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Neural network modeling of forces in drilling of glass/epoxy composites filled with agro-based waste materials

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In this paper, the drilling behavior of a new class of composite materials has been experimentally investigated. The composite laminates have been manufactured using glass fibers, epoxy resin, and filler materials. The abundantly available agro-based waste materials (coconut coir, rice husk, and wheat husk) have been used as filler materials. The drilling experiments have been performed at several levels of feed (0.03 to 0.3 mm/rev.) and speed (90 to 2800 RPM) using different types of drill bits. The effect of these parameters on the drilling forces (axial thrust and torque) has been analyzed for all types of laminates under investigation. The artificial neural network-based models have also been proposed to compute the drilling forces. The fitness of the models has been measured in terms of mean percentage error between the predicted and actual values. From the investigation, it has been found that the drilling forces computed by the neural network models were quite close to the experimental values.

Keywords: Composites, Natural fillers, Drilling, Forces, Neural network

1 Introduction

Manufacturing of polymer composites can be bifurcated into, (i) primary manufacturing and (ii) secondary manufacturing. A near-net-shape product can be obtained through the primary manufacturing of composites. But the manufacturing of intricate products necessitates the fabrication of multiple parts to obtain the final product. These parts are then assembled by installing mechanical fasteners. The traditional drilling operation is an inevitable secondary operation that is extensively used to generate holes in composite to facilitate the installation of mechanical fasteners. But drilling of composites does cause significant damage to the hole which leads to poor structural integrity and assembly tolerance, reduced part life, and load-bearing efficiency. The damage of the hole is significantly influenced by the forces generated during drilling. These forces can be minimized by selecting the optimum drill bit geometry and cutting parameters (feed and speed)[1]. The lower value of drilling forces results in the production of superior quality holes. Singh and Bhatnagar[2] inferred that both axial thrust and torque are increased with feed during drilling of composites. Mohan *et al.*[3] established the fact that the effect of speed and size of the drill bit on the axial thrust is more significant than thethickness of the composite and feed of the drill bit. The effect of drill size and composite thickness were found to be significant parameters for torque. Tsao[4] concluded that the cutting parameters are the vital parameters that exert an influence on the forces and delamination produced during drilling of polymer composites. Krishnaraj *et al.*[5] showed that feed has a substantial influence on the axial thrust, hole size, and delamination. Durao*et al.*[6] stated that maximum axial thrust and delamination are obtained at a higher level of feedand speed. Abrao*et al.*[7] and Mathew *et al.*[8] investigated the influence of solid and hollow drill geometries on the forced induced during drilling of composites. The optimum drill geometry was identified in the context of making damage-free holes in composites. Velayudham and Krishnamurthy[9] established the fact that drill geometry had a significant influence on force and delamination during drilling of glass/phenolic composites. The tripod drill bit produces the least damage to the hole relative to the normal drill bit

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(point angle of 118°) and web thinned drill bit (point angle of 85°). Khashaba[10] stated that the delamination is a function of feed. This implies that the axial thrust is increased with feed during drilling of glass/polyester and glass/epoxy composites. Palanikumar[11] asserted that the axial thrust and delamination are closely related to each other. Hence, an increase in axial thrust results in increased delamination. It was also established that the axial thrust is not the only factor that causes damage to the hole; torque also contributes to the damage of the hole[12]. Hocheng and Dharan[13]emphasized the importance of critical axial thrust above which the delamination occurs. Various analytical models were also proposed to compute the critical axial thrust[14-17]. Tsao and Hocheng[18]developed a relationship among the cutting parameters and axial thrust using a multivariable linear regression approach. Fernandes and Cook[19]proposed the axial thrust and torque models for carbon/epoxy composites during drilling with the 'one-shot' drill bit. Langella *et al.*[20] Proposed a mechanistic model that can compute the forces induced in the drilling of glass/epoxy composites using a traditional twist drill bit. The neural network technique which is more generic was also applied to develop the force models. One of the striking features of the neural network algorithm is that information about the input parameters is not required to solve the complex nonlinear problems. Also, any number of parameters can be considered to solve the problem using neural network architecture. The neural network models were successfully applied to minimize the axial thrust and delamination during drilling of composites[21,22]. Mishra *et al.*[23] Applied the neural network based on the backpropagation algorithm to compute the delamination. It was found that the radial basis function neural network computes the axial thrust more precisely than the response surface methodology[24]. Athijayamani *et al.*[25] also recommended that the neural network models can compute better axial thrust and torque values than the regression models.

From the literature, it was observed that no attempt has been made to investigate the drilling behavior of glass fiber-reinforced composites filled with agro-based waste materials. Hence, the motivation behind the work is to cover the gap in the literature pertaining to the drilling behavior of fiber-reinforced polymer composites. Therefore, in this research endeavors, the drilling behavior of unfilled and agricultural waste-filled glass/epoxy composites is experimentally investigated. The neural network models were also proposed to predict the forces generated during drilling of the developed laminates.

2 Experimental Details

2.1 Composite Preparation

The laminates (thickness of 4 mm) were prepared using a wet lay-up process at ambient temperature. Glass fiber (ρ=2.62 g/cm^{3}and d=10-20 µm) and agro-waste materials were used as reinforcement and filler materials, respectively. Araldite epoxy resin LY556 (ρ=1.12 g/cm^3 at 25°C) and hardener HY 951 (ρ=1 g/cm^3 at 20°C) were used as matrix materials. One of the important characteristics of the epoxy is that it exhibits low shrinkage. It has also excellent adhesion property to a variety of substrate materials. The epoxy molecule also comprises of two ring groups at its center which is able to absorb both thermal and mechanical stresses and thus give the epoxy resin good stiffness, toughness, and heat resistance[26-28]. The fillers were incorporated in a ratio of 5 wt.% of glass fiber. This proportion was decided after a pilot study with an aim to ensure (i) proper wetting between the fiber or filler and matrix and (ii) better mechanical and physical properties of the developed laminates. The properties of the developed composites were evaluated and already published[29]. The benefit of using agricultural waste is that it reduces the weight and cost of the composites. A total of four different types of composites were fabricated(i) unfilled- (GFREC), (ii) rice husk- (GFREC/R),(iii) wheat husk- (GFREC/W), and (iv) coconut coir- (GFREC/RC) filled glass fiber-reinforced epoxy composites.

2.2 Drilling Experiments

The holes were produced in the developed laminates using a radial drilling machine at the feed of 0.03, 0.05, 0.08, 0.12, 0.19, and 0.3 mm/rev. and speed of 90, 224, 450, 900, 1800 and 2800 RPM using solid carbide twist and parabolic drill bits of 4 mm in diameter. The force signals were recorded with the help of a drill dynamometer (9272A, Kistler, Switzerland). The force signals were amplified using a multi-channel charge amplifier (5070A, Kistler, Switzerland). The dynamometer was coupled with a computer via analog-digital (A/D) converter card. The maximum axial thrust (F_z) and torque (M_z) values were recorded for making of 288 holes in different laminates. The scheme of the drilling setup is shown in Fig. 1.

3 Modeling using Levenberg-Marquardt Algorithm (LMA)

The artificial neural network was applied to develop the proposed models for axial thrust and torque. The input-output mapping of axial thrust and torque is quite complex for drilling of composites. LMA was applied over conventionally used error back propagation training algorithms (EBPTA) because LMA enables to acquire more subtle information of a complicated mapping. Basically, it is a Hessian-based algorithm that uses the batch learning process for the optimization of non linear least squares. A code was written in MATLAB (R2008b) to develop the neural network architecture. The developed neural network architecture consists of the following three layers *viz.* input layer, hidden layer, and output layer. The input layer consists of five neurons. Four input variables consist of four neurons and one neuron for the bias. The output layer consists of one neuron which corresponds to one output *i.e.*, either axial thrust or torque. It is worth mentioning that training of the neural architecture for one output variable renders the model less complex. Thus, the model can compute better results. The number of neurons in the hidden layer depends on input classifications and vector size as well. A few neurons may result in under fitting and many neurons may result in over fitting. The optimal solution was found by varying the neurons in the hidden layer. The creation of a good network is time-consuming and hence, a simple approach was followed to find the best network as presented in Fig. 2.

The hidden layer consists of 36 neurons. A total of 38 neurons were used in neural architecture. The activation function considered for the hidden layer was tan-sigmoid function whereas; pure linear function was used for the output layer. The default values for μ^{-1} is 0.1 and μ^{+1} is 10 (where, μ is damping factor). The initial value of μ was 0.001 and the maximum value of μ was set as 1010. The initial weights were kept below 1 in hidden and input layers, respectively. For both proposed models, 230 data sets were randomly selected and used as training data sets. Once, the neural network architecture was trained, the rest 58 data sets were used for testing. The characteristic values of the proposed models are shown in Table 1.The neural network models were trained to yield the minimum mean square error, minimum mean percentage error, and maximum coefficient of correlation between the neural networks computed values and the actual values. All three

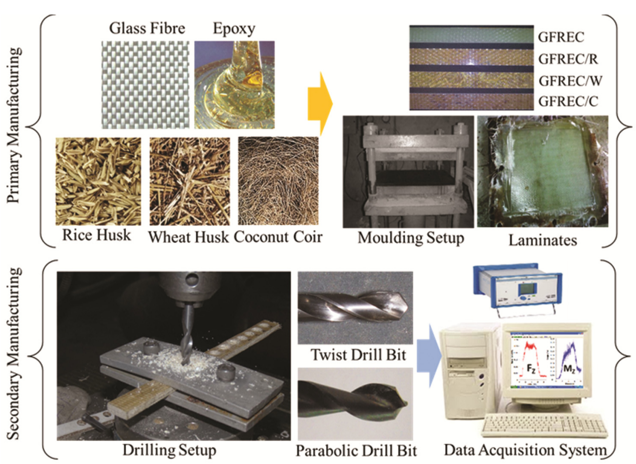

Fig. 1 — Scheme of the experimental setup.

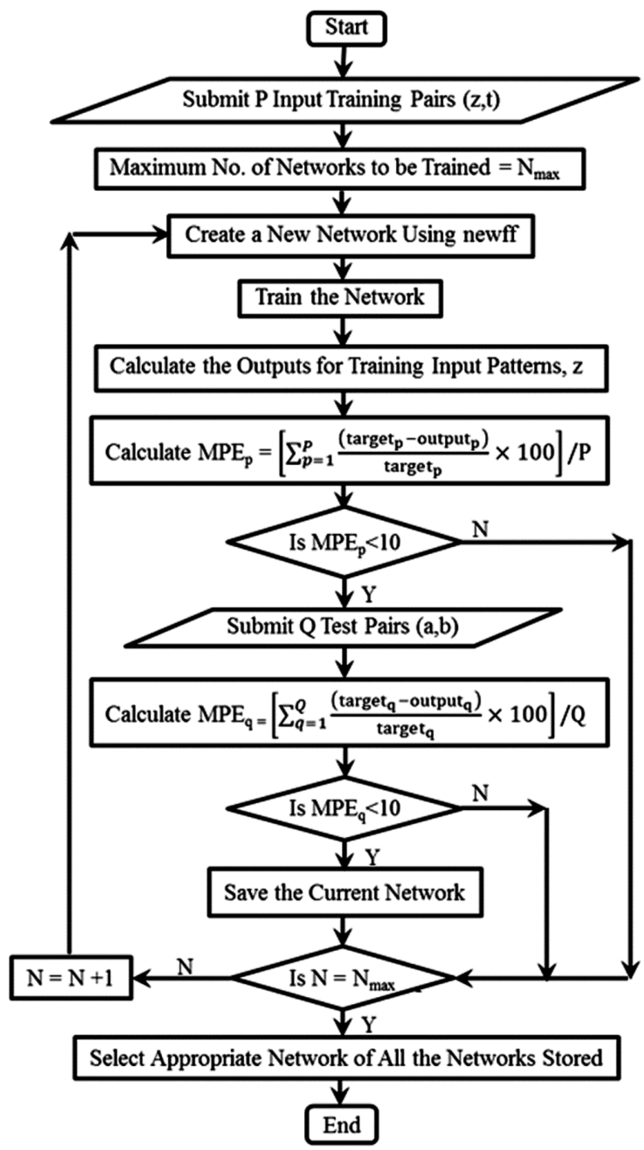

Fig. 2 — Flow chart to find out the best network.

Table 1 — Neural network predictive models.

S.No.	Characteristic values	Axial thrust model	Torque model
1.	Number of training datasets	230	230
2.	Number of testing datasets	58	58
3.	Number of hidden layers	1	1
4.	Activation function used in first layer	Tansigmoid	Tansigmoid
5.	Activation function used in second layer	Pure linear	Pure linear
6.	Mean percentage error in training data sets	3.03 %	4.54 %
7.	Mean percentage error in test data sets	4.93 %	7.45 %
8.	Coefficient of correlation between predicted and experimental values for training data sets	0.9969	0.9920
9.	Coefficient of correlation between predicted and experimental values for testing data sets	0.9925	0.9844
10.	Mean square error in training	19.17	0.81
11.	Mean square error in testing	31.81	1.70

criteria were checked during the training and testing of the models. The mean square error and mean percentage error was calculated using equation 1 and 2, respectively. It was suggested that the mean percentage error should be lower than 10% in training or testing for both the proposed models.

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

where,
E_P = Mean square error,
K = Number of neurons in the output layer,
$O_{k,p}$ = Actual output at the output neuron k for input p,
$d_{k,p}$ = Desired output at the output neuron k for input p, and
P = Total number of training patterns,

$$\text{MPE} = \sum_{p=1}^{P}\frac{(target_p - output_p)}{target_p} \times 100 \quad \dots (2)$$

where,
MPE = Mean percentage error, and
P = Total number of training or testing pairs

4 Results and Discussion

4.1 Analysis of Axial Thrust

The response of axial thrust during drilling of the developed laminates is presented in Fig. 3 to Fig. 5. It was established that the drilling behavior of the laminates with the twist drill bit is substantially different from the parabolic drill bit. It is clear from the figures that the axial thrust generated during drilling with the parabolic drill bit is lower than the twist drill bit under identical experimental conditions. This indicates that the drilling-induced damage is less during drilling with the parabolic drill bit. The chisel edge of the parabolic drill bit is merely a point. On the contrary, the twist drill bit has a flat chisel edge. Moreover, the flank face of the parabolic drill bit is designed in such a fashion that it facilitates easy and quick ejection of formed chips. These features of the parabolic drill bit render the cutting operation smooth[29]. Thus, both the forces and damage produced with parabolic drill bit are relatively less as compared to the twist drill bit. It was also noted that the axial thrust tends to decrease with speed at the lower feed (0.03 mm/rev.) for both the drill bits (Fig. 3(a) and Fig. 3(b)). But at the high feed (0.3 mm/rev.), an abrupt variation in the axial thrust was observed for twist drill bit as indicated in Fig. 4(a). However, the drilling with parabolic drill bit results in a gradual decrease in axial thrust with the speed of the drill bit at the feed of 0.3 mm/rev. (Fig. 4(b)). Both axial thrust and torque are decreased with the speed of the drill bit because the higher speed results in more heat generation at the interface between the drill tip and laminate. The low thermal conductivity of the composite constituents results in the accumulation of heat at the machining zone. The accumulation of heat results in the deformation of epoxy resin as the resin is prone to change its structure at elevated temperatures. The shearing or cutting of deformed or softened polymer necessitates lesser amounts of axial thrust and torque[30]. However, aberrations in the experimental results are detected due to the manufacturing defects such as voids, fiber displacement, and resin-rich areas. This implies that at higher feed the parabolic drill bit renders the cutting of fiber and matrix quite smooth as compared to the twist drill bit.

Figure 5 (a & b) shows that the axial thrust increases linearly with the feed for both the drill bits under investigation. The thickness of the uncut chip is increased with the feed of the drill bit. This indicates that the material offers higher resistance to form the chip. Therefore, higher axial thrust and torque is

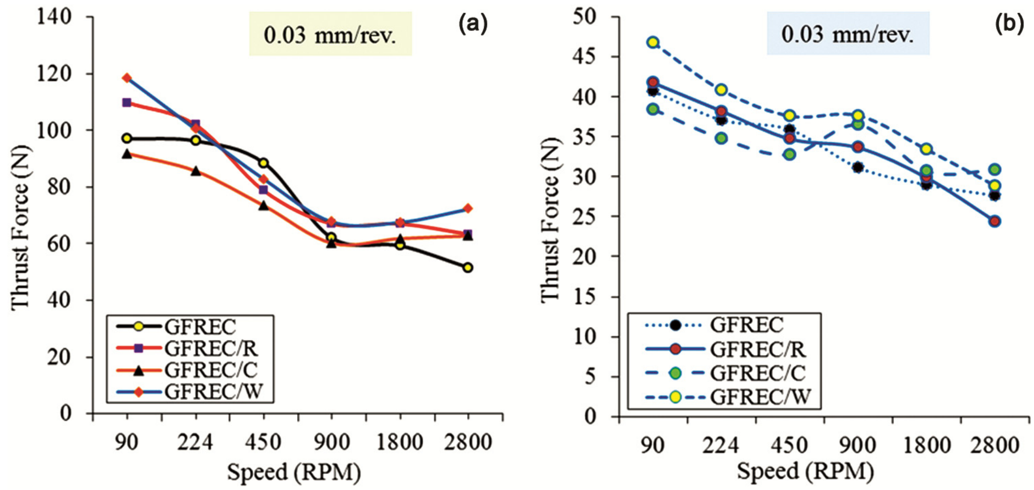

Fig. 3 —Variation of axial thrust with speed obtained at feed of 0.03 mm/rev for (a) twist drill bit and (b) parabolic drill bit.

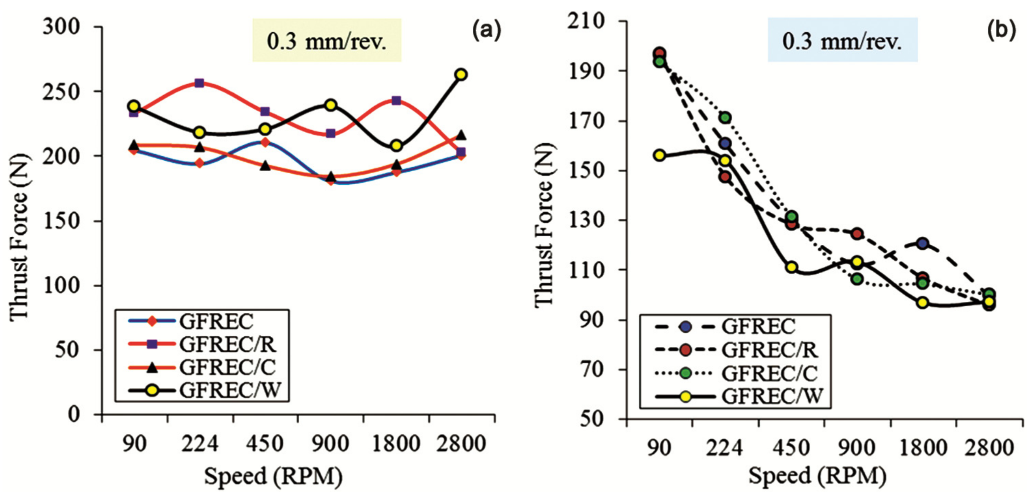

Fig. 4 — Variation of axial thrust with speed obtained at feed of 0.3 mm/rev for (a) twist drill bit and (b) parabolic drill bit.

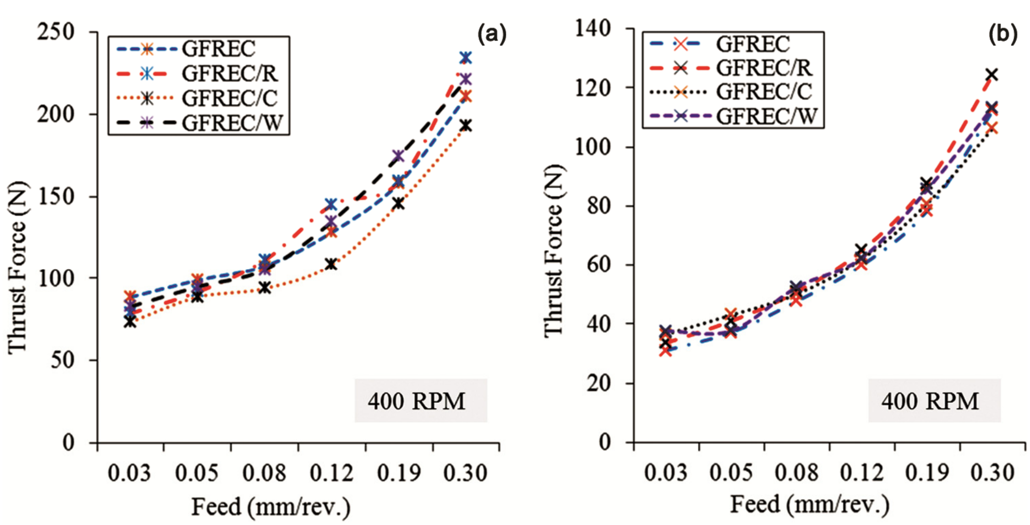

Fig. 5 — Variation of axial thrust with feed for (a) twist drill bit and (b) parabolic drill bit.

required to remove the material. This corroborates the findings of other reported work[30]. The axial thrust obtained during drilling of GFREC filled with natural fillers was less than the unfilled GFREC at most of the speeds and feeds. This recommends that the use of natural fillers does not lead to an increase in axial thrust and hence, less amount of drilling-induced damage is expected. Thus, natural fillers can be used to reduce the weight and cost of the resultant composites. As shown in Fig. 5 (a & b), a linear increase in axial thrust with feed was observed while holes are produced in laminates using both the drill bits. The increase was so steep that the axial thrust generated at a feed of 0.3 mm/rev. is at least twice that of axial thrust recorded at a feed of 0.03 mm/rev.

4.2 Analysis of Torque

The response of torque for all types of laminates is presented in Fig.6 to 8. The figures depict that the torque produced during drilling with the parabolic drill bit is relatively less than the twist drill bit. From Fig. 6, it can also be stated that the torque increases almost linearly with feed at all speeds for all the drill bits and laminates under investigation. The torque generated at a feed of 0.3 mm/rev. is at least three times higher than that generates at a feed of 0.03 mm/rev. The variation of torque with speed for twist and parabolic drill bits are presented in Fig. 7 and Fig.8, respectively. It is quite evident in the figure that the torque initially decreases with speed and then becomes more or less stationary at a higher speed for

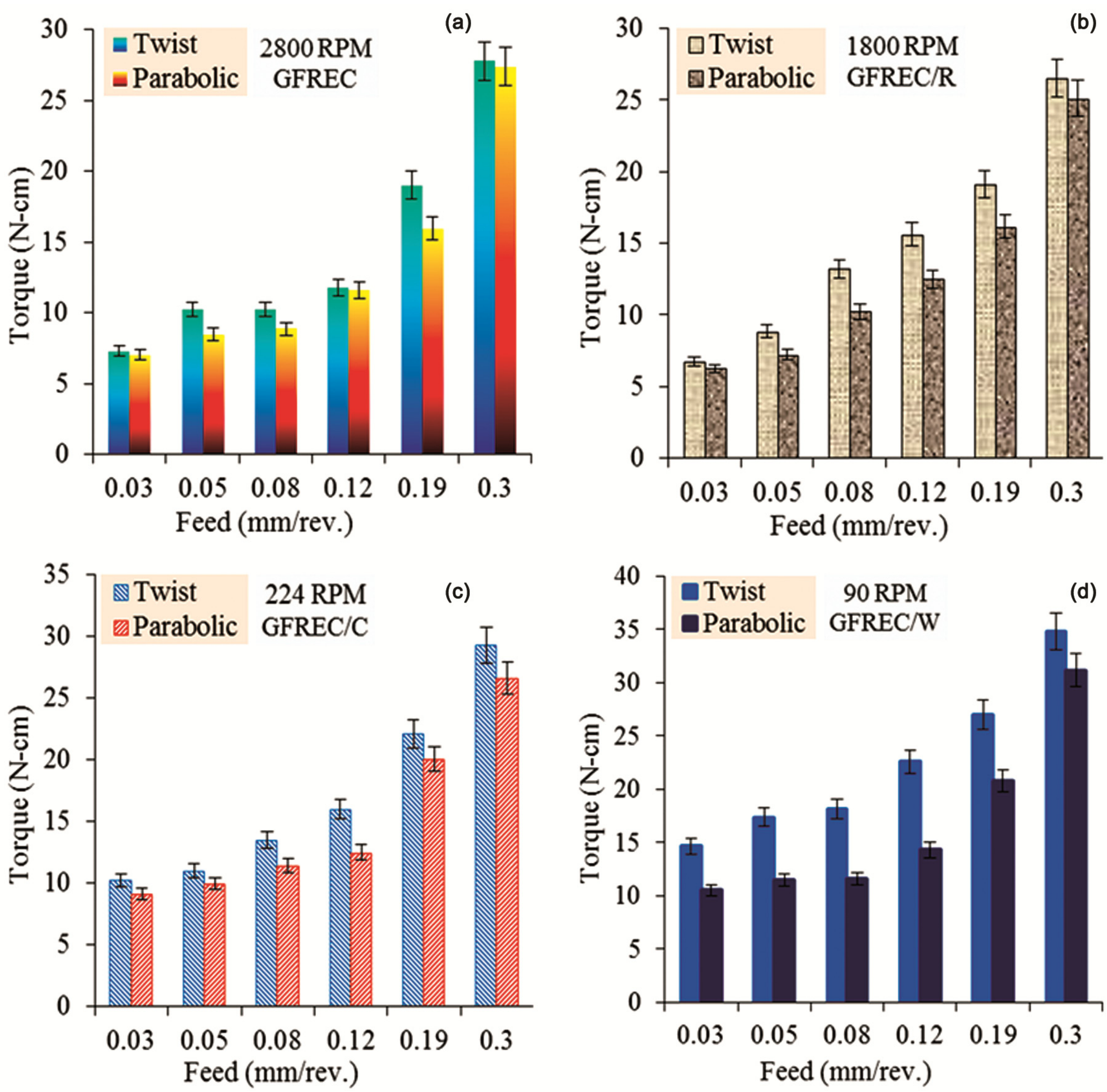

Fig. 6 — Variation of torque with feed for different composite materials.

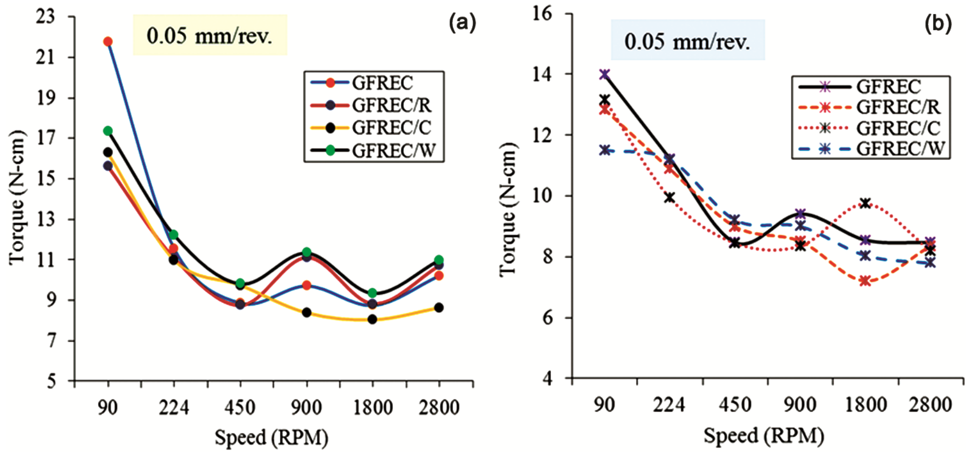

Fig. 7 —Variation of torque with speed obtained at feed of 0.05 mm/rev for (a) twist drill bit and (b) parabolic drill bit.

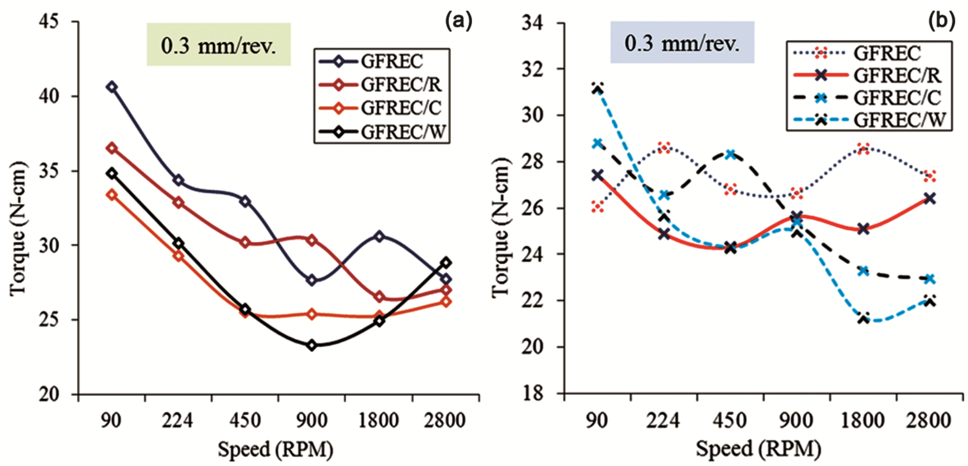

Fig. 8 — Variation of torque with speed obtained at feed of 0.3 mm/rev for (a) twist drill bit and (b) parabolic drill bit.

both the drill bits. The torque value obtained during drilling with a twist drill bit at a feed of 0.05 mm/rev. was low for GFREC/C as shown in Fig. 7(a). Whereas, the torque value obtained during drilling with the parabolic drill bit was low for GFREC/R (Fig. 7(b)). An abrupt variation in torque value was observed while drilling was performed at the high feed of 0.3 mm/rev. for the laminates under investigation as depicted in Fig. 8(a) and Fig. 8(b), respectively.

4.3 Prediction of Axial Thrust and Torque

The axial thrust and torque obtained during drilling of the laminates present a complex mapping. Hence, LMA was applied to develop the proposed neural network models. The accuracy of the proposed models was verified by computing different characteristic values as shown in Table 1. The results indicate that the proposed neural network models are quite adequate to compute the axial thrust and torque precisely. Hence, this is recommended that the proposed models can be utilized to compute the axial thrust and torque generated during drilling of the laminates so that the drilling-induced delamination can be minimized. To validate the accuracy of the models, a comparative study between the actual or experimental and computed values were done for training and testing data sets. Fig. 9 and Fig. 10 represent the relative difference between the computed and actual values of axial thrust for both the training and testing data sets. The figures indicate that the axial thrust computed by the developed model is quite close to the actual axial thrust. Fig. 11 and Fig. 12 shows the adequacy of the neural network models for the torque. The computed values of torque were found to be very close to the actual torque for both training and testing data sets. The error in the computed values of axial thrust and torque was found to be less than 10%. This inferred that the proposed

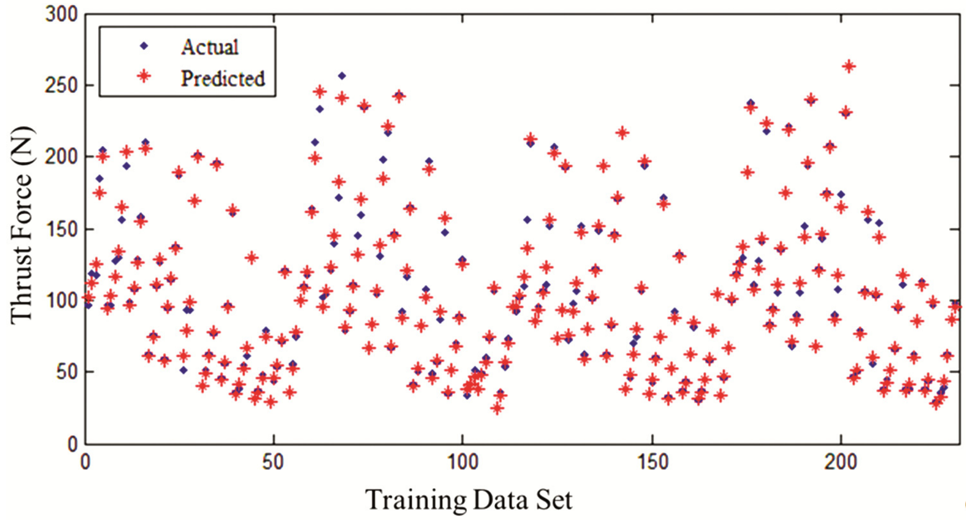

Fig. 9 — Actual versus predicted value of axial thrust for training data set.

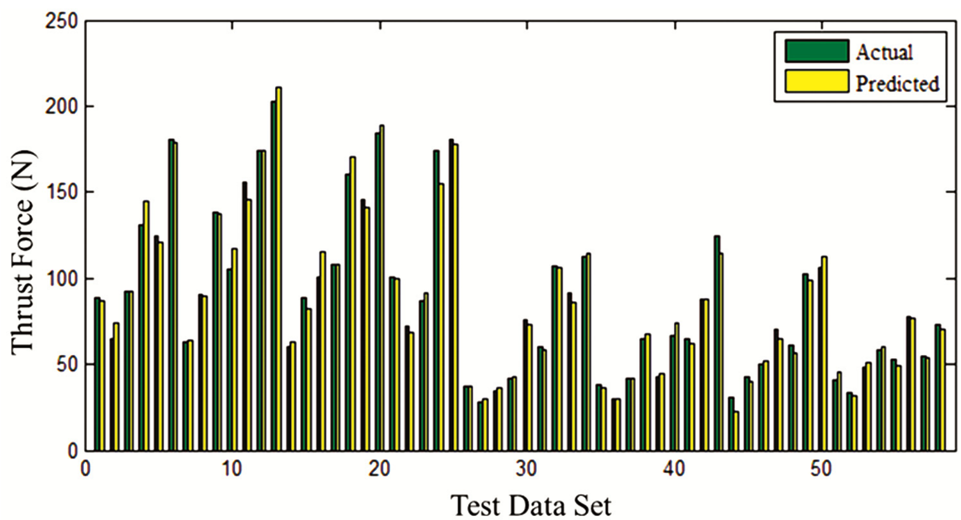

Fig. 10 — Actual versus predicted value of axial thrust for test data set.

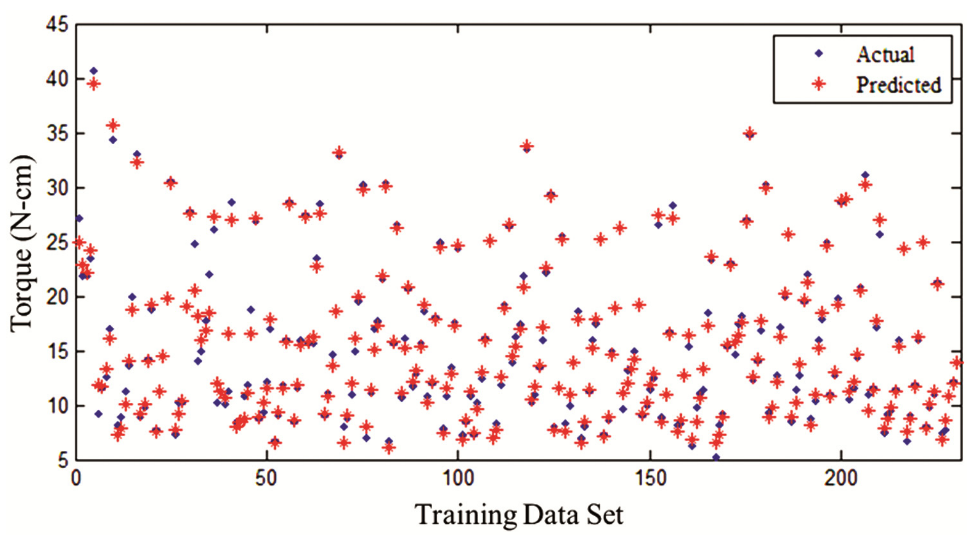

Fig. 11 — Actual versus predicted value of torque for training data set.

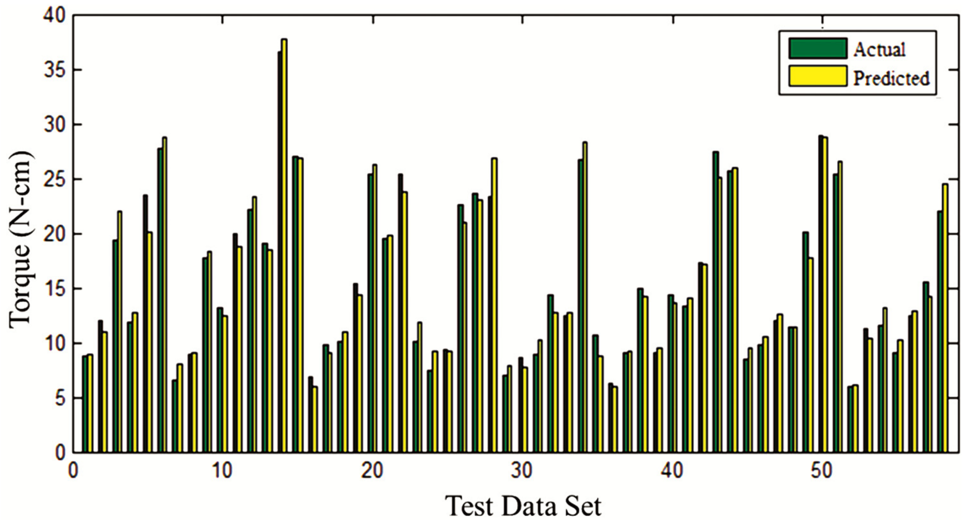

Fig. 12 — Experimental and predicted value of torque for test data sets.

neural network models can compute the values to a great deal of accuracy. This indicates that the learning capabilities of the proposed neural networks are quite efficient.

5 Conclusions

The major findings can be inferred from the present study are:

(i) The axial thrust and torque generated by the parabolic drill bit were quite low as compared to the traditional twist drill bit.

(ii) The drilling with twist drill bit results in decreasing axial thrust with the increasing speed at low feed but no definite trend was observed at the high feed. Whereas, drilling with parabolic drill bit results in a gradual decrease in axial thrust with the speed of the drill bit.

(iii) The axial thrust and torque increased almost linearly with an increase in feed at all speeds with both the drill bits. The torque was found to be decreased with an increase in the speed of the drill bits. However, abrupt variations in torque values were observed during drilling of GFREC and GFREC/R at the high feed.

(iv) The axial thrust generated with the parabolic drill bit is close to each other for all the developed composites. Therefore, agricultural waste can be incorporated with the glass fiber to fabricate the composites to reduce the weight and cost of the resultant composites.

(v) The prediction done by the proposed models using the training and testing data sets were close to the actual values. The mean percentage error was found to be less than 10% in case of training and testing of both the models.

(vi) A similar type of model can be developed to compute the axial thrust and torque and subsequently the damage of the hole for another type of composites and drill bits to assist the industry for the production of clean-cut and damage-free holes in composites.

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