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A study of end milling process parameter's effect on thin wall aluminum-7075 surface roughness under minimum quantity lubrication

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KEYWORDS

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ABSTRACT

The end milling process on thin wall aluminum-7075 under minimum quantity lubrication, as an effort to apply clean technology, has been carried out in this research to obtain the effect of process parameters and lubricant spraying direction on surface roughness. The parameters applied to the process were spindle speed, feeding speed, and depth of cut, while the spraying directions used were in the same and opposite directions of feeding. Statistical analysis was then applied to predict surface roughness values in each combination of parameter levels. All parameters except spindle speed have a significant effect on surface roughness. The prediction equations have MSE values of 1.54×10^{-3} μm^2 and 7.03×10^{-3} μm^2 for the direction of spraying lubricants in the same and opposite directions of feed, respectively.

1.0 INTRODUCTION

Thin wall structures are very important in aerospace because of their ability to reduce aircraft weight while maintaining strength and stability. This weight reduction leads to several benefits, including improved fuel efficiency, increased cruising range, and lower operating costs. However, the structures have very weak stiffness as they are easily deflected during machining. The process of machining is more difficult because there is Built-Up Edge (BUE) phenomenon in ductile

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materials that can negatively affect the surface quality of the machined parts (B et al., 2022; Ibrahim et al., 2023).

Various methods have been proposed to assess and improve the quality of thin wall products. A systematic approach has been recommended to predict and rectify for thickness deviations in thin plates (Huang et al., 2020). Another study also focused on estimating geometric tolerances, such as flatness and cylindricity, to understand their relationship with component configuration (Agarwal & Desai, 2022). Aside from deviation prediction, a new machining process technique has also been recommended in the form of a double-sided cutter, which is applied during milling (Mejbel et al., 2022).

Machining process is very crucial in manufacturing industry, with end milling being one of the most widely used method. In end milling, several process parameters are crucial for achieving the desired product quality, including spendle speed, feeding speed, and depth of cut. Additionally, the choice of cutting fluid plays an important role in determining the final product quality. Specifically, the use of the wrong cutting fluid will have a negative impact on health and specifically the environment. Cutting fluid is considered one of the main sources of environmental pollution (Sankaranarayanan et al., 2021).

A typical method of using environmentally friendly cutting fluid that is widely applied in end milling process is minimum quantity lubrication (MQL) (Cai et al., 2022, 2024; Ismail et al., 2024). In general, MQL is applied by spraying the cutting fluid in the form of a mist to the cutting area using compressed air. This method serves two purposes, namely providing lubrication to reduce friction between the cutting tool and the workpiece and reducing heat generated during the cutting process. Studies have shown that MQL can also contribute to improved surface roughness in machined parts (Nathan et al., 2021; Okafor & Jasra, 2019). Despite its benefits, MQL has not been widely adopted in the manufacture of thin wall structures.

Surface roughness is an important factor in determining the performance of machining processes, including milling (Hanafiah et al., 2021; Mohamad et al., 2024). As a result, numerous studies have focused on predicting surface roughness using various methods. For example, artificial intelligence such as Artificial Neural Networks (ANN) have been used to predict the surface roughness of biomedical alloys in dry end milling process (Dijmărescu et al., 2021). Studies have also combined ANN with Genetic Algorithm (GA) to predict surface roughness in carbon fiber composite plates during dry end milling (Boga & Koroglu, 2021). Another artificial intelligence method such as fuzzy logic has been applied to predict surface roughness in steel alloys based on end milling parameters (Senthilkumar et al., 2023). However, this method is prone to overfitting, potentially limiting reliability in generating accurate prediction equations.

To address the limitations, this study aims to predict surface roughness of aluminum-7075-T651 alloy, a material commonly used in thin wall aircraft components, during end milling process assisted by MQL. Prediction is based on process parameters including spindle speed, feeding speed, and depth of cut. In order to keep with clean technology principles, this study applied environmentally friendly MQL method using vegetable oil, specifically Virgin Coconut Oil (VCO). Commercial VCO is considered to prevent bacteria contamination that can interfere with machining process. In addition, the impact of MQL spray direction on surface roughness has been examined. By comparing the effect of spraying in the same direction as feed in the opposite direction, this study aims to determine the specific method that produces better results.

2.0 MINIMUM QUANTITY LUBRICATION

VCO is used as cutting liquid due to its environmentally friendly nature as vegetable oil. This practice is consistent with clean technology principles in cutting process. The chemical composition of VCO includes 51% lauric acid, 18.5% myristic acid, 9.5% caprylic acid, 7.5% palmitic acid, 5% oleic acid, 4.5% capric acid, 3% stearic acid, and 1% linoleic acid. It is important to be aware that more than 90% VCO composition consists of saturated fatty acid. Consequently, this composition makes the oxidative stabilization of the oil to be strongly resistant in accordance with the character of saturated oil (Xavior & Adithan, 2009).

When using the MQL method, VCO is sprayed by compressed air using a mist spray device, namely MQL LMU100-15. This tool has an oil storage capacity of up to 3,000 cm^3 with an inlet pressure of up to 10 bar. However, the air pressure used in the study is kept constant at 5 bar, and the setup of MQL LMU100-15 tool is shown in Figure 1. Air from the compressor passes through the input hose with the pressure regulated using the pressure control button. VCO comes out of the transparent hose due to pressure in the oil tank and is nebulized in the nozzle by pressurized air coming out of the hose on the other side. Subsequently, the nozzle is directed towards the cutting process, and on LMU100 series equipment, an air blower that can be activated and removed is located at the bottom of the hose.

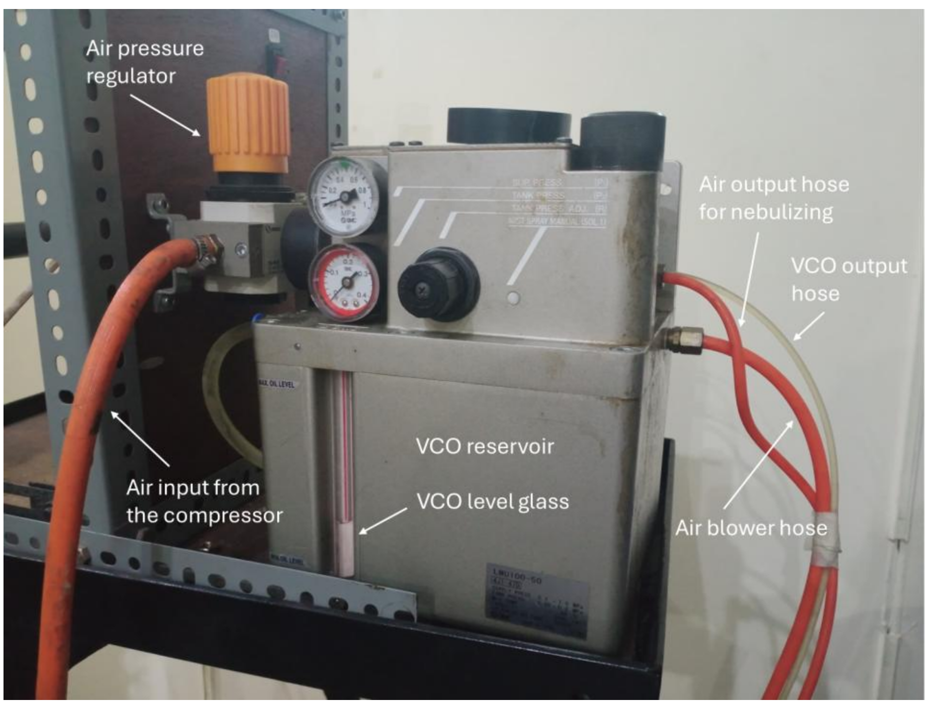
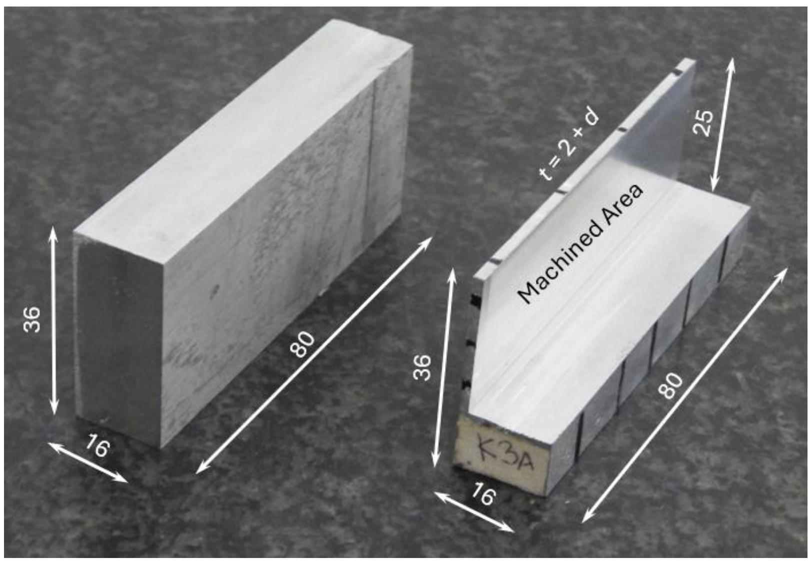


Figure 1: MQL equipment and piping.

3.0 EXPERIMENTAL WORK

3.1 Experimental Setup

The thin wall structure used in this study was made from raw materials, namely aluminum alloy 7075-T651 with a hardness value of 150 BHN. As applied in previous research (Wu et al., 2022), the dimensions of the raw material were 80 mm x 36 mm x 16 mm and were then shaped as shown in Figure 2. Typically, thin wall structure was made as a straight workpiece, and had a height from the base and a width of 25 mm and 80 mm respectively, while the thickness was 2 mm plus the depth of cut (*d*). Following this discussion, the final thickness of the thin wall structure after passing through the cutting process was 2 mm.



(a) (b)

Figure 2: Thin wall structure: (a) raw material, (b) workpiece.

The prepared workpiece was arranged in the CNC milling machine as shown in Figure 3 for machining. The workpiece was gripped on the milling machine table where the surface was facing towards the operator. Additionally, the end mill tool used was carbide tool with a diameter of 8 mm, multiple cutting edges of 3, and a helix angle of 35^0. When conducting the machining process, process parameter and the direction of MQL spraying were varied in this study. Moreover, variations in spraying occurred in the direction of feeding and opposite it.

3.2 Experimental Design

In this study, three EMP parameters were used as independent variables, namely spindle speed, feeding speed, and depth of cut. Each process parameter was varied by 3 levels of adjustment as shown in Table 1. Consequently, variations were also made for the independent variable of MQL liquid spraying direction, but these variations were only 2 levels. For 4 variables, where 1 variable had 2 levels and the other 3 variables had 3 levels, the appropriate experimental design to use was L18 orthogonal array. In addition, there were 18 experimental trials in the array, where each trial had a different combination of variable levels as shown in Table 2. Two replications were carried out on this experiment. The replication needs to be done considering the variability in the machining process, including the end milling process. This variability mainly comes from the rotation of the motor and the drive mechanism that still has random errors even though they have been well controlled.

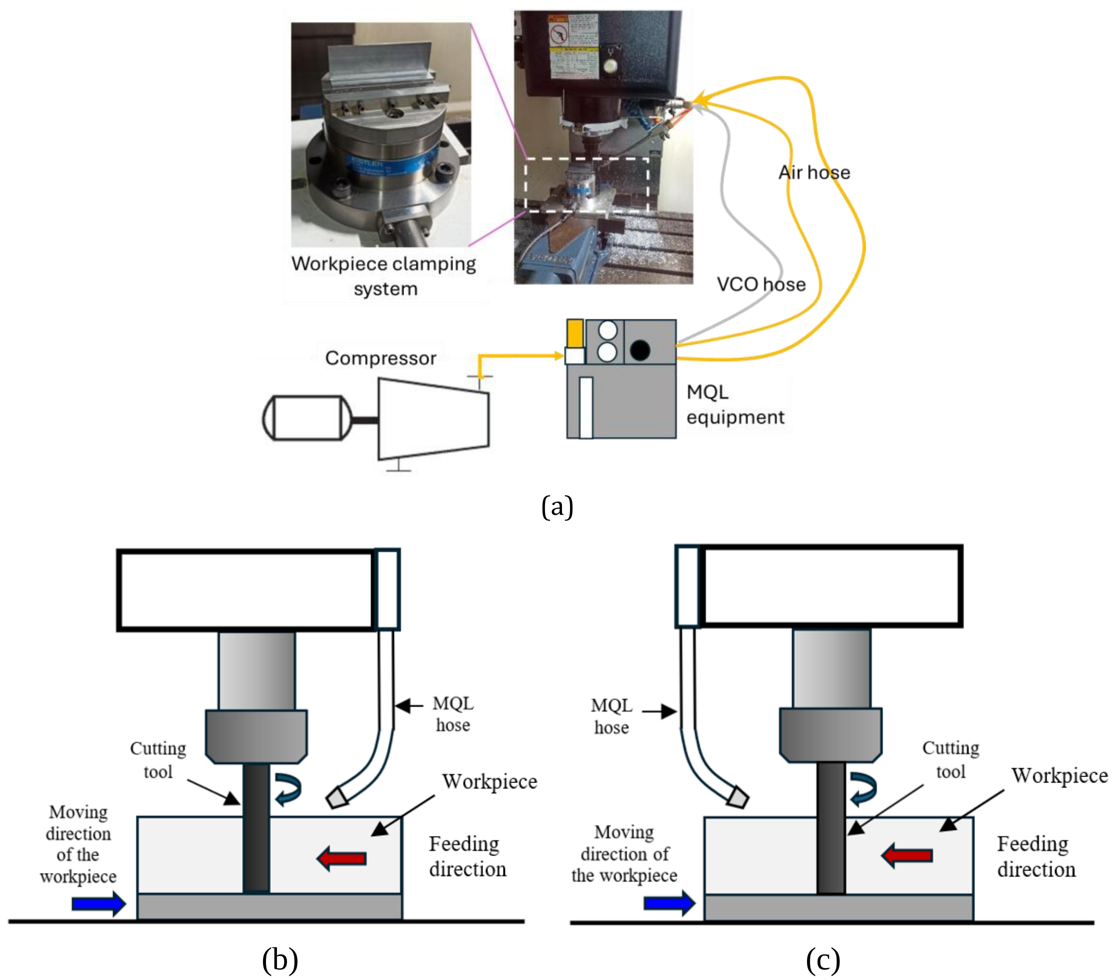


Figure 3: (a) Experimental setup of MQL-assisted thin wall machining in the following way. (b) Spraying MQL in the direction of feeding, (c) spraying MQL in the opposite feeding direction.

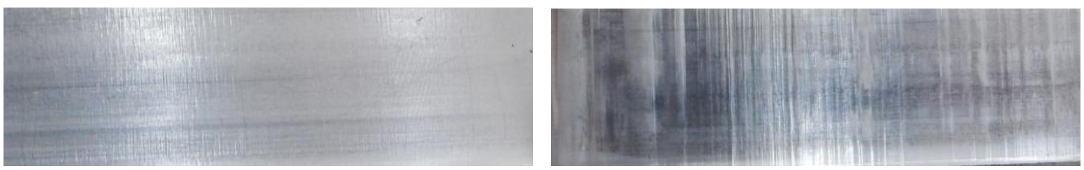
Table 1: Independent variables of EMP.

Independent Variable	**Unit**	**Level**		
		1	**2**	**3**
Spindle Speed (*N*)	rpm	3000	5000	7000
Feeding Speed (v_f)	mm/min	50	100	150
Depth of cut (*d*)	mm	0.25	0.5	0.75
Spray Direction (SD)	-	In the direction of feeding	-	Opposite direction of feeding

4.0 RESULTS AND DISCUSSION

4.1 Analysis of Surface Roughness

The experimental results showed that there were differences in surface quality with different treatments in process parameter and the direction of MQL liquid spraying. Figures 4a, and 4b showed the results from experiments 2 and 12, respectively. Experiment 2 was done on the spindle speed at 3000 rpm, with a feeding speed of 100 mm/min, the depth of cut of 0.5 mm, and MQL spraying to the feed direction. While experiment 12 was done on the spindle at 3000 rpm, with a feeding speed of 150 mm/min, the depth of cut of 0.5 mm, and MQL spraying to the opposite direction of feeding. Observation showed that surface quality of the results from experiment 2 was better than that from 12.



(a) (b)

Figure 4: Surface of experimental results. (a) number 2, which was done on the spindle speed at 3000 rpm, with a feeding speed of 100 mm/min, the depth of cut of 0.5 mm, and MQL spraying to the feed direction, (b) number 12, which was done on the spindle at 3000 rpm, with a feeding speed of 150 mm/min, the depth of cut of 0.5 mm, and MQL spraying to the opposite direction of feeding.

Surface roughness examination was conducted using Mitutoyo SJ-310 surftest which applied the principle of checking contact between the stylus and surface being examined. Additionally, the roughness parameter used was the average surface roughness (Ra). Following this discussion, Equation (1) used to obtain Ra was as follows.

$$Ra = \frac{1}{L}\int_0^L |y(x)|dx \tag{1}$$

where L represented the length of roughness examination sample, y was surface height which was a function of the examination position x. In addition, the results of examining surface roughness obtained from experiments using the tools and equations above were shown in Table 2.

4.2 Discussion

All independent variables were varied, and the significance of the effect of these variables on surface roughness was obtained using the Analysis of Variance (ANOVA) method as shown in Table 3. Relating to the discussion, the hypothesis used in this ANOVA was as follows.

H_0: all μ_i values were the same

H_1: there was at least one different μ_i value

where μ_i represented the population average of surface roughness at i variable level. H_0 denoted the null hypothesis, implying that there was no difference in the population average value of surface roughness at all levels of the independent variable. This statement could be interpreted that there was no significant effect of the analyzed independent variable on surface roughness. Meanwhile, H_1 was an alternative hypothesis, stating that there was at least one population average value of surface roughness at a level of different independent variables. This report meant that the variables analyzed had a significant effect on surface roughness. Moreover, hypothesis selection was determined based on the rejection criterion H_0 when the P value in ANOVA was smaller than the significant level = 0.05.

Table 3 showed that spindle speed and process parameter, did not significantly affect surface roughness. Therefore, only 2 process parameters and 1 MQL spraying direction variable had a significant effect on roughness. The two process parameters, namely feeding speed and depth of cut, were then estimated concerning surface roughness. Moreover, this relationship was made for both spraying MQL liquid in the same direction and against the direction of feeding.

To obtain an estimate of the relationship between process parameter and surface roughness, a non-linear regression method was used in this study. The regression model used was,

$$Ra = \beta_0 + \beta_1 v_f + \beta_2 d + \beta_3 v_f^a + \beta_4 d^b + \epsilon. \tag{2}$$

where $\beta_{0\text{-}4}$ represented a regression constant that was proven to have a significant value, a and b were exponential numbers, and ϵ was an error. After several iterations, the relationship between feeding speed and depth of cut on surface roughness for spraying MQL liquid in the feeding direction was estimated according to Equation (3).

Table 2: Surface roughness examination results.

No	Independent Variable				Surface Roughness Examination	
	Direction of MQL liquid spraying*	**Spindle speed (rpm)**	**Feeding speed (mm/min)**	**Depth of cut (mm)**	**Replication 1**	**Replication 2**
1	1	3000	50	0.25	0.182	0.216
2	1	3000	100	0.5	0.186	0.208
3	1	3000	150	0.75	0.214	0.244
4	1	5000	50	0.25	0.269	0.276
5	1	5000	100	0.5	0.206	0.205
6	1	5000	150	0.75	0.166	0.154
7	1	7000	50	0.5	0.373	0.384
8	1	7000	100	0.75	0.167	0.190
9	1	7000	150	0.25	0.273	0.251
10	2	3000	50	0.75	0.295	0.314
11	2	3000	100	0.25	0.200	0.231
12	2	3000	150	0.5	0.558	0.525
13	2	5000	50	0.5	0.468	0.458
14	2	5000	100	0.75	0.304	0.321
15	2	5000	150	0.25	0.184	0.165
16	2	7000	50	0.75	0.324	0.316
17	2	7000	100	0.25	0.184	0.215
18	2	7000	150	0.5	0.193	0.222

Note: * 1 = In the direction of feeding
2 = Opposite direction of feeding

Table 3: ANOVA Table for the significance examination related to the effect of independent variables on surface roughness.

Source	Degree of Freedom	Sum of Squares	Mean of Squares	F	P	Criteria
Spray direction of MQL liquid	1	0.047888	0.047888	7.52	0.011	Significant
Spindle speed	2	0.003467	0.001734	0.27	0.764	Not significant
Feeding speed	2	0.066463	0.033231	5.22	0.012	Significant
Depth of cut	2	0.080053	0.040026	6.29	0.006	Significant
Error	28	0.178305	0.006368			
Total	35	0.376176				

Subsequently, the coefficient β_i was examined using ANOVA method with the following hypothesis.

H_0: $\beta_i = 0$ where $i = 0, 1, 2, 3, 4$

H_1: at least one $\beta_i \neq 0$

H_0 implied that all regression coefficients were not significant, while H_1 indicated significance in at least one regression coefficient. For H_0 rejection criteria, the significant level = 0.05 was still used, hence ANOVA Table obtained was shown in Table 4. Based on the Table, all coefficients had significant values, showing that Equation (3) was significantly meaningful.

$$\widehat{Ra} = 0.166208 + 0.0035025v_f - 0.672d + 28.9875v_f^{-1} - 0.124125d^{-1} \quad (3)$$

Table 4: ANOVA table to check the significance of the regression coefficient in the direction of MQL liquid spraying according to the feeding.

Source	Degree of Freedom	Sum of Squares	Mean of Squares	F	P	Criteria
Regression	4	0.044280	0.011070	5.1776	0.010199	Significant
β_1	1	0.013200	0.013200	8.8273	0.010824	Significant
β_2	1	0.001965	0.001965	8.1236	0.013652	Significant
β_3	1	0.010854	0.010854	11.6448	0.004630	Significant
β_4	1	0.018260	0.018260	8.5406	0.011885	Significant
Error	13	0.027795	0.002138			
Total	17	0.072074				

The experiment of spraying MQL liquid in the same direction as the feeding was conducted similarly to those in the opposite direction. In both scenarios, the relationship between process parameter and surface roughness was estimated using Equation (2) as follows.

$$\widehat{Ra} = 1.75978 - 0.00136417v_f - 1.23017d - 4.9875v_f^{-1} - 0.263063d^{-1} \quad (4)$$

Each regression coefficient was examined using ANOVA method, and the Table obtained was shown in Table 5.

Table 5: ANOVA Table to examine the significance of the regression coefficient in the direction of spraying MQL liquid opposite to the feeding.

Source	**Degree of Freedom**	**Sum of Squares**	**Mean of Squares**	**F**	**P**	**Criteria**
Regression	4	0.140267	0.0350666	3.93167	0.026339	Significant
β_1	1	0.002863	0.0028630	0.32100	0.580658	Not significant
β_2	1	0.058204	0.0582042	6.52586	0.023984	Significant
β_3	1	0.000737	0.0007370	0.08264	0.778286	Not significant
β_4	1	0.082017	0.0820170	9.19576	0.009619	Significant
Error	13	0.115947	0.0089190			
Total	17	0.256214				

Table 5 showed that the values of β_1 and β_3, representing the coefficients for both linear and non-linear feeding speed process parameter, were not significant. Therefore, the feeding rate was not included in the estimation of the equation that described the relationship between process parameter and surface roughness. The estimated equation was repeated, then Equation (4) was changed to,

$$\widehat{Ra} = 1.33525 - 0.965d - 0.224375d^{-1} \tag{5}$$

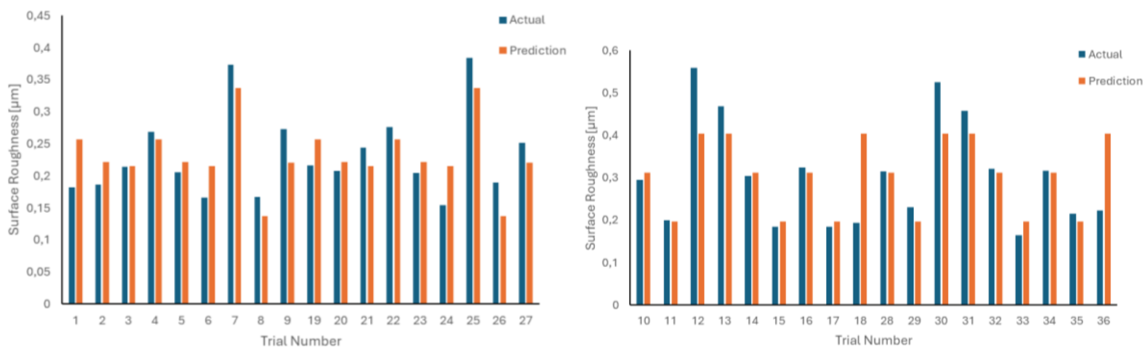
As in the previous equations, each coefficient of Equation (5) was examined using the ANOVA method. The results obtained show that all these coefficients are significant, as shown in Table 6.

Table 6: ANOVA Table to examine the significance of the revised regression coefficient in the direction of spraying MQL liquid opposite to the feeding.

Source	**Degree of Freedom**	**Sum of Squares**	**Mean of Squares**	**F**	**P**	**Criteria**
Regression	2	0.129753	0.064876	7.6952	0.0050136	Significant
β_2	1	0.040252	0.040252	6.3725	0.0233535	Significant
β_4	1	0.089501	0.089501	10.6160	0.0052934	Significant
Error	15	0.126461	0.008431			
Total	17	0.256214				

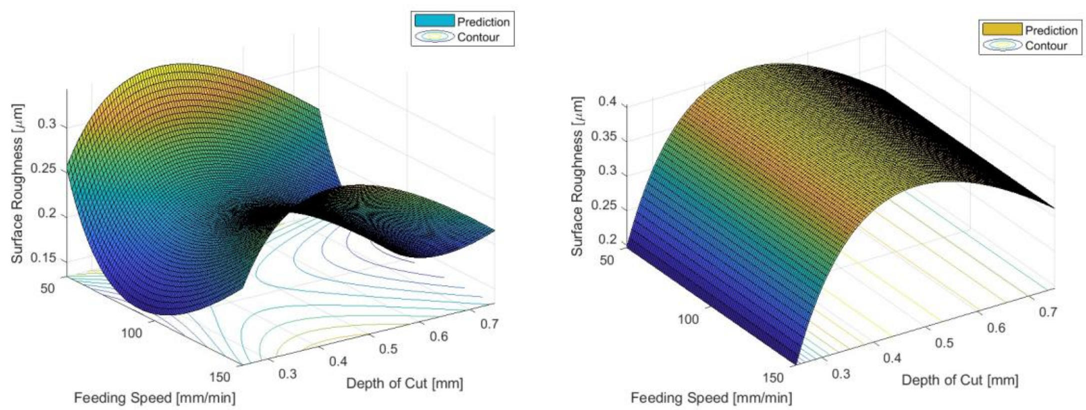
Equations (3) and (5) were then used to predict surface roughness value. The difference between the actual and predicted surface roughness values from Equations (3) and (5) was shown in Figure 5. Moreover, Figure 5 showed that the predicted values followed an increasing or decreasing trend in the actual values, though the error values were positive or negative. The Mean Square Error (MSE) values for both spraying directions in the same direction and against the feeding speed were 1.54×10^{-3} µm^2 and 7.03×10^{-3} µm^2.

To provide an overview of the effect of feeding speed and depth of cut on surface roughness, a three-dimensional graph was created as shown in Figure 6. Specifically, the graph represented both scenarios of MQL liquid spraying in the same and opposite direction as feeding. Additionally, Figure 6b showed that spraying MQL liquid from the opposite direction reduced the effect of feeding speed on surface roughness of the workpiece. The wide range of feeding speeds applied in this experiment, which was between 50 mm/min to 150 mm/min, could not provide significant changes in surface roughness values.



(a) (b)

Figure 5: Comparison of actual experimental results with predicted values. (a) The direction of MQL liquid spraying was in the direction of the feeding speed, and (b) the direction of MQL liquid spraying was opposite to the feeding speed.



(a) (b)

Figure 6: Effect of feeding speed and depth of cut on surface roughness. (a) The direction of MQL liquid spraying was in the direction of the feeding speed, and (b) the direction of MQL liquid spraying was opposite the direction of the feeding speed.

Compared to the spraying direction of MQL liquid, which was opposite to the direction, the feeding speed in Figure 6a significantly affected surface roughness when the spraying direction was the same as the feeding speed. This process occurs because the MQL fluid is not obstructed by the chips generated during cutting, allowing it to reach the cutting zone directly. As a result, cooling and lubrication can occur optimally. Additionally, surface roughness can be improved, with reductions of up to 30% observed under these MQL experimental conditions. Surface roughness then increased significantly when the feeding speed was reduced below 100 mm/min. However, this increase in roughness happened because the tool became blunt due to the formation of a BUE that stuck to the cutting edge at low feeding speeds (Davoudinejad et al., 2017).

Relative to feeding speed, the effect of depth of cut on surface roughness showed a similar trend, both in conditions where MQL liquid spraying direction was the same or opposite to the feeding speed direction. Following this discussion, the cutting results showed low surface roughness at low depth of cuts and increased as the depth of cut increased. However, surface roughness decreased again up to a point around 0.5 mm depth of cut, even though the depth of cut continued to increase (Çolak et al., 2007).

CONCLUSION

In conclusion, the effect of EMP parameter assisted by MQL method on surface roughness was studied using statistical methods. Among the three process parameters, only spindle speed did not have a significant effect on surface roughness. In addition to process parameters, this exploration also examined the direction of MQL liquid spraying. The spraying direction significantly affected the average surface roughness. Moreover, spraying MQL liquid in the opposite direction to the feeding speed reduced changes in surface roughness values, showing that the effect of feeding speed on this condition was not significant.

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