2021

Modeling and optimization of process parameters in face milling of Ti6Al4V alloy using Taguchi and grey relational analysis

Al Mazedur Rahman
The University of Texas Rio Grande Valley

S M Abdur Rob
The University of Texas Rio Grande Valley

Anil K. Srivastava
The University of Texas Rio Grande Valley

Recommended Citation

Rahman, Al Mazedur, SM Abdur Rob, and Anil K. Srivastava. "Modeling and optimization of process parameters in face milling of Ti6Al4V alloy using Taguchi and grey relational analysis." Procedia Manufacturing 53 (2021): 204-212. https://doi.org/10.1016/j.promfg.2021.06.023

Available online at www.sciencedirect.com

ScienceDirect

Procedia Manufacturing 53 (2021) 204–212

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

f49th SME North American Manufacturing Research Conference, NAMRC 49, Ohio, USA

Modeling and optimization of process parameters in face milling of Ti6Al4V alloy using Taguchi and grey relational analysis

Al Mazedur Rahman[a*], S M Abdur Rob[a], Anil K. Srivastava[a]

[a]*University of Texas Rio Grande Valley,1201 W University Dr, Edinburg, TX 78539, USA*

* Corresponding author. Tel: +1 9565296021; *E-mail address:* almazedurrahman@gmail.com

Abstract

Titanium alloys are extensively used in aerospace, missiles, rockets, naval ships, automotive, medical devices, and even the consumer electronics industry where a high strength to density ratio, lightweight, high corrosion resistance, and resistance to high temperatures are important. The machining of these alloys has always been challenging for manufacturers. This article investigates the combined effect of radial depth, cutting speed and feed rate on cutting forces, tool life, and surface roughness during face milling of Ti6Al4V alloy. This study focuses on the significance of radial depth of cut on cutting force, tool life and surface roughness compared to that of cutting speed and feed rate during face milling of Ti6Al4V alloy. In this paper, mono and multi-objective optimization of the response characteristics have been conducted to find out the optimal input parameters, namely, cutting speed, feed rate, and radial depth of cut. Taguchi method and analysis of variance (ANOVA) analysis have been used for mono-objective optimization, while Taguchi-based grey relational analysis has been used for multi-objective optimization. The regression analysis has been performed for developing mathematical models to predict the surface roughness, tool life, and cutting forces. According to ANOVA analysis, the most significant parameters for tool life and cutting force (F_Y) are cutting speed, and radial depth of cut, respectively, while feed rate is observed to be the most significant parameter for surface roughness and force (F_X). The optimal combination of input parameters for tool life and F_Y are 50m/min cutting speed, 0.02mm/rev feed rate, and 7.5mm radial depth of cut. However, the optimal parameters for surface roughness are 65m/min cutting speed, 0.02mm/rev feed rate, and 7.5mm radial depth of cut. For F_X, the optimal condition is observed as cutting speed 57.5m/min, 0.02mm/rev feed rate, and 7.5mm radial depth of cut. A validation experiment, conducted at the optimal parameters of surface roughness, shows an improvement of 31.29% compared to the surface roughness at initial condition. Taguchi-based grey relational analysis for multi-objective optimization shows an improvement of 55.81%, 6.12%, and 23.98% in tool life, surface roughness, and F_Y, respectively. ANOVA analysis based on grey relational grade shows that the radial depth of cut is the most significant parameter for multi-objective optimization during the face milling of Ti6Al4V.

Keywords: Titanium, Face milling, Taguchi method, Tool life, Surface roughness, Cutting Forces, Optimization, Grey relational analysis

1. Introduction

Titanium and its alloys have some extraordinary properties such as extreme corrosion and fracture resistance, high strength-to-density ratio, and unique performance at elevated temperatures. These alloys are about 40% lighter but possess almost similar mechanical and physical properties to steel. Due to these characteristics, titanium alloys are extensively used in the aircraft engine, airframe manufacturing, and military applications for decreasing the weight and enhancing durability in extreme circumstances for increasing mobility and battle efficiency [1,2]. As these alloys show high load-bearing capacity and biocompatibility, these are also used in bridges, implants, chemical, automobile, marine, and biomedical industries [3,4].

Despite having unique properties, titanium alloys are considered as difficult to cut materials. Titanium alloys have high heat capacity, low thermal conductivity, and diffusivity along with low elastic modulus, high chemical reactivity at a higher temperature, and high rigidity [5]. As there is lower heat

10.1016/j.promfg.2021.06.023

dissipation by the chips and workpiece, high thermal stress develops at the cutting edge of the tooltip [6,7]. Due to the low thermal conductivity of Ti6Al4V, the cutting tip absorbs 30% more heat compared to steel [8]. Due to these reasons, a high heat accumulates at the cutting edge of the cutting tool resulting in accelerated tool wear and rapid tool failure [9]. The machining performance can be improved by coating the cutting tool with different techniques, introducing different cooling methods, and/or optimizing parameters for machining.

Surface roughness is considered as one of the most important quality characteristics for determining the machining accuracy and surface quality. Better surface quality facilitates improvements in various characteristics such as corrosion and wear resistance, fatigue strength, friction, etc. To minimize the production cost, manufacturers focus on increasing tool life or reducing tool wear. Tool wear has a significant effect on cutting forces, which play a key role in measuring power consumption and designing of the cutting tool [10]. Therefore, tool life, cutting forces, and surface roughness have been considered for optimization as the performance characteristics in this study.

Saini et al. optimized the process parameters (cutting speed, feed rate, and axial depth of cut) of surface roughness, tool wear, and tool vibration during the face milling of Ti6Al4V alloy using an uncoated carbide insert with Response Surface methodology [11]. Vijay & Krishnaraj performed single objective optimization of cutting forces and surface roughness by varying three cutting parameters as input factors (cutting speed, feed rate, and axial depth of cut) using ANOVA and Taguchi method, where the authors observed that the axial depth of cut and feed per tooth were the most significant input parameters for cutting forces and surface roughness respectively during end-milling of Ti6Al4V alloy [12]. Hassan & Zhen-Qiang studied the effects of cutting parameters (cutting speed, feed rate, and axial depth of cut) on tool life, surface roughness, and material removal rate by using Taguchi analysis and ANOVA and obtained that feed rate was the most significant among the cutting parameters in multi-objective optimization [13]. Kuram & Ozcelik applied the Taguchi method and ANOVA to investigate the impact of input parameters, namely, cutting speed, feed rate, and axial depth of cut on output characteristics (tool wear, surface roughness, and cutting forces) during micro-milling of Ti6Al4V alloy and developed corresponding mathematical models by regression analysis to predict the performance characteristics [14].

Single objective optimization is widely used for optimizing various response characteristics. But this process is not capable of finding the optimized combination of cutting parameters that can improve the multiple output characteristics simultaneously. For solving this problem, various multi-objective optimization techniques have been used in previous studies such as Taguchi-based Grey Relational Analysis, Genetic Algorithm, etc. Recently, Taguchi based Grey Relational Analysis (GRA) has been a popular statistical tool to optimize the complex multi-objective machining systems. It was developed by Deng to find the correlation between input parameters and output characteristics using Grey Relational Grade [15]. Aslantas et al. investigated the micro-milling process of Ti6Al4V alloy using Taguchi-based grey relational analysis for optimization of multiple quality characteristics (surface roughness and burr width) based on the variation of cutting parameters [16]. Du et al. performed the multi-objective optimization of surface roughness, surface microhardness, and surface residual stress by the Taguchi-grey relational analysis method for different cutting parameters during high-speed milling of titanium alloy TB17 [17]. Sarikaya et al. optimized both mono and multi-response characteristics of milling AISI 1050 Steel using Taguchi and Grey relational analysis where the axial depth of cut, feed rate, cutting speed, and type of inserts were used as input parameters [18].

Literature survey reveals that for multi-objective optimization (tool life, surface roughness, and cutting forces) of the face milling of Ti6Al4V alloy, Taguchi-based grey relational analysis has not been applied before. Besides, in most of the research articles, authors have optimized the performance characteristics based on the variation of cutting speed, feed rate, and axial depth of cut, while the radial depth of cut can also be a significant factor in the milling of Ti6Al4V alloy [19].

In order to investigate the impact of radial depth of cut on cutting forces, surface roughness, and tool life during face milling of Ti6Al4V alloy, ANOVA and Taguchi analysis have been applied in this study for mono-objective optimization, and Taguchi-based grey relational analysis has been used for performing multi-objective optimization. Moreover, mathematical models for tool life, surface roughness, and cutting forces (F_X, F_Y) have been developed through regression analysis to predict the corresponding response characteristics.

Nomenclature

S/N	Signal to Noise ratio
$x_i(k)$	Response values after grey relational generation
ψ_i	Grey relational grade
δ_{0i}	Difference between absolute value $x_0(k)$ and $x_i(k)$
ϕ_i	Grey relational co-efficient for ith experiment
β	Coefficient of each term
k	Number of independent variables
ε	Error
SS_T	Total sum of squares
SS_m, SS_e	Mean of squares, Error sum of squares
Adj SS	Adjusted sum of squares
Adj MS	Adjusted mean of squares
Vc	Cutting Speed
f	Feed rate
a_e	Radial depth of cut
F_Y	Cutting force
F_X	Feed force
Ra	Average surface roughness
F test	Fisher test value
ζ	Distinguishing coefficient
$\hat{\theta}$	Estimated grey relational grade
θ_m	Mean of the grey relational grad
θ_i	Mean grey relational grade at the optimal level

2. Experimentation

2.1 Workpiece and tool materials

Face milling experiments were conducted using Ganesh VMC-1814 CNC milling machine. Ti6Al4V alloy of hardness 315-345 BHN was used as the workpiece material in this experiment. Mobilmet S-122 is used at a 1/15 ratio with water as coolant. The workpieces were prepared with a dimension of 152.4 mm×101.6 mm ×101.6 mm (Fig. 1 (a)). Square shaped carbide inserts were used in this study which were physical vapor deposition (PVD) coated with TiN+TiAlN (Fig. 1 (b)). The inserts were of F40M grade with a 0° rake angle.

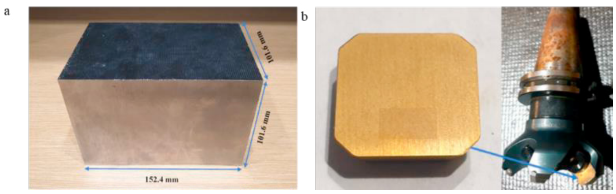

Fig. 1. (a) workpiece; (b) cutting insert and tool holder.

2.2 Design of Experiments using Taguchi Method

In this study, face milling experiments of titanium alloy were designed using the Taguchi design of experiment (DOE) where Taguchi's L9 orthogonal array was used. Cutting speed, feed rate, and radial depth of cut were selected as input factors while cutting forces, surface roughness, and tool life were considered as response characteristics. Levels of input factors and corresponding Taguchi's L9 orthogonal array are shown in Table 1 and Table 2, respectively. Levels of all the factors and the range of parameters were determined based on some trial experiments, and the axial depth of cut was fixed at 2.54 mm.

Table 1. Factors and corresponding levels.

Factors	Level 1	Level 2	Level 3
Cutting speed (m/min)	50	57.5	65
Feed rate (mm/rev)	0.2	0.25	0.3
Radial depth of cut (mm)	7.5	10	12.5

Table 2. DOE using Taguchi L9 orthogonal array.

Experiment	Level of factors		
	Cutting Speed	Feed rate	Radial Depth of cut
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	3
5	2	2	1
6	2	3	2
7	3	1	2
8	3	2	3
9	3	3	1

2.3 Cutting forces, surface roughness and tool wear measurements

Kistler 9255C milling dynamometer was used to measure the cutting forces. A fixture specially made for holding the workpiece was set over the dynamometer and a charge amplifier was used to transfer the corresponding force signal, which was then processed using DynoWare software.

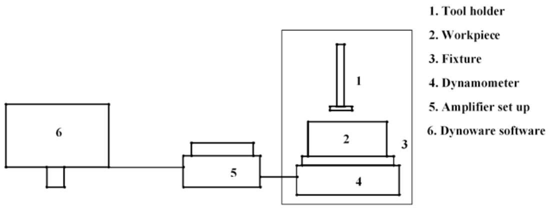

Fig. 2. Schematic diagram of the experimental setup.

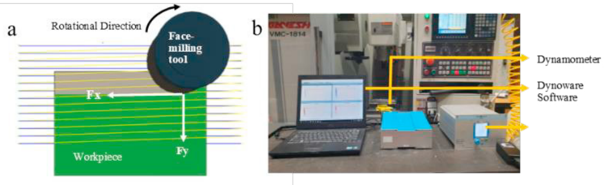

Fig. 3. (a) Force measurement set up; (b) Tool path and cutting force direction.

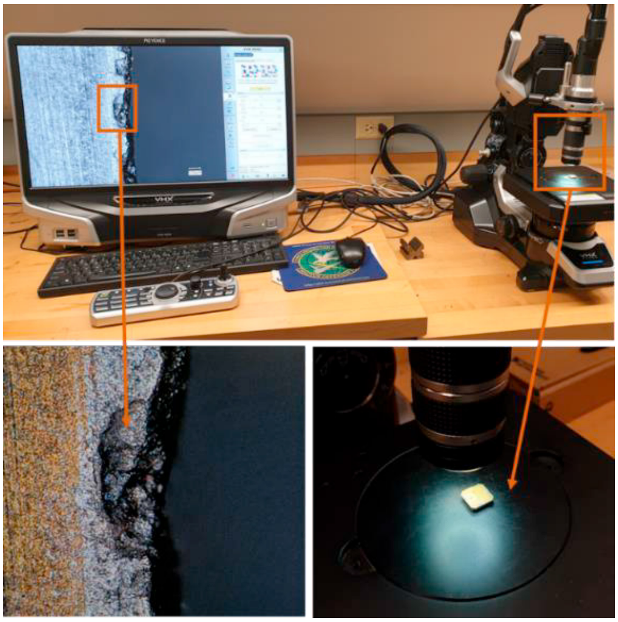

Fig. 4. Tool wear measurement.

The complete schematic diagrams of the experimental setup and force measurements are shown in Fig. 2 and Fig. 3, respectively.

Tool wear was measured using a Keyence VHX-5000 optical microscope. The criteria for maximum tool life corresponded to 0.3 mm flank wear. MahrSurf M 300 C profilometer was used to measure the workpiece surface roughness. Fig. 4 andFig. 5 show the tool wear and surface roughness measurement setup, respectively.

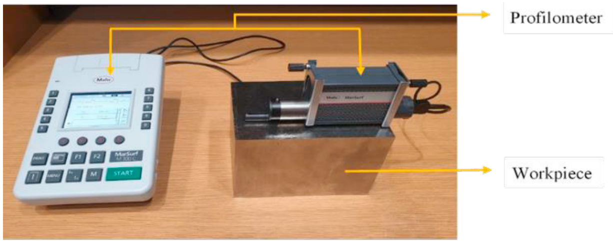

Fig. 5. Surface roughness measurement set up.

3. Results and Discussion

Non-uniform flank wear was found throughout the experiment. Fig. 6 depicts the tool wear from the top view and 45° angle view to get a better observation. The wear in the minor cutting edge was too small to be considered significant for measuring tool life; hence flank wear was measured as the dominant tool wear to find the maximum tool life. When the flank wear reaches 300µm, the corresponding tool life is considered maximum. Flank wear was measured each time after cutting 152.4 mm length of the workpiece. Fig. 7 demonstrates the variation of flank wear with machining time at different machining parameters where a sharp increase in wear was found both at the beginning and the end of the experiments.

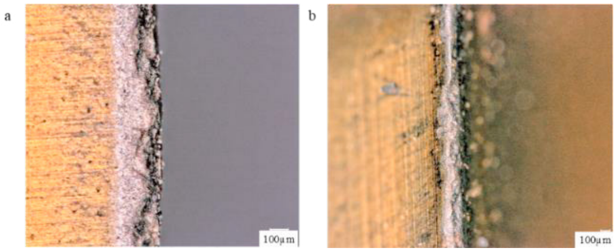

Fig. 6. Tool wear during face milling of Ti6Al4V alloy at feed rate 0.25mm, cutting speed 50m/min and radial depth of cut 10mm (a) top view; (b) view at a 45-degree angle.

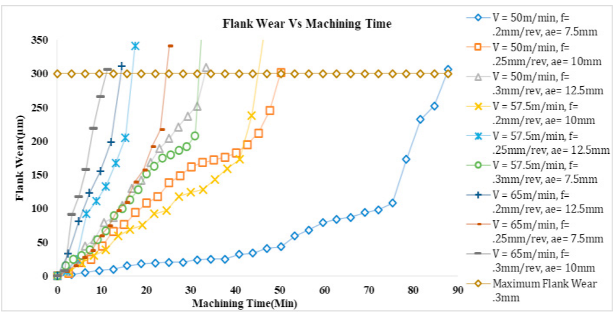

Fig. 7. Variation of Flank wear with machining time at different machining parameter values.

Surface roughness is considered as a vital machining characteristic to evaluate the machining accuracy. Although many factors can have significant impacts on the machined surface, parameters such as cutting speed, feed, and radial depth of cut were varied in this study to find an optimum average surface roughness, Ra. After cutting every 152.4 mm length of the workpiece, Ra was measured at five different places of the machined surface, and then an average value of Ra was taken for every pass to draw the graph, as shown in Fig. 8. In the average surface roughness vs. cutting time graph, some sharp changes were observed in some places due to the fact that the hardness value of the workpiece material was not uniform throughout the whole workpiece [22]. An optical microscopic view of the machined surface is shown in Fig. 9.

The dynamic cutting force has been found to have the most significant impact on tool wear during the face milling process. The vibration caused due to this force results in increased surface roughness.

Average cutting forces were measured in F_X and F_Y direction, as shown in Fig. 10 where, Fz was not considered in this study. Peak to valley (P-to-V) of F_X and F_Y were measured for each 152.4 mm pass and used for the analysis, which are shown in Fig. 11 and Fig. 12, respectively.

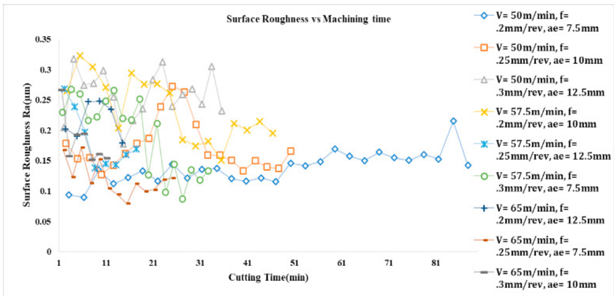

Fig. 8. Average surface roughness vs. Machining time at different machining parameter values.

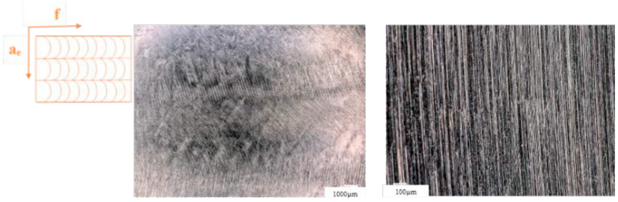

Fig. 9. Optical Microscopic view of workpiece Surfaces at feed .2mm/rev, cutting speed 50m/min and radial depth of cut 7.5mm.

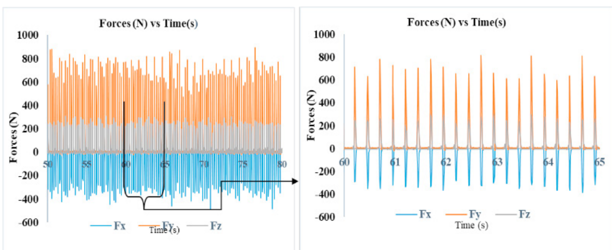

Fig. 10. Cutting force vs. Time graph obtained at feed rate 0.2mm/rev, cutting speed 50m/min and radial depth of cut 7.5 mm.

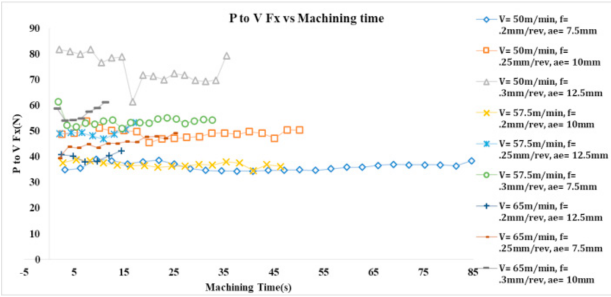

Fig. 11. P-to-V F_X vs. Machining time at different machining parameter values.

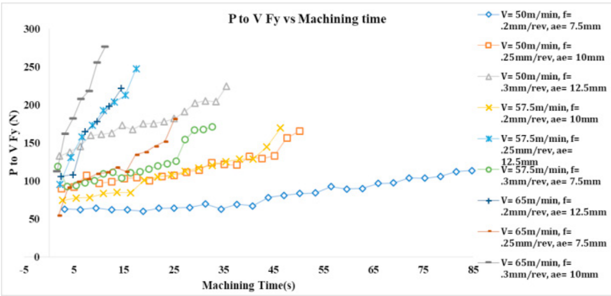

Fig. 12. P-to-V F_Y vs. Machining time at different machining parameter values.

3.1 Signal to Noise (S/N) ratio analysis

Minitab 19 software was used to perform the Taguchi and regression analysis. The impacts of different levels of input parameters on the output characteristics were analyzed using the Signal to Noise (S/N) ratio. During the optimization of cutting forces and surface roughness, the smaller the better characteristic was chosen, and for tool life the larger the better characteristic was chosen, which are shown in Table 3. Fig. 13 illustrates the main effects of S/N ratios, where the optimal parameters are highlighted in red circles. The highest signal to noise ratio indicates the optimal level.

Table 3. Experiment results.

Experiment Number	Tool Life Result (min)	Ra Result (μm)	P-to-V F_X Result (N)	P-to-V F_Y Result (N)
1	87.860	0.138	36.080	82.450
2	50.200	0.173	49.040	115.710
3	33.470	0.260	74.350	175.250
4	56.390	0.147	36.140	108.460
5	17.460	0.182	49.360	176.690
6	32.740	0.192	53.822	121.800
7	14.480	0.153	39.938	162.740
8	25.100	0.119	45.258	119.070
9	11.260	0.182	57.091	202.300

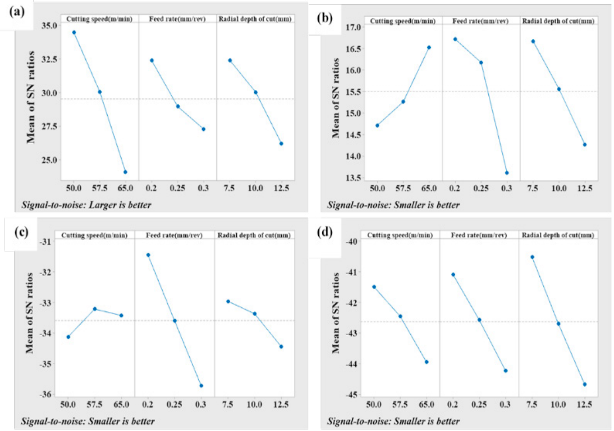

Fig. 13. Main effects plot of S/N ratios for (a) Tool life, (b) Surface roughness, (c) P-to-V FX, (d) P-to-V FY during face milling of Ti6Al4V.

The optimal condition of cutting parameters for surface roughness was found A3B1C1 as shown in Fig. 13 (b), which corresponds to cutting speed 65 m/min, feed rate 0.2 mm/rev, and radial depth of cut 7.5 mm. Surface roughness increased with the decrease in cutting speed and with the increase in feed rate and radial depth of cut. Higher cutting speed results in higher temperatures in the cutting zone, which softens the workpiece material. As a result, machining vibration reduces, and therefore surface roughness Ra reduces. A higher feed rate increases mechanical load and metal removal rate resulting in higher vibrations and material resistance respectively, therefore, the surface quality deteriorates. A similar study was found in the literature [26]. With the decrease in radial depth of cut, the contact area between tool and workpiece decreases, resulting in a reduction in friction between the cutting tool and workpiece surface. As a result, the average surface roughness value decreases.

The optimal condition for P-to-V F_X was found A2B1C1 as shown in Fig. 13 (c), which corresponds to cutting speed 57.5m/min, feed rate 0.2mm/rev, and radial depth of cut 7.5mm and optimum setting for P-to-V F_Y was found A1B1C1 as shown in Fig. 13 (d), which corresponds to cutting speed 50m/min, feed rate 0.2mm/rev, and radial depth of cut 7.5mm. With the increase in feed rate and depth of cut, both P-to-V F_X and P-to-V F_Y increased. For P-to-V F_X, the force decreased initially and then started increasing again with the increase in cutting speed. For P-to-V F_Y, the force increased with the increase in cutting speed. Higher feed rate and radial depth of cut result in a larger contact area and contact length between the workpiece and cutting tool, raising the cutting forces. Similar conclusions were made by J. Park et al. [27].

3.2 ANOVA analysis

For evaluating the significant factors which affect the expected response parameters, ANOVA is performed using a 95% confidence level. Results of ANOVA analysis are shown in Table 4, Table 5, Table 6, Table 7.

Based on Table 4, cutting speed had the highest impact on tool life. Cutting speed showed a significant contribution of 50.06%, and feed rate and radial depth of cut showed 25.59% and 22.80%, respectively. From the experimental findings shown in Fig. 14 (a), the highest S/N ratio (34.461) was found for the lowest cutting speed, which is consistent with ANOVA analysis. F values showed that all the input parameters were statistically significant for tool life.

Table 4. ANOVA results for Tool life (min).

Source	DF	Seq SS	Adj SS	Adj MS	F Value, $\alpha < 0.05$	Contribution
Cutting speed (m/min)	2	2432.37	2432.37	1216.19	32.32	50.06%
Feed rate (mm/rev)	2	1243.22	1243.22	621.61	16.52	25.59%
Radial depth of cut (mm)	2	1108.01	1108.01	554.00	14.72	22.80%
Error	2	75.26	75.26	37.63		1.55%
Total	8	4858.87				100.00%

SS = Sum of Squares; Adj SS= Adjusted Sum of Squares; Adj MS = Adjusted Mean of Squares; DF = Degree of Freedom

According to Table 5,the impact of cutting speed, feed rate, and radial depth of cut on surface roughness are 17.28%, 54.58%, and 27.39%, respectively. So, the feed rate was the most influential parameter for surface roughness. The same result was obtained from the experimental analysis shown in Fig. 14 (b) where, the highest S/N ratio was obtained for the lowest feed rate (16.72 dB). From literature, a similar result was found [13]. All the input parameters were found statistically significant for surface roughness according to their F values.

Table 5. ANOVA results for Surface Roughness (μm).

Source	DF	Seq SS	Adj SS	Adj MS	F-Value, $\alpha < 0.05$	Contribution
Cutting speed (m/min)	2	0.002298	0.002298	0.001149	23.08	17.28%
Feed rate (mm/rev)	2	0.007257	0.007257	0.003628	72.89	54.58%
Radial depth of cut (mm)	2	0.003642	0.003642	0.001821	36.58	27.39%
Error	2	0.000100	0.000100	0.000050		0.75%
Total	8	0.013296				100.00%

From Table 6, it was found that P-to-V F_X was mostly influenced by feed rate. Cutting speed, feed rate, and radial depth of cut had 6.80%, 77.28%, and 12.64% contribution, respectively. From the F values, it was found that the feed rate was the most significant parameter that affects P-to-V F_X. Similarly, the experimental analysis also (Fig. 14 (c)) showed that the lowest feed rate provided the maximum S/N ratio (-31.44 dB). A similar result was found in the previous study [14]. However, the radial depth of cut was found insignificant for P-to-V F_X.

Table 6. ANOVA results for P-to-V F_X (N).

Source	DF	Seq SS	Adj SS	Adj MS	F-Value, $\alpha < 0.05$	Contribution
Cutting speed (m/min)	2	78.88	78.88	39.44	2.07	6.80%
Feed rate (mm/rev)	2	896.40	896.40	448.20	23.56	77.28%
Radial depth of cut (mm)	2	146.57	146.57	73.28	3.85	12.64%
Error	2	38.04	38.04	19.02		3.28%
Total	8	1159.89				100.00%

The most important machining parameter for P-to-V F_Y was the radial depth of cut and it had a 48.34% contribution, as shown in Table 7. The contribution of cutting speed and feed rate was 16.98% and 28.36%, respectively. From the F values, it can be concluded that only radial depth of cut and feed rate were statistically significant. A previous study also showed similar results [12]. The error in P-to- F-Y ANOVA analysis was found above 5%. While taking the Dynamometer data for maximum cutting speed and radial depth of cut, the cutting tool had some unusual tool chipping, resulting in a deviation from the actual cutting force. In some cases, the tool wear crossed the 0.3 mm limit in the middle of the run, but the data was being taken until the run finished. While performing the analysis, those deviations resulted in a 1.32% error over the allowable 5% error. The obtained models from the analysis demonstrated acceptable results compared to the actual experimental results.

Table 7. ANOVA results for P-to-V F_Y (N).

Source	DF	Seq SS	Adj SS	Adj MS	F-Value, $\alpha < 0.05$	Contribution
Cutting speed (m/min)	2	2148.1	2148.1	1074.0	2.69	16.98%
Feed rate (mm/rev)	2	3588.2	3588.2	1794.1	4.49	28.36%
Radial depth of cut (mm)	2	6115.5	6115.5	3057.7	7.65	48.34%
Error	2	799.1	799.1	399.5		6.32%
Total	8	12650.9				100.00%

3.3 Regression Analysis

Statistical software Minitab 19 was used for developing mathematical models and the first-order models, which are illustrated as follows-

$$\text{Tool life}\left(\text{min}\right) = 312.0 - 2.682\ V_c - 270.9\ f - 5.35\ a_e \qquad (1)$$

$$R^2 = 94.73\%; R^2\left(\text{adj}\right) = 91.56\%$$

$$R_a\left(\mu\text{m}\right) = 0.0606 - 0.002600\ V_c + 0.653\ f + 0.00973\ a_e \qquad (2)$$

$$R^2 = 92.04\%; R^2\left(\text{adj}\right) = 87.26\%$$

$$P - \text{to} - V\ Fx\left(N\right) = -8.9 - 0.382\ V_c + 243.7\ f + 1.899\ a_e \qquad (3)$$

$$R^2 = 92.70\%; R^2\left(\text{adj}\right) = 88.32\%$$

$$P - \text{to} - V\ Fy\left(N\right) = -249.9 + 2.460\ V_c + 486\ f + 12.76\ a_e \qquad (4)$$

$$R^2 = 92.35\%; R^2\left(\text{adj}\right) = 87.76\%$$

3.4 Grey Relational Analysis

A level average analysis was performed to explain the results by combining the data of different levels of factors. The greatest difference between the highest and the lowest average responses of any factor is defined as the measurement of the largest effect of that factor. Data preprocessing was performed for all the response characteristics, and the corresponding results are shown in Table 8. Grey Relational coefficient and grey Relational Grade were computed which are shown in Table 9. Tool life, surface roughness Ra, and P-to-V F_Y were considered for multi-objective optimization in this study.

Table 8. Data pre-processing for each performance characteristics.

Run	Tool life $\delta_{Oi}(1)$	P-to-V F_Y $\delta_{Oi}(2)$	Ra $\delta_{Oi}(3)$
1	1.000	1.000	0.865
2	0.508	0.722	0.617
3	0.290	0.226	0.000
4	0.589	0.783	0.801
5	0.081	0.214	0.553
6	0.280	0.672	0.482
7	0.042	0.330	0.759
8	0.181	0.694	1.000
9	0.000	0.000	0.553

The difference between the high and low effect of each factor was used to find the statistic delta, and then a classification was done for finding the foremost influential factor. This process converts the multi-objective optimization problem into a one-objective optimization problem. The condition having a higher grey relational grade will be nearer to the optimal state. The mean of each level of the factors and the total mean of the grey relational grade are calculated using the grey relational grade values obtained in Table 9, which are shown in Table 10. By using the main effect analytical computation method, a response graph is obtained (Fig. 14), which shows that the optimal condition for these experiments is A1B1C1, which corresponds to 50 m/min cutting speed, 0.2 mm feed per revolution, and 7.5 mm radial depth of cut.

According to Table 10, the radial depth of cut has the largest effect on the response characteristics, while cutting speed has the least significant effect.

Table 9. Grey relational coefficient (ξi) of each performance output and grey relational grade (ψ_i).

Run	Grey Relational Coefficient			Grey Relational Grade	Rank
	Φ (1)	Φ (2)	Φ (3)	ψ_i	
1	1.000	1.000	0.788	0.929	1
2	0.504	0.643	0.566	0.571	3
3	0.413	0.392	0.333	0.380	9
4	0.549	0.697	0.716	0.654	4
5	0.352	0.389	0.528	0.423	7
6	0.410	0.604	0.392	0.502	5
7	0.343	0.427	0.580	0.482	6
8	0.379	0.621	1.000	0.667	2
9	0.333	0.333	0.427	0.398	8

Here, distinguishing coefficient ζ= 0.5 is considered.

Table 10. Response table for grey relational grade values.

Level	Cutting Speed	Feed	Radial depth of cut
1	0.627	0.688	0.699
2	0.526	0.554	0.541
3	0.515	0.427	0.428
Delta	0.112	0.261	0.271
Rank	3	2	1

Total mean grey relational grade 0.556

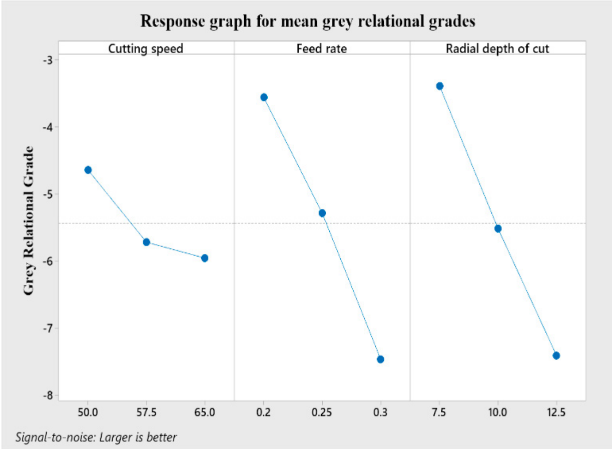

Fig. 14. Response graph for mean grey relational grades.

Table 11. ANOVA results for process factors.

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	Contribution
Cutting speed (m/min)	2	0.023	0.023	0.011	3.28	9.25%
Feed rate (mm/rev)	2	0.103	0.103	0.051	14.98	42.23%
Radial depth of cut (mm)	2	0.111	0.111	0.056	16.21	45.71%
Error	2	0.007	0.007	0.003		2.82%
Total	8	0.243				100.00%

From the ANOVA analysis shown in Table 11, it is observed that feed rate and radial depth of cut have 42.23%, and 45.71% contribution, respectively. The F value obtained from Table 11 infers that feed rate and radial depth of cut are the most significant factors affecting the multiple performance characteristics. The results also indicate that cutting speed has no significant impact on performance characteristics.

4. Confirmation Experiments

4.1 Prediction and Validation for the Taguchi Analysis

The last stage of Taguchi analysis is to conduct an additional experiment to validate the predicted response values, which is called a confirmation experiment. The confirmation experiment was done at the optimal parameters obtained during the analysis of surface roughness Ra. The predicted values for Tool life, Ra, P-to-V F_X, and P-to-V F_Y are compared with the measured values from the confirmation experiment as shown in Fig. 15 (a-d). In A3B1C1 validation experiment, the average percentage error for tool life, surface roughness Ra, P-to-V F_X and P-to-V F_Y were 0.39%, 6.32%, 0.13% and 10.59% respectively. The percent improvement of surface roughness Ra at optimal condition was 31.29%, shown in Table 12.

Table 12. Results of confirmation experiments.

Response Parameter	Initial Setting (A2B1C3)	Optimal Setting (A3B1C1)	Percentage Improved
Ra (µm)	0.147	0.101	31.29%

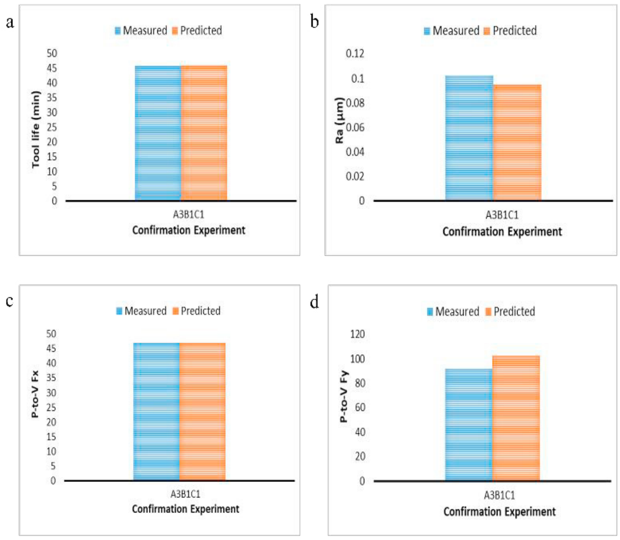

Fig. 15. Results of confirmation experiments (a) Tool life, (b) Ra, (c) P-to-V FX, (d) P-to-V FY.

It was observed that the predicted values obtained from the developed mathematical models in this study were very close to the measured results from the confirmation experiment. Thus, it can be concluded that the mathematical models found in this study can be used for predicting tool life, surface roughness Ra, and cutting forces in the face milling of Ti6Al4V alloy.

4.2 Prediction and Validation for the Grey Relational Analysis

After selecting the optimal level of each factor, the final stage is to predict the output characteristics based on those level of factors. Grey Relational Grade is predicted using the following equation-

$$\hat{\theta} = \theta_m + \sum_{i}^{k} \left(\overline{\theta_i} - \theta_m \right) \quad (5)$$

θ is the estimated grey relational grade, θ_m is the mean of the grey relational grade, θ_i is the mean of the grey relational grade at the optimal level, k is the number of machining parameters that significantly affect the multiple response characteristics. The grey relational grade can be predicted for optimal cutting parameters even when the combination of input parameters cannot be found in the orthogonal array.

Comparison results of output responses at initial and optimal settings are shown in Table 13, where it is found that the tool life, surface roughness Ra, and P-to-V F_Y have improved by 55.81%, 6.12%, and 23.9%, respectively.

Table 13. Results of output responses at an initial and optimal setting using grey Relational Analysis.

	Initial Condition	Optimal Factors		
		Prediction	Experiment	Percent Improved
Level	A2B1C3	A1B1C1	A1B1C1	
Tool Life (min)	56.39		87.86	55.81%
Ra (μm)	0.147		0.138	6.12%
P-to-V F_Y (N)	108.46		82.45	23.98%
Grey Relational Grade	0.654	0.831	0.929	
Improvement of grey relational grade	0.275			

5. Conclusion

For Ti6Al4V alloy, the impacts of various face milling parameters, namely, cutting speed, feed rate, and radial depth of cut on cutting force, surface roughness, and tool life have been investigated using the Taguchi method and grey relational analysis for single and multi-objective optimization respectively. ANOVA analysis has been performed to find out the significance of the input parameters on the response characteristics, and mathematical models have been developed using regression analysis for the prediction of response characteristics.

From S/N ratio analysis, it has been found that the optimal parameter setting for maximizing tool life during face milling of Ti6Al4V alloy is cutting speed 50 m/min, feed rate 0.2 mm/rev, and radial depth of cut 7.5 mm. For minimum surface roughness Ra, the optimal parameters are cutting speed 65 mm/min, feed rate 0.2 mm/rev, and radial depth of cut 7.5 mm. The optimal cutting parameters for minimum P-to-V F_X are cutting speed 57.5 m/min, feed rate 0.2 mm/rev, and radial depth of cut 7.5 mm. For minimum P-to-V F_Y the optimal cutting parameters are cutting speed 50 m/min, feed rate 0.2 mm/rev, and radial depth of cut 7.5 mm. From ANOVA analysis, it is found that the most significant parameter for tool life is cutting speed. For surface roughness and P-to-V F_X, the most significant parameter is feed rate, and for P-to-V F_Y, radial depth of cut is found to be the most significant one. The mathematical models, developed using regression analysis, have been validated by conducting a confirmation experiment. It is concluded that the models can be used to closely predict the tool life, surface roughness, and cutting forces.

From multi-objective optimization (maximizing tool life, minimizing surface roughness and P-to-V F_Y) using grey Relational Analysis, the optimal combination of input parameters is cutting speed 50 m/min, feed rate 0.2 mm/rev, and radial depth of cut 7.5 mm. The significant factors for grey relational grade are feed rate and radial depth of cut. The grey relation grade obtained at the optimal setting shows an improvement of 0.275 compared to the initial condition. Therefore, it can be concluded from this study that the radial depth of cut has a significant impact on the face milling of Ti6Al4V. Significance of radial depth of cut on microstructure and residual stress generated during face milling of Ti6Al4V alloy will be investigated in future of this research work.

Acknowledgment

The authors acknowledge the financial support provided by Dr. Subhash Bose, SSA Foundation, and UTRGV's Presidential Graduate Research Assistantship award.

References

[1] Ezugwu, E. and Z. Wang, Titanium alloys and their machinability—a review. Journal of materials processing technology, 1997. 68(3): p. 262-274.

[2] Nath, C., S.G. Kapoor, and A.K. Srivastava, Finish turning of Ti-6Al-4V with the atomization-based cutting fluid (ACF) spray system. Journal of Manufacturing Processes, 2017. 28: p. 464-471.

[3] Semiatin, S., V. Seetharaman, and I. Weiss, The thermomechanical processing of alpha/beta titanium alloys. Jom, 1997. 49(6): p. 33-39.

[4] Veiga, C., J. Davim, and A. Loureiro, Review on machinability of titanium alloys: the process perspective. Rev. Adv. Mater. Sci, 2013. 34(2): p. 148-164.

[5] Özel, T., et al., Investigations on the effects of multi-layered coated inserts in machining Ti–6Al–4V alloy with experiments and finite element simulations. CIRP annals, 2010. 59(1): p. 77-82.

[6] Ezugwu, E., J. Bonney, and Y. Yamane, An overview of the machinability of aeroengine alloys. Journal of materials processing technology, 2003. 134(2): p. 233-253.

[7] Kuljanic, E., et al., Milling titanium compressor blades with PCD cutter. CIRP Annals, 1998. 47(1): p. 61-64.

[8] Shaw, M., Metal cutting principles. Clarendon. 1984, Oxford.

[9] Le Coz, G., et al., Measuring temperature of rotating cutting tools: Application to MQL drilling and dry milling of aerospace alloys. Applied Thermal Engineering, 2012. 36: p. 434-441.

[10] Sun, S., M. Brandt, and J.P. Mo, Evolution of tool wear and its effect on cutting forces during dry machining of Ti-6Al-4V alloy. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2014. 228(2): p. 191-202.

[11] Saini, A., et al., Multi-process parameter optimization in face milling of Ti6Al4V alloy using response surface methodology. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2018. 232(9): p. 1590-1602.

[12] Vijay, S. and V. Krishnaraj, Machining parameters optimization in end milling of Ti-6Al-4 V. Procedia Engineering, 2013. 64: p. 1079-1088.

[13] Hassan, A. and Y. Zhen-qiang, Multi-objective optimization in the milling of titanium alloys using the MQL technique. Journal of Wuhan University of Technology-Mater. Sci. Ed., 2004. 19(4): p. 26-29.

[14] Kuram, E. and B. Ozcelik, Optimization of machining parameters during micro-milling of Ti6Al4V titanium alloy and Inconel 718 materials using Taguchi method. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2017. 231(2): p. 228-242.

[15] Deng, J.L. Introduction to Grey system theory. 1989.

[16] Aslantas, K., E. Ekici, and A. Cicek, Optimization of process parameters for micro milling of Ti-6Al-4V alloy using Taguchi-based gray relational analysis. Measurement, 2018. 128: p. 419-427.

[17] Du, S., et al., Optimization of process parameters in the high-speed milling of titanium alloy TB17 for surface integrity by the Taguchi-Grey relational analysis method. Advances in Mechanical Engineering, 2016. 8(10): p. 1687814016671442.

[18] Sarıkaya, M., V. Yılmaz, and H. Dilipak, Modeling and multi-response optimization of milling characteristics based on Taguchi and gray relational analysis. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2016. 230(6): p. 1049-1065.

[19] Polini, W. and S. Turchetta, Cutting force, tool life and surface integrity in milling of titanium alloy Ti-6Al-4V with coated carbide tools. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2016. 230(4): p. 694-700.

[20] Hasani, H., S.A. Tabatabaei, and G. Amiri, Grey relational analysis to determine the optimum process parameters for open-end spinning yarns. Journal of Engineered Fibers and Fabrics, 2012. 7(2): p. 155892501200700212.

[21] Lin, C., Use of the Taguchi method and grey relational analysis to optimize turning operations with multiple performance characteristics. Materials and manufacturing processes, 2004. 19(2): p. 209-220.

[22] Derakhshan, E. and A. Akbari. Experimental investigation on the effect of workpiece hardness and cutting speed on surface roughness in hard turning with CBN tools. in Proceedings of the world congress on engineering. 2009.

[23] Sharif, S., A. Jawaid, and S. Koksal, Effect of Edge Geometry on Coated Carbide Tools when Face Milling Titanium Alloy. Internatioanl Journal for Manufacturing Science and Technology, 2000. 2(2): p. 11-17.

[24] Kilickap, E., A. Yardimeden, and Y.H. Çelik, Mathematical modelling and optimization of cutting force, tool wear and surface roughness by using artificial neural network and response surface methodology in milling of Ti-6242S. Applied Sciences, 2017. 7(10): p. 1064.

[25] Li, A., et al., Progressive tool failure in high-speed dry milling of Ti-6Al-4V alloy with coated carbide tools. The International Journal of Advanced Manufacturing Technology, 2012. 58(5-8): p. 465-478.

[26] Ehsan, S., et al., Milling of Ti-6Al-4V alloy using hybrid geometry tooling. The International Journal of Advanced Manufacturing Technology, 2019. 105(12): p. 5045-5059.

[27] Park, J., et al., Evaluation of machinability in the micro end milling of printed circuit boards. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2009.