Using Deep Neural Network Predicting Tensile Strength of Hybrid Composites

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ABSTRACT:- Hybrid composites made from blending of natural and synthetic fibers in a polymer matrix show synergistic effect on properties which canno t be achieved from normal composites. Hybrid composite materials are used in many engineering applications for their versatile properties li ke lightweight, strength to weight ratio, low cost, ease of structure development and high strength. Automobile industry utilizes composites and hybrid composites in many of the interior and exterior applications. A lot of tests has to be conducted for obtaining satisfactory mechani cal properties for the desired application. In this work, the ultimate tensile strength of hybrid short fiber composites made of glass fiber, carb on fiber, and epoxy resin is predicted using artificial neural network techniques. The data for the study has been obtained from tensile test re sults of certain volume fraction combinations of the constituents. This approach leverages the strengths of both experimental procedure and the mathematical modelling of neural networks for the prediction of unknown values

Keywords : Hybrid Composites, Artificial neural network (ANN), Volume Fraction, Ultimate Tensile Strength, Regression.

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INTRODUCTION

A combination of two or more types of fibers in a single polymeric matrix (also known as the hybrid composite) can produce greater stiffness and strength in comparison with the individual corresponding reinforced polymer composites. Different fibers have different properties and characteristics. Thus, if these different properties are known, different fibers can be employed in a way that they can superpose their propert ies towards reaching an optimum behavior when subjected to a certain mechanical loading as a whole. Commonly, some types of fibers in h ybrid composites have low modulus and/or lower cost, such as glass and Kevlar fibers, whilst the other types have high modulus and/or hig h cost such as boron and carbon fibers. Low modulus and inexpensive fibers make hybrid composites more tolerant to damage and reduce the overall cost, while the more expensive fibers with high modulus improve load bearing capabilities and composite stiffness. Hence, hybri dization of composites can provide high stiffness and strength, improve the impact and fatigue resistance, provide high fracture toughness

and simultaneously cut the total weight and cost [1]. Chensong Dong et.al [2] investigated the effect of hybridization on the flexural strength of S-Glass -Carbon-Epoxy composites. It was found that the flexural strength is more than that of pure glass-

epoxy composites but less than pure carbon –

epoxy composites. Belingardi et.al [3] studied the bending fatigue strength of hybrid interply biaxial glass–

carbon fiber reinforced epoxy matrix composite. It was observed that the mechanical strength and elastic modulus depend on the level of lo ading. Gupta et.al [4] reviewed the work done on the study of mechanical properties of hybrid fibers reinforced polymer composites.

The amount of the constituents present in the hybrid composite decide the properties and performance of the composite. To study the effect of volume fraction on the composite

properties, one has to prepare the laminates and test them as per the standards. This procedure need t o be followed for all the possible combination of fibers and matrix. But the mechanical characterization of the composite laminates is a tedio us task and highly sensitive to various external factors like manufacturing method, personnel efficiency, environmental effects etc. In gener al the experiments are combined with the analytical techniques like regression analysis, Artificial Neural Networks (ANN), and optimization t ools to reduce the uncertainty.

ANN is a machine learning technique inspired by human brain. It is used widely across different engineering to solve different engineering p roblems. It is also used in the operation of driverless and autonomous cars. It basically comprises of neurons and has hidden layers. The d ata is processed by hidden layers, which have certain weights assigned to each neuron in the hidden layer. And the final output is gener ated at the output neuron layer [5].

1. MATERIALS AND EXPERIMENTATION

In the present study, hybrid composites are fabricated using the traditional hand layup technique. Glass fiber in the form of chopped strand m at, carbon fiber (T700 - 12K) chopped short fibers are used as the reinforcement. Epoxy (L-12), Hardener (K-6) and diluent, mixed in the ratio of 10:1:1 parts by volume, are used as matrix. The volume fraction of the chopped carbon fibers is varied fro m 0 % to 50 %, and that of glass fiber is varied from 50% to 0%, as the maximum effective fiber volume fraction that can be achieved by hand layup method is 50% [7]. Test specimen of dimensions 250mm x 25mm x 2.5mm are fabricated as per the ASTM standard for chopped stran ded mat composites and are cured at room temperature for 48 hours. Three specimen for each volume fraction was fabricated and the tensile test was performed on an universal testing machine.The average of the three values for each volume fraction was calculated and given as input for both ANN and regression analysis as shown in above Fig 2 (a-b)[8].

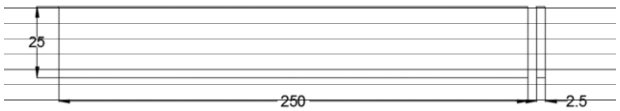

Fig. 2 (a): Tensile test specimen dimensions for short fiber composites as per ASTMD3039

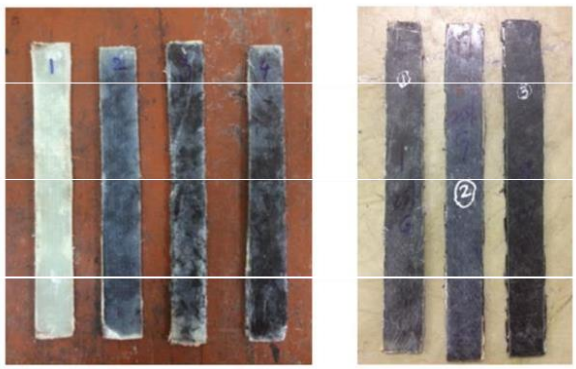

Fig. 2 (b): Composite specimen fabricated as per ASTMD3039 The tensile strength of the composite can be calculated theoretically using rule of mixtures equation [9] given below

$$\sigma_c = V_f \sigma_f + V_m \sigma_m \quad (1)$$

where σc – Tensile strength of composite, Vf – Volume fraction of fiber, Vm – Volume fraction of matrix, σf – Tensile strength of fiber, σm – Tensile strength of matrix. The above equation assumes the composite is homogeneous and continuous mass without any defects and also does not take into consideration the effect of manufacturing variables. In practice, the laminate made with different manufacturing methods a nd under different manufacturing conditions exhibit different properties. So, taking this aspect into consideration, in this work, it is proposed to use prediction techniques for obtaining the values of tensile strength for different composition of fibers. To train and test the neural network, f ew samples of experimental data shown in table 1, is taken as input. ANN uses the data and creates a trend which can be used for predicting unknown values of the tensile strength. A back propagation algorithm was used to calculate the optimal weights required to generate the outp ut vector while minimizing the error function.

Sl. No	VF of Glass fiber (%)	VF of carbon fiber (%)	VF of resin (%)	Experimental UTS (MPa)
1	50	0	50	84.921
2	45	5	50	80.025
3	40	10	50	81.862
4	35	15	50	82.6
5	30	20	50	65.346
6	25	25	50	75.937
7	20	30	50	82.6605
8	0	50	50	76.94

Table 1: Data set used for training and obtaining weighted matrix in ANN

2. Results and Discussion

In ANN topology shown in Fig. 1, the input variable used is the volume fraction of carbon short fibers obtained experimentally and six neurons are used in the hidden layer to obtain the output of the system which is the ultimate tensile strength of the glass-carbon short fiber reinforced hybrid composite. The ANN toolbox in MATLAB was initially used to generate the best fit. Out of eight data sets, four are given as input variables for training the network, two are used for validation and two were used for testing. Fig. 4 shows the regressio n plot generated by the ANN, consisting of four individual graphs representing training data, validation, test and overall data. The x-axis indicates the value of target data given from the experimental UTS values and y-axis represents the value of UTS predicted by ANN after training. The dotted line represents the best correlation that can be generated and t he thick continuous lines represent the actual correlation between the target values and output values. It can be seen that the correlation coef ficient R value for training set is 0.5603 and overall R value is 0.466. The R value for the overall data has to be taken for evaluating the goodn ess of the fit generated by ANN. It can be deduced that the difference in both R values can be due to the unavailability of sufficient data points as shown in below Fig 3.

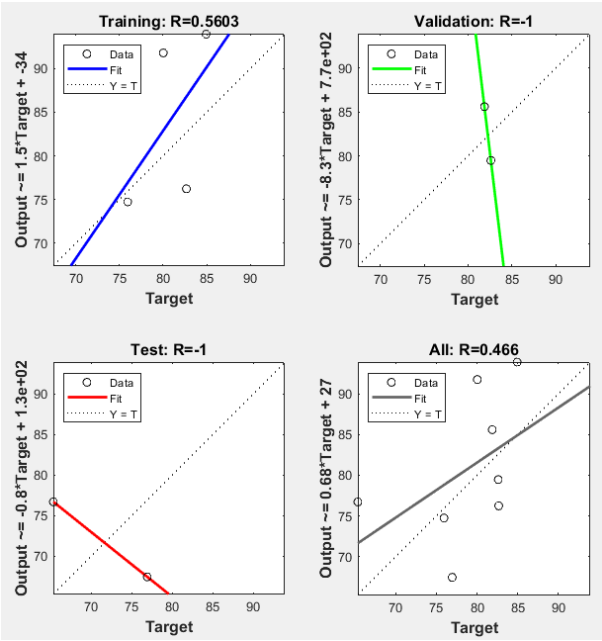

Fig. 3. Regression plot of ANN for eight data sets

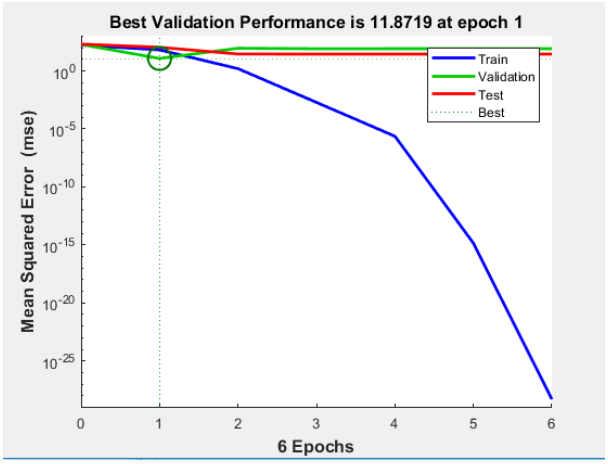

Fig. 4. Performance plot of ANN for 8 datasets

The back propagation algorithm adjusts the weights till it generates the suitable mean squared error. The error of the system is the difference between output generated by the system and the target value given to the system. The value at which the mean squared error of the training, validation and test data converges is called the best validation performance of the network. The number of Epochs represent the number of times the error is back propagated to achieve a minimum convergent value. Because of the insufficient number of data sets, the best validation performance of the network with eight data sets

is obtained as 11.8719 at 1 epochs where in the network has run for 6 epochs which is shown in the Fig.4.

It was observed that with more number of data sets, the network can generate a better correlation and there by good fit that can be used for pr ediction of unknown values. To increase the number of data points, a noise of 2000 random values was introduced into the signal and it was g iven as input to the ANN. The effect of more data points can be seen in the Fig. 5. After the increase in the number of data points, the correlati on coefficient R obtained is almost same for all the data sets which is nearer to the ideal value 1 and the best performance value where the tra ining, validation and test data sets mean squared error converges is 32.5957 at epoch 18 out of 24 epochs run by the network which can be s een in Fig. 6.

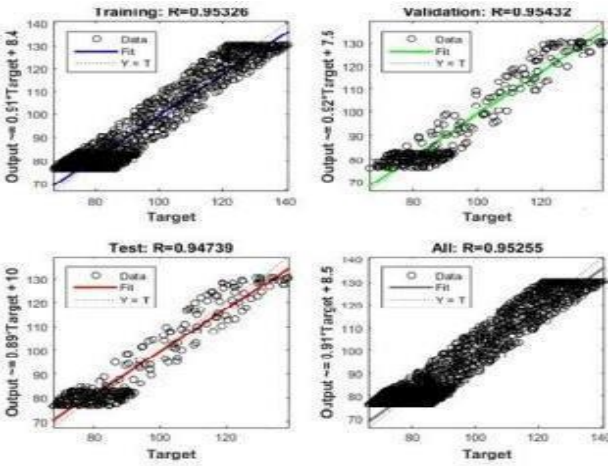

Fig. 5. Regression plot of ANN for eight data sets

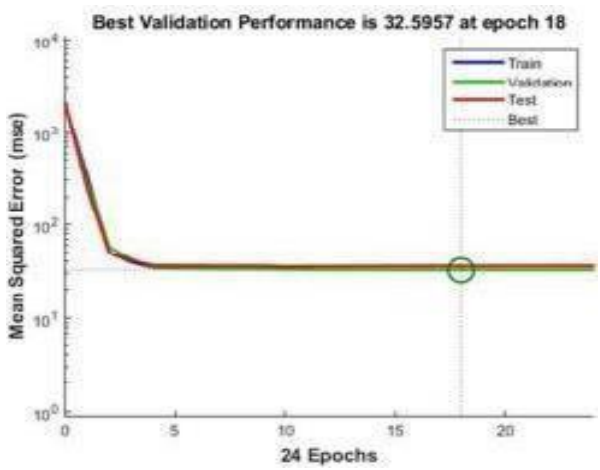

Fig.6. Performance plot of ANN after including noise

A regression analysis was carried out on the experimental data using different types of curves like poly4 (polynomial curve of degree 4), poly 5 (polynomial curve of degree 5) and smoothing spline. These curves were analysed for different values of R2 (co-efficient of determination) and SSE (sum squared error) as shown in Table 2. Poly 5 curve was considered to be the best fit because of its low error values and high R2, adjusted R2 values.

Table 2: Table of fits

Sl. No	Data	Fit Type	SSE	R-square	Adj. R-Square	RMSE (Root mean squared error)
1	UTS vs. VF	poly4	34.163	0.4653	-0.6039	4.133
2	UTS vs. VF	poly5	0.8054	0.9873	0.9243	0.897
3	UTS vs. VF	Smoothing spline	15.57	0.7563	0.2869	2.756

The ANN generated fit was compared with a 5 degree polynomial curve generated using linear regression. The steep increase in the polynomial curve as shown in Fig. 7 was due to the lack of data points between 0.3 and 0.5 volume fraction. These points are difficult to manufacture using hand layup technique. Inspite of missing points between 0.3 and 0.5 volume fractions, ANN was able to generate a reasonably good c urve which is shown in Fig. 7. The values of UTS for some intermediate volume fractions were predicted by using both the poly5 and ANN cur ves. The values were plotted and compared in Fig.7. It can be observed that the values generated by ANN model and linear regression nearl y comply with each other and the deviation at 0.32 VF was due to the paucity of sufficient data in the range of 0.3- 0.5 VF as shown in below Fig 8 and Fig 9.

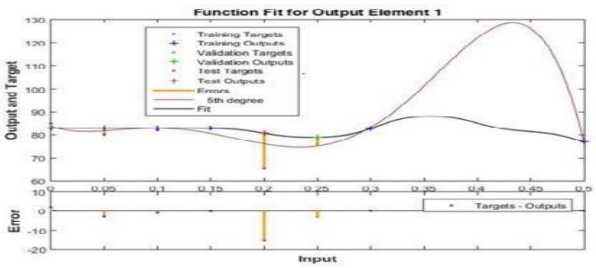

Fig.8. Comparison of plots by ANN and regression

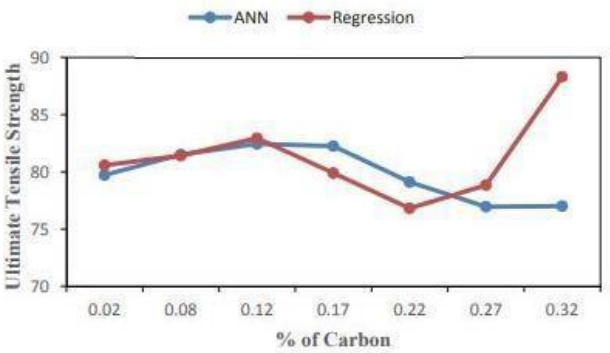

Fig.9. Predicted values of UTS

3. Conclusion

The tensile strength of short fiber hybrid composite materials was predicted using ANN model with the volume fraction of short carbon fibers as input. The data predicted by ANN model was compared with regression model. It was found that ANN can predict the tensile strength valu es more accurately as compared to regression model. The main drawback of using ANN model is to have more data sets which require more experiments to be conducted which is contradicting the main objective. But the drawback can be overcome by creating the database once an d it can be used for predicting the optimal value as per application. The predicted intermediate values are more accurate when the input is fro m experimental data compared to theoretical calculations. This technique can predict other mechanical properties like fatigue, creep, etc., an d also more number of input variables like thickness of the laminate, orientations, manufacturing variables like pressure, temperature etc., ca n be used.

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