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A Study on Influence of Milling Types and Cutting Conditions on Surface Roughness in Milling of Aluminum Alloy Al6061-T6

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Abstract In this study, by using Taguchi method, with four controllable factors-three levels (milling type, axial depth of cut, feed rate, and spindle speed), the orthogonal array L_{27} was used to investigate the effects of milling type and cutting conditions on the surface roughness. By analysis of variance (ANOVA), the influences degree of milling type, axial cutting depth, feed rate, and spindle speed on the surface roughness were 9.26 %, 12.85 %, 12.69 %, and 63.08 %, respectively. The interaction factors of these factors that have a quite small influence on the surface roughness. The surface roughness was modeled as a quadratic regression with the confidence level is more than 99.82%. This model was successfully verified by comparison of experimental and predicted results. The optimization process of surface roughness was performed by both Taguchi method and the ANOVA analysis with the same results. The optimum value of surface roughness was 0.374 µm that was obtained in the half up milling, at a cutting depth of 0.4 mm, a feed rate of 480 mm/min, and a spindle speed of 5000 rpm.

Keywords Surface Roughness, Taguchi Method, ANOVA Analysis, Milling Processes, Al6061-T6

1. Introduction

In the milling processes, the relationship between machining conditions and machining characteristics is very important to predict the quality of machining product, and predict the consumption of power, energy, as well. In order to investigate the influence of machining condition on machining characteristics (surface roughness, tool wear, cutting forces, etc.), many approaches were applied such as Taguchi method, response surface methodology (RSM), statistical methods of signal to noise ratio (SNR), Analysis of variance (ANOVA), and so on.

Taguchi method and ANOVA analysis have been widely used in industrial engineering analysis. Moreover, the Taguchi method employs a special design of orthogonal array through reducing the number of experiments to investigate the effect of the entire machining parameters. Recently, this method has been widely employed in several industrial fields, and research work. Lin et al. [1] and Lajis et al. [2] used Taguchi and ANOVA analysis to research the effect of main machining parameters such as machining polarity, peak current, pulse duration, and so on, on the EDM machining characteristics such as material removal rate, surface roughness. Tsoukalas et al. [3] and Hsu et al. [4] used L_{27} orthogonal array of Taguchi method to determine the optimum conditions leading to minimum porosity in aluminum alloy die castings. Rao et al. applied the Taguchi method and ANOVA in optimization of process parameters for metal removal rate in electrochemical machining of Al/5%SiC composites [5]. Besides, the Taguchi method and ANOVA analysis were also applied to investigate other machining processes such as turning [6-9], drilling [10-12], and milling [13-15].

The surface roughness is important machining characteristics to evaluating the productivity of machining processes. In milling processes, by using Taguchi method and ANOVA analysis, the s and surface roughness could be investigated based on a number of factors such as depth of cut, feed rate, cutting speed, cutting time, workpiece hardness, etc. Several research works had been conducted in different conditions and had also been applied for different workpieces and tool materials [16-19]. The surface roughness was investigated and modeled depending on the cutting speed, depth of cut, feed rate, and cooling method in finishing milling of Hardox 400 steel with PVD TiAlN+TiN coated carbide inserts [20]. The optimization process of surface roughness was performed to determine the optimum values of machining parameters in finished face milling the hard steel SKD61 [21].

Many studies that were conducted to investigate the influence of cutting conditions on machined surface roughness. However, it seems that the influence of milling types and the interaction factors of milling types and cutting conditions on the surface roughness have not been mentioned. This study was carried out to determine the influence of milling types, cutting conditions, and the interaction factors of them on the surface roughness, and to improve the surface roughness of machined part by application of optimization methods.

2. Materials and Methods

2.1. Experimental Setup

2.1.1. Workpiece and Cutter

The workpiece material was Al6061-T6 with the hardness of 95 HB, Young's modulus of 68.9 GPa, Poisson's ratio of 0.33, tensile strength = 310 MPa. And, the compositions of Al6061-T6 are listed in Table 1.

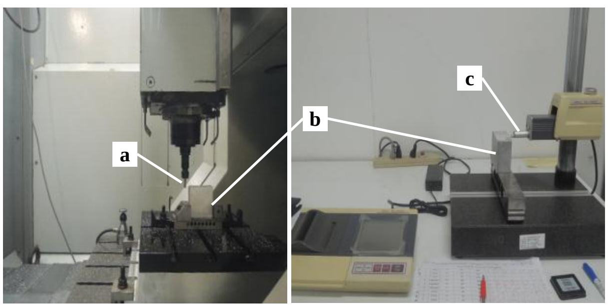
Table 1. Chemical composites of Al6061-T6

Element	Al	Cr	Cu	Fe	Mg	Mn	Si	Ti	Zn
Composite (%)	98	≤ 0.3	≤ 0.4	≤ 0.7	≤ 1.2	≤ 0.15	≤ 0.8	≤ 0.15	≤ 0.25

The cutter that were chosen was a carbide flat-end mill cutter with number of flutes of 4 flutes, a helix angle β of 30^0, a rake angle α_r of 5^0, and a diameter of 10 mm.

2.1.2. CNC Milling Machine and Surface Roughness Tester

The CNC machine and surface roughness tester were used as described in Fig. 1. The experiments were performed at a three-axis vertical machining center (DECKEL MAHO – DMC70V hi-dyn). The surface roughness was measured by Mitutoyo SJ.400 portable surface roughness tester with the cutoff length of 0.8 mm and the evaluation length of 4 mm.



a. Cutter b. Workpiece c. Surface roughness sensor

Figure 1. CNC machine and surface roughness tester

2.1.3. Response Surface Methodology and Analysis of Variance (ANOVA)

Response surface methodology is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response. Almost all Response surface methodology problems use one or both of the first-order model and second-order model of polynomial that are given by Eq. (1) and Eq. (2), respectively [22].

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \quad (1)$$

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i}^{k} \sum_{j}^{k} \beta_{ij\,(i<j)} x_i x_j + \varepsilon \quad (2)$$

where k represents number of independent variables; β_0, β_i, β_{ii} β_{ij} are the constants; ε measures the experimental error (noise).

ANOVA analysis can be used to determine the effect of any given input parameter on any output parameter from a series of experimental results. Let $y_{i.}$ represent the total of the observation under the i^{th} treatment that is given by Eq. (3) and $\bar{y}_{i.}$ represent the average of the observations under the i^{th} treatment that is given by Eq. (4). Similarly, let $y_{..}$ represent the grand total of all the observations that is given by Eq. (5) and $\bar{y}_{..}$ represent the grand average of all the observations that is given by Eq. (6), [22].

$$y_{i.} = \sum_{j=1}^{n} y_{ij} \qquad i = 1, 2, \ldots, m \quad (3)$$

$$\bar{y}_{i.} = \frac{y_{i.}}{n} \qquad i = 1, 2, \ldots, m \quad (4)$$

$$y_{..} = \sum_{i=1}^{m} \sum_{j=1}^{n} y_{ij} \quad (5)$$

$$\bar{y}_{..} = \frac{y_{..}}{N} \quad (6)$$

Where N = (m*n) is the total number of observations.

ANOVA partitions total variation into its appropriate components. Total sum of squares term can be calculated by Eq. (7), [22].

$$SS_T = \sum_{i=1}^{m} \sum_{j=1}^{n} (y_{ij} - \bar{y}_{..})^2 \quad (7)$$

The Eq. (7) can be rewritten by Eq. (8).

$$SS_T = SS_{Treatments} + SS_E \quad (8)$$

Where $SS_{Treatments}$ is a sum of squares of differences between the treatment average and the grand average, and SS_E is a sum of squares of the differences of observations within treatments from the treatment average. $SS_{Treatments}$ and SS_E can be calculated by Eq. (9) and Eq. (10).

$$SS_{Treatments} = n \sum_{j=1}^{n} (y_{i.} - \bar{y}_{..})^2 \quad (9)$$

$$SS_E = \sum_{i=1}^{m} \sum_{j=1}^{n} (y_{ij} - \bar{y}_{.})^2 \quad (10)$$

2.2. Taguchi Method and Experiment Design

Taguchi method is a statistical method used to improve the product quality. It is commonly used in improving industrial product quality due to the proven success. It is an experimental design and also a beneficial technique for high quality system design. In engineering analysis, the Taguchi method is a powerful method and it has been widely used in the world. This method dramatically reduces the number of tests by using orthogonal arrays and minimizes the effects of factors that cannot be controlled [23].

The parameter design study involves control and noise factors. The measurement of interactions between these factors with regard to robustness is signal-to-noise (S/N) ratio. Normally, there are three kinds of quality characteristics in the analysis of the S/N ratio, namely the bigger-the-better, the smaller-the-better, and the nominal-the-better [24-25] that can be calculated by Eq. (11) to Eq. (13). For each level of the process parameters, the S/N ratio is calculated based on the S/N analysis.

The bigger-the-better:

$$\frac{S}{N_s} = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \tag{11}$$

The smaller-the-better:

$$\frac{S}{N_s} = -10\log\left[\frac{1}{n}\sum_{i=1}^{n}y_i^2\right] \tag{12}$$

The nominal-the-better:

$$\frac{S}{N_s} = -10\log\left[\frac{\bar{y}}{S_{\bar{y}}^2}\right] \tag{13}$$

Where, $\bar{y}$ is the average of observed data, S_y^2 is the variance of y, and n is the number of observations.

The cutting types (A), axial depth of cut (B), feed rate (C), and spindle speed (D) were selected as control factors and their levels were expressed in the Table 2. In the experimental layout plan, with four factors and three levels, the most suitable orthogonal array (L_{27} - 3^4) was chosen to analyze the effects of machining parameters on the surface roughness [24-25]. The experimental plan was performed with 27 experiments and detailed as in Table 3.

Table 2. Milling parameters and their levels

No.	Actual factors	Coded factor	Level 1	Level 2	Level 3
			-1	0	1
1	Milling type	A	Half up	Half down	Slotting
2	Axial cutting depth a (mm)	B	0.4	0.8	1.2
3	Feed rate F (mm/min)	C	480	720	960
4	Spindle speed (rpm)	D	1000	3000	5000

Table 3. The experimental design with orthogonal array of Taguchi L_{27} (3^4)

Run No.	Coded factors				R_a [μm]
	A	B	C	D	
1	-1	-1	-1	-1	1.048
2	-1	-1	0	0	1.012
3	-1	-1	1	1	0.446
4	-1	0	-1	0	0.904
5	-1	0	0	1	0.802
6	-1	0	1	-1	1.574
7	-1	1	-1	1	0.492
8	-1	1	0	-1	1.890
9	-1	1	1	0	1.600
10	0	-1	-1	-1	1.244
11	0	-1	0	0	1.146
12	0	-1	1	1	0.476
13	0	0	-1	0	1.018
14	0	0	0	1	0.994
15	0	0	1	-1	1.718
16	0	1	-1	1	0.540
17	0	1	0	-1	2.016
18	0	1	1	0	1.690
19	1	-1	-1	-1	1.600
20	1	-1	0	0	1.460
21	1	-1	1	1	0.662
22	1	0	-1	0	1.300
23	1	0	0	1	1.114
24	1	0	1	-1	2.060
25	1	1	-1	1	0.752
26	1	1	0	-1	2.330
27	1	1	1	0	1.972

3. Results and Discussions

3.1. Analysis of Variance

The surface roughness in milling process were measured and stored as in Table 2. The Analysis of Variance (ANOVA) was used to analyze the effects of cutting type, axial depth of cut, feed rate, and spindle speed on the surface roughness. Using Intercooled Stata 8.2™ software, these ANOVA results were shown in Table 4. The coefficient of determination (R^2) is defined as the ratio of the explained variation to the total variation and is a measure of the fit degree. In this work, this analysis was performed with 95% confidence level and 5 % significance level which indicates that the obtained models are considered to be statistically significant.

In Table 4, the contributions of each factor on the surface roughness were listed in the last column. It is clear from the results of ANOVA that the most important factor affecting on the surface roughness was spindle speed (factor D, 63.08 %). The other factors affect differently on the surface roughness. The axial cutting depth and feed rate had the same influence on the surface roughness (12.85 % for axial cutting depth and 12.69 % for feed rate). The fourth factors that influenced on the surface roughness were milling type (factor A, 9.26 %). The interaction factors of these factors that has quite small influence on the surface roughness.

3.2. Regression and Verification of Surface Roughness Model

In this work, the dependent variable is the surface roughness (Ra), whereas the independent variables are milling type (A), axial depth of cut (B), feed rate (C), and spindle speed (D). By using Intercooled Stata 8.2™ software, the surface roughness was modelled by quadratic function as given by Eq. (20) and Eq. (21). The R^2 values of the equations obtained by quadratic regression model for surface roughness were found to be 99.82%.

$$\begin{cases} \mathrm{Ra} = 1.422 + 0.193\mathrm{A} + 0.233\mathrm{B} + 0.167\mathrm{C} \\ \quad -0.438\mathrm{D} - 0.012\mathrm{BA} + 0.011\mathrm{CA} \\ \quad +0.146\mathrm{CB} - 0.058\mathrm{DA} - 0.032\mathrm{DB} \\ \quad +0.074\mathrm{A}^2 - 0.033\mathrm{B}^2 - 0.230\mathrm{C}^2 - 0.063\mathrm{D}^2 \\ \quad \mathrm{R}^2 = 99.82\%,\ \mathrm{R}^2_{\mathrm{Ajd}} = 99.64\% \end{cases} \tag{20}$$

Where the relationship between actual factors and coded factors was expressed by Eq. (21).

$$\begin{cases} \mathrm{A} = \begin{cases} -1 \text{ if up milling} \\ 0 \text{ if down milling} \\ 1 \text{ if slotting} \end{cases} \\ \mathrm{B} = \frac{a-0.8}{0.4} \\ \mathrm{C} = \frac{F-720}{240} \\ \mathrm{D} = \frac{S-3000}{2000} \end{cases} \tag{21}$$

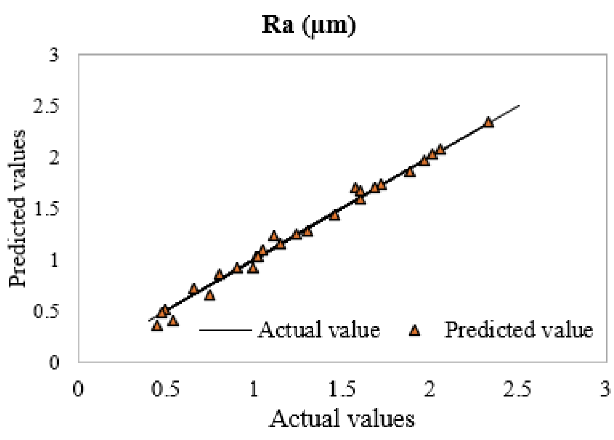


Figure 2. Experimental and predicted values of surface roughness

The verification results of surface roughness model were described in Fig. 2. As seen from this figure, the predicted results were very close to the experimental results. There is a very good relation between predicted values and actual values.

These results showed that the quadratic regression model was shown to be successfully investigated of surface roughness in milling process of aluminum alloy Al6061-T6.

3.2. Parametric Influence on Surface Roughness

The parametric influence of milling types and cutting conditions on the surface roughness was described in Fig 3. It is very clear that in up milling process, the surface roughness value was smallest, down milling gave the larger surface roughness than up milling, and slotting gave the largest surface roughness. Besides, the surface roughness increased with increasing of feed rate. This trend can be explained that when feed rate increased, the undeform chip thickness also increased, and undeform chip thickness is directly proportional to cutting forces. And then, when the cutting forces increased, the stability and damping characteristics of machine-tool system will be affected, that makes more vibrations and ultimately affects the surface roughness.

The surface roughness values exhibited increasing tendency with increasing of axial depth of cut from 0.4 mm to 1.2 mm. Otherwise, the surface roughness decreases with increasing of spindle speed from 1000 rpm to 5000 rpm. So, in order to improve the surface roughness in milling process of aluminum alloy Al6061-T6, the tendency of machining conditions was proposed that the milling type is up milling, the feed rate decreases, the axial depth of cut decreases, and the spindle speed increases. In comparison of this study with other studies [7, 21], it seems that the tendency of surface roughness that was investigated in this study is quite similar to the one in previous studies.

3.4. Estimation of Optimum Surface Roughness by ANOVA Analysis and Taguchi Method

3.4.1. The Optimization Parameter of Milling Process by ANOVA Analysis

The lowest value of surface roughness is very important for quality improvement of the machining product and lowering production costs. The quadratic regression model of surface roughness as presented by Eq. (20) was used to determine the optimized values of surface roughness and machining parameters.

The optimized results of machining parameters were obtained as below:

$$x = [\approx -1,\ \ -1,\ \ -1,\ \ 1] \Longrightarrow A = -1; B = -1; C = -1; D = 1.$$

$$\mathrm{fval} = 0.374$$

So by ANOVA analysis, the optimal parameters of machining process were determined as below:

Milling type: Half up milling

Axial depth of cut: a = 0.4 mm

Feed rate: F = 480 mm/min

Spindle speed: S = 5000 rpm

And the optimization value: Ra = 0.374 μm

3.4.2. The Optimization Parameter of Milling Process by Taguchi Method

By using Taguchi method, the optimal values of control factor were determined by analysis of the signal-to-noise ratio. As in ANOVA analysis, the lowest value of surface roughness is very important to improve the machining product, so the smaller-the-better equation was used for calculation of the S/N ratio that was determined by Eq. (12). The values of the S/N response for observations of surface roughness were listed in Table 5.

Table 4. Results of ANOVA for surface roughness

Number of obs: 27					R-squared: 0.9988		
Root MSE: 0.0307					Adj R-squared: 0.9968		
Variance source		**Sum of squares**	**Degree of freedom**	**Mean square**	**F-value**	**Prob > F**	**Percent contribution (%)**
Model		**7.6239**	**16**	**0.4765**	**505.54**	**0.0000**	
Milling type	A	0.7065	2	0.3533	374.8	0.0000	9.26
a (mm)	B	0.9809	2	0.4905	520.34	0.0000	12.85
F (mm/min)	C	0.9687	2	0.4844	513.9	0.0000	12.69
S (rpm)	D	4.8151	2	2.4076	2554.28	0.0000	63.08
	A*B	0.0036	2	0.0018	1.92	0.1969	0.05
	A*C	0.0033	2	0.0017	1.77	0.2196	0.04
	A*D	0.0404	2	0.0202	21.45	0.0002	0.53
	B*C	0.1007	2	0.0504	106.85	0.0000	1.32
	B*D	0.0046	1	0.0046	4.89	0.0515	0.06
	Error	0.0094	10	0.0009			0.12
Total		7.6332	27	0.2827			100.00

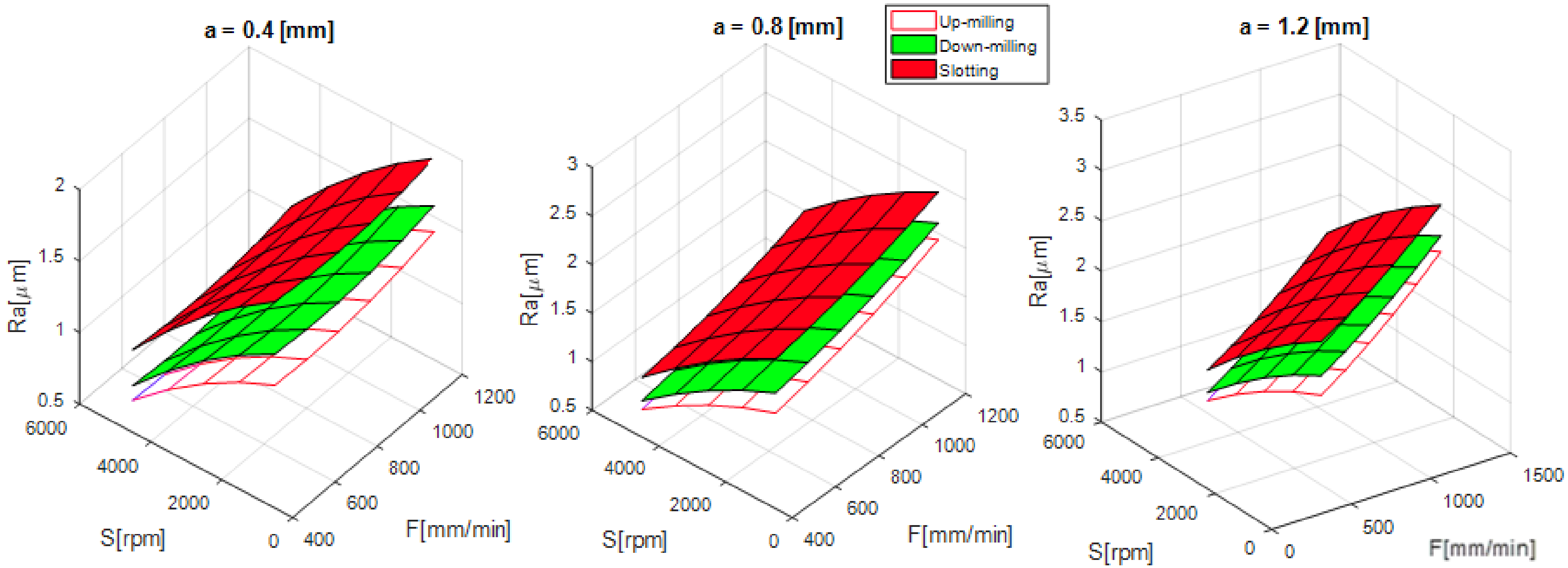


Figure 3. Effect of cutting conditions on surface roughness

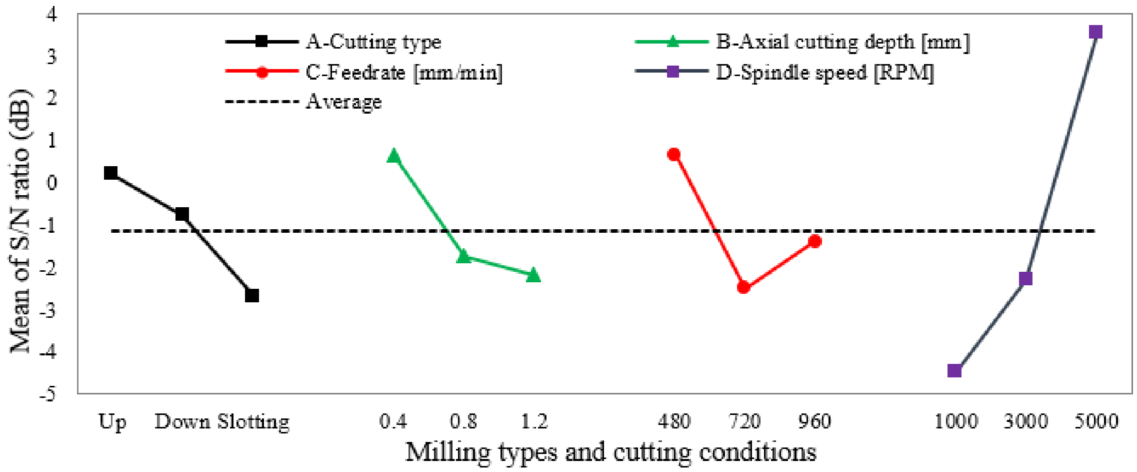


Figure 4. Main effects of each factor on surface roughness

The effect of milling types and cutting conditions on the surface roughness were evaluated and shown in Fig 4. The results from this figure showed that up milling gave the best surface, down milling gave the second good surface, and finally, that is slotting. With other machining parameters, the surface roughness values exhibited decreasing tendency with decreasing of axial depth of cut and feed rate.

Table 5. The S/N response for surface roughness

Levels	Control factors			
	A	B	C	D
Level 1	**0.2063**	**0.6679**	**0.6674**	-4.4757
Level 2	-0.7532	-1.7181	-2.5025	-2.2978
Level 3	-2.6749	-2.1716	-1.3867	**3.5517**
Delta	2.8812	2.8395	3.1699	8.0274

The tendency of surface roughness was reversed with the spindle speed that it decreased with increasing of spindle speed. So, in order to improve the surface roughness in the milling process, the tendency of milling type and machining conditions were proposed that were up milling, decreasing the axial depth of cut, the feed rate, and increasing the spindle speed.

By Taguchi techniques, the best level of each control factor was determined according to the highest S/N ratio at the level of that control factor. By these techniques, from the values of Table 5 and Fig. 5, the level and S/N ratios for input factors that gave the best Ra value were specified as factor A (level -1, S/N = 0.2063 dB), factor B (level -1, S/N = 0.6679 dB), factor C (level -1, S/N = 0.6674 dB), and factor D (level 1, S/N 3.5517 dB). By using Taguchi method, the optimum value of surface roughness was obtained in the up milling (A=-1), at a depth of cut of 0.4 mm (B=-1), a feed rate of 480 mm/min (C=-1), and a spindle speed of 5000 rpm (D=1). So, it can be concluded that the optimized results between ANOVA analysis and Taguchi method are the same.

4. Conclusions

Depending on the analysis of experimental results, the conclusions of this study can be drawn as follows.

The most important factor affecting on the surface roughness was spindle speed. The axial cutting depth and feed rate had the same influence on the surface roughness. Milling type and interaction factors has quite small influence on the surface roughness.

The most suitable regression of surface roughness was a quadratic regression with the confidence level is 99.82 %, and this model was successfully verified by comparison of experimental and predicted results.

In this milling process, up milling gave the best surface, down milling gave the second good surface, and finally, that is slotting. With other machining parameter, the surface roughness values exhibited decreasing tendency with decreasing of axial depth of cut and feed rate. The tendency of surface roughness was reversed with the spindle speed that it decreased with increasing of spindle speed.

The optimized results from Taguchi method and the ANOVA analysis are the same. The optimum value of surface roughness is 0.3735 μm that was obtained in the half-up milling, at a depth of cut of 0.4 mm, a feed rate of 480 mm/min, and a spindle speed of 5000 rpm.

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