MODELING AND PREDICTION OF SURFACE ROUGHNESS IN CYLINDRICAL TRAVERSE CUT GRINDING OF GLASS FIBRE REINFORCED EPOXY COMPOSITE

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Abstract

Materials composed of glass fibre reinforced epoxy composite (GFRP) are getting utilised more and more in fields of engineering. There have been significant progress in the manufacturing of such materials with outstanding levels of dimensional accuracy and exquisite finish. The purpose of the present investigation is to examine how the grinding variables infeed, longitudinal feed, and work speed affect SR in GFRP materials during traverse cut cylindrical grinding. The trial runs have been carried out using a full factorial approach. The impacted elements have been identified using main effect plots and the ANNOVA procedure. The modelling and optimisation of the grinding process to achieve the least amount of SR has been suggested employing RSM combined with a hybrid GA. The anticipated grinding situation has been validated with a confirmation test Materials composed of glass fibre reinforced epoxy composite (GFRP) are getting utilised more and more in fields of engineering. There have been significant progress in the manufacturing of such materials with outstanding levels of dimensional accuracy and exquisite finish. The purpose of the present investigation is to examine how the grinding variables infeed, longitudinal feed, and work speed affect SR in GFRP materials during traverse cut cylindrical grinding. The trial runs have been carried out using a full factorial approach. The impacted elements have been identified using main effect plots and the ANNOVA procedure. The modelling and optimisation of the grinding process to achieve the least amount of SR has been suggested employing RSM combined with a hybrid GA. The anticipated grinding situation has been validated with a confirmation test..

Keywords: Surface roughness (SR), Response surface method (RSM), Full Factorial Design, Cylindrical Traverse cut grinding, Genetic Algorithm (GA) integrating hybrid function

I. INTRODUCTION

In extremely corrosion-prone and exceptionally efficient industrial applications, fiber-reinforced composites have taken the place of stainless steel and various other metals. They are appealing in many industries, including the the aerospace sector, oil, gas, and processing industries, due to their lightweight, mechanical robustness, and chemical resistance. To make precise pieces, GFRP needs to be machined. Due to its anisotropy and non-homogeneous structure, composites cannot be machined like conventional metals [1, 2].

Surface finish is a crucial technological factor in metal cutting operations that has received significant focus for several years now. It is a significant aspect that affects the produced part's functional properties and production costs. For a component to work properly, getting the right SR is crucial [3]. Understanding the mechanics of material extraction and the kinetics of machining operations that affect the effectiveness of the cutter [4] is essential for producing finely finished machined components and relies on the proper selection of process variables. Researchers have looked into drilling and turning processes that occur during the machining of GFRP materials [1, 5]. However, other applications, such as those for automobile, aerospace, and aeroplane parts, demand reasonable high levels of dimensional accuracy, form accuracy, and a high-quality surface finish. When it comes to hard or composite materials like GFRP, aluminium alloys, etc., grind is one of the practical techniques to achieve accurate and extremely close tolerances [6]. However, the grinding process is constrained in its ability to attain precise levels, i.e., attaining better SR, by a number of interacting variables.

The roughness of the surface is a criterion for the components technical quality and has a significant impact on the cost of production and functional properties of the ground part [7]. It is exceedingly challenging to determine the value of SR using theoretical investigation since the procedure underlying its generation is very dynamic, intricate, and process-dependent [8]. Using process optimisation, which necessitates a thorough understanding of the phenomena, particularly in regard to the connection among the process factors and outcome characteristics [9], acceptable surface roughness values can/may be obtained.

Using a factorial approach, the response surface methodology (RSM), paired with a GA (genetic algorithm) with a hybrid function, and a cylindrical traverse cut grinding operation, the current work is intended to investigate the influence of process variables on SR when machining a glass fibre reinforced epoxy composite material.

II. DESIGN OF EXPERIMENTS

In the current research, it is intended to investigate how several significant process variables affect the SR of GFRC components that are being grinded traverse cut cylindrically. To accomplish this, a statistical technique is employed, which is an effective tool for optimising complicated systems and which, in comparison to the conventional trial-and-error method, can minimise the quantity of tests. The term "design of experiment" (DOE) refers to this strategy. In DOE, it is possible to purposefully modify one or more process factors in order to track how those modifications affect one or more response variables. It is a useful method for organising the studies in a way that allows the information collected to be analysed to produce reliable, unbiased results. Full factorial design, RSM, and Taguchi design approaches are important methods in experiment design and are effective at analysing the results and potential interactions between various variables. Applications of complete factorial design and RSM are employed in the current investigation to analyse and model the SR in the cylindrical grinding operation.

A FFD is one wherein each configuration of each variable appears alongside each configuration of every other variable. Design responses are assessed across all possible combinations of the experimental variables' levels, allowing researchers to investigate the impacts of every variable on the response parameter while also examining the influence of factor interaction on the response parameter. A factorial study may be analysed utilising ANNOVA , and estimating the primary consequences for a variable is quite simple. A 3-factor (infeed, longitudinal feed, and work speed) 3-level FFD of experiment was used to determine the implications of grinding variables and their relationships on SR and to establish the optimum grinding settings via main effect plot. The first tableau displays the full factorial design table. The acquired findings were analysed using analysis of variance (ANOVA) based on the linear statistical model and main effect plot was generated utilising the mean of SR.

To investigate the link among one or more response factors and a set of quantitative experimental factors, response surface approach is employed. RSM can be used to identify operational circumstances that result in the most favourable outcome, meet process standards, and identify novel conditions for operation that generate products of greater quality than the quality attained. The quantitative form of the association among the response that is wanted and the independent input parameters can be expressed in the RSM as follows,

$$Y = f(A, B, C) \quad (1)$$

where A, B, and C are the input grinding variables and Y is the response that needs to be optimised.

The factors that are independent (input variables) are considered to be continuous and controllable by trials with minimal errors. The model used in this work is a second-degree response surface, which can be stated as below.,

$$Y = \beta 0 + \beta 1\ (A) + \beta 2\ (B) + \beta 3\ (C) + \beta 11\ (A^2) + \beta 22\ (B^2) + \beta 33\ (C^2) + \beta 12\ (AB) + \beta 13\ (AC) + \beta 23\ (BC) \quad (2)$$

where, all β's are regression coefficients determined by the least square method.

III. EXPERIMENTAL PROCEDURE

The set for experimentation includes a grinder, tail & head stock, workbench, and cooling equipment.. Glass fibre reinforced epoxy composite work-piece is placed between head stock and tail stock of the cylindrical grinding machine.

As the variables for input, 3 different levels of the 3 process factors are chosen: infeed (A) = 0.04, 0.05, and 0.06 mm/cycle; longitudinal feed (B) = 70, 80, and 90 mm/s; and work speed (C) = 80, 112, and 160 rpm. Tests have been carried out as per full factorial design table (27 numbers of experiments). Details of full factorial design are given in section 2. SR was determined after the trials were completed through a stylus-type Profilometer: Talysurf (Taylor Hobson, Sutronic 3+). SR is assessed and averaged at three distinct points on every single component. Table 1 displays the full factorial design matrix and recorded surface roughness values. Root mean square roughness (Rq) is an important roughness parameter, which is treated as technological quality of the machined surface, selected for present analysis.

IV. RESULTS AND ANALYSIS

As already mentioned above, full factorial design has been done and the corresponding output response i.e. surface roughness (Rq) is measured. The output results along with full factorial design matrix are shown in Table 1. These data have been used to analyze and optimize the cylindrical grinding process to improve / minimize the surface roughness by using ANOVA and RSM cum GA with hybrid function.

1. **Analysis of Surface Roughness:** Analysis of variance is performed on experimental data in order to determine the significant direct and interaction effects of process parameters that influence the surface roughness. ANOVA test is made at 95% confidence interval and is shown in Table 2. In ANOVA, P- value is the probability value that is used to identify the significant factors. The importance of the data can be judged by its P-value, if the p-value is zero or closer zero corresponding parameter is considered as most significant. If its value is less than or equal to 0.05 then the effect of the corresponding factor is considered statistically significant. According to obtained P-value, it found that the effect of infeed (A) and the interaction effects of infeed - longitudinal feed (A – B) are statistically significant as their P values are less than 0.05.

Table 1: Full Factorial Design and Output Response

Sr.	Input Parameters			Output Responses
	A	B	C	SR
1	0.04	70	160	2.283
2	0.06	90	80	3.823
3	0.06	90	160	2.080
4	0.05	90	80	1.893
5	0.06	80	112	2.199
6	0.05	90	112	2.793
7	0.04	80	112	4.233
8	0.05	90	160	2.196
9	0.04	80	80	3.811
10	0.04	70	112	2.726
11	0.04	90	80	2.980
12	0.06	70	80	2.523
13	0.05	70	112	3.286
14	0.04	90	160	2.000
15	0.06	80	80	2.129

16	0.05	80	80	2.526
17	0.04	80	160	3.330
18	0.05	70	80	3.533
19	0.05	80	160	2.416
20	0.06	80	160	1.946
21	0.04	70	80	2.143
22	0.06	70	112	1.800
23	0.06	90	112	2.223
24	0.05	80	112	2.906
25	0.04	90	112	2.423
26	0.06	70	160	2.450
27	0.05	70	160	4.112

2. **Factor Effects:** The major effect plots (Fig. 1) are used to investigate how process variables affect surface roughness and also to assess the importance of the components as well as their individual impacts. The greater the disparity across the lowest and highest values in each variable, the greater the influence on surface roughness. According to Fig. 1, infeed (A) has the greatest effect as the variation within the lowest and highest possible values of the input variables is greater than that of longitudinal feed and work speed. Surface roughness (Rq) reduces with increasing infeed and work speed, as illustrated in Figure 1. Surface roughness increases initially and subsequently reduces as longitudinal feed increases.

Table 2: ANOVA for surface roughness (Rq)

Source	DF	Adj SS	Adj MS	F Value	P Value
A	2	1.58	0.7	5.25	0.03
B	2	0.58	0.29	1.95	0.20
C	2	0.37	0.18	1.25	0.34
A-B	4	6.74	1.68	11.1	0.002
A-C	4	1.39	0.34	2.30	0.14
B-C	4	1.23	0.30	2.04	0.18
Error	8	1.20	0.15		
Total	26	13.1			

The model's appropriateness was examined using residual analysis. The discrepancy among the measured and anticipated responses is known as residuals, and it is evaluated through a normal probability plot and a residuals vs. predicted response plot. The residual dots in the normal probability graph ought to form a line that is straight if the model is acceptable. The graph of residuals vs. projected response, should be structureless, with no discernible trend. The residuals fall on a straight line in the normal probability plot (Fig. 2), implying that the errors have a normal distribution. The graphical representation of residual vs. predicted / fitted surface roughness values (Fig. 3) shows the fact that there is no discernible pattern or distinctive structure which indicates that the model suggested is appropriate, and there is no indication for believing that the independence or constant variance assumptions have been violated. [10, 11].

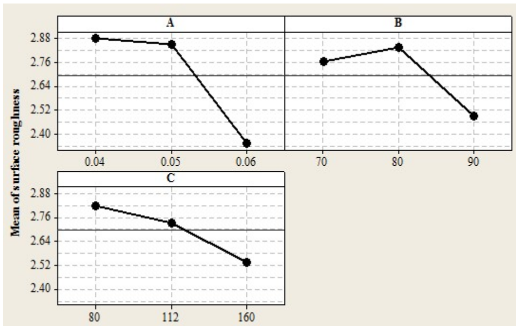


Figure 1: Main effects plot for surface roughness

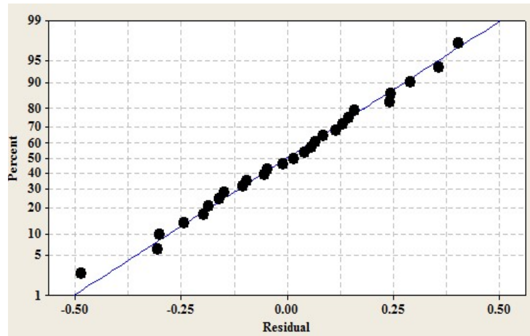
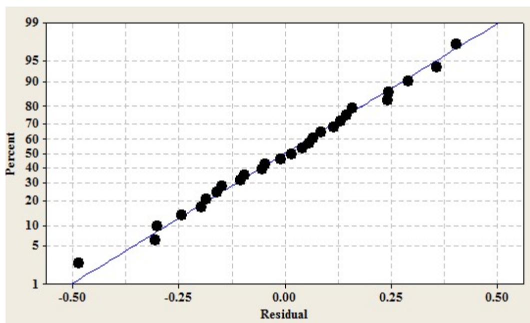


Figure 2: Normal probability plot of residual for surface roughness



3. **Development of Mathematical Model:** In the current investigation, RSM, which is an ensemble of statistical and mathematical methods for empirical development of models, is employed for establishing an appropriate functional association among the response factors (surface roughness, YRq) and the input parameters infeed (A), longitudinal feed (B), and work speed (C). Eq. 2 depicts a second degree mathematical model. Values of all the constants β_0 , β_1 , β_2 , β_3 , β_{11} , β_{22} , β_{33} , β_{12} , β_{13} and β_{23} are determined through the use of experimental results and the application of RSM. Eq.3 depicts the built model.

   YRq = -16.3834 + 143.314*A + 0.347704 *B + 0.0563665 *C - 2344.44*A2 - 0.00206944 *B2 - 0.0000178819*C2 + 0.918333*A*B - 0.0746436 * A*C - 0.000648520 *B*C (3)

4. **Parametric Optimization for better Surface Finish using a Hybrid function with the Genetic Algorithm:** Genetic algorithms are chaotic global exploration and optimisation techniques for addressing optimisation issues. They use operations that imitate the process of natural evolution to determine the best mix of genes, or the best solution to an issue. A collection of individual solutions is continuously modified by the genetic algorithm. At every iteration of a GA, the procedure generates a fresh group of individuals based on their level of fitness in the subject domain and reproduces them via operators derived from natural genetics. The population advances towards the best possible outcome over subsequent generations. Because of the nature of the GA's search, it serves as an excellent technique for determining global optimum values [12-14]. Surface roughness is predicted using the Optimisation toolkit in MATLAB software

version 7.1. The GA optimisation toolset of MATLAB handles the basic operators of GA such as reproduction, crossover, and mutation, and then ultimately presents the optimum circumstances for the desired / lowest value of Rq.

Genetic algorithm can often find global optima within a reasonable time limit, but sometimes it takes a bit longer time to find that optimum point. In the present work, hybrid function combined with GA (i.e. FMINUNC cum GA) has been proposed to solve the mathematical model (Eq.3) to optimize the grinding process more accurately with minimum time frame. Fminunc will begin optimizing at the best point returned by the GA. This function uses a fast derivative based method and it is mainly used for unconstrained minimization problems [14]. Following steps are involved in using the hybrid function combined with GA toolbox in MATLAB software.

- Choosing the function of fitness (i.e. the goal function)
- Choosing the quantity of parameters used for input.
- Setting the smallest and higher bounds for the input variables: the lowest limit = (0.04, 70, and 80), higher limit = (0.06, 90, and 160), then running the solver.

At each run in the GA with hybrid function toolbox, a new set of optimum condition is generated by the GA and when it steps the hybrid function start from the final point returned by GA. Because fminunc can effectively find the minimum in a smooth region and transition to this function once the GA brings the solution into this region. This approach needs only 15 generations to find the optimum value. In the present problem, fminunc is used as output function, which called after each iteration of GA. Best fitness plot is made from the hybrid function with GA and shown in Fig. 4. Optimal parametric condition found by the hybrid function with GA is: surface roughness (Rq) = 1.821 μm at infeed (A) = 0.06 mm/cycle, longitudinal feed (B) = 90 mm/s and work speed (C) = 160 rpm. This condition is obtained in the range of the input parameters used in the study.

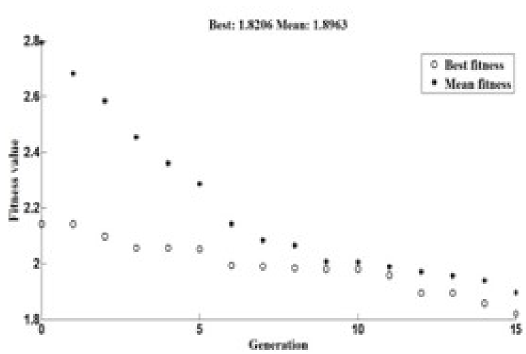


Figure 4: Best fitness value plot

5. **Confirmatory Findings:** To examine / authenticate the proposed process, a confirmation trial is performed under optimised grinding conditions and it is possible to conclude that the optimised parametric combo provided surface roughness (Rq) = 1.853 m, which is deemed the minimal within the tested spectrum (Table 1).

V. CONCLUSION

This paper has described the use of hybrid methodology (full factorial design, RSM and hybrid function with GA) for analyzing, modeling and optimizing the surface roughness (Rq) value in traverse cut cylindrical grinding of glass fibre reinforced epoxy composite material. From the study, the following conclusions are drawn.

The ANOVA findings for;

- It is found that infeed and interaction between infeed and longitudinal feed have significant effect on surface roughness (Rq) value.
- Main effects plots revel that infeed is the most significant factor which has more influence on Rq next is work speed followed by longitudinal feed. Second order mathematical model is developed through RSM to correlate the input parameters and output response. This mathematical model can be used for predicting Rq value for a given set of grinding parameters.
- The optimum grinding condition found by solving the mathematical model by using hybrid function with GA is: surface roughness (R_q) = 1.821 μm at infeed = 0.06 mm in each cycle, longitudinal feed = 90 mm/s and work speed = 160 rpm.
- The result obtained through GA optimization has been validated by confirmatory test.
- The proposed hybrid methodology (full factorial design, RSM cum hybrid function with GA) is expected to be useful for optimization of any machining process accurately in respect of surface roughness or any other response(s), individually.

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