

Machinability assessment of commercially pure titanium (CP-Ti) during turning operation: Application potential of GRA method

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Abstract. This paper explores some of the vital machinability characteristics of commercially pure titanium (CP-Ti) grade 2. Experiments were conducted based on Taguchi's L9 orthogonal array. The selected material was machined on a heavy duty lathe (Model: HMT NH26) using uncoated carbide inserts in dry cutting environment. The selected inserts were designated by ISO as SNMG 120408 (Model: K313) and manufactured by Kennametal. These inserts were rigidly mounted on a right handed tool holder PSBNR 2020K12. Cutting speed, feed rate and depth of cut were selected as three input variables whereas tool wear (VBc) and surface roughness (Ra) were the major attentions. In order to confirm an appreciable machinability of the work part, an optimal parametric combination was attained with the help of grey relational analysis (GRA) approach. Finally, a mathematical model was developed to exhibit the accuracy and acceptability of the proposed methodology using multiple regression equations. The results indicated that, the suggested model is capable of predicting overall grey relational grade within acceptable range.

Keywords: Tool wear; surface roughness; commercially pure titanium; Taguchi method; GRA; Multiple regression analysis

1. Introduction

Recently, titanium and its alloys are gaining enormous attention from several industries due to their attractive inherent properties such as highest strength-to-weight ratio, low density, superior corrosion resistance and excellent bio-compatibility [1-3]. Because of the aforesaid qualities these alloys are widely used in space craft, aerospace, marine, medical and chemical processing industries [4]. 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 aforementioned 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. An optimization technique plays key role in attaining the aforesaid objectives.

In the past few decades, several techniques were employed to identify the influence of cutting variables on the key machining performance in order to confirm the quality of the end product in association with high productivity. In addition to that, various statistical prediction tool were also suggested 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](#) [5] proposed Taguchi based regression model to predict surface roughness (Ra) while turning AISI D2 hardened steel. The results indicated that the suggested model was effectively capable of estimating Ra with a confidence level of 95%. In a different study experimental study [Asilturk and Cunkas](#) [6] 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 & Sangwan](#) [7] 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 & Maity](#) [8] 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 [9, 10]. Moreover, a large number of literature is also available dealing with multi-objective problems while machining a wide range of work materials[11-13]

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 tool wear and surface roughness while machining CP-Ti grade 2 using uncoated carbide inserts. A series of experiments were conducted based on Taguchi's L9 orthogonal array. The aforesaid performance measures i.e. V_Bc and Ra were minimized with the help of grey relational analysis (GRA) method. At the end, a mathematical model was developed to verify the acceptability of the proposed methodology using multiple regression equations.

2. Material and methods

2.1 Experimental details

A cylindrical bar, made of commercially pure titanium (CP-Ti grade 2) having diameter 50 mm and length 500 mm was selected as work material. [Table 1](#) illustrates the chemical composition of workpiece. This work part was turned on a heavy duty lathe (Manufactured by Hindustan Machine Tools, India; Model: NH26) using a square shaped uncoated carbide insert in dry cutting environment. A series of experiments were carried out according to Taguchi's L₉ orthogonal array. Machining length was kept fixed as 250 mm. for each experimental run. The selected inserts were designated by ISO: SNMG 120408 (Manufactured by Kennametal, Grade: K313). During machining operation, these inserts were tightly mounted on a right handed tool holder (ISO: PSBNR 2020K12, Manufactured by WIDIA). A stereo zoom optical microscope was utilized to measure the wear on the flank surfaces of the cutting inserts. In order to confirm the statistical accuracy, the measurement was recorded at three different locations on the flank face of each insert and the average value was calculated for further analysis. Similarly, the roughness of the turned part was measured with the help of a roughness testing

device namely Talysurf (Model: Taylor Hobson, Surtronic 3+). The values of arithmetic surface roughness were also noted at three different locations around the circumference of the machined surface for better accuracy and the average value was considered as final R_a during the investigation. Table 2 illustrates the experimental layout and the outcomes of the present study.

Table 1. Chemical composition of CP-Ti grade II

Element	Carbon	Nitrogen	Oxygen	Iron	Hydrogen	Titanium
Wt. (%)	0.08-0.1	0.03	0.25	0.30	0.015	99.3

Table 2. Experimental results

Run	v (m/min)	f (mm/rev)	d (mm)	VBc (μ m)	Ra (μ m)
1	35	0.08	0.1	73.26	1.68
2	35	0.12	0.3	66.52	1.82
3	35	0.16	0.5	80.04	1.92
4	70	0.08	0.5	112.32	1.72
5	70	0.12	0.1	84.68	1.88
6	70	0.16	0.3	92.22	1.92
7	105	0.08	0.3	132.52	2.04
8	105	0.12	0.5	224.46	2.24
9	105	0.16	0.1	192.48	2.12

2.2 Grey relational analysis (GRA)

In the present investigation, Taguchi based grey relational analysis (GRA) approach was used to determined optimal parametric combination of the process parameters in order to minimize the tool wear and surface roughness. For the purpose, the outcomes of the experiment i.e. measured values of VBc and R_a were initially normalized between 0 and 1 by converting them into a non-dimensional quantity. Data normalization was performed using Equation (1)

$$X_i^*(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \quad (1)$$

where, $i = 1, 2, \dots, m$; $k = 1, 2, \dots, n$; m is the total number of experimental runs and n is the number of output responses; $\min y_i(k)$ and $\max y_i(k)$ are the minimum and maximum values of the output response under consideration. $X_i^*(k)$ is the obtained normalized value.

In the next step, the grey relational coefficient was calculated for each machining parameter related to their normalized values. This was done using Equation (2)

$$\xi_i(k) = \frac{\Delta_{\min} + \tau \Delta_{\max}}{\Delta_{0i}(p) + \tau \Delta_{\max}} \quad (2)$$

where, $\xi_i(k)$ represents the grey relational coefficient, τ is the identification coefficient (or distinguishing factor) which varies from 0 to 1 but it is generally taken as 0.5. For the sensitivity checking one can examine all the values of τ between zero to one. $\Delta_{\min}$ and $\Delta_{\max}$ are the minimum and maximum quality loss values of the normalized sequence.

Finally, the value of grey relational grade (GRG) was computed by averaging the values of grey relational coefficient corresponding to each experimental run by employing Equation (3) as shown below.

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \zeta_i(k) \quad (3)$$

here, γ_i represents the grey relational grade for the corresponding sequence.

Thus, a preference order were assigned to each experimental run by arranging the GRG values in descending order. The experimental run, corresponding to the highest d_G value is referred as the best parametric setting to acquire the desired output.

3. Results and discussion

Initially, all the data sets corresponding to each experimental run were normalized using Equation (1) in order to obtain a dimensionless quantity between 0 and 1. Table 3 depicts the normalized data matrix along with quality loss function for both the selected responses.

Table 3. Normalized data and quality loss function

Run	Normalized Value		Absolute Value (Delta)	
	VB_c	R_a	VB_c	R_a
Ideal Sequence	1	1	1	1
1	0.957	1.000	0.043	0.000
2	1.000	0.750	0.000	0.250
3	0.914	0.571	0.086	0.429
4	0.710	0.929	0.290	0.071
5	0.885	0.643	0.115	0.357
6	0.837	0.571	0.163	0.429
7	0.582	0.357	0.418	0.643
8	0.000	0.000	1.000	1.000
9	0.202	0.214	0.798	0.786

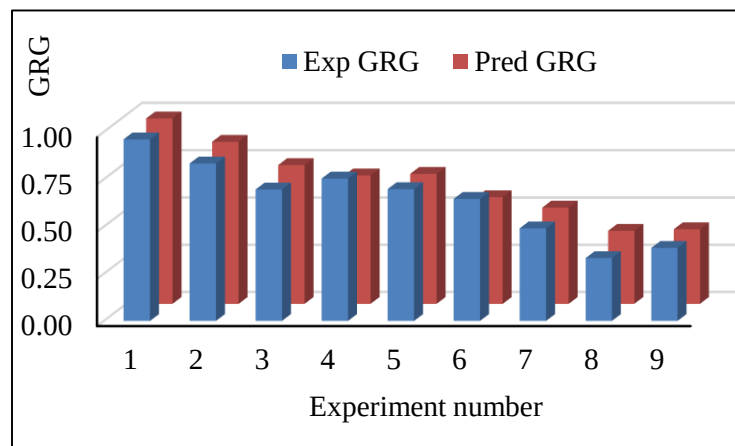
Both the performance characteristics i.e. tool wear and surface roughness were characterized as “smaller-is-better” which necessitates minimum values of the same. Thus, in the next step, grey relational coefficients were calculated by considering equal weights for both the responses with the help of Equation (2). Finally, the grey relational grades (GRG) were determined using equation (3) and listed in Table 4 which indicates all the designated cut qualities of the work material. In this way, multi-objective optimization problem has been converted into a single objective. The parametric combination related to the highest grey relational grade is referred as the best combination within the studied range of process parameters. From the table, it is revealed that experiment number 1 has highest grey relational grade and hence the corresponding parametric setting i.e. cutting speed = 35 m/min, feed rate = 0.08 mm/rev and depth of cut = 0.1 mm can be said as the best combination to attain minimum tool wear and surface roughness. However, this might be limited to the studied range of process variables and the selected machining conditions. At the end, a mathematical model was developed with the help multiple regression analysis (MRA) to exhibit the suitability of the proposed methodology. The following equation shows the relationship between input parameters and GRG (Equation 4):

$$GRG = 1.3743 - 0.0061 \times v - 1.9835 \times f - 0.2188 \times d \quad (4)$$

Table 4. Grey relational grade

Run	Grey relational coefficients		Grey relational grade (GRG)	Rank
	VB_c	R_a		
1	0.921	1.000	0.961	1
2	1.000	0.667	0.833	2
3	0.854	0.538	0.696	5
4	0.633	0.875	0.754	3
5	0.813	0.583	0.698	4
6	0.754	0.538	0.646	6
7	0.545	0.438	0.491	7
8	0.333	0.333	0.333	9
9	0.385	0.389	0.387	8

Figure 1 shows the comparison between calculated and predicted GRG values for each experimental run. It is evidently visualized from the figure that, the predicted values are in good agreement with calculated one. Moreover, predicted values of GRG were observed to be higher for most of the experimental runs. Thus, it can be recommended that, MRA coupled with GRA can be successfully employed for solving multi-objective optimization problems in various academic as well as research institutions within the specified range of process variables.

**Figure 1.** Comparison graph between predicted and calculated GRG values

Finally, the adequacy of the regression model was checked by performing analysis of variance (ANOVA) test. The test was conducted for a significance level of 95% which implies that, if the values of probability of acceptance (P -value) is ≤ 0.05 , then the model is said to be statistically significant. In addition to that, influence of each process parameter was assessed by calculating their percentage contribution on developing the model for predicting GRG. Table 5 illustrates the results of ANOVA test of the current investigation. From the table, it is clearly visualized that the cutting speed is the most influencing machining variable followed by feed rate on GRG which explains 80.16% and 11.12% contribution respectively. On the contrary, depth of cut was found to be insignificant parameter as the P -value related to it, is equal to 0.1344 which is more than 0.05.

Table 5. Results of ANOVA test

Source	DOF	SS	MS	F-value	P-value	% Contribution
Regression	3	0.3217	0.1072	29.7256	0.0012	
v	1	0.2724	0.2725	75.5235	0.0003	80.16
f	1	0.0378	0.0378	10.4688	0.0230	11.12
d	1	0.0115	0.0115	3.1845	0.1344	3.38
Error	5	0.0180	0.0036			5.29
Total	8	0.3398	R-Sq = 94.69%			100.00

4. Conclusions

The present paper proposes GRA method to acquire an optimal parametric combination when machining CP-Ti grade II in dry cutting environment. On the basis of the experimental results attained during the investigation, the following conclusions may be drawn.

1. The highest grey relational grade of 0.961 was noticed for experimental run 1 accordance of which the optimal combination of machining variables are cutting speed = 35 m/min, feed rate = 0.08 mm/rev and depth of cut = 0.1 mm.
2. A close relationship was seen between the predicted and calculated GRG values which describes the adequacy of the MRA approach.
3. Cutting speed was observed as the most influencing machining parameter on GRG with a percentage contribution of 80.16%, followed by feed rate which described as percentage contribution of 11.12%.
4. The suggested methodology can be effectively implemented for solving multi-objective optimization problems associated with various real time manufacturing systems. However, it might be limited to the specified range of process variables and cutting conditions.

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