Springer

KSME

Journal of Mechanical Science and Technology 27 (9) (2013) 2829~2837
www.springerlink.com/content/1738-494x
DOI 10.1007/s12206-013-0731-5

Multiple-response optimization of turning machining by the taguchi method and the utility concept using uni-directional glass fiber-reinforced plastic composite and carbide (k10) cutting tool †

Surinder Kumar[1,*], Meenu[1] and P. S. Satsangi[2]

[1]*Department of Mechanical Engineering, National Institute of Technology, Kurukshetra 136119, India*
[2]*Department of Mechanical Engineering, PEC University of Technology, Chandigarh 160012, India*

(Manuscript Received August 5, 2012; Revised April 21, 2013; Accepted June 14, 2013)

Abstract

This paper presents a utility concept for multi-response optimization in turning uni-directional glass fiber-reinforced plastics composite using Carbide (K10) cutting tool. The single response optimization resulted in the non-optimization of other responses. The Taguchi method (Orthogonal L_{18} array) was employed in the experimental work. The process parameters selected for this study were tool nose radius, tool rake angle, feed rate, cutting speed, depth of cut, and cutting environment. Statistically significant parameters were found to simultaneously minimize surface roughness and maximize the material removal rate by ANOVA. The results were further verified by confirmation experiments.

Keywords: UD-GFRP composites; Multi-response optimization; Carbide (K10) cutting tool; Taguchi approach; Utility concept; Surface roughness; MRR

1. Introduction

Several methodologies were developed to solve multi-response optimization problems. Byrne and Taguchi [1] presented a case in which responses were independently optimized by Taguchi's approach, and the results were then subjectively compared to select the best levels in terms of responses of interest. [2] Multiple regression and linear programming approach were employed for multi-response optimization in the Taguchi method. The Taguchi method is computationally complex, thus difficult to conduct on the shop floor. [3] The multi-response problem was solved by assigning the weights to the signal-to-noise (S/N) ratio of each quality characteristic and then by adding the weighted S/N ratios to measure the overall performance of a process [4]. Multi-response optimization was obtained by implementing the utility concept and the Taguchi method in optimizing the quality characteristics of the MAFM process [5]. The performance of different tool materials, such as ceramic, cemented carbide, cubic boron nitride (CBN), and diamond, was observed while turning. The experimental results showed that only diamond tools are suitable to finish the turning [6]. The turning of glass fiber-reinforced (GFR) polyester and epoxy increased surface roughness with the increase in feed rate, while demonstrating independence on the cutting velocity [7]. The turning process of the glass fiber-reinforced plastic (GFRP) composite material was investigated using a coated cement tool and four parameters that included cutting speed (from 75 rpm to 175 rpm), fiber orientation angle (from 30° to 90°), depth of cut (from 0.5 mm to 1.5 mm), and feed rate (from 0.10 mm/rev to 0.50 mm/rev). Feed rate was identified as the factor with the highest influence on surface roughness, followed by cutting speed [8]. The chip formation process was examined in terms of fiber orientation. Most studies on the cutting of GFRP focused on the mechanism of tool wear and surface roughness [9]. However, for the practical machining of GFRP, optimal machining parameters must be determined to achieve less tool wear and good surface finish, among others [10]. A surface roughness prediction model was developed based on the fuzzy model for the machining of GFRP tubes using a carbide tool (K20). Four parameters, namely, cutting speed, feed rate, depth of cut, and work piece (fiber orientation) were selected to minimize surface roughness. The model can therefore be effectively used to predict surface roughness (Ra) in turning GFRP composites. Multiple regression models were fabricated and checked for accuracy. The predicted surface roughness values were calculated using the obtained regression equation. The difference between the surface roughness values of the measured data and those of the predicted data was used to calculate the error percentage. The error percentage was

*Corresponding author. Tel.: +94 16366065
E-mail address: surinder.asd@gmail.com
† Recommended by Associate Editor Song Min Yoo

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, uni-directional	'E' glass roving	---
4	Water absorption	0.07	%
5	Density	1.95-2.1	gm/cc
6	Tensile strength	(650)	(N/mm^2)
7	Compression strength	(600)	(N/mm^2)
8	Shear strength	255	(N/mm^2)
9	Modulus of elasticity	(320)	(N/mm^2)
10	Thermal conductivity	0.30	Kcal /Mhc°
11	Weight of rod (840 mm in length)	2.30	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

then used to calculate the accuracy of the predicted model. [11, 12] The investigation focused on multiple performance optimizations of the machining characteristics of GFRP composites using the non-dominated sorting genetic algorithm. Three parameters, namely, cutting speed, feed rate, and depth of cut were selected to minimize surface roughness and tool flank wear and to maximize the material removal rate (MRR). A polycrystalline diamond tool was used for the turning operation. In this study, a multi-characteristic optimization model by implementing the Taguchi method and the utility concept was employed to determine the best combination of the turning machining parameters that included tool nose radius, tool rake angle, feed rate, cutting speed, depth of cut, and cutting environment (dry, wet, and cooled) to attain maximum MRR and minimum surface roughness (R_a). The predictive models were obtained for the performance measures. Confirmation tests were also conducted to verify the results.

2. Experimental procedure

2.1 Material

In the this study, Pultrusion-processed uni-directional (UD)-GFRP composite rods, with a diameter of 42 mm and a length of 840 mm, were used. The fiber used in the rod was E-glass and the resin used was epoxy. The properties of the material are shown in Table 1.

2.2 Method

The Taguchi method is a commonly adopted approach in optimizing design parameters. The method was originally proposed to improve the quality of products by applying statistical and engineering concepts. The method is based on the orthogonal array (OA) that provides a significantly reduced variance for the experiment, resulting in the optimum setting of the process control parameters. OA provides a set of well-balanced experiments, with less number of experimental runs, and Taguchi's signal-to-noise ratios (S/N) that are logarithmic functions of the desired output and serving as objective functions in the optimization process. This technique aids in data analysis and in the prediction of optimum results. The Taguchi method uses a statistical measure of performance called the S/N ratio to evaluate optimal parameter settings. The S/N ratio considers both mean and variability. 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. Standard S/N ratios are generally identified as nominal-the-best (NB), lower-the-better (LB), and higher-the-better (HB). The optimal setting is the parameter combination with the highest S/N ratio. In this study, smaller-the-better and larger-the-better principles are considered to minimize surface roughness and to maximize MRR. The corresponding loss function is expressed as follows [13]:

$$\text{Smaller-the-better: S/N} = -10\,\text{Log}\frac{1}{n}\sum y^2 \quad (1)$$

$$\text{Larger-the-better: S/N} = -10\,\text{Log}\frac{1}{n}\sum \frac{1}{y^2} \quad (2)$$

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

2.3 Present problem

The Taguchi's mixed level design was selected because the two levels of tool nose radius were maintained. The five parameters were studied at three levels. The two-level parameter had 1 DOF, and the remaining five three-level parameters had 10 DOF. Thus, the total DOF required was 11 [= (1 × 1 + (5 × 2)]. The most appropriate OA in this case was L_{18} ($2^1 \times 3^7$). The OA was 17 [= 18 − 1] DOF. The standard L_{18} OA was used, with parameters assigned using linear graphs. The unassigned columns were treated as errors. L_{18} OA was selected for the experiments implementing the Taguchi design concept, as shown in Table 2. L_{18} OA had 18 rows, corresponding to the number of tests. The parameters, namely, tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment, and depth of cut were assigned to columns A, B, C, D, E, and F, respectively, as shown in Table 2. The cutting environment parameters (dry, wet, and cooled) were specifically applied to the composite rods. The cutting environment (dry, wet, and cooled) on the work piece was established during the machining of the rod, obtaining a comparative assessment of the performance of the cutting environment, which has not been previously studied. The output responses to measure machinability were surface roughness and MRR. The parameters selected, the designated symbols, and their ranges are listed in Table 3. The machining tests were conducted using a conventional lathe machine with the following specifications: center height of 220 mm, swing over bed of 500 mm, spindle speed range from 60 rpm to 3000 rpm, feed range from 0.04 mm/rev to 2.24 mm/rev, and main motor of 11 kW. A tool holder SVJCR steel EN47 was used during the turning operation**.** The carbide (k10) insert was used for the machining. The geometry of the cutting tool VNMG insert 110404/110408 had the following characteristics: tool rake angle of -6° (negative), 0°, and +6° (positive), and tool nose radius of 0.4 and 0.8 mm. Suitable L_{18} array data points were identified from 54 data points. Surface roughness values were measured from the finished product using a Tokyo Seimitsu Surfcom 130A type instrument. A simplified multi-criterion methodology based on the Taguchi's approach and on the utility concept (given below) was used to achieve the objective of this study. The observed values of the response parameters are given in Table 4.

Table 2. Experimental layout using L_{18} OA.

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

Table 3. Control parameters with levels.

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

3. Results and discussions

The experiments were conducted at each trial condition, as summarized in Table 4. The experiments were replicated thrice for each trial. The estimated surface roughness, MRR, and S/N ratio are indicated in Table 4. A statistical analysis of variance (ANOVA) was performed to determine which proc-

Table 4. Test data summary of the surface roughness and MRR.

Expt. No.	R_a	Average R_a (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	8.60	18.6888
2	1.73/1.77/1.99	1.830	−5.2659	144.96/145.02/145.02	145.00	43.2274
3	2.77/4.12/5.13	4.000	−12.3014	329.98/330.23/330.23	330.15	50.3741
4	2.20/2.18/2.04	2.140	−6.6131	36.24/36.24/36.24	36.24	31.1838
5	1.83/1.83/1.77	1.810	−5.1546	237.96/237.9/238.04	237.97	47.5303
6	2.69/2.88/2.89	2.820	−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	2.540	−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	2.100	−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	2.620	−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	1.570	−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
Average		T_{Ra} = 2.272	−6.941		T_{MRR} = 32.72	39.293

ess parameter was statistically significant to surface roughness and MRR. The optimum conditions for surface roughness and MRR were established by S/N data and raw data analyses. Surface roughness and MRR data were analyzed to determine the effect of various design parameters. The experimental results were then transformed into S/N ratios. Taguchi recommended the use of the S/N ratio to measure quality characteristics that deviate from the desired values. Taguchi's design for the experiments and the regression analysis was adopted to identify the best levels of cutting parameters and their significance. These techniques also effectively optimized the parameters and were employed in modeling. Given the values for the tool nose radius (A), tool rake angle (B), feed rate (C), cutting speed (D), cutting environment parameters (dry, wet, and cooled) E, and depth of cut (F), the number of experimental trials required was 18, which were conducted using different cutting inserts with the same specification to obtain more data. MRR in mm^3/sec was calculated from the following relation:

MRR = volume of material removed per unit time of a work piece

$$\text{MRR} = \frac{\frac{1}{4}D^2L - \frac{1}{4}d^2L}{Tc} \tag{3}$$

where D = initial diameter in mm, d = final diameter in mm, L = length in mm, and f = feed rate in mm/rev. Tc is the machining time defined as Tc = L/f N, where

$$N = \frac{V * 1000 * 60}{\Pi D}$$

L = length of the work piece to be turned

N = spindle speed in rpm.

3.1 Multi-response optimization by the utility concept and the taguchi method of turning process

A product or a process is normally evaluated based on a certain number of quality characteristics that may sometimes naturally conflict. Therefore, a combined measure is necessary to gauge the overall performance, which must consider the relative contribution of all quality characteristics. In the succeeding sections, a methodology based on the utility concept and the Taguchi method is developed to determine the optimal settings of the process parameters for the multi-response/ multi-characteristics process or product. The multi-response optimization of the quality characteristic of turning was performed using this methodology described in this section.

3.2 Utility concept

A customer evaluates a product based on a number of diverse quality characteristics. These evaluations on the different characteristics should be combined to derive a composite index that will result in a rational choice. This composite index represents the utility of a product. The overall utility of a product indicates its usefulness to the evaluator. The utility of a product on a particular characteristic indicates the usefulness of the product characteristic. The overall utility of a product is the sum of the utilities of each quality characteristic. If x_i is the measure of effectiveness of attribute i and n attributes evaluate the outcome space, then the joint utility function can be expressed as [14]

$$U(x_1,\ x_2,\ \cdots,\ x_n) = f[U_1(x_1),\ U_2(x_2),\ \cdots,\ U_n(x_n)] \tag{4}$$

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.

$$U(x_1,\ x_2,\ \cdots x_n) = \sum_{i=1}^{n} U_i(x_i)\,. \tag{5}$$

The attributes may be assigned weights depending on the relative importance or priorities of the characteristics. After assigning weights to the attributes, the overall utility function can be expressed as

$$U(x_1,\ x_2,\ \cdots x_n) = \sum_{i=0}^{n} W_{\mathrm{i}} U_i(x_i) \tag{6}$$

where W_i is the weight assigned to the attribute i. The sum of the weights for all attributes must be equal to 1. If the composite measure (the overall utility) is maximized, the performance characteristics considered to evaluate utility are automatically optimized (maximized or minimized, relative to the case).

3.3 Determination of utility value

A preference scale for each quality characteristic is constructed. These scales are weighed to obtain a composite number (overall utility) to determine the utility value for a number of quality characteristics. The weighing is performed to satisfy the test of indifference on various quality characteristics. The preference scale should be a logarithmic one [15]. The minimum acceptable quality level for each quality characteristic has the preference number of 0, while that of the best available quality is 9. If a log scale is chosen, the preference number (P_i) is given by Eq. (7) [15].

$$P_i = A \times \log\left(\frac{x_i}{x_i'}\right) \tag{7}$$

where x_i = the value of any quality characteristic or attribute i, x_i' = acceptable value of quality characteristic or attribute i, and A = constant.

The value of A conforms to the condition that if $x_i = x^*$ (where x^* is the optimal or best value), then $P_i = 9$.

Therefore

$$A = \frac{9}{\log \frac{x^*}{x_i'}} \tag{8}$$

subject to the condition

$$\sum_{i=1}^{n} W_i = 1 . \tag{9}$$

The overall utility can then be calculated as follows:

$$U = \sum_{i=1}^{n} W_i P_i . \tag{10}$$

Among the various performance characteristics type, such as smaller-the-better, HB, and NB, which were suggested by Taguchi, the utility function would be HB. Therefore, if the utility function is maximized, the performance characteristics considered in evaluating the utility function will automatically be optimized (maximized or minimized as the case may be). The stepwise procedure for the multi-response optimization by the Utility concept and the Taguchi method is illustrated as:

(1) The Taguchi matrix experimental design and analysis is adopted to determine the optimal value of each selected process response.

(2) A preference scale for each response is constructed based on the optimal value and the minimum acceptable level (Eqs. (7) and (8)).

(3) Weights (W_i) are assigned based on experience and customer preference, with the total sum of weights as equal to 1.

(4) The overall utility values for the different experimental trial conditions are identified, with all responses involved in the multi-response optimization (Eq. (10)).

(5) The values obtained in step 4 are used as raw responses under different trial conditions of the experimental matrix. If the trials are repeated, the S/N ratio (HB type) is found because of utility possessing the HB type characteristic [16].

(6) The results are analyzed following the standard procedure suggested by Taguchi [16].

(7) The optimal settings of the process parameters for the mean and the S/N utility are found based on the analysis performed in step 6.

(8) The optimal values of the different response characteristics are predicted for the optimal parametric setting that maximizes the overall utility determined in step 7.

(9) Confirmation experiments are conducted to verify the optimal results.

Based on the methodology developed in the previous sections, the following case is considered to obtain the optimal settings of the process parameters of the lathe turning for the prediction of optimal values of the combined responses. Two quality characteristics, namely, surface roughness (R_a) and MRR are included in the utility response. The Taguchi L_{18} OA (Roy, 1990) is adopted to conduct the experiments. The 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. The response parameters (quality characteristics) are surface roughness (R_a) and MRR at individual optimization. A summary of the results is shown in Table 5. The optimal settings of the process parameters and the optimal values of the surface roughness and MRR (when individually optimized) are already established using Taguchi's design of the experiment.

Table 5. Optimal setting and values of the process parameters (individual quality characteristics optimization).

Quality characteristics	Optimal level of process parameters	Significant process parameters (at a 95% confidence level)	Predicted optimal value of the quality characteristics
Surface roughness	C2D2F1	C, D, F	1.385 μm
MRR	C3D3F3	C, D, F	289.99 mm^3/sec.

* C - feed rate, D - cutting speed and F - depth of cut.

Table 6. Parameters used to find utility.

	Surface roughness	MRR
Optimum value x^*	1.385	289.99
Acceptable value x_i'	5.0 (Maximum)	8.0 (Minimum)
Weights W	1/2	1/2
Preference scale	$-16.18\log\left(\frac{x_i}{5.0}\right)$	$5.77\log\left(\frac{x_i}{8.0}\right)$

* Optimum values are taken from Table 5 and maximum or minimum acceptable values are taken from Table 4.

The stepwise procedure for the transformation of experimental data into utility data is shown in the following. Table 6 shows the values used for the surface roughness and MRR to obtain the utility. The utility values are calculated based on Eq. (10) and are shown in Table 7.

3.4 Determination of optimal settings of process parameters

Data (utility values) are analyzed for both the mean response (mean of the utility at each parameter level) and the S/N ratio. Given that utility is a higher-the-better (*HB*) type of quality characteristic, (S/N) HB has been used. The average and main responses in terms of utility values and S/N ratio (Tables 10 and 11) are plotted in Figs. 1(a)-1(f) in which the 2nd level of the tool nose radius (A2), 3rd level of the tool rake angle (B3), 2nd level of the feed rate (C2), 2nd the level of cutting speed (D2), 2nd level of cutting environment (E2), and 3rd level of depth of cut (F3) are expected to yield a maximum value of the utility and the S/N ratio in the experimental space. The pooled version of the ANOVA for the

Table 7. Calculated utility data based on surface roughness and MRR.

Trial No.	Raw data (utility values)			S/N ratio (db)
	R1	R2	R3	
1	4.095	3.980	4.359	12.3311
2	7.350	7.278	6.865	17.0916
3	6.73	5.338	4.748	14.7052
4	4.772	4.804	5.039	13.7459
5	7.776	7.776	7.898	17.8597
6	5.326	5.083	5.075	14.2487
7	7.397	6.769	6.454	16.7021
8	5.604	5.976	5.782	15.2406
9	5.951	5.49	6.671	15.5343
10	5.125	5.355	5.865	14.6845
11	6.405	6.324	6.745	16.2366
12	5.277	6.863	5.569	15.2585
13	4.69	5.151	4.455	13.5152
14	5.749	6.577	6.437	15.8777
15	6.545	7.721	5.551	16.1635
16	6.619	6.004	7.113	16.2998
17	4.932	4.868	5.563	14.1408
18	6.750	6.169	6.80	16.3295

Table 8. Pooled ANOVA (raw data: surface roughness and MRR).

Source	SS	DOF	V	F ratio	Prob.	SS/	P (%)
Tool nose radius(A)	0.0129	1	0.0129	Pooled	0.840	---	---
Tool rake angle(B)	1.2755	2	0.6377	Pooled	0.142	---	---
Feed rate(C)	8.8768	2	4.4384	14.23*	0.000	8.253	15.16
Cutting speed(D)	9.0857	2	4.5429	14.57*	0.000	8.461	15.54
Cutting Environment(E)	1.1619	2	0.5810	Pooled	0.168	---	---
Depth of cut(F)	20.9329	2	10.4665	33.56*	0.000	20.309	37.30
T	54.4437	53				54.4437	100.00
e (pooled)	13.0979	42	0.3119			16.528	30.36

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 a 95% confidence level.

Table 9. S/N pooled ANOVA (raw data: surface roughness and MRR).

Source	SS	DOF	V	F ratio	Prob.	SS/	P (%)
Tool nose radius(A)	0.0609	1	0.0609	Pooled	0.720	---	---
Tool rake angle(B)	1.3767	2	0.6883	Pooled	0.278	---	---
Feed rate(C)	7.0209	2	3.5105	8.16*	0.019	6.159	18.45
Cutting speed(D)	6.3867	2	3.1934	7.42*	0.024	5.527	16.55
Cutting Environment(E)	0.9582	2	0.4791	Pooled	0.388	---	---
Depth of cut(F)	14.9968	2	7.4984	17.42*	0.003	14.135	42.34
T	33.3829	17				33.3829	100.00
e (pooled)	2.5827	6	0.4305			7.318	21.92

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

utility data and S/N ratio are exhibited in Tables 8 and 9, respectively. Feed rate (C), cutting speed (D), and depth of cut (F) significantly affected the mean of utility values and the S/N ratios because these process parameters are significant in both ANOVAs. The optimal values of the utility and those of the considered response characteristics are predicted at the above levels of significant parameters.

4. Optimal values of the quality characteristics (predicted means surface roughness and MRR)

The average values of all response characteristics at the optimum levels of significant parameters with respect to the utility function are recorded in Table 12. The average values are taken from experimental data. The optimal values of the

Table 10. Main effects of the 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	5.940	5.793	5.447	5.545	5.916	5.147
Level 2	5.971	5.912	6.439	6.516	6.152	6.058
Level 3	---	6.162	5.981	5.806	5.799	6.662
Differences (Δ	0.031	0.369	0.992	0.971	0.353	1.515

Table 11. Average S/N ratio values and the 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	15.27	15.05	14.55	14.69	15.29	14.12
Level 2	15.39	15.24	16.07	16.13	15.63	15.54
Level 3	---	15.71	15.37	15.18	15.07	16.33
Differences (Δ	0.12	0.66	1.53	1.43	0.56	2.21

Table 12. Average values of the various responses at optimal levels.

Levels	Surface roughness (μm)	MRR (mm^3/sec.)
C2	1.976	129.47
D2	2.006	143.47
F3	2.456	204.85

*Average values are obtained from the experimental data.

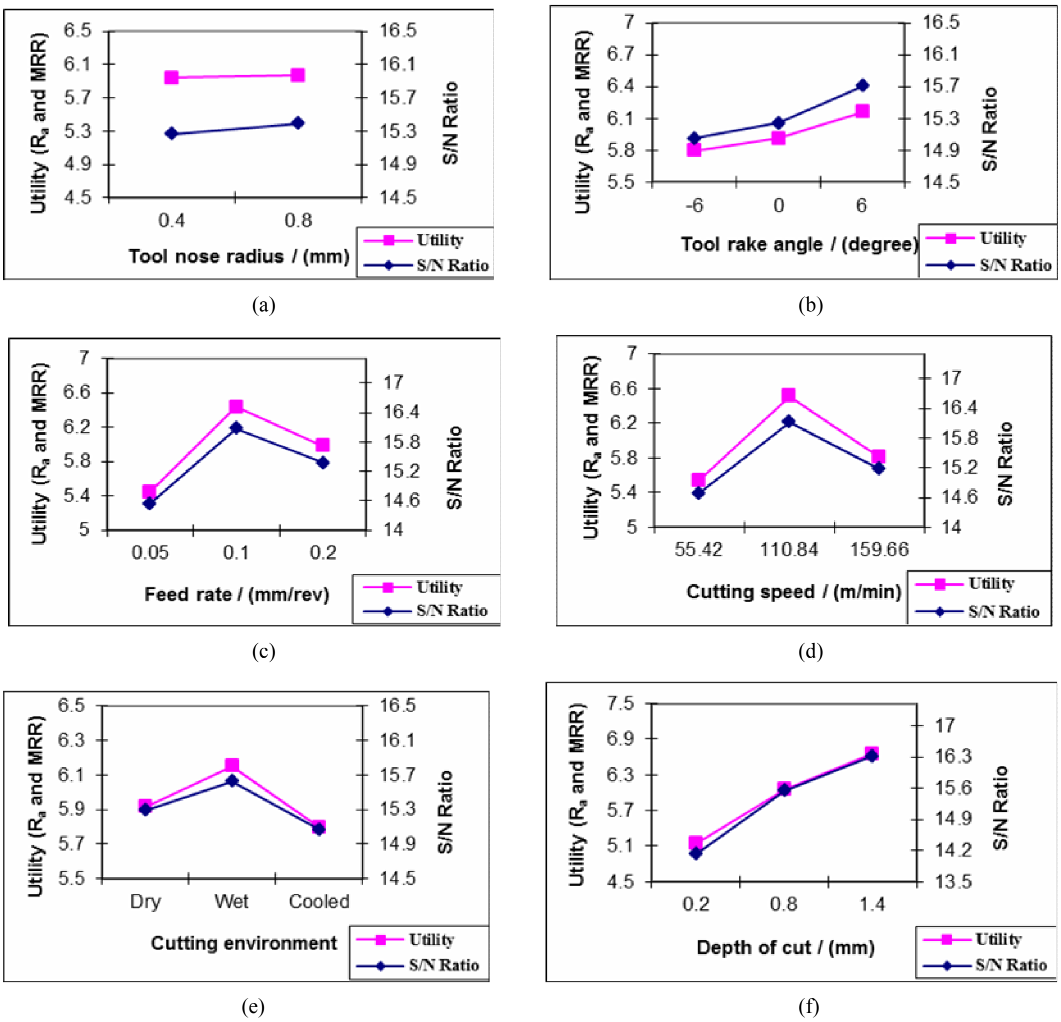

Fig. 1. Utility value and S/N ratio effect of the (a) tool nose radius; (b) tool rake angle; (c) feed rate; (d) cutting speed; (e) cutting environment; (f) depth of cut.

predicted means (μ) of the different response characteristics can be obtained using the following equation:

$$\mu Ra = \overline{TRa} + (\overline{C2} - \overline{TRa}) + (\overline{D2} - \overline{TRa}) + (\overline{F3} - \overline{TRa})$$

where $\overline{TRa}$ = overall mean of surface roughness = 2.272 (Table 4),

$\overline{C2}$ = 1.976, $\overline{D2}$ = 2.006, and $\overline{F3}$ = 2.456 (Table 11). Therefore, μRa = 1.894.

A confidence interval for the predicted mean on a confirmation run can be calculated using Eqs. (11) and (12) [13].

$$CI_{POP} = \sqrt{\frac{F_{\alpha}(1,\ f_e)V_e}{n_{eff}}} \tag{11}$$

$$CI_{CE} = \sqrt{F_{\alpha}(1,\ f_e)V_e\left[\frac{1}{n_{eff}} + \frac{1}{R}\right]} \tag{12}$$

where Fα; (1, fe) = $F_{0.05}$; (1; 42) = 4.08 (tabulated),

α = risk = 0 · 05, f_e = error DOF = 42, N = total number of experiments = 18,

Ve = error variance = 0.1717,

Total DOF associated with the mean (μ_{Ra}) = 11, total trial = 18, N = 18 × 3 = 54,

neff = effective number of replications

$$n_{eff} = \frac{N}{1 + [\text{Total DOF associated in the estimate of the mean}]} = 4.5$$

R = number of repetitions for confirmation experiment = 3, and

CI_{POP} = ± 0.395, CI_{CE} = ± 0.624

The 95% confidence interval of the population is $[\mu_{Ra} - CI] < \mu_{Ra} < [\mu_{Ra} + CI]$, that is, $1.499 < \mu_{Ra} < 2.289$.

The 95% confidence interval of the predicted optimal surface roughness is $[\mu_{Ra} - CI] < \mu_{Ra} < [\mu_{Ra} + CI]$, that is, $1.27 < \mu_{Ra} < 2.518$.

MRR:

$$\mu MRR = \overline{TMRR} + (\overline{C2} - \overline{TMRR}) + (\overline{D2} - \overline{TMRR}) + (\overline{F3} - \overline{TMRR})$$

where $\overline{TMRR}$ = overall mean of MRR = 132.72 (Table 4)

$\overline{C2}$ = 129.47, $\overline{D2}$ = 143.47, $\overline{F3}$ = 204.85 (Table 12).

Therefore, μMRR = 212.35.

The following values are obtained by the ANOVA:

N = 54, f_e = 42, Ve = 983, n_{eff} = 4.5, R = 3, and $F_{0.05}$ (1, 42) = 4.08.

A confidence interval for the predicted mean on a confirmation run can be calculated using Eqs. (11) and (12).

CI_{POP} = ± 29.854, CI_{CE} = ± 47.179

The 95% confidence interval of the population is $[\mu_{MRR} - CI] < \mu_{MRR} < [\mu_{MRR} + CI]$, that is, $182.496 < \mu_{MRR} < 242.204$.

The 95% confidence interval of the predicted optimal surface roughness is $[\mu_{MRR} - CI] < \mu_{MRR} < [\mu_{MRR} + CI]$, that is, $165.171 < \mu_{MRR} < 259.529$.

The optimal values of the process variables at their selected levels are as follows:

Parameters	Level
Feed Rate	2 (0.1 mm/rev)
Cutting Speed	2 (110.84 m/min)
Depth of Cut	3 (1.4 mm).

5. Confirmation experiment

Three experiments are performed at optimal settings as suggested by the Taguchi analysis of utility data. The average values of surface roughness and MRR while turning UD-GFRP using the Carbide (K10) tool were 1.648 μm and 257.18 mm^3/ sec, respectively. These results are within the 95% confidence interval of the predicted optimal value for the selected machining characteristics (surface roughness and MRR). Therefore, the optimal settings of the process parameters, as predicted in the analysis, can be implemented. The conformance of the results obtained by ANOVA and the results obtained using the confirmation are shown.

6. Conclusion

- The multiple performance characteristics are surface roughness and MRR. A model based on the Taguchi approach and the utility concept was developed to achieve these characteristics. The depth of cut, cutting speed, and feed rate had a significant effect on the utility function based on the ANOVA significant process parameters for multiple performances. The percentage contribution of the depth of cut was 37.30%, cutting speed was 15.54%, and feed rate was 15.16%. The proposed model was simple, useful, and provided an appropriate solution to the multi-response optimization problem.
- The selected input parameter significantly improved the utility function (raw data and S/N ratio) that is composed of quality characteristics.
- The optimal setting of the process parameters for a multi-characteristic product can be predicted using the proposed model.
- The 95% confidence interval of the predicted optimal surface roughness is $[\mu_{Ra} - CI] < \mu_{Ra} < [\mu_{Ra} + CI]$, that is, $1.27 < \mu_{Ra} < 2.518$.
- The 95% confidence interval of the predicted optimal surface roughness is $[\mu_{MRR} - CI] < \mu_{MRR} < [\mu_{MRR} + CI]$, that is, $165.171 < \mu_{MRR} < 259.529$.

References

[1] D. M. Byrne and S. Taguchi, The Taguchi approach to parameter design, *Quality Progress*. (1987) 19-26.

[2] N. Logothetis and A. Haigh, Characterizing and optimizing multi-response processes by the Taguchi method, *Quality and Reliability Engineering International*, 17 (5) (1988) 323-331.

[3] G. H. Shiau, A study of the sintering properties of iron ores using the Taguchi's parameter design, *Journal of Chinese Statistical Association*, 28 (1990) 253-275.

[4] S. Singh, H. S. Shan and P. Kumar, Parametric optimization of magnetic-field assisted abrasive flow machining by the

Taguchi method, *Quality Reliability Engineering Int.*, 18 (2002) 273-283.
[5] J. R. Fereirra, N. L. Coppini and L. Neto, Characteristics of carbon-carbon composite turning, *Journal of Materials Processing Technology*, 109 (2001) 65-71.
[6] G. Spur and U. E. Wunsch, Turning of fiber-reinforced plastics, *Manuf Rev.*, 1 (2) (1988) 24-129.
[7] K. Palanikumar, L. Karunamoorthy and R. Karthikeyan, Assessment of factors influencing surface roughness on the machining of glass fiber-reinforced polymer composites, *Materials and Design*, 27 (2006) 862-871.
[8] H. Takeyama and Lijima, *Ann. CIRP*, 37, 93 (1988).
[9] S. O. An, E. S. Lee and S. L. Noh, *Journal material processing*, 68 (60) (1997).
[10] S. A. Hussain, V. Pandurangadu, K. Palanikumar and V. V. Bharathi, A predictive model for surface roughness in turning glass fiber reinforced plastics by carbide tool (K-20) using soft computing, *Jordan Journal of Mechanical and Industrial Engineering*, 5 (5) (2011) 433-438.
[11] B. Huang and J. C. Chen, An in-process neural network-based surface roughness prediction (INN-SRP) system using a dynamometer in end milling operations, *The International journal of Advanced Manufacturing Technology,* 21 (2001) 339-347.
[12] K. Palanikumar, B. Latha, V. S. Senthilkumar and R. Karthikeyan, Multiple performance optimizations in machining of GFRP composites by a PCD tool using non-dominated sorting genetic algorithm (NSGA-II), *Metal. Material Int.,* 15 (2) (2009) 249-258.
[13] P. J. Ross, *Taguchi techniques for quality engineering*, McGraw-Hills Book Company, New York (1988).
[14] W. B. Derek, Analysis for optimal decisions, *John Wiley and Sons*, New York (1982).
[15] V. Gupta and P. N. Murthy, *An introduction to engineering design method*, Tata McGraw-Hill, New Delhi (1980).
[16] R. K. Roy, *A primer on Taguchi method*, Van Nostrand Reinhold. New York (1990).

Surinder Kumar is a research scholar in the Department of Mechanical Engineering, National Institute of Technology, Kurukshetra-136119, (Haryana), India. He graduated with a degree in Mechanical Engineering from S.K.I.E.T, Kurukshetra, Haryana and a post-graduate degree with a specialization in Manufacturing System from M.M Engineering College Mullana, Ambala (Haryana). He is a Ph.D. candidate (Full-time) who had submitted his thesis at NIT Kurukshetra, Haryana, India. He has more than two years of experience in teaching and has published more than 25 papers in various referred national and international journals and conferences. His current areas of research include the machining of composite materials, optimization, and modeling.

Meenu is an associate professor in the Department of Mechanical Engineering, National Institute of Technology, Kurukshetra-136119, (Haryana), India. She has more than 25 years of experience in teaching and research. Her current areas of research include machine vision, image processing, optimization, and modeling.

P.S. Satsangi is an associate professor in the Department of Mechanical Engineering, PEC University of Technology Chandigarh, India. He has more than 25 years of experience in teaching and research. His current areas of research include the machining of composite materials, modern manufacturing, optimization, and modeling.