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ANFIS modeling of surface roughness in abrasive waterjet machining of carbon fiber reinforced plastics †

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Abstract

This study discusses the development of an Adaptive neuro–fuzzy inference system (ANFIS) model for determining the surface roughness (Ra) during machining of multidirectional woven fabric Carbon fiber reinforced plastics (CFRP) using Abrasive waterjet machining (AWM). Three variable input parameters—Jet pressure (JP), Traverse speed (TS), and Standoff distance (SOD)—were selected to assess the roughness of the CFRP along the traverse direction of the cut surface. The experimental results show that a lower JP deteriorated the finish by creating surface rupture. On the other hand, a poor surface finish was observed in the case of machining at higher TS and SOD. Further, the developed ANFIS model was used to validate the results and it was found that the predicted values were in good agreement with a 95 % confidence level. It was also evident that the ANFIS technique is helpful for better prediction of the experimental data with minimum error. Finally, the cut surface morphology was analyzed using a 3D non-contact surface profilometer and the results are discussed.

Keywords: ANFIS; Abrasive waterjet machining; Surface roughness; CFRP

1. Introduction

Carbon fiber reinforced plastics (CFRP) are used in various structural applications. Researchers face challenges in preparing a near net shape product with a good surface quality. Although there are several machining techniques available, Abrasive waterjet machining (AWM) is widely used as it is a cold working process [1]. High pressure water and abrasive particles are mixed in the mixing chamber at the nozzle head. This jet stream is then discharged through the nozzle, which is used for machining. The specimens that are machined using AWM do not show a heat-affected zone, thermal defects, and surface hardening [2]. Thus, the prepared samples have a good surface finish with improved dimensional accuracy.

Various polymer composites have been machined using AWM and the surface roughness (Ra) measured at the cut surface was investigated and reported. However, there is no report on the Ra measurement in a machined surface of woven fabric multidirectional CFRP composites. Wong et al. [3] performed experiments using AWM to investigate the kerf taper and delamination of hybrid FRP (carbon and glass woven fabrics) composites. They developed an empirical model using response surface methodology and concluded that the kerf taper and delamination were highly influenced by the Standoff distance (SOD) and the abrasive flow rate, respectively. Alberdi et al. [4] examined the kerf angle and Ra of CFRP/Ti6Al4V stakes using AWM. The results show the formation of a negative taper angle on the CFRP during cutting and the Ra value was below 6.5 μm in the CFRP, which is because of the presence of the staking material. Madhu and Balasubramanian [5] studied the influence of Jet pressure (JP), SOD, nozzle diameter, and abrasive particle size on the Ra of unidirectional CFRP. The newly developed internal threaded nozzle produced a lower Ra irrespective of varying the cutting conditions. Dhanawade and Kumar [6] performed AWM on unidirectional CFRP composites to evaluate the kerf geometry and delamination. The top kerf width and taper ratio were found to decrease with a decrease in the SOD and Traverse speed (TS). Moreover, an increase in JP increased the delamination and kerf taper ratio.

Recently, modeling of the machining process has attracted great interest. The Adaptive neuro–fuzzy inference system (ANFIS) captures the benefits of both neural networks and fuzzy logic principles [7]. Thus, this model has the potential to predict the best output values in a more efficient and optimal way. Azmi [8] developed an ANFIS model to investigate the

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tool wear and feed force during milling of Glass fiber reinforced polymer composites (GFRPs). The results show a superior predictability of output response within the confidence levels and with reduced error. Azmi et al. [9] also found an improvement in the prediction values of the model and the accuracy of the responses were validated. The developed models helped to determine the time for reconditioning and replacement of the tool effectively. Chaudhari et al. [10] performed high-speed drilling on GFRP composites to measure the delamination at the entrance and exit holes. The ANFIS method was adopted to predict and evaluate the results at 95 % confidence level. Finally, root means square errors of 1.47 % and 2.92 % were observed at the delamination hole entrance and exit, respectively. Though this method predicts near accurate results more effectively, it has not been used for modeling the AWM process during cutting of the CFRP composites.

In this study, the multidirectional woven fabric CFRP composite is machined with AWM to investigate the Ra on a machined surface. The influence of the process parameters such as JP, TS and SOD were analyzed and their significance is reported. Further, an ANFIS model was developed for the experimental results and the predicted values were validated at 95 % confidence level. Finally, the machined surface was examined at the optimum condition using a 3D non-contact surface profilometer.

2. Experimental procedure

2.1 Materials and methods

The Korea Institute of Carbon Convergence supplied the woven fabric multidirectional CFRP composite, which has 0.6 vol. % of fiber. The fibers are oriented in 0° and 90° layers providing a quasi-isotropic behavior whose mechanical properties were measured according to ASTM D638-14 and ASTM D695-15 [11]. Based on the tests conducted, the following results were obtained: Tensile strength = 840 MPa, compression strength = 570 MPa, Young's modulus = 61.5 GPa, shear modulus = 3.7 GPa, density = 155 kg/mm^3 and hardness = 75 HRB.

The machining was performed on a Dardi International Corporation AWM (DWJ1313-FB), which is connected with an ultra-high pressure pump (DIPS6-2230). Garnet of 80 mesh (~177 μm) was used as the abrasive, which was combined with the high pressure water in the mixing chamber. Three factors—JP, TS and SOD—with three levels each were selected for conducting the experiments. Table 1 shows the results of Ra which are used for training and testing. The mean roughness values were measured laterally against the cutting direction. A surface profilometer Mitutoyo–SJ-301 with a range of 350 μm, speed of 0.25 mm/s, and a sampling length of 5 mm was used to record the Ra values. The surface profile was measured using the non-contact 3D surface measurement system NV-2000.

Table 1. Experimental results.

ANFIS	JP (bar)	TS (mm/min)	SOD (mm)	Ra (μm)
Training	220	20	2	4.378
	220	30	1	4.079
	220	30	3	4.774
	220	40	2	4.534
	240	20	1	3.311
	240	20	3	4.231
	240	30	2	4.019
	240	40	1	3.897
	240	40	3	4.742
	260	20	2	3.521
	260	30	1	3.272
	260	30	3	3.835
	260	40	2	3.712
Testing	220	20	1	3.805
	220	20	3	4.518
	220	30	2	4.419
	220	40	1	4.247
	220	40	3	4.798
	240	20	2	3.756
	240	30	1	3.538
	240	30	3	4.379
	240	40	2	4.074
	260	20	1	3.202
	260	20	3	3.68
	260	30	2	3.62
	260	40	1	3.615
	260	40	3	4.036

2.2 Adaptive neuro–fuzzy inference system

The integration of an artificial neural network and a fuzzy system is used in the ANFIS architecture. This method is used to create a model based on the experimental results. Initially, the system is described using a fuzzy system, and the membership functions are produced using an artificial neural network. The five layers used for the training of the parameters are the fuzzy layer, product layer, normalized layer, defuzzification layer, and output layer [12].

In the fuzzy layer, the correlation between the input and output functions are expressed as $O_{1,i} = \mu A_i$ (x), for i = 1, 2 and $O_{1,i} = \mu B_{i-2}$ (y), for i = 3, 4 [13]. In this layer $O_{1,i}$ is the membership grade of fuzzy set A_i or B_i, x and y are the input nodes, and μ can be expressed as:

$$\mu = \frac{1}{1 + \left[\frac{x - c_i^2}{a_i^2} \right]^{b_i}} \tag{1}$$

where $\{a_i, b_i, c_i\}$ are the premise parameters. The output of the product layer is expressed as the product of all incoming signals $(w_i) = \mu A_i (x) \times \mu B_i (y)$, for i = 1, 2. The function of the normalized layer is to standardize the weight functions:

$$\overline{w} = \frac{w_i}{w_1 + w_2} \quad \text{where } i = 1, 2. \tag{2}$$

The consequent parameters $\{p_i, q_i, r_i\}$ of the defuzzification layer is $w_i (p_i x + q_i y + r_i)$. Finally, the overall output is expressed as follows:

$$Output = \Sigma_i \overline{f_i} \frac{\Sigma_i w_i f_i}{\Sigma_i w_i} \tag{3}$$

where $\overline{w_i} f_i$ is the defuzzification relationship between the input and output parameters. It is computed based on the summation of all input signals. The fuzzy rules is then defined based on the Sugeno fuzzy model [14]. In this study, a total of 27 rules were set with a common 'IF' and 'THEN' rules.

Rule 1: If (JP is S) and (TS is S) and (SOD is S) then (Ra is S) else,
Rule 2: If (JP is M) and (TS is L) and (SOD is S) then (Ra is M) else,
Rule 3: …….
:
Rule 27: …….

where the classification of variables such as S, M and L represents small, medium and large, respectively. The developed ANFIS architecture for the present study (Fig. 1) was performed on MATLAB® 2016a software.

3. Results and discussion

3.1 Experimental verification by ANFIS

It is essential to define the patterns before training the experimental data. This data preprocessing is something that should be performed when each of the factors have different ranges. The ranges of JP (220 bar = S, 240 bar = M and 260 bar = L), TS (20 mm/min = S, 30 mm/min = M and 40 mm/min = L) and SOD (1 mm = S, 2 mm = M and 3 mm = L) were set based on the input limits. The membership function plots were then plotted for all the input variables. The typical triangular shaped membership function for the fuzzy interface system variable is shown in Fig. 2. The measured Ra values at different operating conditions were then defined with specific limits. A minimum of Ra value of 3.202 µm was observed during JP at 260 bar, TS at 20 mm/min, and SOD at 1 mm, and a maximum of 4.798 µm was observed during JP at 220 bar, TS at 40 mm/min, and SOD at 3 mm. Subsequently, the functions were saved as a *.fis file and later retrieved for training and testing in ANFIS.

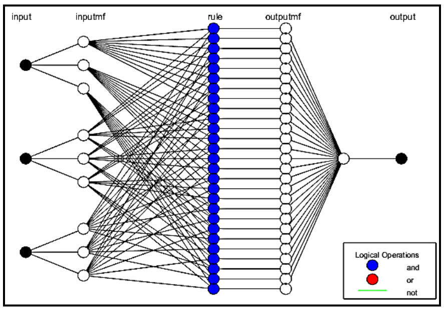


Fig. 1. ANFIS architecture.

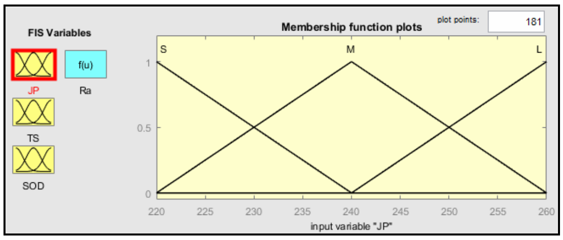


Fig. 2. Typical membership function plot.

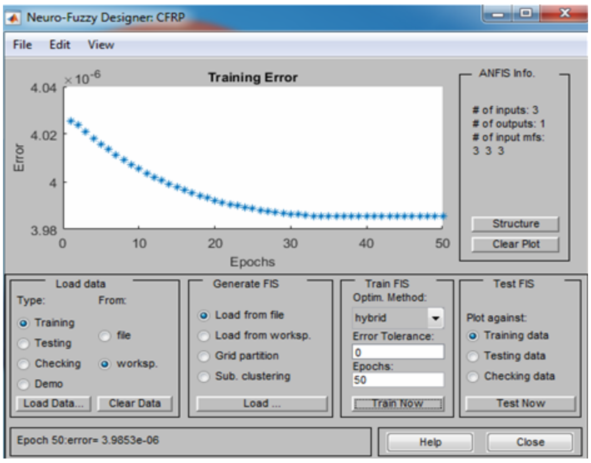


Fig. 3. Training error.

The experimental results were loaded to the neuro–fuzzy designer and the ANFIS structure was trained. The epochs were adjusted till the error value reached < 0.001. Based on the trial and error method, it was observed that when the epoch value was 50, the error value reached 3.9853×10^{-6}. The training graph in Fig. 3 also converged and there is no chance for further reduction of error. Once the ANFIS structure was trained, the results were tested. The testing data output for the trained Ra value is shown in Fig. 4. The hybrid optimum model was selected based on the accuracy of response. They reduce the percentage of error when the predicted values are compared with the experimental values.

Each row in Fig. 5 shows the defined rule, and the first three columns are the input parameters and the fourth column represents the output Ra. A total of 27 rules were made for Ra and the predicted ANFIS output results were obtained. Each input

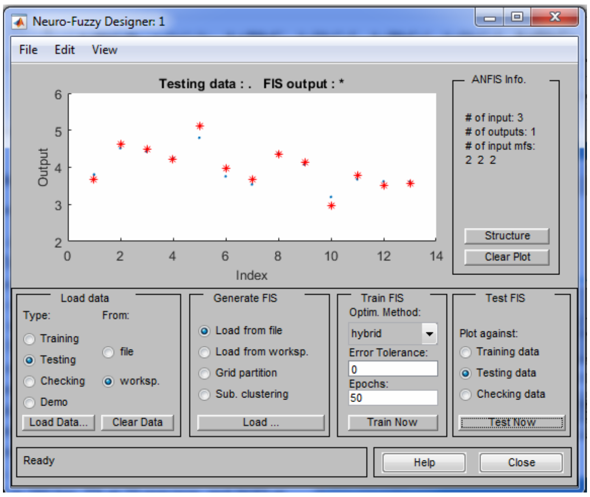


Fig. 4. Testing of output performance.

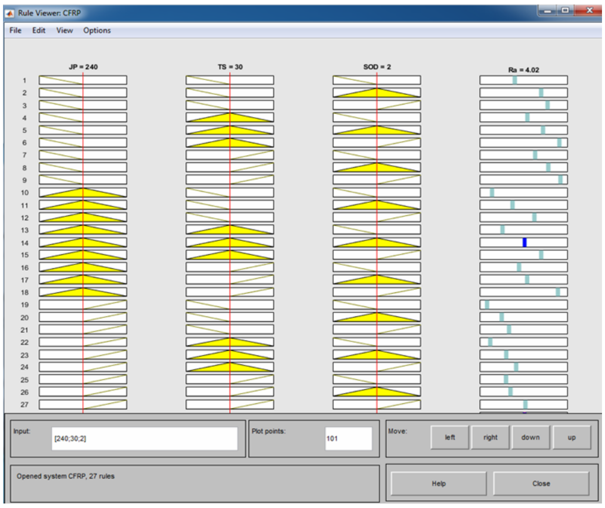


Fig. 5. Rule viewer.

value was initially set in the rule editor and the results were generated. The location of each triangle in the figure indicates the fuzzy sets for each linguistic variable. The membership values of the fuzzy sets are represented based on the height of the darkened area (represented in yellow) in the triangle. Later, the predicted values were compared with the experimental values to validate the results. Thus the developed ANFIS model can be used to forecast future Ra values.

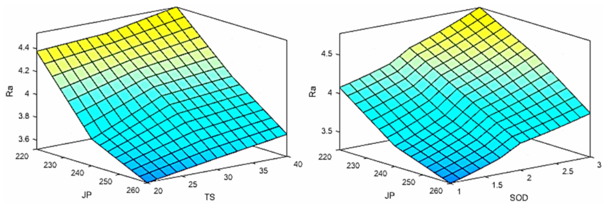
3.2 Influence of input process parameters on Ra

The influence of JP, TS and SOD on the surface roughness is shown in Figs. 6(a) and (b). A lower pressure deteriorated the finish in the cut surface by producing lays and flaws. Strong scratches and grooves were also observed, resulting in an increased Ra value. The kinetic energy of the jet stream determines the surface morphology of the CFRP. At 220 bar, the surface waviness produced a large difference between the peak and valley from the mean line, resulting in a poor finish.

Table 2. ANOVA for Ra.

Source	DoF	Seq. SS	Adj. SS	Adj. MS	Contribution (%)
JP	1	2.7683	0.0029	0.0029	49.19
TS	1	0.5879	0.0004	0.0004	10.45
SOD	1	2.0180	0.0558	0.0558	35.86
JP*JP	1	0.0004	0.0004	0.0004	0.01
TS*TS	1	0.0007	0.0007	0.0006	0.01
SOD*SOD	1	0.0002	0.0002	0.0002	0.00
JP*TS	1	0.0006	0.0006	0.0006	0.01
JP*SOD	1	0.0206	0.0206	0.0206	0.37
TS*SOD	1	0.0072	0.0072	0.0072	0.13
Error	17	0.2236	0.2236	0.0132	3.97
Total	26	5.6275			100.00

DoF= Degree of freedom, SS= Sum of squares,
MS= Mean square



(a) (b)

Fig. 6. Influence of input parameters on Ra.

However, the increased energy at 260 bar improved the cutting efficiency and produced a smooth surface. The time for material removal depends on TS, which leads to an improved finish at 20 mm/min and higher Ra at 40 mm/min. The jet lag at higher TS resulted because of an insufficient time for cutting the CFRP. Thus, the fibers that poked out from the cut surface got fuzzed up with the stylus probe during measurement, increasing the roughness. The increased divergence of the jet flow at 3 mm SOD resulted in a wider top kerf width and narrow bottom kerf width. Conversely, a reverse trend was observed at 1 mm SOD. Though the kerf wall inclination was observed at both the conditions, the kerf angle was found to be minimal at 1 mm SOD. This was the key factor in reducing Ra at lower SOD. Finally, it is concluded that a JP of 260 bar, TS of 20 mm/min, and SOD of 1 mm resulted in the minimum Ra (3.202 μm).

The 3D surface profile of the cut surface of the CFRP composite during machining at the optimum condition is shown in Fig. 7. The Ra value in the X and Y directions were found to be 1.9526 μm and 3.4249 μm, respectively. Some rough patterns were still visible because of the flow of the jet stream. This created many deeper valleys, rather than peaks, on the cut surface.

The statistical Analysis of variance (ANOVA) was performed for Ra to predict the level of contribution of each input parameter. The linear, squared, and interaction effects were

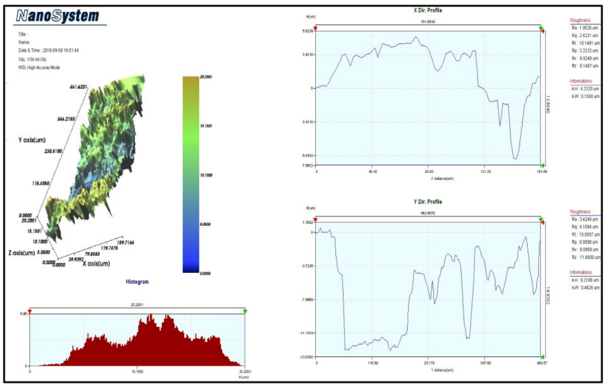


Fig. 7. Surface morphology at optimum condition.

considered for performing the analysis and the results are shown in Table 2. The result indicates that the contribution of JP in affecting Ra was as high as 49.19 % followed by SOD (35.86 %) and TS (10.45 %). It was also found that the squared and interaction effects had no significant influence on the output response.

The influence of TS and the edge quality are directly related. However, the minimum thickness of the composite (6 mm) resulted with an efficient removal of material even at higher TS condition. Thus, the contribution of TS on minimizing Ra is comparatively lower than JP and SOD. However, proper selection of input parameters is essential for obtaining the minimum Ra value during the AWM of the CFRP composite.

3.3 Validation of results

The developed ANFIS model was used to validate the experimental results. The Ra values were fitted to the design to determine the error between the experimental results and the predicted ANFIS model. Further, the probability plot was used to confirm the significance of the developed model.

Generally, the probability should be < 0.001 for it to be significant. The probability plot for Ra (Fig. 8) shows that the results were within the 95 % confidence interval (mean=4 and standard deviation=0.4652). Thus, the result proves that factors such as JP, TS and SOD had a significant effect on Ra. The average percentage of error was found to be as low as 4.23 % (Fig. 9). This shows the adequacy of the developed ANFIS model. Further, the results of the confirmation experiment show that the surface finish was improved by +7.56 % with respect to the experimental and predicted optimum condition (Table 3). Thus, the proposed model is suitable for predicting the Ra value during AWM of CFRP composites.

4. Conclusions

An ANFIS modeling for determining the surface roughness during AWM of CFRP composite was performed and the following conclusions were drawn:

Table 3. Confirmation experiment.

Level	Ra		Improvement
	Experimental	Predicted	
Optimum condition (260 bar, 20 mm/min, 1 mm)	3.202 µm	2.96 µm	+ 7.56 %

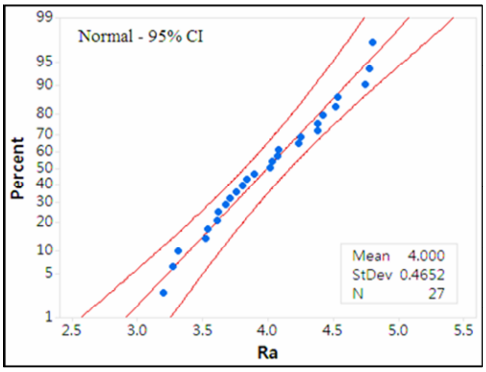


Fig. 8. Probability plot for Ra.

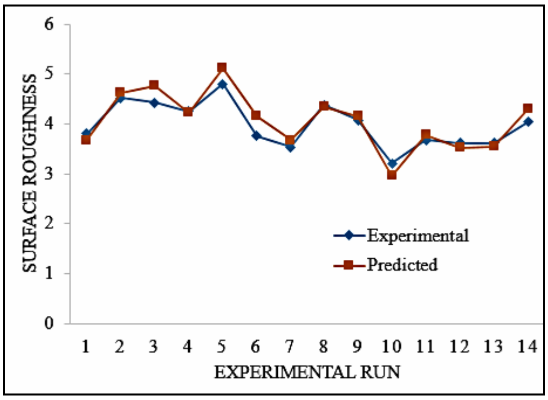


Fig. 9. Error analysis.

- A higher jet pressure and lower traverse speed and standoff distance produced a better finish in the cut surface of the composite.
- The predicted results obtained from the ANFIS model showed a 95 % confidence level. In addition to that, the average percentage of error between the experimental results and predicted ANFIS model was found to be as low as 4.23 %.
- The minimum roughness (3.202 µm) was produced at a jet pressure of 260 bar, traverse speed of 20 mm/min, and a standoff distance of 1 mm.
- Based on the statistical analysis of variance, the dominant parameter affecting the surface roughness was jet pressure (49.19 %), followed by the standoff distance (35.86 %) and the traverse speed (10.45 %).
- The non-contact 3D surface profile of the cut surface of the CFRP composite at the optimum condition was obtained.

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