STUDYING THE EFFECTS OF CUTTING PARAMETERS ON SURFACE ROUGHNESS IN MILLING OF ALUMINIUM ALLOY USING THE TAGUCHI METHOD

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(Received: June 18, 2025; Revised: October 28, 2025; Accepted: November 12, 2025)

DOI: 10.31130/ud-jst.2025.23(11).331

Abstract - In this study, the effects of cutting parameters (cutting speed v, feed rate f, and depth of cut t) on surface roughness during side milling of 6061 aluminium alloy were investigated using the Taguchi method and analysis of variance (ANOVA). The results showed that, f had the most significant effect on surface roughness, followed by t, while v had the least influence. A regression model was developed to predict surface roughness, achieving high reliability with a coefficient of determination (R^2) of 99.62%. The predicted surface roughness values obtained from the regression equation and the actual measurements showed a mean absolute percentage error (%MAE) of 3.154% and a mean squared percentage error (%MSE) of 0.222%. The regression model is suitable for predicting surface roughness during finish milling of 6061 aluminium alloy.

Key words - ANOVA; Milling; Regression equation; Taguchi method

Tóm tắt - Trong nghiên cứu này, ảnh hưởng của các thông số chế độ cắt (tốc độ cắt v, lượng tiến dao f và chiều sâu cắt t) tới độ nhám bề mặt trong gia công phay mặt bên bằng dao phay ngón của chi tiết hợp kim nhôm 6061 được nghiên cứu theo phương pháp Taguchi và phân tích phương sai (ANOVA). Kết quả cho thấy, f ảnh hưởng đáng kể tới độ nhám bề mặt, tiếp đó là t và ảnh hưởng yếu nhất là v. Mô hình hồi quy dùng để dự đoán độ nhám được xác định và độ tin cậy $R^2 = 99{,}62\%$. Độ nhám dự đoán từ hàm hồi quy và độ nhám thực tế có phần trăm sai số trung bình (%MAE) và phần trăm bình phương sai số trung bình (%MSE) lần lượt là 3,154% và 0,222%. Mô hình hồi quy phù hợp để dự đoán độ nhám bề mặt trong quá trình gia công phay tinh hợp kim nhôm 6061.

Từ khóa - ANOVA; Phay; Mô hình hồi quy; Phương pháp Taguchi

1. Introduction

Surface roughness is one of the key criteria for evaluating surface quality and is a characteristic indicator of the geometric properties of machined surfaces [1]. Surface quality plays a critical role in the performance of turning processes; high-quality surfaces after turning can significantly improve fatigue strength, corrosion resistance, and other properties [2]. Surface roughness also affects various characteristics of the part, such as surface contact friction, wear, light reflectivity, load-bearing capacity, surface coating, or resistance to fatigue failure. Therefore, surface roughness is often strictly specified, and appropriate machining processes are selected to achieve the required quality [3].

Researchers have published numerous studies on surface roughness. Ghhani J. A. et al. [4] optimized cutting parameters in face milling of hardened AISI H13 steel using P10 carbide tools coated with TiN under high-speed cutting conditions in both semi-finishing and finishing stages. The effects of machining parameters such as cutting speed, feed rate, and depth of cut, as well as their interactions, were investigated using the Taguchi design of experiments (DOE) method. The study demonstrated that the Taguchi method is suitable for solving the stated problem with a minimal number of experiments compared to the full factorial design approach [4]. Kopac et al. designed various edge-milling parameters to optimise cutting force, machined surface roughness, and material removal rate over time during the machining of cast aluminium alloy plates for die-casting moulds. The optimal combination of milling parameters for multiple process responses was determined using the Grey-Taguchi method, which combines orthogonal array experimental design and grey relational analysis (GRA) [5]. In addition to studies employing the Taguchi method, other approaches have also been applied. Oktem et al. focused on developing an effective method to determine optimal cutting conditions for achieving the lowest surface roughness in die surface milling. This method combines the Response Surface Methodology (RSM) and a developed genetic algorithm [6].

The study by D.D. Trung, in the effect of cutting parameters on surface roughness in face milling of AISI 1045 steel using the Box-Behnken method, indicated that the feed rate f has a significant effect on surface roughness [7]. M.T. Hayajneh et al. reported that feed rate has the most potent effect on surface roughness, followed by cutting speed and depth of cut [8]. Meanwhile, H. González et al. found that cutting speed has the greatest influence on surface roughness among other factors in the milling of AISI 304 steel [9]. A. Hamdan et al. presented an optimisation method for machining parameters in high-speed milling of stainless steel using coated carbide tools under different lubrication conditions. Their study showed that feed rate is the most prominent factor affecting cutting force and surface roughness. Moreover, low feed rate and depth of cut values are recommended to achieve minimal cutting force and improved surface finish [10]. S. Kaining et al., in their optimization of process parameters for surface roughness and microhardness in dry milling of magnesium alloys using the Taguchi method combined with grey relational analysis, concluded that feed rate has the most significant influence on surface roughness, followed by cutting speed and depth of cut [11].

On the other hand, 6061 aluminium alloy is widely used in precision engineering, aerospace, automotive, and mold industries due to its combination of mechanical strength, corrosion resistance, and good machinability [12, 13]. Although many studies have optimised cutting parameters for various alloy steels, stainless steels, and other aluminium alloys, in-depth research on the finish milling of 6061 aluminium alloy remains limited. In the context of increasingly stringent surface quality requirements, systematically determining the effects of cutting speed, feed rate, and depth of cut on surface roughness will help improve machining efficiency.

This study focuses specifically on the finish milling process of 6061 aluminium alloy, applying the Taguchi method combined with analysis of variance (ANOVA) and regression modeling to simultaneously identify the primary influencing factors (v, f, t) and develop a predictive tool for surface roughness. The novelty of this approach lies in its ability to both optimize cutting parameters with a minimal number of experiments and provide a highly accurate predictive model, enabling direct application in production to shorten setup time, reduce experimental costs, and ensure stable machining quality.

2. Research methodology

2.1. Experimental samples and machining tools

6061 aluminium alloy is widely used in commercial applications in the manufacture of automotive parts, construction, and engineering. This material possesses excellent mechanical properties and good corrosion resistance. 6061 aluminium alloy is known for its good mechanical properties and excellent weldability [12]. The chemical composition of 6061 alloy is shown in Table 1 [12, 14]. Figure 1 shows the aluminium alloy specimen used for machining, with dimensions of 120×110×30 mm.

The experiments were conducted on a VCN-430A SG machining center (Mazak, Japan) using a Lasting Victory 884L-Z (100410) end mill. The tool has a diameter of 10 mm, a cutting edge length of 25 mm, and four flutes. Rough milling was first performed to remove a thin layer, followed by finish milling according to the experimental parameters to measure surface roughness. The surface roughness measuring device used in this study was the HANDYSURF+35 (ACCRETECH).

Table 1. *Chemical composition of 6061 aluminium alloy [12, 14]*

No.	Element	%
1	Si	0.49
2	Fe	0.195
3	Cu	0.388
4	Mn	0.068
5	Mg	1.07
6	Zn	0.003
7	Ti	0.019
8	Cr	0.243
9	Al	Balance

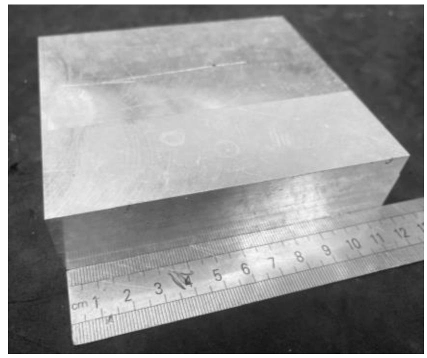

Figure 1. *Experimental specimen*

2.2. Taguchi method

The objective of the Taguchi method is to design a process that is robust to factors causing quality deviations. The aim is to adjust parameters to optimal levels so that the process remains stable at the best possible quality. The Taguchi method employs orthogonal arrays in experimental design, enabling the minimum number of experiments to investigate the effects of parameters on a selected process response, thereby enabling rapid optimisation.

The Taguchi method uses the signal-to-noise (*S/N)* ratio, which is converted from the loss function $L = k(y - m)^2$, where L is the loss due to the deviation of the response value y from the desired response m, and k is a constant. The *S/N* ratio is constructed and transformed for three main cases, as extracted from Chapter 7 of reference [15].

In this study, since the requirement is to minimize surface roughness, the "Lower is better" criterion is used [15]:

$$\frac{S}{N} = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} R_{ai}^2\right) \tag{1}$$

where, i=1,2,...,n (n=3) and R_{ai} is the surface roughness value at each level.

2.3. Experimental design

The selected cutting parameters were cutting speed v, feed rate f and depth of cut t, which are identified as the main factors affecting surface roughness during side milling of aluminium alloy. To investigate the effects of these parameters, the Taguchi method was applied with an L27 orthogonal array. The different levels for each parameter are presented in Table 2, based on the manufacturer's maximum recommended values [16]. Table 3 presents the cutting parameters for each experiment, along with the average surface roughness from three measurements.

Table 2. *Levels of factors*

Symbol	Unit	Low level	Medium level	High level
v	m/min	25	60	95
f	mm/t	0.04	0.06	0.08
t	mm	0.2	0.5	0.8

Table 3. *Experimental parameters and corresponding R_a values*

No.	Cutting parameters			Result
	v (m/min)	f (mm/t)	t (mm)	R_a (µm)
1	25	0.04	0.2	0.184
2	25	0.06	0.5	0.395
3	25	0.08	0.8	0.906
4	25	0.04	0.5	0.224
5	25	0.06	0.8	0.406
6	25	0.08	0.2	0.756
7	25	0.04	0.8	0.247
8	25	0.06	0.2	0.363
9	25	0.08	0.5	0.887
10	60	0.04	0.2	0.205
11	60	0.06	0.5	0.409
12	60	0.08	0.8	0.757
13	60	0.04	0.5	0.289
14	60	0.06	0.8	0.450
15	60	0.08	0.2	0.642
16	60	0.04	0.8	0.325
17	60	0.06	0.2	0.375
18	60	0.08	0.5	0.709
19	95	0.04	0.2	0.186
20	95	0.06	0.5	0.405
21	95	0.08	0.8	0.805
22	95	0.04	0.5	0.199
23	95	0.06	0.8	0.455
24	95	0.08	0.2	0.723
25	95	0.04	0.8	0.224
26	95	0.06	0.2	0.361
27	95	0.08	0.5	0.783

During the experiments, tool wear and cooling factors were also taken into account. Specifically, to assess the effect of tool wear, experiments 28 and 29 were conducted after completing the 27 main experiments (Table 3). Experiments 28 and 29 used the same cutting parameters as experiments 1 and 2 (Table 3). The results showed that experiments 28 and 29 had R_a values of 0.181 μm and 0.392 μm, respectively. The negligible difference in R_a values between experiments 28 and 29 indicate that tool wear did not affect the experimental results. Regarding the cooling factor, the position of the coolant nozzle was kept constant throughout the experiments to minimise its influence.

3. Results and discussion

3.1. Results

Table 3 shows the measured surface roughness results for the 27 experiments. Tables 4 and 6 present the signal-to-noise (S/N) and means. Table 4 shows the S/N ratio for each level of each parameter; from this, the optimal parameter set in the Taguchi experimental design corresponds to $v = 95$ m/min, $f = 0.04$ mm/t and $t = 0.2$ mm. With this optimal parameter set, the predicted optimal surface roughness is $R_a = 0.1747\ \mu m$ calculated using equation (2) [15]:

$$y_{otp} = \bar{y} + \sum_i (\bar{y}_{i,k} - \bar{y}) \quad (2)$$

where, y_{otp} is the predicted value of R_a at the optimal parameter set, $\bar{y}$ is the mean R_a value of all 27 experiments, and $\bar{y}_{i,k}$ is the mean R_a at the optimal level k of parameter i.

Table 4. *Signal-to-noise ratio values for each factor level*

Level	v *(m/min)*	f *(mm/t)*	t *(mm)*
1	7.649	12.866	8.705
2	7.424	7.944	7.518
3	8.005	2.268	6.855
Delta	0.581	10.598	1.850
Rank	3	1	2

To verify the appropriateness of the parameter levels presented in Table 2, the experiment was repeated three times using the optimal parameter set ($v = 95$ m/min, $f = 0.04$ mm/t and $t = 0.2$ mm). The R_a values from these three experiments are shown in Table 5.

Table 5. *R_a results for experiments with the optimal parameter set*

Trial	1	2	3	Average
R_a (μm)	0.183	0.178	0.186	0.182

From the results in Table 5, with a 95% confidence level, the confidence interval (CI) is determined as $CI = 0.0766\ \mu m$. Based on the predicted result $R_a = 0.1747\ \mu m$ and the CI is [0.0981, 0.2513]. The mean surface roughness of the three experimental runs with the optimal parameter set falls within this confidence interval. Thus, it can be concluded that the parameter levels presented in Table 2 are appropriate.

Figures 2 and 3 visually represent the values in Tables 4 and 6. The results show that feed rate (f) has the most significant effect on surface roughness in finish milling, followed by depth of cut (t), while cutting speed (v) has the least influence.

To further clarify the degree of correlation between the variation due to each factor and the random variation, as well as the confidence level, the $F - critical$ value was determined for this study at a significance level of $\alpha = 0.05$ for each factor, which is 3.49. The reliability results for each factor are presented in Table 7.

Moreover, based on the *S/N* ratio values in Table 4, the optimal parameter set is $v = 95$ m/min, $f = 0.04$ mm/t and $t = 0.2$ mm. However, according to the statistical significance analysis in Table 7, the results indicate that f is the primary factor affecting R_a with F = 299.192 and P-value < 0.0001, t is the secondary factor (after f) with F = 9.379 and P-value < 0.05, and v has F = 0.903 and P-value > 0.05, indicating that v does not significantly affect R_a. Therefore, it can be concluded that f = 0.04 and t = 0.2 are decisive values for the optimal parameter set, while v is not significant within the range of 25 - 95 m/min. According to Table 3, the parameter combinations for the lowest R_a values are shown in Table 8.

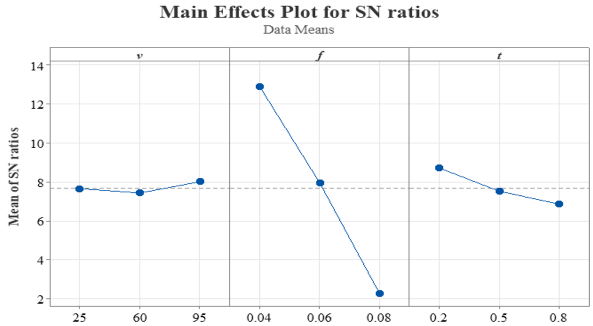

Figure 2. *Signal-to-noise ratio chart*

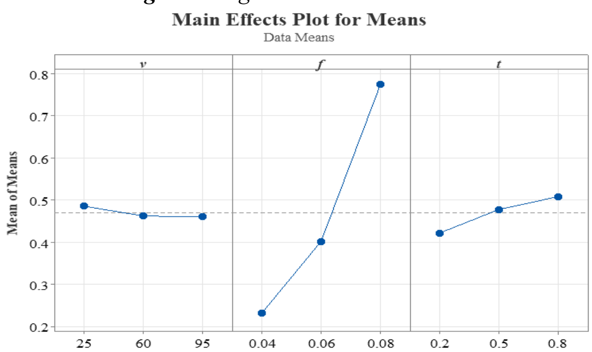

Figure 3. *Mean value chart for each factor*

Table 6. *Mean R_a for each factor level*

Level	*v (m/min)*	*f (mm/t)*	*t (mm)*
1	0.4854	0.2314	0.4217
2	0.4622	0.4019	0.4777
3	0.4599	0.7741	0.5081
Delta	0.0255	0.5427	0.0865
Rank	3	1	2

Table 7. *Statistical significance for each factor*

Factor	SS	DF	MS	F	P-Value
v	1.528	2	0.764	0.903	0.42124
f	506.169	2	253.085	299.192	0.00000
t	15.868	2	7.934	9.379	0.00134
Error	16.918	20	0.846		
Total	540.483	26			

Table 8. *Parameter combinations for the lowest R_a values*

Parameter set	*v (m/min)*	*f (mm/t)*	*t (mm)*
1	25	0.04	0.2
2	60		
3	95		

Additionally, based on the results in Tables 3, 4, 6, and 7, to achieve $R_a \leq 0.21\ \mu m$, f should be kept at 0.04 mm/t, t at 0.2 mm and v can be within the studied range (25 - 95 m/min). When $0.21 < R_a \leq 0.3$, f should be kept at 0.04 mm/t, $t \leq 0.5$ mm and v within 60-95 m/min.

Table 9. *ANOVA for surface roughness R_a*

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	10	1.46441	99.62%	1.46441	0.146441	416.35	0.000
v	1	0.00292	0.20%	0.00318	0.003181	9.04	0.008
f	1	1.32555	90.17%	0.02003	0.020028	56.94	0.000
t	1	0.03366	2.29%	0.00368	0.003685	10.48	0.005
f^2	1	0.06103	4.15%	0.04305	0.043053	122.41	0.000
$v*f$	1	0.00302	0.21%	0.01783	0.017828	50.69	0.000
v^2*f	1	0.00477	0.32%	0.02078	0.020780	59.08	0.000
$v*f^2$	1	0.00436	0.30%	0.02812	0.028120	79.95	0.000
f^2*t	1	0.00146	0.10%	0.00278	0.002777	7.90	0.013
$f*t^2$	1	0.00143	0.10%	0.00143	0.001431	4.07	0.061
v^2*f^2	1	0.02621	1.78%	0.02621	0.026208	74.51	0.000
Error	16	0.00563	0.38%	0.00563	0.000352		
Total	26	1.47004	100.00%				

Table 7 shows that the factor most likely to affect error is feed rate (f) with nearly absolute confidence, (t) is ranked second with over 99% confidence, and (v) has an insignificant effect with 57.8% confidence. The results regarding the effect of each factor in this study are consistent with those reported by S. Kaining et al. [11] in dry milling of magnesium alloys using the Taguchi method combined with grey relational analysis, and by Z. Wang [17] in a study on the effect of cutting parameters during milling of TC17 titanium alloy, where feed rate (f) significantly affected surface roughness. The difference is that the effect of depth of cut on roughness is ranked second, and cutting speed has the least effect.

3.2. Regression model

ANOVA was used to determine the regression model for predicting surface roughness, the contribution of each factor, and the interactions among the factors. The surface roughness data in Table 3 were analysed and plotted to assess whether they follow a normal probability distribution, as shown in Figure 4. In the plot, most data points lie within the two boundary lines, indicating that the data are consistent with a normal probability distribution.

$$\begin{aligned} R_a = {} & 0.827 - 0.0687*v - 41.89*f + 0.1618*t \\ & + 542.5*f^2 + 0.7097*v*f - 0.003744*v^2*f \\ & - 9.59*v*f*t + 37.8*f^2*t - 2.73*f*t^2 \\ & + 0.06025*v^2*f^2 \end{aligned} \tag{3}$$

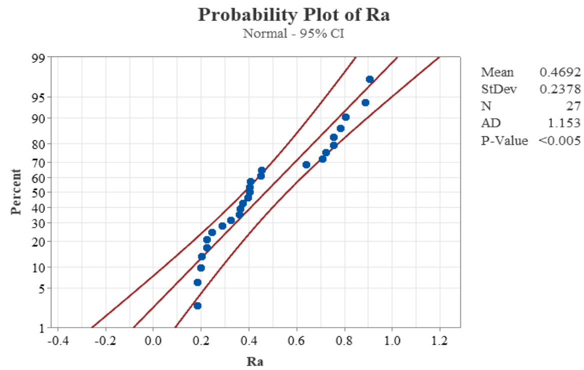

Figure 4. *Probability plot of surface roughness values*

Table 10. *Comparison between predicted and measured R_a values*

No.	Cutting parameters			R_a (µm)	FITS (µm)	Error (%)
	v (m/min)	f (mm/t)	t (mm)			
1	25	0.04	0.2	0.184	0.180	2.178
2	25	0.06	0.5	0.395	0.399	1.011
3	25	0.08	0.8	0.906	0.898	0.851
4	25	0.04	0.5	0.224	0.224	0.118
5	25	0.06	0.8	0.406	0.425	4.717
6	25	0.08	0.2	0.756	0.787	4.072
7	25	0.04	0.8	0.247	0.248	0.469
8	25	0.06	0.2	0.363	0.344	5.220
9	25	0.08	0.5	0.887	0.862	2.778
10	60	0.04	0.2	0.205	0.238	16.176
11	60	0.06	0.5	0.409	0.418	2.297
12	60	0.08	0.8	0.757	0.753	0.548
13	60	0.04	0.5	0.289	0.282	2.474
14	60	0.06	0.8	0.450	0.444	1.366
15	60	0.08	0.2	0.642	0.642	0.050
16	60	0.04	0.8	0.325	0.306	6.061
17	60	0.06	0.2	0.375	0.363	3.089
18	60	0.08	0.5	0.709	0.717	1.070
19	95	0.04	0.2	0.186	0.165	11.538
20	95	0.06	0.5	0.405	0.418	3.267
21	95	0.08	0.8	0.805	0.819	1.748
22	95	0.04	0.5	0.199	0.208	4.844
23	95	0.06	0.8	0.455	0.443	2.488
24	95	0.08	0.2	0.723	0.708	2.180
25	95	0.04	0.8	0.224	0.232	3.896
26	95	0.06	0.2	0.361	0.363	0.625
27	95	0.08	0.5	0.783	0.783	0.018
% Mean absolute error (%MAE)						3.154
% Mean square error (%MSE)						0.222

The ANOVA results are shown in Table 9. From the P-value column, all factors and their interactions have P-values below 0.05, indicating that the cutting parameters significantly affect surface roughness. Among them, feed rate has the lowest P-value (approximately 0), followed by depth of cut (0.005), and cutting speed has the highest P-value (0.008). This result is completely consistent with the study by M. S. Shahrom et al. [18] on the effect of lubrication conditions on surface roughness during milling, which concluded that feed rate has the lowest P-value and a significant effect on surface roughness. From the Contribution column, the greatest effect on roughness is from feed rate f (90.17%), followed by depth of cut t (2.29%) and the least effect is from cutting speed v (0.20%). Therefore, to effectively control R_a, priority should be given to controlling f followed by t and finally v. This is consistent with the studies by D.D. Trung [7] and P. G. Reddy et al. [19], which also showed that surface roughness is most dependent on feed rate. The regression model is presented in equation (3) for the range of cutting parameters in this study. The model has a coefficient of determination $R^2 = 0.9962$, indicating a very good fit for representing the output response. Since R^2 is close to 1, this model can be used as an objective function to predict surface roughness (R_a). Furthermore, the predictive capability of the model, R-sq(pred) reaches 0.9879, indicating that the regression model has very high predictive accuracy for actual surface roughness.

The assumption of normal distribution of errors was checked by plotting the normal probability plot in Figure 5 and the histogram of residuals in Figure 6. Figure 5 shows that the errors are normally distributed, as the residuals lie along a straight line. The distribution of relative errors (Figure 6) is symmetrical about zero, satisfying the normality condition.

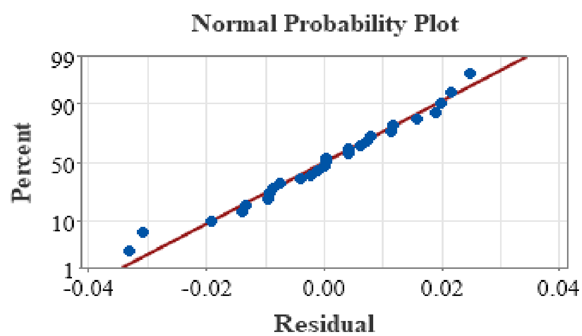

Figure 5. *Normal probability plot*

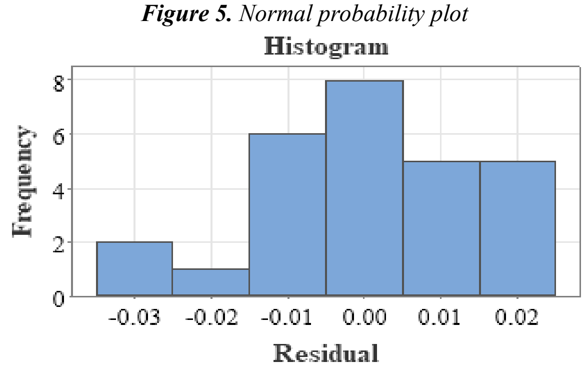

Figure 6. *Histogram of R_a residuals*

Table 10 shows the percentage error between the regression model predictions and the actual R_a values to evaluate the model's suitability. The maximum and minimum percentage errors are 16.176% and 0.018%, respectively. Based on the data in Table 10, the mean absolute percentage error (%MAE) and mean squared percentage error (%MSE) are 3.154% and 0.222%, respectively. The regression model is thus fully suitable for predicting surface roughness in the finish milling of 6061 aluminium alloy.

Table 11. *Predicted R_a results within the studied range*

No.	Cutting parameters			Actual	Predicted	error (µm)	Percentage error (%)
	v (m/phút)	f (mm/r)	t (mm)	R_a (µm)	R_a (µm)		
1	35	0.05	0.3	0.324	0.271	0.053	16.493
2	35	0.065	0.6	0.421	0.495	0.074	17.548
3	50	0.05	0.7	0.410	0.342	0.068	16.639
4	50	0.07	0.3	0.471	0.514	0.043	9.059
5	80	0.065	0.7	0.566	0.506	0.06	10.618
6	80	0.07	0.6	0.589	0.570	0.019	3.247
% Mean absolute error (%MAE)							12.270
% Mean square error (%MSE)							1.770

To assess the regression model's predictive capability for parameter values outside the 27 main experiments, six additional experiments with randomly selected cutting parameters within the studied range were conducted. Table 11 presents the parameters, actual, and predicted surface roughness values. The mean absolute percentage error (%MAE) and mean squared percentage error (%MSE) for these cases are 12.270% and 1.770%, respectively. Although some predictions have errors greater than 10%, most predicted values are lower than the actual measurements. Thus, from a technical perspective, the regression model can be applied to predict R_a for cutting parameter values within the studied range.

4. Conclusion

The study on the effects of cutting parameters on surface roughness during the milling of 6061 aluminium alloy using the Taguchi method and ANOVA, conducted on a Mazak VCN-430A SG machining center with a Lasting Victory 884L-Z (100410) end mill, yielded the following results:

- Among the investigated factors, feed rate (f) has the greatest effect on surface roughness, followed by depth of cut (t), while cutting speed (v) has the least effect.

- In terms of the correlation between the variation due to each factor and the random variation as well as reliability, the results show that feed rate (f) is the most significant factor affecting error, with nearly absolute confidence, (t) is ranked second with over 99% confidence, and (v) has an insignificant effect with 57.8% confidence.

- The regression model for predicting R_a was established with a reliability of $R^2 = 0.9962$.

Analysis of the parameter combination for the lowest surface roughness shows that f = 0.04 and t = 0.2 are the decisive values for the optimal parameter set, while v is not significant and can be chosen within the range of 25 - 95 m/min.

- Comparison between the actual R_a values and the regression model predictions for six additional experiments outside the main 27 experiments yielded a mean absolute percentage error (%MAE) of 12.270% and a mean squared percentage error (%MSE) of 1.770%.

Additionally, with the current development and widespread application of AI models across various fields, AI can be used to predict and optimise cutting parameters to achieve the desired surface roughness. This will be addressed in future research to improve the accuracy of surface roughness prediction further and help minimise errors in actual machining processes.

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