PREDICTION OF DELAMINATION FACTOR IN DRILLING GLASS FIBER REINFORCED EPOXY PLASTICS USING NEURAL NETWORKS

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ABSTRACT

Drilling of holes in fiber reinforced plastics (FRPs) becomes almost unavoidable in order to facilitate joining of parts. The drilling induced damage in FRPs is an area of paramount concern as the delaminated holes act as areas of stress and lead to reduced life and efficiency of parts. The present research initiative is to study the delamination produced in drilling of unidirectional and [(0/90)/0]s glass fiber reinforced epoxy laminates (GFREP). A Carbide Jodrill of two different diameters has been used at three different levels of speeds and feed rates. A predictive model based upon artificial neural networks (ANN) has been developed to predict delamination factor. The results reveal that artificial neural networks can be successfully applied to predict delamination at a given speed and feed for a particular GFREP laminate. In normal cases the predicted values are in close agreement with the experimental values. The mean percentage error in training and test data sets is found to be 1.1 % and 2.25%.

***Keywords**: GFRP, Drilling, Delamination, ANN.*

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1. INTRODUCTION

In the last two decades there has been tremendous increase in the use of FRPs, mainly in the areas of automobile, aerospace and aircraft industries. It is mainly due to ease of manufacturing, high strength to weight ratio, high impact resistance, excellent dimensional stability and corrosion resistance. It is very difficult to think of life without FRPs as they have led to increase in performance and reduction in cost. There are two methods of manufacturing FRPs, Primary manufacturing and Secondary manufacturing methods. Primary manufacturing results in near net shape products but if the design is complicated the product needs to be made in parts. Hence secondary manufacturing which involves machining of parts comes into picture. The use of conventional drilling for the process of hole making is almost unavoidable in order to facilitate the fastening of the parts. Drilling induced damages like peel-up delamination, push down delamination, matrix cracking, matrix burning, debonding, spalling etc., affect the reliability of the component. The holes act as areas of stress and result in poor assembly and reduced life of the component. It therefore becomes imperative to study and minimize the drilling induced damage. Drill geometry, drill material, feed rate and cutting speed are important parameters that effect delamination.

G. Caprino et al., Davim et al. and Durao et al. in various studies concluded that feed rate has highest influence on delamination [1, 2, 3]. Chen stated that in order to improve the surface quality/hole quality at exit, the feed rate at exit needs to be decreased during the drilling process [4]. Singh et al. varied the cutting speed along with feed rate and found that increase in the feed rate resulted in increase in the thrust force for all the values of cutting speeds. This increase in thrust force caused increased delamination [5]. El Sonbaty found that thrust force and torque increased with increasing, drill diameter, feed rate and fibre-volume fractions and decreased with increasing cutting speed [6]. Lin & Chen found that increasing cutting speed accelerated the tool wear which led to increase in thrust force [7].Tagliaferri et al carried out drilling tests on GFRP composites and showed that the width of the damage zone is correlated to the ratio between drilling speed and feed rate (V_r/ V_t). Higher the value, the better the cut quality [8]. The effect of using different tool geometries in drilling of different FRPs was done by various researchers like Abrao et al., Albuquerque et al., Durao et al., Davim et al., Hocheng and Tsao, Singh and Bhatnagar and Sakuma et al. [9 – 18]. An analytical approach for predicting the position of the onset of delamination based on linear elastic fracture mechanics was developed by Tsao & Chen [19]. Khashaba et al.found that fiber volume fraction is directly proportional with thrust force and torque in drilling GFRP

composites [20]. Langella et al. suggested a mechanistic model for predicting thrust and torque during drilling of GFRPs using traditional twist drills [21]. Fernandes and Cook developed a mathematical model of the maximum thrust force and torque during drilling of carbon fibre using a 'one shot' drill bit [22]. Zhang et al proposed a model for the critical thrust force at which delamination is initiated at different ply locations [23]. Singh and Bhatnagar proposed a mathematical damage model for four drill geometries correlating the damage area ratio with the operating variables cutting speed and the feed speed [24]. A neural network control scheme was suggested by Stone and Krishnamurthy to minimize the delamination [25]. An experimental approach for the prediction of thrust force produced by step drill using linear regression analysis of experiments and Radial Basis Function Network (RBFN) was proposed by C CTsao [26]. Karnik et al. made the delamination analysis in high speed drilling by developing an artificial neural network model with spindle speed, feed rate and point angle as the affecting parameters [27]. Mishra et al. [28] and Latha et. al. [29] used neural networks to predict damage in drilling of GFRP. Neuro-fuzzy was used to predict thrust force by Mishra et.al. [30]. Latha and Senthilkumar used fuzzy logic to predict delamination [31] and on another instance to predict thrust force [32] for a particular geometry. Hence various researchers worldwide have done qualitative and quantitative studies on drilling of FRPs. Various mathematical and predictive models have been developed to suit a particular situation but still a need of a good predictive model persists in order to save time and labour. Therefore the present research initiative is to develop a predictive model using neural networks to predict delamination factor for a particular cutting speed and feed rate in drilling of two different type of GFREP laminates using Jodrill.

2. EXPERIMENTAL SET-UP

The specimens of 4 mm thickness were prepared by the hand lay-up technique. Araldite LY556 was used as a resin along with hardener HY951 in the ratio 10:1 parts by weight. Due to the very low cure shrinkage laminates produced are dimensionally stable and practically free from internal stresses. The fiber-volume fraction is taken as 0.6 for all practical purposes. The tensile modulus along the direction of the fibers was found to be 48 GPa using the standard universal testing machine (Instron Type 5582).

A Beaver CNC machine is used to drill holes in the GFRP laminates. The maximum spindle speed that can be achieved using the machine is 4500 rpm and the minimum speed being 52 rpm.

Maximum drill diameter that can be used with the fixture is limited to 12 mm. Delamination on the exit side was characterized and quantified using a non-destructive dye peneteration test and the digital image processing software IMAGE Pro-Plus. The digital images gave a clear view of the damaged zone around the drilled hole as shown in figure 1

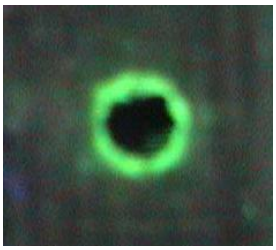

Figure 1: Damage zone around the drilled hole (1500 rpm, 10mm/min)

The delamination factor used to measure the extent of damage is given by ratio of the area of damaged hole to the area of actual hole to be drilled.

$$F_d = \text{Damage area}(D_a) / \text{Hole area}(H_a)$$

Figure 2 shows the schematic diagram of the damage area (D_a) around the drilled hole

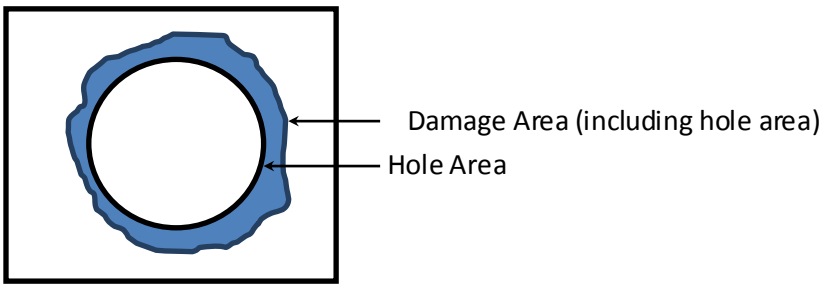

Figure 2: Schematic layout of Damage Area (D_a) and Hole Area (H_a)

3. EXPERIMENTATION

Initial sets of experiments were conducted to select a range for the speed and the feed rate to produce good quality and clean-cut holes. The speed was varied from 4 m/min to 72 m/min. The feed rate was varied from 5 mm/min to 30 mm/min. The damage around the drilled hole was observed qualitatively.

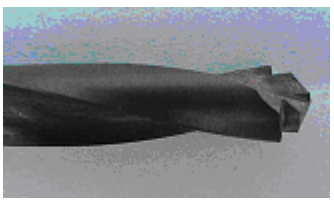

Fig 3: Jodrill

Total 36 experiments were conducted using jodrill of 4 mm and 8 mm diameter to record delamination factor. Figure 3 shows the geometry of a jodrill used. The laminates were uni-directional GFRPs and [(0/90)/0]s GFRP. Cutting speeds of 750, 1500 and 2250 rpm and feed rates of 10, 15 and 20 mm/min were used. The details of the delamination factor obtained in different experiments are given Table 1

TABLE 1

Overall Data Sets					
S.No	**Laminate**	**Drill Dia. (mm)**	**Cutting Speed (rpm)**	**Feed Rate (mm/min)**	**Delamination Factor**
1	UD-GFRP	4	750	10	2.056
2				15	2.17
3				20	2.04
4			1500	10	2.19
5				15	2.2
6				20	2.13
7			2250	10	2.278
8				15	2.25
9				20	2.203
10		8	750	10	2.184
11				15	2.23
12				20	2.186
13			1500	10	2.21
14				15	2.25
15				20	2.2
16			2250	10	2.253
17				15	2.27
18				20	2.184
19	[(0/90)/0]s GFRP	4	750	10	1.92
20				15	1.97
21				20	2.05
22			1500	10	2.04
23				15	2.27
24				20	2.13
25			2250	10	1.816

26				15	1.82
27				20	1.86
28				10	2.292
29			750	15	2.347
30				20	2.375
31		8		10	2.49
32			1500	15	2.43
33				20	2.37
34				10	2.593
35			2250	15	2.51
36				20	2.53

4. NEURAL NETWORKS

An artificial neural network is a system that processes the information and the sytems performance characteristics are in common with biological neural networks. Artificial neural networks has been developed on neural biology [35]. Neural network is trained to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target. The working is shown in figure 4. Conceptually it is more or less the same as in mechanical feedback servo control systems [33].

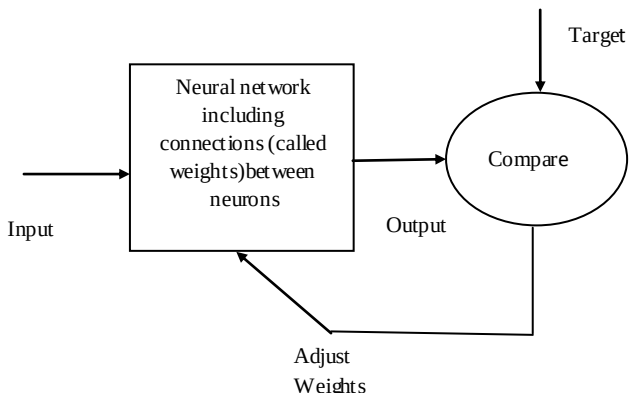

Fig 4: Conceptual working of Artifical Neural Networks [33]

A normal neural network consists of artificial neurons connected through links. The information provided to one neuron as input is processed and propagated to other neurons through synaptic weights of the links connecting the neurons. A general neuron symbol is as shown in Fig 5.

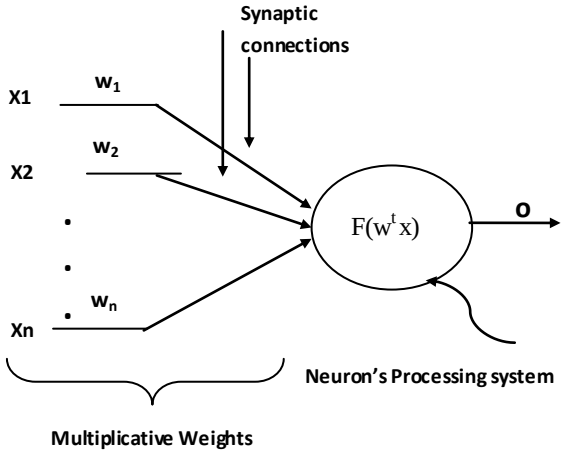

Figure 5: Artificial Neuron Symbol [34]

This symbolic representation shows a set of weights and the neuron's processing unit, or node. The net activation input to the jth neuron is given as:

$$net_j = \sum_{i=1}^{n} w_{ij} x_i$$

where:

w_{ji} = Weight of the link connecting neuron j to I,

x_i =The ith input.

The neuron output is given by $o = f(\sum_{i=1}^{n} w_{ij} x_i)$

The function $f(\sum_{i=1}^{n} w_{ij} x_i)$ is referred to as activation function.

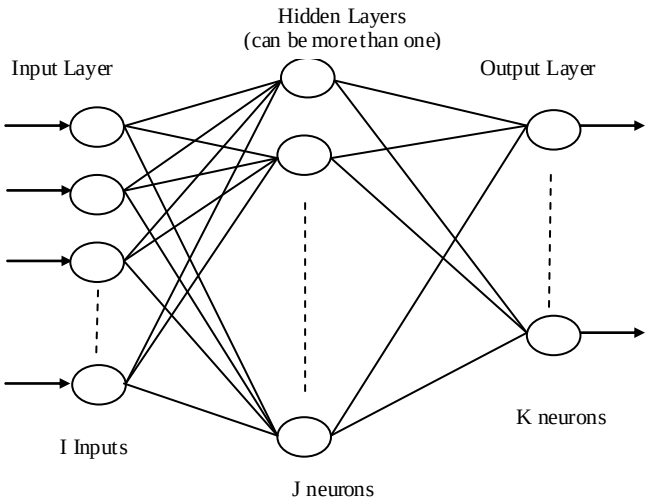

Figure 6: Neural Architecture

Most of the research work done using neural networks is based on EBPTA, Error Back Propagation Training Algorithm. The neural architecture is shown in Figure 6. The EBPTA is a supervised learning algorithm based on a generalized delta rule, which employs a set of inputs and desired outputs, known as training patterns. The ANN training primarily determines the connection weights that are required to give the desired response. The EBPTA is based on the weight updates so as to minimize the sum of the squared error for two output neurons, given as:

$$E_p = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{K}(d_{k,p} - O_{k,p})^2 \qquad (1)$$

where K is the number of outputs for P number of instances. Here $T_{k,p}$ and $O_{k,p}$ are the desired and output values for the pth instance. The weights of the links are updated as

$$w_{ji(n+1)} = w_{ji(n)} + \eta\delta_{pj}O_{pi} + \alpha\,\Delta w_{ji(n)} \qquad (2)$$

where n is the learning step, η is the learning rate, and α is the momentum constant. In Eq. 2, δ_{pj} is the error term, which is given as follows:

(i) For the output layer

$$\delta_{pk} = (d_{k,p} - O_{k,p})(1 - O_{k,p})O_{k,p} \qquad (3)$$

Where $k = 1, \ldots\ldots, K$

(ii) For the hidden layer

$$\delta_{pj} = O_{pj}(1 - O_{pj})\sum \delta_{pk}w_{kj} \qquad (4)$$

Where j = 1, …….,J

The principal steps in the training process are given below:

Step 1 Initialize all of the weights of the links to random values.

Step 2 Present the input-desired output patterns one by one, updating the weights each time using Eq. 2

Step 3 After presenting all of the patterns, compute the mean square error (MSE) due to all outputs, given by Eq. 1

Step 4 If (MSE<MSEtarget) or (epochs >epochsmax), then stop

Else, go to step 2

5. NEURAL NETWORK MODEL FOR PREDICTING DELAMINATION FACTOR

A code based on Error Back Propagation Training Algorithm was written in Matlab version R2007 b. A three layer network (Figure 6) with one input layer, one hidden layer, and one output layer, was used for the present study. The number of input layer neurons was four, the same as the number of input variables (Material, drill diameter, spindle speed, and feed rate). The output layer consisted of one neuron corresponding to one output variable i.e delamination factor. It has to be pointed out here that the number of hidden neurons depends both on input vector size and number of input classifications. Too few neurons can lead to under-fitting, whereas too many neurons can contribute to over-fitting. Hence the number of neurons in hidden layer has to be varied to find an optimal solution. The numbers of neurons were varied from one to fifty and the results were compared. In the present case, number of neurons used in the hidden layer are 40. The data sets were first normalized and sigmoidal function was used as an activation function. The learning rate was 0.15 and momentum factor was kept as 0.9. The error considered was simple error i.e. difference between the desired output value and the value obtained by the model. The number of iterations used was 15000 and the weights were randomly chosen and were kept below one both in input and hidden layer. Firstly, 32 data sets were chosen randomly and were used to train the algorithm and the rest 4 data sets were used to test the program. Figures 7 and 8 gives the details of the predicted values of the neural network model for training and test data respectively.

6. RESULTS AND DISCUSSION

Experimental results clearly indicate that increasing the drill diameter increases the damage. In general damage also increase with speed but there is no fixed trend for damage with feed rate for the range chosen. Prolonged training of ANN model may lead to the ANN memorizing the input–output pattern, which results in poor generalization ability. Therefore, the training dataset was trained for 15,000 iterations. The maximum error in the training data sets was found to be 3.89%, minimum error was 0.022 % and average error was found to be 1.10%. The plot showing comparison between actual and predicted values in training datasets has been shown in figure 7. The adequacy of the developed ANN model was checked by using the test data sets. The maximum error in the test data sets was found to be 4.225%, minimum error was 0.39 % and average error was found to be 2.255 %. The bar graph showing the comparison between the actual and predicted values of delamination factor in

test data sets is shown in figure 8 .The predictive model can be used to predict delamination factor and hence can help in producing damage free holes in fiber reinforced composites.

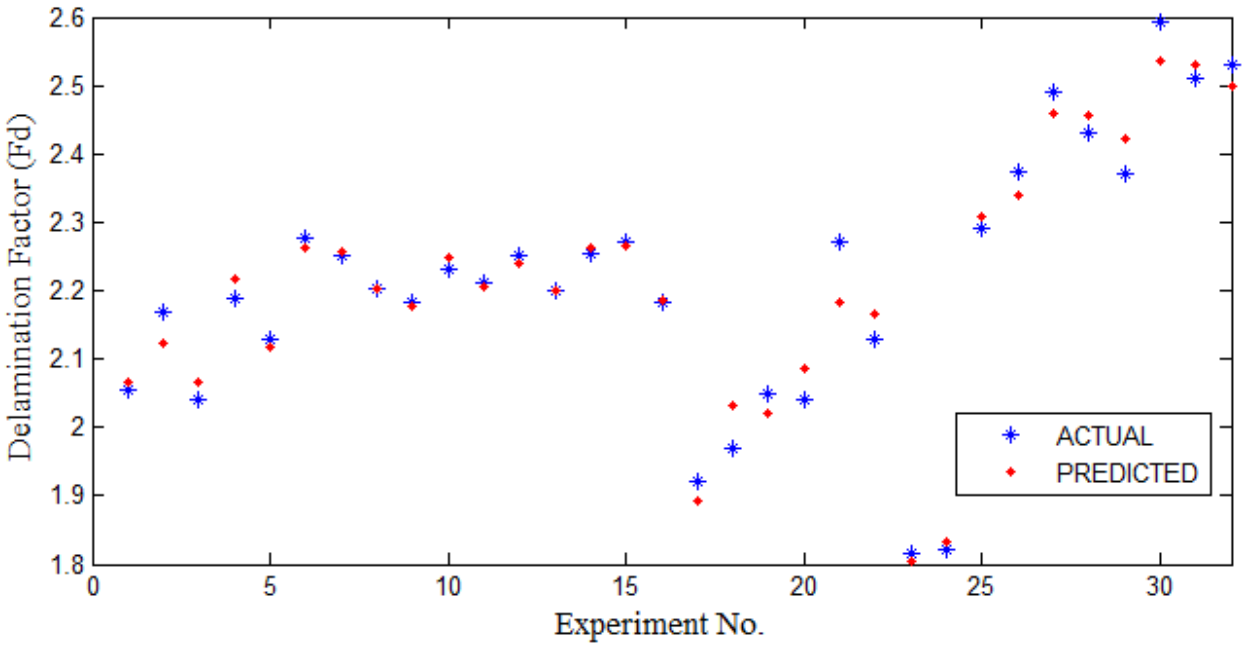

Figure7: Experimental and predicted value of delamination (F_d) for training datasets

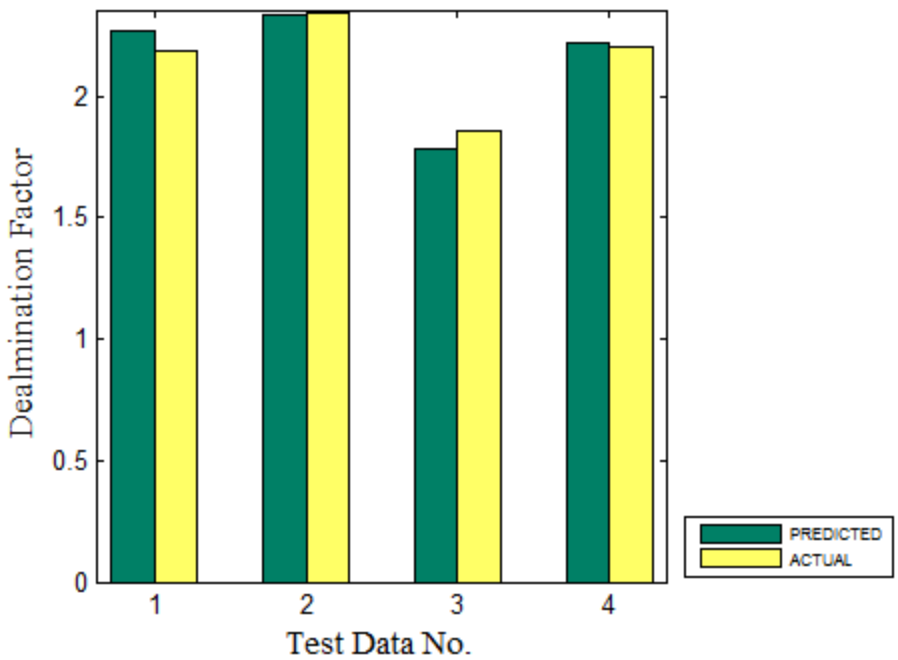

Figure 8: Bar graph of ANN outputs and test data

7. CONCLUSION AND FUTURE SCOPE OF WORK

A predictive model has been developed on the basis of Neural Networks Error Back Propagation Training Algorithm for predicting delamination factor during drilling of UD-GFRP and [(0/90)/0]s GFRP laminates. The following conclusions can be drawn on the basis of the present investigation:

1. Increasing the drill diameter increases the drilling induced damage.
2. The predicted values of delamination factor for training data and testing data using the predictive model were close to the actual values. Overall average percentage error of all the training and test data taken together was less than 2%.
3. More data sets can be incorporated with more experimentation which will lead to higher accuracy of the predictive tool.
4. Similar models can be developed to predict thrust force and torque developed during drilling of FRP laminates.

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