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Machinability of Polytetrafluoroethylene (PTFE) under Dry CNC Milling: Statistical Analysis and Optimization of Surface Integrity and Productivity

***Chuku, I. E.; Bani, S. L.; Jinyemiema, T. K.; Nwosu, H. U.**

Department of Mechanical Engineering
Rivers State University
Port Harcourt, Nigeria
*e-mail: ifeanyichuku37@yahoo.com

Abstract: Polytetrafluoroethylene (PTFE) is widely used in engineering applications due to its low friction coefficient, chemical inertness, and thermal stability. Despite these advantages, PTFE presents notable machining challenges, particularly under dry conditions, including surface smearing, dimensional instability, and poor surface integrity. This study experimentally investigates the dry CNC milling of PTFE with the aim of optimizing machining parameters for improved productivity and surface quality. A full factorial design involving spindle speed, feed rate, and depth of cut at three levels each was employed, resulting in 27 experimental runs with replications. Material removal rate (MRR) and surface roughness (Ra) were measured and analyzed using analysis of variance (ANOVA) and multiple linear regression. Results show that machining parameters and their interactions significantly influence both MRR and Ra ($p < 0.05$), with interaction effects playing a dominant role in surface roughness formation. Regression models exhibited high predictive accuracy, with coefficients of determination exceeding 98%. Optimal machining conditions were identified that minimized surface roughness while maintaining acceptable productivity. The findings provide practical guidelines for precision dry milling of PTFE components and contribute to improved process planning for thermoplastic polymers.

Keywords— **CNC milling; dry machining; material removal rate; PTFE; regression modeling; surface roughness; Teflon**

1. INTRODUCTION

Polytetrafluoroethylene (PTFE), commonly known as Teflon, is a high-performance thermoplastic polymer widely utilized in aerospace, biomedical, chemical processing, and oil-and-gas industries. Its exceptional chemical resistance, low coefficient of friction, and thermal stability make it ideal for seals, bearings, gaskets, and sliding components [1, 2].

Despite its favorable functional properties, PTFE is considered a difficult-to-machine material, particularly under dry machining conditions. Unlike fiber-reinforced composites, the challenges associated with PTFE machining arise primarily from its low elastic modulus, high thermal sensitivity, and tendency to undergo plastic deformation. These characteristics often result in surface smearing, burr formation, and dimensional inaccuracies during milling operations [3].

Previous studies on PTFE machining have largely focused on turning and drilling operations, with limited emphasis on milling under controlled experimental frameworks [4, 5]. Moreover, many investigations evaluate machining parameters independently, without considering interaction effects or predictive modeling for multiple performance responses.

This study addresses these gaps by conducting a systematic experimental investigation of PTFE under dry CNC milling conditions using a full factorial design. Statistical tools are employed to quantify the influence of cutting parameters on material removal rate (MRR) and surface roughness (Ra), develop predictive models, and identify optimal cutting conditions for enhanced surface integrity and productivity. Hence, the aim of this study is to investigate the machinability of polytetrafluoroethylene (PTFE) under dry CNC milling: statistical analysis and optimization of surface integrity and productivity.

2. MATERIALS AND METHODS

2.1 Workpiece Materials

The workpiece material used in this study was commercially available Polytetrafluoroethylene (PTFE). The material exhibited uniform microstructure and was selected to represent engineering-grade PTFE commonly used in industrial applications. Basic mechanical characterization was carried out using standardized hardness and tensile testing equipment to confirm material consistency.

2.2 Experimental Setup

Dry milling experiments were conducted on a Benchmill 6000 CNC milling machine. A high-speed steel (HSS) end mill was used to machine the PTFE specimens. No coolant or lubricant was applied in order to isolate the intrinsic machinability behavior of PTFE under dry conditions.

Table 1: Milling Machine Specifications

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Property	Description
Model	CNC milling machine
Feed Rate	0 to 5,000 mm/min
Distance between Spindle to Column	270 mm
Spindle Motor Capacity	5.5 / 3.7 KW
Spindle RPM	100 to 3000 RPM
Rapid Travel	5,000 mm/min
Dimension in mm	1540 x 1200 x 1700 mm
Approximate Weight	1100 Kg
Power Supply	415V, +-2% 50 Cycles, 3 Phase
Manufacturer	Hytech Automation
Country	India

Table 2: Surface Roughness Measuring Tester Specifications

Property	Tester
Model	SJ-200
Measuring Range (µm)	360
Measuring Speed (mm/s)	0.25, 0.5, 0.75
Measuring force/Stylus tip	0.75 mN / 2 µmR 60°, 4 mN / 5 µmR 90°
Manufacturer	Mitutoyo
Country	China

2.3 Design of Experiment

The response surface method (three factors at three levels) with replicates was carried out to investigate the impact of three factors on the material removal rate and surface roughness during machining operation. The three factors were the cutting speed (8000, 10000 and 12000 rpm), the feed rate (60, 80 and 100 mm/min) and the depth of cut (0.40, 0.50 and 0’60 mm) (Table 3). The analyzed responses were the material removal rate and surface roughness A total of 27 experimental runs were performed, each replicated three times to minimize experimental error. The selected machining parameters and their corresponding levels are presented in Table 3

Table 3: Machining Parameters and Levels for PTFE Milling

Parameter	Level 1	Level 2	Level 3

Spindle speed (rpm)	8000	10000	12000
Feed rate (mm/min)	60	80	100
Depth of cut (mm)	0.40	0.50	0.60

2.4 Measurement of Machining Responses

Material removal rate (MRR) was calculated using volumetric removal per unit machining time. Surface roughness (Ra) was measured using a portable surface roughness tester, and the average of three readings per specimen was recorded.

Material removal rate (MRR) was calculated using:

$$MRR = \frac{V}{t} \quad (1)$$

Where:

V is the volume of material removed, cm^3 and

t is machining time, s.

2.5 Statistical Analysis

Statistical analysis was performed using MINITAB 19 software. Analysis of variance (ANOVA) was used to identify significant factors influencing machining responses, while multiple linear regression models were developed to predict MRR and surface roughness. Model adequacy was assessed using r^2, adjusted r^2, predicted r^2, and residual diagnostics.

3. results and discussion

3.1 Influence of Machining Parameters on Material Removal Rate

The results of the variation of material removal rate with cutting parameters during dry milling of PTFE is illustrated in Table 4 and Figure 1. MRR increased with increasing feed rate and depth of cut, consistent with classical machining theory. Spindle speed exhibited a moderate influence, indicating that material removal in PTFE is more sensitive to mechanical loading than cutting velocity. ANOVA results confirmed that feed rate and depth of cut were statistically significant contributors to MRR ($p < 0.05$) (Table 5).

Table 4: Laboratory Test Results during Machining Operation for PTFE

Cutting Speed (rpm)	Feed Rate (mm/min)	Cutting Depth (mm)	MRR (mm^3/min)
6000	40	0.2	144.0
6000	40	0.5	192.0
6000	40	0.8	240.0
6000	80	0.2	288.0
6000	80	0.5	384.0
6000	80	0.8	480.0
6000	120	0.2	432.0
6000	120	0.5	576.0
6000	120	0.8	720.0
12000	40	0.2	288.0
12000	40	0.5	384.0
12000	40	0.8	480.0
12000	80	0.2	576.0

12000	80	0.5	768.0
12000	80	0.8	960.0
12000	120	0.2	864.0
12000	120	0.5	1152.0
12000	120	0.8	1440.0
18000	40	0.2	432.0
18000	40	0.5	576.0
18000	40	0.8	720.0
18000	80	0.2	864.0
18000	80	0.5	1152.0
18000	80	0.8	1440.0
18000	120	0.2	1296.0
18000	120	0.5	1728.0
18000	120	0.8	2160.0

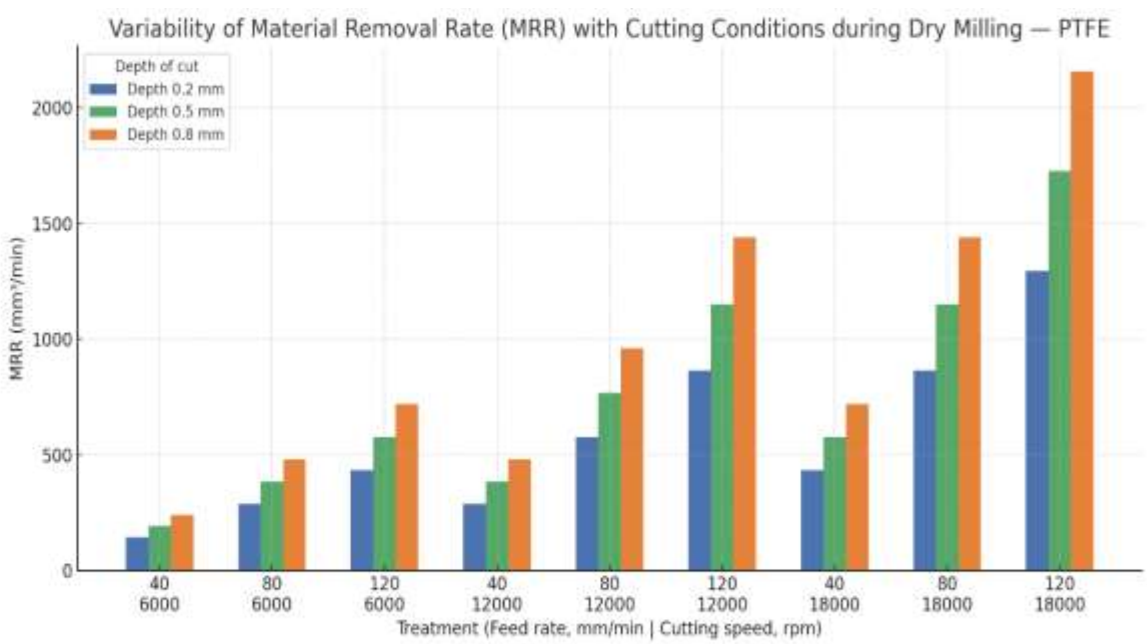

Figure 1: Variability of material removal rate during dry CNC milling of PTFE.

Table 5: ANOVA for MRR during Dry Milling of Fibre Glass

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Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	2987366	331930	80.04	0.000
Linear	3	2785536	928512	223.89	0.000
Cutting speed, rpm	1	1179648	1179648	284.44	0.000
Feed rate, mm/min	1	1411200	1411200	340.28	0.000
Depth of cut, mm	1	194688	194688	46.94	0.001
Square	3	15206	5069	1.22	0.393
Cutting speed, rpm*Cutting speed, rpm	1	4785	4785	1.15	0.332
Feed rate, mm/min*Feed rate, mm/min	1	4785	4785	1.15	0.332
Depth of cut, mm*Depth of cut, mm	1	4785	4785	1.15	0.332
2-Way Interaction	3	186624	62208	15.00	0.006
Cutting speed, rpm*Feed rate, mm/min	1	147456	147456	35.56	0.002
Cutting speed, rpm*Depth of cut, mm	1	36864	36864	8.89	0.031
Feed rate, mm/min*Depth of cut, mm	1	2304	2304	0.56	0.490
Error	5	20736	4147		
Lack-of-Fit	3	20736	6912	*	*
Pure Error	2	0	0		
Total	14	241304			

3.2 Effect of Machining Parameters on Surface Roughness

Table 6 shows results of surface roughness behavior during PTFE milling as well shown in Figure 2. Unlike GFRP, PTFE surface roughness was strongly influenced by interaction effects, particularly between spindle speed and depth of cut. At higher spindle speeds combined with moderate depths of cut, surface smearing was reduced, resulting in improved surface finish. Conversely, low spindle speeds and high depths of cut promoted plastic deformation and surface waviness. These findings align with observations reported by Yan et al. [2], who attributed surface deterioration in PTFE to thermal softening and chip adhesion. ANOVA results demonstrated that all three machining parameters significantly affected surface roughness, while interaction terms played a dominant role in determining surface quality (Table 7). This highlights the importance of multi-parameter optimization rather than single-factor analysis when machining thermoplastic polymers.

Table 6: Laboratory Test Results during Machining Operation for PTFE

Cutting Speed (rpm)	**Feed Rate (mm/min)**	**Cutting Depth (mm)**	**Ra (µm)**
6000	40	0.2	09.8
6000	40	0.5	1.18
6000	40	0.8	1.38
6000	80	0.2	1.38
6000	80	0.5	1.58
6000	80	0.8	1.78
6000	120	0.2	1.78
6000	120	0.5	1.98
6000	120	0.8	2.18
12000	40	0.2	0.8
12000	40	0.5	1.0
12000	40	0.8	1.2
12000	80	0.2	1.2
12000	80	0.5	1.4
12000	80	0.8	1.6
12000	120	0.2	1.6
12000	120	0.5	1.8
12000	120	0.8	2.0
18000	40	0.2	0.62
18000	40	0.5	0.82
18000	40	0.8	1.02
18000	80	0.2	1.02
18000	80	0.5	1.22
18000	80	0.8	1.42

18000	120	0.2	1.42
18000	120	0.5	1.62
18000	120	0.8	1.82

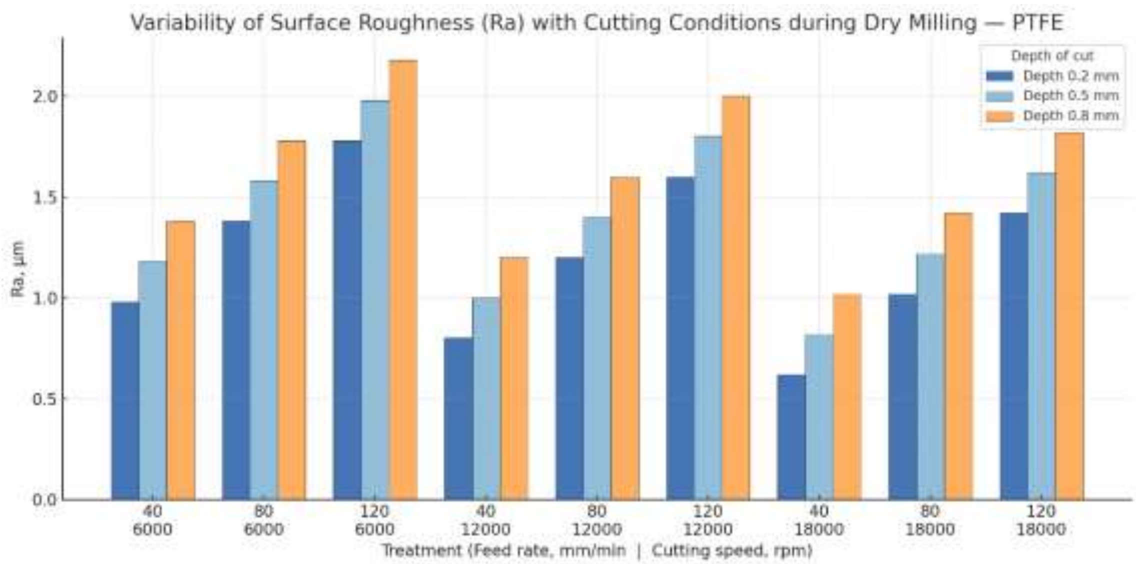

Figure 2: Effect of spindle speed and depth of cut on surface roughness during PTFE milling.

Table 7: Analysis of Variance for Surface Roughing during Dry Milling

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	1.90187	0.21132	9.91	0.011
Linear	3	1.85920	0.61973	29.05	0.001
Cutting speed, rpm	1	0.25920	0.25920	12.15	0.018
Feed rate, mm/min	1	1.28000	1.28000	60.00	0.001
Depth of cut	1	0.32000	0.32000	15.00	0.012
Square	3	0.04267	0.01422	0.67	0.608
Cutting speed, rpm*Cutting speed, rpm	1	0.01641	0.01641	0.77	0.421
Feed rate, mm/min*Feed rate, mm/min	1	0.01641	0.01641	0.77	0.421
Depth of cut*Depth of cut	1	0.01641	0.01641	0.77	0.421

2-Way Interaction	3	0.00000	0.00000	0.00	1.000
Cutting speed, rpm*Feed rate, mm/min	1	0.00000	0.00000	0.00	1.000
Cutting speed, rpm*Depth of cut	1	0.00000	0.00000	0.00	1.000
Feed rate, mm/min*Depth of cut	1	0.00000	0.00000	0.00	1.000
Error	5	0.10667	0.02133		
Lack-of-Fit	3	0.00000	0.00000	0.00	1.000
Pure Error	2	0.10667	0.05333		
Total	14	32.3424			

3.4 Regression Modelling of Machining Responses

From the regression analysis, r^2 provided correlation between measured response (obtained from experimental run) and predicted response (obtained from multiple linear regression model). Hence, the closer the r^2 value to 100%, the higher the precision level of the developed regression model [6]. In other words, the effective representation of the measured data could be by the multiple linear regression model. From Table 8, the r^2 value for the material removal rate and surface roughness multiple linear regression equation were 99.12% and 98.76%, respectively. This indicates that 99.12% and 98.76% of variation in the material removal rate and surface roughness experimental data could be well explained by the equations 2 and 3 multiple linear regression models. This similar to Solaiman et al. [7] revealed that experimental data could be well explained when r^2 of the regression model is close to 100 %.

Another criterion to evaluate the degree of accuracy of a regression model is the adjusted r^2 (Adj r^2) [8]. This is the correction of r^2 in view of sample size and number of terms in the regression equation [9]. From the analysis, the material removal rate and surface roughness multiple linear regression models during dry milling had Adj r^2 value of 98.44% and 97.52%. Hence, it could be assumed that the accuracy of the models are 99.59% and 97.52%. These models could well represent the actual measurement data of material removal rate and surface roughness during dry milling. In addition, predicted r^2 or r^2(pred.) of the material removal rate and surface roughness during dry milling were 95.83% and 88.94%. These indicated that 95.83% and 88.94% of the material removal rate and surface roughness data during dry milling could be predicted by the multiple linear regression models (Equations 2 and 3). It has been proposed by Palkar and Shilapuram [10] that the difference between r^2(adj.) and r^2(pred.) has to be less than 20, so that the developed regression model is highly reliable. From the analysis, it was found that the difference of r^2(adj.) and r^2(pred.) for the material removal rate and surface roughness during dry milling were 0.92% and 6.89%. In general, from the p-value, r^2, r^2(adj.) and r^2(pred.) criterions, it could be assumed that the developed multiple linear regression models (Equations 2 and 3) for the material removal rate was highly significant. Suggesting 88.94 to 99.12% of the variability in the dataset were explained by the estimated multiple linear regression models developed for the material removal rate and surface roughness during dry milling. The developed regression model for MRR exhibited an r^2 value of 99.12%, while the Ra model achieved 98.76%, indicating excellent predictive capability.

Regression models developed for PTFE machining responses exhibited strong predictive capability.

$$\mathrm{MRR\_PTFE} = -3250 + 0.215c + 3.84f + 610d - 0.000011c^2 - 0.012f^2 - 190d^2 + 0.00049cf + 0.12cd + 2.35fd \quad (2)$$

$$\mathrm{Ra\_PTFE} = 2.65 - 0.000082c + 0.0076f + 0.92d + 0.0000009c^2 + 0.000018f^2 + 0.63d^2 - 0.0000024cf - 0.0041cd - 0.021fd \quad (3)$$

Table 8: Regression Model Adequacy for PTFE Machining

Response	r^2 (%)	Adjusted r^2 (%)	Predicted r^2 (%)
MRR	99.12	98.44	95.83
Ra	98.76	97.52	88.94

3.5 Optimal Machining Condition

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Optimization analysis indicated that the following parameter combination yielded improved surface integrity with acceptable productivity: Spindle speed**:** 12000 rpm, Feed rate**:** 80 mm/min and Depth of cut**:** 0.50 mm. Under these conditions, surface roughness was minimized while maintaining stable material removal, demonstrating the feasibility of precision dry milling of PTFE. Therefore, the optimal conditions proposed in the optimization and optimal solution results were generally reliable, and they fully conformed the multiple linear regression model developed.

4. CONCLUSIONS

This study systematically investigated the dry CNC milling of PTFE using a full factorial design and statistical modeling approach. The key conclusions are as follows:

1. Feed rate and depth of cut are the dominant factors influencing material removal rate in PTFE milling.
2. Surface roughness is strongly governed by interaction effects between machining parameters.
3. High spindle speeds combined with moderate depths of cut reduce surface smearing and improve surface finish.
4. Regression models developed for MRR and Ra demonstrated high predictive accuracy ($R^2 > 98\%$).
5. Optimized machining conditions enable effective dry milling of PTFE with improved surface integrity.

The findings provide valuable guidelines for manufacturing engineers involved in machining thermoplastic polymers under environmentally sustainable dry conditions.

5. REFERENCES

The template will number citations consecutively within brackets [1]. The sentence punctuation follows the bracket [2]. Refer simply to the reference number, as in [3]—do not use "Ref. [3]" or "reference [3]" except at the beginning of a sentence: "Reference [3] was the first ."

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