Journal of Engineering Science and Technology
Vol. 6, No. 2 (2011) 191 - 203

DELAMINATION PREDICTION IN DRILLING OF CFRP COMPOSITES USING ARTIFICIAL NEURAL NETWORK

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Abstract

Carbon fibre reinforced plastic (CFRP) materials play a major role in the applications of aeronautic, aerospace, sporting and transportation industries. Machining is indispensible and hence drilling of CFRP materials is considered in this present study with respect to spindle speed in rpm, drill size in mm and feed in mm/min. Delamination is one of the major defects to be dealt with. Experiments are carried out using computer numerical control machine and the results are applied to an artificial neural network (ANN) for the prediction of delamination factor at the exit plane of the CFRP material. It is found that ANN model predicts the delamination for any given set of machining parameters with maximum error of 0.81% and minimum error of 0.03%. Thus an ANN model is highly suitable for the prediction of delamination in CFRP materials.

Keywords: CFRP, Drilling, Delamination, ANN.

1. Introduction

Presently, carbon fibre reinforced plastic (CFRP) composite materials have found wide applications as functional and structural materials due to its static, dynamic, thermal and chemical properties. As a result of these properties it has widespread applications include aerospace industries, automobile, sporting goods, marine, naval, space, machine tools, transportation structures, post strengthening of concrete beams and strengthening masonry shear walls in seismically active regions [1]. CFRP can be used to effectively improve the performance of structural members such as its load carrying capacity, stiffness, ductility, performance under cyclic loading, as well as environmental durability.

Nomenclatures

A	Actual data
D	Actual diameter, mm
D_{max}	Maximum diameter, mm
E	Overall error
F_D	Delamination factor
j	Index representing hidden node
k	Index representing output node
L	Learning rate
M	Momentum coefficient
m	Number of input nodes
O	Calculated output
T	Test data
u	Input node value
v	Hidden node value
w	Weights
x	Weights between layers
y	Activation function

Greek Symbols

Δ	gradient
δ	Error owing to a pattern
η	Learning rate
θ	Threshold values

Abbreviations

ANN	Artificial neural network
BPN	Back propagation network
CFRP	Carbon fiber reinforced plastic
CNC	Computer numerical control
GRNN	Generalized regression neural network
MSE	Mean square error
NNA	Neural network architecture
PNN	Probabilistic neural network

Due to its potential applications, there is a strong need to understand machining of CFRP materials. The non-homogeneity and anisotropic behavior of CFRP materials pose tremendous problems in their machining. Drilling is indispensable and the most frequently employed operation of secondary machining for CFRP material structures. Though many defects are associated in drilling of CFRP, micro cracking, fibre breakage, matrix cratering, thermal damage and delamination are considered as important defects. Among these defects, delamination is found to be one of the major defects that affect the application of CFRP in fastening structures. It is a resin or matrix dominated failure behavior that occurs in interply region.

Davim and Reis [2] established a new comprehensive approach to select cutting parameters for damage free drilling in CFRP materials based on a combination of Taguchi technique and ANOVA. Experiments shows that thrust forces plays significant role on delamination during drilling operations and delamination free drilling may be obtained by the proper selection of tool geometry and drilling parameters. Several other research works have also been carried out in drilling of CFRP composites [3-7].

Artificial neural networks (ANN) are employed commonly in the prediction of output parameters by training the network with the experimental results obtained. Palanikumar et al. [8] predicted the tool wear is using back propagation neural network. This work has considerable implications in the real time monitoring of tool wear in which the actual tool wear can be compared with the predicted ones to signal the onset of wear which in turn prevents damage to the tool wear and the work piece. The ANN predictive model of burr height and burr thickness were developed using a multilayer feed forward neural network, trained using back propagation algorithm [9]. The performance of this ANN model was compared with the second order RSM mathematical model and the accuracy of ANN prediction was clearly proved. Good agreement was observed between the predictive model using ANN and the turning experimental measurements of the turned part surfaces for measuring the surface roughness data [10]. In another work, RSM and radial basis function was compared for an experimental work on drilling of CFRP to predict thrust force for a core center drill [11]. Also, prediction of output parameters like thrust force, surface roughness, delamination analysis in drilling of composites has been carried out using ANN [12-19]. From these works the significance of neural networks in the machining operation is clearly understood.

The objective of the present work is to study the influence of different size of drills and drilling process parameters on delamination of CFRP composites. ANN is used to predict the delamination factor and the results shows good agreement with the experimental results obtained. Hence neural network helps in determining the optimum values of the machining parameters such that the delamination is minimized.

2. Experimental Description

Experiments were conducted on a computer numerical control (CNC) machine with prefixed cutting conditions. The specification of the machine is given in Table 1. CFRP material used in the experiments was manufactured through hand-layup process using epoxy resin. The mechanical properties of the CFRP composite material used are listed in Table 2.

Table 1. Machine Specifications.

CAPACITY	Longitudinal axis (X axis)	700 mm
	Cross axis (Y axis)	350 mm
	Vertical axis(Z axis)	150 mm
TABLE	Table size	1270×254 mm
	T-slots	16×3 mm
SPINDLE	Speed	60- 5000 rpm
	Centre to table	10/450 mm
FEED RATE	Feed rate	upto 3000 mm/min
	Rapid traverse	3000 mm/min

Table 2. Properties of CFRP Material.

Thickness of carbon fiber in the form of filaments is 0.05 mm	
Properties of the Carbon fiber	
Material	Standard grade of Carbon Fiber
Tensile strength (GPa)	3.5
Tensile modulus (GPa)	230
Density (g/ccm)	1.75
Specific strength (GPa)	2.00
Properties of the Epoxy	
Material	EPON Resin 8132
Viscosity (poise)	5-7
Weight per epoxide	192-215
Density (lb/gal)	9.2

The cutting tool used for the investigation is BRAD and SPUR type drill bit made of carbide. The drill bits used in the investigation is presented in Fig. 1. CFRP materials are drilled using this Brad and spur drill bits. The experiments are conducted as per L_{27} orthogonal array which in turn reduce the number of experiments. The cutting parameters considered for the analysis are spindle speed in rpm, feed rate in mm/min and drill diameter in mm. The three different levels of spindle speed are chosen as 500, 1000 and 1500 rpm. Similarly, feed variations are 50,100 and 150 mm/min and the drill size is varied as 4, 8 and 12 mm.

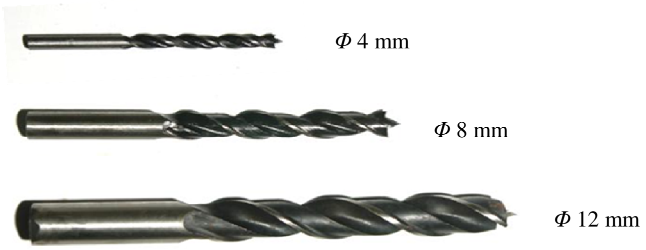

Fig. 1. Brad and Spur Drills used for Experimentation.

A three level, full factorial design of experiments were carried out and hence the delamination factor of the various drilled holes can be calculated using the relation

$$F_d = \frac{D_{\max}}{d} \tag{1}$$

where

F_d	- Delamination factor
D_{max}	- Maximum diameter observed in delamination
D	- Diameter of the drill

3. Artificial Neural Network

Artificial neural networks are highly structured information processing units operating in parallel and attempting to minimize the huge computational ability of the human brain and nervous system [20]. In this attempt to emulate the human brain, neural networks learn from experience, generalize from previous example, abstract essential characteristics from input containing irrelevant data and deal with fuzzy situation. ANN is a data driven self adaptive method and needs few prior assumptions about the process under study. The ability of the ANN to learn and generalize the behavior of any complex and nonlinear process makes it a powerful modelling tool. ANN have been successfully employed in the modelling of several process, especially for manufacturing processes where no satisfactory analytic model exists, or a low order empirical polynomial is inappropriate, neural networks offer a good alternative approach [10].

Neural network architecture consists of neurons connected through links. A variety of neural network architecture have been developed including perceptrons, Hopfield networks, back propagation and Kalmogrov networks [21]. Among these models, back propagation is the best general purpose model and probably the best at generalization [22]. Typical neural network architecture consists of a layered arrangement of neurons, the processing unit. Layers can be divided into an input layer, one or more hidden layers and an output layer as shown in Fig. 2.

The input layer is used to present the data to the network model and the output to create ANN's response. The number of hidden layers is to be determined based on trial and error method, on the basis of the improvement in the error with the number of hidden layers. It is identified that [10] two hidden layers should perform better than a one hidden layer network. The number of neurons in this hidden layer also depends on the error improvement with increasing number of neurons [23]. The hidden layers are connected with each other through variable weights. The number of neurons in input layer depends on the number of input parameters selected and they are fully connected with hidden layers. The number of neurons in the output layer depends on the number of classes or values to be predicted.

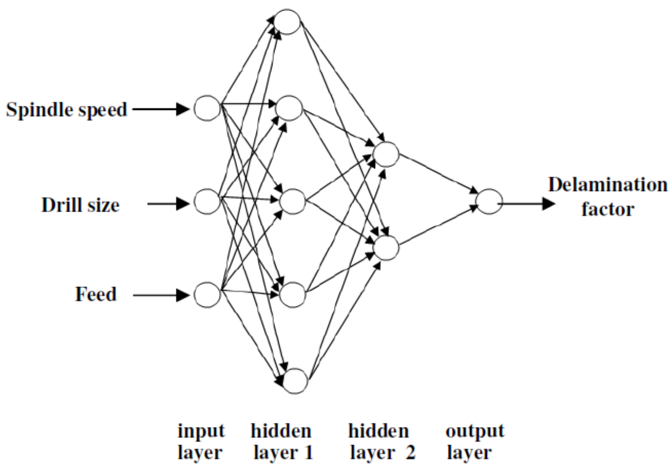

Fig. 2. Neural Network Architecture.

Learning rules used to train the network are basically of two types – supervised and unsupervised. In supervised learning, the network adjusts its weights using a known set of input output pairs and once training is completed, it is expected to produce a correct output in response to an unknown input. In unsupervised training, the network adjusts its weights in response to input patterns without the knowledge of any known associated outputs.

During learning, a neural network gradually modifies its weights and settle down to a set of weights capable of realizing the input –output mapping with either no error or a minimum error set by the user. The most common type of supervised learning are back propagation learning (BPN), radial basis functions (RBF), probabilistic neural network (PNN), generalized regression neural network (GRNN), etc. Several types of activation functions are used to transform the input value of the hidden layer to the output. They include threshold functions, piecewise linear function, sigmoid/hyperbolic functions and logarithmic functions.

During network training, the weights are given quasi-random, intelligently chosen initial values. They are then iteratively updated until convergence to certain known values so as to minimize the mean square error (MSE) between training data set and network prediction. The network training is continued with the entire set of training data and at the end of training, the test data are presented to the trained network and the output value is predicted. The above network training sequence is continued till the predicted output for the test data closely matches with the known experimental values. The error tolerance can be normally set to around two to three decimal places depending on the accuracy desired.

In this work, the input machining parameters considered are speed, drill diameter and feed and the output parameters to be obtained are delamination factors at the exit of the laminates. Hence the number of input and output neurons is chosen to be three and one respectively. The activation function is chosen to be a tansigmoidal nonlinear function given by

$$y = f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The weights, w, and the threshold values, θ, are adjusted until the error is minimized. The weights between the input and output layer is given as

$$x = \sum_{i=1}^{m} w_{ji} u_i + \theta_j, \quad j\text{=1 to } n \tag{3}$$

and between the hidden layer and output layer,

$$x = \sum_{i=1}^{n} w_{ki} v_i + \theta_j, \quad k\text{=1 to } l \tag{4}$$

where m is the number of input nodes, n is the number of hidden nodes and l is the number of output nodes, u and v are the input node and hidden node values. The output y_i of a neuron in successive layer is given by

$$y_i = \frac{1}{1 + e^{-\left(\sum_{i=1}^{m} w_{ji} u_i + \theta_j\right)}} \tag{5}$$

The overall error, E, of all the patterns is given by

$$E = \sum_{p=1}^{n} \frac{1}{2} \sum_{i=1}^{m} \left(T_{pi} - O_{pi}\right)^2 \tag{6}$$

where T_{pi} is the i^{th} component of the desired output vector and O_{pi} is the calculated output of the i^{th} neuron in the output layer. The learning algorithm employed in this work is back propagation method using the steepest gradient method [24]. In order to obtain a gradient descent in E,

$$\Delta_p w_{ij} = \eta \delta_{pi} O_{pi} \tag{7}$$

the weight vectors w_{ji} have to be updated using Eq. (7). Here δ_{pi} for the output layer is given by

$$\delta_{pi} = O_{pi}(1 - O_{pi})(T_{pi} - O_{pi}) \tag{8}$$

and that for the hidden layer is given by

$$\delta_{pi} = O_{pi}(1 - O_{pi}) \sum_{k} \delta_{pk} w_{jk} \tag{9}$$

In these equations η is a constant real number called the learning rate, which determines the influences of error over weight changes, δ_{pi} is the error owing to the p^{th} pattern connected to the j^{th} neuron and O_{pi} is the i^{th} neuron output when the p^{th} pattern is processed by the neural network. The weights of the neural network are updated by the following equation,

$$w(n+1) = w(n) + \eta \delta_{pi} O_{pi} \tag{10}$$

Error lines are computed for drill wear monitoring using ANN by training various neural network architectures [25]. Modelling of tool wear in drilling by statistical analysis and ANN was presented for a comparative study along with experimental data and neural network was found to be satisfactory while validated with experimental results [26]. Prediction of flank wear by using back propagation neural network modelling was carried out and identified that the ANN model based predictions of tool wear classification was accurate for the range it had been trained as compared to its experimental method [27-29]. A study of surface roughness in drilling using mathematical analysis and neural networks was carried out and found that the neural network model produced accurate and reliable results for all combination of input machining parameters [30].

4. Results and Discussion

In this work, a multi layer feed forward network architecture is used to model the experimental investigation on delamination factor at the exit of a CFRP composite material. This model is trained using back propagation algorithm by gradient descent method. Since, the number of machining parameters considered in the experimental work is three, two hidden layers with nonlinear activation functions, tansigmoidal, is chosen with one neuron in the output layer representing the delamination at the exit. However, (2n-1) and (n-1) neurons are considered in the proposed ANN model used for training, where n represents the number of machining parameters. The output layer activation function of this neural network is chosen as ‘pure linear’ in order to get an accurate result.

The ANN is modelled using MATLAB's neural network toolbox. The L_{27} orthogonal array of experimental data is normalized so that they fall within the range [-1 1] and the normalized values of training data is shown in Table 3.

Table 3. Normalized Training Data.

S. No.	Speed	Drill size	Feed	Exit F_d
1	-1	-1	-1	-0.9423
2	-1	-1	0	-0.4551
3	-1	-1	1	0.9038
4	-1	0	-1	-0.9295
5	-1	0	0	-0.4359
6	-1	0	1	0.9487
7	-1	1	-1	-0.8846
8	-1	1	0	-0.4038
9	-1	1	1	1
10	0	-1	-1	-0.9679
11	0	-1	0	-0.4872
12	0	-1	1	0.8782
13	0	0	-1	-0.9359
14	0	0	0	-0.4423
15	0	0	1	0.9103
16	0	1	-1	-0.8974
17	0	1	0	-0.4231
18	0	1	1	0.9679
19	1	-1	-1	-1
20	1	-1	0	-0.5321
21	1	-1	1	0.8333
22	1	0	-1	-0.9551
23	1	0	0	-0.4744
24	1	0	1	0.8718
25	1	1	-1	-0.9231
26	1	1	0	-0.4359
27	1	1	1	0.9231

This training set is used to train the network to predict the delamination factor for various normalized test data tabulated in Table 4.

Table 4. Normalized Test Data.

S.No.	Speed	Drill size	Feed	Exit Fd
1	-1	-1	-1	-1
2	1	1	1	1
3	0	0	0	-0.424
4	-0.2	0	0.6	0.7196
5	-0.6	0.5	0.4	0.4559
6	0.0385	0.0385	0.0385	-0.3602
7	-1	-1	-1	-1
8	1	1	1	1
9	-0.4	0	-0.4	-0.8321

However, twelve different neural network architectures (NNA) with varying training parameters were trained using this set of training data and their corresponding results are tabulated in Table 5. The error goal for training was chosen as 1×10^{-4} and the learning rate increment as 1.05.

Table 5. Training Error for different Neural Network Architecture

Trial No	Net	M	L	MSE X e-005	No. of Epochs	Predicted error in% Max	Min
1	3-4-2-1	0.2	0.25	9.9878	2095	4.33	0.18
2		0.25	0.3	9.99682	22336	0.83	0.07
3		0.25	0.2	9.99942	5484	1.23	0.14
4		0.4	0.5	9.99915	11890	4.18	0.23
5	3-5-2-1	0.2	0.25	9.99987	6215	1.00	0.18
6		0.25	0.3	9.99984	5766	2.43	0.25
7		**0.25**	**0.2**	**9.99974**	**13972**	**0.81**	**0.03**
8		0.4	0.5	9.99877	11942	1.14	0.03
9	3-6-2-1	0.2	0.25	9.99706	1554	2.73	0.28
10		0.25	0.3	9.99897	3121	4.36	0.19
11		0.25	0.2	9.99305	11091	3.88	0.21
12		0.4	0.5	9.99638	18655	4.25	0.22

The mean square error (MSE), maximum error in % and minimum error in % are calculated [25] and listed in the Table 3. It is found that the network architecture, 3-5-2-1, with 0.25 as momentum coefficient (*M*) and 0.2 as learning rate (L) provides an accurate result. The number of epochs required to converge towards the error goal set is found to be 13,972 and the same is depicted in Fig. 3 along with MSE.

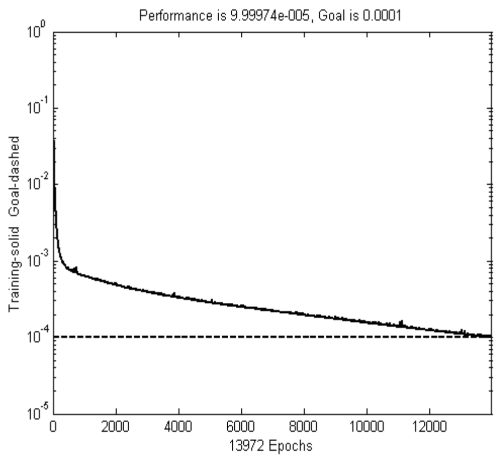

Fig. 3. Variation of MSE during ANN Training.

The trained network is simulated with training data and the comparison of correlation of actual and predicted training patterns for delamination is shown in Fig. 4.

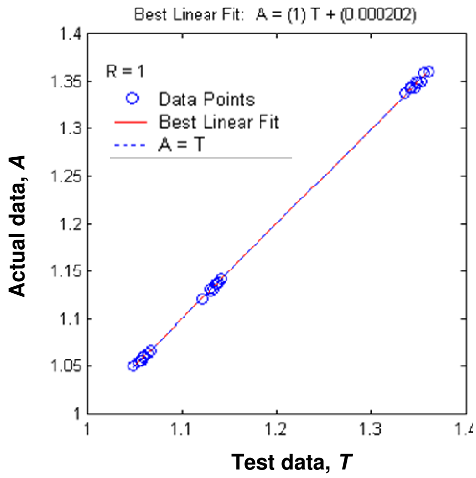

Fig. 4. Comparison of Correlation of Training Pattern for Delamination.

It is seen that the regression coefficient of post regression analysis shows unity and the best linear fit is obtained. The test data is verified using the same network and a comparison of the correlation of actual and predicted test patterns for delamination is shown in Fig. 5. The regression coefficient is 0.998 which is approximately equal to unity. A best linear fit is shown along with the deviation of predicted data points.

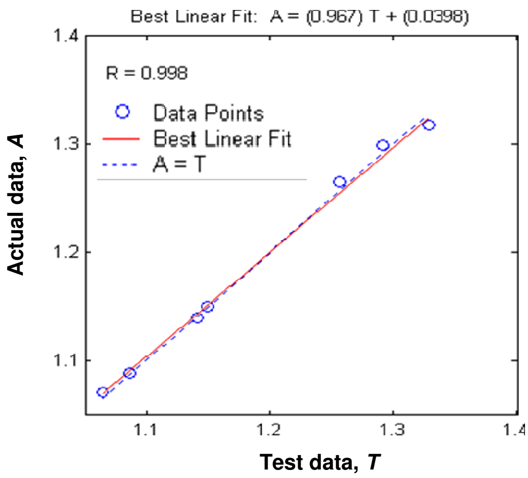

Fig. 5. Comparison of Correlation of Testing Pattern for Delamination.

A maximum error of 0.81% and a minimum error of 0.03% are obtained. The actual test data in unnormalized form is compared with the unnormalized predicted test data and is shown in Fig. 6. As the regression coefficient is 0.998, a slight deviation of actual and predicted values is seen. It can be understood that for any given set of machining parameters that are difficult to machine, but falls within the range of experimental data, it is possible to predict the delamination factor using this ANN model.

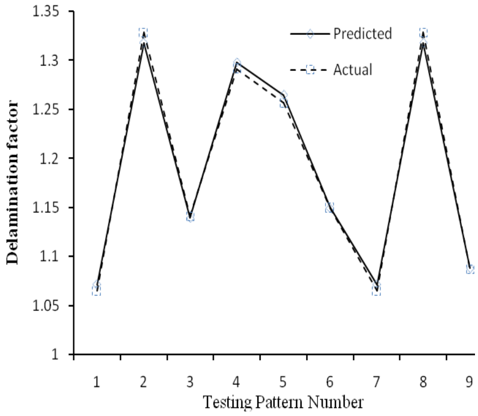

Fig. 6. Comparison of Actual and Predicted Values for Testing Patterns in ANN.

5. Conclusions

This study compares the ANN prediction and experimental calculation of the delamination factor at the exit of a drilled CFRP material. A three level, full factorial design of experiments was conducted to present data required for ANN modelling. Based on the obtained results, the following conclusions are drawn:

- Among a set of twelve different neural network architectures trained, a 3-5-2-1 neural network architecture is found to give an accurate result with a MSE of 9.99974e-5 and a maximum error of 0.81%.
- Post regression analysis of ANN shows a linear regression between the actual and predicted values of delamination factors.
- For any given set of machining parameters within this experimental range, ANN predicts the delamination factor with a maximum error tolerance of 0.81%.

Thus the proposed ANN model can be used as a prediction tool for determining the delamination for any given set of input machining parameters, namely, speed, drill size and feed. Based on the application, an optimum combination of these machining parameters can also be found out for a desired delamination factor.

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