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International Journal of Engineering, Science and Technology
Vol. 3, No. 8, 2011, pp. 248-270

INTERNATIONAL JOURNAL OF ENGINEERING, SCIENCE AND TECHNOLOGY
www.ijest-ng.com

Modeling and analysis for surface roughness and material removal rate in machining of UD-GFRP using PCD tool

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Abstract

In the present paper, an effective approach for the optimization of turning parameters based on the Taugchi's method with regression analysis is presented. This paper discusses the use of Taugchi's technique for minimizing the surface roughness and maximizing the material removal rate in machining unidirectional glass fiber reinforced plastics (UD-GFRP) composite with a polycrystalline diamond (PCD) tool. A multiple objective utility model has been studied to optimize both the dependent parameters. Experiments were conducted based on the established Taguchi's technique L_{18} orthogonal array on a lathe machine. The cutting parameters considered were tool nose radius, tool rake angle, feed rate, cutting speed, depth of cut and cutting environment (dry, wet and cooled) on the surface roughness and material removal rate produced. The performances of the cutting tool were evaluated by measuring surface roughness and material removal rate. A second order mathematical model in terms of cutting parameters is also developed using regression modeling. The results indicate that the developed model is suitable for prediction of surface roughness and material removal rate in machining of unidirectional glass fiber reinforced plastics (UD-GFRP) composites. The predicted values and measured values are fairly close to each other. The results are confirmed by further experiments.

Keywords: UD-GFRP composites, ANOVA, multi response optimization, utility concept, regression modeling, surface roughness, material removal rate, polycrystalline diamond (PCD) tool.

DOI: http://dx.doi.org/10.4314/ijest.v3i8.20

1. Introduction

Fiberglass composites are replacing many of the materials used in industries as they are economical. Glass fibre reinforced polymers (GFRP) are being used in variety of applications that include oil, gas and corrosive environments. Machining of glass fiber-reinforced polymer (GFRP) composite materials have always been a challenge due to host of difficulties encountered such as fiber pull-out, fiber fuzzing, matrix burning, and fiber-matrix debonding leading to subsurface damage, reduced strength and short product service life. The necessities of machining FRP composites come from the requirement of the conversion of raw composite material into engineering component despite the ability to fabricate near-net shape components. The FRPs are one of the 'difficult-to-machine' materials because of the fibre arrangement. Machining of composite parts creates discontinuity in the fibre and thus affects the performance of the part. Besides, the mechanism of material removal is different from that of single-phased materials, such as metals. The material removal process is quite complex. Many variables such as the workpiece material, the cutting tool material, the rigidity of the machine, the set up, the cutting feed, speed, tool wear and chip control must be considered.

Arola and Ramulu (1997) as well as Mahdi and Zhang (2001) applied the finite element method to investigate the cutting of FRPs but the former adopted a homogenized material model and the latter considered the micro details of individual fibre-tool interactions. Fiber reinforced materials generally contain two or more constituents. They are matrix and the fiber to name, to take advantage of the best properties of those, without compromising on the weakness of either. Generally the matrix is of ductile and fiber is of brittle in nature. In fiber reinforced composite materials, fibers act as a load carrying medium and the matrix acts as a load transporting medium (Mohan et al., 2005). Machining glass fibre composite is still a major problem, because of their inert nature, high hardness, and refractoriness (Jain et al., 2002). Because of their different applications, the need for machining FRP material has not been fully eliminated. Glass fibre reinforced plastics (GFRPs) are extremely abrasive, thus proper selection of the cutting tool and cutting parameters is very important for a perfect machining process (Davim et al., 2009). The surface integrity of a GFRP machined composite is hard to control due to varying mechanical properties of the fibre and the matrix (Zang, 2009). Caprino et al. (1998) carried out orthogonal cutting tests using high speed steel tools, to determine the trend of the principal forces on unidirectional-GFRP. The cutting direction was held parallel to the fibre orientation while the tool rake, relief angle and the depth of the cut were varied. The authors concluded that the frictional force generated by the chip sliding up the tool face was negligible so that the tool face-chip interaction resulted in a force practically normal to the face itself. The forces arising at the top flank and cutting edge were a considerable part of the overall cutting forces. The vertical force, due to the compression of the tool against the freshly generated work material surface, was dependant on all the machining parameters. Vertical force decreased with both the rake and relief angles and linearly increased by increasing the depth of the cut. Wang and Zhang (1999) investigated the cutting of carbon fibre-reinforced composites and found that the machinability and surface integrity are mainly controlled by fibre-orientation.

The role of these parameters is to evaluate the surface produced by a machining process and to quantify the amount of machining damage for different process parameters such as cutting speed, feed rate and depth of cut. It has been shown that lower the value of surface roughness, the better is the quality of machined surface. Roughness values also indicate changes in the mechanical properties of machined FRP. Studies have shown that with increasing roughness the fatigue strength and impact strength decreases (Ramulu and Arola, 1995). There is a significant difference between the machining of conventional metals and their alloys and that of FRP materials (Ramulu et al, 1991). This is because FRP materials are anisotropic, inhomogeneous and are mostly prepared in laminate form before undergoing the machining process. Unlike the case of homogeneous metals, where the machining is associated with plastic deformation and shearing, the machining of FRP composites is associated with plowing, cutting and cracking (Wang et al., 1995 and Pwu et al., 1998), it is necessary to control/minimize the occurrence of such defects which poses considerable machinability problems. (Hussain et al., 2010) developed a surface roughness prediction model for the machining of GFRP pipes using response surface methodology by using carbide tool (K20). Four parameters such as cutting speed, feed rate, depth of cut and work piece (fiber orientation) were selected to minimize the surface roughness. It was found that, the depth of cut shows a minimum effect on surface roughness as compared to other parameters. (Ramesh et al., 2008) developed a surface roughness prediction model for the machining of CVD (TiN–TiCN–Al_2O_3–TiN) using response surface methodology by using coated carbide insert under different cutting conditions using taguchi's orthogonal array. Three parameters such as cutting speed, feed rate and depth of cut were selected to minimize the surface roughness. It was found that, the feed rate is the factor, which has great influence on surface roughness, followed as compared to other parameters.

Several methodologies were developed to solve the multi-response optimization problems. Byrne and Taguchi (1987) presented a case where the responses were optimized independently using Taguchi's approach and then the results were compared subjectively to select the best levels in terms of the responses of interest. (Logothetis and Haigh, 1988) employed multiple regressions and a linear programming approach for multi response optimization by Taguchi method. This procedure was computationally complex thereby making its use difficult on shop floor. (Shiau, 1990) solved the multi-response problem by assigning the weights to S/N ratio of each quality characteristic and then summing up the weighted S/N ratios for the measurement of overall performance of a process. (Singh et al., 2002) used multi-response optimization through utility concept and Taguchi method for optimization of the quality characteristics of MAFM process. Isik et al. (2009) proposed an approach for turning of a glass fiber reinforced plastic composites using cemented carbide tool. Three parameters such as depth of cut, cutting speed and feed rate were selected to minimize the Tangential and feed force. Weighting techniques was used. The idea of this technique consists in adding all the objective functions together using different coefficients for each. It means that multicriteria optimization problem is changed to a scalar optimization problem by creating one function of the form. It was found that this technique will be more economical to predict the effect of different influential combination of parameters.

Rajasekaran et al. (2011) used fuzzy logic for modeling and prediction of CFRP work piece. Three parameters such as depth of cut, feed rate and cutting speed were selected to minimize the surface roughness. Cubic boron nitride tool was used for turning process. It was found that the fuzzy logic modeling technique can be effectively used for the prediction of surface roughness in machining of CFRP composites. GFRP is a cheaper option than Carbon or Kevlar, so GFRP rods were used in this work. In this study, the surface roughness and MRR were measured on machining UD-GFRP composite materials. Hussain et al. (2011) developed a surface roughness and cutting force prediction model for the machining of GFRP tubes using response surface methodology by using carbide tool (K20), cubic boron nitride (CBN) and polycrystalline diamond (PCD). Four parameters such as cutting speed, feed rate, depth of cut and work piece (fiber orientation) were selected to minimize the surface roughness and cutting forces. It was found that, the polycrystalline diamond (PCD) cutting tool is better. As seen from the literature, only limited work has been carried out on the machinability aspects of unidirectional glass fiber reinforced plastic (UD-GFRP) composite. Thus, this present work aims at investigating the effects of tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment (dry, wet and cooled) and depth of cut on some aspects of machinability of UD-GFRP composites. In the present investigation, the machinability aspects have been evaluated in terms of surface roughness and material removal rate during the turning of UD-GFRP composites using PCD tools. Regression analyses are applied to identify the best levels of cutting parameters and their significance. Insignificant parameters are not taken into consideration in this Regression modelling. To convert the different performance into a single performance unit, linear regression modeling is used. Also these techniques are effectively used for optimization of parameters and for modeling as well.

2. Experimental Procedure

2.1 Material

In the present study, pultrusion processed unidirectional glass fiber reinforced plastic composite rods is used. The diameter of the rod taken is 42 mm and length 840 mm. The fiber used in the rod is E-glass and resin used is epoxy and properties of material used are shown in Table 1.

Table 1 Mechanical and Thermal Properties of the UD-GFRP Material

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 Rod 840 mm in length	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: (2) At 100° C:	20 KV/cm 20 KV/cm (50 KV / 25 mm)	 KV/cm

2.2 Method

The Taguchi method is a commonly adopted approach for optimizing design parameters. The method was originally proposed as a means of improving the quality of products through the application of statistical and engineering concepts. It is a method based on Orthogonal Array (OA) experiments, which provides much-reduced variance for the experiment resulting is optimum setting of process control parameters. Orthogonal Array (OA) provides a set of well-balanced experiments (with less number of experimental runs) and Taguchi’s signal-to-noise ratios (S/N), which are logarithmic functions of desired output, serves as objective function in the optimization process. This technique helps in data analysis and prediction of optimum results. In order to evaluate optimal parameter settings, Taguchi method uses a statistical measure of performance called signal-to-noise ratio. The S/N ratio takes both the mean and the variability into account. The S/N ratio is the ratio of the mean (Signal) to the standard deviation (Noise). The ratio depends on the quality characteristics of the product/process to be optimized. The standard S/N ratios generally used are as follows:- Nominal-is-Best (NB), lower-the-better (LB) and Higher-the-Better (HB). The optimal setting is the parameter combination, which has the highest S/N ratio.

In this study, material removal rate is taken “higher the better” type and surface roughness is taken “lower the better”. The corresponding loss function can be expressed as follows (Ross, 1988).

Smaller the better:

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

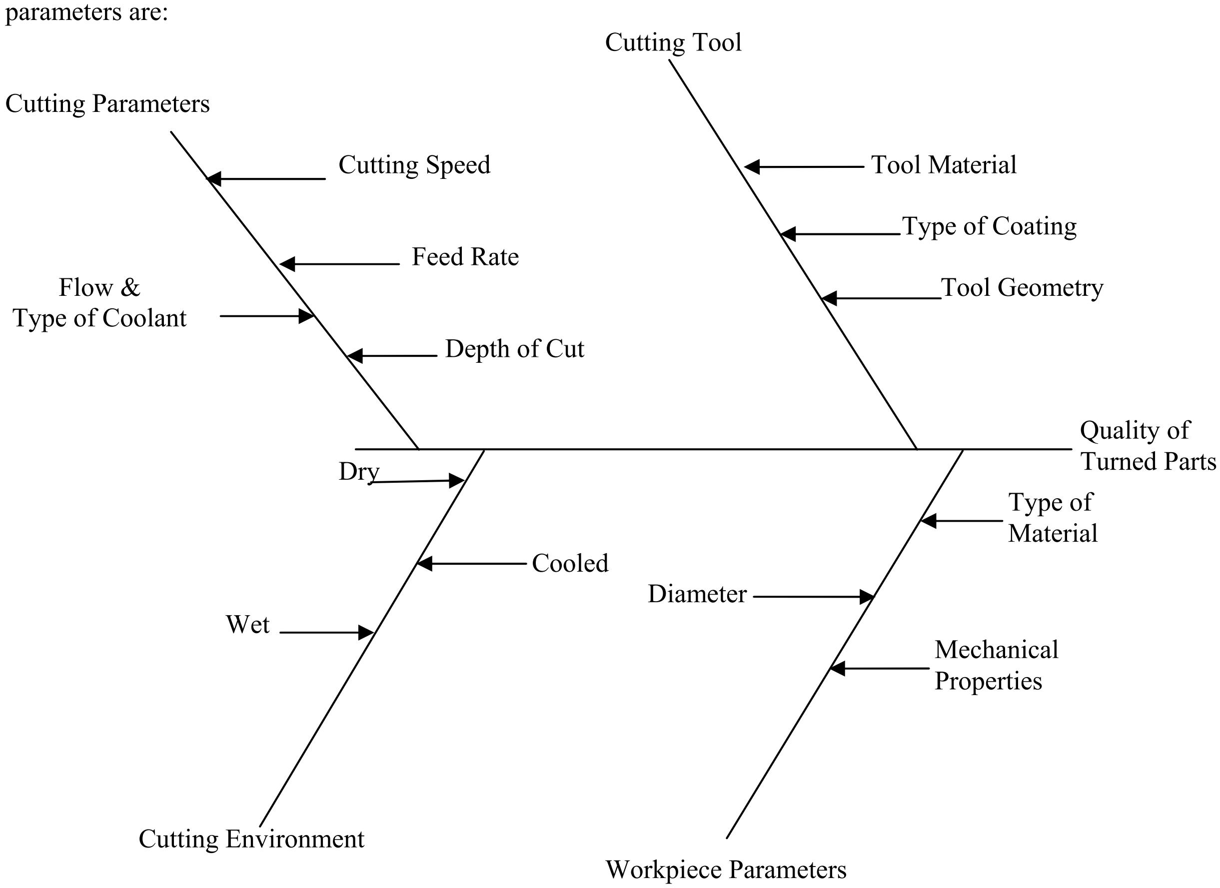
Larger the better:

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

"Where *n* is the number of observations, y is the observed data".

2.3 Present Problem

Taguchi design of experiment is a powerful analysis tool for modeling and analyzing the influence of control factors on performance output. The initial step in the Taguchi model is to build up an input-output database required for the optimization through the turning experiments. In order to have a complete knowledge of turning process over the range of parameters selected, a proper planning of experimentation is essential to reduce the cost and time. In order to identify the process parameters that may affect the machining characteristics of centre lathe machined parts an Ishikawa cause effect diagram was constructed and is shown in Figure 1. The Ishikawa cause-effect gives analysis from the observation based on previous research. The identified process parameters are:



Cutting Parameters: cutting speed, feed rate, depth of cut, flow of current and environment
Cutting tool related Parameters: tool material, tool geometry, type of coating and inserts condition.
Work piece based Parameters: type of material, mechanical properties and diameter.
Cutting Environment: dry, wet and cooled environment

Figure 1: Ishikawa Cause-Effect Diagram of a Turning Process

Although Taguchi's approach towards robust parameter design introduced innovative techniques to improve quality, a few concerns regarding his philosophy have been raised. Some of these concerns relate to the signal to noise ratios defined to reduce variations in the response and some others are related to the absence of the means to test for higher-order control factor interactions when his orthogonal arrays are used as inner arrays for the design. For these reasons, other approaches to carry out robust parameter design have been suggested including response modeling and the use of $\ln s_i^2$ in the place of the signal to noise ratios in the dispersion model. In response modeling, the noise factors are included in the model as additional factors, along with the other control factors. The most significant limitation of these techniques relates to process data availability and quality. Current databases were not designed for process improvement, resulting in potential difficulties for the Taguchi experimentation, where available data does not explain all the variability in process outcomes. The limitation of OA is that it can only be applied at the initial stage of the product/process design system. There are some situations whereby OA techniques are not applicable, such as a process involving influencing factors that vary in time and cannot be quantified exactly (Weibull, 2012).

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 L_{18} (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. According to the Taguchi design concept, a L_{18} orthogonal array is chosen for the experiments as shown in Table 2.

Table 2 Experimental Layout using L_{18} Orthogonal Array

Expt. No.	A	B	C	D	E	F	---	---
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

The L_{18} orthogonal array has 18 rows corresponding to the number of tests. The parameters tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment and depth of cut are assigned to columns (A, B, C, D, E, F) respectively as shown in Table 2. Out of which cutting environment parameters (dry, wet and cooled) are especially applied to composite rods. The cutting environment (dry, wet and cooled) on the workpiece was set during the machining of the rod, so as to obtain a comparative assessment of the performance of cutting environment which has not been studied earlier. So, it can be used for the cutting environment. The cutting fluid used in flooded machining is CASTROL water miscible soluble coolant contains 1:6 volumetric concentration is flushed at cutting zone. The spray is concentrated on rake and flank surface along the cutting edges, minimize the friction, lubricity abilities and reduce the tool wear (Kodandaram et al., 2010). Cutting environment: Wet (33-38° temperature) and Cooled (5-7° temperature) is used. The output responses used to measure the machinability are surface roughness and material removal rate. The parameters selected, the designated symbols, and their ranges are given in Table 3.

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 Control Parameters and their Level

The machining tests were conducted on a conventional lathe machine as shown in Figure 2 with the following specifications: a height of center 220 mm, swing over bed 500 mm, spindle speed range 60 – 3000 rpm, feed range 0.04 – 2.24 mm /rev and main motor 11 kW. A tool holder SVJCR steel EN47 was used during the turning operation. The different cutting tool inserts as shown in Figure 3(a) & 3(b) are made of polycrystalline diamond. The geometry of the cutting tool VNMG insert 110404/110408 is as follow: NQA BS EN ISO 9001-2000, tool rake angle -6° (negative), 0°, and +6° (positive) and tool nose radius 0.4mm & 0.8mm. From these 54 data points, the suitable L_{18} array data points were chosen. With the finished product, the surface roughness values were measured. The surface roughness was measured by using Tokyo Seimitsu Surfcom 130A type instrument as shown in Figure 4. For each trial, experiments were replicated (three times). A statistical analysis of variance (ANOVA) is performed to see which process parameter is statistically significant for surface roughness and material removal rate property. The optimum condition for surface roughness and material removal rate characteristic has been established through S/N data analysis aided by raw data analysis. Surface roughness and material removal rate data are analyzed to determine the effect of the various design parameters. The experimental results are then transformed into signal-to-noise (S/N) ratio. Taguchi recommends the use of S/N ratio to measure the quality characteristics deviating from the desired values. The material removal rate, in mm^3/ sec., has been calculated from the following relation: Material Removal rate = It is the volume of material being removed per unit time the work piece,

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

Where, D = initial dia in mm, d = final dia in mm, L = length in mm, f = feed rate in mm/rev. where T_c per pass is defined as: T_c = L /f N is the machining time, F =feed rate in mm/rev.
L = length of the workpiece to be turned, N = spindle speed in rpm

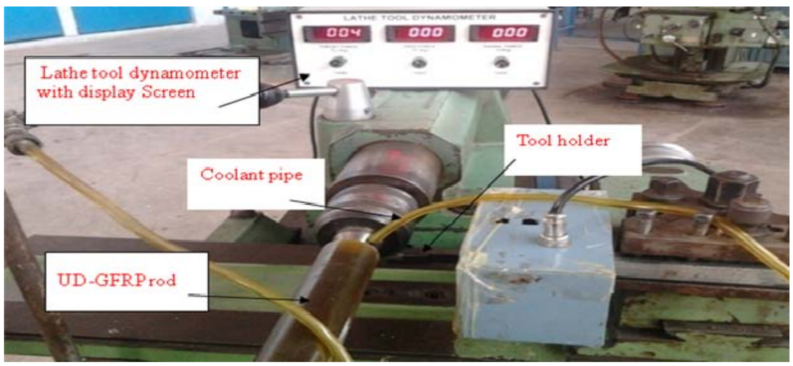


Figure 2: Experimental set up

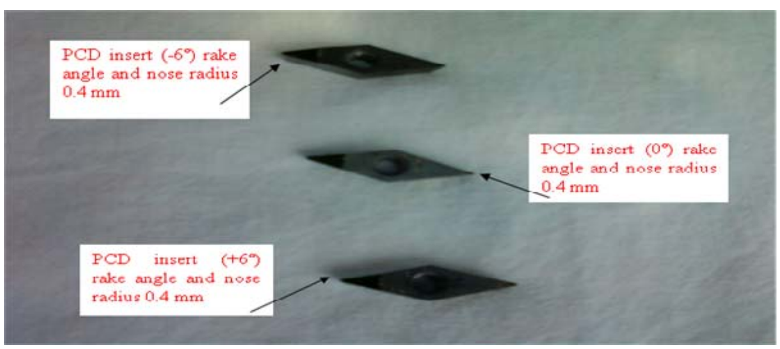


Figure 3(a): PCD cutting tool inserts used on the experiment

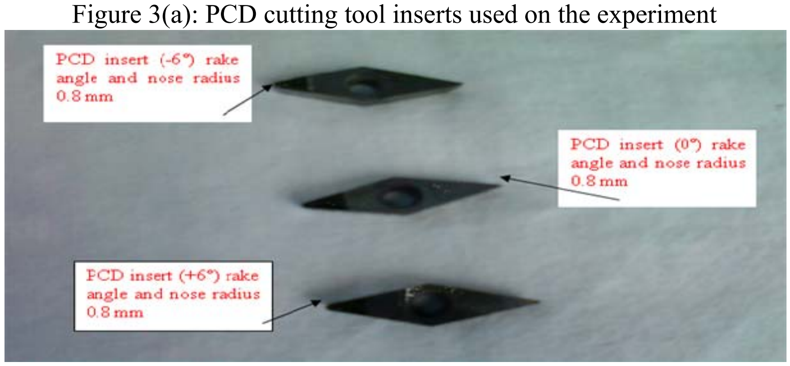


Figure 3(b): PCD cutting tool inserts used on the experiments

Figure 4: Surface Roughness Tester: - Tokyo Seimitsu Surfcom 130A

3. Results and Discussions

The analysis is made using the popular software MINITAB 15 specifically used for design of experiment applications, Table **4 test** data summary shows the experimental results for surface roughness, *MRR* and their S/N ratios based on the experimental parameter combinations.

Table 4 Test Data Summary for Surface Roughness and Material Removal Rate

Expt. No.	R_a	Average R_a (µm)	S/N ratio (dB)	*MRR*	Average *MRR* (mm^3/sec.)	S/N ratio (dB)
1	1.38/1.46/1.35	1.397	-2.90665	8.6/8.5/8.7	8.60	18.6888
2	1.67/1.36/1.33	1.453	-3.29561	145.00/145.02/144.95	144.99	43.2268
3	3.00/2.79/3.44	3.076	-9.79513	327.58/347.03/347.23	340.61	50.6354
4	1.31/1.47/1.32	1.366	-2.72569	36.24/36.24/36.24	36.24	31.1838
5	1.70/1.24/1.65	1.530	-3.77191	249.90/249.96/249.88	249.91	47.9558
6	2.05/2.93/2.22	2.400	-7.71240	106.02/105.86/105.90	105.93	40.5001
7	1.61/1.33/1.60	1.513	-3.63048	125.00/124.98/124.98	124.99	41.9373
8	1.67/1.79/1.45	1.636	-4.31122	52.96/52.99/52.97	52.97	34.4811
9	2.43/2.20/2.16	2.263	-7.10695	144.97/144.97/145.02	144.99	43.2266
10	1.38/1.83/1.43	1.547	-3.86095	104.42/104.38/104.40	104.40	40.3740
11	1.52/1.43/1.87	1.606	-4.17870	125.00/125.00/125.00	125.00	41.9382
12	2.24/1.90/1.76	1.966	-5.91999	73.57/73.58/73.55	73.57	37.3336
13	1.57/1.57/1.65	1.597	-4.06671	18.39/18.39/18.39	18.39	25.2916
14	1.40/1.86/1.63	1.630	-4.30102	208.72/208.92/208.92	208.85	46.3968
15	2.14/1.80/2.77	2.237	-7.13000	250.09/250.09/250.05	250.08	47.9615
16	2.12/1.940/1.90	1.940	-5.77660	180.00/180.04/180.00	180.01	45.1061
17	1.23/1.486/1.70	1.486	-3.51783	18.38/18.38/18.38	18.38	25.2869
18	1.98/1.973/2.28	1.973	-5.97490	275.93/275.87/275.75	275.85	48.8135
Average		$\overline{T_{Ra}} = 1.812$	–4.999		$\overline{T_{MRR}} = 136.875$	39.463

The mean response refers to the average value of the performance characteristic for each parameter at different levels. The average values of surface roughness for each parameter at levels 1, 2 and 3 are calculated. The main effects (raw data and S/N ratio) of the various process parameters when they change from the lower to higher levels can be visualized from the Figure 5 (a, b, c, d, e, f) shows the response graphs of surface roughness for this tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment and depth of cut. It is clear from the Figure 5 (a, b, c, d, e, f) that the surface roughness is lowest at *A*2, *B*2, *C*2, *D*2, *E*1 and *F*2. Figure 5 (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 composites. The results indicated that the increase of tool nose radius reduce the surface roughness up to 0.8 mm as shown in Figure 5 (a). The surface roughness increased with increase in tool rake angle as shown in Figure 5 (b). The figure indicates that the surface roughness increased at higher feed rates and cutting speed as shown in Figure 5 (c & d). The reason being, the increase in the feed rate increases the heat generation and hence, tool wear, which resulted in the higher surface roughness. The increase in the feed rate also increases the chatter and it produces incomplete machining at faster traverse, which leads to higher surface roughness. At higher cutting speed debonding and fiber breakage are the reasons for poor surface roughness. The results indicated that the surface roughness increases with increase in cutting environment and depth of cut and is presented in Figure 5 (e & f).

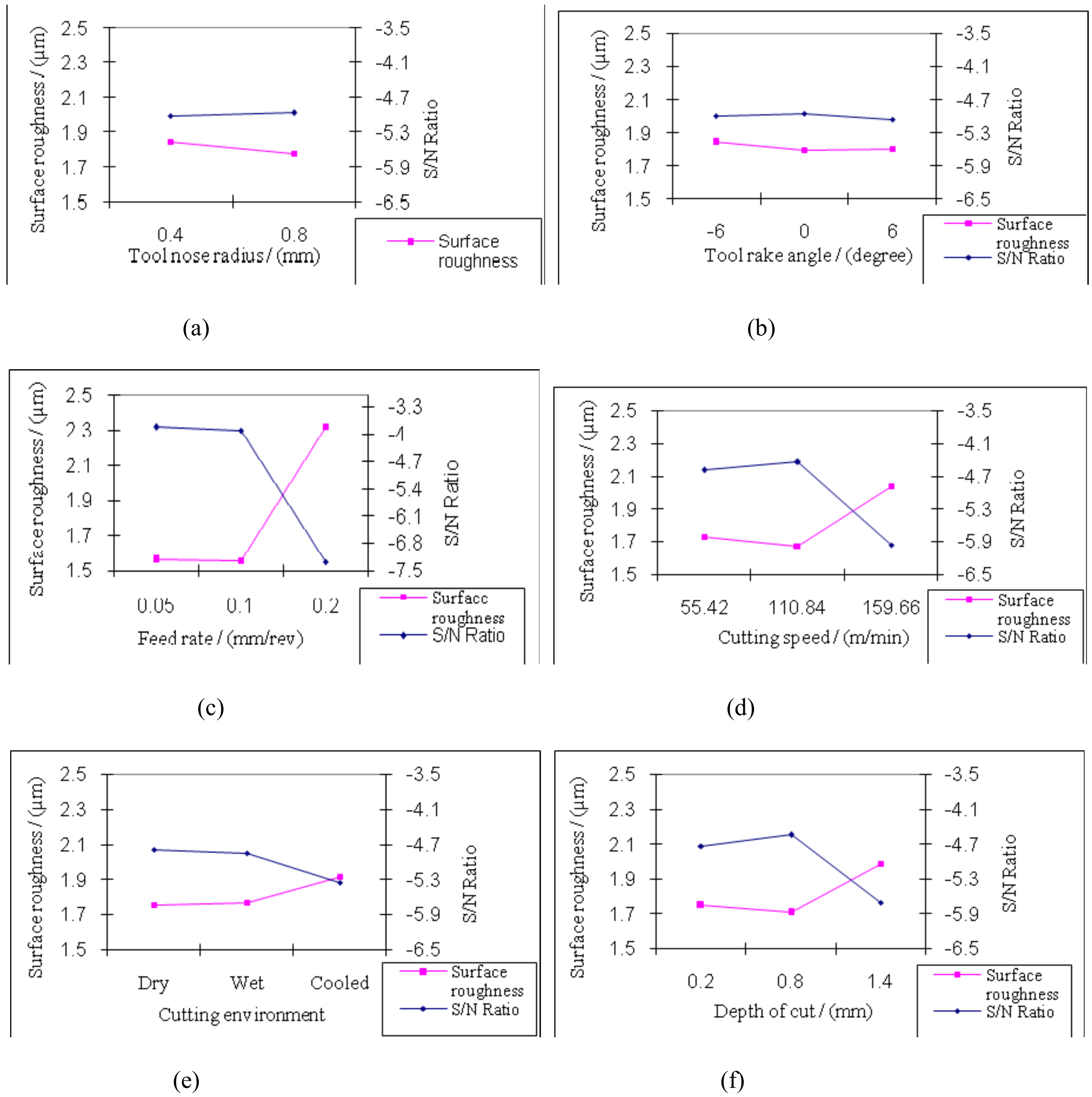


Figure 5 Response and S/N ratio (a) effect of tool nose radius, (b) effect of tool rake angle, (c) effect of feed rate, (d) effect of cutting speed, (e) effect of cutting environment and (f) effect of depth of cut

The pooled version of ANOVA of the raw data and S/N ratio for surface roughness is given in Table 5(A) and 5(B). From Table 5(A) and 5(B), it is clear that parameters C, D and F significantly affect both, the mean and variation, in the surface roughness value. The average of three measurements has been taken as the value of the Ra for the purpose of the analysis. The optimum value of surface roughness is predicted at the selected levels of significant parameters. The percent contributions of parameters as quantified under column P of Table 5(A) and 5(B) reveal that the influence of feed rate in affecting surface roughness is significantly larger than the cutting speed and depth of cut. The percent contributions of feed rate (54.399 %), cutting speed (10.119%) and depth of cut (5.355%) in affecting the variation of surface roughness are significantly larger (95 % confidence level) as compared to the contribution of the other parameters as shown by Table 5(A).

Table 5(A) Pooled ANOVA (Raw Data: Surface Roughness)

Source	SS	DOF	V	F ratio	Prob.	$SS^/$	P (%)
Tool nose radius(A)	0.07114	1	0.07114	Pooled	0.321	---	---
Tool rake angle(B)	0.02324	2	0.01162	Pooled	0.848	---	---
Feed rate(C)	6.94648	2	3.47324	49.34*	0.000	6.806	54.399
Cutting speed(D)	1.40654	2	0.70327	9.99*	0.000	1.266	10.119
Cutting Environment(E)	0.29613	2	0.14807	Pooled	0.135	---	---
Depth of cut(F)	0.81130	2	0.40565	5.76*	0.006	0.670	5.355
T	12.51133	53				12.51133	100.00
e (pooled)	2.95649	42	0.07039			3.731	29.821

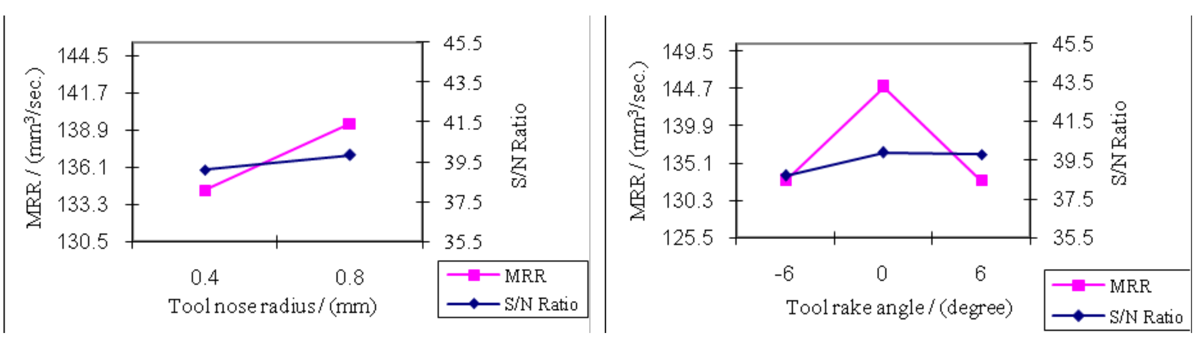
SS = sum of squares, DOF = degrees of freedom, variance (V) = (SS/DOF), T = total, $SS^/$ = pure sum of squares, P = percent contribution, e = error, F_{ratio} = (V/error), Tabulated F-ratio at 95% confidence level
* Significant at 95% confidence level.

Table 5 (B) S/N Pooled ANOVA (Raw Data: Surface Roughness)

Source	SS	DOF	V	F ratio	Prob.	$SS^/$	P (%)
Tool nose radius(A)	0.0156	1	0.0156	Pooled	0.859	---	---
Tool rake angle(B)	0.0314	2	0.0157	Pooled	0.966	---	---
Feed rate(C)	46.5614	2	23.2807	51.09*	0.000	45.65	71.808
Cutting speed(D)	8.3717	2	4.1858	9.19*	0.015	7.460	11.735
Cutting Environment(E)	1.1464	2	0.5732	Pooled	0.350	---	---
Depth of cut(F)	4.7120	2	2.3560	5.17*	0.050	3.801	5.979
T	63.5727	17				63.5727	100.00
e (pooled)	2.7343	6	0.4557			7.747	12.19

The average values of material removal rate for each parameter at levels 1, 2 and 3 are calculated. The main effects (raw data and S/N ratio) of the various process parameters when they change from the lower to higher levels can be visualized from the Figure 6 (a, b, c, d, e, f). Figure 6 (a-f) shows that the response graph for material removal rate for parameters is highest at the (A2, B2, C3, D3, E3 and F3). The S/N ratio analysis also (Figure 6) suggests same levels of the parameters (A2, B2, C3, D3, E3 and F3) as the best levels for highest material removal rate of the unidirectional glass fiber reinforced plastic composite. The basic purposes of cutting fluid application are: (1) Cooling of the job and the tool to reduce the detrimental effects of cutting temperature on the job and the tool and (2) lubrication at the chip–tool interface and friction and thus the amount of heat generation. Figure 6 (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 moderate with increase in tool rake angle. The pooled version of ANOVA of the raw data and S/N ratio for material removal rate is given in Table 6(A) and 6(B). From Table 6(A) and 6(B), it is clear that parameters C, D and F significantly affect both, the mean and variation, in the material removal rate value.

The percent contributions of parameters as quantified under column P of Table 6(A) and 6(B) reveal that the influence of depth of cut in affecting material removal rate is significantly larger than the feed rate and cutting speed. The percent contributions of depth of cut (52.168%), feed rate (26.179%) and cutting speed (8.838%) in affecting the variation of material removal rate are significantly larger (95 % confidence level) as compared to the contribution of the other parameters as shown by Table 6(A).



(a) (b)

Figure 6. Response and S/N ratio (a) effect of tool nose radius, (b) effect of tool rake angle

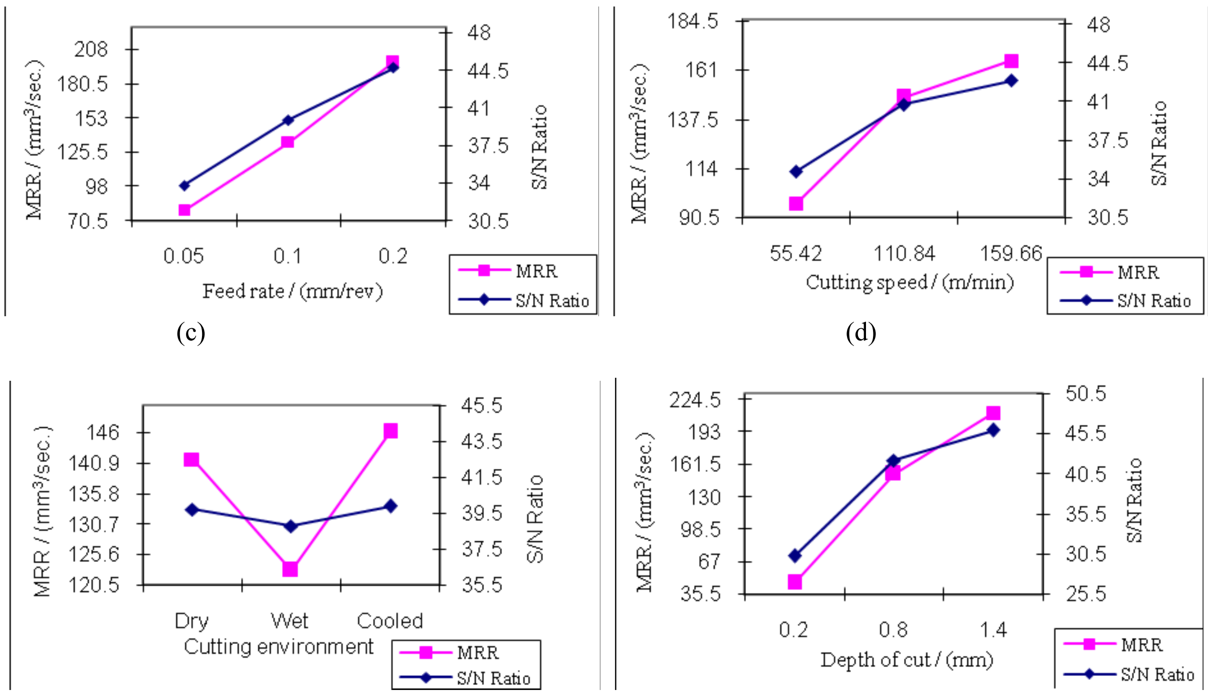


Figure 6. Response and S/N ratio (c) effect of feed rate, (d) effect of cutting speed, (e) effect of cutting environment and (f) effect of depth of cut.

Table 6(A) Pooled ANOVA (Raw Data: Material Removal Rate)

Source	SS	DOF	V	F ratio	Prob.	SS/	P (%)
Tool nose radius(A)	342	1	342	Pooled	0.595	---	---
Tool rake angle(B)	1739	2	869	Pooled	0.487	---	---
Feed rate(C)	129356	2	64678	54.41*	0.000	126978	26.179
Cutting speed(D)	45233	2	22616	19.03*	0.000	42855	8.835
Cutting Environment(E)	5404	2	2702	Pooled	0.116	---	---
Depth of cut(F)	253033	2	126516	106.43*	0.000	253032	52.168
T	485034	53				485034	100.00
e (pooled)	49927	42	1189			63006	12.99

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.

Table 6(B) S/N Pooled ANOVA (Raw Data: Material Removal Rate

Source	SS	DOF	V	F ratio	Prob.	SS/	P (%)
Tool nose radius(A)	2.47	1	2.47	Pooled	0.359	---	---
Tool rake angle(B)	5.27	2	2.63	Pooled	0.405	---	---
Feed rate(C)	363.35	2	181.68	72.69*	0.000	358.35	25.410
Cutting speed(D)	216.91	2	108.46	43.40*	0.000	211.91	15.026
Cutting Environment(E)	4.10	2	2.05	Pooled	0.484	---	---
Depth of cut(F)	803.17	2	401.58	160.68*	0.000	798.17	56.597
T	1410.27	17				1410.27	100.00
e (pooled)	15.00	6	2.50			42.5	3.01

4. Regression Analysis

Multiple linear 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 a range specified. The functional relationship between dependent output parameter with the independent variables under investigation could be postulated by Equation 4.

$$Y = K\,(X_1)^{a}\,(X_2)^{b}\,(X_3)^{c} \tag{4}$$

Where Y is dependent output variable such as surface roughness and material removal rate X□, X□ and X□, 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.

$$\text{Log } Y = \log K + a.\log(X_1) + b.\log(X_2) + c.\log(X_3) \tag{5}$$

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

$$\eta = \beta_0 + \beta_1.x_1 + \beta_2.x_2 + \beta_3.x_3 \tag{6}$$

Where, η is the true value of dependent surface roughness and material removal rate on a logarithmic scale, x_1, x_2 and x_3 are respectively, the logarithmic transformation of the different parameters, 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 η = y-ε, 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

$$\hat{Y} = b_0 + b_1x_1 + b_2x_2 + b_3x_3 \tag{7}$$

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 are 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, the below mentioned second order model has been developed and its form is given below.

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

Insignificant parameters are not taken into consideration as shown in Table 7. The developed empirical model by regression analysis for surface roughness (Ra) and material removal rate (MRR) is given below:

$Ra = 5.87 + 2.43\,x_1 + (-4.65)\,x_2 + 0.009\,x_3 + (-0.129)\,x_1x_2 + 0.065\,x_1x_3 + 0.152\,x_2x_3 + 0.944\,x_1^2 + 1.20\,x_2^2 + 0.339\,x_3^2$
$MRR = 0.005 + 1.52\,x_1 + 2.65\,x_2 + 1.08\,x3 + (-0.684)\,x_1x_2 + (-0.347)\,x_1x_3 + (-0.334)\,x_2x_3 + (-0.325)\,x_1^2 + (-0.651)\,x_2^2 + (-0.250)\,x_3^2$

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. It has been seen that relative error of surface roughness and material removal rate are well within limits.

Table 7 Empirical Expressions Developed by Second Order Model

Predictor	Coefficient of surface roughness	Predictor	Coefficient of material removal rate
b_o	5.87	b_o	0.005
X_1	2.43	X_1	1.52
X_2	- 4.65	X_2	2.65
X_3	0.009	X_3	1.08
$X_1 X_2$	- 0.129	$X_1 X_2$	- 0.684
$X_1 X_3$	0.065	$X_1 X_3$	- 0.347
$X_2 X_3$	0.152	$X_2 X_3$	- 0.334
X_1^2	0.944	X_1^2	- 0.325
X_2^2	1.20	X_2^2	- 0.651
X_3^2	0.339	X_3^2	- 0.250

Thus, it can be stated that empirical equation build by using second-order model can be used. Relative error between predicted and measured observed values for surface roughness and material removal rate is calculated and presented in Table 8. The significance of predictors, shown in Table 7, is also analyzed further as shown in Table 8

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	1.493	1.397	6.430	7.674	8.60	-12.067
2	1.364	1.453	-6.525	151.705	144.99	4.426
3	2.897	3.076	-6.843	394.457	340.61	13.651
4	1.333	1.366	-2.476	37.670	36.24	3.796
5	1.588	1.530	3.652	228.560	249.91	-9.341
6	2.339	2.400	-2.608	96.161	105.93	-10.159
7	1.588	1.513	4.723	129.419	124.99	3.422
8	1.656	1.636	1.208	54.954	52.97	3.610
9	2.051	2.263	-10.336	153.109	144.99	5.303
10	1.714	1.547	9.743	108.893	104.40	4.126
11	1.538	1.606	-4.421	129.419	125.00	3.414
12	1.999	1.966	1.651	77.446	73.57	5.003
13	1.445	1.597	-10.519	19.011	18.39	3.266
14	1.675	1.630	2.686	188.799	208.85	-10.620
15	2.355	2.237	5.011	229.615	250.08	-8.913
16	1.999	1.940	2.951	168.655	180.01	-6.733
17	1.476	1.486	-0.677	19.142	18.38	3.981
18	2.000	1.973	1.350	247.742	275.85	-11.346

5. Goodness of Fit for Surface Roughness and Material Removal Rate

To test whether the discrepancies between the observed and expected frequencies can be attributed to chance, we use the statistic for test of goodness of fit for surface roughness and material removal rate as given by equation 9.

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{9}$$

Criterion: Chosen for either to accept or reject the null hypothesis is:
If $\chi^2 > 8.672$ (tabulated values), reject the null hypothesis

Table 9 showed that $\chi 2 = 0.0054$ and 1.1078 for surface roughness and material removal rate respectively for 17 degrees of freedom where as degrees of freedom is given by: (rows-1) x (col-1) = (18-1) x (2-1) = 17
Therefore the analysis of data does suggest perception is correct with 95 % confidence level. Otherwise, there is reason to believe that the program does give correct output as shown in Table 9.

6. 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 least significant for surface roughness and cutting speed is least significant for material removal rate as observed for ANOVA Table 5 (a) and 6 (a). So depth of cut and cutting speed remained constant at 0.8 mm and 110.84 m/min respectively for validation and other parameter put the same level are shown in Table 2.

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 the Table 10. Table 10 also shows the prediction error of output parameters i.e. surface roughness and material removal rate. It has been seen that the maximum and minimum error percentage for surface roughness is 8.235% and -7.509% and the maximum and minimum error percentage for material removal rate is 10.064% and -10.923%, which is very much satisfactory. Graphical comparison of actual and predicted values of surface roughness and material removal rate is shown in Figure 7 and Figure 8.

Table 9 Statistic for Test of Goodness of Fit Surface Roughness and Material Removal Rate

	Surface Roughness			Material Removal Rate		
Expt. No.	Observed Value	Expected Value	$(O_i - E_i)^2 / E_i$	Observed Value	Expected Value	$(O_i - E_i)^2 / E_i$
1	1.397	1.493	0.0061	8.60	7.674	0.1117
2	1.453	1.364	0.0058	144.99	151.705	0.2972
3	3.076	2.897	0.0110	340.61	394.457	7.3506
4	1.366	1.333	0.0008	36.24	37.670	0.0542
5	1.530	1.588	0.0021	249.91	228.560	1.9943
6	2.400	2.339	0.0015	105.93	96.161	0.9924
7	1.513	1.588	0.0035	124.99	129.419	0.1515
8	1.636	1.656	0.0002	52.97	54.954	0.0716
9	2.263	2.051	0.0219	144.99	153.109	0.4305
10	1.547	1.714	0.0162	104.40	108.893	0.1853
11	1.606	1.538	0.0030	125.00	129.419	0.1508
12	1.966	1.999	0.0005	73.57	77.446	0.1939
13	1.597	1.445	0.0159	18.39	19.011	0.0202
14	1.630	1.675	0.0012	208.85	188.799	2.1294
15	2.237	2.355	0.0059	250.08	229.615	1.8239
16	1.940	1.999	0.0017	180.01	168.655	0.7644
17	1.486	1.476	0.0001	18.38	19.142	0.0303
18	1.973	2.000	0.0003	275.85	247.742	3.189
Average			$\chi2 = 0.0054$			$\chi2 = 1.1078$

*Test level of significance: α = 95%

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	1.470	1.370	6.803	8.880	9.850	-10.923
2	1.380	1.435	-3.985	152.605	143.000	6.294
3	2.920	3.100	-6.164	395.337	355.550	10.064
4	1.305	1.350	-3.448	35.670	34.240	4.009
5	1.570	1.505	4.140	230.545	252.880	-9.688
6	2.350	2.415	-2.766	95.110	103.000	-8.296
7	1.560	1.498	3.974	131.220	127.000	3.216
8	1.670	1.640	1.796	56.990	54.970	3.544
9	2.120	2.230	-5.189	150.110	141.000	6.069
10	1.700	1.560	8.235	110.793	106.20	4.146
11	1.545	1.595	-3.236	132.000	127.000	3.788
12	1.989	1.950	1.515	75.246	71.370	5.151
13	1.465	1.575	-7.509	19.000	18.000	5.263
14	1.645	1.625	1.216	192.703	204.550	-6.148
15	2.380	2.248	5.546	233.615	255.060	-9.180
16	1.992	1.945	2.359	166.230	178.000	-7.080
17	1.455	1.470	-1.031	19.342	18.880	2.388
18	2.100	2.050	2.381	251.144	272.850	-8.643

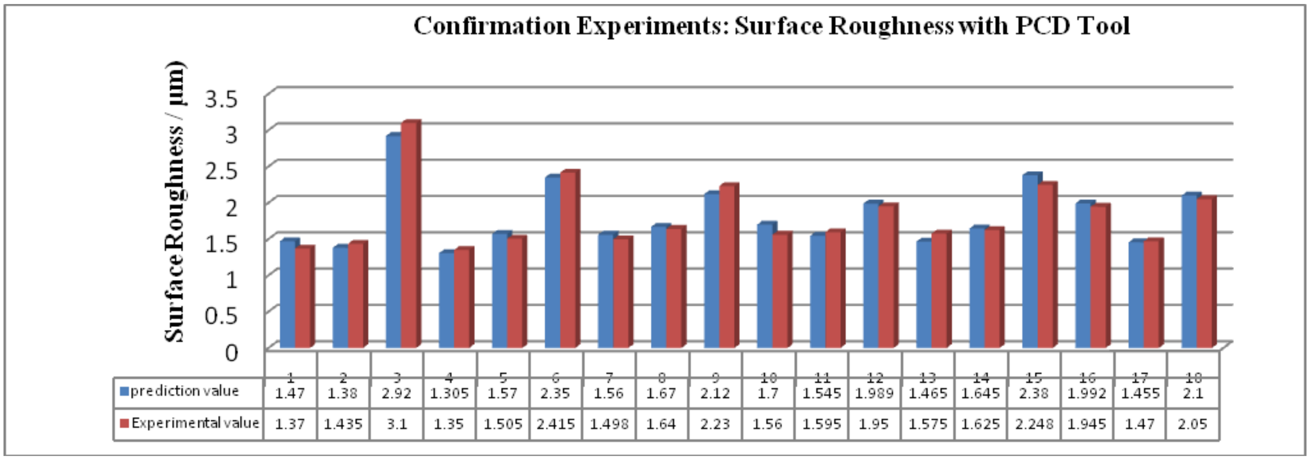


Figure 7: Comparison between Actual and Predicted Values of Surface Roughness

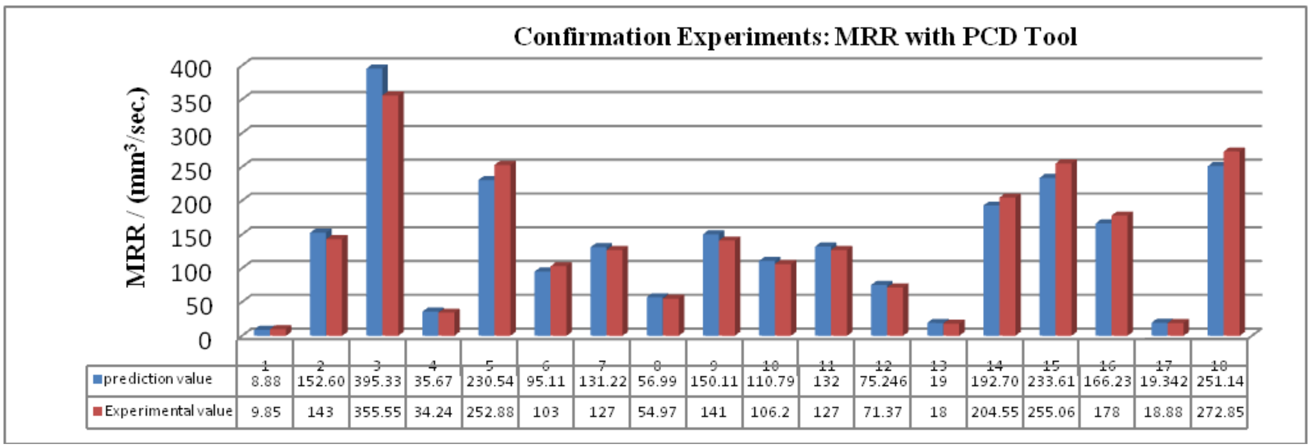


Figure 8: Comparison between Actual and Predicted Values of Material Removal Rate

7. Utility Concept

A customer evaluates a product on a number of diverse quality characteristics. To be able to make a rational choice, these evaluations on different characteristics should be combined to give a composite index. Such a composite index represents the utility of a product. The overall utility of a product measures the usefulness of that product in the eyes of the evaluator. The utility of a product on a particular characteristic measures the usefulness of that particular characteristic of the product. The overall utility of a product is the sum of utilities of each of the quality characteristics. Thus if xi is the measure of effectiveness of the attribute (characteristic) i and there are n attributes evaluating the outcome space, then the joint utility function can be expressed as (Bunn, 1982):

$$U(x_1, x_2, \ldots, x_n) = f[U_1(x_1), U_2(x_2), \ldots, U_n(x_n)] \tag{9}$$

Where $U_i\,(X_i)$ is the utility of the i^{th} attribute

The overall Utility function is the sum of individual utilities if the attributes are independent, and is given as follows:

$$U(X_1, X_2, \ldots, X_n) = \sum_{i=1}^{n} u_i(X_i) \tag{10}$$

The attributes may be assigned weights depending upon the relative importance or priorities of the characteristics. The overall utility function after assigning weights to the attributes can be expressed as:

$$U(X_1, X_2, \ldots, X_n) = \sum_{i=1}^{n} W_i u_i(X_i) \tag{11}$$

Where W_i is the weight assigned to the attribute i. The sum of the weights for all the attributes must be equal to 1. If the composite measure (the overall utility) is maximized, the quality characteristics considered for evaluation of utility will automatically be optimized (maximized or minimized what so ever the case may be).

8. Determination of Utility Value

A preference scale for each quality characteristic is constructed. To determine the utility value for a number of quality characteristics later these scales are weighted to obtain a composite number (overall utility). The weighting is done to satisfy the test of indifference on the various quality characteristics. The preference scale should be a logarithmic one (Gupta and Murthy 1980). The minimum acceptable quality level for each quality characteristic is set out at 0 preference number and the best available quality is assigned a preference number of 9. If a log scale is chosen the preference number (Pi) is given by Eq. 12 (Gupta and Murthy, 1980).

$$P_i = A\log\left(\frac{x_i}{x_i'}\right) \tag{12}$$

Where, $X_i =$ value of any quality characteristic or attribute i
X_i' = just acceptable value of quality characteristic or attribute i
A = constant
The value of A can be found by the condition that if $X_i = X^*$ (where X^* is the optimal or best value), then $P_i = 9$
Therefore,

$$A = \frac{9}{\log\left(\frac{X^*}{X_i'}\right)} \tag{13}$$

Subject to the condition:

$$\sum_{i=1}^{n} W_i = 1 \tag{14}$$

The overall utility can be calculated as follows:

$$U = \sum_{i=0}^{n} W_i P_i \tag{15}$$

Among various quality characteristics type viz. smaller the better, higher the better, and nominal the better suggested by Taguchi, the Utility function would be higher the better type. Therefore, if the Utility function is maximized, the quality characteristics considered for its evaluation will automatically be optimized (maximized or minimized as the case may be). The stepwise procedure for carrying out multi-response optimization with Utility concept and Taguchi method is illustrated as

1. Use the Taguchi matrix experimental design and analysis to find out the optimal value of each of the selected process responses.
2. Construct a preference scale for each response based on their optimal value and minimum acceptable level (Eqs.12 & 13).
3. Assign weights (W_i) based on the experience and customer preference, keeping in view that the total sum of weights is equal to 1 such that the (Eq. 14).
4. Find overall utility values for different experimental trial conditions considering all the responses involved in multi-response optimization (Eq. 15).
5. Use the values determined in step 4 as raw responses of different trial conditions of the experimental matrix. If trials are repeated, find S/N ratios (HB type), as the utility is a higher-the-better type characteristic (Roy, 1990).
6. Analyze the results as per the standard procedure suggested by Taguchi (Roy, 1990).
7. Find the optimal settings of process parameters for mean and S/N utility based on the analysis performed in step 6.
8. Predict optimal values of different response characteristics for the optimal parametric setting that maximizes the overall utility as determined in step 7.
9. Conduct confirmation experiments to verify the optimal results.

Based upon the methodology developed in the previous sections, following case have been considered to obtain the optimal settings of the process parameters of lathe turning for predicting the optimal values of combined responses. The two quality characteristics (Surface Roughness (R_a) and Material Removal Rate (*MRR*)) are included in utility response. Taguchi L_{18} orthogonal array (OA) (Roy, 1990) has been adopted for conducting the experiments. Tool nose radius (A), tool rake angle (B), feed rate (*C*), cutting speed (*D*), cutting environment (*E*) and depth of cut (*F*) are selected as input parameters. Response parameters (quality characteristics) are Surface Roughness (R_a) and Material Removal Rate (*MRR*) when they are optimized individually; the summary of results is produced in Table 11.

Table 11 Optimal Setting and Values of Process Parameters (Individual Quality Characteristics optimization)

Quality Characteristics	Optimal Level of Process Parameters	Significant Process Parameters (at 95% confidence level)	Predicted Optimal Value of Quality Characteristics
Surface Roughness	$C_2D_2F_2$	*C, D, F*	1.311 µm
Material Removal Rate	$C_3D_3F_3$	*C, D, F*	301.98 mm^3/sec.

* *C* – feed rate, *D* – cutting speed and *F* – depth of cut
** Subscripts represent levels of the process parameters.

The optimal settings of process parameters and the optimal values of Surface roughness and material removal rate (when they are optimized individually) have already been established by using Taguchi's design of experiment.
Following is the stepwise procedure for transforming experimental data into utility data.

(i) Construction of preference scales

(a) Surface Roughness (R_a)
X^* = optimum value of R_a (when optimized individually) = 1.311µm (Table 11)
X'_i = maximum acceptable value of R_a = 3.0 µm (Table 4) assumed
(All the R_a values in Table 4 are in between: 1.23 and 3.44 μm)
Using these values and the Eq. 11 & Eq. 12, the following preference scale for R_a has been found:

$$P_{Ra} = -25.07\log\left(\frac{x_i}{3.0}\right) \quad (16)$$

(b) Material Removal Rate (MRR)
X^* = optimum value of material removal rate (when optimized individually) = 301.98 mm^3/ sec. (Table 11)
X'_i = minimum acceptable value of material removal rate = 8 mm^3/ sec. (Table 4) assumed
(All the material removal rate values in Table 4 are in between: 8.50 and 347.23 mm^3/sec.)
Using these values and the Eq. 11 & Eq. 12, the following preference scale for material removal rate has been found:

$$P_{MRR} = 5.711\log\left(\frac{x_i}{8.0}\right) \quad (17)$$

(ii) Weights of quality characteristic

It has been assumed that both the quality characteristics are equally important and hence an equal weight has been assigned. However, there is no constraint on the weights and it can be any value between 0 and 1 subjected to the condition specified in Equation 14 (Singh and Kumar, 2006).
WR_a = weights for R_a = 1/2
W_{MRR} = weights for *MRR* = 1/2

(iii) Utility value calculation

The following relation was used to calculate the utility function based upon the experimental trials:

$$U(n, R) = P_{Ra}(n, R) \times W_{Ra} + P_{MRR}(n, R) \times W_{MRR} \quad (18)$$

Where, *n* is the trial number (*n* = 1, 2, 3… 18) and R is the repetition number (*R* = 1, 2, 3). The calculated Utility values are shown in Table 12.

Table 12 Calculated Utility Data Based on Responses
(a) Surface Roughness (b) Material Removal Rate

Trial No.	Raw Data (Utility Values)			S/N Ratio (db)
	*R*1	*R*2	*R*3	
1	4.312	3.997	4.452	12.5485
2	6.776	7.889	8.016	17.4950
3	4.603	5.062	3.934	12.9861
4	6.373	5.746	6.335	15.7497
5	7.364	8.082	7.512	17.9331
6	5.271	3.326	4.843	12.4917
7	6.790	7.831	6.828	17.0300
8	5.528	5.152	6.302	14.9676
9	4.732	5.284	5.384	14.1653
10	7.410	5.884	7.220	16.5574
11	7.104	7.442	5.976	16.5842
12	4.341	5.234	5.645	13.9451
13	4.553	4.553	4.277	12.9772
14	8.192	6.640	7.355	17.2841
15	6.098	7.038	5.692	15.1096
16	5.753	6.630	6.342	15.8599
17	5.882	4.691	4.127	13.5308
18	6.647	7.61	5.880	16.3938

9. Determination of Optimal Settings of Process Parameters

The data (utility values) have been analyzed both for mean response (mean of utility at each level of each parameter) and signal-to-noise (S/N) ratio. Since utility is a higher-the-better (*HB*) type of quality characteristic, (S/N) *HB* has been used. The average and main response in terms of Utility values and S/N ratio (Tables 15 and 16) are plotted in Figure 9 (a-f). It can be observed from Figure 9 (a-f) that the 2nd level of tool nose radius (*A*2), 2nd level of tool rake angle (B2), 2nd level of feed rate (C2), 2nd level of cutting speed (D2), 2nd level of cutting environment (*E*2) and 2nd level of depth of cut (F2) are expected to yield a maximum values of the utility and S/N ratio within the experimental space.

The pooled version of ANOVA for utility data and S/N ratio are given in Tables 13 and 14 respectively. It can be noticed from Table 13 that the input parameters feed rate (*C*), cutting speed (*D*), cutting environment (*E*) and depth of cut (*F*) significant effect (at 95% confidence level) on the utility function. On the other hand, from Table 14 shows that the feed rate and depth of cut have significant effect on the S/N ratio of utility function. So, other insignificant parameters for S/N ratio can be taken as economy factor. The optimal values of utility and thus the optimal values of response characteristics in consideration are predicted at the above levels of significant parameters.

Table 13 Pooled ANOVA (Raw Data: Surface Roughness and MRR)

Source	SS	DOF	V	F ratio	Prob.	SS/	P (%)
Tool nose radius(*A*)	0.7805	1	0.7805	Pooled	0.222	---	---
Tool rake angle(*B*)	0.4346	2	0.2173	Pooled	0.654	---	---
Feed rate(*C*)	15.5603	2	7.7802	15.35*	0.000	14.546	17.11
Cutting speed(*D*)	6.6768	2	3.3384	6.59*	0.003	5.663	6.66
Cutting Environment(*E*)	3.8117	2	1.9058	3.76*	0.031	2.797	3.29
Depth of cut(F)	36.4492	2	18.2246	35.95*	0.000	35.435	41.67
T	85.0045	53				85.0045	100.00
e (pooled)	21.2914	42	0.5069			26.867	31.60

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 $F_{0.05;\,1;\,42} = 4.08$, $F_{0.05;\,2;\,42} = 3.23$, * Significant at 95% confidence level

Table 14 S/N Pooled ANOVA (Raw Data: Surface Roughness and MRR)

Source	SS	DOF	*V*	F ratio	Prob.	SS/	P (%)
Tool nose radius(*A*)	0.8434	1	0.8434	Pooled	0.336	---	---
Tool rake angle(*B*)	0.3861	2	0.1930	Pooled	0.786	---	---
Feed rate(*C*)	11.4733	2	5.7367	7.43*	0.024	9.929	18.05
Cutting speed(*D*)	4.5265	2	2.2632	Pooled	0.129	---	---
Cutting Environment(*E*)	3.2354	2	1.6177	Pooled	0.204	---	---
Depth of cut(*F*)	29.9230	2	14.9615	19.39*	0.002	28.379	51.58
T	55.0179	17				55.0179	100.00
e (pooled)	4.6303	6	0.7717			13.119	23.84

Tabulated F-ratio at 95% confidence level $F_{0.05;\,1;\,6} = 5.99$, $F_{0.05;\,2;\,6} = 5.14$

Table 15 Main Effects of Utility (Raw Data: Surface Roughness and MRR)

	Nose radius (A)	Tool rake angle (B)	Feed rate (C)	Cutting speed (D)	Cutting Environment (E)	Depth of cut (F)
Level 1	5.842	5.850	5.849	5.592	6.139	4.805
Level 2	6.082	6.069	6.668	6.435	6.161	6.632
Level 3	---	5.966	5.368	5.858	5.586	6.449
Differences(Δ)	0.240	0.220	1.300	0.842	0.574	1.827

Table 16 Average S/N Ratio values and main effects (Surface Roughness and MRR)

	Nose radius (A)	Tool rake angle (B)	Feed rate (C)	Cutting speed (D)	Cutting Environment (E)	Depth of cut (F)
Level 1	15.01	15.02	15.12	14.74	15.39	13.41
Level 2	15.44	15.34	16.25	15.92	15.65	16.27
Level 3	---	15.32	14.31	15.02	14.65	15.99
Differences(Δ)	0.43	0.32	1.95	1.18	1.00	2.86

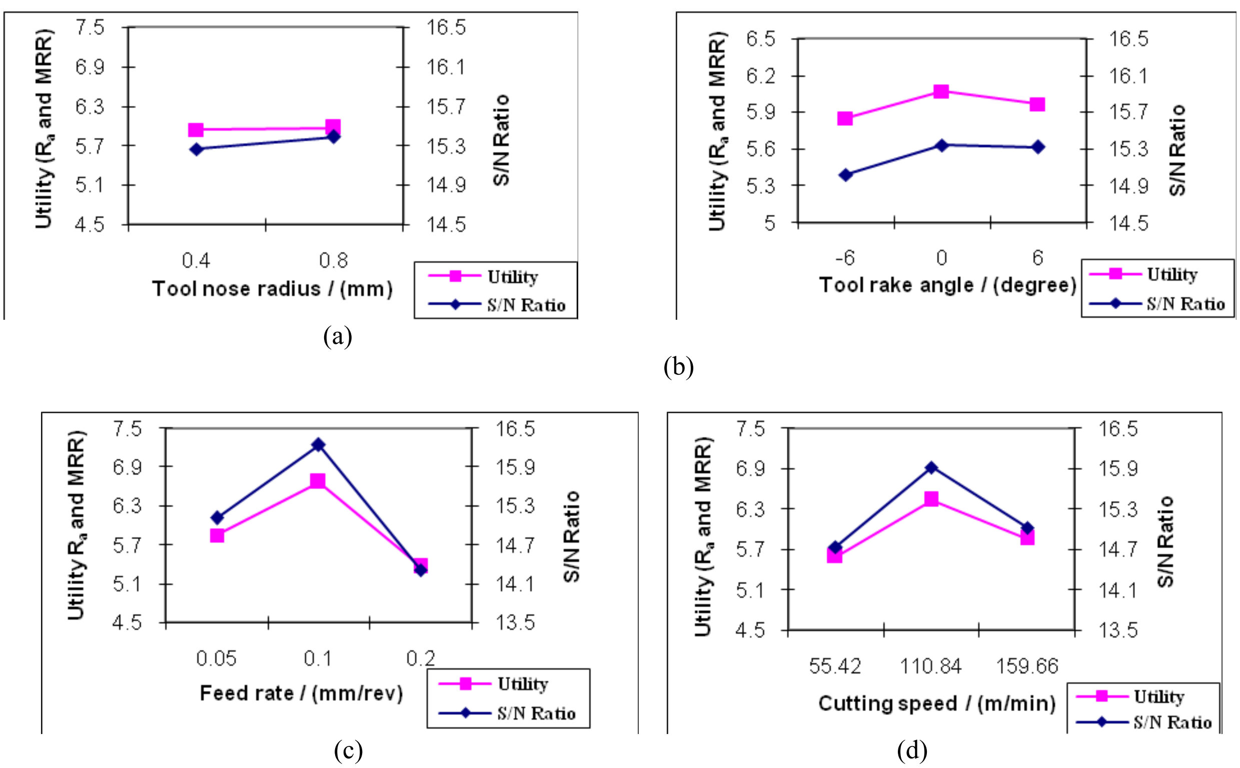
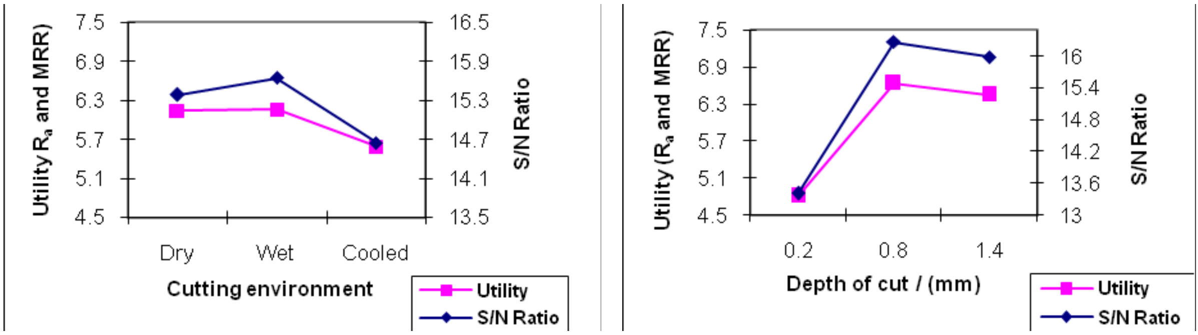


Figure 9: Utility value and S/N ratio (a) effect of tool nose radius, (b) effect of tool rake angle, (c) effect of feed rate, (d) effect of cutting speed



(e) (f)

Figure 9: Utility value and S/N ratio (e) effect of cutting environment, (f) effect of depth of cut.

Table 17 Average values of various responses at optimal levels

Levels	Surface Roughness (µm)	Material Removal Rate (mm^3/sec.)
*C*2	1.557	133.35
*D*2	1.672	147.95
*E*2	1.767	122.98
*F*2	1.706	152.55

*The average values are taken from experimental data.

10. Optimal Values of Quality Characteristics (Predicted Means Surface Roughness)

The average values of all the response characteristics at the optimum levels of significant parameters with respect to Utility function are recorded in Table 17. *The average values are taken from experimental data.
The optimal values of the predicted means (μ) of different response characteristics can be obtained from the following equation:

$$\mu_{Ra} = \overline{T}_{Ra} + (\overline{C2} - \overline{T}_{Ra}) + (\overline{D2} - \overline{T}_{Ra}) + (\overline{E2} - \overline{T}_{Ra}) + (\overline{F2} - \overline{T}_{Ra})$$

$\overline{C2}$ = second level of feed rate, $\overline{D2}$ = second level of cutting speed, $\overline{E2}$ = second level of Cutting environment cut, $\overline{F2}$ = second level of depth of cut, $\overline{T}_{Ra}$ = Overall mean
Where T_{Ra} = overall mean of surface roughness = 1.812 (Table 4)
$\overline{C2}$, $\overline{D2}$, $\overline{E2}$ and $\overline{F2}$ are the mean values of surface roughness with parameters at optimum levels. $\overline{C2}$ =1.557, $\overline{D2}$ =1.672, $\overline{E2}$ =1.767, $\overline{F2}$ =1.706 (Table 17):
Hence μ_{Ra} = 1.266
A confidence interval for the predicted mean on a confirmation run can be calculated using the equation 19 and 20 respectively (Ross, 1996):

$$CI_{POP} = \sqrt{\frac{F_a(1, f_e)V_e}{n_{eff}}} \tag{19}$$

$$CI_{CE} = \sqrt{F_a(1, f_e)V_e\left[\frac{1}{n_{eff}} + \frac{1}{R}\right]} \tag{20}$$

Where F_α; $(1, f_e)$ = $F_{0.05}$; (1; 42) = 4.08 (tabulated).
α = risk = 0·05,
f_e = error DOF = 42 Table 5 (A)
N = total number of experiments = 18
V_e = error variance = 0.07039 Table 5 (A)
Total DOF associated with the mean (μ_{Ra}) = 11, Total trial =18, N=18×3 = 54,
n_{eff} = effective number of replications

$$n_{eff} = \frac{N}{1 + [\text{Total DOF associated with the estimate of the mean}]}$$

$n_{eff} = 54 / (1 + 11) = 4.5$
R = number of repetitions for confirmation experiment = 3
$CI_{POP} = \pm 0.253$
$CI_{CE} = \pm 0.399$

The 95% confidence interval of the population is: $[\mu_{Ra} - CI] < \mu_{Ra} < [\mu_{Ra} + CI]$ i.e. $1.013 < \mu_{Ra} < 1.519$
The 95% confidence interval of the predicted optimal surface roughness is: $[\mu_{Ra} - CI] < \mu_{Ra} < [\mu_{Ra} + CI]$ i.e. $0.867 < \mu_{Ra} < 1.665$

MRR:
$\mu_{MRR} = \overline{T_{MRR}} + (\overline{C2} - \overline{T_{MRR}}) + (\overline{D2} - \overline{T_{MRR}}) + (\overline{E2} - \overline{T_{MRR}}) + (\overline{F2} - \overline{T_{MRR}})$
Where $\overline{T_{MRR}}$ = overall mean of material removal rate = 136.875 (Table 4)
$\overline{C2}$, $\overline{D2}$, $\overline{E2}$ and $\overline{F2}$ are the mean values of material removal rate with parameters at optimum levels. $\overline{C2}$ =133.35, $\overline{D2}$ =147.95, $\overline{E2}$ =122.98, $\overline{F2}$ =152.55 (Table 17):
Hence μ_{MRR} = 146.205
The following values have been obtained by the ANOVA:

$N = 54$, $f_e = 42$, $V_e = 1189$ Table 6 (A), $n_{eff} = 4.5$, $R = 3$, $F_{0.05}(1, 42) = 4.08$

A confidence interval for the predicted mean on a confirmation run can be calculated using the equation 19 and 20 respectively.
$CI_{POP} = \pm 32.833$
$CI_{CE} = \pm 51.889$

The 95% confidence interval of the population is:
$[\mu_{MRR} - CI] < \mu_{MRR} < [\mu_{MRR} + CI]$ i.e. $113.372 < \mu_{MRR} < 179.038$
The 95% confidence interval of the predicted optimal material removal rate is:
$[\mu_{MRR} - CI] < \mu_{MRR} < [\mu_{MRR} + CI]$ i.e. $94.316 < \mu_{MRR} < 198.094$
The optimal values of process variables at their selected levels are as follows:

Parameter	Level
Feed Rate (C)	2 (0.1 mm/ rev)
Cutting Speed (D)	2 (110.84 m/ min)
Cutting Environment (E)	2 (Wet)
Depth of Cut (F)	2 (0.8 mm)

11. Confirmation Experiments

Three experiments are performed at optimal settings as suggested by Taguchi analysis of Utility data. The average value of surface roughness and material removal rate, while turning UD-GFRP with PCD tool is found to be 1.411µm and 195.033mm^3/sec. This result is within the 95% confidence interval of the predicted optimal value of the selected machining characteristic (surface roughness and material removal rate). Hence the optimal settings of the process parameters, as predicted in the analysis, can be implemented. Shows the conformance of results obtained in ANOVA as well as the results obtained using confirmation.

12. Genetic Algorithm (GA)

Genetic algorithms are search methods that employ processes found in natural biological evolution. These algorithms search or operate on a given population of potential solutions to find the optimum solution. To do this, the algorithm applies the principle of survival of the fittest to find better and better approximations. At each generation, a new set of approximations is created by the process of selecting individual potential solutions (individuals) according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation.

The GA generally includes the three fundamental genetic operations of selection, crossover and mutation. These operations are used to modify the chosen solutions and select the most appropriate offspring to pass on to succeeding generations. GAs consider many points in the search space simultaneously and have been found to provide a rapid convergence to a near optimum solution in many types of problems; in other words, they usually exhibit a reduced chance of converging to local minima. GA suffers from the problem of excessive complexity if used on problems that are too large.

The GA works with a population of feasible solutions and, therefore, it can be used in multi-objective optimization problems to simultaneously capture a number of solutions (Kuriakose and Shunmugam, 2005). The non-dominate sorting Genetic Algorithm (NSGA-II) which was introduced by (Mandal, 2007). It is a powerful general purpose optimization tool to solve optimizing problems in mathematics and engineering. This algorithm is fast, but it has been as a controversial method and has been opposed due to some difficulty and complexity when it comes to computational approach. The Non-dominating Sorting GA-II (NSGA-II) is a fast, elitist multi-objective genetic algorithm that is widely used for generating the Pareto frontier. Its main advantage in solving multi-objective problems is that it leads the search toward the global Pareto front while maintaining diversity of the solution set along that front (Akundi et al., 2005). So, both single and multi-objective optimization genetic algorithms can be used in the given parametric combination.

13. Conclusions

- From the experimental results, it is evident that the surface roughness increases as feed rate increases.
- From S/N ratio and response table, it is observed that the feed is the most influencing parameter for surface roughness. By increasing the feed, the surfaces roughness increases. The higher feed rate led cutting tool to traverse the work piece so rapidly that deteriorates the surface quality.
- For achieving good surface finish on the unidirectional glass fiber reinforced plastic composite using polycrystalline diamond insert, larger tool nose radius, moderate tool rake angle, moderate feed rate, moderate cutting speed, environment (dry) and moderate depth of cut were preferred. The optimal parametric combination for polycrystalline diamond insert cutting insert was reported as *A*2, *B*2, *C*2-*D*2-*E*1 and *F*2.
- Feed rate is the factor, which has great influence on surface roughness, followed by cutting speed.
- From the ANOVA result, it is concluded that *C* – feed rate, *D* – cutting speed, *F* – Depth of cut, have significant effect on material removal rate *A, B, 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 second-order model for surface roughness and material removal rate has been developed from the observed data. The prediction error of output parameters i.e. surface roughness and material removal rate. It was found that the maximum and minimum error percentage for surface roughness is 8.235% and -7.509% and the maximum and minimum error percentage for material removal rate is 10.064% and -10.923%, which is very much satisfactory.
- The multiple performance characteristics are surface roughness and material removal rate. On the basis of Taguchi approach and Utility concept, a model was developed to achieve this. Based on the ANOVA significant process parameters for multiple performances are depth of cut, feed rate, cutting speed and cutting environment has significant effect on the utility function. The percentage contribution of Depth of cut (41.67%), Feed rate (17.11%), Cutting speed (6.66%) and cutting environment (3.29%). It is found that the proposed model based on Taguchi approach and Utility concept is simple, useful and provides an appropriate solution for multi-response optimization problems.
- The 95% confidence interval of the predicted optimal surface roughness is: $[\mu_{Ra} - CI] < \mu_{Ra} < [\mu_{Ra} + CI]$ i.e. $0.867 < \mu_{Ra} < 1.665$
- The 95% confidence interval of the predicted optimal material removal rate is: $[\mu_{MRR} - CI] < \mu_{MRR} < [\mu_{MRR} + CI]$ i.e. $94.316 < \mu_{MRR} < 198.094$

The future scope of work includes the following: (1) the number of machining parameters can be extended and hence, the data base can be improved by extensive experimentation. (2)The same problem can be modeled and analyzed by a genetic algorithm.

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Acknowledgement

The authors are indebted to Maharashtra Engineering Industry, India (P) Limited, Satara Maharashtra for supplying the UD- GFRP rods used in this work.

Nomenclature

B_0, b_1, b_2, b_3	Estimates of parameters
a, b, c	Exponentially determined constant
x_0, x_1, x_2, x_3	logarithmic transformations of machining parameters
Ra	Surface Roughness
MRR	Material Removal Rate

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
K	Constant
η	Surface Roughness & MRR response
y	Measured Surface Roughness & MRR
ε	Experimental error
$\hat{Y}$	Estimated response based on second order model (µm & mm^3/sec.)
χ^2	Chi-square

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Received December 2011
Accepted May 2012
Final acceptance in revised form June 2012