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Optimal machining conditions for turning Ti-6Al-4V using response surface methodology

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Abstract Machining titanium is one of ever-increasing magnitude problems due to its characteristics such as low thermal conductivity, modulus of elasticity and work hardening. The efficient titanium alloy machining involves a proper selection of process parameters to minimize the tangential force (F_z) and surface roughness (R_a). In the present work, the performance of PVD/TiAlN coated carbide inserts was investigated using response surface methodology (RSM) for turning Ti-6Al-4V. The effects of process parameters such as speed (v), feed (f), depth of cut (d) and back rake angle (γ_y) on F_z and R_a were investigated. The experimental plan used for four factors and three levels was designed based on face centered, central composite design (CCD). The experimental results indicated that F_z increased with the increase in d, f and decreased with the increase in v and γ_y, whereas R_a decreased with the increase in v and γ_y, and increased with d and v. The goodness of fit of the regression equations and model fits (R^2) for F_z and R_a were found to be 0.968 and 0.970, which demonstrated that it was an effective model. A confirmation test was also conducted in order to verify the correctness of the model.

Keywords Ti-6Al-4V · Response surface methodology · Cutting force · Surface roughness

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1 Introduction

Application of titanium alloys has increased in aerospace, marine and automobile industries because of their light weight, good fatigue strength and corrosion-resistance properties. The specific weight of titanium is about two thirds that of steel and about 60% higher than that of aluminum. However, titanium's strength is far greater than that of many alloy steels, and it has the highest strength-to-weight ratio when compared to any of structural metals nowadays. Ti-6Al-4V is one of the most widely used titanium alloys, which is an alpha-beta type containing 6 wt% aluminum and 4 wt% vanadium [1]. Machining titanium and titanium alloys would always be a problem, no matter what techniques are employed to transform this metal into chips, as reported in Refs. [1, 2]. The machining technique of titanium alloys is hindered basically due to their low thermal conductivity and high chemical reactivity. Due to the low thermal conductivity of titanium, heat generated by the cutting action cannot dissipate quickly. Therefore, most of heat is concentrated on the cutting edge and the tool face, which will adversely affect the life of the cutting tool. The chemical reactivity of titanium alloys with different tool materials and their consequent welding by adhesion onto the cutting tool during machining lead to excessive chipping and/or premature tool failure and poor surface finish [3]. Additionally, high strength is maintained at elevated temperature and low modulus of elasticity further impairs machinability [4].

In order to enhance the product quality and machining efficiency, there has been increasing focus on improvement of R_a. A good surface finish can lead to improvement in strength properties, such as fatigue strength, corrosion resistance, and thermal resistance [5]. In order to develop a model, it is necessary to design and carry out an experiment involving work material and cutting tool. The experimental work provides the response data as a function of speed (v), feed (f), depth of cut (d) and back rake angle (γ_y). According to Ernst [6], the term ''machinability'' means a complex physical property of metal. Design of experiment methods such as factorial design, response surface methodology (RSM), and Taguchi methods is now widely used in industries to reduce the cost and time of machining.

In machinability studies, statistical design of experiments is used quite extensively. Statistical design of experiments refers to the process of planning the experiments so that the appropriate data can be analyzed by statistical methods, resulting in valid and objective conclusions [7]. Thiele and Melkote [8] used four-factor and two-level fractional factorial design to find out the effects of cutting edge geometry, workpiece hardness, f, and v on surface roughness (R_a) and resultant forces in the hard finish turning of AISI H13 steel. Neseli et al [9] investigated the influence of tool geometry on surface finish using RSM and indicated that nose radius contributed much to R_a. Masounave et al. [10] used a full factorial design involving six factors to investigate the effects of cutting and tool parameters on the resulting R_a and built up edge formation in the dry turning of carbon steel. Makadia and Nanavati [11] studied the effects of turning parameters and nose radius on R_a using Taguchi's technique and the effects of those chosen parameters were investigated using RSM. Choudhury and El-Baradie [12] used RSM and 2^3 factorial designs to estimate the R_a during the turning process of high strength steel. Fnides et al [13] developed a statistical model using RSM for cutting force during hard turning of AISI H11 steel by mixed ceramic tool and concluded that d was the dominant factor that affected the tangential force (F_z). Saint et al [14] developed a model to predict R_a and tool wear in finish hard turning and found that with lower f and higher v a significant increase in surface quality was achieved using RSM-Box behnken method. Mandal et al [15] investigated the effects of cutting parameters on machining forces using RSM during finish hard turning of AISI 4340 steel with ZTA inserted and obtained 76.51% desirability level. Tsourveloudis [16] used RSM and fuzzy logic system through the adaptive neuro-fuzzy inference system (ANFIS) for Ti6Al4V titanium alloy. The f had been verified as the most important parameter for the surface of Ti-6Al-4V. The two factor interaction (2FI) model was the only successful one among the polynomial models that had been employed to predict R_a of Ti-6Al-4V turning. Ramesh et al [17] used RSM for machining titanium alloy with CVD coated carbide inserts and developed a 2FI R_a model in terms of cutting parameters, such as v, f, and d. The results indicated that f was the main influencing factor on R_a. R_a increased with f and d, but decreased with the increase in v.

From mentioned literatures, it is very clear that statistical technique such as RSM is effective for investigating the machinability of various metals and alloys. However, there is very little mention of RSM used for optimization of machining parameters using TiAlN coated carbide tool insert for machining titanium alloy (Ti-6Al-4V) using factor, γ_y. In the present work, machining parameters such as v, f, d, and γ_y are considered independent variables. Based on the preliminary experiments, the effects of these machining parameters on R_a and F_z have been investigated through the set of planned experiments based on the four factors at three levels. The RSM uses face centered, central composite design (CCD) of experiments to explore the responses and construct the model.

2 RSM

The experiments were conducted to find the optimal results, under which a certain process attains, i.e., optimum could be either a maximum or a minimum of a function with the design parameters. One of methodologies for obtaining the optimum values is RSM. RSM is a combination of mathematical theory and statistical techniques, and useful for modeling and analyzing problems in which a response of interest is influenced by several variables and the objective is to optimize this response. RSM also quantifies the relationship between the controllable input parameters and the obtained response surfaces.

The Design Expert® software (Stat-Ease Inc., USA) version 8.0.7.1 was used to develop the experimental plan for RSM. The software was also used to analyze data collected from experimentation. The RSM was employed for modeling and analyzing machining parameters in dry turning process in order to obtain the machinability performances of R_a and F_z. In RSM, the relationship between desired response and independent input variables can be represented in the following equation:

$$y = \varphi(v, f, d, \gamma_y), \tag{1}$$

where y is the desired response and φ is the response function (or response surface). In the procedure of analysis, the approximation of y is proposed using 2FI model. The 2FI model of y can be written as follows:

$$y = \beta_0 + \sum_{i=1}^{4} \beta_i x_i + \sum_{i<j}^{4} \beta_{ij} x_i x_j, \tag{2}$$

where β_0 is constant, and β_i, β_{ij} the coefficient of linear and the cross-product terms respectively. x_i the coded variable that corresponds to the study in the machining parameters. The coded variable x_i, (i = 1, 2, 3, 4) is obtained from the following transformation equations:

$$x_1 = \frac{v - v_0}{\Delta v}, \quad (3)$$

$$x_2 = \frac{f - f_0}{\Delta f}, \quad (4)$$

$$x_3 = \frac{d - d_0}{\Delta d}, \quad (5)$$

$$x_4 = \frac{\gamma_y - \gamma_{y_0}}{\Delta \gamma_y}, \quad (6)$$

where x_1, x_2, x_3, and x_4 are the coded values of v, f, d, and γ_y, respectively. v_0, f_0, d_0, and γ_{y_0} are the value of v, f, d, and γ_y at zero level. Δv, Δf, Δd and $\Delta \gamma_y$ are the intervals of the variations in v, f, d and γ_y, respectively. The F_z and R_a were analyzed as responses using 2FI model of φ in this study. This model not only investigates over the entire factor space, but also locates the region of being desired target where the response approaches its optimum or near optimal value.

3 Experimental

3.1 Experimental setup

The objective of the experiments is to establish the relationship between the machining parameters and the machinability performance, including F_z and R_a. The turning experiments were carried out in order to obtain experimental data under dry machining conditions on a MAGNUM precision lathe machine which is a high precision grade 1 accuracy lathe. The experimental setup is shown in Fig. 1. The cutting forces generated during machining trials were measured using piezoelectric tool post dynamometer (Kistler, 9272). The force signals generated during machining were fed into a charge amplifier (Kistler, 5070) connected to the dynamometer. This amplifier converted the analogue signal to digital signal that was continuously recorded by the data acquisition system connected to the charge amplifier. The average R_a obtained on workpiece after first pass of machining with each tool, was measured with a portable R_a tester (Handy Surf, E-35) with a cut off length of 0.8 mm.

3.2 Work material

The work material used for conducting the experiments was titanium alloy (Ti-6Al-4V) in the form of round bars with 65 mm diameter and 200 mm cutting length. The chemical composition and mechanical properties of the workpiece material are listed in Table 1.

3.3 Insert and tool holder details

Coated carbide is the most common tool material, and the coated carbide tools are employed in the machining of titanium alloys due to their improved performance in terms of tool wear relative to others. PVD/TiAlN coated carbide inserts with the ISO designation CNMG 120408AP TN6025 along with the tool holder PCLNR 2020 M12 was used. The geometry details are shown in Table 2.

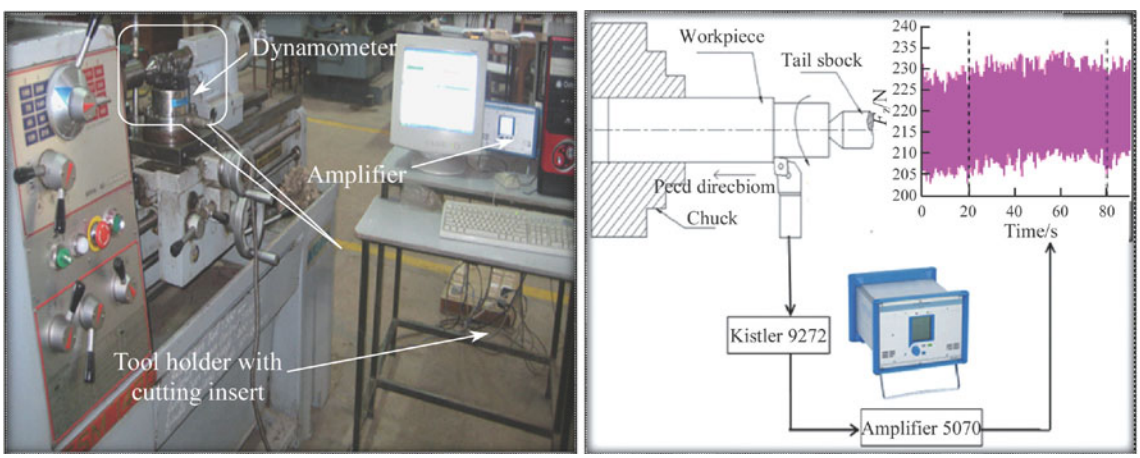

Fig. 1 Experimental set-up

Table 1 Chemical and mechanical properties of titanium alloy (Ti-6Al-4V)

Chemical composition/wt%					Mechanical properties			
C	V	Al	Fe	Ti	Density/(g·cm^{-3})	Tensile strength/MPa	Thermal conductivity/(W·m^{-1}·°C^{-1})	Hardness/HRC
0.002	3.99	6.01	0.037	Remaining	4.42	950	6.7	36

3.4 Experimental design

The aim of experimental design was to reduce the test activity and maximize the result quality. In the present work, the experimental data were collected by the face centered, CCD technique. The factorial portion of the CCD is a full factorial design with all combinations of factors at two levels (low −1 and high +1) and composed of eight star points, six central points (coded levels 0), between the high and low levels is the midpoint. The star points at face of the cubic portion on the design corresponding to a value of 1. This type of design is commonly called face centered. Table 3 shows the four machining parameters at three levels with their ranges.

4 Results and discussion

The design matrix (coded values) and results from the experimental plan of R_a and F_z are shown in Table 4.

From Table 5 it is clear that 2FI model is suggested with face-centered CCD for both F_z and R_a. Therefore, the test for significance of the regression model, individual model coefficients, and the test for lack-of-fit was performed to verify the goodness-of-fit for the obtained 2FI model. The analysis of variance (ANOVA) was applied to summarize the above mentioned performing tests. Without performing any transformation on the response, examination of the fit and summary output revealed that the 2FI model was statistically significant for both responses, and therefore it was used in further analysis.

4.1 ANOVA analysis

In the ANOVA analysis the test for significance in individual model coefficients, and test for lack-of-fit was necessary. Table 6 shows the ANOVA data for response

Table 2 Details of insert and tool holder geometry

Description	Insert geometry	Tool holder details
Material	PVD/TiAlN Coated carbide inserts	EN31
ISO coding	CNMG 120408AP TN6025	PCLNR 2020 M12
	C: insert shape (rhombohedra)	P: Insert clamping system
	N: relief angle (0°)	C: insert shape (rhombohedra)
	M: tolerance class	L: tool holder style
	G: insert type	N: relief angle (0°)
	12: insert size (12.9 mm)	R: right hand tool holder
	04: thickness (4.76 mm)	20: shank height (20 mm)
	08: corner radius (0.8 mm)	20: shank width (20 mm)
	TN6025: grade of insert	M: holder length (125 mm)
		12: Insert size (12.9 mm)

Table 3 Cutting parameters and their limits

Cutting parameter	Low level (−1)	Medium level (0)	High level (+1)
$v/(\mathrm{m{\cdot}min^{-1}})$	45	60	75
$f/(\mathrm{mm{\cdot}r^{-1}})$	0.25	0.30	0.35
d/mm	0.25	0.5	0.75
$\gamma_y/(°)$	−7	−5	−3

Table 4 Design of experiments by central composite design for RSM studies

Std. order	Run order	v	f	d	γ_y	Coefficients assesses by full factorial	Response parameters F_z	R_a
1	30	−1	−1	−1	−1	2^4 design	412	0.628
2	4	1	−1	−1	−1	(16 expts)	323	0.507
3	15	−1	1	−1	−1		564	0.887
4	3	1	1	−1	−1		380	0.589
5	22	−1	−1	1	−1		545	0.777
6	18	1	−1	1	−1		481	0.512
7	21	−1	1	1	−1		814	0.997
8	11	1	1	1	−1		631	0.71
9	5	−1	−1	−1	1		288	0.417
10	24	1	−1	−1	1		251	0.37
11	20	−1	1	−1	1		376	0.667
12	17	1	1	−1	1		246	0.483
13	23	−1	−1	1	1		472	0.477
14	2	1	−1	1	1		395	0.413
15	27	−1	1	1	1		645	0.79
16	16	1	1	1	1		467	0.563
17	13	−1	0	0	0	Star points	453	0.663
18	9	1	0	0	0	(8 expts)	414	0.518
19	10	0	−1	0	0		426	0.513
20	6	0	1	0	0		443	0.7
21	26	0	0	−1	0		334	0.52
22	28	0	0	1	0		546	0.66
23	7	0	0	0	−1		519	0.71
24	12	0	0	0	1		412	0.533
25	8	0	0	0	0	Central points	442	0.654
26	29	0	0	0	0	(6 expts)	439	0.621
27	1	0	0	0	0		435	0.632
28	19	0	0	0	0		440	0.64
29	14	0	0	0	0		437	0.645
30	25	0	0	0	0		441	0.65

Table 5 Regression model significance

	Source	Sequential P-value	Lack of fit P-value	Adjusted R-squared	Predicted R-squared	Remarks
F_z	Linear	<0.0001	<0.0001	0.891	0.845	
	2FI	0.0005	<0.0001	0.955	0.925	Suggested
	Quadratic	0.3328	<0.0001	0.957	0.894	
	Cubic	<0.0001	0.3772	0.999	0.989	Aliased
R_a	Linear	<0.0001	0.0033	0.901648	0.858	
	2FI	0.0003	0.0274	0.962239	0.922	Suggested
	Quadratic	0.5492	0.0218	0.960498	0.896	
	Cubic	0.8175	0.0035	0.946506	−0.852	Aliased

Table 6 Results for ANOVA table for 2FI model for F_z and R_a

	Source	Sum of squares	df	Mean square	F-value	P-value (Prob> F)	Remarks
F_z	Model	385364.3	10	38536.43	62.867	<0.0001	Significant
	v	5015.796	1	5015.796	8.183	0.0100	
	f	2316.294	1	2316.294	3.779	0.0669	
	d	94.76313	1	94.76313	0.155	0.6986	
	γ_y	144.8544	1	144.8544	0.236	0.6324	
	vf	10404	1	10404	16.973	0.0006	
	vd	240.25	1	240.25	0.392	0.5387	
	$v\gamma_y$	600.25	1	600.25	0.979	0.3348	
	fd	8649	1	8649	14.110	0.0013	
	$f\gamma_y$	5625	1	5625	9.176	0.0069	
	$d\gamma_y$	42.25	1	42.25	0.0689	0.7957	
	Residual	11646.72	19	612.985			
	Lack of fit	11612.72	14	829.480	121.982	<0.0001	Significant
	Pure error	34	5	6.8			
	Cor total	397011	29				
R_a	Model	0.538	10	0.0538	74.898	<0.0001	Significant
	v	0.149	1	0.1491	207.545	<0.0001	
	f	0.174	1	0.1744	242.889	<0.0001	
	d	0.038	1	0.0383	53.417	<0.0001	
	γ_y	0.1429	1	0.1429	199.017	<0.0001	
	vf	0.0156	1	0.0156	21.669	0.0002	
	vd	0.0023	1	0.0023	3.242	0.0877	
	$v\gamma_y$	0.0126	1	0.0126	17.544	0.0005	
	fd	0.001958	1	0.0019	2.726	0.1151	
	$f\gamma_y$	0.000281	1	0.00028	0.391	0.5394	
	$d\gamma_y$	0.00039	1	0.00039	0.543	0.4701	
	Residual	0.013646	19	0.000718			
	Lack of fit	0.0129	14	0.000921	6.182	0.0274	Significant
	Pure error	0.000745	5	0.000149			
	Cor total	0.551565	29				

surface 2FI model for F_z and R_a. By selecting the backward elimination procedure to automatically reduce the terms that are not significant. The ANOVA table for the reduced 2FI model for F_z and R_a is shown in Table 7, which indicates that the model is significant in both cases, and the terms in the model have a significant effect on the

Table 7 Results of ANOVA table for reduced 2FI model for F_z and R_a

	Source	Sum of squares	df	Mean square	F-value	P-value (Prob> F)	Remarks
F_z	Model	384481.5	7	54925.93	96.442	<0.0001	Significant
	v	4208.205	1	4208.205	7.389	0.0126	
	f	2316.294	1	2316.294	4.067	0.0561	
	d	635.5033	1	635.5033	1.115	0.3023	
	γ_y	1103.7	1	1103.7	1.938	0.1778	
	vf	10404	1	10404	18.268	0.0003	
	fd	8649	1	8649	15.186	0.0008	
	$f\gamma_y$	5625	1	5625	9.877	0.0047	
	Residual	12529.47	22	569.5212			
	Pure error	34	5	6.8			
	Cor total	397011	29				
	Std. dev.	23.86		R-squared		0.9684	
	Mean	449.03		Adj R-squared		0.9584	
	C.V. %	5.31		Pred R-squared		0.9445	
	PRESS	22051.31		Adeq precision		46.298	
R_a	Model	0.54	7	0.076	103.37	<0.0001	Significant
	v-speed	0.15	1	0.15	201.5	<0.0001	
	f-feed	0.17	1	0.17	235.81	<0.0001	
	d-depth of cut	0.038	1	0.038	51.86	<0.0001	
	γ_y-angle	0.14	1	0.14	193.22	<0.0001	
	vf	0.016	1	0.016	21.04	0.0001	
	fd	2.33E−03	1	2.33E−03	3.15	0.0899	
	$f\gamma_y$	0.013	1	0.013	17.03	0.0004	
	Residual	0.016	22	7.40E−04			
	Pure error	7.45E−04	5	1.49E−04			
	Cor total	0.55	29				
	Std. dev.	0.0271		R-squared		0.9700	
	Mean	0.6148		Adj R-squared		0.9611	
	C.V. %	4.4234		Pred R-squared		0.9395	
	PRESS	0.0334		Adeq precision		46.239	

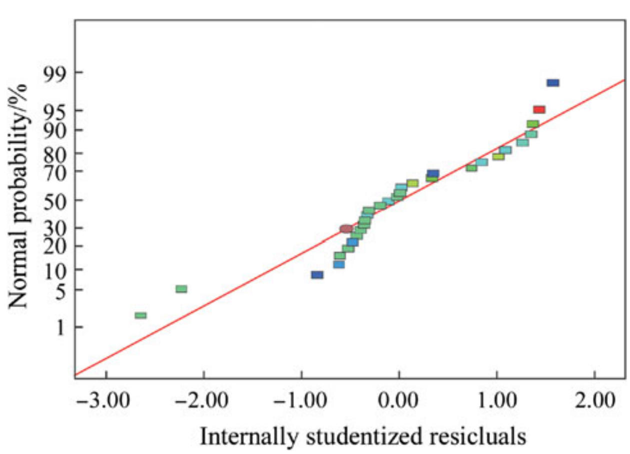

Fig. 2 Normal probability plot of residuals for F_z

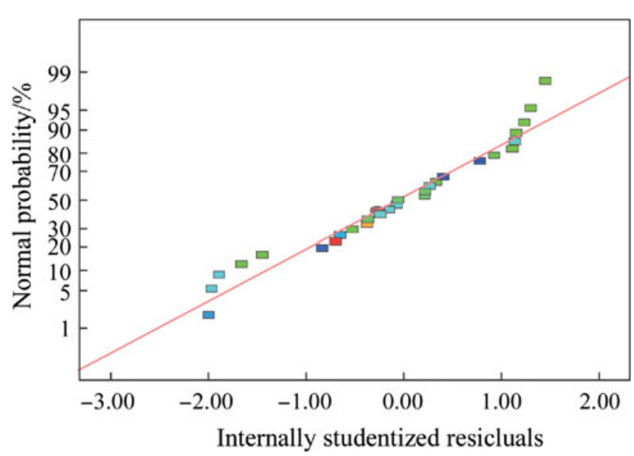

Fig. 3 Normal probability plot of residuals for R_a

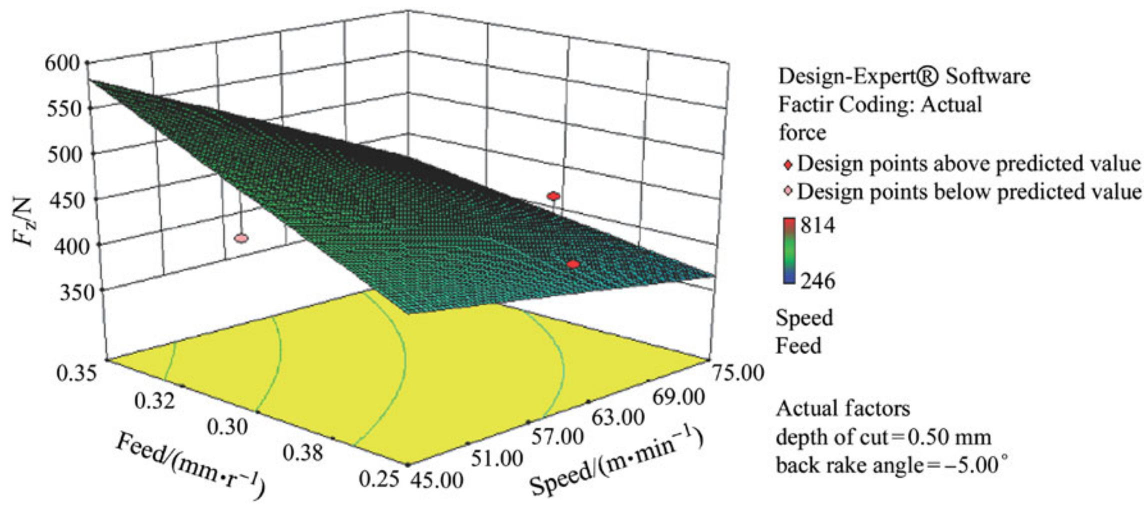

Fig. 4 Response surface plot of F_z according to f and v

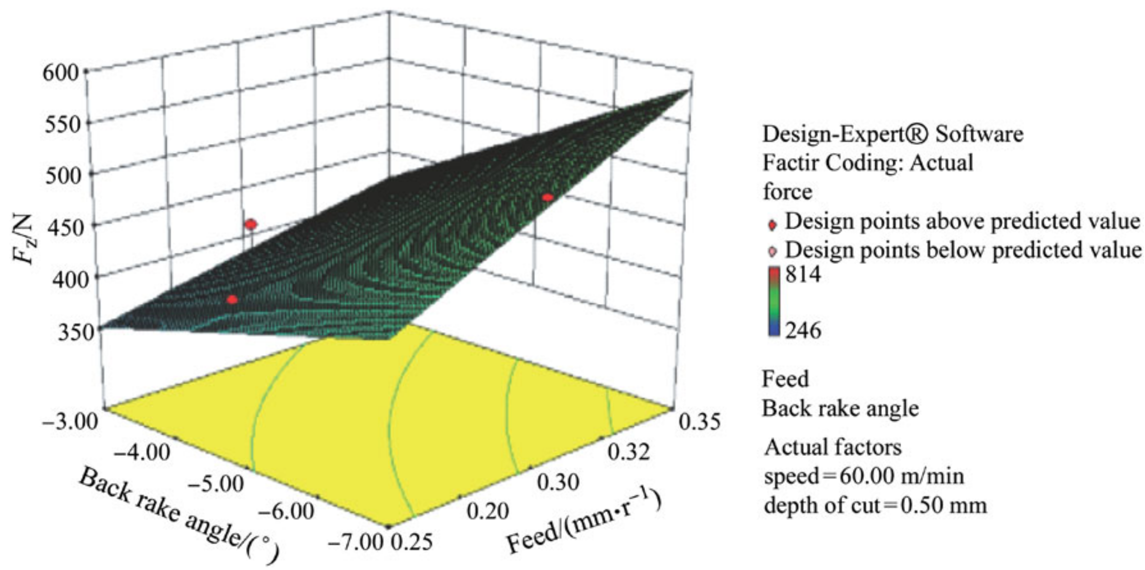

Fig. 5 Response surface plot of F_z according to γ_y and f

response. It can also be observed from Table 7 that the multiple correlation R^2 is estimated for F_z is 0.9684 and R_a is 0.970 from the estimated values of F_z and R_a with the model developed using the process parameters. This means that 96.84% of F_z and 97% of R_a explained uniquely or jointly by the independent variables and hence the model developed is fairly strong enough to be used in predicting F_z and R_a. There is little difference between the predicted and actual results. Furthermore, the value of adequate precision in the model, which compares with the range of value at the design point to the average prediction error, should be well above 4.

The 2FI model for F_z and R_a in terms of actual factors is shown as follows:

$$F_z = -66.63 + 6.57v + 1253.61f - 153.11d - 34vf + 1860fd - 187.50f\gamma_y \tag{7}$$

$$R_a = -1.053 + 0.0127v + 4.464f + 0.378d - 0.1007\gamma_y - 0.0416vf - 0.000322vd + 0.0000935v\gamma_y. \tag{8}$$

4.2 Effect of process parameters on response variables

After 2FI models of F_z and R_a were established, the model adequacy checking was performed in order to verify that the underlying assumption of regression analysis is not violated. Figures 2 and 3 illustrate the normal probability plots of the residual, which show no sign of the violation

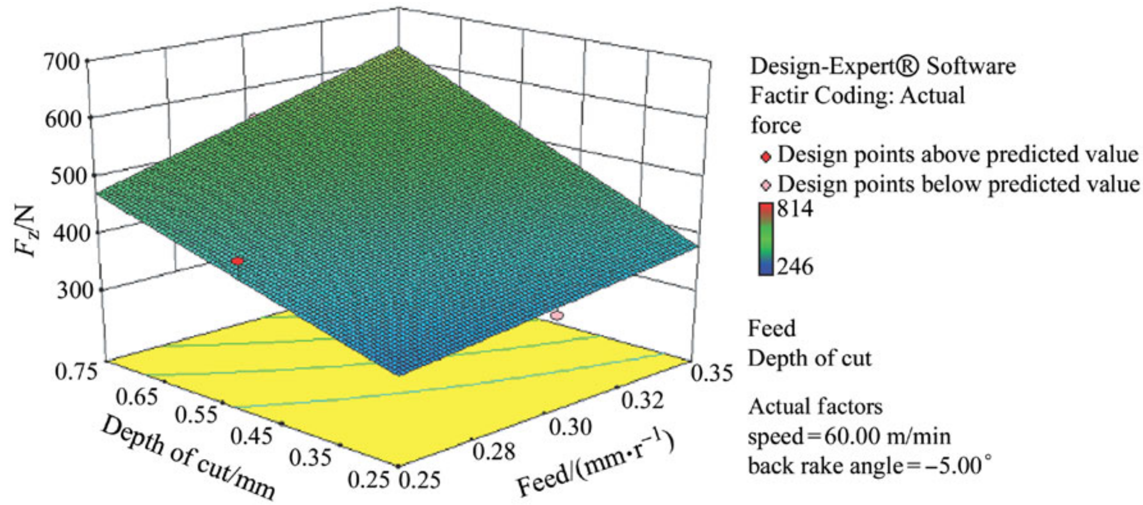

Fig. 6 Response surface plot of R_a according to f and d

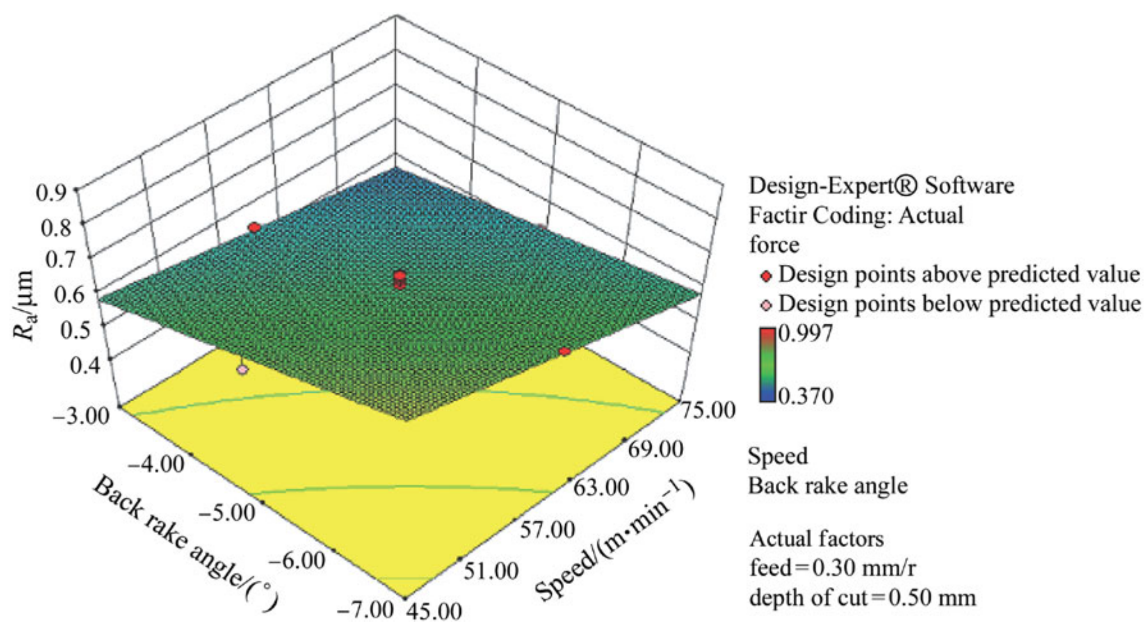

Fig. 7 Response surface plot of R_a according to v and γ_y

since each point follows a straight line pattern implying that the errors are distributed normally.

Three-dimensional response surfaces plots are shown in Figs. 4–9 to investigate the influences of machining parameters on F_z and R_a. Figures 4–6 present the influences of machining parameters on F_z of the machined part, such as f and v, γ_y and f, d and f, respectively. Also, Figs. 7–9 present the influences of machining parameters, such as v and γ_y, v and d, v and f, respectively, on F_z of the machined part.

From the Figs. 4–6, it could be seen that F_z increases with d, f and decreases with increase in v and γ_y. This is because at larger feeds or depths of cut, larger volume of the deformed metal and consequently is the resistance of the material to chip formation is greater leading to an increase in F_z. A decreasing trend in was observed with increase in v because as v increases chips are thinner and shear angle is bigger. Thus, the decreasing trend in chip reduction coefficient and chip strains means that plastic deformation of metal takes place with less strain because of smaller shear angles. This leads to decrease in power consumption as well. A decreasing trend in F_z was also observed with an increase in γ_y due to the decrease in tool-chip contact area.

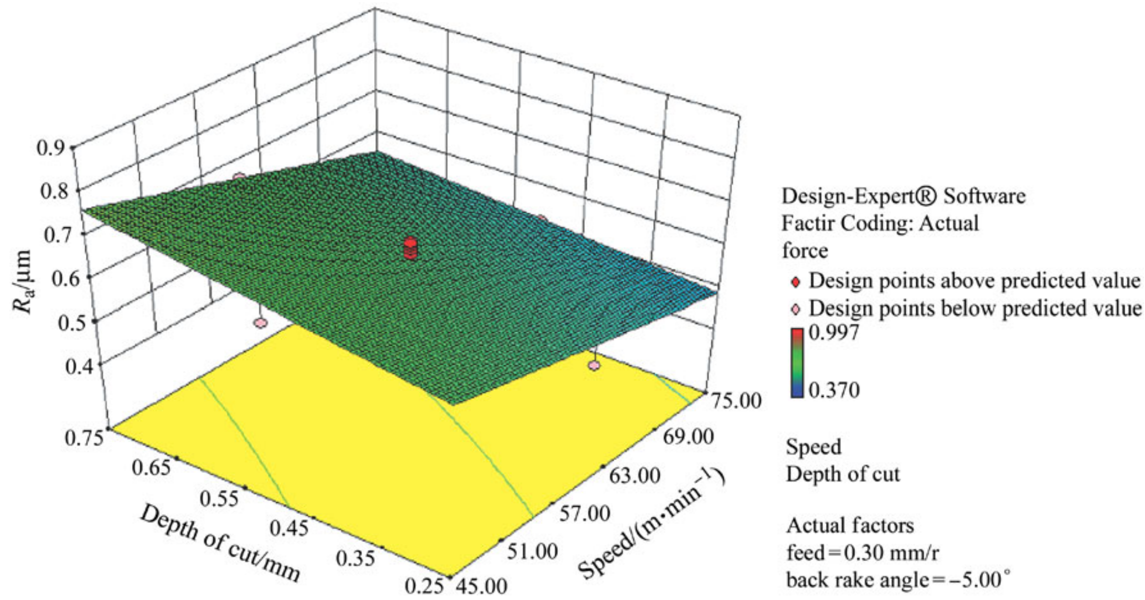

Fig. 8 Response surface plot of R_a according to v and d

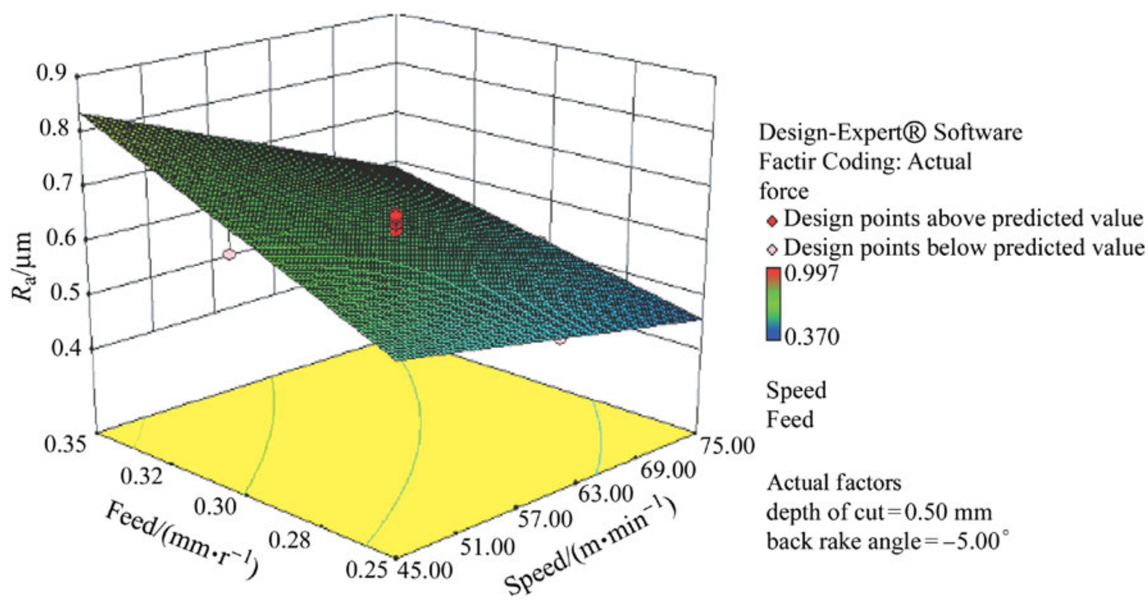

Fig. 9 Response surface plot of R_a according to v and f

From Figs. 7–9, it could be observed that R_a decreases with increase in v and γ_y, and increases with d and f. This established behavior can be explained by observing the variation of maximum chip thickness with the turning parameters. Increase in d or f causes the maximum chip thickness to increase, thereby formation of larger uncut ridge results in the formation of poor surface finish. The surface finish has been observed to increase with cutting v due to increased temperature at high speeds. Low cutting speeds resulting in the formation of an increase in the height of uncut ridge lead to poor surface finish when compared to higher speeds. The γ_y increases and F_z decreases, which will lead to decrease in R_a.

One of the most important aims of the experiments related to manufacturing is to obtain cutting parameters corresponding to minimum F_z and R_a. RSM is an ideal technique for the determination of the best cutting parameters in turning operation [18]. RSM optimization

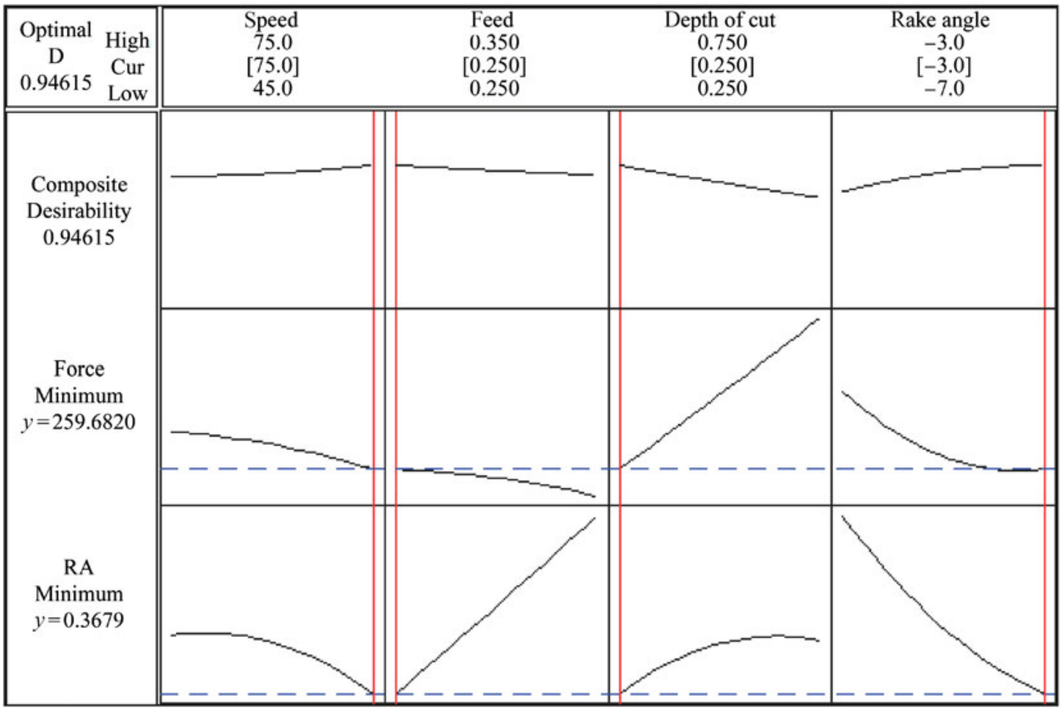

Fig. 10 Response optimization for force and R_a parameters

Table 8 Response optimization for force and R_a parameters

Parameter	Optimal conditions				Target	Desirability
	$v/(\mathrm{m \cdot min^{-1}})$	$f/(\mathrm{mm \cdot r^{-1}})$	d/mm	$\gamma_y/(°)$		
F_z	75	0.25	0.25	−3	259.68	0.94615
R_a		0.25	0.25	−3	0.368	0.94615

Table 9 Results of conformation test for F_z and R_a

Machining parameters				F_z/N				R_a/μm			
v	f	d	γ_y	A	B	C	% error	A	B	C	% error
75	0.25	0.25	−3	251	259.7	8.7	3.46	0.375	0.368	−0.007	−1.86
45	0.25	0.25	−3	288	305.3	17.3	6.0	0.417	0.402	−0.015	−3.60
75	0.25	0.5	−3	336	318.1	−17.9	−5.32	0.373	0.393	0.02	5.36

A = Experimental; B = Predicted; C = Residual

results for R_a and F_z are shown in Fig. 10 and Table 8. Optimum cutting parameters are 75 m/min, 0.25 mm/r, 0.25 mm and −3°. The optimized R_a and F_z are 0.3679 μm and 259.682 N.

4.3 Confirmation test

For the confirmation of 2FI model, three confirmation experiments are performed for F_z and R_a in order to verify the adequacy of obtained 2FI model. Using the point prediction capability of the software, F_z and R_a of the selected experiments were predicted together with the prediction interval of 95%. The predicted value and actual experimental value were compared, and the residual and percentage error were calculated. The results of the confirmation test and their comparisons with the predicted values for F_z and R_a are listed in Table 9. The results in Table 9 show that both the residual and percentage error are small. The percentage error range between the actual and predicted value of F_z lies between 2.5% and 6%, and

R_a lies in the range of 1.86% to 5.36%. All the experimental values of confirmation test are within the 95% prediction interval.

5 Conclusions

In the present work, the 2FI models for F_z and R_a have been developed to investigate the influences of machining parameters in turning of titanium (Ti-6Al-4V) alloy. The experimental plan is based on face centered, CCD. The effects of machining parameters such as cutting v, f, d and γ_y, have been evaluated by using RSM. The following conclusions are drawn based on this study:

(i) The results show that the optimal combination of machining parameters are 75 m/min, 0.25 r/min, 0.25 mm and $-3°$ for cutting v, f, d and γ_y, respectively.

(ii) F_z increases with d and f, this is because of the fact that at larger feeds or depths of cut, larger volume of the deformed metal and consequently the resistance of the material to chip formation is greater.

(iii) F_z decreases with increase in v and γ_y, this is because as v increases, chips are thinner and shear angle increases and increase in rake angle leads to decrease in tool-chip contact area.

(iv) Increase in d or f causes the maximum chip thickness to increase, thereby formation of larger uncut ridge results in the formation of poor surface finish.

(v) The surface finish has been observed to increase with v because of the increased temperature at high speeds. The negative rake angles also cause larger contact area resulting in higher chip volume, which both result in increased heat generation leading to decrease in R_a.

(vi) 2FI models developed using RSM are reasonably accurate and can be used for prediction within the limits of the investigated factors.

(vii) The results of ANOVA have proved that the 2FI models can complete prediction of F_z and R_a with 97% confidence interval.

(viii) Verification of the experiments carried out shows that the empirical models developed can be used for turning of Ti-6Al-4V with coated carbides within 5.36% error against an error of 6% when machined with CVD tools.

Therefore, the approach presented experimentally and statistically in this study can be considered as a proper method for the optimization of turning process.

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