Multi-Characteristics Optimization in Micro-milling of Ti6Al4V Alloy

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Abstract. Nowadays, Ti6Al4V alloy is widely used to fabricate miniaturized prostheses, orthopedic and dental implants. Surface quality is an essential aspect of the implant parts owing to its effect on service life, which could be achieved through a proper selection of precise micromachining parameters. In this research, the mechanical micromachining of Ti6Al4V alloy has been performed, and optimized process parameters are considered for analysis. Surface roughness (Ra) of the machined microchannels, cutting force in the feed direction (Fy), cross-feed direction (Fx), and vibration on the top surface plate along the spindle axis (az) have been taken as the response variables and were analyzed. The tests were accomplished at various rotational speed (N), feed per tooth (fz), axial depth of cut (ap), and cutter diameter (D) as machining parameters, each at three levels. The significant factors and their levels are identified using analysis of variance (ANOVA) and S/N ratios of response plot. According to the GRA test, N : 15000 rpm, fz : 0.2 μm/tooth, ap : 30 μm, and D : 200 μm are optimal parameters setting for better machinability of Ti6Al4V. ANOVA results indicated that feed rate is the most influential factor for lower cutting forces, surface roughness, and workpiece vibration. Fast Fourier transform (FFT) analysis depicts the stiffness of different micro end-mills significantly affect the machining performance like vibration amplitude during the micro-milling of Ti6Al4V alloy.

1. Introduction
Titanium alloys have wide applications in biomedical, automobile, aeronautics, optics, communications, precision dies, watch making, and electronics industries due to outstanding properties like exceptionally good corrosion resistance, high specific strength, high fatigue strength, and biocompatible behavior. However, Titanium alloy is graded as “difficult to machine” material due to its inadequate thermal conductivity, high chemical reactivity with the cutting tools, work hardening characteristics, workpiece material adhesion to the cutting tool edges, and low elastic modulus [1-2]. Micromachining is one of the most emerging fabrication method due to the increasing importance of the miniaturization of products. Mechanical micromachining processes are more beneficial as compared to lithography-based micromachining techniques due to the flexibility to manufacture 3D complex parts from various materials [3-4]. Unlike macro-milling, the micro-milling strategy faces several issues, for example; tool deflection, negative rake angle, vibration, tool life, chip, and burr formation etc. due to its small diameter and inadequate rigidity [5].

In micro-milling, the size of the tool edge radius is comparable to uncut chip thickness, feed per tooth, and grain size of materials. The size effect phenomenon is depicted by a ratio of feed per tooth to the tool edge radius, which substantially impacts the deformation of materials in the chip-tool interaction and specific cutting energy [6-7]. Chip removal takes place either in shearing mode or a combination of the
shearing-ploughing action. However, suppose uncut chip thickness or feed per tooth is lesser than minimum uncut chip thickness. In that case, no chip is produced, only ploughing or rubbing action will take place on the workpiece, which causes the generation of the rough machined surface [8]. The magnitude of cutting forces and vibration is significantly less in the micromilling process [9].

Thepsonthi and ozel [2] suggested the optimal parameters for micromachining of superalloy Ti64 relating to lower surface roughness and burr generation. Lekkala et al. [10] examined the importance of various cutting parameters on burr formation and surface quality. They reported that higher values of the cutting parameters and the number of flutes improved the surface quality, while with the increase in the tool diameter, a rough surface was obtained. Filitz et al. [11] conducted micromachining tests on pure copper 101 employing different cutting speed and feed rate. The cutting forces, surface roughness in the bottom of micro-channel, tool wear, and top burr width were taken for micro-machinability study. Fast fourier transform had been done for the frequency domain analysis of signals. Aramcharoen and Mativenga [15] explored the impact of spindle speed, depth of cut, the ratio of uncut chip thickness to cutting edge radius, and machining situations on surface roughness, top burr width, percentage diameter reduction, and tool wear.

Kuram and Ozcelik [12] applied optimum conditions to attenuate lower tool wear, cutting forces, and surface roughness in micro-milling of Al7075 alloy using 800 μm diameter ball end-mills. They revealed that the lowest value of machining parameters was optimal and resulted in better responses. The influence of diverse cutting parameters, and tool diameter on surface roughness in micro-milling of brass had been studied by Wang et al. [13]. They found that tool diameter was the most prominent factor concerning surface finish. Recently, Awale and Inamdar [14] adopted a grey relational tool to find the best criterion for better machinability and surface integrity of AISI S7 tool steel during high speed turning.

The literature study confirm that very few research work has been done on the optimization of multiple performance characteristics in micro-milling of Ti6Al4V alloy. The optimal value of machining parameters is determined to get the desired surface quality of micro-channels and reduce the cutting forces and workpiece vibration. In the present work, a comprehensive study of micro-milling of Ti6Al4V is carried out. Experiments are designed as per Taguchi’s L9 (3^4) orthogonal arrangement. In this work, feed per tooth (fz), rotational speed (N), depth of cut (ap), and cutter diameter (D) are chosen as the process parameters. Workpiece vibration (az), surface roughness (Rz), cutting forces in the feed (Fy), and cross-feed direction (Fx) are taken as the response variables. Optimal conditions of different micro-milling parameters have been determined using Taguchi based grey relational approach. Fast fourier transform analysis for workpiece vibration has been performed using Matlab 2015a software. The Larger diameter micro end-mill demonstrates a lower vibration amplitude in micromilling.

2. Experimental details
In the present study, Ti6Al4V titanium alloy has been utilized as work material. The microstructure and EDS profile pictures of the Ti6Al4V alloy are illustrated in Figs. 1(a)-(b), which shows alpha and beta phases in the Ti6Al4V alloy. The EDS profile provides information about the percentage composition of each element in Ti6Al4V alloy (Fig. 1(b)). The tests have been executed on a Ti6Al4V plate of 50×45×5 mm³ on a DT-110 micro-machine. The details of specification of DT-110 micro-machine are as follows: maximum rotational speed 60,000 RPM and positional accuracy +/-1μm per 100 mm. Before performing the experiments, skin cut is given to the upper surface of the workpiece plate by 3 mm diameter end mill to ensure the uniform flatness of the plate. The tool overhang of 15 mm is chosen in all experimental runs to avoid the tool run-out and chatter phenomenon during micro-milling operation. The detailed view of the micro-milling machine and the experimental setup belonging to present work is illustrated in Fig. 2. The factors and their levels are listed in Table 1. Preliminary trials were conducted to set the machining parameters. After test runs, a wide range of high spindle speed, lower feed per tooth, and depth of cut were
considered. The cutters are commercially available in the form of two rims uncoated tungsten carbide (WC) micro end mills of 500 μm, 200 μm, and 100 μm diameter, which possess 1 mm flute length, 30° helix angle, and 3 mm shank diameter (make: Axis Tools, India). As the tool diameter decreases, strength and stiffness of micro-end-mill decline drastically such that the little amount of fluctuation in cutting forces and vibration leads to tool failure. Total micro-channel length (75 mm) was fabricated using 200 μm and 500 μm tool diameter; besides in the case of 100 μm tool diameter, machining was continued until the breakage of the tool.

![Figure 1. Microstructure of Ti6Al4V alloy (a) optical microscopy image (b) EDS profile for Ti6Al4V](image)

| Factors                  | Notation | Level 1 | Level 2 | Level 3 |
|--------------------------|----------|---------|---------|---------|
| Feed per teeth (μm/tooth)| f_t      | 0.2     | 0.6     | 1       |
| Rotational speed (rpm)   | N        | 15000   | 30000   | 45000   |
| Depth of cut (μm)        | a_p      | 10      | 20      | 30      |
| Cutter diameter (μm)     | D        | 100     | 200     | 500     |

Micromilling at each combination of parameters was conducted using a new tool. The 3D optical profilometer was attached with a multifunction tribometer (make: Rtec Instruments) to measure the average surface roughness (R_a) ahead of the feed direction in the bottom of slots. Mini-dynamometer 9256C2 (make: Kistler) and uniaxial accelerometer sensor (make: Bruel and Kajer 4507) attached with NI-cDAQ 9188 have been used for measuring cutting forces (cross-feed force (F_x) and feed force (F_y)) and acceleration (a_x) on the top surface of the plate, respectively (Refer Fig. 2). Cutting forces and vibration signals were recorded for 10 s in the middle of the microchannel with a sampling frequency rate of 50000 Hz and 25000 Hz, respectively. RMS values of cutting forces (F_x, F_y) and vibration are considered for analysis. The Ti6Al4V plate is tightly mounted over the mini dynamometer, which is attached with a computer via a charge amplifier 5070A.
3. Results and discussion

Experimental runs of various sets of cutting parameters applying the Taguchi orthogonal array (L9) are listed in Table 2. Minimizing quality loss means maximizing the signal-to-noise (S/N) ratio. Generally, the signal is desirable to output. Noise is an undesirable effect for responses.

Table 2. Experimental test runs and measured data of $F_x$, $F_y$, $R_a$, and $a_z$

| Exp. no. | N (rpm) | $f_z$ (μm/tooth) | $a_p$ (μm) | $D$ (μm) | $F_y$ (N) | $F_x$ (N) | $R_a$ (μm) | $a_z$ (m/s²) |
|----------|---------|-----------------|-------------|----------|-----------|-----------|------------|--------------|
| 1        | 15000   | 0.2             | 10          | 100      | 0.20074   | 0.10686   | 0.127      | 0.68965      |
| 2        | 15000   | 0.6             | 20          | 200      | 0.36557   | 0.37211   | 0.1333     | 0.75993      |
| 3        | 15000   | 1.0             | 30          | 500      | 0.42352   | 0.40723   | 0.23       | 0.80699      |
| 4        | 30000   | 0.2             | 20          | 500      | 0.30182   | 0.27615   | 0.27       | 0.71772      |
| 5        | 30000   | 0.6             | 30          | 100      | 0.35352   | 0.31723   | 0.323      | 0.86077      |
| 6        | 30000   | 1.0             | 10          | 200      | 0.55203   | 0.43968   | 0.3966     | 0.85843      |
| 7        | 45000   | 0.2             | 30          | 200      | 0.24109   | 0.21685   | 0.1073     | 0.84482      |
| 8        | 45000   | 0.6             | 10          | 500      | 0.46218   | 0.37346   | 0.38       | 0.81673      |
| 9        | 45000   | 1.0             | 20          | 100      | 0.54115   | 0.56372   | 0.3722     | 0.9821       |

The optimum condition gives the highest values of S/N ratios. Since the smaller value of cutting forces ($F_x$ and $F_y$), surface roughness ($R_a$), and vibration ($a_z$) are required, the “smaller-the-better” criteria are used to form the response plots by Eq. 1.

\[
S/N \text{ ratios } (\eta) = -10 \log_{10} \left( \frac{1}{n} \sum_{i=1}^{n} y_i^2 \right)
\]  

(1)
Where \( n \) is the number of experimental combinations, \( y_i \) is the result of the measured response.

The optimal value of process parameters for outcomes like \( R_a, a_z, F_x, \) and \( F_y \) are shown in Fig. 3 (a-d). The optimal process characteristic condition for low \( R_a \) is \( N_1 f_z a_p D_2 \) (Fig. 3(a)). For low \( R_a \), the optimum parameters are \( N = 15000 \) rpm, \( f_z = 0.2 \mu m/\text{tooth}, a_p = 30 \mu m, \) and \( D = 200 \mu m \). Surface roughness first increases with spindle speed up to 30000 rpm, then decreases with higher spindle speed beyond 30000 rpm. Surface roughness reduction occurs at spindle speeds beyond 30000 rpm due to high heat generation, resulting in the thermal relieving of the materials and materials easily removed with the better surface finish. Surface roughness exacerbates with increased feed per tooth due to increased cutting forces and workpiece vibration with feed rate. However, the increment of surface roughness is more intense below the 0.6 \( \mu m/\text{tooth} \) feed rate, which shows the size effect phenomenon in micro-milling. By increasing the cutting depth, the surface roughness decreases. For tool diameter above the 200 \( \mu m \), the surface produced is having higher roughness. \( N_1 f_z a_p D_3 \) is the optimal situation for lower \( a_z \) (Fig. 3(b)). Thus the best combination values for minimizing the vibration of the workpiece (\( a_z \)) are \( N = 15000 \) rpm, \( f_z = 0.2 \mu m/\text{tooth}, a_p = 10 \mu m, \) and \( D = 500 \mu m \). Vibration on the uppermost surface of the Ti6Al4V plate increases with an enhancement in rotational speed, feed per tooth, and cutting depth. But, it decreases with a rise in cutter diameter. It is revealed that with the increase in cutter diameter, the tool becomes stiffer and achieves a stable condition for micro-machining of hard material. Vibration exacerbates with an increase in spindle speed, feed rate, and cutting depth due to rise in the volumetric material removal rate and chip load of the microchannel.

The assessment of the result illustrates that the optimal value of micro-milling factors for feed force (\( F_y \)) is \( N_1 f_z a_p D_1 \) (Refer Fig. 3(d)), namely, \( N = 15000 \) rpm, \( f_z = 0.2 \mu m/\text{tooth}, a_p = 30 \mu m, \) and \( D = 100 \mu m \). The optimum combination of process parameters for \( F_x \) is \( N_1 f_z a_p D_1 \) (Refer Fig. 3(c)); namely, \( N = \)
15000 rpm, \( f_z = 0.2 \, \mu m/tooth \), \( a_p = 10 \, \mu m \), and \( D = 100 \, \mu m \). Based on Fig. 3 (c, d), the feed force and cross-feed force increase with an increase in spindle speed, but the increment of cutting forces is not significant beyond the 30000 rpm. At the higher speed, interface temperature between tool and chip increases and causes thermal softening of the workpiece, which reduces the material shear strength. An increment in cutting forces with an enlargement in feed rate shows the effect because the larger chip cross-sectional area comes into contact with the cutting tool and clogging of chips during micro-milling.

3.1 Analysis of variance (ANOVA)
Analysis of variance (ANOVA) determines the influence of control parameters on response by the disintegration of variance [16]. ANOVA is used to depict the significance of control parameters along with its percentage of contribution on each of the responses (surface roughness, feed force, cross-feed force, and workpiece vibration). F-ratio is determined as the ratio of the mean sum of the square of the parameter to the error variance. A larger F-ratio means the effect of the factor is more on the response. The percentage contribution of the parameter is determined by the ratio of the sequential sum of square of the parameter to the total sum of square multiplied with 100 to get in terms of percentage. ANOVA results of different responses are given in Tables 3-6. In this analysis, the level of confidence is taken as 95%. All respective process parameters like \( N \), \( f_z \), and \( a_p \) and \( D \) were influenced surface roughness by 21.11 %, 37.85 %, 9.16 %, and 2.38 %, respectively (Refer Table 3).

Table 3. ANOVA for surface roughness

| Source          | DF | Seq SS     | Adj MS    | F ratio | P     | Contribution (%) |
|-----------------|----|------------|-----------|---------|-------|-----------------|
| Regression      | 4  | 0.075903   | 0.0189758 | 2.38888 | 0.209833 |                 |
| \( N \) (rpm)   | 1  | 0.022718   | 0.0227181 | 2.86001 | 0.166068 | 21.11           |
| \( f_z \) (\( \mu m/tooth \)) | 1  | 0.040755   | 0.0407550 | 5.13070 | 0.086193 | 37.85           |
| \( a_p \) (\( \mu m \)) | 1  | 0.009866   | 0.0098658 | 1.24202 | 0.327525 | 9.16            |
| \( D \) (\( \mu m \)) | 1  | 0.002564   | 0.0025641 | 0.32280 | 0.600305 | 2.38            |
| Error           | 4  | 0.031773   | 0.0079434 |         |       | 29.5            |
| Total           | 8  | 0.107677   |           |         |       | 100             |

In the case of vibration, the most notable characteristic is the \( f_z \), with a percentage contribution of 42.65% (Refer to Table 4). The second most prominent factor is the rotational speed (40.89%).

Table 4. ANOVA for vibration

| Source          | DF | Seq SS     | Adj MS    | F-ratio | P Value | Contribution (%) |
|-----------------|----|------------|-----------|---------|---------|-----------------|
| Regression      | 4  | 0.0608011  | 0.0152003 | 227.787 | 0.0000571 |                 |
| \( N \) (rpm)   | 1  | 0.0249718  | 0.0249718 | 374.220 | 0.0000421 | 40.89           |
| \( f_z \) (\( \mu m/tooth \)) | 1  | 0.0260476  | 0.0260476 | 390.342 | 0.0000387 | 42.65           |
| \( a_p \) (\( \mu m \)) | 1  | 0.0036393  | 0.0036393 | 54.538  | 0.0017925 | 5.96            |
| \( D \) (\( \mu m \)) | 1  | 0.0061424  | 0.0061424 | 92.048  | 0.0006596 | 10.06           |
| Error           | 4  | 0.0002669  | 0.000067  |         | 0.44     |                 |
| Total           | 8  | 0.0610681  |           |         |         | 100             |
Table 5. ANOVA for feed force

| Source            | DF  | Seq SS   | Adj MS  | F-ratio | P value | Contribution (%) |
|-------------------|-----|----------|---------|---------|---------|------------------|
| Regression        | 4   | 0.118008 | 0.0295019 | 25.6359 | 0.004123 |                  |
| N (rpm)           | 1   | 0.010803 | 0.010803 | 9.8371  | 0.037518 | 8.81             |
| fz (μm/tooth)     | 1   | 0.099601 | 0.099601 | 86.5490 | 0.000743 | 81.23            |
| ap (μm)           | 1   | 0.006456 | 0.006456 | 5.6103  | 0.076938 | 5.27             |
| D (μm)            | 1   | 0.001148 | 0.001148 | 0.9972  | 0.374497 | 0.94             |
| Error             | 4   | 0.004603 | 0.0011508 | 3.75    |         | 3.75             |
| Total             | 8   | 0.122611 |         | 100     |         |                  |

The most predominant factor for F_y and F_x is the feed per tooth, with a percentage contribution of 81.23% (Refer Table 5) and 77.83% (Refer Table 6).

Table 6. ANOVA for Cross-feed force

| Source            | DF  | Seq SS   | Adj MS  | F-ratio | P-value | Contribution (%) |
|-------------------|-----|----------|---------|---------|---------|------------------|
| Regression        | 4   | 0.122278 | 0.030570 | 6.6186  | 0.047163 |                  |
| N (rpm)           | 1   | 0.011955 | 0.011955 | 2.5885  | 0.182926 | 8.49             |
| fz (μm/tooth)     | 1   | 0.109558 | 0.109558 | 23.7205 | 0.008218 | 77.83            |
| ap (μm)           | 1   | 0.000076 | 0.000076 | 0.0164  | 0.904318 | 0.05             |
| D (μm)            | 1   | 0.000689 | 0.000689 | 0.1492  | 0.718976 | 0.5              |
| Error             | 4   | 0.018475 | 0.004619 | 13.13   |         | 13.13            |
| Total             | 8   | 0.140753 |         | 100     |         |                  |

3.2 Grey relational analysis

Grey relational analysis (GRA) is accustomed to transforming several performance attributes into single attributes in grey relational grade. The main focus of the work is to select the optimal setting, which simultaneously minimized the effects of cutting forces (F_x and F_y), average surface roughness (R_a), and vibration on the workpiece (a_z). Procedure steps of GRA are such that:

Step 1 Data pre-processing and define reference sequence

Experimental values of micromilling forces (F_x and F_y), average surface roughness (R_a), and vibration on the top face of the workpiece plate are normalized between 0 to 1 using GRA. In the case of GRA, three kinds of normalization methods are used to normalize the experimental data, such as (i) larger-the-better, (ii) smaller-the-better (iii) specific target value. Since in the present study, the vibration (a_z), cutting forces (F_x and F_y), and the surface roughness (R_a) are to be minimized; hence the “smaller-the-better” condition is adapted. The cutting forces surface roughness and vibration on the workpiece (a_z) are normalized (Nor.) following the smaller-the-better procedure expressed as:
\[ x_i^* (k) = \frac{\max (x^0_i (k)) - x_i^0 (k)}{\max (x^0_i (k)) - \min (x_i^0 (k))} \]  

(2)

Where, \( x_i^* (k) \) depicts the normalized value of \( k^{th} \) performance in the \( i^{th} \) experiment, the original sequence is \( x_i^0 (k) \). \( \max x_i^0 (k) \) and \( \min x_i^0 (k) \) are the highest and lowest value of \( x_i^0 (k) \) for the \( k^{th} \) characteristic; where \( k = 1,2, \ldots, m \) number of performances characteristics or responses, \( i = 1,2, \ldots, n \) number of experimental runs. In this experimental study, \( k \) being 1 for vibration (ax), 2 for cross-feed force (Fx), feed force (Fy), and surface roughness (Ra), and \( i = 1,2, \ldots, 9 \).

The performance of experiment \( i \) is the best choice for performance characteristics or objective function \( k \), if the normalization value \( x_i^* (k) \) is 1 or nearer to 1. Thus, a reference sequence \( x_i^0 (k) = 1 \) (for \( k = 1,2, \ldots, m \)) is used to compare comparability sequences. Comparability sequences are nothing but the normalized values of the series of experiments \( i \). Normalized values for vibration (ax), surface roughness (Ra), and cutting forces (Fx, and Fy) are calculated by using Eq. 2. The results are shown in Table 7.

**Step 2 Calculations of grey relational coefficients**

Grey relational coefficients (GRC) are quantified to express the interrelationship between the ideal and the actual experimental results.

\[ \gamma (x_i^0 (k), x_i^* (k)) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{\min} (k) + \zeta \Delta_{\max}} \]  

(3)

where, \( \Delta_{\min} (k) \) is the variation of reference sequences \( x_i^0 (k) \) and normalized value \( x_i^* (k) \) of \( k^{th} \) performance in \( i^{th} \) experiment.

\( \Delta_{\min} = \min \{ \min_i \Delta_{\max} \} \) and \( \Delta_{\max} = \max \{ \max_i \Delta_{\max} \} \) and \( \zeta \) is the distinguishing coefficient set between 0 and 1 [17]. In the present study, it is considered \( \zeta \) is equal to 0.5. GRC of outcomes are computed using Eq. 3 shown in Table 8.

**Table 7. Normalized values of the outcomes**

| Exp. no. | \( a_x (m/s^2) \) | \( F_x \) (N) | \( F_y \) (N) | \( R_a \) (μm) | Nor. \( a_x \) | Nor. \( F_x \) | Nor. \( F_y \) | Nor. \( R_a \) |
|---------|------------------|---------------|---------------|----------------|--------------|--------------|--------------|--------------|
| 1       | 0.68965          | 0.10686       | 0.20074       | 0.127          | 1            | 1            | 1            | 0.9319       |
| 2       | 0.75993          | 0.37211       | 0.36557       | 0.1333         | 0.75968      | 0.41941      | 0.53078      | 0.91012      |
| 3       | 0.80699          | 0.40723       | 0.42352       | 0.23           | 0.59877      | 0.34254      | 0.36582      | 0.57587      |
| 4       | 0.71772          | 0.27615       | 0.30182       | 0.27           | 0.90401      | 0.62946      | 0.71226      | 0.4376       |
| 5       | 0.86077          | 0.31723       | 0.35352       | 0.323          | 0.41487      | 0.53954      | 0.56508      | 0.2544       |
| 6       | 0.85843          | 0.43968       | 0.55203       | 0.3966         | 0.42287      | 0.27151      | 0             | 0             |
| 7       | 0.84482          | 0.21685       | 0.24109       | 0.1073         | 0.46941      | 0.75926      | 0.88513      | 1             |
| 8       | 0.81673          | 0.37346       | 0.46218       | 0.38           | 0.56546      | 0.41646      | 0.25771      | 0.05737      |
| 9       | 0.9821           | 0.56372       | 0.54115       | 0.3722         | 0             | 0            | 0.03097      | 0.08434      |
Step 3 Calculations of grey relational grades

Grey relational grade (GRG) is obtained by averaging the GRC, which is shown in Table 8. Higher the GRG indicates the result nearer to optimal condition. The “Larger–the-better” condition is used in the case of the grey relational grade. Signal to noise ratio of larger-the-better is calculated using the following Eq. 4:

$$\frac{S}{N} \text{ ratio } (\eta) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right)$$  \hspace{1cm} (4)

Table 8. Grey relational coefficients

| Exp. no. | GRC of $a_z$ | GRC $F_x$ | GRC $F_y$ | GRC $R_a$ | (GRG)  |
|----------|--------------|-----------|-----------|-----------|--------|
| 1        | 1            | 1         | 1         | 0.88013   | 0.97003|
| 2        | 0.67538      | 0.46271   | 0.51587   | 0.48763   | 0.62539|
| 3        | 0.55479      | 0.43198   | 0.404084  | 0.54105   | 0.49216|
| 4        | 0.83894      | 0.57436   | 0.63473   | 0.47063   | 0.62966|
| 5        | 0.46077      | 0.52058   | 0.5348    | 0.40141   | 0.47939|
| 6        | 0.46419      | 0.407     | 0.33333   | 0.33333   | 0.38446|
| 7        | 0.48515      | 0.675     | 0.81318   | 1         | 0.74333|
| 8        | 0.53502      | 0.46145   | 0.40248   | 0.34658   | 0.43638|
| 9        | 0.33333      | 0.33333   | 0.34036   | 0.35319   | 0.34005|

From the plots, N1 $f_z$1 $a_p$3 D2 is found to be optimum conditions, which can also be concluded from S/N ratio plots, as shown in Fig. 4. The confirmatory experiment is conducted at optimal condition N1 $f_z$1 $a_p$3 D2. From confirmatory result, it is found the optimised parametric combination produced $F_x = 0.11194$ N, $F_y = 0.17713$N, $R_a = 0.1133$, and $a_z = 0.40385$ m/s².

Figure 4. Main effects graph of S/N ratios for the GRG
Table 9 shows the ANOVA results of GRG of multi-response variables. As estimated, the percentage contribution of rotational speed, feed per tooth, depth of cut, and cutter diameter in multiple performance characteristics are 17%, 66.91%, 0.31%, and 3.23%, respectively.

| Source                  | DF | Seq SS   | Adj MS   | F ratio | P value | Contribution (%) |
|-------------------------|----|----------|----------|---------|---------|------------------|
| Regression              | 4  | 0.276361 | 0.069090 | 6.9675  | 0.043304 |                  |
| N (rpm)                 | 1  | 0.053737 | 0.053737 | 5.4191  | 0.080437 | 17               |
| f<sub>s</sub> (μm/tooth)| 1  | 0.211444 | 0.211444 | 21.3232 | 0.009898 | 66.91            |
| a<sub>p</sub> (μm)      | 1  | 0.000962 | 0.000962 | 0.0971  | 0.770954 | 0.31             |
| D (μm)                  | 1  | 0.010218 | 0.010218 | 1.0305  | 0.367459 | 3.23             |
| Error                   | 4  | 0.039665 | 0.009916 |         |         | 12.55            |
| Total                   | 8  | 0.316026 |          |         |         |                  |

3.3 Fast Fourier transform (FFT) analysis of vibration

FFT analysis of vibration signal acquired for various combinations of cutting parameters are illustrated in Figs. 5-7. FFT depicts amplitude versus frequency plot in which the unit of amplitude is m/s<sup>2</sup>, and frequency is denoted as Hz.

**Figure 5.** FFT analysis for 200 μm diameter tool at different micro-milling conditions: (a) N = 45000 rpm, f<sub>s</sub> = 0.2 μm/tooth, a<sub>p</sub> = 30 μm; (b) N = 15000 rpm, f<sub>s</sub> = 0.6 μm/tooth, a<sub>p</sub> = 20 μm; (c) N = 30000 rpm, f<sub>s</sub> = 1 μm/tooth, a<sub>p</sub> = 10 μm

**Figure 6** FFT analysis for 100 μm diameter tool at different micro-milling conditions: (a) N = 15000 rpm, f<sub>s</sub> = 0.2 μm/tooth, a<sub>p</sub> = 10 μm (b) N = 30000 rpm, f<sub>s</sub> = 0.6 μm/tooth, a<sub>p</sub> = 30 μm (c) N = 45000 rpm, f<sub>s</sub> = 1 μm/tooth, a<sub>p</sub> = 20 μm
Figure 5(a-c) illustrates the influence of machining parameters on FFT analysis of vibration signals for cutting tool diameter 200 μm. Higher amplitude at frequency 11820 Hz was obtained in case of first of three experiment condition (refer Fig. 5 (a)) as followed by Fig. 5 (b,c) because of low feed per tooth, which causes ploughing and minimum chip thickness effects resulted in a higher vibration. Similarly, effects are observed in the case of 100 and 500 μm diameter cutting tools due to the ploughing phenomenon. The larger tool diameter shows lower vibration amplitude than the other two diameters due to better stiffness and less susceptible to tool wear (Refer Figures. 5-7).

![ FFT analysis plots for different cutting tool diameters. ]

**Figure 7.** FFT analysis for 500 μm diameter tool at different micro-milling conditions: (a) N = 30000 rpm, f_z = 0.2 μm/tooth, a_p = 20 μm (b) N = 45000 rpm, f_z = 0.6 μm/tooth, a_p = 10 μm (c) N = 15000 rpm, f_z = 1 μm/tooth, a_p = 30 μm

### 4. Conclusions

In this investigation, the grey relational analysis was applied to optimize the micro-milling conditions, namely spindle speed, feed per tooth, depth of cut, and cutter diameter for better machinability indices of Ti6Al4V alloy. On the other hand, the optimum condition for feed force, cross-feed force, surface roughness, and vibration were determined using Taguchi’s S/N ratio. From S/N interpretation, it was found that the optimum values for minimum F_y were N =15000 rpm, f_z= 0.2 μm/tooth, a_p=30 μm, and D =100 μm. For feed force, optimum factors were N=15000 rpm, f_z= 0.2 μm/tooth, a_p = 10 μm, and D = 100 μm. For surface roughness, optimum factors were N = 15000 rpm, f_z = 0.2 μm/tooth, a_p = 30 μm, and D =200 μm. The optimum condition for vibration was N = 15000 rpm, f_z = 0.2 μm/tooth, a_p = 10 μm, and D = 500 μm. For multi-response variables, the optimum condition for multi-response variables, i.e., higher grey relation grade was obtained in N = 15000 rpm, f_z = 0.2 μm/tooth, a_p = 30 μm, and D = 200 μm. The FFT plots revealed that larger tool diameters (500 μm) experienced lower vibration amplitude than the other two diameters due to better stiffness and less susceptibility to tool wear. Further, this investigation may lead to the use of small diameter coated tools and sustainable environments for micro-milling of titanium and nickel-based superalloys.

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