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Optimization of the surface roughness and material removal rate in turning of unidirectional glass fiber reinforced plastics using the fuzzy-grey relational technique

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In this paper fuzzy-grey relation technique is applied to experimental results in order to optimize the turning of unidirectional glass fiber reinforced plastics composite with consideration to multiple performance measures. The overall grey relational grade is found using fuzzy logic. To conduct experimentation L_{18} orthogonal array of Taguchi is used. Cutting speed, depth of cut, feed rate, tool rake angle, tool nose radius and environment (dry, wet, cool) are taken as parameters for experimentation. Castrol water miscible soluble coolant (1:6) volumetric concentrations is used as cutting fluid. A1B1C1D1E3F1 is found to be the optimal setting for optimizing material removal rate and surface roughness. Depth of cut followed by cutting speed is found to be most influential factor by the average of grey relational grade analysis using Fuzzy logic.

Keywords: Unidirectional glass fiber reinforced plastics, Polycrystalline diamond cutting tool, fuzzy-grey, Material removal rate, Surface roughness

Composites ease of combination with other materials and due to exhibition of desirable properties makes it one of the most widely used materials. Manufacturing companies such as military, aerospace, automobile should replace cast iron and steel with ceramics, Al alloys and metal matrix composites. Composite materials can be divided into metals, ceramics and polymer matrices with reinforcing fibers. UD-GFRP can be used for making structural member bearing loads in one direction. UD-GFRP is widely used as structural member due to strength along the fiber direction and high specific stiffness GFRP consist of a polymer resin in matrix form and glass fiber as reinforcement. This material is light, tough, resilient, flexible and has a very good "ratio of strength and weight". High abrasiveness of glass fiber and non-homogeneous structure of this composite make it very difficult to be machined[1]. Machining glass fiber composites is a complex and challenging task. Major difficulties encountered are reported[1] as surface damage by delamination, burning, cracks, rapid tool wear, subsurface damage and bouncing back phenomenon of work piece material. Palanikumar *et al*.[2] optimized the cutting speed, depth of cut, feed and machining time and fiber orientation during turning glass fiber reinforced plastics by fuzzy logic. The surface roughnss was considered as performance characteristics .

Aravindan *et al*.[3] used statistical techniques to investigate the machinability of hand lay-up GFRP pipes. Surface finish of 4 to 8 microns, was observed whereas the roughness of un-machined surface was about 80 to 100 microns. Palanikumar *et al*.[4] using non-dominated sorting genetic algorithm to maximize the material removal rate and minimize the surface roughness and tool flank wear during turning with PCD tool. The parameters chosen were cutting speed, feed rate and depth of cut. Rajasekaran *et al*.[5] used fuzzy logic to model surface roughness and material removal rate in turning of CFRP composite using cemented carbide tool. Cutting speed, feed rate and depth of cut were taken as process parameters. Hussain *et al*.[6] used response surface methodology to develop surface roughness model in machining of GFRP piping K20 carbide tool. Work-piece orientation, cutting speed, feed rate, depth of cut and fiber were the parameters chosen. Depth of cut was having minimum effect as compared to other parameters. Hussain *et al*.[7] developed fuzzy based surface roughness model for machining of GFRP

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tubes by K20 carbide tool. To minimize the surface roughness speed, feed, depth of cut and work-piece orientation, were selected along fiber direction. Raj *et al*.[8] used response surface methodology and ANN to model surface roughness and delamination using coated and uncoated K10 cutting tool. Tool material, feed, speed, depth of cut were selected as process parameters. ANN model was found to have good interpolation capability and hence an effective model for surface roughness and delamination. It was found that the developed good surface finish coated tool performs better than uncoated tool.

Hashmi *et al*.[9,10] used triangular membership function fuzzy logic to select cutting conditions with single input (material hardness) and single output (cutting speed). Kumar *et al*.[11] investigated the turning process of the unidirectional glass fiber reinforced plastic (UD-GFRP) composites. Polycrystalline diamond (PCD) tool during turning was used and effect of six parameters such as tool nose radius, tool rake angle, feed rate, cutting speed, depth of cut and along with cutting environment (dry, wet and cooled (5-7° temperature)) was found on the surface roughness produced. It was found that the feed rate is the factor, which has great influence on surface roughness, followed by cutting speed. Xu *et al*.[12] evaluated the machinability of high-strength T800S/250F CFRP laminate by using CVD coated twist drill and CVD coated dagger drill. The drilling forces, burr defect, hole wall surface morphology and delamination damage were considered as the performance characteristics. The feed rate was found to be most significant factor affecting the machined surface finish followed by the spindle speed. The performance of dagger drill was better than the twist drill and was more suitable for drilling of T800S/250F CFRP laminate. Xu *et al*.[13] investigated the machining process of T800S/250F CFRP laminate by using carbide twist drill and dragger drill bits. The machinability of T800S/250F was investigated in term of drilling force, burr morphology and delamination factor. It was found that the thrust force reduces with high spindle speed and low feed rate for both the tools. Smaller burr defect and lower delamination was found for the dragger drill. Xu *et al*.[14] investigated the drilling-induced defects for CFRP composites using a series of new criteria proposed for the assessment of burrs, tearing and delamination. Both the digital microscope and ultrasonic C-scan technique were utilized to detect and characterize the drilling-induced damage. It was found that the feed rate is the most significant factor which influences the extents of the drilled composite defects. Brad spur drill yielded the best cutting performance during the drilling of T800/X850 CFRP. Meenu and Kumar[15] used the grey relation analysis to find the optimum parameters in the turning of unidirectional GFRP composites. The grey relation analysis was used to optimize the parameters affecting the response. The cutting speed was the factor, which has great influence on surface roughness and material removal rate followed by feed rate. It was found that the, surface roughness of 1.761 μm and material removal rate of 275.78 mm^3 were achieved.

It is concluded that the experimental values agreed with the predicted results indicating suitability of the multiple regression models. This paper presents a new methodology for the optimization of the machining parameters for turning unidirectional glass fiber reinforced plastics composite. Taguchi's L_{18} orthogonal array is used for experimental design. The machining process parameters such as tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment and depth of cut are optimized with multiple performance considerations namely surface roughness and material removal rate. The cutting environment (dry, wet and cooled) is set during the machining of the rod; so as to get a comparative assessment of the performance of cutting environment which has not been studied earlier. Fuzzy logic is used to find the grey relational grade. ANOVA is used to find the significant parameters.

Material and Experimental Technique

Pultrusion processed UD-GFRP composite rods consisting of epoxy resin and E-glass as fiber is used. The properties of material are given in Table 1. The work-piece of 840 mm length and 42 mm dia is used as shown in Fig. 1(a). NH22 lathe of make HMT, 11 kW spindle power and maximum speed of 3000 rpm is used for the experimentation as shown in Fig. 1(b) installed at workshop Laboratory of Mechanical Engineering Department. The cutting tool insert with two tool nose radius of 0.4 and 0.8 mm and three rake angles -6°, 0°, +6° are used as shown in Figs 2(a) and 2(b). A tool holder made of steel EN47 is used. The details of the PCD inserts are given in Table 2. To ascertain the surface roughness and material removal rate, the experimental results of turning of UD-GFRP are evaluated. Tokyo Seimitsu Surfcom 130A type

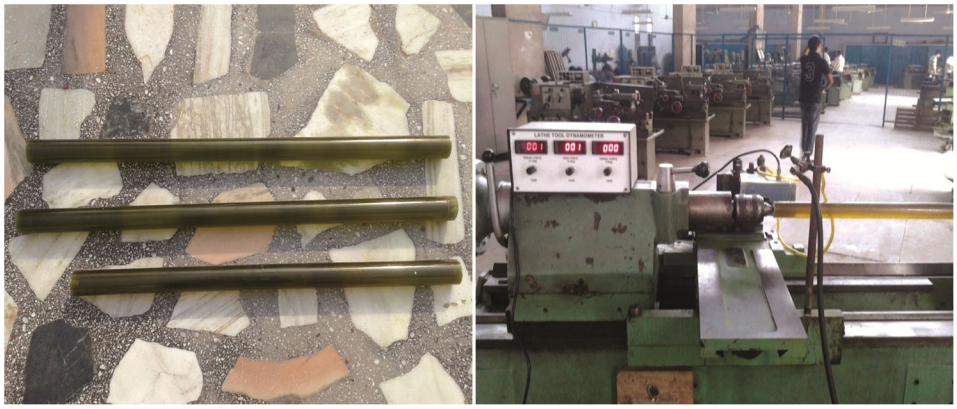


Fig. 1 — Experimental setup (a) before machining and (b) during machining

Table 1 — Physical and mechanical properties of UD-GFRP

Sr. No.	Particular	Value	Unit
1	Glass content (by wt)	75±5	%
2	Epoxy resin content (by wt)	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	kg /cm^2
7	Compression strength	6000	kg /cm^2
8	Shear strength	255 kgf	kg / cm^2
9	Modulus of elasticity	3200	10 kg/cm^2
10	Thermal conductivity	0.30	kcal /Mh°C
11	Weight of rod 840 mm in length	2.300	kg
12	Electrical strength (radial)	3.5	kV /mm
13	Working temperature class	Class 'F' (155)	°C
14	Martens heat distortion temperature	210	°C
15	Test in oil : (1) At 20°C:	20 kV/cm	kV/cm
	(2) At 100°C:	20 kV/cm (50 kV / 25 mm)	

Table 2 — Properties of PCD tool

Clearance angle	7º
Grade	M10
Density	3.80-4.50 g/cm^3
Hardness	1600 Vickers kg/mm^2
Transverse Rupture strength	1200-1700 N/mm^2
Thermal conductivity	150-550 W/mK
Compressive Strength	7000-8000 N/mm^2
Thermal Expansion coefficient	3.2-4.6 10%C
Young's modulus	800-900 GPa
Cutting edge inclination angle top	7º
Front clearance	10º
Tool rake angle	-6°, 0°, +6°
Tool nose radius	0.4 mm, 0.8 mm

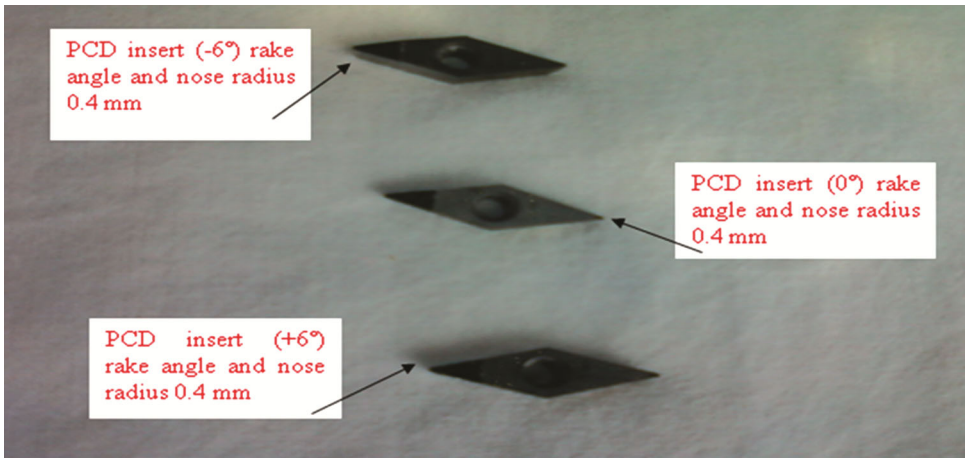
instrument shown in Fig. 3 is used for measuring surface roughness. The cut-off length of 0.8 mm with a transverse length of 4 mm is used. As there are two levels of tool nose radius, Taugchi's mixed level design is selected. The number of degree of freedom for tool nose radius is 1 and number of degree of freedom for other five parameters is 2. So, total number of degree of freedom for one two level parameters and five three level parameters is (1*1+ (5*2). So, L_{18} orthogonal array with 17 degree of freedom is selected. Parameters are assigned to columns using linear graphs. The unassigned columns are considered as error. The ranges of the parameter are given in Table 3. The material removal rate (MRR) in turning operations is the volume of material/metal that is removed per unit time in mm^3/s. The material removal rate, in mm^3/s, is calculated from the following relation:

$$MRR = \frac{\frac{\pi}{4}Do^2L - \frac{\pi}{4}Di^2L}{L/CN} \quad \ldots (1)$$

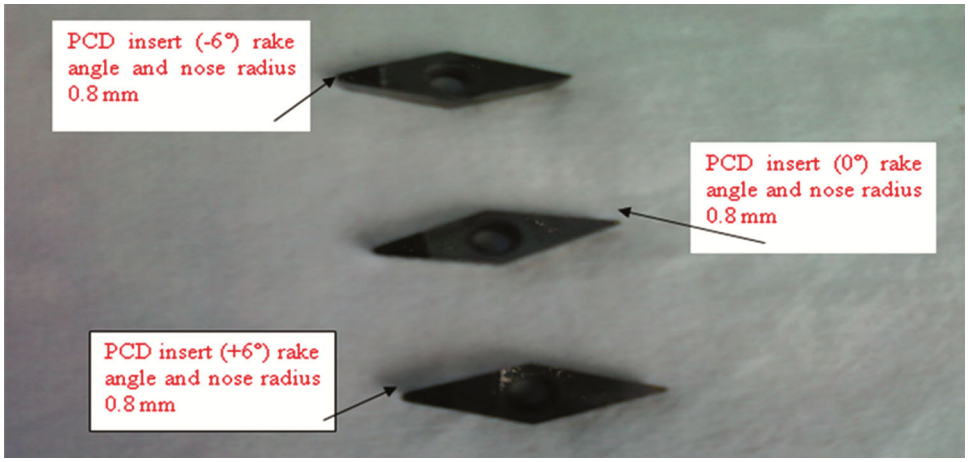
where, D_0 is initial dia in mm, D_i is final dia in mm, L is length of the work-piece to be turned in mm, N is spindle speed in rpm, C is feed rate in mm/rev.

Grey Relation Analysis

Dynamic process of system can be quantitatively analysed by grey relational analysis. The degree of



2 (a)



2 (b)

Fig. 2 — PCD cutting tool inserts used in the experiment (a) 0.4 mm and (b) 0.8 mm

Fig. 3 — Surface roughness tester

proximity according to similarity is measured by it. The steps of GRA to optimize multiple response characteristics are: (i) conduction of experiments according to orthogonal array, (ii) normalization of experimental results, (iii) to find quality loss function, (iv) to find grey relational coefficient and (v) to find grey relational grade using fuzzy logic.

Normalization of data

The raw data is normalized to get a comparable sequence in the range 0 to 1. For lower, the best (R_a) Eq. (2) is used and for higher the best material removal rate as Eq. (3) is used.

$$x_i^*(k) = \frac{maxx_i(k) - x_i(k)}{maxx_i(k) - minx_i(k)} \quad \ldots (2)$$

$$x_i^*(k) = \frac{x_i(k) - minx_i(k)}{maxx_i(k) - minx_i(k)} \quad \ldots (3)$$

where, n and m represent the number of response variable S and number of experiments, respectively. Where $x_i(k)$ is the original sequence of the surface roughness and material removal rate, $x_i^*(k)$ is the comparable sequence after data normalization, max $x_i(k)$ and min $x_i(k)$ are the largest value and smallest value of $x_i(k)$. In this paper, m =18, n = 2 is taken.

Table 3 — Control Parameters and their Level

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

Calculation of quality loss function

where as $x_o^*(k) = 1$ and quality loss function

$$\Delta_{oi}(k) = x_o^*(k) - x_i^*(k) \quad \ldots (4)$$

Calculation of grey relational coefficient

Grey relational coefficient is given by Eq. (5).

$$\gamma\left(x_o^*(k), x_i^*(k)\right) = \frac{\Delta_{min} + \zeta \Delta_{max}}{\Delta_{oi}(k) + \zeta \Delta_{max}} \quad \ldots (5)$$

ζ is the distinguishing coefficient lies between 0 and. ζ is set at 0.5.

$\Delta_{min} = \min \min \Delta_{oi}(k)$

$\forall_i \forall_k$

$\Delta_{max} = \max \max \Delta_{oi}(k)$

$\forall_i \forall_k$

$(\Delta R_a)\ 01 = 1\text{-}0.0181 = 0.9819$

$(\Delta \text{MRR})\ 01 = 1\text{-}0.000 = 1.000$

From the data in Table 9 we can find the following:

$\Delta_{max} = \Delta\ 03(R_a) = \Delta\ 03(\text{MRR}) = 1.000,$

$\Delta_{min} = \Delta\ 4\ (R_a) = \Delta\ 01(\text{MRR}) = 0.000,$

The gray relation coefficient coefficient calculated according to Eq. (5) is given by

$\zeta_1\ (R_a) = [0.000 + (0.5 \times 1.000)] / [0.9819 + (0.5 \times 1.000)] = 0.3374$

$\zeta_1\ (\text{MRR}) = [0.000 + (0.5 \times 1.000)] / [1.000 + (0.5 \times 1.000)] = 0.3333$

Calculation of grey relational grade

The grey relational grade is a weighted average of the grey relational coefficients of multi-objective. It is determined as

$$\psi(x_o^*, x_i^*) = \sum_{k=1}^{n} \omega_k \gamma(x_o^*(k), x_i^*(k)) \quad \ldots (6)$$

where ω_k is the weight of the k^{th} performance characteristics and $\sum_{k=1}^{n} \omega_k = 1$ By assigning weightage of R_a = 0.5 for both R_a and MMR = 0.5, GR grade is calculated (Table 9).

Fuzzy Logic

World cannot be defined in true or false statements as it is continually changing. With the help of fuzzy logic, a definite conclusion is reached in case of imprecise, vague, ambiguous, noisy and missing input information. Nonlinear systems are introduced by fuzzy logic which is difficult to model mathematically. The fuzzy logic was first proposed by Zadeh[16]. According to him, fuzzification is a methodology to generalize any specific theory from discrete to fuzzy. In a fuzzy logic system, nonlinear mapping of input to output take place. Fuzzy logic handles partial truth. Variables in the fuzzy logic have the truth values between value between 0 and 1. To express rules and facts, non numerical values are used where as in mathematics, numerical values are used[17]. Similarly Fuzzy subset F of a set S can be represented defined as an ordered pairs with first element from S and second element from the range [0, 1]. The zero means non-numerical between represent complete membership. Different shapes of membership functions are Gaussian, bell-shaped, triangular, trapezoidal, piecewise-linear, etc. Fuzzy expert systems map numeric data to linguistic such as “low,” “medium,” “large,” “few”. Inputs that can be processed are from 1-8 or more and outputs that can be processed are from 1-4 or more because of rule-based approach. It uses simple rules such as IF X and Y then Z to control the problem. The conclusion is the disjunction of the individual consequents of each rule. Figure 4 shows the fuzzy inference system. Fuzzy logic system consists of (1) fuzzifier, (2) knowledge base, (3) inference engine and (4) defuzzifier.

Fuzzifier

It identifies the input and output of the system. A crisp set of input data are converted to a fuzzy set using fuzzy linguistic variables and membership functions.

Knowledge base

The knowledge base contains linguistic rules. Experts provide the rule or it can be expressed from numeric data. Then FIS system maps an input vector to output vector.

Inference engine

All the values are evaluated and their truth value is determined and an output obtained from each rule is combined into a single fuzzy set using fuzzy aggregation operator.

Defuzzification

The crisp output is obtained by defuzzification of overall result.

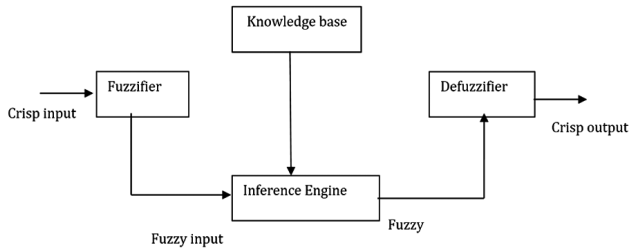


Fig. 4 — Fuzzy inference system

Results and Discussion

Experimental results are shown in Tables 4 and 5[11]. Tables 6 and 7 show the response tables of surface roughness and material removal rate, respectively. As seen from Table 6, the contribution of feed rate is (Δ = 0.762) followed by speed (Δ = 0.366) and depth of cut (Δ = 0.278). As seen from Table 7, the contribution of depth of cut is highest (Δ = 65.46) followed by feed rate (Δ = 119.73) and cutting speed (Δ = 68.25). Tool geometry affects of surface roughness. The surface roughness is reduced by increasing tool nose radius. It is found that the rake angle close 0° gives better surface finish. This finding has close relationship with the reported results[18]. Further increase in rake angle decreases surface finish due to weakening of the rake angle. The result also indicates that the surface roughness firstly decreases than increases with tool rake angle as shown in Fig. 5(b). However, decrease or increase is not significant. It is also evident from the plots that surface roughness decreases up to 0° then increases. It is found that the rake angle close to 0° gives better surface finish due to weakening of tool. So increase in tool rake angle causes unsuitable results in terms of

Table 4 — Test data summary for surface roughness

	Input Parameters						Responses				
	A	B	C	D	E	F	Raw data			Average SR, (μm)	S/N ratio (dB)
Expt. No.	Nose radius (mm)	Rake angle (°)	Feed rate (mm/rev)	Cutting speed (m/min)RPM	Cutting environment	Depth of cut (mm)	Surface R1	roughness R2	(μm) R3		
1	0.4	-6°	0.05	(55.42) 420	Dry (1)	0.2	1.38	1.46	1.35	1.397	-2.906
2	0.4	-6°	0.1	(110.84) 840	Wet (2)	0.8	1.67	1.36	1.33	1.453	-3.295
3	0.4	-6°	0.2	(159.66) 1210	Cooled (3)	1.4	3.00	2.79	3.44	3.076	-9.795
4	0.4	0°	0.05	(55.42) 420	Wet (2)	0.8	1.31	1.47	1.32	1.366	-2.725
5	0.4	0°	0.1	(110.84) 840	Cooled (3)	1.4	1.70	1.24	1.65	1.530	-3.771
6	0.4	0°	0.2	(159.66) 1210	Dry (1)	0.2	2.05	2.93	2.22	2.400	-7.712
7	0.4	+6°	0.05	(110.84) 840	Dry (1)	1.4	1.61	1.33	1.60	1.513	-3.630
8	0.4	+6°	0.1	(159.66) 1210	Wet (2)	0.2	1.67	1.79	1.45	1.636	-4.311
9	0.4	+6°	0.2	(55.42) 420	Cooled (3)	0.8	2.43	2.20	2.16	2.263	-7.106
10	0.8	-6°	0.05	(159.66) 1210	Cooled (3)	0.8	1.38	1.83	1.43	1.547	-3.860
11	0.8	-6°	0.1	(55.42) 420	Dry (1)	1.4	1.52	1.43	1.87	1.606	-4.178
12	0.8	-6°	0.2	(110.84) 840	Wet (2)	0.2	2.24	1.90	1.76	1.966	-5.919
13	0.8	0°	0.05	(110.84) 840	Cooled (3)	0.2	1.57	1.57	1.65	1.597	-4.066
14	0.8	0°	0.1	(159.66) 1210	Dry (1)	0.8	1.40	1.86	1.63	1.630	-4.301
15	0.8	0°	0.2	(55.42) 420	Wet (2)	1.4	2.14	1.80	2.77	2.237	-7.130
16	0.8	+6°	0.05	(159.66) 1210	Wet (2)	1.4	2.12	1.80	1.90	1.940	-5.776
17	0.8	+6°	0.1	(55.42) 420	Cooled (3)	0.2	1.23	1.53	1.70	1.486	-3.517
18	0.8	+6°	0.2	(110.84) 840	Dry (1)	0.8	1.98	1.66	2.28	1.973	-5.974
				Total						O M. = 1.812	

Table 5 — Test data summary for MRR

	Input Parameters						Responses				
	A	B	C	D	E	F	Raw Data			Average MRR (mm^3/s)	S/N ratio (dB)
Expt. No.	Nose Radius (mm)	Rake angle (°)	Feed rate (mm/rev)	Cutting speed (m/min)RPM	Cutting environment	Depth of cut (mm)	Material Removal Rate (mm^3/s) R1	R2	R3		
1	0.4	-6°	0.05	(55.42) 420	Dry (1)	0.2	8.60	8.50	8.70	8.60	18.688
2	0.4	-6°	0.1	(110.84) 840	Wet (2)	0.8	145.00	145.02	144.95	144.99	43.226
3	0.4	-6°	0.2	(159.66) 1210	Cooled (3)	1.4	327.58	347.03	347.23	340.61	50.635
4	0.4	0°	0.05	(55.42) 420	Wet (2)	0.8	36.24	36.24	36.24	36.24	31.183
5	0.4	0°	0.1	(110.84) 840	Cooled (3)	1.4	249.90	249.96	249.88	249.91	47.955
6	0.4	0°	0.2	(159.66) 1210	Dry (1)	0.2	106.02	105.86	105.90	105.93	40.500
7	0.4	+6°	0.05	(110.84) 840	Dry (1)	1.4	125.00	124.98	124.98	124.99	41.937
8	0.4	+6°	0.1	(159.66) 1210	Wet (2)	0.2	52.96	52.99	52.97	52.97	34.481
9	0.4	+6°	0.2	(55.42) 420	Cooled (3)	0.8	144.97	144.97	145.02	144.99	43.226
10	0.8	-6°	0.05	(159.66) 1210	Cooled (3)	0.8	104.42	104.38	104.40	104.40	40.374
11	0.8	-6°	0.1	(55.42) 420	Dry (1)	1.4	125.00	125.00	125.00	125.00	41.938
12	0.8	-6°	0.2	(110.84) 840	Wet (2)	0.2	73.57	73.58	73.55	73.57	37.333
13	0.8	0°	0.05	(110.84) 840	Cooled (3)	0.2	18.39	18.39	18.39	18.39	25.291
14	0.8	0°	0.1	(159.66) 1210	Dry (1)	0.8	208.72	208.92	208.92	208.85	46.396
15	0.8	0°	0.2	(55.42) 420	Wet (2)	1.4	250.09	250.09	250.05	250.08	47.961
16	0.8	+6°	0.05	(159.66) 1210	Wet (2)	1.4	180.00	180.04	180.00	180.01	45.106
17	0.8	+6°	0.1	(55.42) 420	Cooled (3)	0.2	18.38	18.38	18.38	18.38	25.286
18	0.8	+6°	0.2	(110.84) 840	Dry (1)	0.8	275.93	275.87	275.75	275.85	48.813
				Total						O.M. = 136.87	

Table 6 — Response table for surface roughness

	Tool nose radius (A)	Tool rake angle (B)	Feed rate (C)	Cutting speed (D)	Cutting environment (E)	Depth of cut (F)
Level 1	1.849	1.841	1.560	1.726	1.753	1.747
Level 2	1.776	1.793	1.557	1.672	1.767	1.706
Level 3	---	1.802	2.319	2.038	1.917	1.984
Differences(Δ)	0.073	0.048	0.762	0.366	0.163	0.278
Rank	5	6	1	2	4	3

Table 7 — Response table for material removal rate

	Tool nose radius (A)	Tool rake angle (B)	Feed rate (C)	Cutting speed (D)	Cutting environment (E)	Depth of cut (F)
Level 1	134.36	132.86	78.77	97.21	141.54	46.31
Level 2	139.39	144.90	133.35	147.95	122.98	152.55
Level 3	---	132.87	198.50	165.46	146.11	211.77
Differences	5.03	12.04	119.73	68.25	23.14	165.46
Rank	6	5	2	3	4	1

the glass fiber reinforced plastics. Unlike the fiber that could be fractured or folded, the matrix can be machined suitably. Figure 5(c) shows that change in feed rate from 0.05 to 0.1 does not affect the surface roughness but increasing feed rate beyond 0.1 results in drastic change in roughness because with increase in feed rate heat is generated, tool wear take place and surface roughness increases. Increase in feed rate produces incomplete machining at high feed rate due to chatter which results in higher surface roughness. Increase in speed and feed results in increase in surface roughness but the rate of increase in surface roughness is less with increase in rate of speed as compared to feed as shown in Figs 5(c) and 5(d). Debonding and fiber breakage are the reasons for poor surface roughness at high feed rate as shown in Figs 5(c) and 5(d). The cooled cutting environment increased the surface roughness as shown in Fig. 5(e).

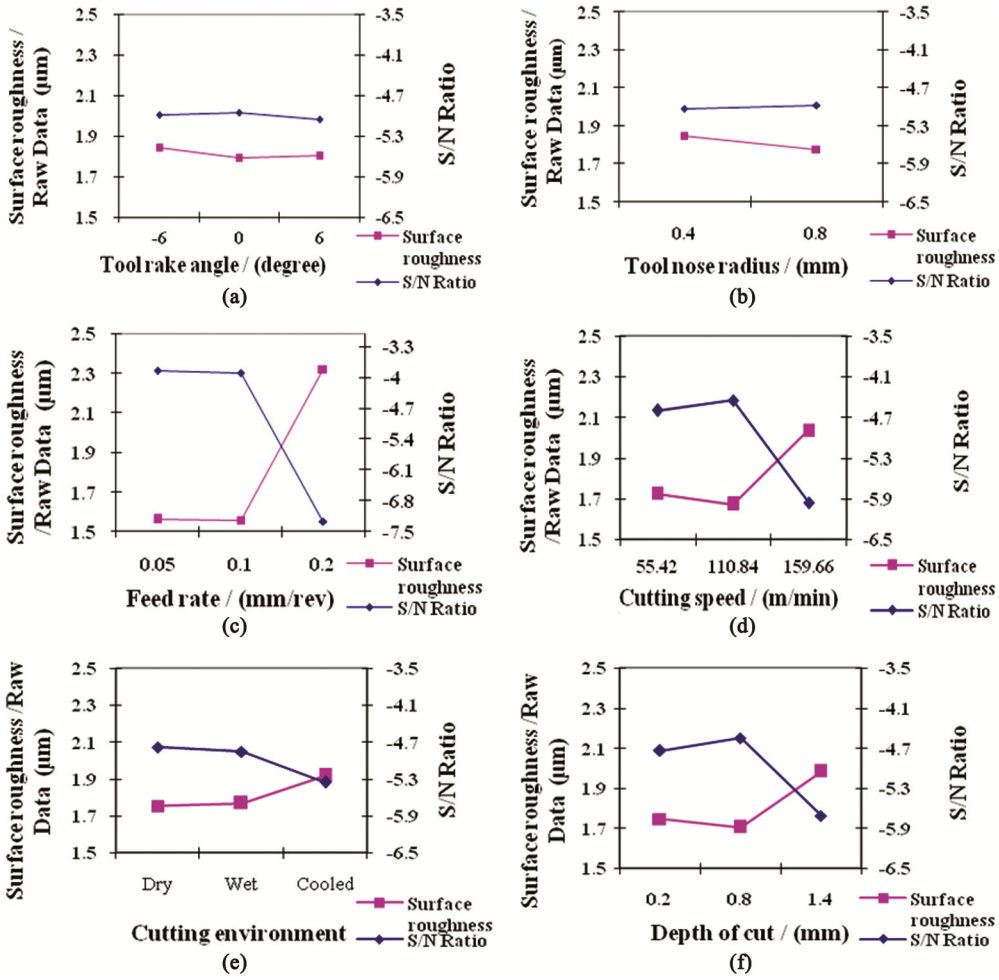


Fig. 5 — Effect of (a) tool nose radius, (b) tool rake angle, (c) feed rate, (d) cutting speed, (e) cutting environment and (f) depth of cut, on surface roughness (response graph and S/N ratio)

The surface roughness increases with increase in depth of cut but at low rate as shown in Fig. 5(f). The role of depth of cut is less as compared to speed and feed rate, but the higher depth of cut causes a deleterious effect on surface roughness quality hence preference of moderate depth of cut is there in the machining GFRP. This finding has close relationship with the reported results[19]. The raw data for average value of material removal rate and S/N ratio of each parameter is given in Table 5. The response graphs for raw data and S/N ratio of MRR are shown in Fig. 6 (a-f). Material removal rate increases with cutting speed, feed rate, cutting environment and tool nose radius but moderate increase was observed as tool rake angle increased.

A fuzzy logic tool box graphical user interface available in MATLAB is used for training the experimental values. Grey-fuzzy relation analysis was adopted to optimize the turning process with multiple performance characteristics MRR and SR. In fuzzy logic system, membership function is used to fuzzify GRC of SR and MRR. Six linguistic grades for SR (GRC), MRR (GRC) and total GRG are very low (V_LOW), low (LOW), medium (MED),very medium (V_MED), high (HIGH), very high (V_HIGH). Figure 7 exhibits six types of membership functions (MF) used for developing model corresponding to the input parameters as well as output parameter. The fuzzy control rules with respective to six linguistic grades for SR (GRC) and MRR (GRC) is constructed as shown in Table 8. For example, the cell (2,3) denotes: If SR (GC) is (LOW) and MRR (GC) is MED then GRD is (LOW). Mamdani method[20] which is built on fuzzy set theory is used. Centroid method is used for

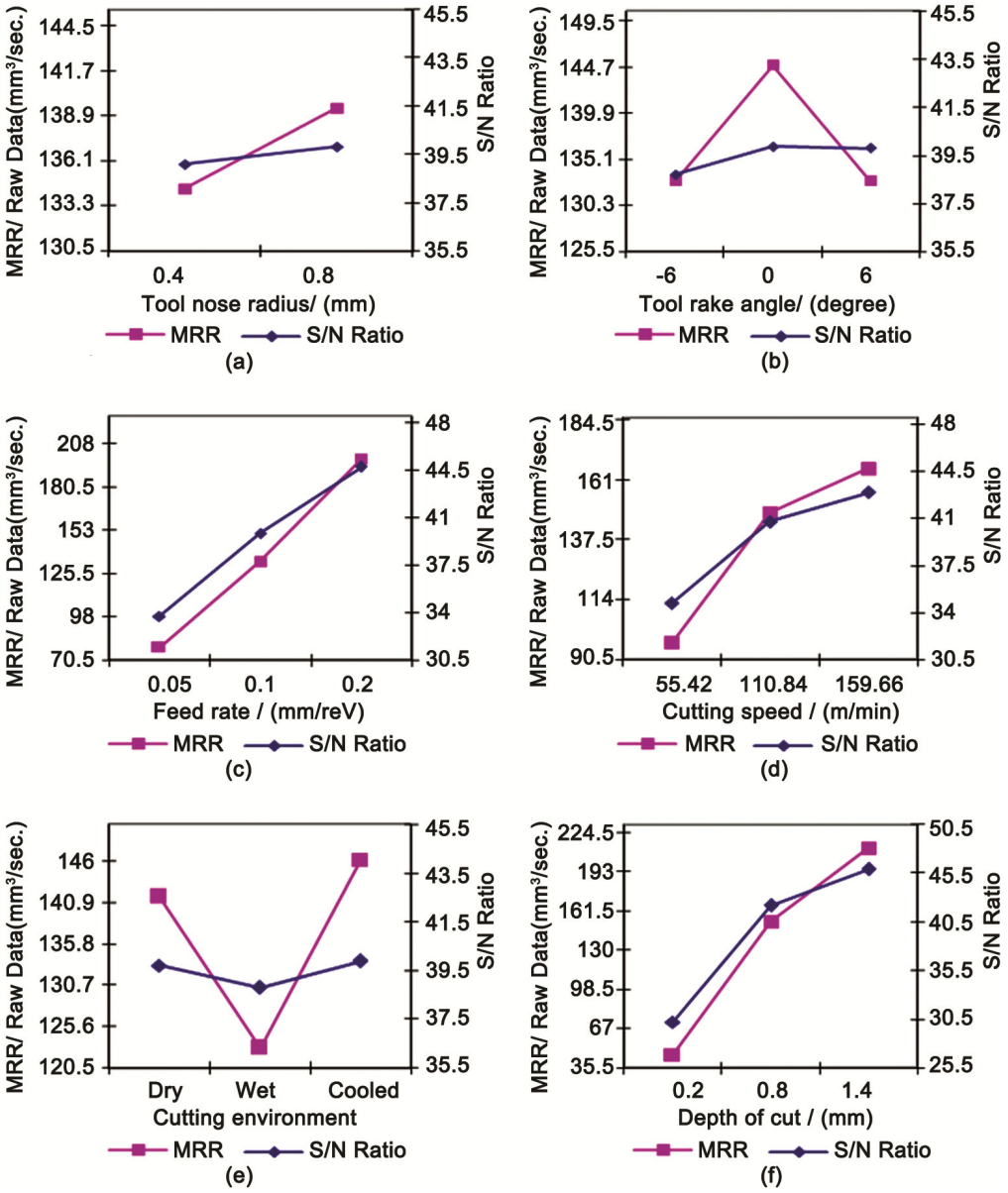


Fig. 6 — Effect of (a) tool nose radius, (b) tool rake angle, (c) feed rate, (d) cutting speed, (e) cutting environment and (f) depth of cut, MRR (response graph and S/N ratio)

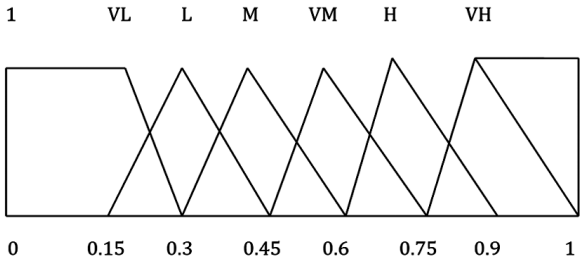


Fig. 7 — Membership functions for SR (GRC) and MRR

defuzzification, Let x^* be the central of area occupied by Fuzzy set then it is given by Eq. (7).

$$x^* = \frac{\sum_{i=1}^{n} x_i u_i(x_i)}{\sum_{i=1}^{n} \mu(x_i)} \quad \ldots (7)$$

Table 8 — Fuzzy Rule Matrix

SR(GRC)	MRR(GRC)						
	V_LOW	LOW	MED	V_MED	HIGH	V_HIGH
V_LOW	V_LOW	V_LOW	LOW	LOW	MED	V_MED
LOW	V_LOW	LOW	LOW	MED	MED	V_MED
MED	LOW	LOW	MED	MED	V_MED	HIGH
V_MED	LOW	LOW	MED	MED	V_MED	HIGH
HIGH	LOW	MED	MED	V_MED	HIGH	HIGH
V_HIGH	MED	MED	V_MED	HIGH	HIGH	V_HIGH

Table 9 — Grey relational grade data

S. No.	Mean (R_a) normalized	Mean (MRR) normalized	Δ_{Ra}	Δ_{MRR}	GR coeff. (R_a)	GR coeff. (MRR)	GR Grade	GR grade mean
1	0.0181	0.0000	0.9819	1.0000	0.3374	0.3333	0.34	0.34
2	0.0509	0.4108	0.9491	0.5892	0.3450	0.4591	0.35	0.35
3	1.0000	1.0000	0.0000	0.0000	1.0000	1.0000	0.91	0.91
4	0.0000	0.0833	1.0000	0.9167	0.3333	0.3529	0.342	0.342
5	0.0959	0.7268	0.9041	0.2732	0.3561	0.6467	0.498	0.498
6	0.6047	0.2932	0.3953	0.7068	0.5585	0.4143	0.408	0.408
7	0.0860	0.3506	0.9140	0.6494	0.3536	0.4350	0.358	0.358
8	0.157	0.1336	0.8421	0.8664	0.3726	0.3659	0.37	0.37
9	0.5246	0.4108	0.4754	0.5892	0.5126	0.4591	0.45	0.45
10	0.1058	0.2885	0.8942	0.7115	0.3586	0.4127	0.362	0.362
11	0.1404	0.3506	0.8596	0.6494	0.3678	0.4350	0.369	0.369
12	0.3509	0.1957	0.6491	0.8043	0.4351	0.3833	0.382	0.382
13	0.1351	0.0295	0.8649	0.9705	0.3663	0.3400	0.361	0.361
14	0.1544	0.6031	0.8456	0.3969	0.3716	0.5575	0.395	0.395
15	0.5094	0.7273	0.4906	0.2727	0.5047	0.6471	0.498	0.498
16	0.3357	0.5163	0.6643	0.4837	0.4294	0.5083	0.42	0.42
17	0.0702	0.0295	0.9298	0.9705	0.3497	0.3400	0.347	0.347
18	0.3550	0.8049	0.6450	0.1951	0.4367	0.7194	0.562	0.562

Here n represents the number of elements in the sample, x^* are the elements and μ (x_i) is its membership function.

Table 9 shows the overall grey relational grade for eighteen experiments. Higher grey relation grade value means optimal combination of factors. It is clear from the experiments that experiment number 3 has largest value of grade. Therefore, it provides best combination for multiple performance characteristics. Grey relational graph is plotted as shown in Fig. 8. Mean value of grey relational grade is 0.429. Basically, the larger the grey relational grade, the better is the multiple performance characteristics. Combination of A1B1C1D1E3 and F1 showed larger value of grey relational grade for factors A, B, C, D, E and F, respectively. Therefore, A1B1C1D1E3F1 is optimal parameter combination for two performance characteristics. However, significant contributions of process parameters still need to be known to predict optimal values of performance characteristics. Residual plots for machining parameters (a) normal

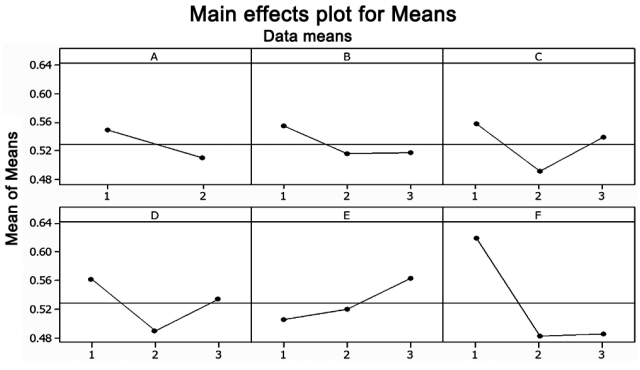


Fig. 8 — Effects of process parameters on Grey relational grade

probability plot of residuals for grey raw data, (b) residuals vs. the order of the data, (c) plot of residuals vs. the fitted values grey value, (d) histogram are shown in Fig. 9. It can be seen from Fig. 9(a) that all the points on the normal plot lie close to the straight line (mean line). This implies that the data are fairly normal and a little deviation from the normality is observed. In addition, Fig. 9 (b), (c) and (d) shows

that there is no noticeable pattern or unusual structure in the data.

Table 10 shows the average of each response characteristic for each level of each factor and delta statistic. The delta statistic is the highest minus the lowest average for each factor. Rank 1 given to the highest delta value and rank 2 to second highest and so on. The rank tells about the relative importance of the factor. The difference of a factor of response variable is the change in the response when the factor goes from its level 1 to level 3. The mean response refers to the average value of the performance characteristic for each parameter at different levels. The difference of raw data between level 1 and 3 indicates that depth of cut has the highest effect

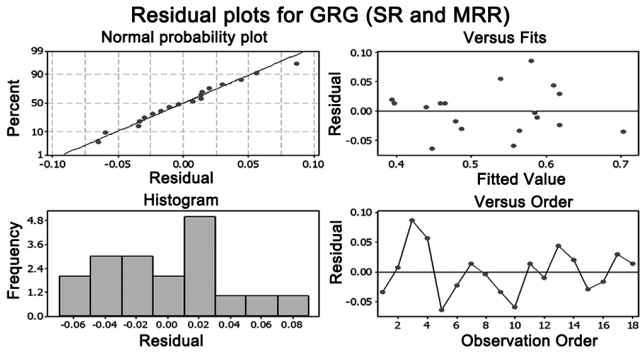


Fig. 9 — Plot to show that the errors are normally distributed and independent, unequal error variance (a) normal probability plot of residuals, (b) histogram of residuals, (c) a residual vs fits plot and (d) residual vs order plot

(Δ = max-min = 0.185) followed by cutting speed (Δ = max-min = 0.0723). Analysis of variance (ANOVA) of the overall grade is done to show the significant parameters. The computed F value is compared with the critical F value to determine the significance of the parameters on the response. Variation observed in experiments is reflected in % contribution (P) which shows relative power of factor or interaction to reduce variation. If the P value for a factor becomes less than 0.05 then that factor is considered as significant factor at 95% confidence level. The results of ANOVA for the grey relational grades are listed in Table 11. It shows that the depth of cut (*F*) is found to be the major factors with the selected multiple performance characteristics, because their corresponding *P* ratio is less than 0.05. The percentage error can be used to evaluate if an experiment possesses feasibility and sufficiency or not, since it is related to the uncertain or uncontrollable factors. The % error of 48.699% shows that the proposed method and the outcome are highly acceptable.

Confirmation of experiment

The experimental is done to verify the results. The confirmation run is performed at the predicted optimum conditions for significant factor and insignificant factors are set at economic level. The average of the results of the confirmation experiment is compared with the anticipated average based on the parameters and levels tested. The confirmation experiment is a crucial step and is highly

Table 10 — Response table for means (SR and MRR)

Level	Tool nose radius, (mm)	Tool rake Angle, (°)	Feed rate, (mm/rev)	Cutting speed, (m/min)	Cutting environment	Depth of cut, (mm)
Level 1	0.5485	0.5556	0.5578	0.5626	0.5057	0.6205
Level 2	0.5103	0.5159	0.4911	0.4903	0.5195	0.4820
Level 3	----	0.5167	0.5391	0.5352	0.5630	0.4856
Delta (max-min)	0.0382	0.0397	0.0667	0.0723	0.0574	0.1385
Rank	6	5	3	2	4	1

Table 11 — Analysis of variance for GRG (SR and MRR)

Source	SS	DOF	V	F ratio	P value	SS/	P (%)
Tool nose radius	0.006563	1	0.006563	Pooled	0.270	---	---
Tool rake angle	0.006185	2	0.003092	Pooled	0.535	---	---
Feed rate	0.014211	2	0.007105	Pooled	0.278	---	---
Cutting speed	0.016013	2	0.008006	Pooled	0.244	---	---
Cutting environment	0.010750	2	0.005375	Pooled	0.363	---	---
Depth of cut	0.074806	2	0.037403	8.40*	0.018	0.0659	42.450
T	0.155239	17	0.004452			0.155239	100.00
e (pooled)	0.026711	6				0.0756	48.699

S = 0.0667225 R-Sq = 82.79% R-Sq(adj) = 51.25%

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

Table 12 — Predicted and experimental values at optimal setting

Performance characteristics	Optimal combination	Predicted grey relational grade	Predicted value	Experimental value
Surface Roughness	A1B1C1D1E3F1	0.6205	2.837	3.076
MRR			344.59	340.61

recommended by Taguchi to verify the experimental conclusions[21]. Three confirmation experiments are done at the optimal settings of the turning process parameters recommended by the investigation. The optimal grey relational grade (μ_{GRG}) is predicted at the selected optimal setting of process parameters. The significant parameters with optimal levels are already selected as: F1. The estimated mean of the response characteristic is computed as per Ref.[21]

$$\mu_{GRG} = \overline{T_{GRG}} + (\overline{F1} - \overline{T_{GRG}}) \quad \ldots (8)$$

where $\overline{T_{GRG}}$ = overall mean of grey relational grade = 0.429

F1 is the mean values of grey relational grade with parameters at optimum levels. From Fig. 8, $\overline{F1}$ = 0.6205

Hence, μ_{GRG} = 0.812, A confidence interval for the predicted mean on a confirmation run is calculated using the Eq. (9)[21].

$$CI_{CE} = \sqrt{F_a(1, f_e) V_e \left[\frac{1}{n_{eff}} + \frac{1}{R}\right]} \quad \ldots (9)$$

where tabulated values of F_a; $(1, f_e)$ = 5.99

$\alpha = 0{\cdot}05$, f_e = error DOF = 6

N 18, V_e = 0.004452

Total DOF associated with the mean = 11

$n_{eff} = N/\{1 + [\text{Total DOF associated in the estimate of mean}]\} = 54 / (1 + 11) = 4.5$

R = number of repetitions for confirmation experiment = 3

A confidence interval for the predicted mean on a confirmation run is ± 0.1217

The 95% confidence interval of the predicted optimal grey relational grade is: $[\mu_{GRG} - CI] < \mu_{GRG} < [\mu_{GRG} + CI]$ i.e. $0.6903 < \mu_{GRG} < 0.9337$

Experimental results shown in Table 12 confirm the predicted values at optimum settings. The results show that GRA can generate reliable solutions. For more important comparability sequence, grey relational grade is higher. Therefore A1B1C1D1E3F1 is the condition for the optimal parameter combination of the turning of UD-GFRP to minimize average surface roughness and maximum material removal rate. This can be clearly presented by means of the grey relational grade graph. It shows the change in the response, when the factors go for their level 1 to level 3 as shown in Fig. 8. The greater value of average grey relational grades gives the low surface roughness and roundness.

Conclusions

The present work is concerned with determining the optimum setting of process parameters for multi-response optimization during turning of unidirectional glass fiber reinforced composite using PCD tool. The L_{18} OA is used for experimental planning. Fuzzy GRA is applied to determine optimal process parameters for optimization of surface roughness and material removal rate, which are investigated during rough cutting operation. In multi-response optimization, the analysis of means establishes that a of largest value of the GRG is for the lowest tool nose radius (0.4 mm), lowest tool rake angle of (-6°), largest feed rate (0.2 mm/rev), largest cutting speed (159.66 m/min), cooled cutting environment and the largest depth of cut (1.4 mm). Using GRA, optimal setting of process parameters for multiple performance characteristics is A1B1C1D1E3F1. By the average of grey relational grade analysis using Fuzzy logic, depth of cut followed by cutting speed is found to be the most influential factor for minimization surface roughness and maximization material removal rate in turning process. The work can be expanded in future by increasing the number of machining parameters. Problem analyzed be modeled by using artificial neural network and optimization can be followed by genetic algorithm, simulated annealing particle swarm optimization etc.

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