig” and the sigmoid function used in this experimentation is shown in equation,

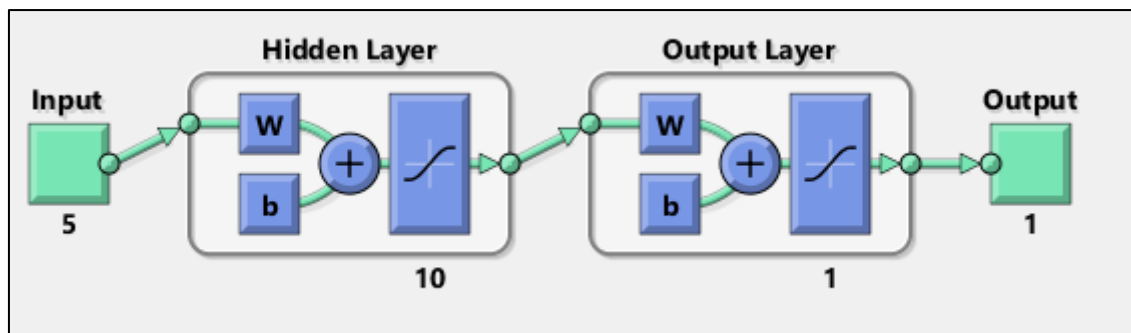
$$f(x) = \frac{1}{1 + e^{-x}} \quad (3)$$

The hidden layer type was altered progressively into single and multi-layer types with different neuronal values using trial and error method for the best configuration with least MSE value and better coefficient of determination. 27 readings were used for training the model and 5 readings were randomly selected for testing. The RMSE was considered as quadratic scoring rule for the measurement of average magnitude of the error. Data are trained to get the value of coefficient of determination and training is done continuously to get the high value of coefficient of determination and lowest value of MSE as shown in table 7. Among these configurations, 5-10-1 topology was selected as the best topology for estimation of surface roughness shown in table 7 as it has a minimum mean square error (MSE). Based on above training, randomly selected 5 readings were

tested/simulated on artificial neural network for prediction of surface roughness. The surface roughness for the respected readings is then predicted as well as validated with experimental results as shown in table 8. The average absolute error between ANN and experimental results for surface roughness is found to be 7.5% which shows that the ANN can predict surface roughness with good accuracy.

**Table 7** Training of ANN data

Model Name	Training Performance $R^2$ (%)	Test Performance $R^2$ (%)	MSE
5-10-1	94.823	91.416	0.0133
5-11-1	98.19	98.39	0.203
5-12-1	93.57	99.53	0.0376
5-10-10-1	89.88	93.99	0.178
5-11-11-1	97.25	77.69	0.0697
5-12-12-1	94.18	98.67	0.0771



**Figure 8** ANN architecture

**Table 8** Surface roughness prediction by ANN

$V_c$ (m/min)	F (mm/rev)	$a_p$ (mm)	F (N)	A ( $m/sec^2$ )	$R_a$ ( $\mu m$ ) (ANN)	$R_a$ ( $\mu m$ ) (Exp)	%Error
130	0.15	0.95	318.3	2.396	2.512	2.705	-7.71
130	0.19	0.75	379.7	2.041	2.453	2.305	6.043
180	0.19	0.55	413.1	2.168	2.012	2.213	-6.81
230	0.11	0.75	219.3	4.160	1.827	1.973	-7.99
230	0.15	0.55	334.6	3.784	1.783	1.622	9.02

## 5. Conclusions

In the present work turning process was performed over Ti-6Al-4V and three process control variables, namely cutting speed, feed rate and depth of cut were chosen for measuring responses. Design of experiments was done using general full factorial method and 27 machining experiments were carried out. Four responses, namely main cutting force, feed force, acceleration and surface roughness were measured for each experiment. Surface roughness prediction model is developed

using cutting parameters as well as resultant force and tool vibrations in order to incorporate dynamic effect of machining over surface roughness. Prediction model developed using RSM and ANN shown good agreement with experimental results. Based on the results obtained following conclusion can be drawn:

1. Design of experiments is well structured methodology for planning and designing a sequence of experiments to explore the effect of each variable range over response in minimum number of experiments.
2. ANN model with average absolute error of 7.5% performed well over RSM model with average absolute error of 10.2 %.
3. It can be concluded that considering dynamic effects of tool movement i.e. cutting force and tool vibrations in addition to cutting parameter gives better prediction of surface roughness.

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