Influence of Cutting Parameter and Multi-Objective Optimization on Turning Titanium Alloy

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Abstract. Turning is one of the conventional material removal processes and it is essential in today’s manufacturing industry. Nowadays, titanium alloys are favorable and widely used material due to its superior material properties. However, despite having superior material properties, titanium alloys are hard to machine and will result in shortened tool life. Hence it is important to determine the suitable turning parameter to prolong tool life with best surface roughness. This work focused on investigating the influence of machining parameters in machining titanium alloy under dry cutting condition. The influence of three machining parameters namely feeds rate, cutting speed and depth of cut are investigated using a full factorial design. Surface roughness and tool wear were the responses variables. Analysis of variance was utilized in the analysis to determine their contribution ratio and interaction on each response. The experimental results showed that the feed rate was identified as the most influential factor on surface roughness and tool wear at 54% and 33% contribution ratio respectively. Further multi-response objective optimization was adopted through the desirability function analysis method. For the titanium turning operation, the minimal surface roughness and tool wear were significantly obtained through the specified machining parameters at cutting speed of 44 m/min, feed rate of 0.05 mm/rev and depth of cut of 0.5 mm. The results showed that the single objective response successfully converted into multi-objective optimization through the desirability function analysis method.

1. Introduction

Turning is one of the classic machining processes of material removal, which cuts away a rotating unwanted material by single cutting tool. Even though a conventional process but still it is essential in the manufacturing industry. Carbide cutting tools are widely used in metal cutting industry for the various application on hard materials. Because of their superior properties, lightweight materials such as titanium alloys are commonly used in industrial aerospace engineering, such as excellent strength to weight ratio, good corrosion resistance and the ability to sustain high strength at high temperatures [1]. This demand resulted in the need to increase the rate of machining and hence the rate of material removal. However, due to their low thermal conductivity, high chemical reactivity of cutting tool materials and low elasticity modulus, these materials are rated as difficult to machine [2]. These unique characteristics result in high cutting temperature, high level of tool vibration and shorten tool life.
Therefore, the need for suitable parameters is crucial to improve cutting efficiency, the process at low cost and produce high-quality products. On the other hand, surface roughness is another important parameter that can influence the performance of mechanical parts and production cost [3].

In several fields, surface roughness plays an important role and is one of the variables of great importance in determining the precision of machining. For a given machining setup, machining parameters such as cutting speed, feed rate, and cutting depth have a major impact on the surface roughness. Furthermore, tool wear is the change of shape of the tool from its original look amid cutting, caused by the gradual loss of tool material or deformation. Several factors can cause an impact on the tool wear, such as material and geometry of the tool, workpiece material, cutting fluids and cutting parameters [8]. Tool wear is mostly located near the cutting edge of the rake and flank faces of the cutting tool insert. Two common types of tool wear are flank wear and crater wear. According to ISO 3685:1993, tool lifetime is often measured in terms of crater or flank wear [4]. The study shows that wear mostly happens in the flank area. Thus, the evaluation of the tool wear was focused more on the flank area for the tool wear result.

There is a possibility to have multiple output responses from a machining operation. Most of its quality characteristic issues are solved based on time-saving, quality of machining and cost of the material. As such, it is difficult to choose the ideal process parameters that could satisfy all the performance requirements. If the value of a single response is greater, then other essential quality will be affected. Researchers have proposed different forms of multi-objective optimization methods and techniques to solve this sort of optimization problems. Several sorts of multi-objective optimization approaches and techniques have been suggested by researchers e.g. Grey relational analysis (GRA) [5,6], Principal component analysis (PCA), Response surface methodology (RSM) [6–8] and desirability function analysis (DFA) [9–11].

This work investigated the influence of machining parameters in machining titanium alloy under dry cutting condition. The influence of three machining parameters namely feeds rate, cutting speed and depth of cut are investigated using a full factorial design. Surface roughness and tool wear were the responses variables. Analysis of variance was utilized in the analysis to determine their contribution ratio and interaction on each response. Further desirability function analysis was used to determine the multi-objective optimization of the responses.

2. Methodology

High Speed Precision Lathe LG-460A series was utilized in this work and Figure 1 shows the experimental setup. All the experimental works were performed in dry cutting condition and carried out at different cutting speed, feed rate and depth of cut. An experiment was designed to check various parameters involved in machining and relate to surface roughness and tool wear. The influence of three machining parameters i.e. cutting speed, feed rate and depth of cut were optimized using a full factorial design [3]. According to the most current practices of relevant literature and tool manufacturer, the cutting parameter levels were selected to align with machine limitation. Table 1 denotes the design of experiment layout with every test parameters condition conducted in experiment.

The workpiece material used was Ti-6Al-4V (Grade 5) with a dimension of 400 mm in length and 26 mm in diameter. The cutting tool insert used were titanium coated (CCMT120412-MM VP15TF) with TF15 micro-grain cemented carbide [4]. All cutting tools insert were inspected before and after machining process using NK Vision Microscope as shown in figure 2. To minimize quality variations, all cutting tool insert were sourced from the same production batch. All tests started with a new cutting tool. The response variables measured were surface roughness and tool wear. Three different positions on the machined surface (each test) were measured and the average value are taken as average surface roughness response. The machined surface was measured by using Alicona Infinite Focus (Optical 3D surface metrology) as shown in figure 3. For tool wear response evaluation, flank wear was chosen according to ISO 3685:1993 [7]. Table 2 shows the configuration of the experiment layout, with every test parameter condition performed in the experiment. Two responses were evaluated namely surface
roughness and tool wear for the corresponding experimental. The analysis of the data was divided into 2 Phases. Phase 1 involved analyzing the influence of each cutting parameter factors and their interaction on surface roughness and tool wear response. Phase 2 involved the converted multi-responses objective into a single response characteristic termed composite desirability by desirability function analysis (DFA) method. Steps involved in the DFA method were:

Step 1. Calculate the individual desirability function index for the corresponding response.
Step 2. Compute the composite desirability function index.
Step 3. Determine the optimal parameter and its level combination.
Step 4. Perform ANOVA for identifying the significant parameters.

Analysis of Variance (ANOVA) couple with Minitab Software was utilized to verify the adequacy of the experimental results.

| Test No. | Feed rate (mm/rev) | Cutting speed (m/min) | Depth of cut (mm) | Surface Roughness (μm) | Tool Wear (mm) |
|----------|---------------------|-----------------------|-------------------|------------------------|----------------|
| Test 1   | 0.05                | 45                    | 0.5               | 0.810                  | 1.354          |
| Test 2   | 0.05                | 80                    | 0.5               | 0.830                  | 3.045          |
| Test 3   | 0.10                | 45                    | 0.5               | 0.819                  | 2.045          |
| Test 4   | 0.10                | 80                    | 0.5               | 0.837                  | 3.106          |
| Test 5   | 0.05                | 45                    | 1.0               | 0.824                  | 2.471          |
| Test 6   | 0.05                | 80                    | 1.0               | 0.830                  | 3.344          |
| Test 7   | 0.10                | 45                    | 1.0               | 0.840                  | 3.059          |
| Test 8   | 0.10                | 80                    | 1.0               | 0.844                  | 3.396          |

**Table 1. Factors and levels of machining parameters**

| Factor                      | Low level (-1) | High level (+1) |
|-----------------------------|-----------------|-----------------|
| (A) Feed rate (mm/rev)      | 0.05            | 0.1             |
| (B) Cutting speed (m/mm)    | 45              | 80              |
| (C) Depth of cut (mm)       | 0.5             | 1.0             |
3. Result and Discussion

3.1 Surface roughness

The response of the mean surface roughness is presented in Figure 3. Generally, surface roughness ranged between 0.810 µm to 0.844 µm $R_a$. With parameters of feed rate 0.05 mm/rev, cutting speed 45 m/min and depth of cut 0.5mm of Test 1, surface roughness values of 0.810 µm $R_a$ was among the lowest of all the tests. Test 8 with feed rate 0.1 mm/rev, cutting speed 80 m/min and depth of cut 1.0 mm shows the highest value of surface roughness (0.844 µm $R_a$). Despite using high cutting parameters, the surface roughness was higher probably due to tool wear.

Figure 4 shows the half-normal probability plot of each parameters effect and their interaction from the largest effect to the smallest effect. It clearly shows the feed rate (A) among the highest effect on surface roughness. Increasing the feed rate also increased the surface roughness, which probably due to the higher peak and crest on the machine surface. Further analysis using analysis of variance (ANOVA) was used for details analysis. Table 3 shows details of ANOVA results for surface roughness response. The model with F-value of 485 implies that the ANOVA model is significant at 95% confidence level. There is only 3.47% chance that a “model F-value” this large could happen due to noise. The indicated model terms are significant with the values of “Prob>f” less than 0.0500. In this case, the model terms of $A$, $B$, $C$, and $AC$ are significant. However, the value greater than 0.0500 indicates the model terms are not significant.

All three variable cutting parameters were found to statically significant where the feed rate shows the highest percentage contribution ratio with 33%. This was succeeded by cutting speed and depth of cut at 29% and 25% respectively. Two-level interaction between feed rate and depth of cut was also found significant with the percentage ratio of 10%. The correlated main effect plots and interaction plots for mean surface roughness are shown in figure 5 and figure 6 respectively. From figure 5, it clearly shows that the lowest surface roughness could be archived at low cutting parameters i.e. cutting feed rate 0.05 mm/rev, speed 45 m/min, and depth of cut 0.5mm. Based on analysis of variance, it was found that the feed rate was the most influential factor to surface roughness with a percentage contribution of 33%. Sasan Yousefi and Mehdi Zohoor [12] when hard turning of MDN250 steel found feed rate is the most significant factor that influences surface roughness. The effect of feed rate on surface roughness is the most pronounced as reported in the literature [8], [13]. The final equation model for surface roughness in terms of actual factors is shown as follows:
Surface roughness ($R_a$) = 0.75988 + 0.70145* Feed rate + 7.94798E-005* cutting speed + 0.042399* Depth of cut - 8.67052E-004* Feed rate * Cutting speed – 0.53064* Feed rate * Depth of cut + 2.60116E-004* Cutting speed * Depth of cut

**Figure 3.** Surface roughness result

**Figure 4.** Surface roughness effects- half-normal plot

**Table 3.** Surface roughness- analysis of variance

| Source         | Sum of Squares | DF | Mean square | F value | Prob>F | PCR | % PCR |
|----------------|----------------|----|-------------|---------|--------|-----|-------|
| Model          | 0.000886       | 6  | 0.000148    | 485     | 0.0347 |     |       |
| Feed rate (A)  | 0.000293       | 1  | 0.000293    | 961     | 0.0205 | 0.32978 | 33% |
| Cutting speed (B) | 0.000256    | 1  | 0.000256    | 841     | 0.0219 | 0.28856 | 29% |
| Depth of cut (C) | 0.000222    | 1  | 0.000222    | 729     | 0.0236 | 0.25009 | 25% |
| AB             | 2.74x10^{-6}  | 1  | 2.74x10^{-6} | 9       | 0.2048 | 0.00275 | 0%  |
| AC             | 8.8x10^{-5}   | 1  | 8.8x10^{-5} | 289     | 0.0374 | 0.09894 | 10% |
| BC             | 2.47x10^{-5}  | 1  | 2.47x10^{-5} | 81      | 0.0704 | 0.02748 | 3%  |
| Residual       | 3.04x10^{-7}  | 1  | 3.04x10^{-7} |  |        |     |       |
| Cor Total      | 0.000886       | 7  |             |         |        |     |       |

**Figure 5.** Surface roughness main effect plot

**Figure 6.** Surface roughness interaction plot
3.2 Tool wear

Amidst the turning process, there was contact between the cutting tool and workpiece. Thus, friction between the cutting tool and workpiece was responsible for the tool wear. The tool wear increased as cutting length increased. The higher of tool wear at higher cutting parameters is probably due to abrasion at the rake face and flank face as the cutting length increased. Figure 7 shows the rake face and flank face of the cutting tool insert for Test 1 and Test 8 after the turning test. Tool wear flank face was measured for all cutter insert after each test and used as a tool wear response. The tool wear response for all tests is depicted in Figure 8. In general, the tool wear ranged between 1.354 mm to 3.396 mm. Test 1 with feed rate 0.05 mm/rev, cutting speed of 45 m/min and depth of cut 0.5mm shows the lowest tool wear values of 1.354 mm among all the tests. Test 8 with feed rate 0.1 mm/rev, cutting speed of 80 m/min and depth of cut 1.0 mm shows the highest value of tool wear with 3.396 mm. At high cutting parameters (Test 8), the tool wear was higher probably due to tool wear progressive higher at higher cutting parameters.

Figure 9 shows the half-normal probability plot of each parameter effect and their interaction from the largest effect to the smallest effect for tool wear response. Graphically, it clearly shows that cutting speed (A) was among the highest effect on tool wear. Thus, a further investigation using analysis of variance (ANOVA) was used for details analysis. Table 4 shows details of ANOVA results for tool wear response. The model with F-value of 543 implies that the ANOVA model is significant at 95% confidence level. There is only 3.28% chance that a “model F-value” this large could occur due to noise. The indicated model terms are significant with the values of “Prob>f” less than 0.0500. In this case, the model terms of A, B, C, and AC are significant. However, the value greater than 0.0500 indicates the model terms are not significant.

All three variable cutting parameters were found to be statically significant where the feed rate shows the highest percentage contribution ratio with 54%. This was succeeded by cutting speed and depth of cut at 7% and 26% respectively. Two-level interaction between feed rate and depth of cut was also found significant with a percentage of ratio 8%. The associated main effect plots and interaction plots for mean surface roughness are shown in figure 10 and figure 11 respectively. In figure 10, it clearly shows that the lowest tool wear could be archived at low cutting parameters i.e. feed rate 0.05 mm/rev, cutting speed 45 m/min and depth of cut 0.5mm. The final equation model for tool wear in terms of actual factors is shown as follows:

\[
\text{Tool wear (}\bar{V}_B\text{)} = -3.23046 + 58.26836 \times \text{Feed rate} + 0.024197 \times \text{Cutting speed} + 3.81884 \times \text{Depth of cut} - 0.21605 \times \text{Feed rate} \times \text{Cutting speed} - 30.82614 \times \text{Feed rate} \times \text{Depth of cut} - 2.0607E-003 \times \text{Cutting speed} \times \text{Depth of cut}
\]
Figure 7. Cutting insert tool wear for Test 1 and Test 8.

Figure 8. Tool wear result

Figure 9. Tool wear effects- Half-normal plot

Table 4. Tool wear Analysis of variance

| Source       | Sum of Squares | DF | Mean square | F value | Prob>F | PCR | % PCR |
|--------------|----------------|----|-------------|---------|--------|-----|-------|
| Model        | 3.598635       | 6  | 0.599772    | 543     | 0.0328 | Significant |
| Feed rate (A)| 1.961963       | 1  | 1.961963    | 1776    | 0.0151 | 0.54472 | 54% |
| Cutting speed (B)| 0.242454 | 1  | 0.242454    | 220     | 0.0429 | 0.06705 | 7% |
| Depth of cut (C)| 0.92557    | 1  | 0.92557     | 838     | 0.0220 | 0.25681 | 26% |
| AB           | 0.170147       | 1  | 0.170147    | 154     | 0.0512 | 0.04696 | 5% |
| AC           | 0.296953       | 1  | 0.296953    | 269     | 0.0388 | 0.08219 | 8% |
| BC           | 0.001548       | 1  | 0.001548    | 1       | 0.4465 | 0.00012 | 0% |
| Residual     | 0.001104       | 1  | 0.001104    |         |        |      |       |
| Cor Total    | 3.599739       | 7  |             |         |        |      |       |
3.3 Desirability function analysis

One of the most important goals in machining is to succeed the desire surface roughness and prolong the cutting tool life. Thus, desirability function index analysis was adopted to transforms the surface roughness responses and tool wear responses into a normalize assessment named as an individual desirability function index. Then, followed by a calculated composite desirability function index. According to the calculated composite desirability function index, the optimal cutting parameter setting for lower surface roughness and lower tool wear can be determined. At highest composite desirability function index shows the optimum responses. The calculated composite desirability function index value 1 is considered as ideal parametric setup based on parameters of the input. Table 5 shows the surface roughness, tool wear and the overall desirability index for each experimental data in terms of individual desirability function.

The highest composite desirability function index value, i.e. 1.00 in table 5 corresponds to the optimal parametric setting. Table 6 shows the composite desirability response on each factor. From table 6, the best cutting parameter setting was at feed rate 0.05 mm/rev, cutting speed 45 m/min and depth of cut 0.5mm. The analysis of variance in Table 7 shows, the composite desirability function is significant at 95% confidence level.

### Table 5. Desirability function analysis

| Orthogonal array | Responses | Individual Desirability Function | Composite Desirability Function | Order |
|------------------|-----------|----------------------------------|----------------------------------|-------|
|                  | A B C     | Surface Roughness (μm) | Tool Wear (mm) | Surface Roughness | Tool Wear |                      |                     |
| Test 1           | 0.05 45 0.5 | 0.810            | 1.354            | 1.000             | 1.000     | 1.000                | 1                   |
| Test 2           | 0.05 80 0.5 | 0.830            | 3.045            | 0.412             | 0.172     | 0.137                | 4                   |
| Test 3           | 0.10 45 0.5 | 0.819            | 2.045            | 0.735             | 0.662     | 0.582                | 2                   |
| Test 4           | 0.10 80 0.5 | 0.837            | 3.106            | 0.206             | 0.142     | 0.071                | 5                   |
| Test 5           | 0.05 45 1   | 0.824            | 2.471            | 0.588             | 0.453     | 0.371                | 3                   |
| Test 6           | 0.05 80 1   | 0.830            | 3.344            | 0.412             | 0.025     | 0.033                | 6                   |
| Test 7           | 0.10 45 1   | 0.840            | 3.059            | 0.118             | 0.165     | 0.052                | 7                   |
| Test 8           | 0.10 80 1   | 0.844            | 3.396            | 0.000             | 0.000     | 0.000                | 8                   |
Table 6. The composite desirability response table

| Factor                  | Grey Relational Grade | Level 1 | Level 2 | Max-Min | Rank |
|-------------------------|-----------------------|---------|---------|---------|------|
| (A) Feed rate (mm/rev)  | 0.4476*               | 0.1139  | 0.3337  |         | 1    |
| (B) Cutting speed (m/mm)| 0.3852*               | 0.1763  | 0.2089  |         | 3    |
| (C) Depth of cut (mm)   | 0.5013*               | 0.2407  | 0.2606  |         | 2    |

The composite desirability total mean of: 0.3108

Table 7. The composite desirability analysis of variance

| Source     | Sum of squares | DF | Mean square | F value | Prob>F | PCR | % PCR |
|------------|----------------|----|-------------|---------|--------|-----|-------|
| Model      | 0.8733         | 6  | 0.1456      | 276.5181| 0.0460 | Significant |
| Feed rate (A) | 0.3893     | 1  | 0.3893      | 739.5142| 0.0234 | 0.4449 | 44% |
| Cutting speed (B) | 0.0873   | 1  | 0.0873      | 165.8260| 0.0493 | 0.0993 | 10% |
| Depth of cut (C) | 0.2227    | 1  | 0.2227      | 423.0827| 0.0309 | 0.2543 | 25% |
| AB         | 0.0507        | 1  | 0.0507      | 96.3825 | 0.0646 | 0.0575 | 6%  |
| AC         | 0.1211        | 1  | 0.1211      | 230.1416| 0.0419 | 0.1380 | 14% |
| BC         | 0.0022        | 1  | 0.0022      | 4.1619  | 0.2901 | 0.0019 | 0%  |
| Residual   | 0.0005        | 1  | 0.0005      |         |        |      |      |
| Cor Total  | 0.8738        | 7  |             |         |        |      |      |

4. Conclusion
This work aimed to quantify the influence of each cutting parameters on titanium alloy as a workpiece (surface roughness) and insert coated carbide (tool wear) responses, respectively. To investigate the influence of each cutting parameters that contribute to the minimization of surface roughness and tool wear responses, the full factorial design L8 was used. Using ANOVA, the significant effect of each cutting parameter and their interaction on surface roughness and tool wear responses could be determined. The result revealed that:

1. Feed rate seems to influence surface roughness response by 33% contribution ratio more significantly than cutting speed (29%) and depth of cut (25%).
2. Feed rate also seems to influence tool wear response by 54% contribution ratio more significantly than the depth of cut (26%) and cutting speed (7%).

To figure out the individual desirability attribute to the surface roughness and tool wear, the desirability function index was used. Then utilizing the composite desirability function, the single combined value of each run was determined and the optimal parameter setting was eventually achieved. It showed that by using the method proposed in this study, the multiple performance features of the titanium alloy turning process have successfully achieved with composite desirability value of 0.3108.

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