PARAMETRIC OPTIMIZATION FOR TURNING OF GFRP COMPOSITES USING ELITIST TEACHING LEARNING BASED OPTIMIZATION (ETLBO)

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Abstract

Glass fibre reinforced polymer (GFRP) composite materials are a feasible alternative to many engineering materials and being used in advanced technology applications like space, naval marine etc. Machining of these materials to obtain desired quality levels, are very important area of research. In machining processes, process parameter selection plays key role to obtain good surface finish on machined parts. In the present work, process parameters of turning operation has been optimized for minimizing surface roughness of GFRP materials. Elitist teaching learning based optimization (ETLBO) technique has been utilized for that purpose. Two dimensional contour plots have been made to study factor effects on surface roughness and optimize them. Same problem had been attempted in [1] by genetic algorithm. However, comparison results show that ETLBO produced better surface roughness value than GA.

Index terms: Turning, Surface Roughness, GFRP composites, ETLBO

I. INTRODUCTION

Glass fibre reinforced polymer composites have gained its growth in variety of industrial applications which includes aerospace, automobile, electronics, marine, power industry, oil industry [2], etc. These materials need to be machined / finished to obtain required quality levels i.e. desired dimensional accuracy and good surface finish because, high speed machineries and aerospace vehicles need fine finish and closer tolerances of many of the components. The mechanism of machining of glass fibre reinforced composites is quite different from that of conventional metals. Rapid tool wear, rough surface finish on machined parts, delamination and a defective sub-surface layer with cracks are some of the problems encountered during machining [3]. Hence, machining of glass fibre reinforced composite materials for improving surface qualities has been of considerable research interest [4], [5], [6], [7], [8].

Fibre composite materials are processed by different machining operations like turning, drilling, milling grinding etc., to obtain required shape, size and quality characteristics. Among the other metal cutting operations turning is one of the important process used machine various traditional materials and advanced materials like fibre composites. Surface roughness is one of the important quality parameters for any machined surface [9]. Many researchers had done analysis on surface roughness of fibre composites in turning operation. In turning operation, obtaining good surface roughness is mainly depends on correct selection of process parameters. So, systematic optimization methodology is required to select the optimal parametric setting. Optimization of process parameters helps machining economics [10]. Design of experiments techniques like factorial design, Taguchi method and response surface methodology are some of the considerable techniques used for experimenting, analyzing, modeling and optimization of machining / manufacturing processes. But, these techniques are failed to produce global optimum values for given problem. To overcome the drawbacks of DOE techniques, few researchers attempted DOE techniques combined with advanced optimization techniques like genetic algorithm (GA), simulated annealing algorithm (SAA), particle swarm optimization (PSO), etc. to optimize engineering problems to obtain global optimal values. These integrated techniques have been applied to various optimization problems and proved its effectiveness in solving of given problems. However, effective of GA SAA and PSO depends on determination of optimum algorithm specific controlling parameters [11]**.** Example GA required crossover rate and mutation rate, SAA requires initial setting of temperature and PSO requires fine tuning of intertia weight and some other factors. Due to the above mentioned difficulties, these techniques are failed to produce optimum solution for specific problems. Hence, recently, new optimization introduced technique i.e. teaching learning based optimization (TLBO) was introduced in [12] [13] which do not require any specific algorithm parameter setting [11].

II. TEACHING LEARNING BASED OPTIMIZATION

Teaching-learning is an important process where every individual tries to learn something from other individuals to improve themselves. In references [12] and [13] a new algorithm proposed, known as Teaching-Learning-Based Optimization (TLBO), which simulates the traditional teaching learning phenomenon of a classroom. The algorithm simulates two fundamental modes of learning: (i) through the teacher (known as the teacher phase) and (ii) interacting with other learners (known as the learner phase). TLBO is a population-based algorithm, where a group of students (i.e. learner) is considered the population and the different subjects offered to the learners are analogous with the different design variables of the optimization problem. The results of the learner are analogous to the fitness value of the optimization problem. The best solution in the entire population is considered as the teacher. The operation of the TLBO algorithm is explained below with the teacher phase and learner phase [14].

A. Teacher phase

This phase of the algorithm simulates the learning of the students (i.e. learners) through the teacher. During this phase, a Teacher conveys knowledge among the learners and makes an effort to increase the mean result of the class. Suppose there are 'm' number of subjects (i.e. design variables) offered to 'n' number of learners (i.e. population size, k = 1, 2,...,n). At any sequential teaching-learning cycle, i, M_j, i is the mean result of the learners in a particular subject 'j' (j = 1,2,...,m). Since a teacher is the most experienced and knowledgeable person on a subject, the best learner in the entire population is considered a teacher in the algorithm. Let $X_{total-kbest,I}$ be the result of the best learner considering all the subjects who is identified as a teacher for that cycle. The teacher will put maximum effort into increasing the knowledge level of the whole class, but learners will gain knowledge according to the quality of teaching delivered by a teacher and the quality of learners present in the class. Considering this fact, the difference between the result of the teacher and the mean result of the learners in each subject is expressed as:

$$\text{Difference\_Mean}_{j,i} = r_i(X_{j,kbest,i} - T_F M_{j,i}), \quad (1)$$

where X $_{j,kbest,i}$ is the result of the teacher (i.e. best learner) in subject j. TF is the teaching factor, which decides the value of mean to be changed, and r_i is the random number in the range [0,1]. The value of TF can be either 1 or 2. The value of TF is decided randomly with equal probability as:

$$T_F = \text{round}[1 + \text{rand}(0, 1)\{2 - 1\}], \quad (2)$$

Where rand is the random number in the range [0, 1].TF is not a parameter of the TLBO algorithm. The value of TF is not given as an input to the algorithm and its value is randomly decided by the algorithm using Eq. (2). Based on the Difference_Mean j, i, the existing solution is Updated in the teacher phase according to the following expression:

$$X'_{j,k,i} = X_{j,k,i} + \text{Difference\_Mean}_{j,i} \quad (3)$$

Where X′ $_{j,k,i}$ is the updated value of X $_{j,k,i}$. Accept X′ $_{j,k,i}$ if it gives a better function value. All the accepted function values at the end of the teacher phase are maintained, and these values become the input to the learner phase.

B. Learner phase

This phase of the algorithm simulates the learning of the Students (i.e. learners) through interaction among themselves. The students can also gain knowledge by discussing and interacting with other students. A learner will learn new information if the other learners have more knowledge than him or her. The learning phenomenon of this phase is expressed below.

Randomly select two learners, P and Q, such that X′ $_{total-P,i}$/ # X′ $_{total-Q,I}$, where, X′ $_{total-P,i}$ and X′ $_{total-Q,i}$ are the updated values of X $_{total-P,i}$ and X $_{total-Q,i}$, respectively, at the end of the teacher phase.

$$X''_{j,P,i} = X'_{j,P,i} + r_i(X'_{j,P,i} - X'_{j,Q,i}), \quad \text{If } X'_{total-P,i} < X'_{total-Q,i} \quad (4)$$

$$X''_{j,P,i} = X'_{j,P,i} + r_i*(X'_{j,Q,i} - X'_{j,P,i}), \quad \text{If } X'_{total-Q,i} < X'_{total-P,i} \quad (5)$$

Accept X’’$_{j,P,i}$, if it gives a better function value. All the accepted function values at the end of the learner phase are maintained and these values become the input to the teacher phase of the next iteration. The values of r_i used in Eqs. (1), (4) and (5) can be different. Repeat the procedure of teacher phase and learner phase till the termination criterion is met. The flow chart for TLBO was given in

C. Elitist TLBO (ETLBO) algorithm

The concept of elitism is utilized in most of the evolutionary and swarm intelligence algorithms where during every generation the worst solutions are replaced by the elite solutions. The ETLBO technique was proposed in [14]. The next section, the effectiveness of the advanced optimization algorithm (ETLBO) is tested for parametric optimization in turning of glass fibre reinforced polymer. The effects of process parameters on output response surface roughness are illustrated through contour plots.

III. CASE STUDY

In reference [1] research investigation had done on optimization of surface roughness of glass fibre reinforced polymer (GFRP) composite material in turning. Cutting speed, feed, depth of cut and fibre orientation angle of work piece were selected as input parameters. Experiments had been conducted in all geared lathe using poly crystalline diamond (PCD) tool. The relationship between the input parameters and output response (surface roughness) had been developed using response surface methodology (RSM) and shown as Equation 6.

Y_{Ra}= 1.19-0.0111*V + 1.84*f - 1.64*d + 0.0552*ϕ + 0.000059*(V^2) - 2.93*(f^2) + 1.36*(d^2) + 0.000055*(ϕ ^2) - 0.0122*(V*f) + 0.00723*(V*d) - 0.000206 *(V*ϕ) + 4.05*(f*d) + 0.0141*(f* ϕ) - 0.0381*(d* ϕ) (6)

Then optimal parametric condition was obtained by solving obtained mathematical model (Eq. 6) with use of genetic algorithm (GA). Predicted condition by GA is given in Table 1. In the present study, elitist teaching learning based optimization (ETLBO) technique has been applied to solve the same mathematical model (Eq.6) which solved in [1]. The implementation steps of the ETLBO are summarized below:

Step 1: Initialization of population (i.e. learners') and design variables of the optimization problem (i.e. number of subjects offered to the learner) with random generation and evaluating them

Step 2: Selecting the best learner of each subject as a teacher for that subject and calculating the mean result of learners in each subject

Step 3: Evaluating the difference between current mean result and best mean result according to Equation 2 by utilizing the teaching factor (TF)

Step 4: Updating the learners' knowledge with the help of teacher's knowledge according to Equation 3

Step 5: Updating the learners' knowledge by utilizing the knowledge of some other learner according to Equation s. 4 and 5

Step 6: Replacing worst solutions with elite solutions (elite value 0 is selected in the present case)

Step 7: Repeating the procedure from step 2 to step 6 till the termination criterion is met

In each of the ETLBO runs, optimal parametric condition and the corresponding output response value are produced. In the present case, optimal parametric setting has been obtained in first run itself. Obtained parametric condition is also listed in Table 1.

The comparative analysis has been made between the results obtained by GA [1] and ETLBO. From Table 1, it is found that ETLBO technique produced better surface roughness value i.e. 0.8755 μm compared to surface roughness value (=1.2057 μm) obtained by GA. Surface roughness value of GFRP is improved from 1.2057 μm to 0.8755 μm (27%). Thus, it is found from the resent analysis that ETLBO is advantageous than the GA to optimize turning of GFRP.

A. *Factor effects*

Individual and interaction effects of the process parameters on surface roughness have been studied through contour plots which drawn from mathematical model of surface roughness (Eq. 6). The contour plots are drawn using MINITAB 16.1 software and shown in Figs. 1-5. A contour plot shows the variations of response variable due to change in the levels of two input variables while the third and fourth input parameters are held constant at some particular level.

The shape of the corresponding contour plot shows whether the process parameters influence the output response significantly or not. An elliptical nature of the contour plots indicates that the interactions between the input parameters significantly influence the output response. If the curvature lines in the contour plot indicates more interaction effect of input parameters on the corresponding response variable. Straighter lines in contour plot indicate no interaction effect on response.

Contour plots (Figs. 1-5) depicts that interaction effects are prominent on surface roughness. Contour plots can also give idea about where roughness value is minimized. Any parametric setting at red colour region will produce optimized / minimized surface roughness value. Optimal parametric combination obtained from contour plots (Figs. 1-5) of surface roughness of GFRP turning is: cutting speed (V) = 179 m/min, feed (f) = 0.048 mm/rev, depth of cut (d) = 1.25 mm and fibre orientation angle (ϕ) = 90 deg, and corresponding minimized surface roughness is 0.8755 μm. Obtained optimum results from contour plots prove the results predicted by ETLBO. Thus, it is found from present work that ELTO produced better roughness value than the genetic algorithm (Table 1).

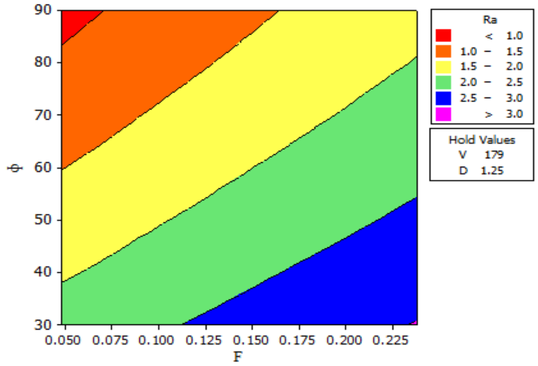

Fig. 1 Contour plot of surface roughness according to change of feed (F) and fibre orientation angle at cutting speed (V) = 179 m/min and depth of cut (d) = 1.25 mm

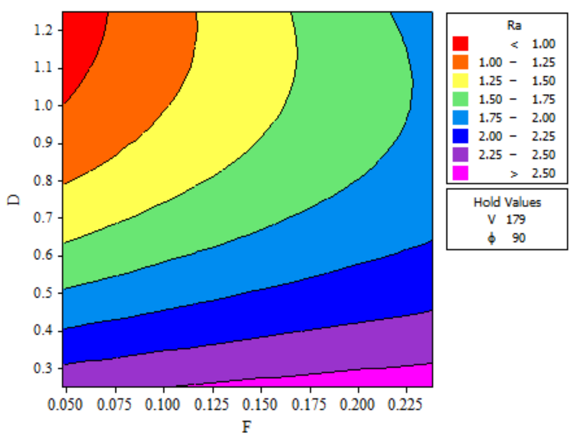

Fig. 2 Contour plot of surface roughness according to change of depth of cut (d) and feed (F) at cutting speed (V) = 179 m/min and fibre orientation angle (ϕ) = 90 deg.

IV. CONCLUSIONS

In the present work, parametric optimization is made for turning operation for minimizing the surface roughness of GFRP composite using a new algorithm. The same problem was earlier attempted by other researchers using genetic algorithm (GA). The ETLBO has given the improvement of approximately 27% over GA. Thus it is concluded form the present analysis that ETLBO is advantageous than the GA to optimize surface roughness of GFRP composite in turning operation. The ETLBO can be applied to optimize performance measures in machining / manufacturing processes.

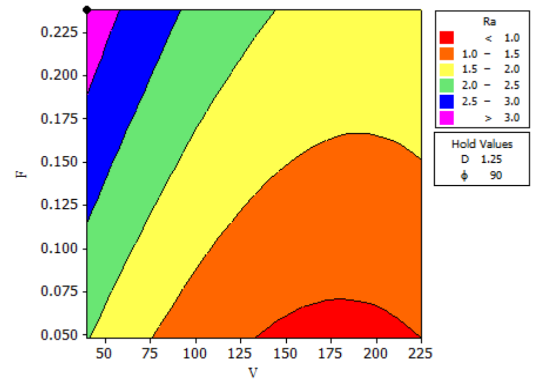

Fig. 3 Contour plot of surface roughness according to change of feed (F) and cutting speed (V) at depth of cut (d) = 1.25 mm and fibre orientation angle(ϕ) = 90 deg.

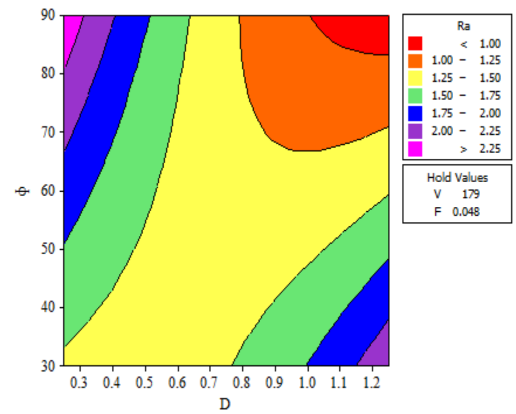

Fig. 4 Contour plot of surface roughness according to change of depth of cut (d) and fibre orientation angle(ϕ) at feed (F) = 0.048 mm/rev and cutting speed (V) = 179 m/min.

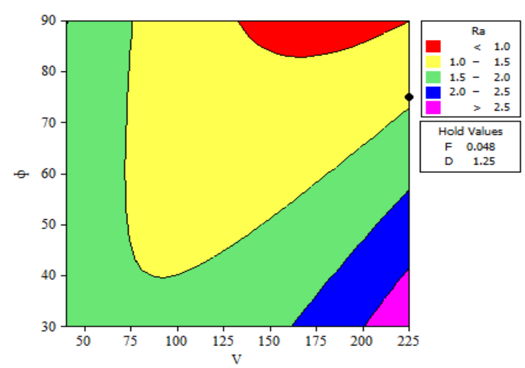

Fig. 5 Contour plot of surface roughness according to change of fibre orientation angle(ϕ) and cutting speed (V) at depth of cut (d) = 1.25 m/min and feed (F) = 0.048 mm/rev.

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Table 1 Obtained optimal results by GA and ETLBO

	Results obtained by GA (Hussain et al., 2014)		Results obtained by ETLBO	
	Optimal parametric condition	Minimized surface roughness	Optimal parametric condition	Minimized surface roughness
cutting speed (V)	130.769 m/min	1.2057 μm	179.56 m/min	0.8755 μm
feed (f)	0.05 mm/rev		0.048 mm/rev	
depth of cut (d)	0.697 mm		1.25 mm	
fibre orientation angle (ϕ)	32.60 deg.		90 deg.	