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PREDICTIVE MODELLING OF MACHINING PARAMETERS IN TURNING OF CP-TI GRADE 2 USING MULTIPLE REGRESSION ANALYSIS

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ABSTRACT
Titanium alloys are classified as well-known "Space-Age-Metal" due to their inherent characteristics such as high chemical affinity, superior resistance to corrosion, highest strength-to-weight ratio etc. In spite of the aforesaid properties these alloys are also identified as "hard-to-cut" type materials. Machining of such materials offer a significant challenge to the scientific community around the globe. Therefore, selecting an appropriate combination of process parameters become an essential task in order to confirm the dimensional accuracy as well as the quality of the end product. The present paper proposes an approximation tool for the estimation of various cutting responses during machining of commercially pure titanium (CP-Ti) grade 2. A series of experiments were conducted based on Taguchi's L_9 orthogonal array design. Cutting speed, feed rate and depth of cut were considered as three distinct input variables whereas cutting force (F_c) and surface roughness (R_a) were selected as output parameters. Further, a prediction model was also developed to estimate the aforementioned responses using multiple regression analysis (MRA). The adequacy of the model was verified by performing analysis of variance (ANOVA) test. The results indicated that the proposed regression model was capable of estimating F_c and R_a competently as the values of determination coefficient was noticed as 0.99 and 0.98 respectively.

Keywords:
CP-Ti grade 2; Surface roughness; Regression analysis; Cutting force

INTRODUCTION

Titanium and its alloys are gaining enormous attention from numerous industries due to their attractive inherent properties such as highest strength-to-weight ratio, low density, superior corrosion resistance and excellent bio-compatibility [1-5]. Because of the aforesaid qualities these alloys are widely used in space craft, aerospace, marine, medical and chemical processing industries [6]. Therefore, titanium alloys are receiving an appreciable attention around the globe and the researchers are focusing on exploration of various machinability aspects of these alloys.

In spite of the afore-mentioned activities, the investigations on titanium alloys are sturdily limited because of the high cost and difficulty associated with their extraction. In addition to that, low thermal conductivity and high chemical reactivity also act as a barrier during the study of the key machining characteristics of titanium alloys. Poor thermal conductivity of these alloys restricts high speed machining and hence resulted in low production rate. According to the available literature on titanium machining, the suggested values of the spindle speed during titanium machining ranges from 30 to 60 m/min when using uncoated carbide inserts. On the other hand, high speed machining of these alloys causes high cutting temperature owing to rapid tool wear. Tool failure at its pre-mature stage also contributes in diminishing the quality of the machined surface as well as the dimensional accuracy of the end product. Furthermore, high chemical reactivity of titanium alloys introduces several defects such as built-up edge formation, chipping, development of shear cracks etc. which in turn curtails the life cycle of the cutting tool material. In such situation, an appropriate selection of machining parameter becomes necessary in order to attain an efficient machining performance without compromising the quality. In turning operation, surface quality of the machined part is signified as one of the most desirable need for an end user and is termed as surface roughness. This surface phenomena is strongly influenced by the process parameters viz. tool geometry (i.e. nose radius, rake angle etc.) and cutting condition (i.e. speed, feed and depth of cut).

In the past few decades, several techniques were employed to identify the influence of cutting variables on the surface quality of the finished product. In addition to that, various statistical prediction tool were also suggested

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to approximate the key machining responses such as response surface methodology (RSM), artificial neural network (ANN), genetic algorithm (GA), multiple regression analysis (MRA) etc. Sahoo[7] proposed Taguchi based regression model to predict surface roughness (R_a) while turning AISI D2 hardened steel. The results indicated that the suggested model was effectively capable of estimating R_a with a confidence level of 95%. In a different study experimental study Asilturk and Cunkas[8] also used multiple regression model and artificial neural network for prediction surface roughness when turning AISI 1040 steel. They concluded that the ANN model was more efficient in comparison to MRA approach. However, the results might be limited to the studied range of machining parameters. Kant and Sangwan[9] in their study, recommended ANN coupled with GA to predict surface while turning AISI 1060 steel in dry cutting environment. The results revealed that the proposed methodologies were capable enough in estimating and minimizing the surface roughness of the machined part. Khan and Maity[10] studied the impact of machining variables on cutting force, surface roughness, material removal rate and machining temperature. They utilized MRA approach for prediction and desirability function analysis (DFA) method for optimizing the multiple responses. In addition to that, they also proposed some multi-criteria decision making (MCDM) based techniques to identify the optimal parametric combination of input variables [11, 12]. Although several statistical prediction and optimization tools were reported in the past decades to predict the surface quality of various materials such as steel alloy, nickel base alloy, titanium alloy (particularly Ti-6Al-4V, grade 5), machining characteristics of commercially pure titanium (CP-Ti) is not adequately addressed so far. Therefore, the present investigation aimed at estimating R_a and F_c while machining CP-Ti grade 2 using uncoated carbide inserts. A series of experiments were conducted based on Taguchi's L_9 orthogonal array. The aforesaid performance measures i.e. R_a and F_c were predicted with the help of multiple regression equations. The adequacy and flexibility of the proposed MRA model was verified by performing analysis of variance (ANOVA) test.

MATERIALS AND METHODS

The layout of the present investigation was planned according to Taguchi's orthogonal array which also helps in conducting effective machining with reduced number of trials. In the current study, the experiments were carried out based on L_9 orthogonal array as displayed in Table 1. Cutting speed, feed rate and depth of cut were selected as three distinct controllable factors whereas cutting force and surface roughness were considered as key machining responses of the investigation. The workpiece material made of commercially pure titanium having diameter 55 mm and 600 mm length was turned on a heavy duty lathe (Manufactured by Hindustan Machine Tools, India) having maximum spindle speed of 1040 rpm and spindle power of 10 kW in dry cutting environment. Square shaped uncoated carbide inserts were used for experimentation. These inserts were tightly mounted on a right handed tool holder. Figure 1 shows the experimental setup of the present investigation. The arithmetic average surface roughness (R_a) of the machined part was measured with the help of a roughness tester device namely Taylor Hobson: *Surtronic 3+*. The value of R_a was recorded at three different locations along the circumference of the turned work part and the average value was considered. Similarly, a three dimensional force measuring dynamometer was used to measure the cutting force. The resultant cutting force was evaluated and adopted for the analysis purpose.

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Table 1. Domain of the experiment

Run	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)
1	35	0.08	0.1
2	35	0.12	0.3
3	35	0.16	0.5
4	70	0.08	0.5
5	70	0.12	0.1
6	70	0.16	0.3
7	105	0.08	0.3
8	105	0.12	0.5
9	105	0.16	0.1

Fig. 1. Photographic view of the experimental setup

RESULTS AND DISSCUSSION

The current investigation concentrates in examining of two vital machining features viz. surface roughness and cutting force. The outcomes of the present investigation are summarized in Table 2.

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Table 2. Experimental results

Run	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Fc (N)	Ra (μm)
1	35	0.08	0.1	45.552	1.187
2	35	0.12	0.3	76.714	1.230
3	35	0.16	0.5	124.531	1.190
4	70	0.08	0.5	62.682	1.327
5	70	0.12	0.1	31.969	1.210
6	70	0.16	0.3	75.113	1.543
7	105	0.08	0.3	60.885	1.340
8	105	0.12	0.5	91.318	1.073
9	105	0.16	0.1	73.389	1.120

Effect of cutting variables on R_a

Figure 2 portrays the variation of mean value of R_a with respect to speed, feed and depth of cut. From the figure, it is revealed that the average surface roughness firstly increases with increasing cutting speed and then decreases with further increase in the spindle speed. It was found to be minimum at spindle speed of 105 m/min. Surface roughness of the turned part was observed to be less at medium feed rate (i.e. 0.12 mm/rev) whereas it was noticed to be less at depth of cut of 0.1 mm. The higher feed value offers rapid traverse of the cutting tool towards the work part which in turn results in poor surface quality. Therefore, the roughness value was notice maximum at higher feed rate when compared to the other feed values. In general, surface roughness decreases with increase in cutting speed. But, in the present study, it was initially increased with cutting speed and then decreased with further increase in the same. Initial increment of R_a might be contributed to the higher chemical affinity of CP-Ti grade 2. Furthermore, at higher cutting speeds the temperature at machining zone (particularly at primary and secondary deformation zone) enhanced to a great extent and thus resulted in softening of the material. This might be due to poor thermal conductivity of the material. Thermal softening of the work material produces smooth surface at higher cutting speeds. Similar observations were made in the current investigation while focusing the impact of depth of cut.

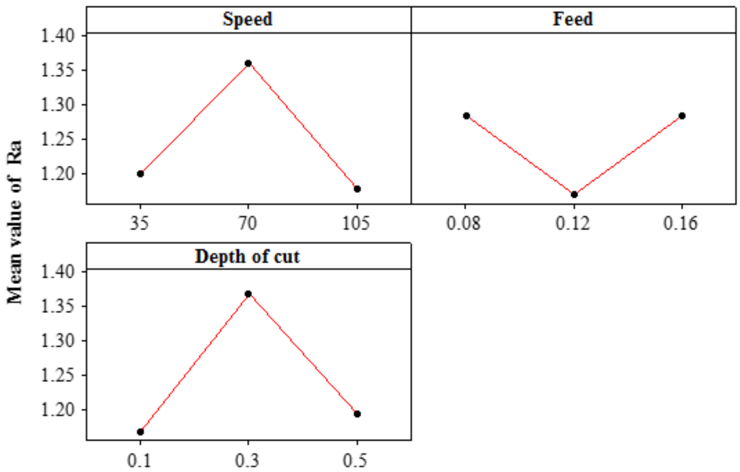

Fig. 2. Variation in R_a with respect of speed, feed and depth of cut

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Effect of cutting variable on F_c

The variation attained in resultant cutting force in displayed in Fig. 3. From the figure it is clearly visualized that each cutting parameter has significant impact of F_c. The resultant cutting force decreased with increasing speed whereas it increases with further increase continuously with increase in feed and depth of cut. Low thermal conductivity, high machining temperature and high chemical reactivity of the work material might be contributed to this phenomena. However, the aforesaid observations might be limited to the studied range of machining parameters.

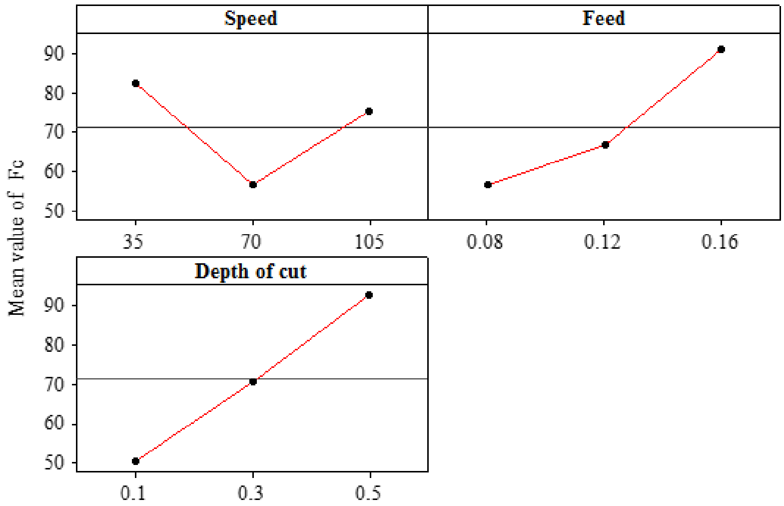

Fig. 3. Variation in F_c with respect of speed, feed and depth of cut

3.3 Multiple regression model for the prediction of R_a and F_c

Finally, a mathematical model was developed to predict surface roughness and cutting force using multiple regression analysis and represented by equations 1 and 2. The analysis was done for a level of confidence of 95%. In the suggested regression model, higher values of determination coefficient (R-Sq) explains the adequacy of the model. The analysis was further extended by performing ANOVA tests. The results of the ANOVA test are listed in Tables 3 and 4 for R_a and F_c respectively. From the tables it is revealed that the proposed models are statistically significant as the P-value of each term of the model was found to be less than 0.05. If the value of probability of acceptance (P-value) is observed $\leq$ 0.05, then the model is said to be significant for a confidence level of 95%, which was found to be true in the present investigation.

$$Ra = 1.25 - 0.00032 \times v - 0.01 \times f + 0.067 \times d \tag{1}$$

$$Fc = -5.4 - 0.101 \times v + 433 \times f + 106 \times d \tag{2}$$

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Table 3. ANOVA test results for R_a

Source	DOF	SS	MS	F-value	P-value
Cutting speed	2	0.0592	0.0296	29.40	0.033
Feed	2	0.0259	0.0129	12.86	0.042
Depth of cut	2	0.0716	0.0358	35.49	0.027
Residual error	2	0.0020	0.0010		
Total	8	0.1588			
R-Sq = 98.7%		R-Sq (Adj.) = 94.9%			

Table 4. ANOVA test results for F_c

Source	DOF	SS	MS	F-value	P-value
Cutting speed	2	1055.63	527.81	186.36	0.005
Feed	2	1898.42	949.21	335.15	0.003
Depth of cut	2	2715.40	1357.70	479.39	0.002
Residual error	2	5.66	2.83		
Total	8	5675.11			
R-Sq = 99.9%		R-Sq (Adj.) = 99.6%			

Furthermore, the influence of each machining parameter was determined with the help of response table for means as depicted in Tables 5 and 6. From the afore-mentioned tables it is revealed that the depth of cut is the most effective machining parameter on both the studied output characteristics i.e. R_a and F_c respectively. On the other hand, cutting speed was observed to be least influencing machining variable on F_c whereas feed rate was spotted as of less importance for predicting R_a.

Table 5. Response table for R_a

Level	Cutting speed	Feed	Depth of cut
1	1.199	1.283	1.169
2	1.359	1.169	1.370
3	1.177	1.282	1.196
Delta	0.182	0.114	0.201
Rank	2	3	1

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Table 6. Response table for F_c

Level	Cutting speed	Feed	Depth of cut
1	82.27	56.37	60.30
2	56.59	66.67	70.90
3	75.20	91.01	92.84
Delta	25.68	34.64	42.54
Rank	3	2	1

CONCLUSIONS

The following conclusions can be drawn after a successful approximation of surface roughness and resultant cutting force while turning CP-Ti using uncoated carbide inserts:

1. The impact of depth of cut was identified more predominant for achieving better surface quality and lower cutting force in comparison to speed and feed rate.
2. Minimum value of R_a and F_c was observed at lowest depth of cut i.e. 0.1 mm which suggests that lower depth of cut would be preferred for attaining superior surface integrity along with adequate force value.
3. The results of ANOVA tests indicated the significance of the proposed model as the P-values were less than 0.05 for each term of the model.
4. Higher value of determination coefficient showed the fitness of the model. It can be concluded that the suggested regression model can be used for estimating R_a and F_c in dry cutting environment. However this might be limited to the studied range of machining parameters.

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