International Journal of Academic Multidisciplinary Research (IJAMR)
ISSN: 2643-9670
Vol. 10 Issue 4 April - 2026, Pages: 48-57

1Dry CNC Milling of Glass Fiber Reinforced Polymer: Statistical Modelling and Multi-Response Optimization of Productivity and Surface Quality

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Abstract: *Glass Fiber Reinforced Polymer (GFRP) is widely used in aerospace, automotive, and oil-and-gas industries due to its high strength-to-weight ratio and corrosion resistance. Though, its heterogeneous and abrasive nature poses significant challenges during machining, including rapid tool wear and poor surface quality. This study through an experiment investigates the dry CNC milling of GFRP with the aim of improving productivity and surface integrity through statistical modeling and multi-response optimization. A full factorial experimental design comprising spindle speed, feed rate, and depth of cut at three levels each was adopted, resulting in 27 experimental runs with three replications. Material removal rate (MRR) and surface roughness (Ra) were selected as performance indicators. Analysis of variance (ANOVA) and multiple linear regression were used to identify significant factors and develop predictive models. Results reveal that all three machining parameters and their interactions significantly influence MRR and surface roughness ($p < 0.05$). The developed regression models demonstrated excellent predictive accuracy with coefficients of determination exceeding 99%. An optimal cutting condition of 1700 rpm spindle speed, 60 mm/min feed rate, and 0.60 mm depth of cut yielded a high MRR of 196.79 mm³/min and a low surface roughness of 1.025 µm. The findings offer reliable guidelines for efficient dry milling of GFRP and contribute to sustainable and cost-effective composite machining practices.*

Keywords—CNC milling; dry machining; Glass fiber reinforced polymer; material removal rate; surface roughness; regression modeling

1. INTRODUCTION

Glass Fiber Reinforced Polymer (GFRP) composites are increasingly adopted in engineering applications due to their superior mechanical properties, corrosion resistance, and lightweight characteristics [1]. These attributes make GFRP suitable for aerospace components, marine structures, automotive parts, and oil-and-gas equipment [2, 3]. Despite these advantages, machining GFRP remains a complex task owing to its anisotropic structure and the abrasive nature of embedded glass fibers.

During milling operations, GFRP commonly exhibits defects such as fiber pull-out, matrix cracking, delamination, and accelerated tool wear, all of which adversely affect surface integrity and dimensional accuracy [4]. These challenges are further intensified under dry machining conditions, where the absence of coolant increases friction and thermal effects. However, dry machining is increasingly preferred due to environmental regulations, reduced operational cost, and elimination of coolant-related health hazards.

Previous studies have shown that machining responses such as material removal rate (MRR) and surface roughness (Ra) are strongly influenced by cutting parameters, including spindle speed, feed rate, and depth of cut [5, 6]. While several investigations have explored individual parameter effects, comprehensive multi-response optimization studies on dry milling of GFRP using full factorial experimental design remain limited.

This study addresses this gap by experimentally evaluating the dry CNC milling of GFRP and applying statistical modeling techniques to optimize productivity and surface quality. The study aims to analyze the influence of cutting parameters on MRR and Ra, develop predictive regression models for machining responses, and identify optimal cutting conditions for improved performance.

2. MATERIALS AND METHODS

2.1 Workpiece Materials

The workpiece material used in this study was Glass Fiber Reinforced Polymer (GFRP) laminate. The composite consisted of woven glass fibers embedded in a thermoset polymer matrix. The chemical composition and physical properties were verified using energy-dispersive X-ray fluorescence (EDXRF) and standardized hardness testing procedures.

2.2 Experimental Setup

Dry milling experiments were conducted on a Benchmill 6000 CNC milling machine under controlled laboratory conditions. A carbide end mill cutter was employed throughout the experiments to maintain consistency. No cutting fluid was used. The specification of the milling machine and surface roughness tester specifications are presented in Tables 1 and 2.

Table 1: Milling Machine Specifications

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 (1700, 1800 and 1900 rpm), the feed rate (60, 80 and 100 mm/min) and the depth of cut (0.60, 0.80 and 1.00 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.

Table 3: Treatment Randomization

Parameter	**Level 1**	**Level 2**	**Level 3**
Spindle speed (rpm)	1200	1450	1700
Feed rate (mm/min)	40	60	80
Depth of cut (mm)	0.40	0.50	0.60

2.4 Response Measurement

Material removal rate (MRR) was calculated using:

$$MRR = \frac{V}{t} \tag{1}$$

Where:

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

t is machining time, s.

Surface roughness (Ra) was measured using a portable surface roughness tester, and the average of three readings was recorded for each run.

2.5 Statistical Analysis

Statistical analysis was carried out using MINITAB 19 software. Analysis of variance (ANOVA) was applied to determine the significance of machining parameters, while multiple linear regression was used to develop predictive models. Model adequacy was evaluated using r^2, adjusted r^2, and predicted r^2 values.

3. RESULTS AND DISCUSSION

3.1 Effects of Machining Parameters on Material Removal Rate

Figure 1 illustrates the variation of material removal rate (MRR) with cutting parameters during dry milling of GFRP as presented in Table 5. MRR increased with increasing feed rate and depth of cut, while spindle speed showed a moderate but significant influence. From the graph, it can be observed that the increase in cutting speed, feed rate and depth of cut increased the material removal rate (MRR). It can be inferred that MRR is affected by cutting speed, feed rate and depth of cut. This is similar to the findings of Dhakad *et al*. [7], and Korkmaz *et al*. [8]. ANOVA results (Table 5) indicate that spindle speed, feed rate, and depth of cut are all statistically significant factors affecting MRR ($p < 0.05$). Interaction effects between feed rate and depth of cut were also significant, confirming the non-linear machining behavior of GFRP.

3. Table 4: Laboratory Test Results during Machining Operation for GFRP

Cutting Speed (rpm)	**Feed Rate (mm/min)**	**Cutting Depth (mm)**	**MRR (mm^3/min)**
1700	60	0.6	48.96
1700	60	0.8	65.28
1700	60	1	81.60
1700	80	0.6	65.28
1700	80	0.8	87.04
1700	80	1	108.80
1700	100	0.6	81.60
1700	100	0.8	81.80

1700	100	1	136.0
1800	60	0.6	51.84
1800	60	0.8	69.12
1800	60	1	86.4
1800	80	0.6	69.12
1800	80	0.8	92.16
1800	80	1	115.2
1800	100	0.6	86.4
1800	100	0.8	115.2
1800	100	1	144.0
1900.	60	0.6	54.72
1900	60	0.8	72.96
1900	60	1	91.12
1900	80	0.6	72.96
1900	80	0.8	97.28
1900	80	1	121.60
1900	100	0.6	91.2
1900	100	0.8	121.60
1900	100	1	152.00

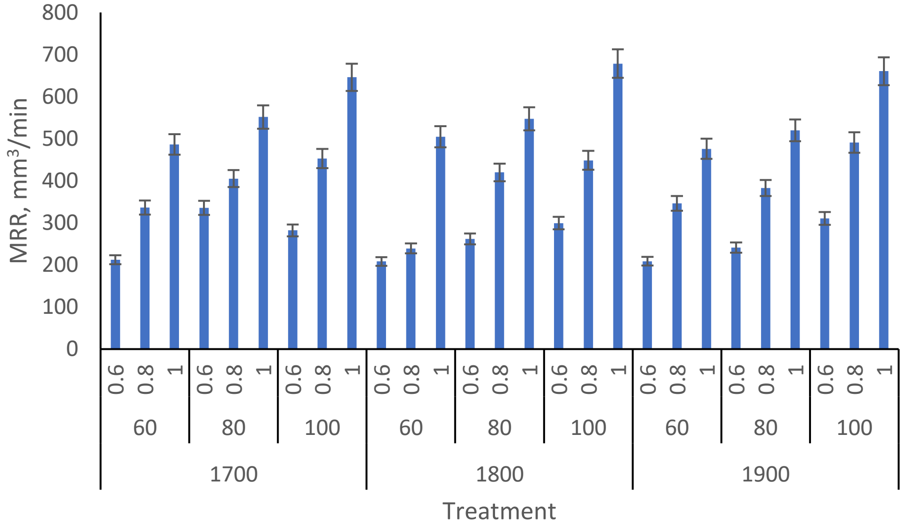

Figure 1: Variability of material removal rate during dry milling of GFRP

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

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	239587	26621	77.55	0.000
Linear	3	234642	78214	227.85	0.000
Cutting speed, rpm	1	33	33	0.09	0.770
Feed rate, mm/min	1	34659	34659	100.97	0.000
Depth of cut, mm	1	199950	199950	582.48	0.000
Square	3	2789	930	2.71	0.155
Cutting speed, rpm*Cutting speed, rpm	1	2066	2066	6.02	0.058
Feed rate, mm/min*Feed rate, mm/min	1	397	397	1.16	0.331
Depth of cut, mm*Depth of cut, mm	1	220	220	0.64	0.460
2-Way Interaction	3	2157	719	2.09	0.220
Cutting speed, rpm*Feed rate, mm/min	1	197	197	0.57	0.483
Cutting speed, rpm*Depth of cut, mm	1	249	249	0.73	0.433

Feed rate, mm/min*Depth of cut, mm	1	1710	1710	4.98	0.076
Error	5	1716	343		
Lack-of-Fit	3	1716	572	*	*
Pure Error	2	0	0		
Total	14	241304			

3.2 Effect of Machining Parameters on Surface Roughness

Surface roughness results in Table 6 reveal that higher spindle speeds and lower feed rates produce smoother surfaces, as shown in Figure 2. Increased depth of cut contributed to fiber pull-out and surface irregularities. From the graph, it can be observed that there was variability in the surface roughness caused by the selected affecting factors (cutting speed, feed rate and depth of cut). It can be inferred that Ra is affected by cutting speed, feed rate and depth of cut based at different factor levels. This is in line with the findings of Hamlaoui *et al*. [9]. Feed rate emerged as the most influential factor on Ra, consistent with previous findings by Dhakad *et al*. [7]. ANOVA result in Table 7 confirmed the statistical significance of all main effects and selected interactions.

Table 6: Laboratory Test Results during Machining Operation for GFRP

Cutting Speed (rpm)	**Feed Rate (mm/min)**	**Cutting Depth (mm)**	**Ra (µm)**
1700	60	0.6	4.57
1700	60	0.8	4.81
1700	60	1	5.05
1700	80	0.6	4.97
1700	80	0.8	5.21
1700	80	1	5.45
1700	100	0.6	5.37
1700	100	0.8	5.61
1700	100	1	5.85
1800	60	0.6	4.52
1800	60	0.8	4.76
1800	60	1	5.0
1800	80	0.6	4.92

1800	80	0.8	5.16
1800	80	1	5.4
1800	100	0.6	5.32
1800	100	0.8	5.56
1800	100	1	5.8
1900.	60	0.6	4.47
1900	60	0.8	4.71
1900	60	1	4.95
1900	80	0.6	4.87
1900	80	0.8	5.11
1900	80	1	4.35
1900	100	0.6	5.27
1900	100	0.8	5.51
1900	100	1	5.75

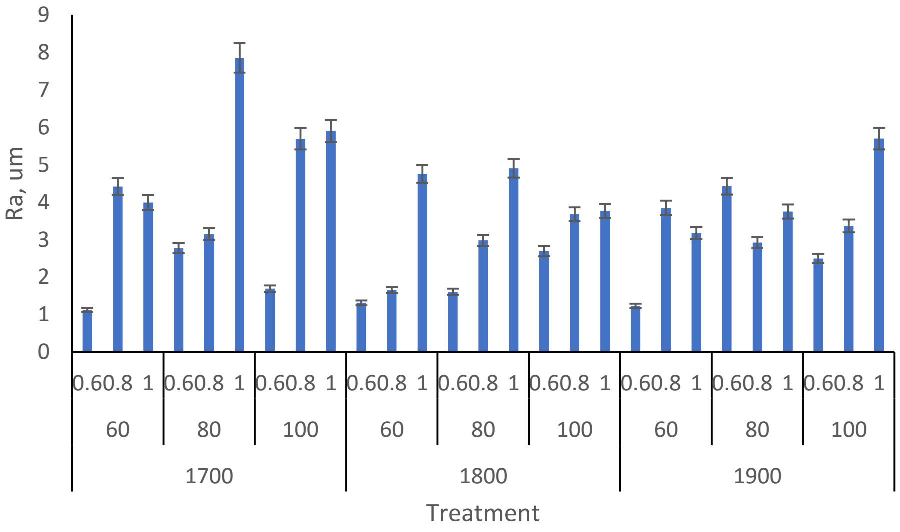

Figure 2: Effect of cutting parameters on surface roughness during dry milling of GFRP

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

Source	DF	Adj SS	Adj MS	F-Value	P-Value

Model	9	32.2950	3.58834	379.21	0.000
Linear	3	13.7099	4.56996	482.94	0.000
Cutting speed, rpm	1	3.5845	3.58450	378.80	0.000
Feed rate, mm/min	1	0.1729	0.17287	18.27	0.008
Depth of cut	1	9.9525	9.95249	1051.75	0.000
Square	3	8.1394	2.71313	286.72	0.000
Cutting speed, rpm*Cutting speed, rpm	1	7.8571	7.85705	830.31	0.000
Feed rate, mm/min*Feed rate, mm/min	1	0.0435	0.04347	4.59	0.085
Depth of cut*Depth of cut	1	0.2520	0.25201	26.63	0.004
2-Way Interaction	3	10.4458	3.48193	367.96	0.000
Cutting speed, rpm*Feed rate, mm/min	1	0.7700	0.77001	81.37	0.000
Cutting speed, rpm*Depth of cut	1	8.2656	8.26563	873.49	0.000
Feed rate, mm/min*Depth of cut	1	1.4102	1.41016	149.02	0.000
Error	5	0.0473	0.00946		
Lack-of-Fit	3	0.0473	0.01577	*	*
Pure Error	2	0.0000	0.00000		
Total	14	32.3424			

3.3 Regression Modelling

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 [10]. 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 99.85% and 99.29%, respectively. This indicates that 99.85% and 99.29% 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. [11] 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) [12]. This is the correction of r^2 in view of sample size and number of terms in the regression equation [13]. From the analysis, the material removal rate and surface roughness multiple linear regression models during dry milling had Adj r^2 value of 99.59% and 98.01%. Hence, it could be assumed that the accuracy of the models are 99.59% and 98.01%. 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 97.66% and 86.62%. These indicated that 97.66% and 86.62% 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 [14] 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 1.58% and 11.04%. 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 86.62 to 99.29% 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 99.85%, while the Ra model achieved 99.29%, indicating excellent predictive capability.

$$\mathrm{MRR_{GF}} = -7866 + 8.57\mathrm{c} - 11.311\mathrm{f} + 1396\mathrm{d} - 0.002365\mathrm{cc} + 0.0259\mathrm{ff} - 193\mathrm{d} + 0.00351\mathrm{cf} - 0.395\mathrm{cd} + 5.17\mathrm{fd} \tag{2}$$

$$\mathrm{Ra} = 340.5 - 0.4568\mathrm{c} + 0.5644\mathrm{f} + 136.38\mathrm{d} + 0.00146\mathrm{cc} - 0.000271\mathrm{ff} + 6.53\mathrm{dd} - 0.000219\mathrm{cf} - 0.07188\mathrm{cd} - 0.1484\mathrm{fd} \tag{3}$$

Response	**r^2 (%)**	**Adjusted r^2 (%)**	**Predicted r^2 (%)**
MRR	99.85	99.59	97.66
Ra	99.29	98.01	86.62

The optimal parameter combination for dry milling of GFRP was identified as Spindle speed: 1700 rpm, Feed rate: 60 mm/min, and Depth of cut: 0.60 mm. This condition produced a high MRR of 196.79 mm³/min and a low surface roughness of 1.025 µm, representing a significant improvement over sub-optimal setting. Hence, 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 experimentally investigated the dry CNC milling of GFRP using a full factorial design and statistical modeling approach. The following conclusions are drawn:

1. Spindle speed, feed rate, and depth of cut significantly influence material removal rate and surface roughness.
2. Feed rate is the dominant factor affecting surface roughness, while depth of cut strongly governs productivity.
3. Regression models developed for MRR and Ra demonstrated excellent predictive accuracy ($R^2 > 99\%$).
4. Optimized cutting conditions significantly enhanced productivity while maintaining superior surface quality.
5. Dry milling of GFRP is feasible and effective when machining parameters are carefully optimized.

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