Predictive Modeling of Surface Roughness and Material Removal Rate in Turning of UD-GFRP Composites using Carbide (K10) Tool

S. Kumar* & M. Gupta
Department of Mechanical Engineering,
National Institute of Technology, Kurukshetra 136119, India
E-mail: surinder.asd@gmail.com
*Corresponding author

P. S. Satsangi
Department of Mechanical Engineering,
PEC University of Technology, Chandigarh 160012, India

H. K. Sardana
Department of Computational Instrumentation,
CSIO, Chandigarh 160030, India

Received: 8 May 2012, Revised: 27 August 2012, Accepted 17 April 2013

Abstract: This work presents an experimental investigation on the influence of six important machining parameters (tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment (dry, wet and cooled) and depth of cut) on surface roughness & material removal rate in the machining unidirectional glass fiber reinforced plastics (UD-GFRP) composite using carbide (K10) cutting tool during turning operation. Orthogonal L_{18} array in Taguchi method was employed to carry out the experimental work. ANOVA is performed for significant parameter and later Regression model is developed for the significant parameters. Validation (confirmatory) results indicate that the model is suitable for surface roughness & material removal rate during the study.

Keywords: ANOVA, Carbide (K10) Tool, Material Removal Rate, Regression Modeling, Surface Roughness, Unidirectional Glass Fiber Reinforced Plastics (UD-GFRP) Composite

Reference: Kumar, S., Gupta, M., Satsangi, P. S., and Sardanai, H. K., “Predictive Modeling of Surface Roughness and Material Removal Rate in Turning of UD-GFRP Composites using Carbide (K10) Tool”, Int J of Advanced Design and Manufacturing Technology, Vol. 6/ No. 2, 2013, pp. 37-49.

Biographical notes: S. Kumar, is a research scholar in the Department of Mechanical Engineering, National Institute of Technology, Kurukshetra-136119, India. He is currently a PhD student at NIT Kurukshetra, Haryana, India. He was graduated in Mechanical Engineering from S.K.I.E.T, Kurukshetra, Haryana and Post graduated in the specialization of Manufacturing System from M.M Engineering College Mullana, Ambala (Haryana). His current area of research includes Machining of composite materials, Optimization, and Modeling. **M. Gupta** is an Associate professor in the Department of Mechanical Engineering, National Institute of Technology, Kurukshetra-136119, (Haryana), India. **P. S. Satsangi** is an Associate professor in the Department of Mechanical Engineering, PEC University of Technology Chandigarh, India. **H. K. Sardana** is a Scientist ‘G’ & Head of the Department of Computational Instrumentation, CSIO, Chandigarh-160030, India. His current area of research includes, Signal Processing, Computer Aided Design and Simulation, Human Physiology and Bio-Instrumentation, Digital Image Processing, Soft Computing Techniques, Computer Aided Metrology and Machine Vision.

1 INTRODUCTION

Currently, the use of composite materials has increased in various areas of science and technology due to their special physical and mechanical properties. Aerospace, Automotive, sport, construction, and military (Navy ship structures, military armored vehicles) companies need to replace steel and cast iron in mechanical components with lighter high strength alloys like Al and Metal Matrix Composites (MMC), Polymer Matrix Composites and CMC. Composite materials can be broken down into several different categories, which include ceramic, metal and polymer matrices with reinforcing fibers of the same or different materials, each having advantages and limitations, as material performance is dictated by application environment as well as material-specific properties.

Glass fiber reinforced plastics (GFRP) is the most commonly used composite materials, where GFRP consists of two distinct materials, a polymer resin as matrix, and reinforced with ceramic (glass) fibers. This material is light, tough, resilient and flexible and has a very good strength to weight ratio. High abrasiveness of glass fiber and non-homogeneous structure of this composite makes it very difficult to be machined [1]. Machining glass fiber composites is a complex and challenging task, where major difficulties encountered are reported as surface damage by delamination, burning or cracks, rapid tool wear, accuracy affected by debonding, subsurface damage and bouncing back phenomenon of work piece material [2].

Machining of fiber-reinforced materials requires special considerations with regard to the wear resistance of the tool. High speed steel (HSS) is not suitable for cutting purpose due to its high rate of tool wear and poor surface finish, hence carbide and diamond tools are used as suitable cutting tool materials [3]. Investigation by Palanikumar et al. focused on the multiple performance machining characteristics of GFRP composites using carbide (K10) tool [4]. Five parameters such as work piece (fiber orientation), cutting speed, feed rate, depth of cut and machining time were selected to minimize the surface roughness. It was found that, the machining performance in the composite machining process may be improved by including more number of parameters and levels.

Davim et al. investigated the machinability in turning process of glass fibers reinforced plastics (GFRP) using polycrystalline diamond and cemented carbide tool [5]. While, two parameters such as cutting speed and feed rate were selected, it was observed that, the polycrystalline diamond provide a better machinability index in comparison to cemented carbide tool (K15). Arul et al. worked on the optimization of GFRP material machining, where they analyzed data of thrust force, torque and tool life by using a group method data handling algorithm [6].

Hussain et al. developed a surface roughness prediction model for the machining of GFRP pipes using Response Surface Methodology and carbide tool (K20), where four parameters such as cutting speed, feed rate, depth of cut and work piece (fiber orientation) were selected [7]. It was found that, the depth of cut shows a minimum effect on surface roughness as compared to other parameters. Further, Hussain et al. developed a surface roughness and cutting force prediction model for the machining of GFRP tubes by using carbide tool (K20), cubic boron nitride (CBN) and polycrystalline diamond (PCD) using Response Surface Methodology [8]. Four parameters such as cutting speed, feed rate, depth of cut and work piece (fiber orientation) were selected, where it was found that, the polycrystalline diamond (PCD) cutting tool is better than other two tools used.

Rajasekaran et al. used fuzzy logic for modeling and prediction of CFRP work piece [9]. Three parameters such as depth of cut, feed rate and cutting speed were selected to minimize surface roughness. Cubic boron nitride tool was used for turning process, where it was observed that, the fuzzy logic modeling technique may be effectively used for prediction of surface roughness in machining of CFRP composites.

Isik et al. proposed an approach for turning of a glass fiber reinforced plastic composites using cemented carbide tool [10]. Three parameters such as depth of cut, cutting speed and feed rate were selected to minimize tangential and feed force. Weighting techniques was used for optimization of objective function. The idea of this technique is adding all the objective functions together using different coefficients for each. It means that the multi-criteria optimization problem is changed to a scalar optimization problem by creating one function. It was found that, technique will be more economical to predict the effect of different influential combination of parameters.

Khan et al. proposed an approach for turning of a glass fiber reinforced plastic composite using two different alumina cutting tools, namely, a Ti[C, N] mixed alumina cutting tool (CC650) and a SiC whisker reinforced alumina cutting tool (CC670) [11]. Three parameters such as cutting speed, depth of cut and feed rate were selected to minimize surface roughness. It was found that the performance of the SiC whisker reinforced alumina cutting tool is better than that of the Ti[C, N] mixed alumina cutting tool for machining the GFRP composite. Recent studies on unidirectional glass fiber composites revealed the formation of chip in orthogonal cutting. In case of long oriented glass fiber, degradation of the matrix adjacent to the fiber occurs first, followed by failure of the fiber at its rear side [12]. In orthogonal turning process, influence of fiber orientation, cutting parameters, and tool geometry in GFRP has been studied [13, 14].

In order to develop the mathematical models based on experimental data, careful planning of the experimentation is essential. In the present study, six parameters, namely, tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment (dry, wet and cooled) and depth of cut are considered. The ranges of these parameters are selected based on preliminary investigations. In the present investigation, the machinability aspects have been evaluated in terms of surface roughness (Ra) and material removal rate (MRR) during the turning of UD-GFRP composite using carbide (K10) tools. The regression model based on second order model is used, where the regression analyses is applied in order to identify the best levels of cutting parameters and their significance. As a matter of fact insignificant parameters are not taken into consideration in this Regression modeling.

2 MATERIAL AND EXPERIMENTAL TECHNIQUE

In this investigation, pultrusion processed unidirectional glass fiber reinforced composite rods are used. The fiber used in this rod is E-glass and the applied resin is epoxy while the material properties are shown in Table 1. The rod specimen's size is 840 mm in length and 42 mm in diameter.

Table 1 Properties of UD-GFRP

Sr. No.	Particular	Value	Unit
1	Glass Content (by weight)	75±5	%
2	Epoxy Resin content (by weight)	25±5	%
3	Reinforcement, unidirectional	'E' Glass Roving	---
4	Water absorption	0.07	%
5	Density	1.95-2.1	gm/cc
6	Tensile Strength	6500 or (650)	Kg / cm^2 or (N/mm^2)
7	Compression Strength	6000 or (600)	Kg / cm^2 or (N/mm^2)
8	Shear Strength	255	Kg / cm^2 or (N/mm^2)
9	Modulus of elasticity	3200 or (320)	Kg / cm^2 or (N/mm^2)
10	Thermal Conductivity	0.30	Kcal /Mhc°
11	Weight of 840 mm in length Rod	2.300	Kgs
12	Electrical strength (Radial):	3.5	KV / mm
13	Working Temperature Class:	Class 'F' (155)	Centigrade
14	Martens Heat Distortion Temperature	210	Centigrade
15	Test in oil : (1) At 20° C:	20 KV/cm	
	(2) At 100° C:	20 KV/cm (50 KV / 25 mm)	KV/cm

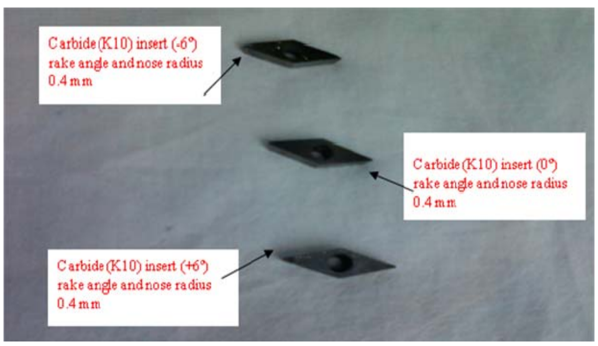


Fig. 1 a) Carbide (K10) cutting tool inserts used in the experiment

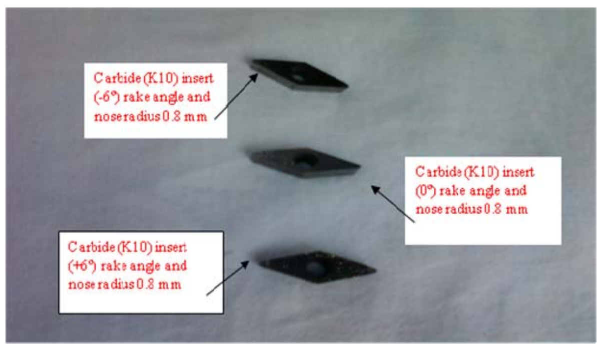


Fig. 1 b) Carbide (K10) cutting tool inserts used in the experiment

The experiments are carried out on a NH22 lathe machine of 11 kW spindle power and maximum speed of 3000 rpm using carbide (K10) tools. The cutting tool insert with various rake angle (-6°, 0°, +6°) and tool nose radius (0.4 mm & 0.8 mm) are used as shown in Figures 1(a) & 1(b).

A tool holder SVJCR steel EN47 was used during the turning operation. The experimental results of turning of unidirectional glass fiber reinforced plastic composite is evaluated to ascertain the machining performance, such as (1) surface roughness (Ra) and (2) material removal rate (MRR).

The surface roughness of the turned surface was measured using a Tokyo Seimitsu Surfcom 130A type instrument as shown in Figure 2. The instrument was set to a cutoff length of 0.8 mm with a transverse length of 4 mm.

Fig. 2 Surface Roughness Tester: Tokyo Seimitsu Surfcom 130A

The experimental design (DOE) was set according to an L_{18} orthogonal array based on Taguchi method. The Taguchi method use the S/N ratio to analyze the average value of the test run data to derive values for evaluating the characteristics of cutting parameters. This is because the S/N ratio represents both the average and the variation in quality characteristics, where the units of the S/N ratio are decimals. The Taguchi parameter design is used to determine the optimum conditions of the engineering parameters (the controllable parameters) and also to minimize any variation in the noise (the uncontrollable parameters). In meantime, the S/N ratio provides a measure of the robustness. In this study, the smaller the better principle is considered to minimize the surface roughness and the higher the better is considered for MRR. The response for S/N ratio may be computed [15, 16] as follows.

Smaller the best characteristics :

$$S/N = -10 \, \text{Log} \frac{1}{n} \sum y^2 \tag{1}$$

Larger the best characteristics :

$$S/N = -10 \, \text{Log} \frac{1}{n} \sum \frac{1}{y^2} \tag{2}$$

where n is the number of observations, and y is the observed data.

The material removal rate in mm^3/sec, has been calculated from the following relation:

Material Removal Rate (MRR) = It is the volume of material being removed per unit time,

$$MRR = \frac{\frac{\pi}{4} D^2 L - \frac{\pi}{4} d^2 L}{Tc} \tag{3}$$

Where N = spindle speed in rpm, D = initial Dia in mm, d = final dia in mm, L = length in mm, f = feed rate in mm/rev. However regarding Tc (machining time), if L is the length of the workpiece to be turned, then the time of cutting Tc per pass is given by, Tc = L /f N.

The Taguchi's mixed level design was selected as it was decided to keep two levels of tool nose radius. The rest five parameters were studied at three levels. Two level parameter has 1 DOF, and the remaining five three level parameters have 10 DOF, i.e., the total DOF required will be 11 [= (1*1+ (5*2)].

The most appropriate orthogonal array in this case is L18 (2^1 * 3^7) OA with 17 [= 18-1] DOF. Standard L_{18} OA with the parameters assigned by using linear graphs is used. The unassigned columns will be treated as error. The process parameters, their designated symbol and ranges are also given in Table 2. The plan is made of 18 tests (array rows) in which the tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment (dry, wet and cooled) and depth of cut are assigned to columns 1 to 6 respectively as shown in Table 3. The cutting environment (dry, wet and cooled) was set during the machining of the rod, so as to get a comparative assessment of the performance of cutting environment which has not been studied earlier.

Table 2 Control parameters and their level

Process Parameters Design	Process Parameters	Levels		
		Level (1)	Level (2)	Level (3)
A	Tool nose Radius / mm	0.4	0.8	NIL
B	Tool Rake angle / Degree	-6	0	+6
C	Feed rate / (mm/rev.)	0.05	0.1	0.2
D	Cutting speed / (m/min.) & rpm	(55.42) 420	(110.84) 840	(159.66) 1210
E	Cutting environment	Dry (1)	Wet (2)	Cooled (3)
F	Depth of cut / mm	0.2	0.8	1.4

Table 3 Experimental layout using L_{18} orthogonal array

Expt. No.	1 A	2 B	3 C	4 D	5 E	6 F	7 ---	8 ---
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

Table 4 Test data summary for surface roughness and Material Removal Rate

Expt. No.	Ra	Average Ra (µm)	S/N ratio (dB)	MRR	Average MRR (mm^3/sec.)	S/N ratio (dB)
1	1.59/1.65/ 1.49	1.577	-3.9624	8.5/8.6/8.7	8.6	18.6888
2	1.73/1.77/1.99	1.83	-5.2659	144.96/145.02/145.02	145	43.2274
3	2.77/4.12/5.13	4.00	-12.3014	329.98/330.23/330.23	330.15	50.3741
4	2.20/2.18/2.04	2.14	-6.6131	36.24/36.24/36.24	36.24	31.1838
5	1.83/1.83/1.77	1.81	-5.1546	237.96/237.9/238.04	237.97	47.5303
6	2.69/2.88/2.89	2.82	-9.0096	99.0/98.9/98.93	98.93	39.9077
7	1.62/1.94/2.12	1.893	-5.5960	125.03/125.02/125.02	125.02	41.9398
8	1.99/1.79/1.89	1.890	-5.5373	52.98/52.95/52.99	52.97	34.4811
9	2.58/2.94/2.10	2.54	-8.1757	144.92/145.02/144.90	144.95	43.2242
10	2.90/2.72/2.35	2.656	-8.5189	104.39/104.41/104.39	104.40	40.3737
11	2.15/2.20/ 1.95	2.1	-6.4559	124.96/124.96/124.96	124.96	41.9354
12	2.45/1.56/2.26	2. 09	-6.5462	73.54/73.53/73.51	73.53	37.3289
13	1.77/1.55/1.89	1.736	-4.8228	18.39/18.39/18.38	18.39	25.2901
14	3.05/2.41/ 2.51	2.656	-8.5351	197.7/197.06/197.92	197.56	45.9139
15	2.61/1.87/3.38	2.62	-8.6001	240.94/241.06/240.92	240.97	47.6394
16	2.26/2.69/1.96	2.303	-7.3200	170.00/170.09/170.00	170.03	44.6105
17	1.65/1.68/1.38	1.57	-3.9499	18.38/18.38/18.39	18.38	25.2885
18	2.53/2.99/2.50	2.673	-8.5715	261.00/260.93/260.8	260.91	48.3298

3 RESULTS AND DISCUSSION

Table 4 shows the experimental results of surface roughness (Ra) for the carbide (K10) tool insert and corresponding S/N ratio. The analysis of experimental results for surface roughness in the turning test is summarized below. Table 4 shows the experimental conditions using Taguchi L_{18} orthogonal array and measured values of surface roughness for three different trial runs.

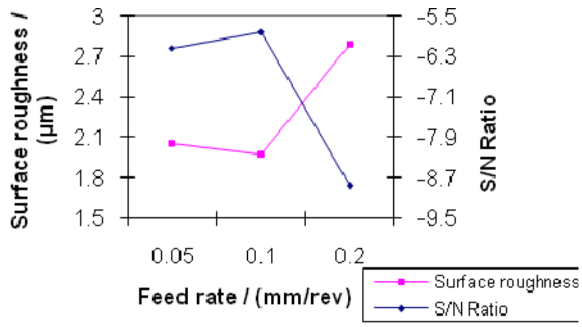
The pooled versions of ANOVA of the raw data for surface roughness are also shown in Table 5. The percent contributions of feed rate (29.110 %), cutting speed (21.595%) and depth of cut (10.584 %) in affecting the variation of surface roughness are significantly larger (95 % confidence level) as compared to the contribution of the cutting speed as shown by Table 5. This analysis was carried out for a level of significance of 5%, i.e. for a level of confidence of 95%.

Table 5 ANOVA results for Surface roughness (raw data)

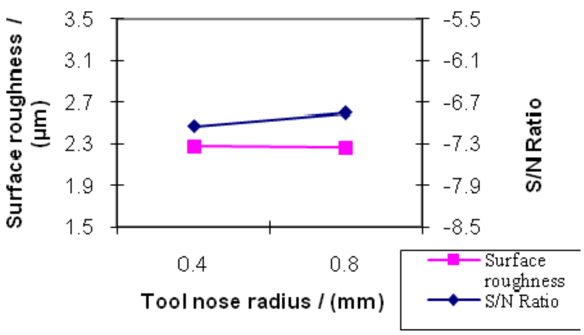
Source	SS	DOF	V	F ratio	Prob.	SS/	P (%)
Tool nose radius (A)	0.0017	1	0.0017	Pooled	0.922	---	---
Tool rake angle (B)	0.4989	2	0.2495	Pooled	0.245	---	---
Feed rate (C)	7.3151	2	3.6575	21.30*	0.000	6.972	29.110
Cutting speed (D)	5.5154	2	2.7577	16.06*	0.000	5.172	21.595
Cutting Environment (E)	0.5283	2	0.2641	Pooled	0.227	---	---
Depth of cut (F)	2.8789	2	1.4394	8.38*	0.001	2.535	10.584
T	23.9501	53				23.9501	100.00
e (pooled)	7.2119	42	0.1717			9.101	37.99

SS = sum of squares, DOF = degrees of freedom, variance (V) = (SS/DOF), T = total, SS/ = pure sum of squares, P = percent contribution, e = error, F_{ratio} = (V/error), Tabulated F-ratio at 95% confidence level, * Significant at 95% confidence level

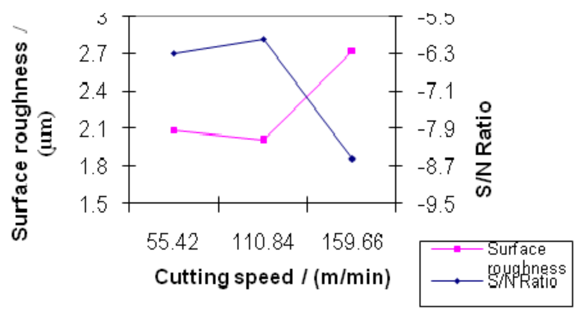
From the ANOVA result, it is concluded that C – feed rate, D - Cutting speed, F - depth of cut have significant effect on surface roughness A, B and E has no effect at 95% confidence level. It is found that feed rate is more significant factor than other parameters, whilst depth of cut is the least significant parameter**.** The surface roughness produced on the UD-GFRP workpiece is mainly due to the feed rate. The graph for surface roughness raw data & S/N ratios is presented in Figure 3a–f.



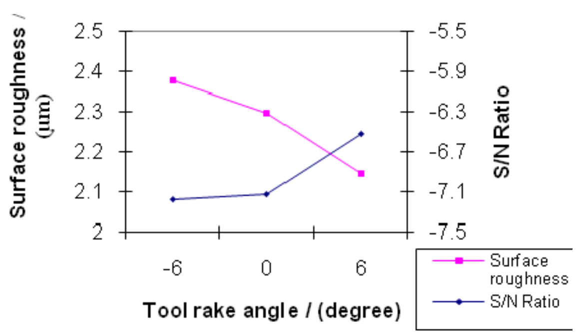
(c)



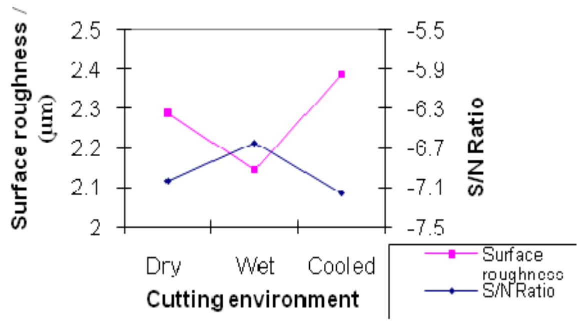
(a)



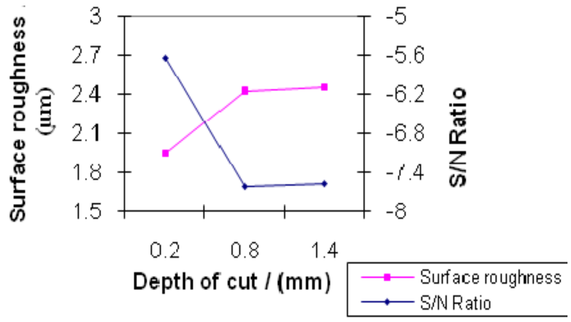
(d)



(b)



(e)



(f)

Fig. 3 Response and S/N ratio surface roughness (a) effect of tool nose radius, (b) effect of tool rake angle, (c) effect of feed rate, (d) effect of cutting speed, (e) effect of cutting environment, (f) effect of depth of cut

Figure 3 (a-f) shows the effect of tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment (dry, wet and cooled) and depth of cut on surface roughness in turning of UD-GFRP composite. The results indicated that the increase of tool nose radius reduces the surface roughness up to 0.8 mm. The surface roughness decreases with increase in tool rake angle as shown in Figure 3b. The figure indicates that the surface roughness increased at higher feed rates as shown in Figure 3c. The reason is the fact that with increase in feed rate the surface roughness and fracture of the composite material increases.

Figure 3d shows that the surface roughness increases with increase in cutting speed. The roughness observed at 55.42 m/min is more than the surface roughness observed at 159.66 m/min. The results indicated that the surface roughness increases with increase in cutting environment and depth of cut and is presented in Figure 3 (e & f). The optimum combination levels of process parameters are determined from the raw data response graphs plotted in Figure 3 (a-f). As seen from Figure 3(a-f), the selected tool nose radius at level 2 (0.8 mm), tool rake angle at level 3 (+6 degree), feed rate at level 2 (0.1 mm/rev), cutting speed at level 2 (110.84 m/min), cutting environment at level 2 (wet) and the optimal depth of cut at level 1 (0.2 mm). Therefore, the optimized combination of levels for the six control factors from the analysis so far was A2-B3-C2-D2-E2-F1.

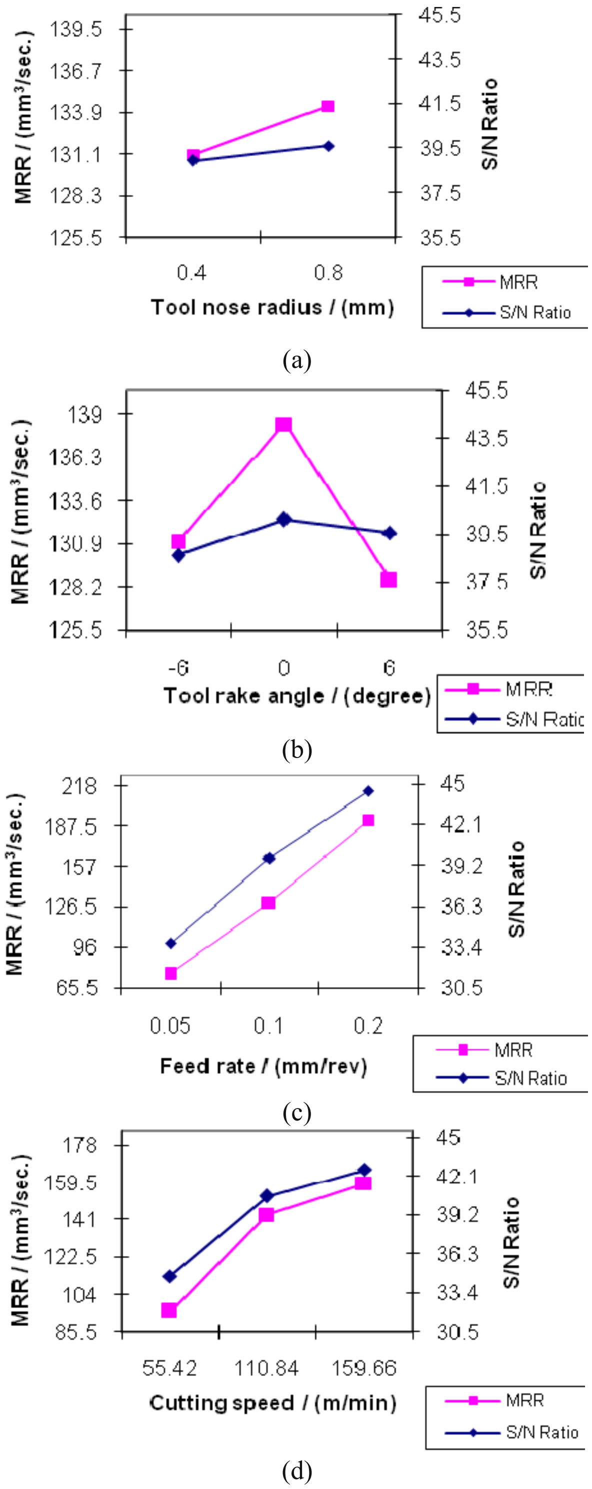
Table 4 also shows the experimental results of material removal rate (MRR) for the carbide (K10) tool insert and corresponding S/N ratio using Taguchi L_{18} orthogonal array and measured values of material removal rate for three different trial runs. The pooled versions of ANOVA of the raw data for material removal rate are shown in Table 6. It is clear that the parameters C, D and F significantly affect the MRR values. The percentage contribution of depth of cut is high (53.116%), feed rate (26.377%) and cutting speed (8.452%). This analysis was carried out for a level of significance of 5%, i.e. for a level of confidence of 95%. From the ANOVA result, it is concluded that C–feed rate, D-Cutting speed, F-depth of cut have significant effect on MRR, where A, B and E have no effect at 95% confidence level. It is found that depth of cut is more significant factor than other parameters, whilst cutting speed is the least significant parameter**.** The MRR produced on the UD-GFRP workpiece is mainly due to the depth of cut.

Table 6 ANOVA results for Material removal rate (raw data)

Source	SS	DOF	V	F ratio	Prob.	SS/	P (%)
Tool nose radius(A)	143	1	143	Pooled	0.705	---	---
Tool rake angle(B)	906	2	453	Pooled	0.634	---	---
Feed rate(C)	118198	2	59099	60.10*	0.000	116232	26.377
Cutting speed(D)	39209	2	19605	19.94*	0.000	37243	8.452
Cutting Environment(E)	4879	2	2440	Pooled	0.096	---	---
Depth of cut(F)	236028	2	118014	120.02*	0.000	234062	53.116
T	40662	53				440662	100.00
e (pooled)	1300	42	983			52113	1.826

SS = sum of squares, DOF = degrees of freedom, variance (V) = (SS/DOF), T = total, SS/ = pure sum of squares, P = percent contribution, e = error, F_{ratio} = (V/error), Tabulated F-ratio at 95% confidence level, * Significant at 95% confidence level

The optimum combination levels of process parameters are determined from the raw data response graphs plotted in Figure 4 (a-f). Figure 4 (a-f) shows the graph of Material Removal Rate. The results indicated that the material removal rate increases with increase in tool nose radius, feed rate, cutting speed, cutting environment, depth of cut and decrease with increase in tool rake angle. The data plotted in these graphs may be used to determine the optimal set of parameters. The arrows in the graphs indicate the levels at which the MRR and S/N ratio effects are at their optimal magnitudes, i.e. the MRR effect at its highest magnitude and the S/N ratio effect at its highest magnitude. A conflict appears in the graph of tool nose radius effects. The MRR effect is optimized at level 2, while the S/N ratio effect is optimized at level 2, tool rake angle effects; the MRR effect is optimized at level 2, while the S/N ratio effect is optimized at level 2. Feed rate, cutting speed, cutting environment and depth of cut (MRR & S/N ratio) effects are optimized both at the same level 3.



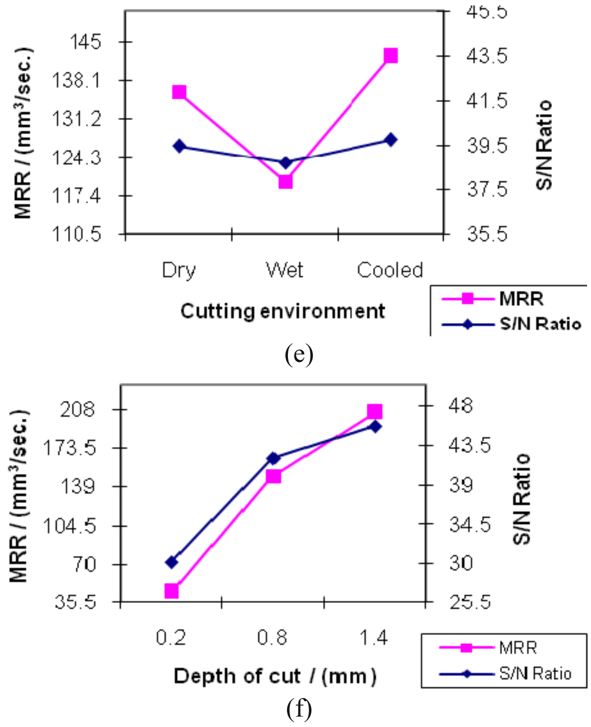


Fig. 4 Response and S/N ratio (a) effect of tool nose radius, (b) effect of tool rake angle, (c) effect of feed rate, (d) effect of cutting speed, (e) effect of cutting environment, (f) effect of depth of cut

3.1. Regression prediction models

Formulation:

Multiple regression equations were modeled for a relationship between process parameters in a bid to evaluate surface roughness and material removal rate for any combinations of factors levels in the specified range. The functional relationship between dependent output parameters with the independent variables under investigation may be postulated by Equation 4.

$$Y = A\,(X_1)^a\,(X_2)^b\,(X_3)^c \quad \ldots \qquad (4)$$

Where, Y is dependent output variable such as surface roughness and material removal rate. X_1, X_2 and X_3 are independent variables such as feed rate, cutting speed and depth of cut. The constants a, b and c are the exponents of independent variables. To convert the above non-linear equation into linear form, a logarithmic transformation is applied into the above equation and written as Equation 5.

$$\text{Log } y = \log A + a.\log(X_1) + b.\log(X_2) + c.\log(X_3) \quad (5)$$

This is one of the most commonly used data transformation methods for empirical model building. Now the above equation is written as Equation 6.

$\eta = \beta_0 + \beta_1.x_1 + \beta_2.x_2 + \beta_3.x_3 \quad \ldots \qquad (6)$

Where, η is the true value of dependent surface roughness and material removal rate on a logarithmic scale and x_1, x_2 and x_3 are the logarithmic transformation of the different parameters respectively, while β_0, β_1, β_2 and β_3 are the corresponding parameters to be estimated. Due to the experimental error, the true response $\eta = y-\varepsilon$, where y is the logarithmic transformation of the measured surface roughness and material removal rate parameters and the ε is the experimental error. For simplicity the equation is rewritten as:

$\hat{Y} = b_0 + b_1x_1 + b_2x_2 + b_3x_3 \quad \ldots \qquad (7)$

Where $\hat{Y}$ is the predicted surface roughness and material removal rate value after logarithmic transformation and b_0, b_1, b_2 and b_3 are the estimates of the parameters β_1, β_2 and β_3 respectively. The values of b_0, b_1, b_2 and b_3 is found out by linear regression analysis, (second order model) which is conducted with MINITAB standard version software (MINITAB 15.0 for windows), using the experimental data. The first order model for surface roughness and material removal rate reveals lack of fitness due to high prediction errors for surface roughness and material removal rate. As a result, second order model has been developed ignoring the non-significant parameters according to Equation 8.

$\hat{Y} = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{23}x_2x_3 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 \quad \cdots \qquad (8)$

The developed empirical model for surface roughness (Ra) and material removal rate (MRR) are given in Equation 8.

$Ra = 7.35 + 1.41\, x_1 + (-\,6.61)\, x_2 + 0.268\, x_3 + 0.312\, x_1 x_2 + 0.133\, x_1 x_3 + (-\,0.069)\, x_2 x_3 + 0.898\, x_1^2 + 1.82\, x_2^2 + (-\,0.229)\, x_3^2$

$MRR = -\,0.17 + 1.53\, x_1 + 2.84\, x_2 + 1.10\, x_3 + (-\,0.712)\, x_1 x_2 + (-\,0.340)\, x_1 x_3 + (-\,0.349)\, x_2 x_3 + (-\,0.340)\, x_1^2 + (-\,0.715)\, x_2^2 + (-\,0.265)\, x_3^2$

Predicted output values for surface roughness and material removal rate are calculated with the help of above equation and the given coefficients as shown in Table 7. The relative error between predicted and measured observed values for surface roughness and material removal rate is calculated and presented in Table 8. It has been found that relative error of surface roughness and material removal rate are well within limits. Thus, it can be stated that empirical equation built by using second-order model may be used.

Table 7 Empirical expressions developed by second order model

Predictor	Coefficient of surface roughness	Predictor	Coefficient of material removal rate
b_o	7.35	b_o	- 0.17
X_1	1.41	X_1	1.53
X_2	- 6.61	X_2	2.84
X_3	0.268	X_3	1.10
$X_1 X_2$	0.312	$X_1 X_2$	- 0.712
$X_1 X_3$	0.133	$X_1 X_3$	- 0.340
$X_2 X_3$	- 0.069	$X_2 X_3$	- 0.349
X_1^2	0.898	X_1^2	- 0.340
X_2^2	1.82	X_2^2	-0.715
X_3^2	-0.229	X_3^2	-0.265

Table 8 Comparison between experimental and predicted values of surface roughness and material removal rate

	Surface Roughness			Material Removal Rate		
Expt. No.	Prediction value	Experimental value	% Error	Prediction value	Experimental value	% Error
1	1.746	1.577	9.679	7.499	8.60	-14.682
2	1.959	1.830	6.585	144.878	145.00	-0.084
3	3.908	4.000	-2.354	358.922	330.15	8.016
4	2.173	2.140	1.519	36.644	36.24	1.102
5	1.941	1.810	6.749	215.774	237.97	-10.287
6	2.924	2.820	3.557	89.125	98.93	-11.001
7	1.941	1.893	2.473	123.310	125.02	-1.387
8	2.094	1.890	9.742	51.999	52.97	-1.867
9	2.656	2.540	4.367	146.893	144.95	1.323
10	2.606	2.656	-1.919	103.276	104.40	-1.088
11	1.995	2.100	-5.263	124.451	124.96	-0.409
12	2.070	2.090	-0.966	73.114	73.53	-0.569
13	1.659	1.736	-4.641	18.493	18.39	0.557
14	2.636	2.656	-0.759	177.011	197.56	-11.609
15	2.723	2.620	3.783	219.280	240.97	-9.937
16	2.506	2.303	8.100	158.125	170.03	-7.529
17	1.513	1.570	-3.767	18.578	18.38	1.066
18	2.792	2.673	4.262	232.809	260.91	-12.070

Table 9 Parametric setting for surface roughness and material removal rate for validation of regression model

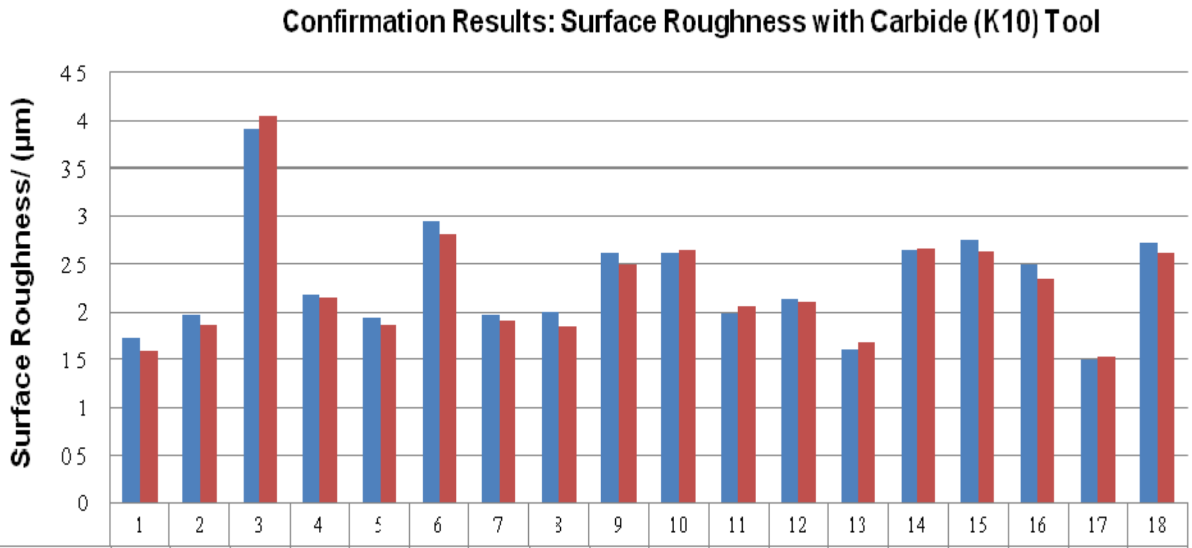
	Surface Roughness						Material Removal Rate					
Expt. No.	1 Nose Radius /mm (A)	2 Rake Angle / Degree (B)	3 Feed Rate/(mm /rev.) (C)	4 Cutting Speed / (m/min) & rpm (D)	5 Cutting Environment (E)	6 Depth of Cut / mm (F)	1 Nose Radius /mm (A)	2 Rake Angle / Degree (B)	3 Feed Rate / (mm/rev.) (C)	4 Cutting Speed / (m/min) & rpm (D)	5 Cutting Environment (E)	6 Depth of Cut / mm (F)
1	0.4	-6°	0.05	(55.42) 420	(Dry) 1	0.8	0.4	-6°	0.05	(110.84) 840	(Dry) 1	0.2
2	0.4	-6°	0.1	(110.84) 840	(Wet) 2	0.8	0.4	-6°	0.1	(110.84) 840	(Wet) 2	0.8
3	0.4	-6°	0.2	(159.66) 1210	(Cooled) 3	0.8	0.4	-6°	0.2	(110.84) 840	(Cooled) 3	1.4
4	0.4	0°	0.05	(55.42) 420	(Wet) 2	0.8	0.4	0°	0.05	(110.84) 840	(Wet) 2	0.8
5	0.4	0°	0.1	(110.84) 840	(Cooled) 3	0.8	0.4	0°	0.1	(110.84) 840	(Cooled) 3	1.4
6	0.4	0°	0.2	(159.66) 1210	(Dry) 1	0.8	0.4	0°	0.2	(110.84) 840	(Dry) 1	0.2
7	0.4	+6°	0.05	(110.84) 840	(Dry) 1	0.8	0.4	+6°	0.05	(110.84) 840	(Dry) 1	1.4
8	0.4	+6°	0.1	(159.66) 1210	(Wet) 2	0.8	0.4	+6°	0.1	(110.84) 840	(Wet) 2	0.2
9	0.4	+6°	0.2	(55.42) 420	(Cooled) 3	0.8	0.4	+6°	0.2	(110.84) 840	(Cooled) 3	0.8
10	0.8	-6°	0.05	(159.66) 1210	(Cooled) 3	0.8	0.8	-6°	0.05	(110.84) 840	(Cooled) 3	0.8
11	0.8	-6°	0.1	(55.42) 420	(Dry) 1	0.8	0.8	-6°	0.1	(110.84) 840	(Dry) 1	1.4
12	0.8	-6°	0.2	(110.84) 840	(Wet) 2	0.8	0.8	-6°	0.2	(110.84) 840	(Wet) 2	0.2
13	0.8	0°	0.05	(110.84) 840	(Cooled) 3	0.8	0.8	0°	0.05	(110.84) 840	(Cooled) 3	0.2
14	0.8	0°	0.1	(159.66) 1210	(Dry) 1	0.8	0.8	0°	0.1	(110.84) 840	(Dry) 1	0.8
15	0.8	0°	0.2	(55.42) 420	(Wet) 2	0.8	0.8	0°	0.2	(110.84) 840	(Wet) 2	1.4
16	0.8	+6°	0.05	(159.66) 1210	(Wet) 2	0.8	0.8	+6°	0.05	(110.84) 840	(Wet) 2	1.4
17	0.8	+6°	0.1	(55.42) 420	(Cooled) 3	0.8	0.8	+6°	0.1	(110.84) 840	(Cooled) 3	0.2
18	0.8	+6°	0.2	(110.84) 840	(Dry) 1	0.8	0.8	+6°	0.2	(110.84) 840	(Dry) 1	0.8

4 CONFIRMATION EXPERIMENTS

The experimental study is carried out to validate the earlier developed empirical expressions for surface roughness and material removal rate. Depth of cut is the least significant for surface roughness and cutting speed is the least significant for material removal rate as observed for ANOVA Table 5 and 6. So depth of cut and cutting speed remained constant at 0.8 mm and 110.84 m/min respectively for validation where other parameters have the same level are shown in Table 3. Surface roughness and material removal rate is shown in Table 9. To verify the goodness of the predicted model, the observed values and their predictive values of the surface roughness and material removal rate are given in Table 10. It has been found that the maximum and minimum error percentage for surface roughness is (8.092% and -5.444%) and material removal rate is (7.264% and -10.081%) which is perfectly satisfactory. Graphical comparison of actual and predicted values of surface roughness and material removal rate is shown in Figure 5 and Figure 6.

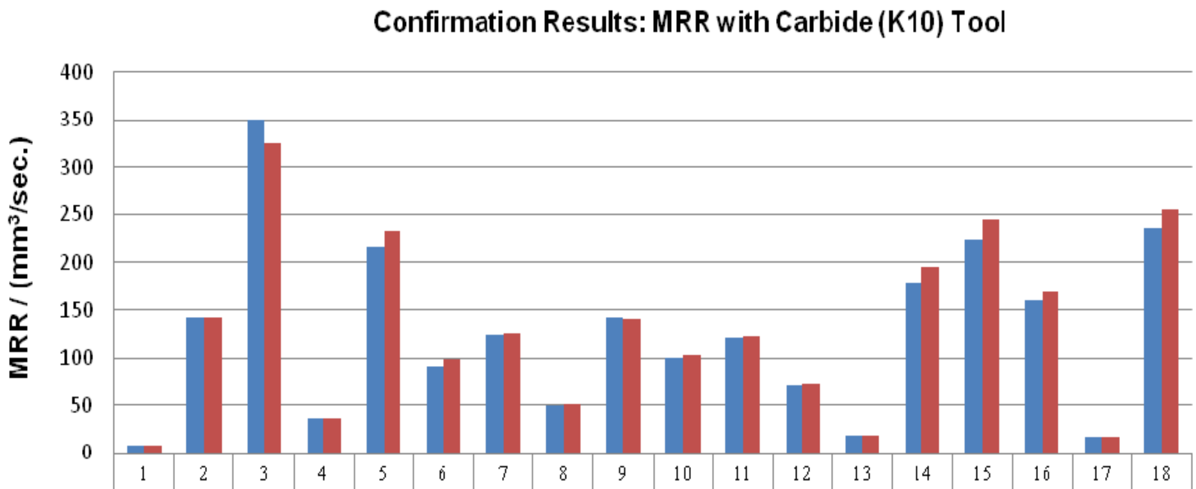
Table 10 Validation between experimental and predicted results surface roughness and material removal rate

	Surface Roughness			Material Removal Rate		
Expt. No.	Prediction value	Experimental value	% Error	Prediction value	Experimental value	% Error
1	1.730	1.590	8.092	8.580	9.445	-10.081
2	1.968	1.865	5.234	142.555	143.220	-0.466
3	3.915	4.050	-3.448	350.620	325.150	7.264
4	2.170	2.135	1.613	37.221	36.980	0.647
5	1.948	1.868	4.107	217.117	233.770	-7.670
6	2.940	2.805	4.592	92.125	99.940	-8.483
7	1.973	1.910	3.193	124.410	127.000	-2.082
8	2.000	1.854	7.300	50.660	51.770	-2.191
9	2.618	2.500	4.507	142.693	141.220	1.032
10	2.614	2.645	-1.186	101.076	103.400	-2.299
11	1.985	2.050	-3.274	122.151	123.990	-1.505
12	2.120	2.100	0.943	72.000	73.000	-1.389
13	1.598	1.685	-5.444	19.500	19.200	1.538
14	2.649	2.669	-0.755	180.033	195.570	-8.630
15	2.757	2.630	4.606	224.340	245.970	-9.642
16	2.496	2.340	6.250	160.225	170.000	-6.101
17	1.500	1.533	-2.200	18.500	18.000	2.703
18	2.728	2.627	3.702	236.800	255.890	-8.062



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
prediction value	1.73	1.968	3 915	2.17	1.948	2.94	1.973	2	2.618	2.614	1.985	2.12	1.598	2.649	2.757	2.496	1.5	2.728
Experimental value	1.59	1.865	4.05	2.135	1.868	2.805	1.9[illegible]	1.854	2.5	2.645	2.05	2.1	1.685	2.669	2.63	2.34	1.533	2.627

Fig. 5 Comparison between actual and predicted values of surface roughness



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
prediction value	8.58	142.55	350 62	37.221	217.11	92.125	124.41	50.66	142.69	101.07	122.15	72	19.5	180.03	224.34	160.22	18.5	236.8
Experimental value	9.445	143.22	325 15	35.98	233.77	99 94	127	51.77	141.22	103.4	12[illegible].99	73	19.2	195.57	245.97	170	18	255.89

Fig. 6 Comparison between actual and predicted values of Material Removal Rate

5 CONCLUSION

Experiments are conducted on a lathe machine for machining unidirectional glass fiber reinforced plastic (UD-GFRP). The tool used for the machining operation is a Carbide (K10) tool. The response surface roughness and material removal rate was studied.

- From the ANOVA result, it is concluded that C–feed rate, D–cutting speed, F–Depth of cut, have significant effect on surface roughness. [A], [B], [E] have no effect at 95% confidence level.
- Based on the Taguchi method and ANOVA, feed rate has a dominant effect of almost 29.110% in contribution ratio, while cutting speed has 21.595% and depth of cut has 10.589% influence on the surface roughness in turning of unidirectional glass fiber reinforced plastic (UD-GFRP).

- Feed rate is the factor which has great influence on surface roughness, followed by cutting speed. Depth of cut has less influence on surface roughness.
- Material removal rate have been calculated. Its analysis based on ANOVA depicts that increase of any machining parameters, increases the material removal rate. For material removal rate, feed as well as depth of cut takes key role followed by cutting speed. The percent contributions of depth of cut (53.116%), feed rate (26.377%) and cutting speed (8.452%) on material removal rate are significantly larger (95 % confidence level) as compared to the contribution of the tool nose radius. The wet cutting environment reduced the surface roughness and material removal rate.
- The second-order models were developed to predict the surface roughness and material removal rate using regression modeling.
- The developed models for surface roughness and material removal rate using regression modeling are highly adequate as their R^2 values are very close to 1 and hence all the models may be used for reliable prediction [R^2 value for surface roughness is 95.8% and MRR value is 99.7%].
- The second-order model for surface roughness and material removal rate has been developed from the observed data. It was found that the maximum and minimum error percentage for surface roughness is 8.092% and -5.444% and material removal rate is 7.264% and -10.081% which is thoroughly satisfactory.

6 NOMENCLATURE

b_0, b_1, b_2, b_3, b_4	Estimates of parameters
a, b, c, d	Exponentially determined constant
x_0, x_1, x_2, x_3	logarithmic transformations of machining parameters
A	Tool nose Radius / mm
B	Tool Rake angle / Degree
C	Feed rate / (mm/rev)
D	Cutting speed / (m/min.) & rpm
E	Cutting environment
F	Depth of cut / mm
η	Surface roughness and MRR response
y	Measured Surface roughness and MRR
ε	Experimental error
L	Length of the workpiece to be turned
Tc	Time of cutting

ACKNOWLEDGMENTS

The author is very grateful to Dr. Meenu Gupta, Department of Mechanical Engineering, National Institute of Technology, Kurukshetra, India, and Dr. P. S. Satsangi, Department of Mechanical Engineering, PEC University of Technology, Chandigarh, India, for the support rendered. The authors are indebted to Maharashtra Engineering Industry, India (P) Limited, Satara Maharashtra for supplying the UD- GFRP rods used in this work.

REFERENCES

[1] Teti, R., “Machining of composite materials”, CIRP Annals-Manufacturing Technology, Vol. 51, No. 2, 2002, pp. 611- 634.

[2] Paulo Davim, J., “Machining Composite Materials”, Wiley-ISTE, 2009.

[3] Paulo Davim, J., and Reis, P., “Multiple regression analysis (MRA) in modeling milling of glass fibre reinforced plastics (GFRP)”, Int. Journal Manufacturing Technology Manag, Vol. 6(1/2), 2004, pp. 85-197.

[4] Palanikumar, K., Karunamoorthy, L., and Karthikeyan, R., “Multiple performance optimization of machining parameters on the machining of GFRP composites using carbide (K10) tool”, Materials and Manufacturing Processes, Vol. 21, 2006, pp. 846-852.

[5] Paulo Davim, J., and Mata, F., “New machinability study of glass fibre reinforced plastics using polycrystalline diamond and cemented carbide (K15) tools”, Materials and Design, Vol. 28, 2007, pp. 1050-1054.

[6] Arul, S., Raj, D., Vijayaraghavan, L, Malhotra, S. K., and Krishnamurthy, R., “Modeling and optimization of process parameters for defect toleranced drilling of GFRP composites”, Material Manufacturing Process, Vol. 21, No. 4, 2006, pp. 357-365.

[7] Hussain, S. A., Pandurangadu, V., and Palanikumar, K., “Surface roughness analysis in machining of GFRP composite by carbide tool (K20)”, European Journal of Scientific Research, Vol. 41, No. 1, 2010, pp. 84-98.

[8] Hussain, S. A., Pandurangadu, V., and Palanikumar, K., “Machinability of glass fiber reinforced plastic (GFRP) composite materials”, Int. Journal of Engineering, Science and Technology, Vol. 3, No. 4, 2011, pp. 103-118.

[9] Rajasekaran, T., Palanikumar, K., and Vinayagam, B. K., “Application of fuzzy logic for modeling surface roughness in turning CFRP composites using CBN tool”, Production Engineering Res. Deve, Vol. 5, 2011, pp. 191-199.

[10] Isik, B., and Kentli, A., “Multicriteria optimization of cutting parameters in turning of UD-GFRP materials considering sensitivity”, Int. Journal Advance Manufacturing Technology, Vol. 44, 2009, pp. 1144-1153.

[11] Khan, M., and Adam Kumar, A., “Senthil, Machinability of glass fibre reinforced plastic (GFRP)

composite using alumina-based ceramic cutting tools", Journal of Manufacturing Processes, Vol. 13, 2011, pp. 67-73.

[12] Rao, G., Mahajan, P., and Bhatnagar, N., "Machining of UD-GFRP composites chip formation mechanism", Composites Science and Technology, Vol. 67, No. 11-12, 2007, pp. 2271-2281.

[13] Mikaddem, A., Ibrahim, C., and El Mansori, M., "A micro–macro combined approach using FEM for modelling of machining of FRP composites: Cutting forces analysis", Composites Science and Technology, Vol. 68, No. 15-16, 2008, pp. 3123-3127.

[14] Palanikumar, K., "Modeling and analysis for surface roughness in machining glass fibre reinforced plastics using response surface methodology", Materials & Design, Vol. 28, Issue 10, 2007, pp. 2611-2618.

[15] Ross, P. J., "Taguchi Techniques for Quality Engineering", McGraw-Hills Book Company, New York, 1988.

[16] Roy, R. K., "A Primer on Taguchi Method", Van Nostrand Reinhold, New York. 1990.