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Optimization of Machining Parameter for Surface Roughness in Turning GFRP Composite Using RSM-GA Approach

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Abstract This paper deals with the analysis of surface roughness in turning GFRP composite through experimental investigation and Response surface methodology (RSM) based optimization modeling incorporated with Genetic Algorithm (GA). The investigation has been carried out in dry condition where cutting speed, feed rate and depth of cut has been considered as input parameters to check the desired surface roughness response. This experiment has been designed using RSM central composite design (CCD). Afterwards the response model has been formulated using quadratic RSM model and Genetic algorithm. The correlation coefficient value of 0.9989 suggests the adequacy of the formulated model. Main effect plot and 3D surface plot have been used to evaluate the effect of input parameters followed by Desirability Function Analysis (DFA) through response surface equation of the machining response. Machining parameters were then optimized using GA approach which indicated that to attain advantageous machining response cutting speed and feed rate need to be at 78 m/min and 0.10 mm/rev respectively. These findings are also analogous with the result of DFA which validates both the model. By employing the model, surface roughness of as minimum as 0.056 μm can be achieved.

Keywords: *GFRP composite, turning, surface roughness, response surface methodology, desirability function analysis, genetic algorithm*

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1. Introduction

Glass Fiber Reinforced Polymers (GFRPs) is a fiber reinforced polymer made of a plastic matrix reinforced by fine fibers of glass. Although strength properties are somewhat lower than carbon fiber and it is less stiff, the material is typically far less brittle, and the raw materials are much less expensive. Its bulk strength and weight properties are very favorable when compared to metals, and it can be easily formed using molding processes [1,2].

Composite materials are replacing the traditional materials, because of its superior properties such as high tensile strength, low thermal expansion, high strength to weight ratio. The developments of new materials are on the anvil and are growing day by day. Natural fiber composites such as sisal and jute polymer composites became more attractive due to their high specific strength, lightweight and biodegradability. Among different composite materials, fiber-reinforced polymer (FRP) composites show a tremendous increase in application due to combined properties of high strength or stiffness, low density, good corrosion as well as fatigue resistance. Mixing of natural fiber with Glass-Fiber Reinforced Polymers (GFRPs) are finding increased applications [3]. Although in common occurrence, composite products are manufactured with near-net shapes, secondary processes involving machining are often necessary as to achieve the required geometrical shapes and dimensional tolerances.

Various machining processes such as turning, drilling and milling have been used to machine composite materials for different product requirements. Despite the existing experience in machining traditional materials such as metals, it has been a challenge to maintain consistent results in terms of machining quality for composite materials [4]. Turning is a commonly used machining operation in the industry, producing a variety of components and meeting high accuracy and reliability requirements. Mating surfaces for many tribological applications are processed currently by turning operations. Turning of GFRPs differs from turning of metals, because of their anisotropic and inhomogeneous material. The physical and thermal properties of fibers and polymer matrix are different and depend largely on the type of fiber, fiber content, fiber orientation and variability in the matrix material. This fact has an important influence on the machinability and the tribological behavior of GFRPs **[5]**. During most research, Researchers are focused on the influence of cutting speed, feed rate and depth of cut on the delamination damage and surface roughness on Glass Fiber Reinforced Polymeric composite material (GFRP) during end milling. Reddy S. employed taguchi analysis to investigate the machining characteristics of GFRP. From the results of ANOVA, it is concluded that cutting speed and depth of cut are the most significant factors affecting the responses based on their percentage of contribution in an order of 26.84% and 40.44% respectively [7].

An attempt has been made to model the surface roughness through response surface method (RSM) in machining GFRP composites by K. Palinikumar. Analysis of variance (ANOVA) was used to check the validity of the model & also significant parameters student's t-test was practiced. Surface finish of GFRP composite work piece have been identified by using cutting speed, work piece fiber orientation angle, depth of cut and feed rate. At that study it was found that very high cutting speed was found to cause a large deformation rate of glass fiber and it produces imperfection in surface and hence the cutting speed has been fixed between 50 and 200 m/min [9].

In an attempt to analyze the effect of surface roughness is drilling fiber-reinforced plastics, Ranjan et. al developed a model that predicted surface roughness to evaluate the effect of feed rate and drill bit diameter while reducing surface roughness. The combined effect of the process parameters on both the surface roughness, namely R_a and R_q are quite similar while different from the delamination factor (F_d). Smaller value of drill diameter was required for the minimum surface roughness. Feed rate was stated to have significant effect on the response parameters while the spindle speed being the negligible one [6].

In a research, Wang J. studied on turning of Fiber Reinforced Plastics (FRPs) with Polycrystalline Diamond (PCD) tool which reported that surface roughness increases with increase in feed rate and decreases when cutting speed increases [10,11]. Petropoulos and Mata dealt with studying the impact of cutting conditions (cutting speed and feed) on surface roughness in turning of Polyamide PA-6, using two different cutting tool materials namely, Polycrystalline Diamond (PCD) and K15 cemented carbide. By applying Response surface methodology (RSM) and Analysis of Variance (ANOVA) to the experimental data. The suggested models using RSM exhibit admirable correlation; the calculated coefficients of determination varied from 0.988 to 0.996 for turning with the K15 tool and from 0.988 to 0.992 using the PCD tool. Finally, it was shown that RSM may be applied for modelling the behavior of surface roughness in turning of a polyamide material [12].

Application of Taguchi and response surface methodologies for minimizing the surface roughness in machining glass fiber reinforced (GFRP) plastics with a polycrystalline diamond (PCD) tool was investigated by K. Palanikumar. In that attempt, cutting speed, feed and depth of cut were used as cutting parameters. The effect of cutting parameters on surface roughness was evaluated and the optimum cutting condition for minimizing the surface roughness was determined. The surface roughness in the turning process was being measured for machining of GFRP composites under different cutting conditions with a PCD tool using Taguchi's orthogonal array, in the study he assessed the machining parameters on the surface roughness with the help of Taguchi method, followed by optimized machining conditions to minimize the surface roughness. Feed rate was found to be the dominant parameter for surface roughness followed by the cutting speed [13]. However, while evaluating the influence of machining parameters on the machining of GFRP composites, a procedure was developed to measure the chosen factors to attain minimum surface roughness by incorporating: response table and response graph; normal probability plot; interaction graphs and analysis of variance (ANOVA) technique by L. Karunamoorthy et al. [14].

This presented study reveals the impact of different cutting parameter while turning GFRP composites under dry cutting condition considering a range of cutting speed, feed rate and depth of cut. Experimental data is taken using coated carbide insert. Main effect plot and 3D surface plot is used to evaluate the impact of various parameters while a predictive modeling is developed using quadratic model. However, not a lot of attempt has been made to model surface roughness using combined RSM-GA approach. This research work suffices the need of incorporating RSM-GA approach while establishing a fairly effective modeling of surface roughness.

2. Materials and Methods

2.1. Materials and Experimental Details

To attain objective of this experimental work, GFRP composite (epoxy matrix with 65% of glass fiber) were used. Glass fiber reinforced epoxy composite were fabricated using a plastic cylindrical mold with a fiber orientation of ± 60º. Dimension of the work-piece which was a solid cylindrical bar was length of 300 mm and an external diameter of 100 mm. The experimental investigation was carried out using a center lathe machine by using coated carbide insert. Experimental set up is shown in Figure 1.

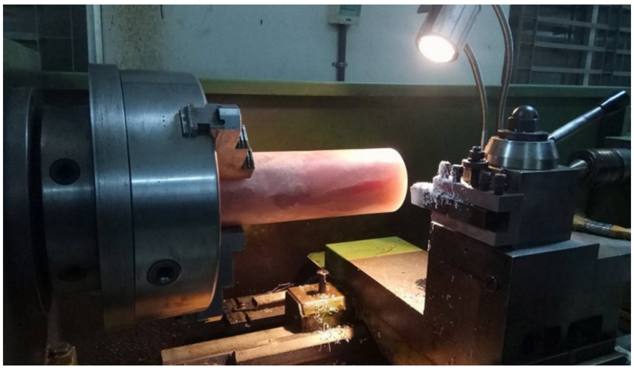

Figure 1. Experimental Setup

In this work machining was initiated with sharp insert and was performed under dry cutting condition with three level of depth of cut, cutting speed and feed rate. The measurements were carried out by varying three machining parameters: Cutting speed (v_c), feed rate (f) and depth of cut (s) which was considered as input variables and dispersed into levels as shown in Table 1. The combinations of machining parameter and surface roughness values are shown in Table 2.

Table 1. Assignments of factor to different level

Variables	Units	Low	High	-alpha	+alpha
Depth of Cut	mm	1	2.5	1	2.5
Cutting Speed	m/min	78	190	78	190
Feed Rate	mm/rev	0.1	0.14	0.1	0.14

Table 2. Experimental design matrix with input variables and measured responses

		Factor 1	Factor 2	Factor 3	Response 1
Std	Run	A:Depth of Cut (mm)	B:Cutting Velocity (m/min)	C:Feed Rate (mm/rev)	Surface Roughness (μm)
3	**1**	1	190	0.1	0.485
9	**2**	1	134	0.12	1.915
19	**3**	1.75	134	0.12	1.9
17	**4**	1.75	134	0.12	1.87
14	**5**	1.75	134	0.14	2.67
8	**6**	2.5	190	0.14	1.99
20	**7**	1.75	134	0.12	1.902
10	**8**	2.5	134	0.12	1.89
11	**9**	1.75	78	0.12	2.57
5	**10**	1	78	0.14	3.34
18	**11**	1.75	134	0.12	1.92
15	**12**	1.75	134	0.12	1.9
6	**13**	2.5	78	0.14	3.32
16	**14**	1.75	134	0.12	1.93
1	**15**	1	78	0.1	1.81
2	**16**	2.5	78	0.1	1.79
4	**17**	2.5	190	0.1	0.46
13	**18**	1.75	134	0.1	1.14
12	**19**	1.75	190	0.12	1.23
7	**20**	1	190	0.14	2.01

2.2. Response Surface Methodology

Response surface methodology establishes the relationships between several explanatory variables and one or more responses or outcomes. RSM is an empirical modeling approach for determining the relationship between various process parameters and responses for establishing the significance of these process parameters on the coupled responses. It is basically a combination of design of experiments, regression analysis and statistical inferences. RSM model can be utilized to state the degree of co-relation between one or more response and some selected control variables, to determine through goodness of fit-statistical significance of the factors connected with a particular response and to determine the optimum settings within the higher or lower level of control variables to minimize or maximize the response of interest [15].

In present work, central composite design(CCD) concept of RSM was adopted to design the experimental run. CCD design is frequently used together with response models of the second order. Statistical analysis of variance (ANOVA) is also connected with RSM.

2.3. Genetic Algorithm

Genetic algorithm in one of the most evolutionary optimization algorithms which have been implemented successfully in the past for typical multi-objective optimization problems by researchers. [16,17,18,19] GA starts with a randomly generated population of individuals, each one made by strings of the design variables, representing a set of points spanning the search space. Each individual is suitably coded into a chromosome made by a string of genes: each gene encodes one of the design parameters, by means of a string of bits, a real number or other alphabets.

In present investigation, an optimization technique, based on genetic algorithms was implemented to optimize the cutting parameters in turning processes and to predict surface roughness.

3. Results

3.1. Analysis of Variance

Analysis of variance for the response surface models were conducted in this study. Sum of squares (SS), degree fo freedom (df), mean square (MS), F-value and P-value for all the input variables along with their square and interaction terms are shown in Table 3. From the table, cutting velocity seems to have most dominance influence. The Model F-value of 5228.68 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

P-values less than 0.0500 indicate model terms are significant. In this case, B (cutting velocity) and C (feed rate) are most significant model terms.

Table 3. ANOVA for surface roughness

Source	Sum of Squares	df	Mean Square	F- value	p-value	
Model	10.27	9	1.14	5228.68	< 0.0001	significant
A-Depth of Cut	0.0012	1	0.0012	5.54	0.0404	
B-Cutting Velocity	4.43	1	4.43	20284.20	< 0.0001	
C-Feed Rate	5.84	1	5.84	26768.05	< 0.0001	
AB	3.125E-06	1	3.125E-06	0.0143	0.9071	
AC	3.125E-06	1	3.125E-06	0.0143	0.9071	
BC	3.125E-06	1	3.125E-06	0.0143	0.9071	
A^2	2.750E-06	1	2.750E-06	0.0126	0.9129	
B^2	0.0000	1	0.0000	0.1543	0.7027	
C^2	6.188E-06	1	6.188E-06	0.0283	0.8697	
Residual	0.0022	10	0.0002			
Lack of Fit	0.0001	5	0.0000	0.0283	0.9993	not significant
Pure Error	0.0021	5	0.0004			
Cor Total	10.28	19				

Table 4. Fit summary response for surface roughness

Linear	< 0.0001	1.0000	0.9997	0.9998	Suggested
2FI	0.9965	0.9999	0.9997	0.9997	
Quadratic	0.9647	0.9993	0.9996	0.9997	
Cubic	0.9956	0.9888	0.9993	0.9997	Aliased
Std. Dev.	0.0148		R^2		0.9998
Mean	1.90		Adjusted R^2		0.9996
C.V. %	0.7768		Predicted R^2		0.9997
			Adeq Precision		275.8289

Moreover, Fit summary response for surface roughness is shown in Table 4 where R^2 value is 0.9998 suggesting a very reasonable goodness of fit of the model. The adjusted R^2 value of 0.9996 is in reasonable agreement with predicted R^2 value.

3.2. Main Effect Plot and 3D Response Surface Plot

With respect to input parameters, measure of mean of surface response is studied here. We can visualize the main effect plot for surface roughness with respect to depth of cut, cutting speed and feed rate form Figure 2. It is suggested that lower surface roughness value is assocciated with higher depth of cut and higer cutting speed whereas, minimum surface roughness an be obtained using lower feed rate value. Cutting speed and feed rate cause great array of surface roughness which associated with the findings of ANOVA analysis.

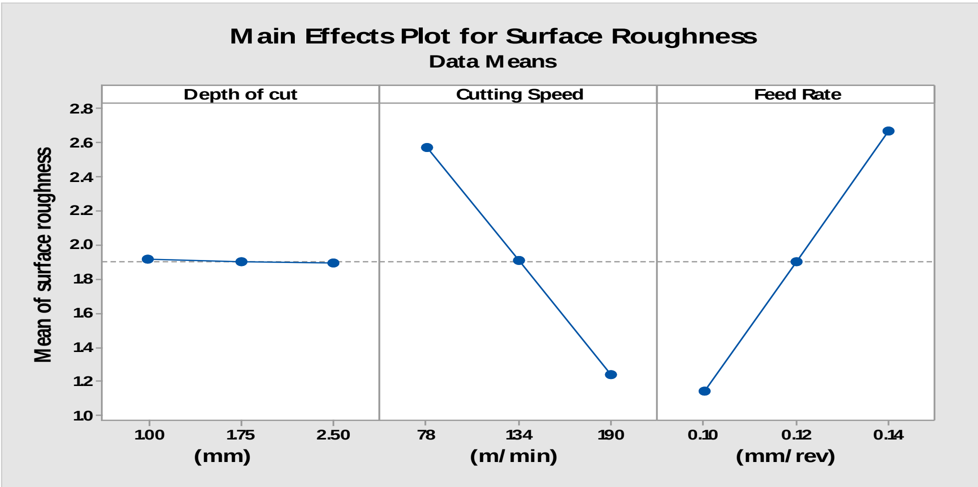

Figure 2. Main effects plot for surface roughness

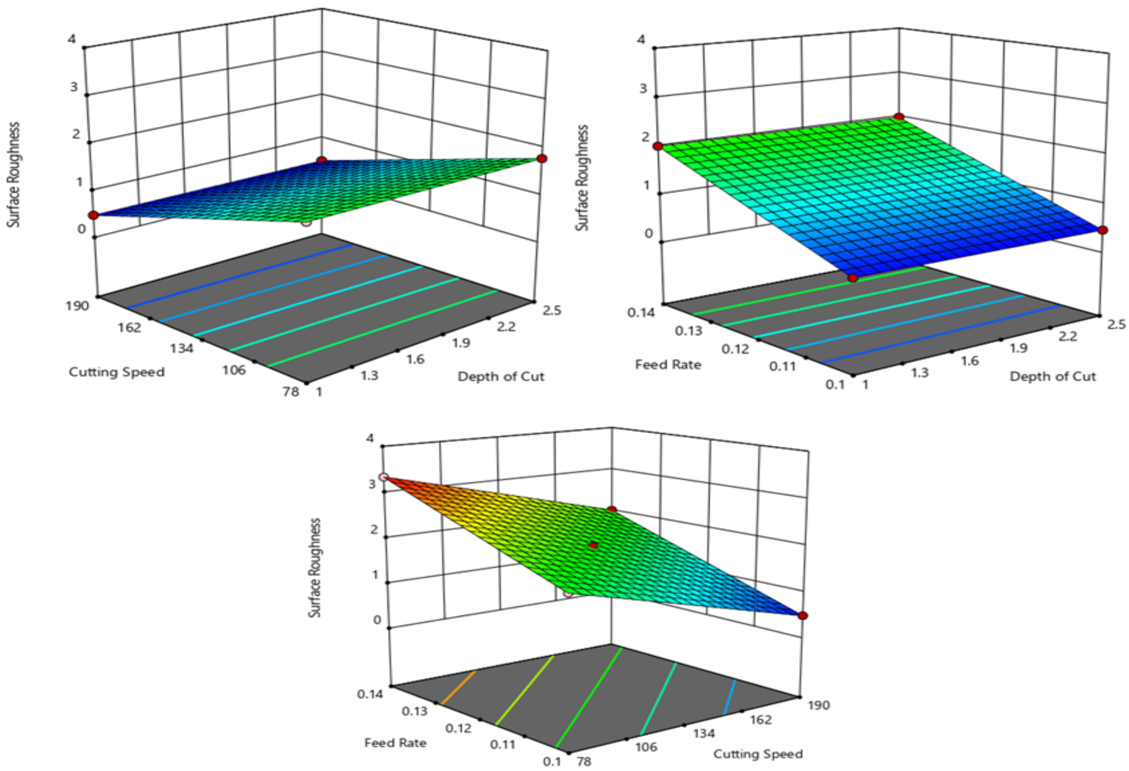

Figure 3. 3D surface plot of surface roughness with respect to cutting speed and depth of cut, with respect to feed rate and depth of cut and with respect to feed rate and cutting speed

A **3D surface plot** is a three-dimensional **graph** that is useful for investigating desirable response values and operating conditions. It is used to see how a response variable relates to two predictor variables. From Figure 3, we can visualize that higher cutting speed, lower feed rate and lower-to-medium depth of cut is responsible to generate lower surface roughness.

3.3. Quadratic Model by RSM

Quadratic equation developed by RSM is shown in by eqn. (1). As found from the analysis correlation co-efficient (R^2) is found to be 99.98% which indicate that formulated RSM value can be used to predict the surface roughness value.

$$\begin{aligned} R = & -1.04048 - 0.011450 * d - 0.011492 * V_c \\ & + 37.32686 * f - 0.000015 * (d * V_c) \\ & + 0.041667 (d * f) - 0.000558 (V_c * f) \\ & - 0.001778 * d^2 - 1.11607E-06 * V_c^2 + 3.75 f^2. \end{aligned} \quad (1)$$

3.4. Comparison of Experimental Values with RSM Model

The predicted surface roughness value by RSM are shown in Table 5. The assocaiated absoute percentage error (APE) has also been calcuated. As there are very little variation of data in between experimental and predicted surface roughness value, APE in most case is very minimal. As a result Mean absoute percentage error value is as low as 0.305%.

Linear regression for the both experimental and RSM predicted values of surface roughness are shown in Figure 4. R^2 value of 0.9994 and 0.99186 thus proves the effectiveness of the developed model.

3.5. Optimization by Desirability Function

Multi-objective numerical optimization by desirability function was conducted by employing response surface equations of the machining response. Desirability is an objective function (D), the value of which ranges from 0 to 1 [20]. This function can find out a point in a specific space within the constraints level of factor settings as shown in Table 6.

Optimum solutions are mentioned in Table 7. According to the best result (desirability = 1), the optimum cutting parameters of 2.496 mm depth of cut, feed rate of 0.10 mm/rev and cutting speed of 189.962 m/min can produce optimum surface roughness value of R = 0.46 µm. Desirability of individual factor and response are portrayed in Figure 5.

Table 5. Comparison of experimental surface roughness with RSM predicted values

Run	Experimental Surface Roughness (µm)	RSM Predicted Surface Roughness (µm)	APE (%)	MAPE (%)
1	0.485	0.483	0.325	
2	1.915	1.914	0.075	
3	1.9	1.904	0.187	
4	1.87	1.904	1.794	
5	2.67	2.670	0.017	
6	1.99	1.988	0.106	
7	1.902	1.904	0.082	
8	1.89	1.904	0.082	
9	2.57	2.566	0.172	
10	3.34	3.341	0.029	**0.305**
11	1.92	1.904	0.857	
12	1.9	1.904	0.187	
13	3.32	3.321	0.043	
14	1.93	1.904	1.370	
15	1.81	1.812	0.108	
16	1.79	1.792	0.003	
17	0.46	0.459	0.241	
18	1.14	1.444	0.049	
19	1.23	1.235	0.369	
20	2.01	2.012	0.004	

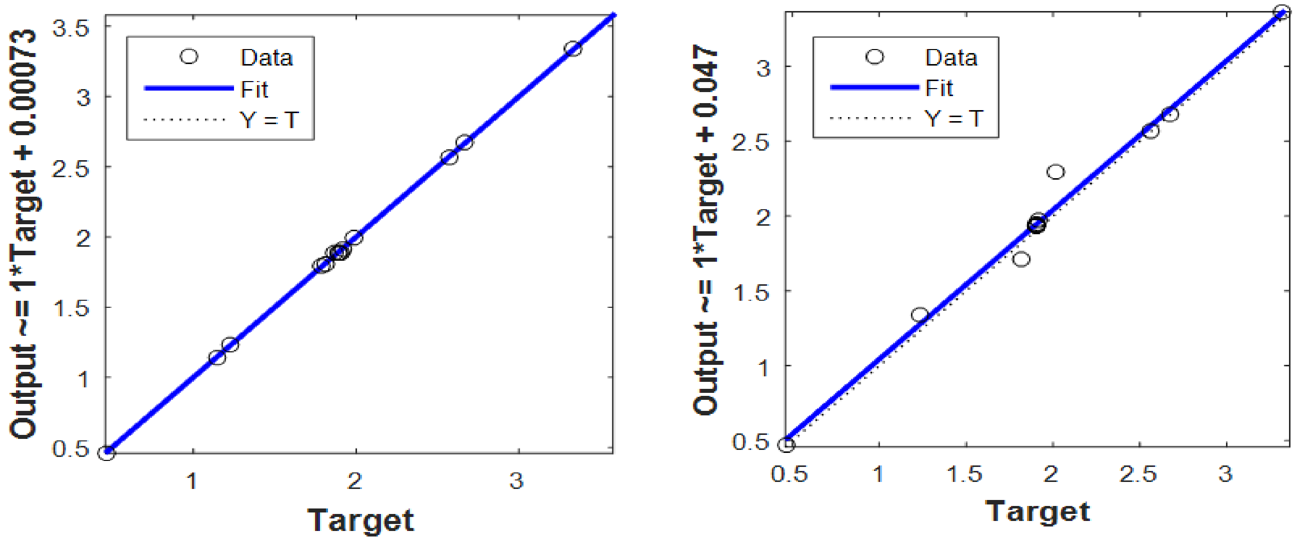

Figure 4. Linear Regressions plot for Experimental values of surface roughness (**R^2 = 0.99994**) and RSM Predicted values of surface roughness (**R^2 = 0.99186**)

Table 6. Constraints of the desirability optimization

Name	Goal	Lower Limit	Upper limit	Lower weight	Upper weight	Importance
A:Depth of Cut	is in range	1	2.5	1	1	3
B:Cutting Speed	is in range	78	190	1	1	3
C:Feed Rate	is in range	0.1	0.14	1	1	3
Surface Roughness	is target = 0.46	0.46	3.34	1.04713	1	3

Table 7. Desirability optimization solutions

No.	Depth of Cut	Cutting Velocity	Feed Rate	Surface Roughness	Desirability	
1	**2.496**	**189.963**	**0.100**	**0.460**	**1.000**	**Selected**
2	2.450	189.999	0.100	0.460	1.000	
3	2.457	189.984	0.100	0.460	1.000	
4	2.465	189.974	0.100	0.460	1.000	
5	2.471	189.991	0.100	0.460	1.000	
6	2.489	189.960	0.100	0.460	1.000	
7	2.443	190.000	0.100	0.460	1.000	
8	2.433	190.000	0.100	0.460	1.000	
9	2.361	190.000	0.100	0.462	0.999	
10	2.350	190.000	0.100	0.462	0.999	
11	2.327	190.000	0.100	0.462	0.999	

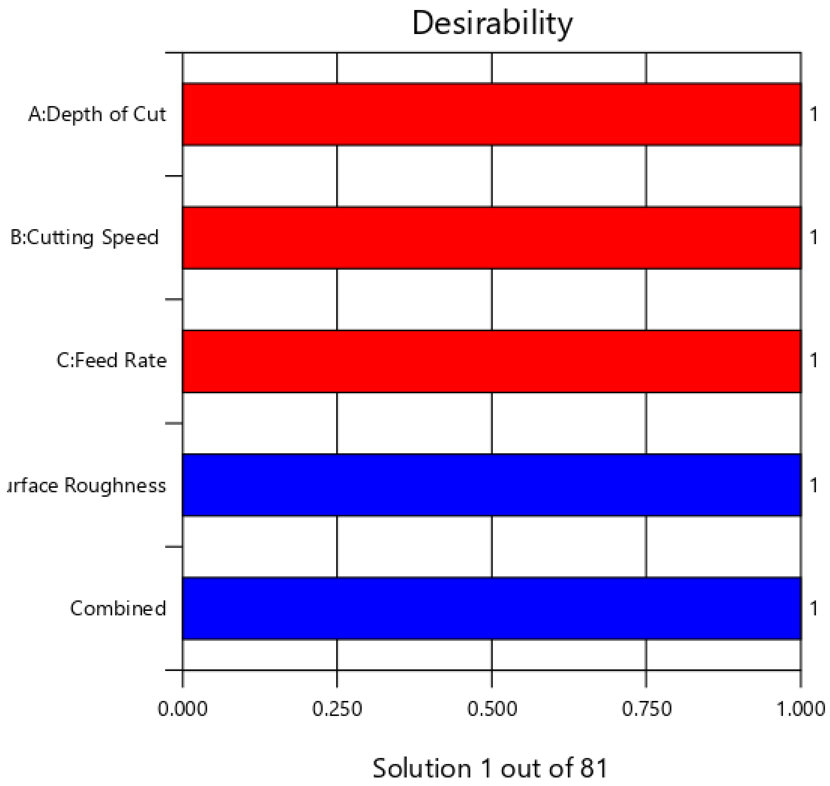

Figure 5. Bar chart of individual desirability

3.6. Optimization by GA

Optimization algorithm are the branch of intelligent methods used to find optimal machining conditions [21]. In this study objective function was to minimize the surface roughness and the constrains are: depth of cut from 1.0 to 2.5 (mm), cutting speed from 78 to 190 (m/min) and feed rate from 0.10 to 0.14 (mm/rev) The optimized roughness value which was found from the Algorithm was 0.467956 µm. So, the value close to or equal to the optimized value should be selected. The optimal achieved value for roughness and cutting conditions for optimum machining after using genetic algorithm has been shown in Figure 6.

For surface roughness prediction, we selected the following evolutionary parameters: population size 50, maximum number of generations to be run 300, probability of migration 0.2, probability of crossover 0.8.

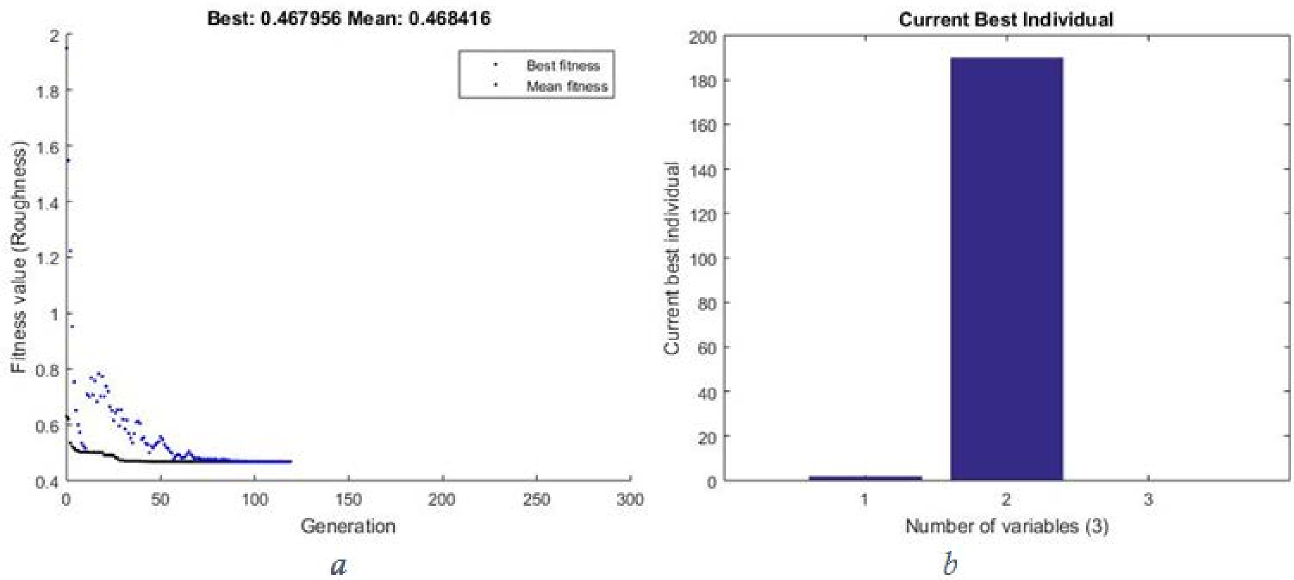

Figure 6. Optimal value selection of (a) surface roughness and (b) cutting speed using genetic algorithm

4. Discussion

This research works deals with the possibilities of performing specific machining operation in difficult to machine polymer matrix composite. Experimental investigation was conducted to analyze the effect of various machining parameters in turning glass fiber reinforced composite. Cutting speed, feed rate and depth of cut was considered as input parameter whereas surface roughness was measured as response parameter. Experimental run was taken under dry cutting condition followed by predictive modeling of surface roughness by RSM. Afterwards, by using Desirability function analysis and Genetic Algorithm, machining parameter were optimized. From experimental run and data analysis, findings can be listed as follows:

- From Analysis of variance for surface roughness using ANOVA, Model P-value from ANOVA is found to be at 0.0001 which signifies that the model is significant. It was found that cutting velocity seems to have the most dominant factor followed by Feed rate.
- It is suggested that to generate lower surface roughness, higher cutting speed and lower feed rate is advantageous under specified cutting conditions. Depth of cut of lower-to-medium range can suffice the objective of lessening the response parameter. In this instance, cutting speed is 190 m/min and feed rate is 0.10 mm/rev.
- The quadratic model by RSM can be used to predict surface roughness value merely accurately as the mathematical model suggested that correlation coefficient value (R^2) is at 99.98 % whereas after implementing predictive modeling R^2 value is at 99.97%. This clearly indicated the validation of the quadratic equation-based modeling.
- While modeling for surface roughness by RSM, mean absolute percentage value (MAPE) was found 0.305%. whereas, linear regression curve for experimental and RSM predicted values of surface roughness proves to generate an outstanding correlation coefficient value (R^2) of 0.99994 and 0.99186 respectively which clearly indicates the authenticity of the quadratic model.
- Desirability function analysis recommended that ideal surface response value of 0.46 µm can be achieved when feed rate is 0.10 mm/rev and cutting speed is at 189.96 m/min and depth of cut is 2.496 mm.
- Based on Genetic Algorithm it is suggested that to retain the surface roughness at its minimum value which is 0.467956 in this scenario, cutting speed need to be kept at 190 m/min followed by a feed rate 0.10 mm/rev and depth of cut of 2.5 mm which is also allied with the desirability function analysis and thus validating both the models.

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Conflicts of Interest

The authors declare no conflict of interest.

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