ARTIFICIAL INTELLIGENCE BASED TOOL FOR PREDICTING OF DAMAGE DURING DRILLING OF FRP'S

Hitesh Sharma[1], Ujendra K. Komal[2], Inderdeep Singh[3], Dinesh Kumar[4] and Joy P. Misra[5]

[1] Department of Mechanical Engineering, National Institute of Technology Uttarakhand, Srinagar (Garhwal), Uttarakhand, India-246174, hiteshsharmaiitr9@gmail.com
[2-4] Department of Mechanical and Industrial Engineering, Indian Institute of Technology Roorkee, Roorkee, Uttarakhand, India- 247667, ujendrakomal@gmail.com, dr.inderdeep@gmail.com, dinesfme@iitr.ac.in
[5]Department of Mechanical Engineering, National Institute of Technology Kurukshetra, Haryana, India-136119, joyprakash.misra@gmail.com

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ABSTRACT

GFRP is an immensely versatile material, which is lightweight and has inherent strength to provide a weather resistance finish, with a variety of surface texture and an unlimited colour ranges available. Therefore, it is used in number of applications such as storage tanks, building, piping etc. [1, 2]. These applications require drilling of GFRP laminates in order to prepare various types of assemblies and hence the quality of drilled holes is of permanent concern [3]. The present research endeavour is to design and develop an artificial intelligence tool to foresee the damage induced during machining (drilling) of fiber reinforced plastic (FRP) laminates. Generally, the user faces the dilemma regarding the selection of the input parameters in order to ensure a smooth and good quality drilling. The graphical user interface (GUI) developed in current research work serves as an artificial intelligence tool which gives the values of delamination factor, thrust force and torque for given set of input parameters. Thus, the user can check that for a particular value of input, such as drill geometry, cutting speed, drill diameter and feed rate, what would be the damage caused to the hole. Moreover, the GUI integrates adaptive system into it, ensuring that with time as more and more volume of experimental data is collected for training the tool, the predictive accuracy can improve and will be close to practical results. The user interface developed can also be used to compare the extent of drilling-induced damage for two different set of input parameters and thus the input parameters which will lead to minimization of damage and process optimization can be easily predicted.

1 INTRODUCTION

GFRP are being used as excellent materials for structural applications. The drilling of these materials is entirely different as compared to drilling in metals because of their anisotropic nature, due to which the tool has to cut distinct phases simultaneously. The effect of drilling depends on the various parameters, such as properties of matrix and reinforcement, fiber volume fraction, fiber orientation etc. Drilling of GFRP, causes various kind of damage within the composite and at its surface [4]. Drilling-induced damage (delamination, deformation, cracking, fiber pull-out and hole ovality) has a severe impact on the structural integrity of composite parts. Drilling process parameters such as cutting speed, feed rate, tool material and tool geometry, are some of the main factors which governs the quality of drilled holes. Optimization of these parameters, numerical modelling and Artificial Intelligence (AI) are some of the important research area which have been undertaken to optimize the drilling operation in order to obtain the damage free holes. The various AI tools such as Artificial Neuron Network (ANN), Adaptive Network-based Fuzzy Inference System (ANFIS), Genetic Algorithm etc. can be used for the optimization in various fields.

2 EXPERIMENTAL DETAILS

2.1 Fabrication of composite specimens

The GFRP laminates of 4 mm thickness were fabricated using hand lay-up technique. Araldite AW 106 along with hardener HV 953U was used as resin.

2.2 Drilling set up

Drilling of the developed GFRP laminates was conducted on a radial drilling machine using solid carbide drills. The details of operating variables are presented in Table 1. Four-component piezoelectric drill dynamometer (Make: Kistler, Type: 9272) was used to record the thrust force and torque signals. The dynamometer is attached to the charge meters (Make: Kistler, Type: 5015) and the output of the charge meters is supplied as an input to the personal computer using an analogue/ digital card.

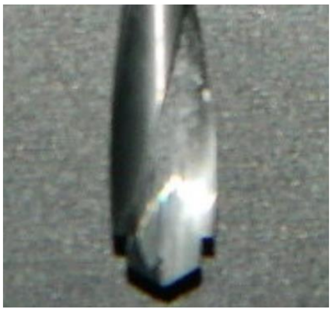
2.3 Input parameters

2.3.1 Operating variables

The range of data of various operating variable is presented in table below:

Operating Variable	Range
Cutting Speed	90 to 2800 RPM
Feed Rate	0.03 to 0.30 mm/rev
Drill diameter	4mm and 8mm
Drill geometry	Jo drill-1, Parabolic drill – 2, Twist drill-3

Table 1: Operating variables



Jo drill

Parabolic drill

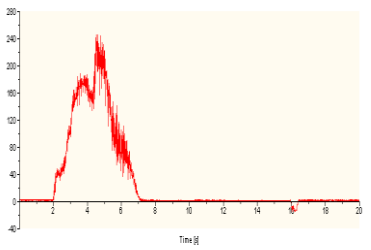
Twist drill

Figure 1: Different drill geometries.

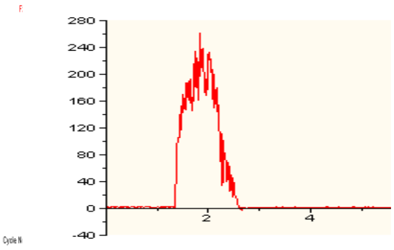
2.4 Output parameters

2.4.1 Thrust force and Torque

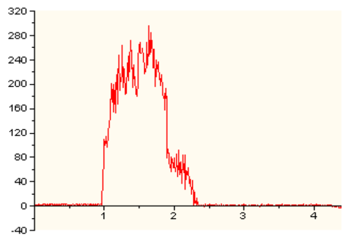
In order to record the thrust force and torque generated during drilling operation, a drill dynamometer (Kistler Type 9272) was used. The signals obtained were analysed and study was done to link the forces and torque with the ensuing damage around the hole. It has been established that, lower feed rates resulted into lower thrust forces and higher feed rate results in the value of thrust force to increase considerably which can be because of increase in shear area. An increase in thrust force and torque was noted with increase in the size of the drill due to increase in shear area so it can be said that there is some consequence of drill dimensions on the thrust force and torque. The thrust force has been recognised as the key reason of damage in drilling of GFRPs. A decrease in feed rate eases the thrust force which can ease the extent of induced delamination [5].



Thrust force signal at feed rate 0.3 mm/rev and speed 900 rpm with 8mm Jo drill

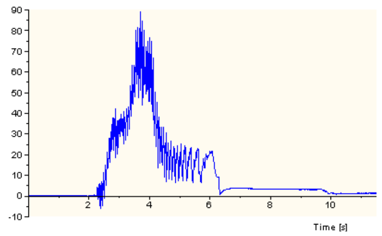


Thrust force signal at feed rate 0.3 mm/rev and speed 900 rpm with 8mm Parabolic drill.

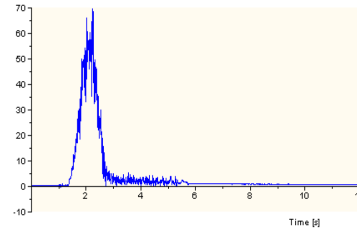


Thrust force signal at feed rate 0.3 mm/rev and speed 900 rpm with 8mm Twist drill

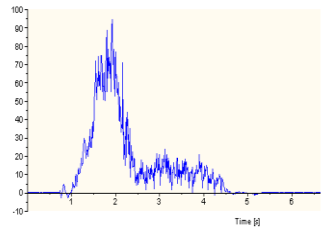
Figure 2: Thrust force signals for various drill point geometries (diameter: 8 mm)



Torque signal at feed rate 0.3 mm/rev and speed 900 rpm with 8mm Jo drill



Torque signal at feed rate 0.3 mm/rev and speed 900 rpm with 8mm Parabolic drill.



Torque signal at feed rate 0.3 mm/rev and speed 900 rpm with 8mm Twist drill

Figure 3: Torque signals for various drill point geometries (diameter: 8 mm)

2.4.2 Delamination

It is essential to develop a precise model to observe the consequences of various parameters of drilling process on delamination. Delamination factor was calculated by ratio of area of damage around the hole and actual area of hole. There are different methodologies available to quantify drilling induced damage or delamination. But still the most common technique used is dye penetrant testing. When observed under sunlight, dye penetrated into the damage area around the hole giving a clear picture of damage around the hole:

Figure 2: GFRP specimen after penetration of the dye showing damage around hole

Digital pictures of the damage around the hole were recorded using a digital camera. Using Image J, public domain software, the damaged area was obtained and it was found out that delamination factor is minimum with Jo drill and maximum with Twist drill.

3 ARTIFICIAL INTELLIGENCE TOOLS

The artificial intelligence tools like ANN, ANFIS, Genetic Algorithm, etc. can be used for prediction of thrust force, torque and delamination. In the present work, the drilling of FRP have been carried out on a radial drilling machine to which a Kistler make piezoelectric drill dynamometer (Type 9272) is connected and it is used to acquire highly accurate force and torque signals. The dynamometer is connected to the charge meter Kistler make (type 5015) through distribution box and connecting cables. The charge meter gives a digital display of output signals in the units specified in the input file. No separate calibration is required to convert the output signals into desired units. During the drilling process, the dynamometer measures the thrust force and torque and generates the signals which are recorded and analyzed.

3.1 ANN model

In order to develop an ANN model which can predict thrust force and torque, identification of input and output factors are very important. In the projected model, the input parameters considered are cutting speed (V), feed rate (f), drill diameter (d) and drill geometry. These parameters can be selected in advance, which means that they are controllable in nature and can be selected before performing of experiments. The schematic of the ANN model that we are going to use to predict thrust force, torque and delamination factor is illustrated below;

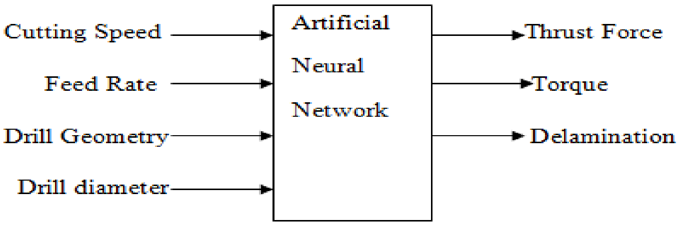


Figure 5: Schematic diagram of ANN for thrust force, torque and delamination

Before the ANN is trained by serving the dataset to the network and the input-output mapping, one major task is to process the experimental data into patterns. Training and testing pattern data points are made before input-output dataset are fed to network. A total of 396 holes were drilled using different combination of input parameters out of which 316 data points were used for training and 80 data points were used for testing.

3.1.1 Neural network design and training

In the proposed model, multilayer feed-forward back-propagation type neural network has been considered. The designing of neural network has been done in MATLAB 7.1 software. In this model, there are four neurons equivalent to corresponding four drilling parameters in the input layer and the output layer consists of three neurons equivalent to three outputs. The ANN configuration is represented as 4-10-3. The input layer contains four input neurons, the hidden layer contains ten neurons and the output layer contains three neurons. The trial and error method helps in determining number of neurons in the hidden layer after designing and examining numerous networks which can vary from their structure, transfer function to training algorithm etc. There are 316 training patterns considered for ANN modelling. After training, the weights are frozen and the developed model is tested with 80 testing points for validation.

Network configuration	4-10-3
Learning rate	0.5
No. of iterations	1000
Best validation performance	At 25 epoch
Error	Less than 8%

Table 2: Details of architecture used and results

The learning rate was kept as 0.5, the maximum number of training epochs was set to 1000 and thus ANN was trained for 1000 iterations. Mean square having lesser values are considered better. Mean square error is decreasing continuously and becomes constant at epoch 25. The training continued for further iterations before the training clogged. The error comes out to be less than 8% which is acceptable. To validate the network is of utmost importance and that is achieved by creating a regression plot. The training data, validation data, testing data and overall data is represented by four axes. The target line is represented as dashed line in each of the axis which is obtained by subtracting the outputs from the perfect results. The preeminent fit linear regression line is represented by the solid line, this solid line is between outputs and targets. Regression (R) value measures the connection between outputs and targets, for close relationship between targets and outputs the value of R should be one, whereas R value of zero means random relationship. As the value of R is around 0.97 for training data, validation data, testing data and overall data, we can say, there is close relationship between targets and outputs.

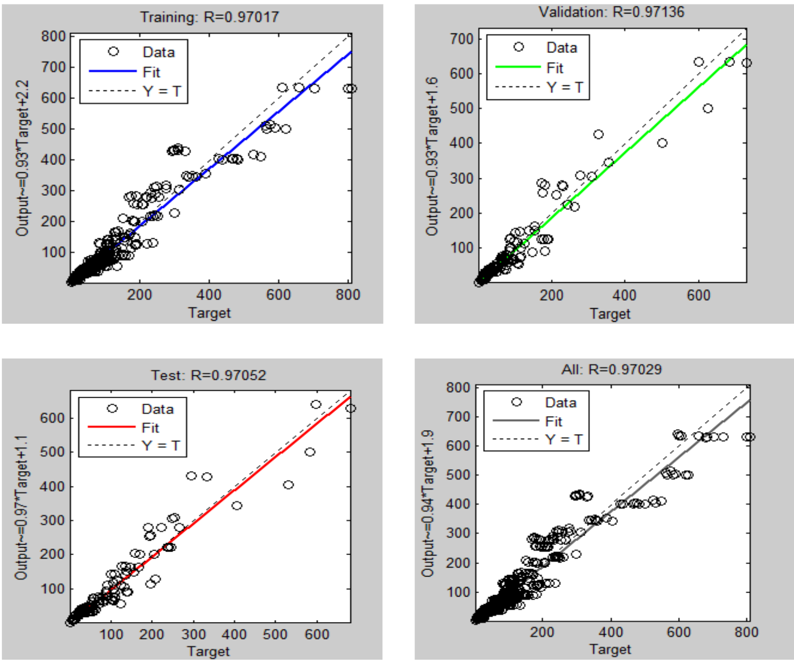


Figure 3 Regression plots

3.2 ANFIS model

The main difference between ANFIS and FIS is that in FIS we have to enter the rules which were finally deciding the output but in ANFIS these rules are generated by the program only, ANFIS uses learning technique to do this [6]. To train a network, there are two types of passes i.e. forward pass which carries the input vector through the network layer by layer and a backward pass in which the error is referred back in a manner similar to back propagation.

3.2.1 FIS model development, training by ANFIS along with the results

As like ANN again four input parameters were taken into consideration which are drill geometry, drill diameter, cutting speed and feed rate. FIS and ANFIS user interface tool in MATLAB 7.10.0 (R2010a) is used for predicting the output. Three different interface systems were developed for each output which are delamination, thrust force and torque, separately. After developing individual interface for each output, it was tested separately and then joined together in GUI. Bell type generation function for creating Fuzzy Inference System is used here, again 316 data points were used for training and 80 points for the testing.

3.3.2 Input variables

Four input variables are used for developing Fuzzy System.

(a) Drill geometry: As the name suggest, this variable consists of three different drill geometries. The three drill bits used are Jo-drill, parabolic drill and Twist drill. After training by ANFIS we get particular membership function of drill geometry.

Range of mf: LOW- 0.4 2 1 MEDIUM- 0.4 2 2 HIGH- 0.4 2 3

(b) Drill diameter: Second input variable is mainly concerned with size of the drill hole. Drill diameter is one of the paramount vital factors affecting quality of the hole drilled.

Range of mf: LOW- 0.8 2 4 MEDIUM- 0.8 2 6 HIGH- 0.8 2 8

(c) Cutting speed: The increase in the cutting speed gives indications towards an increased drill wear and maximum drilling prompted damage so it is very important to get a proper membership function, again we used ANFIS to get membership function which gives the precise results.

Range of mf: LOW- 542 2 90 MEDIUM- 542 2 1445 HIGH- 542 2 2800

(d) Feed rate: It is one of the most vital functional variables of drilling process. It influences the thrust force and torque. The range of membership function of feed rate generated by the training of Fuzzy System by ANFIS is given below;

Range of mf: LOW- .054 2 0.03 MEDIUM- .054 2 0.165 HIGH- .054 2 0.30

3.3.3 Output parameters

(a) Delamination factor: It is the ratio of damaged area and desired area of the hole. If delamination factor is equal to 1, it means the hole generated by drilling process is very precise and there is no defect in the hole. Sometimes it is also calculated as the ratio of actual and desired diameter of the hole.
(b) Thrust force and Torque: FIS of thrust force and torque was trained in ANFIS and membership functions and rules were generated.

4 DEVELOPMENT OF GUI

GUI developed is the primary form which takes four inputs and gives three outputs each from ANN and ANFIS models. Now a *.m file* was developed which helped in joining all the different models and program developed in ANN and ANFIS. Three ANN and ANFIS models were integrated in this *.m file* and coding was completed for push buttons, input menus and output menus. In order to check, for a particular value of thrust force, torque and delamination what would be optimum drill geometry, cutting speed and feed rate at which we can get the good quality holes, we can change the parameters in GUI and code them accordingly, but the problem comes in knowing the accurate values of outputs used because variables trained according to ANN and ANFIS sometimes gives the output in decimals. However, based on the experimental data, we can set particular range of thrust force and torque by which we can decide that at particular values of torque and thrust force which one would be drill geometry, what would be the values of drill diameter, cutting speed and feed rate. The thrust force has varied between 25.33 N and 807.68 N whereas torque has varied between 6.67 N-cm and 116.27 N-cm whereas delamination has varied between 1 and 2.5 respectively. The ranges are given below in Table 3

S.no	Thrust Force (N)	Torque (N-cm)	Delamination	Drill dia. (mm)	Drill geometry	Speed (rpm)	Feed (mm/rev)
1	25 -110	6-20	1.02 -1.3	4-8	1,2	90-355	0.03-0.08
2	110-300	20-50	1.3-1.7	4-8	1,2,3	355-710	0.08-0.19
3	300-820	50-120	1.7-2.5	8	3	900-2800	0.3

Table 3: Range of process parameters for thrust force, torque and delamination

5 RESULTS AND OBSERVATIONS

The predicted values using ANN were compared with the various corresponding experimental values and the comparative graphs were plotted for thrust force, torque and delamination factor.

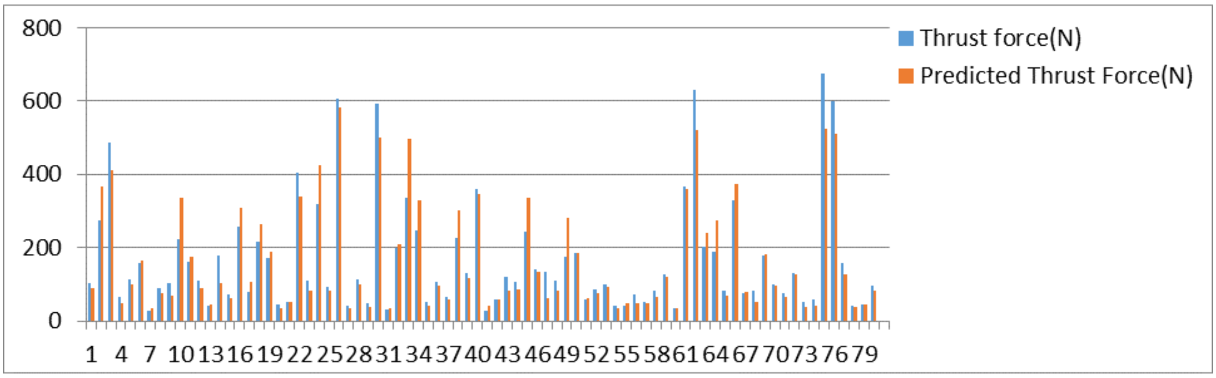


Figure 7: Experimental thrust vs. predicted thrust using ANN model.

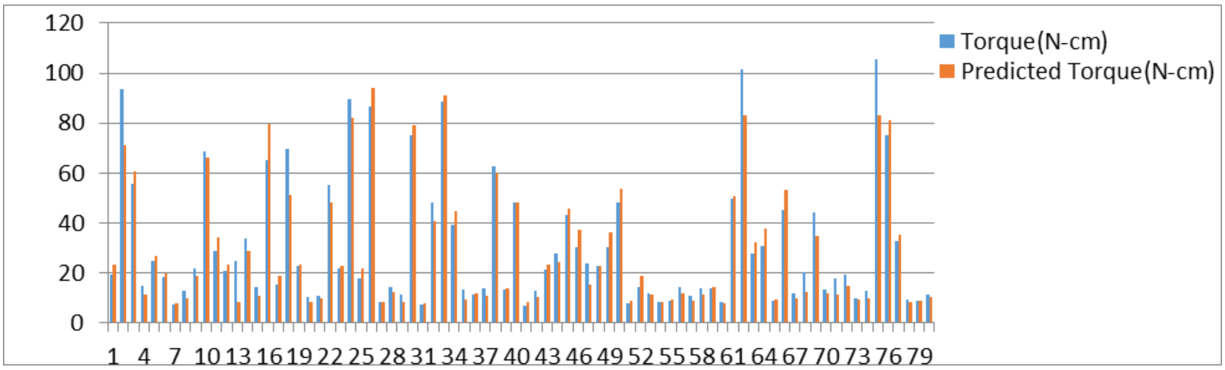


Figure 4: Experimental torque vs. predicted torque using ANN model.

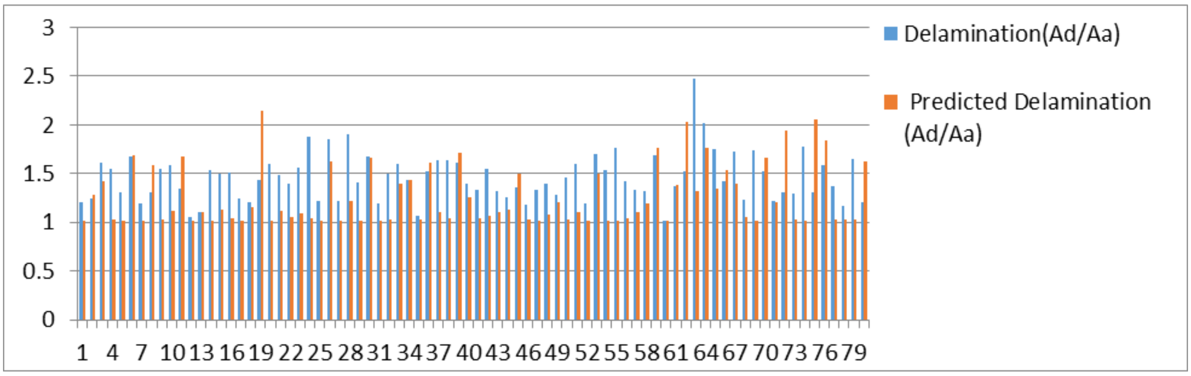


Figure 9: Experimental delamination factor vs. predicted delamination factor using ANN model.

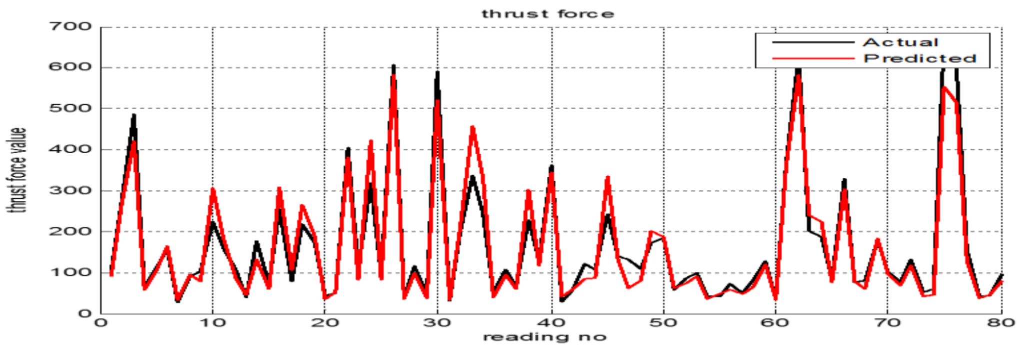


Figure 10: Experimental thrust vs. predicted thrust using ANFIS model

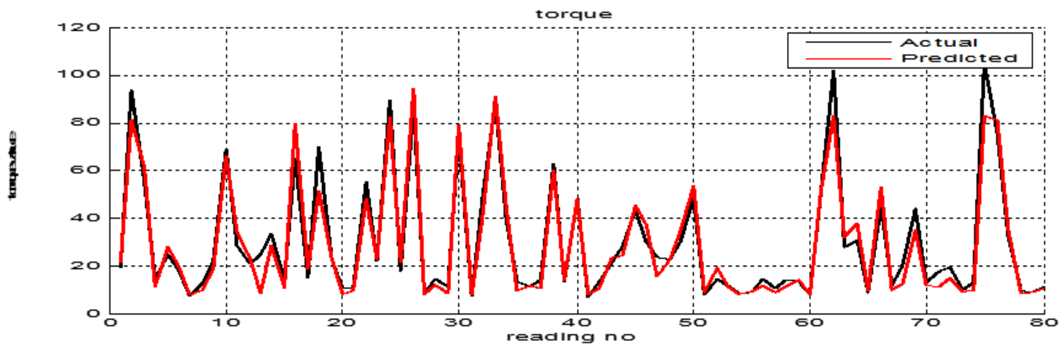


Figure 5: Experimental torque vs. predicted torque using ANFIS model

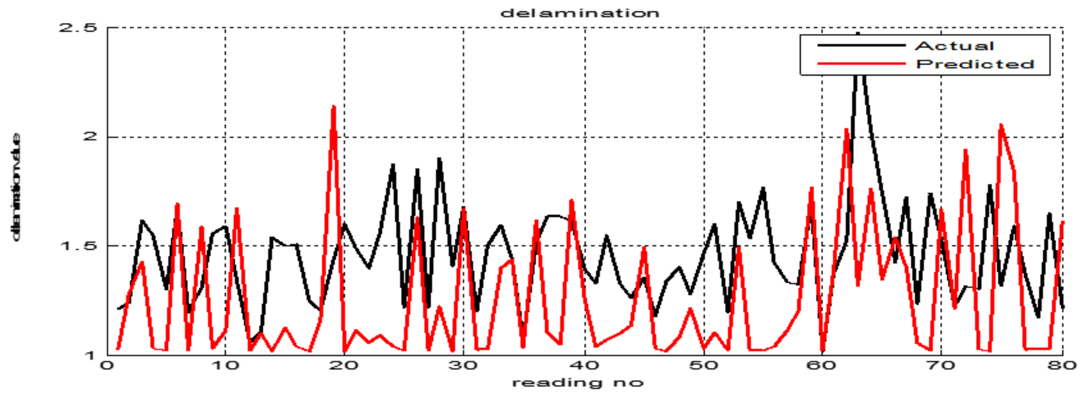


Figure 12: Experimental delamination factor vs. predicted delamination factor using ANFIS model.

It is quite obvious from the results that the prediction accuracy is good and matches with the experimental values. Therefore, the prediction model can be used for estimation of thrust force, torque and delamination factor. The main objective of this work was to assist the user in analyzing, comparing and selecting drill geometry and appropriate cutting parameters in order to attain the process optimization for drilling of GFRP laminates. By process optimization, the drilling induced damage must be minimized and the efficiency of the process should be increased. The assistance is provided by the development of the user friendly Graphical User Interface (GUI) which returns the values of the delamination factor, thrust force and torque by ANN and ANFIS methods for specific values of input parameters. On the basis of these parameters, the user gets a range of values for all three outputs and can decide on whether to go ahead with the drilling processes for specified drilling parameters. The output parameters provide following results to the user:

- It was observed that thrust force and torque increases with increase in diameter of the drill, due to escalation in shear area so it can be said that there is influence of drill dimensions on thrust force and torque.
- The outcomes indicate that accurate and precise holes are produced at moderate spindle speed, lower feed rate and at minimum diameter of drill.

6 CONCLUSIONS

The experiments were conducted on GFRP laminates made up by hand lay-up technique. The various input parameters considered for experimentation were, drill diameter, spindle speed, feed rate and drill geometry. ANN and ANFIS artificial intelligence tools were used for predicting of thrust force, torque and delamination factor. A total of 396 holes were drilled using different combination of input parameters out of which 316 data points were used for training and 80 data points were used for testing. The following possibilities can be drawn from the present research endeavor;

- The drilling parameters affects the drilling forces and subsequently the drilling induced damage.
- The thrust force and torque increases with increase in drill diameter.
- The precision holes were obtained at medium spindle speed, low feed rate and at minimal drill diameter.
- The delamination factor was found minimum in case of Jo drill and maximum with Twist drill.
- The GUI developed as a part of the current research endeavor can predict the thrust force, torque and the delamination factor with high degree of accuracy.

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