Modeling and Prediction of Surface Roughness in Cylindrical Traverse Cut Grinding of Glass Fibre Reinforced Epoxy Composite

Dr. Arun Patil[*1], Dr. Anil Wanare[*2]
[1]Asst. Prof. JSPM, BSIOTR,Wagholi, [2]Prof. JSPM, BSIOTR,Wagholi
[1]patil.mailme@gmail.com,
[2] alwanare_entc@jspmbsiotr.edu.in

Abstract— **Glass fibre reinforced epoxy composite (GFRP) materials are increasingly used in many engineering applications. Making these materials with a high level of dimensional accuracy and fine finish has increased enormously. Present work is planned to investigate the effects of grinding parameters infeed, longitudinal feed and work speed on surface roughness in traverse cut cylindrical grinding of GFRP composites. Full factorial design has been used to conduct the experimental runs. Analysis of variance technique and main effect plots graph has been used to identify the influenced factors. Response surface methodology cum genetic algorithm with hybrid function has been proposed to model and optimize the grinding process to attain the minimum surface roughness. A confirmatory test has been conducted to validate the predicted grinding condition.**

Keywords— **Cylindrical traverse cut grinding, surface roughness, full factorial design, response surface methodology, genetic algorithm with hybrid function**

I. Introduction

Fiber-reinforced composite materials are replaced stainless steel and other materials in highly corrosive as well as high performance industrial applications. Their low weight, mechanical strength and chemical resistance make them attractive in many fields such as aerospace, oil, gas and process industries. The machining of GFRP is required to produce accurate parts. The machining of composite is different from the other metals due to its anisotropic and non-homogeneous nature [1, 2].

Surface finish is an important technological parameter in metal cutting processes which has serious attentions for many years. It is key factor which influences manufacturing cost and operational characteristics of the machined part. Obtaining the desired surface finish is of great importance for the functional behaviour of a part [3]. For achieving fine finished machined parts, it is necessary to understand the mechanisms of the material removal, kinetics of the machining processes affecting the performance of the cutting tool [4] and also depends upon correct choice of process parameters. Some researchers had done investigation on drilling, turning operations while machining of GFRP materials [1, 5]. But some applications like aerospace, automotive/ aircraft parts etc. need reasonably high dimensional, form accuracy and good surface finish. Such cases grinding is one of the practical ways to obtain those accurate / close tolerances on composite / hard materials such as GFRP, aluminium alloys etc. [6]. But, Lot of interactive parameters are associated in grinding process which limiting ability of grinding process to reach accurate levels, i.e., obtaining better surface roughness value.

Surface roughness is a measure of the technological quality of a product and a factor that greatly influences manufacturing cost and operational characteristics of the ground part [7]. The mechanism behind the formation of surface roughness is very dynamic, complicated and process dependent in nature and it is very difficult to calculate its value through theoretical analysis [8]. Good surface roughness values can / may obtain through process optimization, which needs a deep knowledge of the phenomena, mainly concerning the relationship between the process parameters and output characteristics [9].

Present work is planned to study the effects of processes parameters on surface roughness by using factorial design – response surface methodology (RSM) cum genetic algorithm (GA) with hybrid function in cylindrical traverse cut grinding operation while machining of glass fibre reinforced epoxy composite material.

II. DESIGN OF EXPERIMENTS

The present work is planned to study the effect of some important process parameters on surface roughness in traverse cut cylindrical grinding of GFRC work-pieces. In doing so, a statistical approach is used, which is a powerful tool to optimize complex systems; it can also reduce the number of experiments compared to the traditional trial and error method This approach is known as design of experiment (DOE). In DOE, one can consciously change one or more process variables in order to observe the effect the changes have on one or more response variables. It is an efficient procedure for planning the experiments so that the data obtained can be analyzed to yield valid and objective conclusions. Major approaches in design of experiments are full factorial design, response surface methodology and Taguchi design. These are efficient at evaluating the effects and possible interactions of several factors. In the present analysis, applications of full factorial design and RSM are used for analyzing and modeling the surface roughness in cylindrical grinding process.

A design in which every setting of every factor appears with every setting of every other factor is a full factorial design. In these, design responses are measured at all combinations of the experimental factor levels and it allows studying the effects of each factor on the response variable, as well as the effects of interactions between factors on the response variable. A factorial experiment can be analyzed using analysis of variance and it is relatively easy to estimate the main effects for a factor. For determining the effects of grinding parameters and their interactions on the surface roughness, and to find the optimum grinding conditions through main effect plot, a three-factor (infeed, longitudinal feed and work speed) three-level full factorial design of experiment has been used. Full factorial design table is shown in Table 1. Analysis of variance (ANOVA) based on the linear statistical model has been used to analyze the obtained results. Main effect plot has also been drawn based on mean of surface roughness.

Response surface methodology is used to examine the relationship between one or more response variables and a set of quantitative experimental variables. RSM may be applied, where one can finds the operating conditions that produce the best response, satisfy process specifications and identifies new operating conditions that produce improved product quality over the quality achieved. In the RSM, the quantitative form of relationship between the desired response and independent input variables can be represented as follows,

$$Y = f\,(A, B, C) \tag{1}$$

where, A, B, C are input grinding parameters and Y is the response, which is required to be optimized. Here, it is assumed that the independent variables (input parameters) are continuous and controllable by experiments with negligible errors. In this study, the model chosen is a second-degree response surface expressed as follows,

$$Y = \beta_0 + \beta_1 (A) + \beta_2 (B) + \beta_3 (C) + \beta_{11} (A^2) + \beta_{22} (B^2) + \beta_{33} (C^2) + \beta_{12} (AB) + \beta_{13} (AC) + \beta_{23} (BC) \tag{2}$$

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

III. EXPERIMENTAL PROCEDURE

The experimental set consists of several systems, such as grinding wheel, tail stock, head stock, work table and cooling system. Glass fibre reinforced epoxy composite work-piece is placed between head stock and tail stock of the cylindrical grinding machine.

Three varied levels of the three process variables: 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 are selected as input parameters. Experimental runs have been conducted as per full factorial design table (27 numbers of experiments). Details of full factorial design are given in section 2. After completing the experiments, surface roughness has been measured using stylus-type Profilometer: Talysurf (Taylor Hobson, Sutronic 3+). Surface roughness is measured in three different places of each work piece and averaged. Full factorial design matrix and measured surface roughness values shown in Table 1. 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 (R_q) 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.

A. 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 I

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

B. Factor Effects

The main effect plots (Fig. 1) are drawn to study the effects of process parameters on surface roughness. The significance of the factors and also individual effects can be evaluated from these plots.

The higher the difference between the minimum and the maximum value in each factor is the higher the effect on the surface roughness. Fig. 1 indicates that infeed (A) has the highest effect because difference between the minimum and maximum values of input parameters is higher as compared to longitudinal feed and work speed. From Fig. 1, it also can be observed that surface roughness (R_q) decreases with the increase of infeed and work speed. Surface roughness is increased initially and then decreases with the increase of longitudinal feed.

TABLE II
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 adequacy of the model has been investigated by the examination of residuals. The difference between the respective observed response and the predicted response is called residuals; those are examined by using normal probability plot and plot of the residuals vs. predicted response. if the model is adequate, the residual points on the normal probability plot should from a straight line. On the other hand, the plot of residuals vs. predicted response should be structure less i.e., it should contain no apparent pattern. From the normal probability plot (Fig. 2), it is found that the residuals fall on a straight line; it implies that the errors are distributed normally. The plot of residual vs. predicted / fitted surface roughness values (Fig. 3) reveals there is no obvious pattern and unusual structure. This implies that the proposed model is adequate and there is no reason to suspect any violation of the independence or constant variance assumption [10, 11].

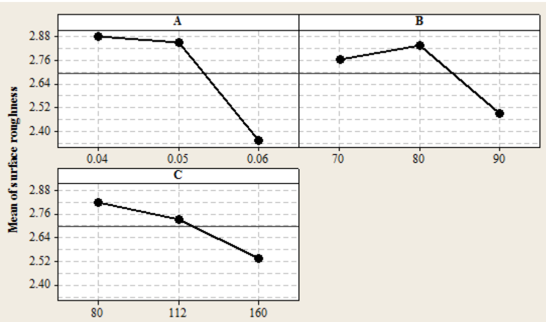

Fig. 1 Main effects plot for surface roughness

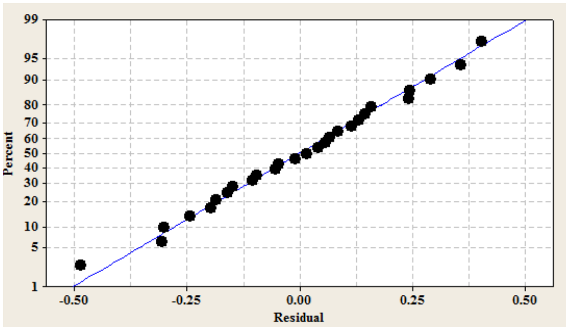

Fig. 2 Normal probability plot of residual for surface roughness

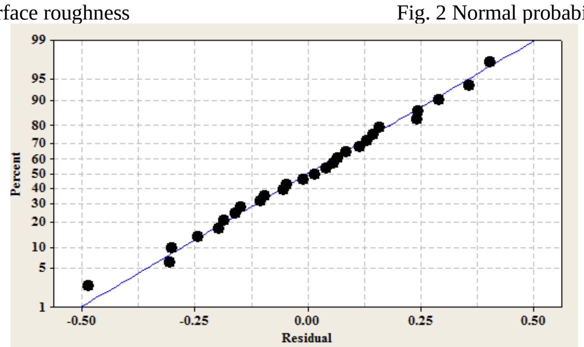

Fig. 3 Plot of residual vs. fitted surface roughness values

C. Development of Mathematical Model

RSM, which consists of collection of mathematical and statistical techniques for empirical model building, is used in the present study to develop the adequate functional relationship between the response variable (surface roughness, YRq) and input variables infeed (A), longitudinal feed (B) and work speed (C). General model of second order mathematical model is shown in Eq. 2. Values of all the constants β0 , β1 , β2 , β3 , β11 , β22 , β33 , β12 , β13 and β23 are determined by using experimental data and application of RSM. The developed model is shown in Eq.3.

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

D. Parametric Optimization for better Surface Finish using a Hybrid function with the Genetic Algorithm

Genetic algorithms are stochastic global search and optimization methods, used for solving optimization problems, employing operations that mimic natural evolution to search for the fittest combination of genes i.e., the optimal solution to a problem. The genetic algorithm repeatedly modifies a population of individual solutions. At each generation of a GA, a new set of individuals is generated by the process according to their fitness in the problem domain and reproducing them using operators borrowed from natural genetics. Over successive generations, the population evolves toward an optimal solution. Because of the nature of the search done by the GA, it is often effective tool to find the global optimum values [12-14]. Optimization toolbox in the MATLAB software version 7.1 is used to predict surface roughness. GA's fundamental operators like reproduction, crossover and mutation are taken care of by GA optimization toolbox of MATLAB and it finally provides the optimum conditions for the desired / minimum 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.

- Selecting the fitness function (i.e. (objective function) that is to be optimized
- Selecting number of input variables (in the present case – three i.e., infeed, longitudinal feed and work speed)
- Fixing lower and upper bonds of input parameters: lower bound = (0.04, 70 and 80), upper bound = (0.06, 90 and 160) and
- 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.

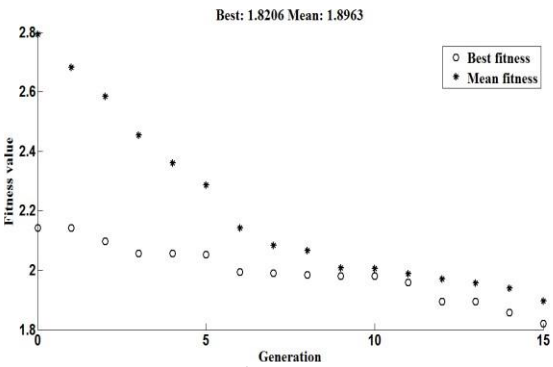

Fig. 4 Best fitness value plot

E. Confirmatory findings

Confirmatory experiment is conducted at optimized grinding condition to check / validate the proposed methodology. From the confirmatory result, it can be concluded that the optimized parametric combination produced surface roughness (Rq) = 1.853 µm, which may be considered minimum in respect of the experimental range (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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