https://erjm.journals.ekb.eg
ISSN: 1110-1180

DOI: ---------

ERJ
Engineering Research Journal
Faculty of Engineering
Menoufia University

A Study of Surface Roughness and Material Removal Rate for Optimal Parametric Combination in Turning of GFRP Composites

A Bahei El-Deen

Production and Mechanical Design Dept., Faculty of Engineering, Menoufia University, Egypt

Ahmed.Basyouni@sh-eng.menofia.edu.eg

ABSTRACT

High surface quality and/or dimensional accuracy of the products produced by machining plays an important role in the part performance. The use of polymer materials is gradually replacing that of metallic materials. Due to their anisotropy and non-homogeneity, their machining behavior differs greatly from that of normal metallic materials. Because the phenomena responsible for material removal while cutting fiber reinforced plastic composite materials and those of typical metals and their alloys differ fundamentally, particular attention must be paid to the choice of the proper tool and machining conditions. The present study examines various turning process parameters, including cutting speed, feed rate, depth of cut, and their significance in determining the surface roughness and material removal rate of glass fiber reinforced polyester (GFRP) tubes. The experimental work is carried out on a CNC lathe. After turning the external diameter of the workpiece according to predetermined turning conditions, average surface roughness (Ra) was measured, and material removal rate (MRR) was calculated. The study utilizes the methodology of Grey Relational Analysis (GRA) and Analysis of Variance (ANOVA) to determine the optimal parametric combination giving the smallest values of Ra and the highest values of MRR. GRA and ANOVA of gray relational grade revealed that the spindle speed has the greatest impact on both Ra and MRR with a contribution percentage of 47.88%, followed by depth of cut with a contribution percentage of 22.03 %, and lastly feed rate with a contribution percentage of 16.86%.

Keywords: *Composites; Turning; GRA; Roughness; ANOVA.*

1. Introduction

Meenu and Surinder [1] looked into the turning process machinability of composites made of unidirectional glass fiber reinforced polymers (UD-GFRP). An orthogonal Taguchi L18 array was utilized to plan the experiment. Surface roughness and material removal rate were the two response variables that had been attempted to be modelled using Principal Component Analysis (PCA). It was clear from the experimental data that as feed rate increased, so did surface roughness. Additionally, it was shown that cutting speed and depth of cut were secondary to feed rate as the most important element. With reference to the most important recent research works in the area, Alessandra [2] conducted a study of the essential difficulties that are related to the machining of fiber reinforced plastic composite materials. According to his review, it was claimed that additional research into chip formation and the optimization of the machining process was needed to raise the caliber of machined parts. A summary of the key problems with regard to the machining of fiber-reinforced plastic composite materials was provided by Lopresto et al. [3] in their publication. For instance, they noted that detrimental fiber orientations relative to the cutting direction can seriously harm the workpiece. In order to significantly increase tool life in FRP composite machining, innovative tool materials, sophisticated tool design, and the best cutting parameter selection were needed. GFRP composite tubes with various fiber orientation angles were turned while being studied for power consumption by Hussain et al. [4]. With three distinct cutting tools, machining studies were conducted. The established L25 orthogonal array used in Taguchi's Design of Experiments (DOE) was the foundation for the experiments. A second order mathematical model was created using Response surface approach after the acquired data underwent statistical analysis using the ANOVA technique (RSM). As a result of the findings, it was concluded that the created model could accurately forecast the amount of power required to turn GFRP composites. Through experimental research and RSM-based optimization modelling combined with Genetic Algorithms, Rezaul et al. [5] addressed the analysis of surface roughness in rotating GFRP composite (GA). Cutting speed, feed rate, and depth of cut were taken into consideration as input parameters during the experiment in order to test the appropriate surface roughness response. The quadratic RSM model and GA were used to create the response model. To assess the impact of the input parameters, a main effect plot and a 3D surface plot were utilized, followed by a Desirability Function Analysis (DFA) using the response surface equation of the machining response. The GA technique was used to optimize the machining parameters. A literature review on the machinability characteristics and associated methods for CFRP and GFRP composite materials was undertaken by Meltem et al. [6]. ANOVA, ANN model, Taguchi's optimization methodology, Finite Element Method (FEM), and linear regression technique were all used to get the results of these investigations. With the use of optical, scanning electron, and profilometric microscopy, failure mechanisms and surface quality were explored. Rahul et al. [7] concentrated in their thesis on turning GFRP composite components using a single point HSS cutting tool. By using a grey Taguchi approach to combine the multiple responses into a single response, the most advantageous combination of process parameters (spindle speed, feed rate, and depth of cut) had been discovered in light of numerous requirements of machining performance, such as tool tip temperature and surface roughness. Rajesh et al. [8] aimed in their work to emphasize the research on GFRP composites and the manufacturing-related machining issues. They stated that it was not advised to machine composites using ordinary tools. Their method could be suggested for ongoing process/product quality improvement and offline quality control in any manufacturing environment. In their work, Srinivas and Venkatesh [9] sought to demonstrate the steps taken when applying the Taguchi Method to a lathe facing process. The performance parameters of the facing operation were investigated using the orthogonal array, signal-to-noise ratio, and analysis of variance. Surface roughness was assessed following the experiments, and the Signal to Noise ratio was computed. The best parameter values were discovered using graphs. During turning process, Khleif et al. [10] studied the impact of cutting tool form, coating material, and cutting parameters on surface roughness. Cutting tools with and without coatings (TIN) were employed. A computer numerically controlled (CNC) turning unit was used for the procedure. According to their findings, cutting speed was the most crucial factor in determining surface roughness, followed by feed rate and tool coating, in that order. While turning silicon carbide particle reinforced Al 7075 metal matrix composite in an atmosphere of air-water spray cooling, Diptikanta et al. [11] studied the effects of machining process parameters on average surface roughness and rate of material removal. For the responses, quadratic models were created. To simultaneously optimize surface roughness and material removal, Taguchi-based grey relational analysis was applied. Through Analysis of Variance, their findings supported the significance of process parameters on the multi-response quality index. The Multi-Objective Genetic Algorithm was used by Abdur et al. [12] to compare the best machining parameters for coated and uncoated carbide inserts for turning CFRP composites. It was discovered that while turning CFRP composites, coated carbide inserts produced lower tool wear and surface roughness but larger cutting forces compared to those of uncoated carbide inserts. The significance of their study focused on the differences in cutting force, tool wear, and surface roughness between coated and uncoated carbide inserts when turning CFRP composites. This was accomplished by combining various machining parameters and using data analysis tools like Taguchi Analysis, Regression Analysis, and Multi-Objective Optimization. Pankaj [13] employed the Taguchi approach to optimize metal removal rate (MRR) and surface roughness during machining operation on an aluminum alloy. The selected cutting parameters included feed rate, depth of cut, and shaft speed. To determine the rate of metal removal, turning was done using a CNC lathe. The main goal of the study was to investigate the effects of procedure parameters on the rate of metal removal and surface roughness during turning operations on aluminum composite using CNC machining.

With the aid of grey relation analysis, Sharma et al. [14] optimized machining parameters including feed, speed, and depth of cut to maximize material removal rate and to minimize surface roughness in CNC turning process performed on Aluminum alloy AA6262-T6 using an uncoated carbide insert tool under dry cutting conditions. The GRA prediction revealed a significant increase in Material Removal Rate of 14.55 percent and a significant decrease in Surface Roughness of 8.9 percent.

On AA6061 matrix-based hybrid composites reinforced with boron carbide and carbon nanotube tubes, Gnanavelbabu et al [15] accomplished CNC turning. Tangential force, cutting power, and tool wear were taken into account for the optimization along with various cutting rates, feeds, depths of cut, and percentages of B_4C. Taguchi L27 orthogonal array was used to guide the creation of the experimental design, and Grey-fuzzy analytical tool was used to guide the optimization. In accordance with G-Fuzzy analysis, the grey relational coefficient, grey relational grade, and grey fuzzy reasoning grade were produced. Modeling and study of the CNC machining of a cylindrical AA6082-T6 workpiece with a Tungsten Carbide tip tool were carried out by Aseerullah et al. [16]. CATIA V5 was used to create the first 3D model, and Ansys software was used to continue the investigation. To support the work, experimental and analytical findings were used. The spindle speed, feed rate, and depth of cut were the cutting parameters employed in CNC machining. In comparison to shear stress and shear strain, the percentage error number for normal stress fluctuated excessively. This demonstrated that aluminium could be used more effectively and was suited for machining procedures. Three distinct aluminium alloy-based composites were created by employing as matrix materials and graphene as a reinforcing material, and Joel and Anthony [17] investigated optimization on machining parameters of aluminium alloy hybrid composite using carbide insert. The process of hot extrusion after powder metallurgy was used to fabricate nano-composites. Turning tests were performed on the three composite extruded samples to examine their machinability. For the turning tests, five factors are taken into account: the kind of work material, the material of the cutting tool, the cutting speed, the feed rate, and the depth of cut. Three levels of each parameter are present in the Taguchi L18 mixed orthogonal array. The importance of each variable parameter on the response parameter was assessed using the experimental data and Analysis of Variance (ANOVA).

In the present study, external turning tests were performed to study the influence of cutting speed, feed rate and depth of cut on surface roughness and metal removal rate of glass fiber reinforced polyester tubes (workpieces) that had been wound using a wet and helical method with a fiber volume fraction (v_f) of 55% and a fiber orientation angle of ±55º. Turning tests were conducted by a CNC Lathe. In order to choose the best process parameter that produced better surface characteristics and a higher MRR, the impact of the chosen turning process variables (spindle speed, feed rate, and depth of cut) on surface roughness and MRR was also evaluated. The methodology of Grey Relational Analysis (GRA) was conducted to determine the optimal parametric combination giving the smallest values of Ra and the highest values of MRR of the turned GFRP tubes. Additionally, an ANOVA on Grey Relational Grade (GRG) was conducted to examine the impact of distinct parameters on the attributes of the output quality.

2. Experimental Work

2.1. Specimen Preparation

In the Delta Fiber facility in Cairo, Egypt, using the wet and helical filament winding process, four tubes measuring 50 cm long, 25 mm inside and 42 mm outside, consisting of oriented glass fibers at an angle of 55° and polyester were produced with a volume fraction (v_f) of 55% and an orientation angle of ±55º as shown in figure (1). Figure (2) displays the fabricated GFRP composite tubes. The actual specimens for CNC turning were cut from manufactured GFRP tubes at a length of 10 cm, an inner diameter of 25 mm, and an outer diameter of 40 mm. A thin layer of 2 mm was then removed from the external surfaces of the specimen by external turning operation at the initial cutting conditions, namely spindle speed of 400 rpm , feed of 0.08 mm/rev and depth of cut of 1mm. This new turned surface of all samples can be taken as a reference surface for subsequent turning tests. The properties of composite constituents are listed in Table (1) as specified and supplied by the manufacturer.

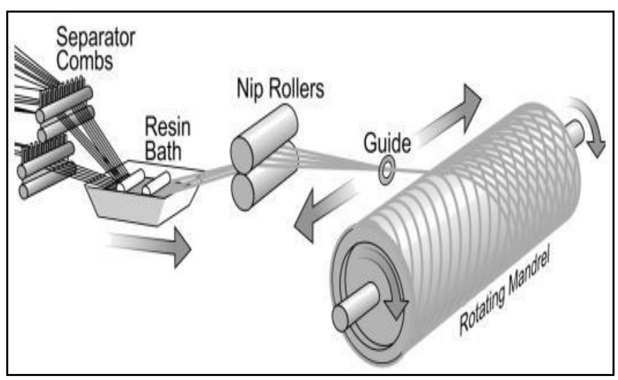

Figure 1- Filament winding method used to manufacture GFRP composite tubes

.

Figure 2- A photograph of the prepared GFRP specimen tubes cut from the initial filament wound tubes to be externally turned.

2.2. Plan of Experiments

Utilizing Taguchi's approach for three factors at three levels, the experimentation plan was developed. The turning process parameters and their ranges are given in Table (2). The L9 (3^3) array was selected, which has 9 rows equal to the number of tests. The L9 orthogonal array's experimental design is shown in Table (3).

Table 1- The mechanical properties of reinforcing phase and matrix phase of GFRP composite

Mechanical Property	Reinforcing phase (E-Glass fibres)	Matrix phase (polyester)
Modulus of Elasticity, GPa	72	1
Tensile Strength, MPa	3300	50
Poisson Ratio	0.2	0.28
Elongation at fracture, %	4.8	1

Table 2- Process parameters and their levels.

Levels	Process parameters and their levels		
	Spindle Speed(Ns),rpm	Feed (f),mm/rev	Depth of Cut(DOC), mm
1	500	0.10	1
2	750	0.15	1.5
3	1000	0.20	2

Table 3- Taguchi L9 (3^3) orthogonal array

Exp. No.	Spindle Speed(Ns),rpm	Feed (fr),mm/rev	Depth of Cut(DOC), mm
1	500	0.10	1.0
2	500	0.15	1.5
3	500	0.20	2.0
4	750	0.10	1.5
5	750	0.15	2.0
6	750	0.20	1.0
7	1000	0.10	2.0
8	1000	0.15	1.0
9	1000	0.20	1.5

2.3. Turning tests

At the engineering workshop in Sadat City, Egypt, external turning on GFRP composite specimens were performed under various cutting conditions, namely; spindle speed, feed and depth of cut using a CNC lathe made by German-Sieglo. As tool wear effect was not taken into consideration in the current work, nine test specimens in accordance with Taguchi orthogonal array L9 (3^3) were turned externally to a length of 50 mm by corresponding nine fresh cutting tools in dry lubrication. Figure (3) displays a picture of the experimental setup used for turning experiments. Figure (4) shows the nine brand-new HSS cutting tools used during the turning process, and Figure (5) shows the samples of turning process.

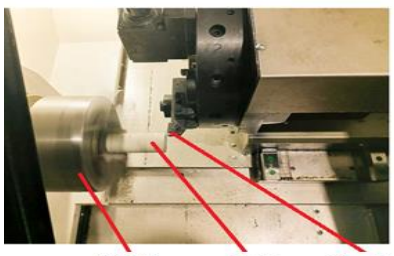

Figure 3- The photograph of the experimental set up during turning tests on CNC Lathe German – Sieglo.

Figure 4- Nine fresh HSS insert turning tools used for turning tests.

Figure 5- A photograph of GFRP tubes after turning along with their own fresh insert turning tools.

2.4. Surface Roughness Measurement

At the metrology lab at the college of engineering, Shebin El- Kom, Menoufia University, Egypt, the surface roughness measurements of the turned GFRP workpieces were taken using a portable roughness tester (TR 210) with setting of 12.5 mm traverse length and 2.5 mm cut-off value. This setting was selected according to the length of the turned workpiece which is 50 mm as stated previously. The workpieces were handled carefully to avoid scratching their surface and no further formal cleaning procedure was applied. The arithmetic mean value (Ra), which is expressed in µm, was used to measure the surface roughness parameter. Figure 6 depicts a snapshot of the GFRP composite specimen surface roughness measurement setup. The surface roughness measurements were made along the feed direction of the turned surface within a travelling distance of 37.5 mm for the moving stylus tip. This is due to the impossibility and the inaccessibility of stylus tip to travel though the total turned length (50 mm). Therefore only three measurements were made along the travelling length at an initial position of the workpiece. By rotating the workpiece by 90º, another three measurements were taken along the travelling length. Rotating workpiece and taking another three measurements were repeated three times besides the first three measurements taken at the initial position (position 1) of the workpiece. Therefore twelve measurements of surface roughness were made and averaged to a single value for each specimen as listed in Table 4. The initial surface roughness measurements of the reference surface of all samples before turning tests were measured and gave average surface roughness of 5.2 µm. Figure 7 is a schematic showing how the 12 measurements of surface roughness for each sample were determined at four positions of the workpiece along the travelling length. It is obvious from Table 4 that the measured values of surface roughness after turning tests were improved when compared to the initial surface roughness (5.2 µm) measured for sample preparation before turning tests.

Figure 6- A photograph of the surface roughness measurement setup of turned GFRP specimen

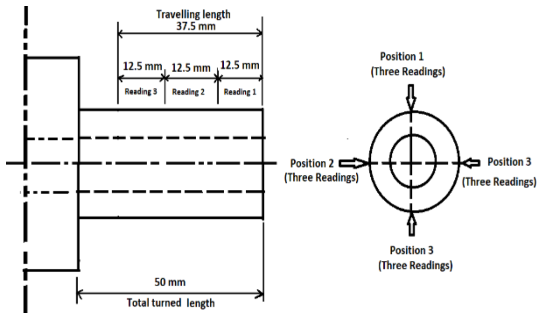

Figure 7: Different positions of the worepiece for surface roughness measurements

2.5. Material Removal Rate Measurement

The volume of the workpiece before and after turning operation, which represents the volume removed from the workpiece, has been used to compute the material removal rate. MRR was determined for each experiment by dividing the volume removed from the workpiece over the machining time recorded using a digital stopwatch during turning operation. Table (5) is a summary of MRR calculation.

3. Optimization methodology using Grey Relational Analysis (GRA)

Step 1:

First, the data must be normalized to remove any varying units and to lower the variability. Since the variation of one data differs from that of other data, it is essentially necessary. To create an array between 0 and 1, an appropriate value is deduced from the starting value. Generally speaking, it is a technique for transforming the original data into equivalent data [18]. Equation (1) is meant to normalize the reaction to scale it into an acceptable range if the response is to be minimized, with smaller-the-better characteristics.

$$x_i^*(k) = \frac{max\ x_i(k) - \ x_i(k)}{max\ x_i(k) - min\ x_i(k)} \qquad (1)$$

The larger-the-better characteristics are meant for normalization to scale the reaction into an appropriate range if the response is to be maximized. This is done using equation (2).

Table 4- Average values of surface roughness values after tuning tests

Exp. No.	1	2	3	4	5	6	7	8	9
Average (Ra), µm	4.82	2.35	3.52	1.73	1.25	1.63	2.19	2.66	2.02

Table 5- Measured values of Material Removal Rate (MRR)

Exp. No.	Removed Volume from workpiece, mm^3	Machining Time, T_m, sec.	MRR, mm^3/s
1	6128.6	63	97.3
2	9075	43	211
3	11942.9	33	361.9
4	9075	43	211
5	11942.9	28	426.5
6	6128.6	22	278.6
7	11942.9	33	361.9
8	6128.6	22	278.6
9	9075	17	533.8

$$x_i^*(k) = \frac{x_i(k) - min\ x_i(k)}{max\ x_i(k) - min\ x_i(k)} \qquad (2)$$

Where n is the number of replies and m is the number of experimental data, and i = 1,..., m; k = 1,..., n. $x_i(k)$ stands for the initial sequence, $x_i^*(k)$ for the sequence following data preprocessing, and max $x_i(k)$ for the highest value of the initial sequence. min $x_i(k)$ indicates the value of $x_i(k)$ that is the smallest [19].

Step 2:

Next step is to calculate grey relational coefficient, $\xi_i(k)$ from the normalized values by the following formula as follows:

$$\xi_i(k) = \frac{\Delta_{min} + \xi\Delta_{max}}{\Delta_{oi}(k) + \xi\Delta_{max}} \quad (3)$$

Where, Δ_{oi} is the deviation sequence of the reference sequence and the comparability sequence and $\Delta_{\mathrm{oi}} = \|\mathrm{x}_{\mathrm{oi}} - \mathrm{x}_{\mathrm{i}}(\mathrm{k})\|$

Where $x_i(k)$ is referred to as the comparability sequence and $x_{oi}(k)$ is the reference sequence. The absolute differences (Δ_{oi}) of all comparison sequences' minimum and maximum values are represented by the terms Δ_{min} and Δ_{max}. ζ is an identifying or distinguishing coefficient, with a range of 0 to 1. ζ is typically taken to have a value of 0.5.

Step 3:

To find out the grey relational grade (GRG) as follows

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k) \quad (4)$$

Where n is the number of answer characteristics and γ_i is the minimum required grey relational grade for the experiment in question. The correlation between the reference sequence and the comparability sequence is represented by the grey relational grade, which serves as a general representation of all the quality characteristics [18].

Step 4:

Then, using a greater grey relational grade, which denotes a higher level of product quality, an optimal level of process parameters is established. This can be accomplished by determining the average grade values for each level of the process parameter.

Step 5:

The analysis of variance (ANOVA) is then conducted to identify the relevant parameters influencing the multi-responses providing crucial information about the experimental data. ANOVA analysis will be useful to determine the percentage of contribution to identify the effects. The goal of ANOVA is to disentangle the contributions of each parameter and error from the response's overall variability (sum of squared deviations from the grand mean) [19].

3.1. Implementation of methodology to find multi-response parametric optimization

Step 1:

The experimental data are shown in Table (6) under the heading "grey relational generations" after being normalized for surface roughness and material removal rate using equations (1) and (2), respectively.

Step 2:

Equation (3) has been used to calculate the grey relational coefficients from the normalized data set of Table (6). Table (7) presents the grey relational coefficients.

Step 3:

The results of the grey relational coefficients have then been used to determine the grey relational grade (GRG) using Equation (4). Table (7) presents the GRG findings.

Step 4:

The effects of each process parameter at various levels are plotted and shown in Figure 8 from the value of GRG, and the mean grey relational grade is reported in Table (8). On the basis of higher mean grey relationship grade values from Table (8), the best parametric combination is selected. Greater performance and a stronger correlation to the reference sequence are represented by a higher value for the grey relational grade. Therefore, the optimal settings for multi-responses becomes, Ns2-f3-DOC2 (spindle speed of 1000 rpm, feed of 0.20 mm/rev, and depth of cut of 1.5 mm, respectively) .

Table 6- Grey relational generation values

Exp. No.	Normalized Ra	Normalized MRR
	Smaller the better	Larger the better
1	0.000	0.000
2	0.692	0.260
3	0.363	0.606
4	0.865	0.260
5	1.000	0.754
6	0.894	0.415
7	0.737	0.606
8	0.605	0.415
9	0.783	1.000

Table 7- Grey relational coefficient and grey relational grade values

Exp. No.	(Deviation Sequence) Evaluation of $\Delta 0i$		Grey Relational Coefficient (GRC)		GRG	Rank
	SR	MRR	SR	MRR		
1	1.000	1.000	0.333	0.333	0.333	9
2	0.308	0.740	0.619	0.403	0.511	6
3	0.637	0.394	0.440	0.559	0.500	8
4	0.135	0.740	0.788	0.403	0.596	5
5	0.000	0.246	1.000	0.670	0.835	2
6	0.106	0.585	0.825	0.461	0.643	3
7	0.263	0.394	0.655	0.559	0.607	4
8	0.395	0.585	0.559	0.461	0.510	7
9	0.217	0.000	0.697	1.000	0.848	1

The lower values of surface roughness and the highest values of MRR are given by the higher values of mean grey relational grade as shown in Figure (8). Table 8 shows that the spindle speed (Rank 1) has the greatest impact on Ra and MRR followed by depth of cut (Rank 2) and lastly feed rate (Rank 3) based on the difference of maximum and minimum values of mean GRG for the process parameters.

From Figure (8), the effect of process parameters on both Ra and MRR combined in a single response (mean GRG) could be analyzed in turning GFRP composites as anisotropic and heterogeneous materials differing in machining behavior from traditional metallic materials.

Table 8- Main effects on mean grey relational grade.

Level	(Ns), rpm	(f), mm/rev	(DOC), mm
1	0.4480	0.5120	0.4953
2	0.6913	0.6187	0.6517
3	0.6550	0.6637	0.6473
Delta	0.2433	0.1517	0.1563
Rank	1	3	2
Total mean grey relational grade = 0.5995			

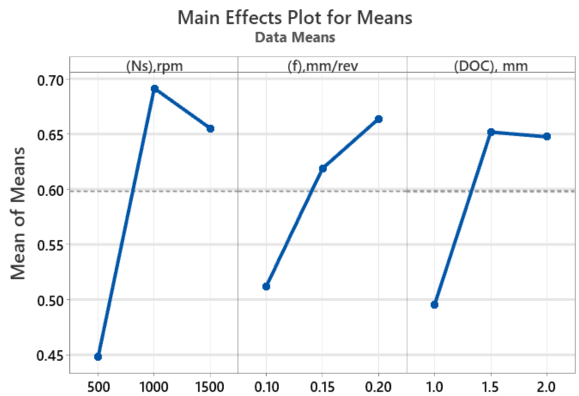

Figure 8- Main effect plot of grey relational grade

Concerning spindle speed effect, mean GRG increases as Ns increases from the lowest level (500 rpm) up to the middle level (1000 rpm). Then it decreases abruptly as Ns increases from the middle level up to the highest level (1500 rpm). At the highest level of spindle speed, the high principal cutting force results in a temperature rise in the composite causing matrix-fiber damages such delamination, matrix cracks, fiber breakage, fiber pullout, thermal matrix-fiber damages (heat affected zone) and fiber-matrix debond. These damages consequently results in higher Ra although MRR is increased due to increased cutting force. At the lowest level of spindle speed, the deformation and strain induced in the matrix and fiber reinforcing phases during cutting is small resulting in higher Ra and lower MRR. At the middle level (optimum level) of spindle speed (1000 rpm) the mean GRG has the highest value corresponding to lower Ra and higher MRR due to a moderate principal cutting force. Concerning feed effect, Mean GRG increase as feed increases from the lowest level (0.1 mm/rev) up to the highest level (0.2 mm/rev). At the highest level (optimum level) of feed, the effect of feed force on the temperature rise is small due to anisotropic and heterogeneous effects resulting in lower Ra and higher MRR. The high resistance and high shear strength of glass fibers and matrix make little effect of the feed force on the induced fiber-matrix damage.

At the lowest level of feed, the strain and deformation occurring in both the matrix and the fibers of composites during cutting is small resulting in higher Ra and lower MRR. Concerning depth of cut, Mean GRG increase as DOC increases from the lowest level (1mm) to the middle level (1.5 mm). Then it decreases slightly as DOC increases from the middle level up to the highest level (2 mm). This is because at the highest level of DOC, the high radial force results in a temperature rise leading to different fiber-matrix damages such as thermal damages. These damages results in higher Ra although MRR is increased due to increased depth of cut. At the lowest value of DOC, the small value of strain and deformation induced in the composite material results in higher Ra and lower MRR due to decreased depth of cut. Therefor at the middle level (optimum level) of depth of cut (1.5 mm), the mean GRG has the highest value equivalent to lower Ra and higher MRR at a moderate radial force. It can be said according to the previous analysis that GRA is a powerful tool in multioptimization of responses converted in a single response (GRG) rather than dealing with each response independently and separately as a single optimization technique like Taguchi's approach.

Step 5:

Next, analysis of variance (ANOVA) is formulated considering grey relational grade as shown in Table 9. ANOVA table gives the significance of process parameters on multi-responses. This method finds the crucial variables and determines the percentage influence of each variable on several quality traits like surface roughness and MRR. According to ANOVA of grey relational grade, the spindle speed (Ns), with a contribution percentage of 47.88%, the depth of cut (DOC) with a contribution percentage of 22.03 %, and lastly the feed rate (f), with a contribution percentage of 16.86%, were found to have an impact on surface roughness and material removal rate.

Table 9- Results of ANOVA on grey relational grade.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
(Ns),rpm	2	0.10338	%47.88	0.10338	0.05169	3.62	0.217
(f),mm/rev	2	0.03641	%16.86	0.03641	0.01820	1.27	0.440
(DOC), mm	2	0.04756	%22.03	0.04756	0.02378	1.66	0.375
Error	2	0.02857	%13.23	0.02857	0.01429		
Total	8	0.21592	%100.00				

4. Conclusions

This paper presents the findings of multi-criteria optimization of process parameters in turning of GFRP under dry environment through grey relational analysis combined with orthogonal array of Taguchi's approach.
Based on the analysis, following conclusions were drawn.

1- Based on Grey relation analysis, the optimal settings for multi-responses become , Ns2-f3-DOC2(spindle speed of 1000 rpm, feed of 0.20 mm/rev, and depth of cut of 1.5 mm)
2- From ANOVA on grey relational grade, the spindle speed (Ns), with a contribution percentage of 47.88%, the depth of cut (DOC) with a contribution percentage of 22.03 %, and lastly the feed rate (f), with a contribution percentage of 16.86%, were found to have an impact on surface roughness and material removal rate.

5. References

[1] Meenu Gupta and Surinder Kumar "Investigation of surface roughness and MRR for turning of UD-GFRP using PCA and Taguchi method" International journal of Engineering Science and Technology,18 (2015) 70-81.

[2] Alessandra Caggiano "Machining of Fiber Reinforced Plastic Composite Materials" Materials 2018, 11, 442.

[3] V. Lopresto, A. Caggiano and R. Teti "High Performance Cutting of Fiber Reinforced Plastic Composite Materials" Procedia CIRP 46 (2016) 71 – 82.

[4] Syed Altaf Hussain, V. Pandurangadu, K. Palani Kumar "Cutting power prediction model for turning of GFRP composites using response surface methodology" International Journal of Engineering, Science and Technology, Vol. 3, No. 6, 2011, pp. 161-171.

[5] Rezaul Karim, Sayem Ahmed, Samia Salahuddin "Optimization of Machining Parameter for Surface Roughness in Turning GFRP Composite Using RSM-GA Approach" American Journal of Materials Science and Engineering, 2018, Vol. 6, No. 1, 18-25.

[6] Meltem Altin Karatas and Hasan Gökkaya "A review on machinability of carbon fiber reinforced polymer (CFRP) and glass fiber reinforced polymer (GFRP) composite materials" Defence Technology 14 (2018) 318:326.

[7] Rahul Ghatole, Sagar Birari, Mayur Murtadak,Vijayant Patil "Study of Optimization of Machining Performance Yields During Turning of GFRP Composites: A Grey Based Taguchi Approach" IJARSE, Vol.(5), Issue (2), 2016.

[8] Rajesh Kumar Verma, Saurav Datta and Pradip Kumar Pal "Machining of Unidirectional Glass Fibre Reinforced Polymers (UD-GFRP) Composites" Int. J. Mech. Eng. & Rob. Res Vol. 4, No. 2, April 2015.

[9] Srinivas Athreya and Y.D.Venkatesh "Application of Taguchi method for optimization of process parameters in improving the surface roughness of lathe facing operation" International Refereed Journal of Engineering and Science (IRJES), Volume 1, Issue 3 (November 2012), PP.13-19.

[10] Ali Abbar Khleif, Farhad M Othman and Frzdaq Nabeel Thamer "Experimental and numerical investigation of cutting parameters, coated and uncoated tools on surface roughness during turning operation" IOP Conference Series: Materials Science and Engineering, 1094 (2021) 012152.

[11] Diptikanta Das, Amit Chapagain, Ramesh Kumar Nayak, Bharat Chandra Routara "Multiple-response optimization for surface quality and productivity during turning Al 7075/SiCp composite in spray cooling environment" materials today: PROCEEDINGS, Vol. 5, Issue 9, Part 3, (2018) 18052-18060.

[12] S M Abdur Rob and Anil K. Srivastava "Turning of Carbon Fiber Reinforced Polymer (CFRP) Composites: Process Modeling and Optimization using Taguchi Analysis and Multi- Objective Genetic Algorithm" Manufacturing Letters 33 (2022) 29–40.

[13] Pankaj Kumar Singh "Optimization of Machining Parameters for Turning of Aluminium Alloy-2011 using Taguchi Method" IOP Conf. Series: Materials Science and Engineering, 1116, (2021) 012092.

[14] Rahul Sharma, Kamal Sharma, Bhupendra Kumar Saraswat "Machining process parameters optimization of Aluminium Alloy AA6262 T6

for CNC Turning by Grey Relational Analysis" IOP Conf. Series: Materials Science and Engineering , 1116. (2021) 012016.

[15] A Gnanavelbabu , V Arunachalam1, K T Sunu Surendran1 and K Rajkumar "Optimization of machining parameters in CNC turning of AA6061-B4C-CNT hybrid composites using Grey-fuzzy method" IOP Conf. Series: Materials Science and Engineering 764 (2020) 012010.

[16] Mohd Aseerullah, C. Bhushan and R. Vishwakarma "Analysis of CNC turning process of AA6082-T6 using Ansys software" IOP Conf. Series: Materials Science and Engineering, 1259 (2022) 012017.

[17] Joel J and Anthony XaviorM "Optimization on machining parameters of aluminium alloy hybrid composite using carbide insert" Mater. Res. Express 6 (2019) 116532.

[18] Haq, A. N., Marimuthu, P., & Jeyapaul, R. "Multi response optimization of machining parameters of drilling Al/SiC metal matrix composite using grey relational analysis in the Taguchi method". The International Journal of Advanced Manufacturing Technology, 2008, 37(3-4), 250-255.

[19] Tosun, N., & Pihtili, H. "Gray relational analysis of performance characteristics in MQL milling of 7075 Al alloy". The International Journal of Advanced Manufacturing Technology, (2010),46(5-8), 509- 515.

[19] Datta, S., Bandyopadhyay, A., & Pal, P. K. "Slag recycling in submerged arc welding and its influence on weld quality leading to parametric optimization". The International Journal of Advanced Manufacturing Technology, 2008, 39(3-4), 229-238.