© 2016 IJEDR | Volume 4, Issue 3 | ISSN: 2321-9939

Parametric Optimization during Dry Machining of Titanium Alloy (Ti6Al4V) with Innovative Textured Tools for Optimum Product Quality

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Abstract **- The quality of the surface generated through a machining process depends to a great extent on the conditions at the chip-tool interface. A reduction of friction and tendency of formation of built up edge (BUE) during the machining of a titanium alloy reduces the cutting forces, temperature generation and improves the surface finish and tool life. Friction at the tool-chip interface can be reduced by either proper application of the cutting fluid or modifying the geometry of the tool. In this research, textures have been developed at the rake face of the cutting tool insert. The textured inserts have been subsequently coated with Zr/WS_2 solid lubricants through pulsed DC magnetron sputtering process. The various parameters of the textures have been varied to study their effect on the friction between the chip and rake face of the tool. Cutting speed is also varied keeping feed rate and depth of cut constant. The textures reduced the friction by reducing the chip-tool contact area and acting as reservoirs for the solid lubricant. The best combination of the cutting parameters viz. cutting speed, width of grooves, depth of grooves and pitch of grooves have been achieved through Genetic Algorithm. The lowest surface roughness achieved with non-textured tools was 0.3722 µm at 60 m/min cutting speed and that for textured tools was 0.2626 µm at 60 m/min cutting speed and texture dimensions 3µm width, 3 µm depth and 5 µm pitch. It indicates an improvement of 29.44 %. The optimized tool further improved the surface finish by 18.66%.**

Keywords **- Ti6Al4V machining, Focused ion beam machining, Solid lubricant, Genetic algorithm, Optimization, Pulsed DC magnetron sputtering.**

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1. Introduction

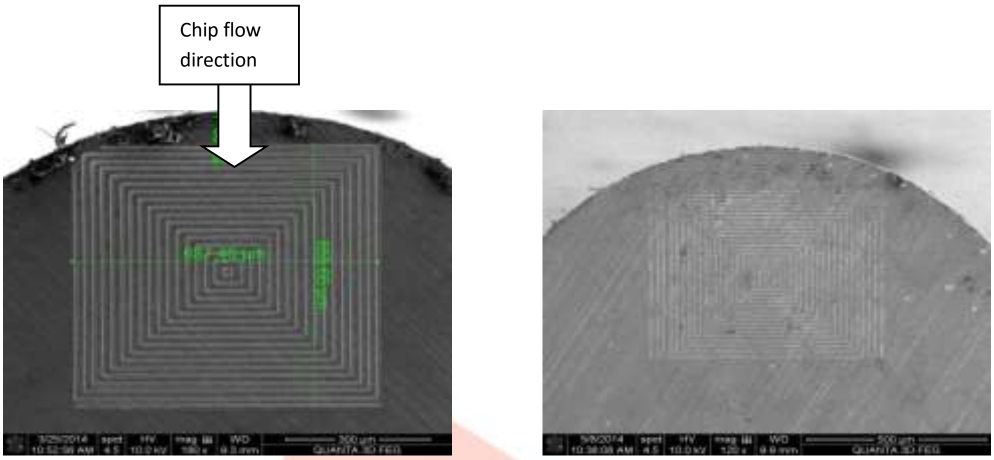
Titanium alloys are used extensively for a large number of critical applications because of their high hot strength, high strength to weight ratio, and excellent corrosion resistance. Examples include aircraft (high strength in combination with low density), aero-engines (high strength, low density, and good creep resistance up to about 550 ^{0}C), biomedical devices (corrosion resistance and high strength), and components in chemical processing equipment (corrosion resistance). Titanium alloys are usually machined with uncoated straight grade cemented carbide (WC-Co) tools at cutting speeds less than 60 m/min and 30 m/min using HSS tool. [1] Machining at high speed conditions tend to generate high temperature close to the tool nose resulting in excessive stresses which result in severe plastic deformation and subsequent failure of the tool [2]. At interfacial temperature of 500 ^{0}C and above, titanium and titanium alloys are very reactive with most of the conventional tool materials. [3] Since temperature plays a major part in tool failure during machining, it is essential to minimize the temperature generated at the tool-work piece and tool-chip interfaces. This can be achieved by reducing the friction at the chip-tool interface, which is effective when machining at lower speed conditions when temperatures at the cutting zone are relatively low. This can be achieved by using a solid lubricant as a coating and modifying the rake surface of the tool. Siekmann [4] has pointed out that 'machining of titanium and its alloys would always be a problem, no matter what techniques are employed to transform this metal into chips' and, Komanduri and Reed [5] have commented that 'this is still true in so far as cutting tool materials are concerned'. [6]

Lubricious coatings reduce heat generation by decreasing friction. These lubricious coatings include the coatings of solid lubricants such as molybdenum disulfide, tungsten disulfide, calcium fluoride, graphite, etc. which have low coefficients of friction and can provide lubrication during the cutting action. WS_2 is a solid lubricant having a very low coefficient of friction and anti-galling property. WS_2 can sustain its properties till 800 ^{0}C temperature. In the present study, WS2 has been coated by pulsed DC magnetron sputtering process to get a uniform layer. Surface textures at the rake face help in retaining the solid lubricant even after the top layer has been removed due to abrasion [7]. Surface textures have another advantage of reducing the chip-tool contact area and thereby reduce friction at the chip-tool interface [8, 9]. Novel textures are developed at the rake face of the cutting tool inserts and coated with Zr/WS_2 solid lubricant. The present study attempts to optimize the dimensions of square textures (width, depth and pitch), and surface roughness in the machining of Ti6Al4V alloy.

2. Experimental Procedure

PCLNL2020K12 cutting tool holder having Inclination Angle (λ_s)= -6^0 Orthogonal Rake Angle (γ_o)= -6^0 and the WC insert CNMA120408 having Nose radius Rε =0.8mm are used for conducting the experiments. The cutting tool inserts are coated with Zr/WS_2 solid lubricants using pulsed DC magnetron sputtering. The textures at the rake face of the cutting tool inserts were created using focused ion beam machining. The textures start a distance of 50µm from the cutting edge in order to retain the strength of the tool at the tip. The dimensions of the texture parameters were width of the grooves= 1 to 5 µm, Depth of grooves=1 to 5 µm, and pitch of grooves=5 to 25 µm. The width of the texture perpendicular to the chip flow direction is about

700 µm and length of the texture along the chip flow direction is 700 µm. Fig. 1 (a) shows the chip flow direction with respect to the orientation of the surface texture. Fig. 1(a) shows the textured tool without coating and Fig.1 (b) shows the textured tool with Zr/WS_2 coating. The experimental setup is shown in Fig. 2. The dynamometer is attached to the turret with the help of a machine adapter and the tool holder is fixed on the dynamometer. Ti6Al4V round bar of diameter 50 mm and 100 mm length was turned with the textured, WS_2 coated inserts on a Leadwell CNC turning centre. The cutting parameters were; feed rate=0.1 mm/rev, depth of cut=0.5 mm and cutting speed was varied from 60 m/min to 140 m/min. Feed rate and depth of cut were kept constant throughout the experiments. Experimentation was carried out using various textured tools at different cutting speeds. Machining was carried out without the use of cutting fluid. Experiments were designed using central composite design. Hence, with four variables and five levels, 30 experiments were conducted with textured tools to evaluate the effect of all the parameters (depth, width and pitch of the grooves in the textures and cutting velocity) on surface finish during Ti6Al4V machining.



(a) Uncoated (b) WS_2 Coated

Fig.1 Surface textures developed at the rake face of cutting tools

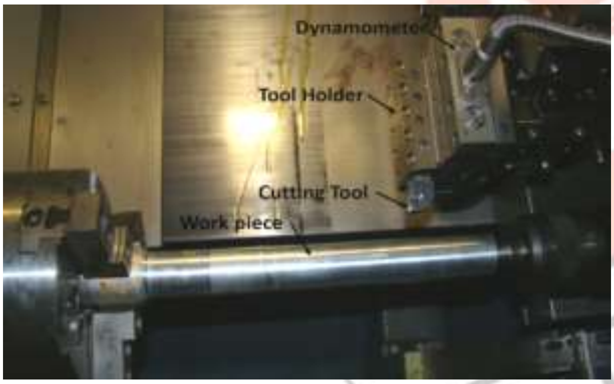


Fig.2 Photographic view of the Experimental Setup

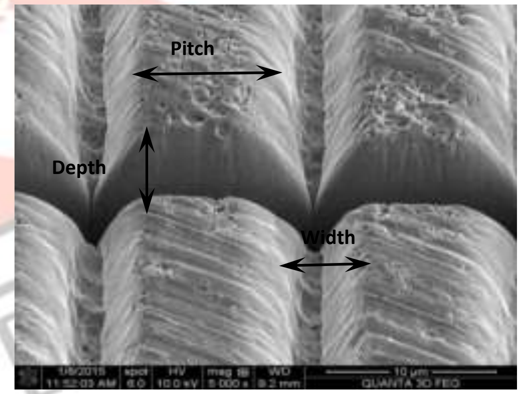


Fig. 3 Cross section of the grooves

The responses measured were the cutting force components (main cutting force P_z, axial thrust force P_x and radial thrust force P_y) and surface roughness. For force measurement, a dynamometer (Kistler 9129) with charge amplifier (multichannel charge amplifier type 5070A) was employed. The forces reported were measured when the process was in the steady stable state. Surface roughness of the machined surface was measured by Form Talysurf surface roughness tester.

3. Design of Experiments

The aim of Design of Experiments (DOE) is to identify the active factors and evaluate their effects on the selected responses. A meticulously planned and properly implemented experimental procedure results in an effective and accurate experimental program. For a design of experiments containing 4 factors and each factor having five levels, a full factorial design would require 625 (5^4) experiments. This is expensive considering the cost and time requirements. And many a time, it is not required also. Central Composite Design (CCD) is a technique which reduces the number of experiments and provides adequate representation of all the factors.

Experiments were conducted using central composite design. In the present investigation, the independent variables are cutting speed and depth, width and pitch of the surface texture. The responses measured are cutting force and surface roughness. CCD technique is useful in studying the sequential effect of the independent process variables on the contemplated responses. Implementation of CCD has also reduced the number of experiments from 625 to 30. It is also useful to see the repeatability of the experimental results.

Central composite design (CCD) is the most popular class of second order design suggested by Box and Wilson [10-12]. This central composite design provides five levels for each independent variable low axial, low factorial, centre, high factorial and high axial. With these many levels, it generates enough information to fit a second order polynomial called “quadratic”. Table 2 shows the parameters and their levels.

Table 1 Process parameters and their levels

Factors	-2	-1	0	+1	+2
Cutting speed in m/min	60	80	100	120	140
Depth of grooves in µm	1	2	3	4	5
Width of grooves in µm	1	2	3	4	5
Pitch of grooves in µm	5	10	15	20	25

Central composite design is capable to predict independent, quadratic and interaction effects of different parameters on the response. A central composite design consisting of 30 experiments (16 factorial runs, 8 axial runs, 6 central points) as shown in Table 4 was chosen to design the experiments. The factorial points represent a first-order model. The center points, midpoint of each factor range, provide information about existence of curvature. And, the axial points allow estimation of the pure quadratic properties of the model.

3.1 Analysis of Experimental Results

The results of the cutting forces and surface roughness under dry machining condition are shown in Table 2.

Table 2 Experimental results of cutting force and surface roughness

S. No.	V, m/min	W, µm	D, µm	P, µm	P_x, N	P_y, N	P_z, N	Ra, µm
1	80	2	4	20	63.48	79.79	142.9	0.4579
2	100	3	3	5	30.29	53.09	88.83	0.412
3	100	3	3	25	46.46	66.48	112.34	0.3752
4	80	4	2	20	37.85	58.17	106.1	0.2626
5	140	3	3	15	74.49	102.56	146	0.4579
6	120	2	2	10	62.49	83.41	131.7	0.5438
7	100	3	3	15	52.31	69.39	127.1	0.4715
8	120	2	2	20	58.37	83.97	126.3	0.5579
9	80	4	2	10	46.9	67.09	120.93	0.4422
10	120	4	4	10	49.92	79.2	116.91	0.5141
11	100	3	3	15	52.73	85.55	119.9	0.3939
12	80	4	4	10	31.38	56.98	92.45	0.3275
13	60	3	3	15	55.06	76.47	134.2	0.3044
14	100	5	3	15	42.84	66.57	109.55	0.5012
15	100	1	3	15	60.61	82.1	137.7	0.7112
16	100	3	3	15	55.42	77.86	132.6	0.5012
17	100	3	1	15	63.5	90.08	142.7	0.6218
18	120	4	4	20	58.68	78.31	128.5	0.5822
19	120	2	4	10	45.36	77.9	123.4	0.4796
20	80	2	2	10	51.62	68.08	132.8	0.5984
21	100	3	3	15	64.85	81.81	134	0.5295
22	100	3	3	15	53.48	81.52	123.78	0.4041
23	120	2	4	20	59.7	84	133.8	0.5228
24	100	3	3	15	56.28	85.76	132.6	0.4522
25	80	4	4	20	48.9	64.47	115.91	0.3103
26	80	2	4	10	50.87	78.51	132.6	0.3884
27	120	4	2	20	63.63	95.16	137.7	0.4559
28	100	3	5	15	52.28	68.89	127.3	0.5114
29	80	2	2	20	53.58	79.4	128	0.5022
30	120	4	2	10	72.43	92.6	150.3	0.4992

Where, V=cutting speed, W=width of grooves, D=depth of grooves, P=Pitch of grooves
P_x=axial cutting force, P_y=radial cutting force, P_z=main cutting force, Ra=surface roughness, µm
Surface quality being the main criterion through which product quality is judged; process parameters are optimized for minimum surface roughness.

Using Design expert software (Version 8.01), the experimental data points were analyzed through the following procedures;

- Analysis of variance (ANOVA) (Analysis of variance is performed to find the effect of factors and their interactions with the responses. ANOVA provides an estimate of variance via the mean square of the residuals).
- Lack of fit test (Lack of fit test implies whether the model adequately describes the actual response surface.)
- Model summary statistics (Analysis of R-squared values) (R^2 is the corresponding reduction in error in estimating the response for the experimental variation in the independent variables. That is, R^2 reflects the number of errors made when using the regression model to assess the value of the responses, mean as the basis for estimating all results).

The ANOVA process gives an insight into which independent variables have main effects, interaction effects, less significant and noise. This decides the most relevant factors for conducting the analysis. Response equations for all the target parameters have been developed based on the mean responses. This will be useful to predict the target parameters.

3.2 Mathematical Modeling

The purpose of developing a mathematical model relating the machining responses and the variables is to facilitate the optimization of the machining process. RSM is a collection of mathematical and statistical techniques. RSM is useful for optimizing (minimizing or maximizing) the response function which is influenced by several independent or interrelated variables. The RSM is a set of statistical techniques to design experiments, intrinsic regression modeling, and optimization methods useful for almost all engineering applications [13].

RSM's model based technique is useful when sequential experimentation is possible in metal cutting processes. And, it is suitable for process problems where a lower-order-polynomial regression equation exists to establish the relationship between response and decision variables at an early stage of experimentation [14].

By conducting experiments and applying regression analysis, a model explaining the influence of the independent variables on the response(s) can be built. Regression analysis is conducted to investigate the functional relationship between output and input decision variables of a cutting process and may be useful for cutting process data description, parameter estimation, and control [14].

3.3 Optimization of surface roughness and texture dimensions

Optimization of machining parameters enhances productivity and also improves the product quality. The main objective of the present work is to optimize the Ti6Al4V machining conditions in order to achieve minimum surface roughness as it is an important property affecting the quality machining and machined components. In this context, an effort has been made to minimize the surface roughness using Genetic Algorithm (GA).

Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection and cross over.

The evolution is an iterative process that usually starts from a population of randomly generated individuals. The population in each iteration called a 'generation'. The fitness of every individual in each generation in the population is evaluated. Fitness is the value of the objective function in the optimization problem being solved. The fittest individuals are stochastically selected from the current population, and the genome of each individual is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm.

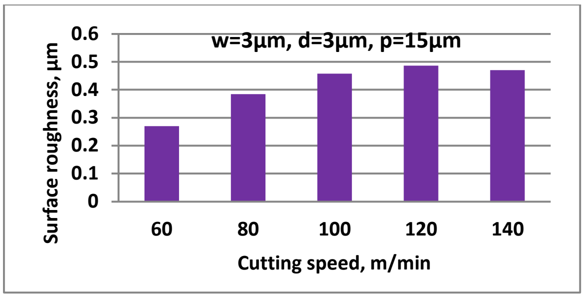
An algorithm is a series of steps for solving a problem. The genetic algorithm is based on biological evolution. It is a method of natural selection for solving both constrained and unconstrained optimization problems. The solution of an optimization problem with the GA algorithm begins with a set potential solution that is known as 'chromosomes'. The population comprising of the chromosomes is randomly selected. The chromosomes evolve during several iterations or generations. Crossover and mutation generate new generations called "offspring". Crossover is the process of splitting two chromosomes and then combining one-half of each chromosome with the other pair. Mutation involves the process of flipping a chromosome. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children (offspring) for the next generation. Over successive generations, the population evolves toward an optimal solution [12].

In short, the basic four steps used in simple Genetic Algorithm to solve a problem are,[15]

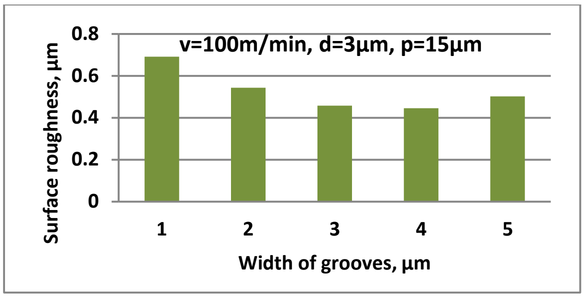
1. Suitable representation of the problem.
2. Calculate the fitness.
3. Identify the variables and parameters which control the algorithm
4. Present the results and specify the way of terminating the algorithm

4. Surface Roughness Model

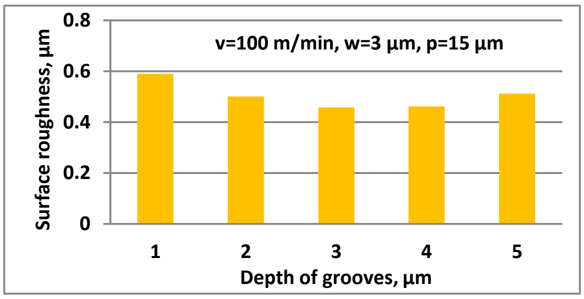
The dimensional accuracy and surface finish of any manufacturing process become critical because of the increased quality demands. There are various factors which govern surface finish in Ti-6Al-4V machining. Hence, the development of an analytical or empirical model for reliable prediction of machining performance becomes imperative.



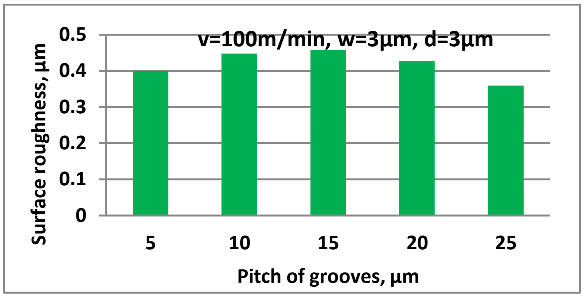
(a) Effect of cutting speed on surface roughness



(b) Effect of width of grooves on surface roughness



(c) Effect of depth of grooves on surface roughness



(d) Effect of pitch of grooves on surface roughness

Fig.4 Influence of process variables on surface roughness

Fig. 4 shows the influence of cutting speed, width, depth and pitch of grooves on surface roughness. Surface roughness increases with increase in cutting speed and pitch of grooves, and decreases with increases with increase in depth and width of grooves. The reason is increase in cutting speed increases workpiece vibrations due to the low modulus of elasticity of Ti6Al4V material. Increase in width and depth of grooves and decrease in pitch increases the capacity of the textures to retain solid lubricants, resulting in reduced friction at the tool-chip interface.

The second order surface roughness model developed using Response Surface Methodology is as follows.

Final Equation in Terms of Actual Factors

$$Ra = +1.72884 + 2.49833E\text{-}003*V - 0.45910*W - 0.44264*D - 7.01167E\text{-}003*P + 1.72375E\text{-}003*V*W + 1.13500E\text{-}003*V*D + 4.3911E\text{-}003*V*P + 0.026738*W*D - 2.53250E\text{-}003*W*P + 5.85750E\text{-}003*D*P - 5.74792E\text{-}005*V^2 + 0.033271*W^2 + 0.023371*D^2 - 7.95167E\text{-}004*P^2 \quad (1)$$

Table 3 Regression analysis of surface roughness

Std. Dev.	0.040	R-Squared	0.9168
Mean	0.47	Adj. R-Squared	0.8391
C.V. %	8.46	Pred. R-Squared	0.7364
PRESS	0.075	Adeq. Precision	14.689

The multiple regression coefficient of the quadratic surface roughness model is estimated to 0.9075. This means that 90.75% of the variance in the surface roughness is explained uniquely or jointly by the independent variable and hence quadratic surface roughness model developed is strong enough to be used in predicting the surface roughness.

The "Pred. R-Squared" of 0.7364 is in reasonable agreement with the "Adj. R-Squared" of 0.8391. "Adeq. Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. The ratio of 14.689 indicates an adequate signal. Reasonable agreement between these two terms of regression shows that data obtained through the experimental investigations is properly fitted through the mathematical models obtained through the regression analysis.

Table 4 ANOVA for the quadratic surface roughness model

Source	Sum of squares	Degrees of freedom	Mean of squares	F Ratio	Remarks
Model	0.26	14	0.019	11.80	Significant
Residual	0.024	15	1.578E-003		
Lack of Fit	9.460E-003	10	9.460E-003	0.33	Not Significant
Pure Error	0.014	5	2.841E-003		
Total	0.28	29			

Table 4 shows the ANOVA table for the quadratic surface roughness model for dry machining.

The multiple regression coefficient of the quadratic model is estimated as 0.9168. This means that 91.68% of the variance in the surface roughness is explained uniquely or jointly by the independent variables and hence quadratic model developed is fairly strong enough to be used in predicting surface roughness. Table 5 shows the probability values for each individual variable.

Table 5 Tests on the individual variable for the quadratic surface roughness model

Source	Sum of Squares	Degrees of freedom	Mean Square	F value	Probability Prob > F	Remarks
Model	0.26	14	0.019	11.80	< 0.0001	Significant
V	0.057	1	0.057	36.34	< 0.0001	
W	0.048	1	0.048	30.63	< 0.0001	
D	0.010	1	0.010	6.61	0.0213	
P	1.926-003	1	1.926E-003	1.22	0.2866	
V*W	0.019	1	0.019	12.05	0.0034	
V*D	8.245E-003	1	8.245E-003	5.23	0.0372	
V*P	5.837E-003	1	5.837E-003	3.70	0.0736	
W*D	0.011	1	0.011	7.25	0.0167	
W*P	2.565E-003	1	2.565E-003	1.63	0.2216	
D*P	0.014	1	0.014	8.70	0.0099	
V^2	0.014	1	0.014	9.19	0.0084	
W^2	0.030	1	0.030	19.24	0.0005	
D^2	0.015	1	0.015	9.50	0.0076	
P^2	0.011	1	0.011	6.87	0.0193	

The Model F-value of 11.80 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant.

In this case V, W, D, V*W, V*D, W*D, CD, V^2, W^2, D^2, P^2 are significant model terms. Cutting speed (V) and Groove width (W) are the most significant term in surface roughness. Depth of grooves (D) is the next significant term. Least significant term out of four process parameters chosen for the present research work is pitch of grooves (P). Values greater than 0.1000 indicate the model terms are not significant.

The "Lack of Fit F-value" of 0.33 implies the Lack of Fit is not significant relative to the pure error. There is a 93.46% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good.

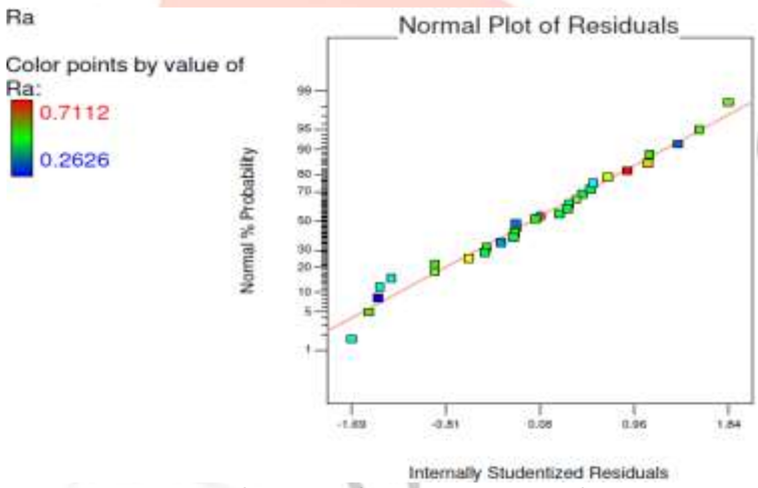


Fig.5 Normal probability of residuals for the Quadratic surface roughness model

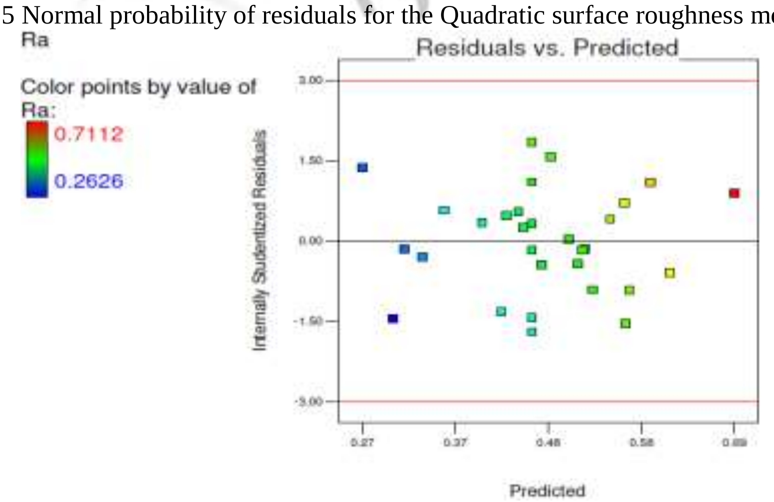


Fig.6 Plot of residuals versus predicted for quadratic surface roughness model.

None of the residuals and studentized residuals is large enough to indicate any problem with the obtained response model. Further adequacy of developed model has also been checked from the normal probability plot and residuals v/s predicted response plot. The residuals plotted above are studentized; in other words, none of the actual response data is deleted prior to calculating their deviation from the model prediction. The studentization is essential for accurately diagnosing residuals because it adjusts for varying leverage in design points. Fig.5 and Fig.6 show the normal probability plot of the residuals and plot of the residual versus the predicted response for the quadratic surface roughness model respectively. It is observed from these plots that the residuals fall on a straight line implying that the errors are distributed normally. Figure.6 reveals that there is no obvious increase in residuals with predicted level, which supports the underlying assumption of constant variance. This implies that the model proposed is adequate and there is no reason to suspect any violation of the independent or constant variance assumption. Hence, it can be concluded that the model developed is statistically solid and it can be used for further analysis to determine effects of various parameters on the response.

The mathematical model, given by Equation (1) can be used to predict the surface roughness by substituting the coded values of the respective parameters.

4.1 Optimization of surface roughness using GA

A GA code was used in the present study to optimize the surface roughness in Ti-6Al-4V machining using experimental results and the subsequent models developed in previous sections. The problem of optimization of Ti-6Al-4V machining can be described as minimizing the surface roughness subjected to criteria with the set of constraints on process parameters. The Genetic Algorithm tool in MATLAB was used for solving the current problem.

$$Y=+1.68447 + 2.76458E\text{-}003*x_1 - 0.45023*x_2 - 0.44087*x_3 - 5.23667E\text{-}003*x_4 + 1.59062E\text{-}003*x_1*x_2 + 1.26813E\text{-}003*x_1*x_3 + 1.64375E\text{-}004*x_1*x_4 + 0.024075*x_2*x_3 - 2.00000E\text{-}003*x_2*x_4 + 5.32500E\text{-}003*x_3*x_4 - 5.63698E\text{-}005*x_1^2 + 0.033715*x_2^2 + 0.023815*x_3^2 - 7.77417E\text{-}004*x_4^2 \quad (6)$$

Where Y = surface roughness, x_1 = Cutting speed m/min, x_2 = width of grooves µm, x_3 = depth of grooves µm, x_4 = pitch of grooves µm.

Subject to

$60 \leq x_1 \leq 140$

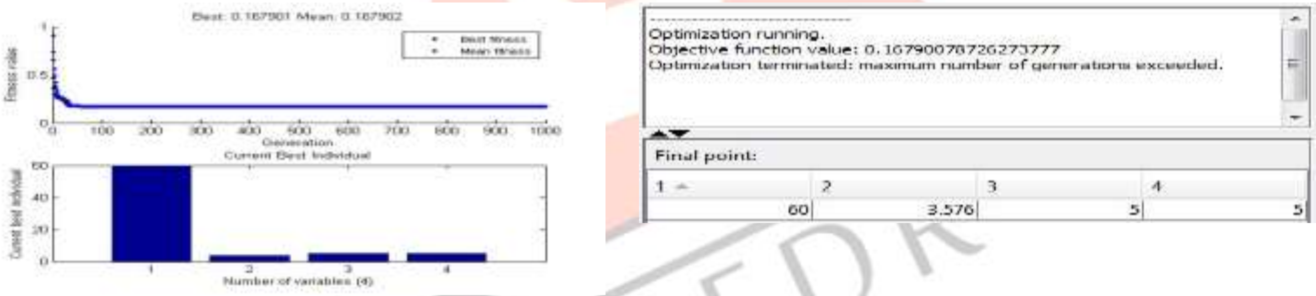
$1 \leq x_2 \leq 5$

$1 \leq x_3 \leq 5$

$5 \leq x_4 \leq 25$

GA operational parameters are the same as that for main cutting force

Fig.7 (a) and (b) show the solution obtained from GA for cutting force



(a) Variation of fitness value corresponding to generations (b) Optimum cutting conditions derived using GA

Fig.7 Genetic Algorithm optimization results

The optimum levels of parameters obtained were;

- Cutting velocity: 60 m/min
- Width of grooves: 4 µm
- Depth of grooves: 5 µm
- Pitch of grooves: 5 µm

Corresponding to this optimum condition, the minimum predicted value of surface roughness was 0.1679µm. The actual surface roughness obtained using the optimized tool is 0.2136 µm.

Table 6 Improvement in results using optimized tool

Material	Lowest achieved with textured tools	Achieved with optimized tool	%age Improvement
	Ra, µm	Ra µm	Ra µm
Ti6Al4V	0.2626	0.2136	18.66

5. Conclusions

Novel textures were created on cemented carbide tool inserts using focused ion beam machining (FIB). The inserts were coated with Zr/WS_2 by pulsed DC magnetron sputtering process. Titanium alloy Ti6Al4V was turned using textured and subsequently coated tools at a range of cutting speeds and texture dimensions. The cutting speed and texture dimensions as independent factors affecting surface roughness have been optimized using Genetic Algorithm. The following conclusions were arrived at;

1. Textured tools effectively reduce cutting forces and coefficient of friction as compared to the non-textured tools.
2. The analysis of variance (ANOVA) showed that the mathematical model developed using response surface methodology is adequate.
3. The optimized parameters of cutting speed, width of grooves, depth of grooves and pitch of grooves on application of Genetic algorithm were found to be 60 m/min, 4 µm, 5 µm and 5 µm respectively for the optimum surface roughness.

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