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Dry Milling Machining: Optimization of Cutting Parameters Affecting Surface Roughness of Aluminum 6061 using the Taguchi Method

Shamsuddin Sulaiman[1], Mohammad Sh Alajmi[1], Wan Norizawati Wan Isahak[1], Muhammad Yusuf[2], Muhammad Sayuti[3*]

[1]*Faculty of Engineering, Department of Mechanical and Manufacturing Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia*
[2]*Department of Mechanical Engineering, Faculty of Engineering, Universitas Malikussaleh, 24351 Aceh Indonesia*
[3]*Department of Industrial Engineering, Faculty of Engineering, Universitas Malikussaleh, 24351 Aceh Indonesia*

Abstract. In this paper, the application of dry machining as part of contributions for development of a sustainable environment in the machining industry is explained. Achieving a good surface roughness product is one the most important factors that must be considered in the metal machining process. Surface quality control is a complicated process, and a reliable technique is required during machining operation. Currently, an appropriate cutting conditions in most of machining cases are determined by trial and error, which leads to time increased, energy consumption, and manufacturing costs. Most of the previous studies have investigated factors that affect surface roughness, but different machining conditions require the control of different factors. In this study, experiments were conducted to optimize cutting parameters and determine the factors significant for the surface roughness quality. Machining experiments were conducted on a vertical milling machine using square non-coated two flutes HSS Co end mill with selected cutting parameters on aluminum 6061. This study focused on the surface roughness in one direction and combined with the Taguchi design method. Signal-to-noise (S/N) ratio and analysis of variance (ANOVA) were employed to examine and reveal the factors that are significant in affecting surface roughness quality. The analysis result revealed that cutting speed exerts the highest effect on surface roughness, followed by feed rate and depth of cut. Finally, the combination of dry machining performance and an eco-friendly environment would result in competitive sustainable growth of the machining industry.

Keywords: ANOVA; Machining process; Signal-to-noise; Surface roughness; Taguchi method

1. Introduction

In the machining industry, a liquid coolant, also called a cutting fluid, is used to remove the heat produced during machining. However, the use of cutting fluids incurs considerable economic and ecological burden, which is continuously increasing (Wickramasinghe et al., 2020). Therefore, researchers have attempted to utilize machining components without using cutting fluids, which is referred to dry machining.

In the last few years, the monitoring of surface roughness has been developed, and a few different measuring systems are also available to measure surface roughness (Saif and

*Corresponding author's email: sayuti_m@unimal.ac.id, Tel.: +6285277293401
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Tiwari, 2021). To obtain the desired surface quality of parts by end-milling machining, few cutting parameters should be selected and controlled appropriately during machining, including cutting speed, feed rate, and depth of cut. Poor selection of machining parameters leads to the rapid wear and breakage of cutting tools.

A few number of processes that can be utilized to produce raw materials of any desired shape from its initial stage to its final stage are available. Among various machining processes, end milling is one of the most widely employed material removal processes in industries (Nisar et al., 2021). Cutting operations by end mills can be as simple as face milling on the top of a flat surface using a rigid cutter or the milling of extremely complex parts (Hoang et al., 2019). Aluminum is mainly used in industries to produce various parts, especially for the assembly of machine parts (Daghfas et al., 2017).

Typically, surface roughness is utilized as an extremely good performance predictor of mechanical components of machined materials as irregular surface properties may lead to cracks or corrosion (Dinesh et al., 2014). Sometimes, although surface roughness is undesirable for certain manufacturing products, it is quite difficult to control and may incur higher machining costs (Singh et al., 2020).

Elmunafi (2015) has reported that cutting speed is the most significant cutting parameter, followed by feed rate and depth of cut (Elmunafi et al., 2015; Tapadar et al., 2017). On the other hand, Liu (2016) has reported that feed rate is the most significant factor that affects surface roughness, followed by depth of cut and cutting velocity, for minimizing energy consumption (Liu et al., 2016). Shah and Bhavsar (2020) have investigated four machining parameters, namely cutting speed, feed rate, depth of cut, and nose radius, respectively, to examine the maximum tool life and minimum power consumption (Shah and Bhavsar, 2020). Their study results revealed that cutting speed is the most significant parameter to achieve the maximum tool life with minimum power consumption, followed by depth of cut, feed rate, and nose radius.

In studies on surface roughness, various methodologies and practices have been employed and applied for the prediction of quality surface roughness, such as artificial intelligence or soft computing techniques, the Taguchi method, response surface methodology (RSM), machining theory, classical experimental design, and artificial neural network (Qehaja et al., 2015; Kilickap et al., 2017). Recently, the design of experiments (DOE) method has been widely used in various industries for several years to improve the product and manufacturing process (Razavykia et al., 2015). Vishnu Vardhan (2017) has applied the Taguchi method to investigate the effects of feed rate, cutting speed, nose radius, depth of cut, and cutting environment of AISI P20 tool steel machining on power consumption. The results revealed that cutting speed is the most significant factor, followed by feed rate and depth of cut (Vishnu Vardhan et al., 2017). Meanwhile, Qasim (2015) has employed the Taguchi design and analysis of variance (ANOVA) to investigate the effect of cutting parameters on surface finish and power consumption during the high-speed machining of AISI 1045 steel with a coated carbide tool (Qasim et al., 2015). The result revealed that cutting speed is the most significant factor, followed by depth of cut, to reduce power consumption. Therefore, generally, it is complicated to determine the relationship between cutting parameter as a machining control parameter and response characteristics due to various factors that affect surface finish (Singh et al., 2020).

ANOVA has been used predominantly in experiments for statistical analysis and to reveal cutting parameters that significantly affect response variables as well as performance characteristics (Rathod et al., 2021). In addition, ANOVA can determine the effect of machining parameters on various responses, including power consumption, cutting force, and material removal rate (MRR), etc. (Khentout et al., 2019). In the analysis, the sum of squares (SS) and variance of square are calculated, and the F-test ratio at the 95% confidence level is employed to determine the significant factors that affect machining (Ahmed et al., 2015). Usually, at a high F-ratio, the machining factor significantly affects the response variable (Maiyar et al., 2013). Thus, according to ANOVA, a high F-ratio value indicates a large significant of control factors. In addition, the probability value (P) also revealed the level of significance of each control factor. Low P values indicated that control factor values exhibit a high probability of falling within the ranges, thereby impacting the experiment results (Qasim et al., 2015).

2. Methodology

This study consists of three major parts: First, machining experiments are conducted, with focus on three parameters, and machining is conducted under different parameter setting values according to DOE are observed. Second, surface roughness measurements are conducted with the main objective to define the effectiveness of machining parameter settings toward surface finish on workpieces. In addition, the correlation between three control parameters with surface roughness is determined. Third, surface morphology analysis is conducted to define the surface morphology of different samples. Figure 1 shows the overall steps of this methodology.

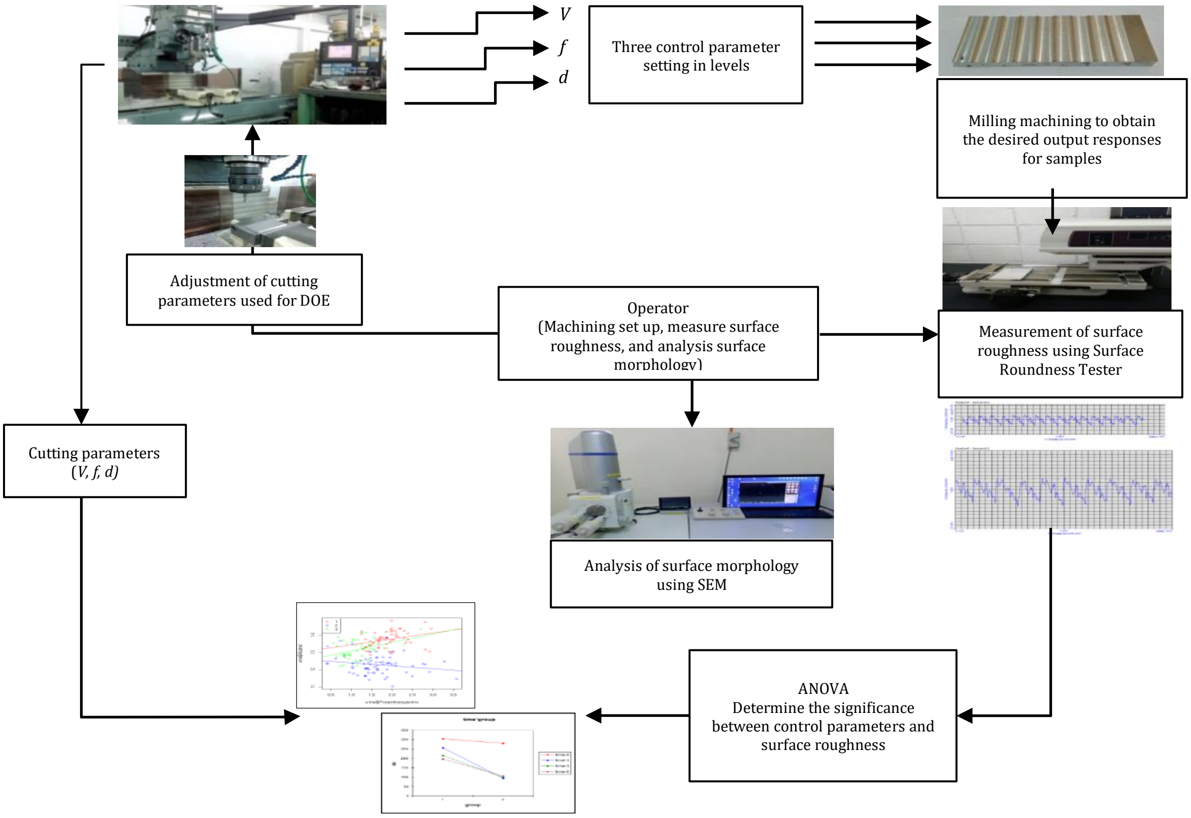


Figure 1 Methodology steps of the overall project

Before machining is started, control parameters such as cutting speed, feed rate, and depth of cut are considered. The surface finish results after machining processes are utilized to predict the optimization of each cutting parameter to obtain the minimum surface roughness and determine the correlation between the three control parameters and output response. The experiment is conducted by using the Makino AE74 vertical milling machine.

In this experiment, a 100 mm × 50 mm × 10 mm block of aged aluminum 6061 was used as the work material (Figure 2). Aluminum exhibits high strength, good workability, and high corrosion resistance. The block was subjected to forging at a temperature interval of 350°C to 500°C. Table 1 and Table 2 summarize the chemical composition and mechanical properties of this material, respectively.

Table 1 Chemical composition of aluminum 6061

Chemical Composition (%)					
Al	Si	Fe	Cu	Mn	Mg
95.8–98.6	0.4–0.8	<0.7	0.15–0.40	<0.15	0.80–1.20
Cr	Zn	Ti	Others		
0.04–0.35	<0.25	<0.15	0.05		

Table 2 Mechanical properties of Al6061

Properties	Strength MPa
Tensile Strength	310
Yield Strength	276
Shear Strength	207
Fatigue Strength	96.5

A Nachi square milling cutter with two flute end mills was used as the cutting tool. The cutting tool was 8% cobalt high-speed steel with excellent high resistance and toughness-improved hard carbide created by mixing W, Mo, Cr, and V with iron, which is used for all types of cutting, including rough cut, semi-finish cut, and finish cut. In addition, it is used for general purposes, such as slotting and side milling, etc. The same tool is used in all experiments.

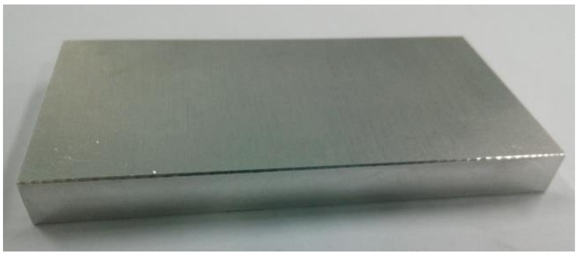


Figure 2 Al 6061 workpiece

The combined selection of cutting parameters in this experiment is adapted from the Taguchi experimental design only. Table 3 summarizes the three control parameters of cutting speed (V), feed rate (f), and depth of cut (d), respectively, selected for machining experiments.

Table 3 Factors and levels used in the experiment

Factor / Level	L1	L2	L3
A - Cutting speed (m/min)	200	250	300
B - Feed rate (mm/rev)	150	200	250
C - Depth of cut (mm)	0.5	1	1.5

The selection range of machining parameters is based on those commonly used in the metal cutting industry to produce the desired surface roughness for common parts used in related industries. For this experiment, a Taguchi L_9 orthogonal array is employed, with a full factorial experiment that requires 3^3, with 9 entitled trials. There are three independent variables at three different setting levels for machining experiments. Table 4 summarizes the experiment set design.

Table 4 Experimental set

Experiment run	Design of Experiment	Cutting speed, V (m/min)	Feed rate, f (m/rev)	Depth of cut, d (mm)
Exp 1	E1	200	150	0.5
Exp 2	E2	200	200	1.0
Exp 3	E3	200	250	1.5
Exp 4	E4	250	150	1.0
Exp 5	E5	250	200	1.5
Exp 6	E6	250	250	0.5
Exp 7	E7	300	150	1.5
Exp 8	E8	300	200	0.5
Exp 9	E9	300	250	1.0

The surface roughness after machining is measured with a contouring measurement system. The experimental design is based on the Taguchi L9 orthogonal array, which involves the selection of three parameters as independent variables to produce one response variable and determines the interactions between each parameter and output response. An orthogonal array signal-to-noise (S/N) and ANOVA are employed, which is run using Minitab 16 software. These two analysis methods are crucial to reveal the parameters that significantly affect the roughness of output materials.

3. Results and Discussion

Figure 3 shows the outcome of the workpiece after experiments were conducted. Figure 4 shows some of the typical results of surface roughness. The S/N ratio results shown in Table 5 revealed that the highest S/N ratio value is –2.019, where the condition of cutting parameters is a cutting speed at level 3 (300 m/min), feed rate at level 1 (150 mm/rev), and a depth of cut at level 3 (1.5 mm). Meanwhile, the lowest S/N ratio value is –7.290, where the condition of cutting parameters is a cutting speed at level 1 (200 m/min), a feed rate at level 3 (300 mm/rev), and a depth of cut at level 3 (1.5 mm). In addition, the delta value is calculated, which represents the difference between the highest and lowest values of S/N at all different levels.

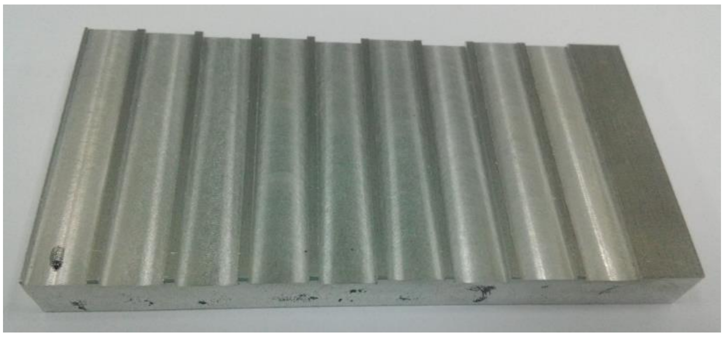


Figure 3 Workpiece after experiment with a 7.5-mm end mill line width and nine slots of lines

Each factor parameter is ranked according to their delta value. The delta and rank shown in Table 6 revealed that the factor with the highest delta value is the most effective and significant that affects the response in milling machining. Based on the sequence rank, it revealed that spindle speed is the most crucial cutting parameter that significantly affects surface roughness, followed by feed rate and depth of cut.

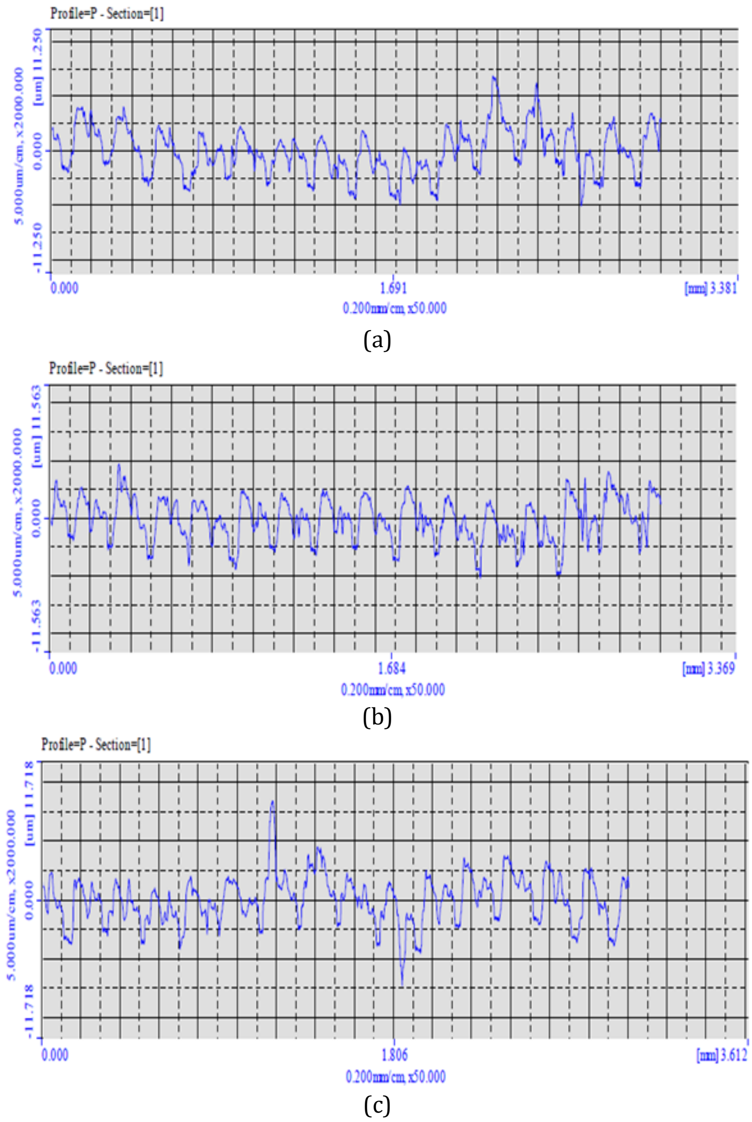


Figure 4 Typical measurement results of surface roughness (Ra) at three points of the experiment: (a) starting point, Ra1 = 1.367 µm; (b) center point, Ra2 = 1.349 µm; and (c) ending point, Ra3 = 1.477 µm

Table 5 Signal-to-noise ratios and means

Experiment run	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	*Ra*	SNRA1	MEAN1
Exp 1	200	150	0.5	1.459	–3.283	1.459
Exp 2	200	200	1.0	1.672	–4.466	1.672
Exp 3	200	250	1.5	2.315	–7.290	2.315
Exp 4	250	150	1.0	1.398	–2.908	1.398
Exp 5	250	200	1.5	1.581	–3.980	1.581
Exp 6	250	250	0.5	1.591	–4.033	1.591
Exp 7	300	150	1.5	1.262	–2.019	1.262
Exp 8	300	200	0.5	1.295	–2.245	1.295
Exp 9	300	250	1.0	1.456	–3.263	1.456

Table 6 Response table for signal-to-noise ratios

Level	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)
1	–5.013	–2.737	–3.187
2	–3.641	–3.564	–3.546
3	–2.509	–4.862	–4.43
Delta	2.504	2.125	1.242
Rank	1	2	3

The graph of the main effects for S/N ratios clearly revealed the trend of the response of each cutting parameter to surface roughness with a smaller-the-better characteristic. As can be observed from the graphs in Figure 5, the cutting speed at level 3 (300 m/min) exhibits the best result. Meanwhile, the feed rate affords the best result at level 1 (150 mm/rev), and the depth of cut provides the best result at level 1 (0.5 mm).

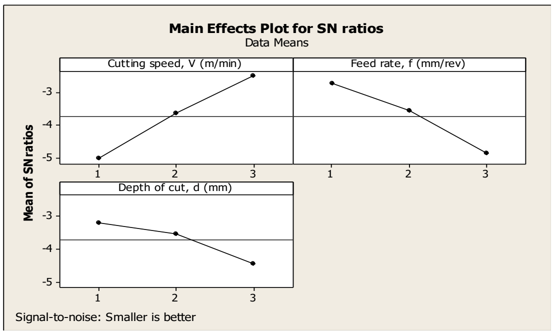


Figure 5 Main effect plots of S/N ratios

Table 7 and Figure 6 show the ANOVA results in identifying the significant control factors and F-ratio. The analysis was conducted for a significance level of p-value (probability of significance) at the 95% confidence level. According to the p-value results, the cutting speed exhibits the lowest value (0.136), followed by feed rate, 0.171. Meanwhile, the depth of cut exhibits a considerably different p-value, i.e., 0.312, compared to those of the two control factors. Similarly, the F-ratio for cutting speed exhibits the highest value (6.34%). Meanwhile, a moderate feed rate is obtained, with an F-ratio of 4.84%, followed by depth of cut with an F-ratio value of 2.21%.

Table 7 ANOVA for surface roughness

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Cutting speed, V (m/min)	2	0.3	0.34822	0.17411	6.34 (1)	0.136
Feed rate, f (mm/rev)	2	0.26566	0.26566	0.13283	4.84 (2)	0.171
Depth of cut, d (mm)	2	0.12128	0.12128	0.06064	2.21 (3)	0.312
Error	2	0.05491	0.05491	0.02746		
Total	8	0.79007				
S = 0.165702		R-Sq = 93.05%			R-Sq(adj) = 72.20%	

From this table, the P-value for these three control factors is greater than 0.05. According to the p-value result, the cutting speed is the lowest (0.136), followed by feed rate, 0.171. Meanwhile, the depth of cut exhibits a considerably different p-value of 0.312 compared with those of the other two control factors. Similarly, the F-ratio for the cutting speed exhibits the highest value (6.34%). Meanwhile, a moderate feed rate is obtained, with an F-ratio value of 4.84%, followed by the depth of cut with an F-ratio value of 2.21%.

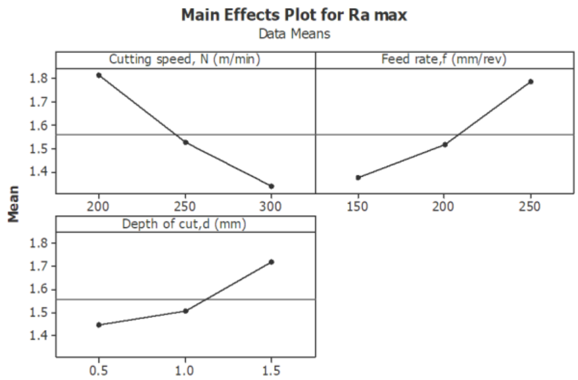
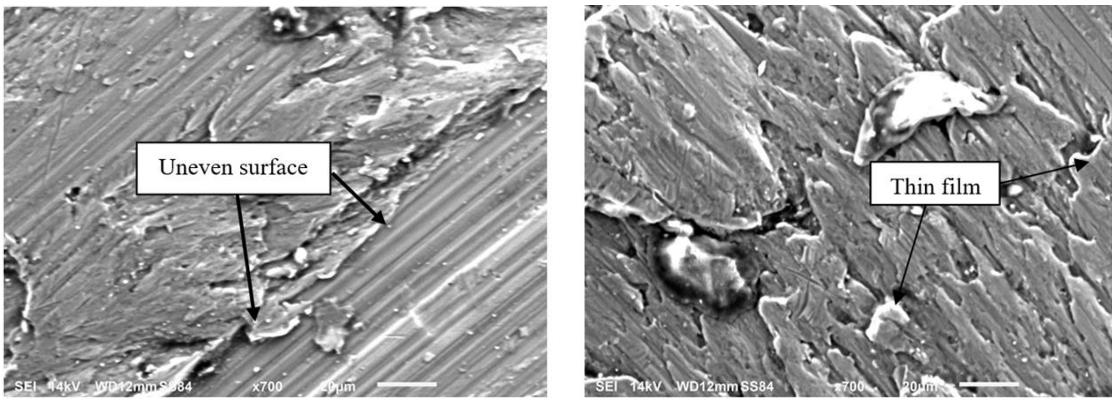


Figure 6 Main effect plots of Ra by ANOVA

The analysis revealed a significant result based on ANOVA, with the three control factors being significant for surface roughness. In addition, ANOVA revealed that the obtained result is similar to the S/N ratio, which is obtained from the response table for S/N ratios with the smaller-the-better characteristic, indicating that cutting speed exhibits the highest significance in terms of surface roughness, followed by feed rate (moderately significant), and depth of cut (lowest significance).

In this study, scanning electron microscopy (SEM) was employed to examine the surface finish morphology. The machined surface samples from nine sets of experiments were observed by SEM, and the images were analyzed in terms of the exact similarity with the S/N ratio and ANOVA analysis results. Figure 7 shows the SEM surface morphology images. Figure 7a shows the SEM image of the machined surface at the highest surface roughness value, and Figure 7b shows the SEM image of the machined surface at the lowest surface roughness.



(a) (b)

Figure 7 SEM sample image of the machined surface: (a) SEM image for experiment 3; and (b) SEM image for experiment 7

The topographical and elemental information of surface finish is obtained by SEM with a virtually limitless depth of area at 700× magnification. Feed marks of the machined surface are clearly observed in the SEM images of all experiment samples. Aluminum is machined into high-quality products where friction is generated as a result of metal removal techniques, subsequently generating heat. In a continuous cutting process, excess heat is detrimental to metal removal, affording an uneven surface on the machined surface, small exfoliations, and thin film shedding of the surface layer. Thin-film shedding of the surface layer is less disruptive to surface finish. The formation of a thin film, which is developed on feed marks of a machined surface, leads to less friction and thermal deformation between the cutting tool and workpiece via surface contact. Thus, this process certainly increases the surface finishing quality; hence, surface properties are successfully enhanced. Uneven surfaces on the machined surface caused rough finishing. Therefore, the uneven surface deteriorates the surface finish quality of the workpiece with a high surface roughness.

4. Conclusions

In conclusion, dry machining was demonstrated to contribute to an eco-friendly environment in the machining industry. In this study, an experimental study for the prediction and optimization of cutting parameter is discussed, where a minimum surface roughness of aluminum 6061 using an HSS-Co Helical Shank Insert is subjected to a dry milling cutting condition. The Taguchi method combined with the design of experiment is applied for the response characteristic optimization. The relationship between control parameters (e.g., cutting speed, feed rate, and depth of cut) and surface roughness on the basis of different levels by the DOE method is determined. Analysis in terms of the significant effect clearly revealed that the three control parameters exhibit an important correlation between each other. In terms of the three control parameters, surface roughness quality mainly depends on cutting speed, followed by feed rate and depth of cut. A high cutting speed affords high surface roughness quality. However, surface roughness quality decreases with a low feed rate and depth of cut.

The S/N ratio analysis revealed that the cutting speed is the most significant factor affecting surface roughness, followed by feed rate (moderately significant) and depth of cut (least significant factor), of a machined surface. The optimal combination of the control parameters in minimizing surface roughness is A3B1C1, indicating a cutting speed of 300 m/min (level 3), a feed rate of 150 mm/rev (level 1), and a depth of cut of 0.5 mm (level 1). Similarly, ANOVA results also revealed the same result as that of S/N ratio analysis.

SEM analysis is employed to observe the morphology of the machined surface on the workpiece material. SEM images revealed that surface roughness is uneven when machining is conducted under a lower cutting speed and the surface is covered by a thin film, and it is less uneven when machining is conducted under a higher cutting speed, which affords a better surface roughness quality. Besides, a low feed rate and depth of cut contribute to a better surface finish quality compared with a higher feed rate and depth of cut, leading to disruption in the metal removal process.

Finally, positive outcomes of the dry machining process should be implemented in the machining industry worldwide, especially in Euro-Mediterranean countries. The combination of dry machining performance and an eco-friendly environment would lead to competitive sustainable growth in the machining industry.

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