OPTIMIZATION OF MACHINING PARAMETERS IN END MILLING OF GFRP USING RSM-SA

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ABSTRACT- Fiber Reinforced Plastic (FRP), a high-level polymeric grid composite material, is generally utilized in a mixture of application which includes airplane, robots and machine instruments. Machining of Glass Fiber Reinforced Plastic (GFRP) composite is a significant movement in the coordination of these high-level materials into designing application. Machining harm because of uneven cutting boundary might bring about dismissal of the composite parts at the last phase of their production cycle. Surface roughness a sign of surface quality is one of the major client necessities for machined parts. This review applied modeling and simulation techniques to determining the solution of the optimum cutting conditions to obtain the good surface roughness when end milling GFRP. Considering a set of trial machining information, the numerical model is created utilizing Response Surface Methodology (RSM). The best model was considered to formulate the fitness function of the simulated annealing (SA). Subsequently, it was found that by using simulated annealing, the minimum surface roughness can be obtained.

Keywords – Glass Fibre Reinforced Plastic (GFRP), Surface Roughness, End Milling, Response Surface Methodology (RSM), Simulated Annealing (SA).

1. INTRODUCTION

Glass fibre reinforced plastic (GFRP) composites are most widely used in aerospace, automobile and marine industries owing to their potential properties such as a high strength to weight ratio, and a high specific stiffness. The machining of GFRP has necessitated manufacturing near net-shaped components. The machining of a composite is different from the conventional machining of metals due to the composites anisotropic and non homogeneous nature. Among several industrial machining processes, milling is a fundamental machining operation. End milling is the most common metal removal operation encountered. It is widely used in a variety of manufacturing industries including the aerospace and automotive sectors, where quality is an important factor in the production of slots and dies. The quality of the surface plays a very important role in the performance of milling as a good-quality milled surface significantly improves fatigue strength, corrosion resistance, and creep life. Surface roughness also affects several functional attributes of parts, such as wearing, heat transmission, and ability of holding a lubricant, coating, or resisting fatigue. Therefore, the desired surface finish is usually specified and the appropriate processes are selected to reach the required quality. Several factors influence the final surface roughness in end milling operation. [1, 2]

Surface roughness is characteristic that could influence the dimensional precision, the performance of the mechanical pieces and production cost. For these reasons there has been a lot of research and development with the objectives of optimizing cutting conditions to obtain a determined surface roughness. [3, 4]

Because of the inhomogeneous nature of composite materials, their response to machining may involve undesirable consequences such as rapid tool wear, fibre pullout, surface burning and smearing, pitting and delamination. All of these responses are

directly related to the cutting tool force applied to the work piece edge. Delamination in particular is strongly dependent on the cutting parameter component normal to the stacking plane in unidirectional and multidirectional laminate composite. The delamination of fibres from matrix
due to excessive cutting parameter is a major problem in machining, which results in the lowering of bearing strength and is detrimental to the durability by reducing the in-service life under fatigue loads. [5, 6]

Several optimization techniques, which can be classified as conventional and non-conventional (soft computing), could be effectively applied to optimize the cutting conditions that affect the *Ra* value. The conventional optimization techniques include Taguchi method, factorial technique, and response surface methodology (RSM). Among the conventional optimization techniques, RSM was mostly applied by researchers. [7]

The selection of efficient machining parameters is of great concern in manufacturing industries, where economy of machining operations plays a key role in the competitive market. Many researchers have dealt with the optimization of machining parameters. The RSM is a dynamic and foremost important tool of Design of Experiment (DOE) where in the relationship between process output(s) and its input decision variables, it is mapped to achieve the objective of maximization or minimization of the output properties. RSM was successfully applied for prediction and optimization of cutting parameters. **[**8, 9**]**

Some of the established soft computing techniques applied by previous researchers in machining applications are genetic algorithm (GA), tabu search (TS), ant colony optimization (ACO), and particle swarm optimization (PSO) One of the alternatives in using soft computing is the application of SA in estimating the optimal cutting parameters, particularly for the *Ra* value in end milling process. [10]

SA was used to optimize the cutting parameters for multi-pass milling process *(Wang et al., 2005). Juan et al. (2003)* based on polynomial network to determine the optimal cutting parameters for minimum production cost in high speed machining (HSM) SKD61 tool steels. SA was also considered in optimization of machining conditions for minimum production of spur gears *(Sankar and Ponnambalan, 2008)* and for wire electrical discharge machining *(Tarng et al., 1995).*

Despite the numerous capabilities of SA, its application in optimization of cutting conditions for various machining performances was given less attention by researchers. In this paper, simulated annealing is employed as it normally exhibits fast convergence and straightforward implementation.

2. EXPERIMENTAL DETAILS AND MEASUREMENTS

2.1 Materials and experimental setup

Eight layered UD-GFRP specimens of 6.5mm thickness were prepared using the hand lay-up process. The reinforcement was in the form of uni-directional E-glass fiber tape and matrix was epoxy, Araldite LY556 with hardener HY 951 (Aliphatic primary amine). A gel coat was applied on the mould prior to the lay-up process to facilitate easy removal of the laminate. Specimens were cured at room temperature having a fiber orientation of 0/90°.

The Tools that were chosen for milling were K10 end mills of Solid Carbide, Titanium Nitride (TiNamite) and Aluminium Titanium Nitride (TiNamite A) having four flute each with Square Ends. The last two being coated tools. The factors were set depending upon their micro-hardness levels. The tools used for the study is SGS Carbide make. The milling operation was conducted using a Universal Milling machine with a spindle speed of 45-1400m/min, longitudinal feed of 18 mm/min and cross feed range of 16-800 mm/min. The machine has a Vertical feed of 6.3-315 m/min and a clamping area of 300 X 1000 mm. The fixation of the composite material was made in such a way so as to eliminate the vibration and displacement. The specifications of the machine are shown in table 1.

2.2 Design of experiment

The Cutting speed v (m/min), feed f (mm/min), depth of cut d (mm) and tool material T are the four parameters under investigation in the present study. A full factorial experimental design with a total of 27 experiment runs was carried out. The factors and respective levels are shown in Table 1. The surface roughness were the response variable recorded for each run. The treatment of experimental result is based on the analysis of variance (ANOVA). The analysis of variance of the experimental data for the surface roughness generated during end milling of GFRP is done to study the relative significance of the cutting speed, feed, depth of cut and tool material.

Table 1 Factor and Respective Levels

FACTORS	NOTATION USED	LEVELS		
		-1	0	1
CUTTING SPEED (m/min)	A	100	700	1300
FEED(mm /min)	B	50	350	650
DEPTH OF CUT (mm)	C	1	2	3
TOOL MATERIAL (Micro Hardness value)	D	SOLID CARBIDE	TITANIUM NITRIDE COATED	ALUMINIUM TITANIUM NITRIDE COATED

2.3 Measurements of surface roughness

Surface Roughness is measure of texture of a surface. It is quantified by the vertical deviations of a real surface from its ideal from. If theses deviations are large, the surface is rough; if they are small the surface is smooth. Roughness is typically considered to be the high frequency, short wavelength component of a measured surface. The surface roughness (Ra) was evaluated using Surfcoder SE 1700.The measurements were made with the cut-off (0.8mm) according to ISO. The results are being tabulated as shown in table 2.

Table 2 Experimental Results

Run Order	Speed (m/ min)	Feed (mm /min)	Depth of cut (mm)	Tool material	Surface roughness (Micron)
1	0	-1	0	-1	1.4465
2	0	0	0	0	1.5845
3	-1	0	0	-1	2.0311
4	1	0	1	0	1.8571
5	1	0	0	1	1.8571
6	0	1	0	1	1.4225
7	0	-1	0	1	1.0195
8	-1	0	0	1	1.3911
9	-1	0	1	0	1.2345
10	0	0	0	0	1.7225
11	0	0	-1	-1	1.1991
12	0	-1	1	0	1.2755
13	1	0	-1	0	0.9221
14	1	0	0	-1	1.2588
15	-1	0	-1	0	1.5524
16	0	1	0	-1	1.9951
17	0	1	1	0	1.2337
18	-1	-1	0	0	1.5235
19	0	0	0	0	1.5121
20	0	0	-1	1	1.2081
21	0	-1	-1	0	0.9813
22	0	0	1	-1	1.8711
23	0	0	1	1	1.1895
24	1	-1	0	0	1.3831
25	1	1	0	0	1.6895
26	-1	1	0	0	1.8451
27	0	1	-1	0	1.8261

2.4 Simulated Annealing Method

Simulated annealing algorithm is a nature-inspired method which is adapted from the process of gradual cooling of metals in nature. In the metallurgical annealing process, a solid is melted at high temperature until all molecules can move about freely, and then a cooling process is performed until thermal mobility is lost. The perfect crystal is the one in which all atoms are arranged in a low level lattice, so the crystal reaches the minimum energy. At the temperature of *T*, the solid is allowed to reach a certain thermal equilibrium status. The probability of being at the energy level of *E* is determined by the Boltzmann distribution:

$$\mathbf{Pr\ (E)} = \frac{1}{Z(T)} \times exp\left(-\frac{E}{KB.T}\right) \qquad (1)$$

Where *Z (T)* is a normalization factor and is dependent to the temperature *T*. The parameter *KB* is the Boltzmann constant and the exponential term is the Boltzmann coefficient.

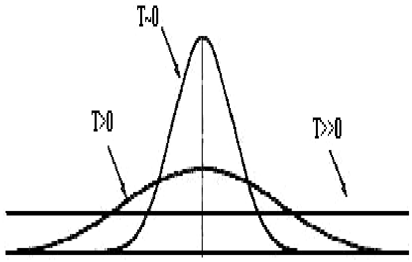

Figure 2 Distribution of probability for three different temperatures

With the decrease of temperature, the Boltzmann distribution focuses on a state with lowest energy and finally as the temperature comes close to zero, this becomes the only possible state as showing Fig. 2.

3. RESULT AND DISCUSSION

3.1 RSM Modeling

A regression model was developed to estimate the surface roughness values. The models were based on the Box-Behnkn design method. The developed second order Mathematical Model was developed for surface roughness with a confidence level of 95% as shown in Eq.2

Surface roughness (Ra) = 0.914038 - 0.00254186(A) + 0.00288564(B) + 1.25682(C) - 1.58E-04 (D) + 1.33E-07(A) (A) - 7.25E-07(B)(B) - 3.24E-09 (D) (D)- 2.08E-08(A)(B) - 9.91E-08(B)(D) **(2)**

Subsequently, Eq. (2) will be proposed as the objective function for optimization solution of the SA.

3.2 SA Optimization Process

SA is a method for solving unconstrained and bound-constrained optimization problems. It models the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimizing the system energy. At each iteration of the SA algorithm, a new point is randomly generated. The distance of the new point from the current point, or the extent of the search, is based on a probability distribution with a scale proportional to the temperature. The algorithm accepts all new points that lower the objective, but also, with a certain probability points that raise the objective. By accepting

Points that raise the objective, the algorithm avoids being trapped in a local minimum, and is able to explore globally for more possible solutions. An annealing schedule is selected to systematically decrease the temperature as the algorithm proceeds. As the temperature decreases, the algorithm reduces the extent of its search to converge to a minimum. An important part of the SA process is how the inputs are randomized. The randomization process takes the previous input values and the current temperature as inputs. The input values are then randomized according to the temperature. A higher temperature will result in more randomization; a lower temperature will result in less randomization. There is no specific method defined by the SA algorithm for how to randomize the inputs. The exact nature by which this is done often depends upon the nature of the problem being solved. Fig. 3 illustrates the flow on how the SA technique operates in order to search the optimal solution.

The target of the optimization process in this study is to determine the optimal values of the process parameters that lead to the minimum value of Ra. To formulate the optimization problem, the regression model which is proposed in Eq. (2) is taken to be the fitness function of the optimization solution.

The minimization of the fitness function value is subjected to the boundaries of the process parameters. The range of values of experimental process parameters in Table **2** is selected to present the limitations of the optimization solution and is given as follows:

$100 \leq X1 \leq 130$ (3a)

$50 \leq X2 \leq 650$ (3b)

$1 \leq X3 \leq 3$ (3c)

$1500 \leq X4 \leq 3300$ (3d)

The process parameters that lead to the minimum Ra of the regression model as given in Table 4 will be chosen to be the initial points for the SA solution and are given as follows:

INITIAL POINT OF X1 = 700 (4a)

INITIAL POINT OF X2 = 350 (4b)

INITIAL POINT OF X3 = 2 (4c)

INITIAL POINT OF X4 = 2400 (4d)

Basically, to obtain the optimal solutions, some criteria must be considered by the SA algorithm as listed in Table 3.

Table 3 Combination of SA parameter rates leading to the optimal solution.

Parameters	Setting value/function type
Annealing function	Boltzmann Annealing
Re-annealing interval	100°C
Temperature update function	Exponential Temp
Initial temperature	100°C
Acceptance probability function	Simulated Annealing

By using the fitness function formulated in Eq. (2), the limitations of process parameters formulated in Eqs. (3a)- (3e), the initial points formulated in Eqs. (4a)–(4e), and the SA parameters given in Table 3, the Matlab Optimization Toolbox is next applied to find the minimum values of Ra at the optimal points. The results of the Matlab Optimization Toolbox are given in Figs. 4 and 5. The optimal solution is obtained at the 10434-th iteration of the SA algorithm.

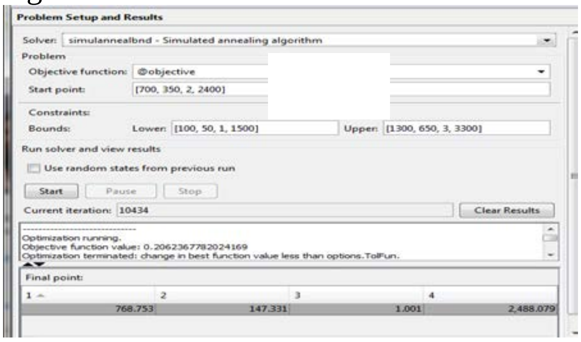

Figure. 4 The results of the Matlab Optimization Toolbox

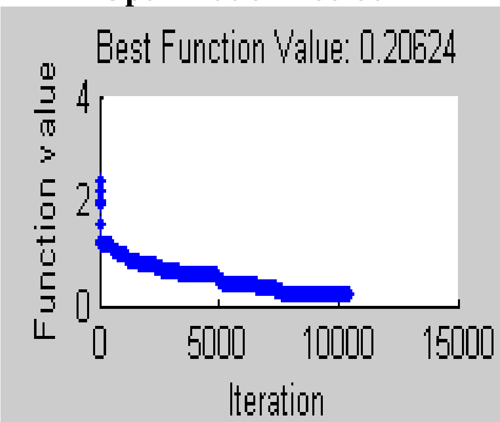

Figure 5 The results of the Matlab Optimization Toolbox

CONCLUSION

This study reports on the application of the SA technique in order to estimate the optimal solutions of cutting conditions that lead to a minimum *Ra* value. The regression model equation has been selected to be the fitness function equation for the SA optimization. The results of the SA optimization can be summarized in Table 4. It was found that SA is an effective technique for estimating the minimum *Ra* values as compared to the experimental. It has also been discovered that the optimal value for each of the cutting conditions recommended by the SA which lead to the minimum *Ra* values satisfies the range of minimum and maximum coded value of the experimental design. The target of the optimization process is also to determine the optimal values of decision variables that could lead to the minimum *Ra* value. Therefore, with 770 mm/min for cutting speed, 147 mm/min for feed, 1.00 mm depth of cut and Titanium Nitride Coated for tool material the best *Ra* value obtained was 0.20. As such SA is suitable to be used as one of the optimization tool in evaluating machining performance.

Table 4 Comparison between the optimal cutting condition results of Experiment and SA

Technique	Cutting speed mm/min	Feed mm/min	Depth of cut mm	Tool material	Surface roughness (Ra)
Experimental	1300	350	1	Titanium Nitride Coated	**0.9221**
SA	770	147	1	Titanium Nitride Coated	**0.2062**

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