Selection of Optimal Machining Parameters in Turning of CP-Ti Grade 2 using a Hybrid Optimization Technique

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Abstract
A new composition of Taguchi and multi-objective optimization based on ratio analysis (MOORA) in combination with principal component analysis has been explored. The aim of the investigation was to determine the optimal combination of process parameters during turning of commercially pure titanium grade 2. Cutting speed, feed rate and depth of cut were considered as three input variables. The key output responses selected for the present investigation were cutting force and surface roughness. Experiments were conducted according to Taguchi's L_9 orthogonal array. The experimental results were optimized by using MOORA method. The weights for each response was evaluated by utilizing the principal component analysis approach and further analyzed by multi-objective optimization. The results indicated that the output responses viz. cutting force and surface roughness can be minimized significantly with the following combination of machining parameters: cutting speed of 35 m/min, feed rate of 0.08 mm/rev and depth of cut of 0.1 mm.

Keywords: Taguchi; MOORA; Principal component analysis; Multi-objective optimization.

1. INTRODUCTION

Titanium and its alloys possess excellent resistance to corrosion, superior bio-compatibility along with appreciable tissue inertness, high weld-ability etc. [1-3]. These alloys have extensive applications in a wide range of fields such as chemical processing plant, oil and gas plant, marine and aviation sectors and medical industries [4]. The above mentioned inherent properties and applicability of titanium alloys attract research community to explore and to examine various machining characteristics of these alloys. In recent times, the investigations on the machinability aspects of these alloys are gaining strong attention from the other commercial and industrial sectors as well [5].

On the contrary, high initial cost and difficulties associated with the extraction process results limited utilization of titanium alloys. Furthermore, high chemical affinity and poor thermal conductivity of these alloys restrict its machining within a specified range of cutting speeds (generally 30-60 m/min) owing to less productivity. Machining titanium alloys at high cutting speed produces high temperature at machining zone which in turn causes rapid tool wear thus deteriorates the surface quality of the finished part. It also contributed to high machining cost along with compromising accuracy. In such situations, an appropriate selection of the machining variables play an important role to confirm the improved productivity in combination with competent product quality.

An optimization method helps in achieving the aforesaid objectives. Literature indicated that the Taguchi based orthogonal array (OA) provides better productivity in comprising with attractive dimensional accuracy. Although this approach is effective and efficient, it is limited to single objective problems. On the other hand, most of the problems in a real time manufacturing environment consist of multiple attributes to be optimized. Therefore, previous researchers paid attention towards multi-objective optimization approaches viz. Taguchi based grey relational analysis (TGRA), utility concept, desirability function analysis (DFA), principal component analysis (PCA) etc. Some of the researchers also utilized well-known evolutionary algorithms such as genetic algorithm (GA), harmonic search algorithm, particle swarm optimization (PSO), simulated annealing (SA), artificial neural network (ANN) etc.

Khan and Maity [6] investigated the effects of turning parameters on some of the key machining responses such as cutting force, surface roughness, material removal rate and workpiece surface temperature by expending DFA technique. In some different studies [7, 8] they proposed multi-objective decision making (MODM) approaches to select the best combination of input variable during machining of the work part. These studies exhibited the application potential of the reported methodologies to solve a MODM problem in a real time manufacturing environment. Majumder et al. [9] used TGRA coupled with PCA to minimize the cutting time and surface roughness during wire electro discharge machining of Inconel 800. Saha and Majumder [10] proposed process capability index model for the selection of optimal parametric combination in turning of ASTM A36. In a different investigation the aforesaid authors [11] used two distinct MODM approaches. They reported a comparative analysis between TOPSIS-PCA and MOORA-PCA methods. The results of the investigation revealed that the MOORA embedded with PCA showed better performance in comparison to its TOPSIS-PCA counterpart. Therefore, an attempt has been made to showcase the flexibility and adequacy of the proposed methodology in the current study. A total of nine distinct experimental trials were performed according to Taguchi's L_9 orthogonal array design with an aim to identify the best parametric combination which can significantly minimize the cutting force and surface roughness of the turned part.

2. Experimental details

A cylindrical bar made of commercially pure titanium (CP-Ti) was selected as the work-piece material. The chemical composition of CP-Ti grade 2 is listed in Table 1. The work part was turned using a square shaped carbide insert (ISO:

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SNMG 120408). These inserts were tightly fitted on a right handed tool holder (ISO: PSBNR 2020K12).

A series of experiments were carried out on a heavy duty lathe (HMT, NH26) according to Taguchi's L_9 orthogonal array. Figure 1 depicts the experimental setup of the present investigation. A three dimensional piezoelectric dynamometer was used to measure the three distinct components of cutting force. Then, the resultant cutting force was calculated and reported in the present paper. Each component of the cutting force was recorded at three different locations along the total machining length and the average value was considered during the evaluation of the resultant force. The surface roughness of the machined part was measured with the help of a roughness tester device. The value of the average surface roughness (R_a) was recorded at four different locations (roughly 90^0 apart) and the mean of these readings was considered as final R_a value.

Table 1. Chemical composition of CP-Ti grade 2

Element	C	N	O	Fe	H	Ti
Wt. (%)	0.08	0.03	0.25	0.30	0.015	Balance

Fig. 1. Experimental setup

3. Methodology

Multi-response optimization is defined as the process of optimizing multiple (two or more) characteristics together along with certain constraints taken into account. Most of the times, these output characteristics are observed to be of conflicting natures. Some of them are meant for maximization the profit whereas the others are aimed at minimizing the cost of production. Keeping this in mind, several multi-response optimization approaches are introduced and implied as an efficient tool for selecting an appropriate and optimal alternative from a bunch of alternatives available. Multi-objective optimization based on ration analysis (MOORA) is such an effective approach which can be easily implemented to resolve a wide range of complex problems associated in a real time manufacturing environment.

The proposed MOORA method comprises of the following steps:

Step 1. Formation of a decision matrix consisting of all alternatives in combination with their corresponding outcomes (See equation 1).

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & \dots & a_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ a_{m1} & a_{m2} & \dots & \dots & a_{mn} \end{bmatrix} \qquad (1)$$

where, a_{ij} = Performance measure of the ith alternative on jth attribute. m = number of alternatives and n = number of attributes.

Step 2. Development of a ratio system for each alternative. This can be done by normalizing the data sets of the decision matrix. The normalization can be performed using the following formula (See equation 2):

$$a_{ij}^{*} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^{2}}} \qquad (j = 1, 2, \dots\dots n) \qquad (2)$$

where, a_{ij}^{*} = Normalized value of the ith alternative on jth and lies between 0 to 1.

Step 3. Calculation of overall assessment value using equation (3) as given below:

$$y_i = \sum_{j=1}^{g} w_j\, a_{ij}^{*} - \sum_{j=g+1}^{n} w_j\, a_{ij}^{*} \; (j = 1, 2, \dots.., n) \qquad (3)$$

here, g = number of attributes to be maximized, (n-g) = number of attributes to be minimized, y_i = overall assessment value and w_j = weight of the jth alternative.

The values of w_j was determined with the help of principal component analysis (PCA) technique. Initially the eigenvalues for each performance characteristics were obtained and listed in Table 2. Secondly, the higher eigenvalue was selected to calculate the value of the w_j corresponding to each response. Finally, the square of these values were calculated which represents the actual weight of the attribute as shown in Table 3.

Table 2. Eigenvalues and their proportions

Principal component	Eigenvalues	Proportions (%)
First	1.2818	64.1
Second	0.7182	35.9

Table 3. Eigenvectors and their contribution

Response	Eigenvectors		
	PC_1	PC_2	Contribution
Cutting force	0.707	0.707	0.499 ≈ 0.5
Surface roughness	0.707	-0.707	0.499 ≈ 0.5

Step 4. Allocation of the ranking for each alternative. In this, highest value of the y_i represents the best alternative whereas the lowest one indicates the worst one.

4. Results and discussion

In the present investigation, spindle speed (v), feed rate (f) and depth of cut (d) were selected as three distinct input variables whereas cutting force (F_c) and surface roughness (R_a) were considered as the two attributes to be minimized simultaneously. Table 4, depicts the experimental values of the aforesaid attributes corresponding to each trial.

Table 4. Experimental results

Run	v (m/min)	f (mm/rev)	d (mm)	Fc (N)	Ra (μm)
1	35	0.08	0.1	45.55	0.80
2	35	0.12	0.3	76.71	1.23
3	35	0.16	0.5	124.53	1.20
4	70	0.08	0.5	62.68	1.16
5	70	0.12	0.1	31.97	1.08
6	70	0.16	0.3	75.11	1.58
7	105	0.08	0.3	60.89	1.34
8	105	0.12	0.5	91.32	1.07
9	105	0.16	0.1	73.39	1.12

Initially, these values were converted into a non-dimensional quantity using the data normalization process. The values of F_c and R_a were normalized from 0 to 1 with the help of equation (2) and listed in Table 5. Further, in order to estimate the overall assessment value (y_i) for each trial, relative weights of both the attributes (w_1 and w_2) were obtained using PCA method. This task was performed in MINITAB 16.0 software and the results are shown in Tables 2 and 3 respectively. From the tables it can be seen that, both F_c and R_a are having equal weightage. However, this might be true within the studied range of machining parameters and can be different for other set of the same.

At the end, the values of y_i were evaluated using equation (3) as displayed in Table 6. As mentioned in the step 4 of the proposed methodology, ranking of each alternative was performed. It is revealed from the table that, the trial number 1 has the highest y_i value. Therefore, it can be stated that the optimal parametric combination for the present study is $v_1f_1d_1$ (i.e. v_1 = 35 m/min, f_1 = 0.08 mm/rev and d_1 = 0.1 mm respectively).

In addition, the adequacy of the proposed MOORA method was further checked by conducting analysis of variance (ANOVA) test. The test was performed for a level of confidence of 95% and the results of the same are portrayed in Table 7. Larger value of the determination coefficient (R-sq = 0.99) indicates the goodness of fit of the reported methodology. On the other hand, if the P-value corresponding to the terms attained in the ANOVA table is observed ≤ 0.05, then the model is said to be statistically significant. From the aforesaid table, it is clear that two parameters namely feed rate and depth of cut were significant at 95% confidence level. Figure 2, shows the percentage contribution of each machining parameter on y_i. It is evident from the figure that, depth of cut is the most influencing cutting parameter followed by feed rate and spindle speed respectively.

Table 5. Normalized data matrix

Run	v	f	d	Normalized value	
				Fc	Ra
1	35	0.08	0.1	0.201	0.224
2	35	0.12	0.3	0.338	0.345
3	35	0.16	0.5	0.549	0.336
4	70	0.08	0.5	0.276	0.323
5	70	0.12	0.1	0.141	0.302
6	70	0.16	0.3	0.331	0.442
7	105	0.08	0.3	0.268	0.375
8	105	0.12	0.5	0.402	0.298
9	105	0.16	0.1	0.323	0.313

Table 6. Overall assessment values for each trial

Run	v	f	d	yi	Rank
1	35	0.08	0.1	-0.212	*1*
2	35	0.12	0.3	-0.341	6
3	35	0.16	0.5	-0.442	9
4	70	0.08	0.5	-0.300	3
5	70	0.12	0.1	-0.221	2
6	70	0.16	0.3	-0.386	8
7	105	0.08	0.3	-0.322	5
8	105	0.12	0.5	-0.350	7
9	105	0.16	0.1	-0.318	4

Table 7. Results of the ANOVA test

Source	DOF	SS	MS	F-value	P-value
Spindle speed	2	0.2839	0.1419	4.12	0.195
Feed rate	2	3.0468	1.5234	44.26	0.022
Depth of cut	2	3.6343	1.8172	52.79	0.019
Residual error	2	0.0688	0.0344		
Total	8	7.0339			

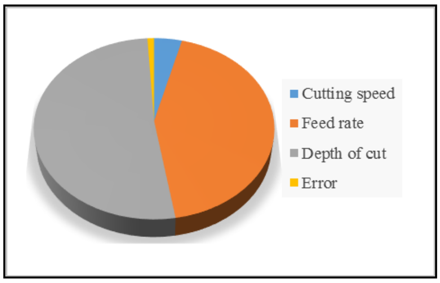

Fig. 2. Percentage contribution of machining parameters

5. Conclusion

The present study reports the application potential of MOORA embedded PCA technique for the selection of optimal alternative within a specified range of machining parameters. The proposed methodology helps in identifying the most appropriate choice from among a large no. of alternatives available. On the other hand, the MOORA method also considers all the attributes in association with their significance which in turn gives more accuracy in the evaluation of the best possible alternative. This approach is mathematically very simple and robust.

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