Artificial Neural Network Based Stresses Prediction of Glass Fibre Orientated Polymer Laminates

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Abstract – The mechanical properties of GFRP laminates by using hand lay-up and press moulding fabrication techniques, the testing samples are prepared as per ASTM-D882, ASTM- D790, ASTM-D785 standard by varying orientation from experimentation. These specimens are tested under tensile test, flexural test (three-point bend test) and hardness test. The results of tensile strength, percentage of elongation, flexural strength, flexural modulus and hardness of the composite were used as the inputs for the MATLAB coding. However, the highest values respectively suggesting fibre orientation for effective and maximum stress transfer in laminated composites. The prediction values for the tests of three different orientations are obtained from both linear interpolation and Spline interpolation MATLAB coding.

Index Terms – Artificial Neural Networks, Glass fibre reinforced polymer (GFRP), Hand lay-up Technique, Mechanical properties, MATLAB.

1. INTRODUCTION

Reinforcement materials like fibres, fillers, particles and flakes that surrounded in a matrix (resin) for example polyester, epoxy, and vinyl ester to fabricate composites. The resin holds the fibres together to create products with any shape and transfer the applied load to the fibres. Most of the applied loads are taken by the fibres. The mechanical properties are different in different directions while the mechanical properties are same in any direction in isotropic materials. However, fibre reinforced polymers are directional materials or in other words, the optimum mechanical properties are in the direction of reinforcement. Therefore, the fibres are placed in the composite materials according to the applied load. Also, the type and direction of reinforcements are selected according to the application.

2. EXPERIMENTATION

Laminates are prepared by using hand lay-up technique varying orientation ($0^0/0^0$, $0^0/135^0$, $0^0/90^0$) of the fibre and number of glass layers are constant. The testing samples are prepared as per the ASTM Standards. During the experimentation tests of tensile (ASTM-D 882), flexural (ASTM-D 790) and Hardness (ASTM-D 785) are done on the GFRP laminates of different orientations. The experimentation work provides the mechanical responses of different orientation GFRP laminate such as Stresses, Tensile strength, Modulus of elasticity, Ultimate tensile load. The experimentation is carried under calibrated machines at reputed institute. The Analysis was carried out in framework of ABAQUS and HyperMesh FEA packages, the objective of this FEA analysis of Polymer laminates is to predict the mechanical properties and their response of the polymer laminates such as tensile and flexural then the results will be compared with experimental results. The material constants used in the analysis of the composite laminate are Young's Modulus E_1 = 71660.0 MPa, Young's Modulus E_2= 20700.0 MPa, Poisson's Ratio for the given material is NU_{12} = 0.244, Shear Modulus of the given material are G_{12}= 10690.0 MPa, G_{1Z} = 10690.0 MPa, G_{2Z} = 11000 MPa and density 2.6e -24 kg-m^3.

3. MATLAB PREDICTION

For the prediction of the stresses of GFRP laminates, it is considered that the stresses obtained from the experimental data is used as inputs in the programming of the prediction. The programming conditions that are used for the prediction of stresses are Linear Interpolation and Spline Interpolation. From the Literature survey it concluded that Spline Interpolation has the better view for the prediction of the results for the unknown values. The application of composites as engineering materials has become state of art and fatigue is one of the most complicated problems for fibre composites. The fatigue life prediction of a newly developed material is costly and time consuming. Artificial neural networks (ANNs) offer a potential solution to this problem. In recent years ANN have been used for the prediction of fatigue lives of composite materials. The ANN approach to predict the fatigue life of unidirectional glass fiber composite materials. ANN prediction on carbon/glass fiber reinforced plastic laminate. In their study they have used only one lay up to evaluate a possible ANN structure. Recently presented a review paper on the application of neural network to polymer composites. They have suggested that further improvement in this technique is required to find out the correlations between measured parameters and complex properties considered various types of ANN such as modular, self-organizing, radial basis, and principal component analysis networks for improving the prediction accuracy. A comparison of such ANN structures in predicting fatigue behaviour of unidirectional glass fiber/epoxy composite laminate for various fiber orientation angles and stress ratios is investigated. The work showed that, compared to the classical feed forward neural network, other types of ANN could be used to improve the fatigue life prediction of composite materials. Modeling of material behavior generally involves the development of a mathematical model derived from observations and experimental data. In a survey it is used an alternative way i.e. back propagation artificial neural network (ANN) to model Two-Parameter Model (TPM) in the fracture of cementations material. The results of an ANN-based TPM look viable and very promising. Artificial neural networks (ANNs) were used to predict the residual strength of glass fiber-reinforced plastic beams pre-fatigued in flexure up to different portions of fatigue life. An optimization of the network configuration was carried out, using the root-mean square error calculated in the training stage as the optimization parameter. The predictive accuracy of the optimized ANN, consisting of two nodes in the input layer, four nodes in the component layer, and a single node in the output layer, was tested out by the "leave-out" method. From the results obtained, ANN provide quiet reliable predictions when the applied load was sufficiently far from the failure load, performing better than a previous theoretical model, relying on fracture mechanics concept. Therefore, ANN is shown to be a valid tool in the evaluation of composite materials employed in fatigue-sensitive applications.

4. RESULTS AND DISCUSSIONS

Tensile Test Stresses Prediction:

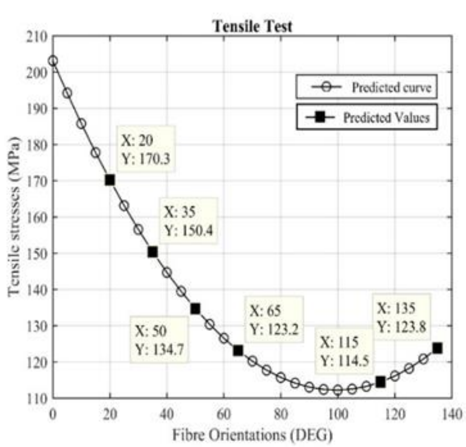

Figure 1 Tensile Test Stresses Prediction on Spline Interpolation

The prediction values of the tensile are generated by using the interpolation code written in MATLAB. The interpolation code written in the MATLAB gives the prediction values between the known values, which are given as the inputs in the program. The prediction values are plotted on the spline curve in the form of graphical representation as shown in the above Fig. Here X axis represent the Fibre orientation and Y-axis represents the tensile stresses of the composite material with respect to orientation. The predicted curve has numerous points, which represent prediction values of the tensile stresses.

Flexural Test Stresses Prediction:

The prediction values of the tensile are generated by using the interpolation code written in MATLAB. The interpolation code written in the MATLAB gives the prediction values between the known values which are given as the inputs in the program from the experimental values. The prediction values are plotted on the spline curve in the form of graphical representation as shown in the above Fig. Here X axis represent the Fibre orientation and Y-axis represents the Flexural stresses of the composite material with respect to orientation. The predicted curve has numerous points, which represent prediction values the flexural stresses.

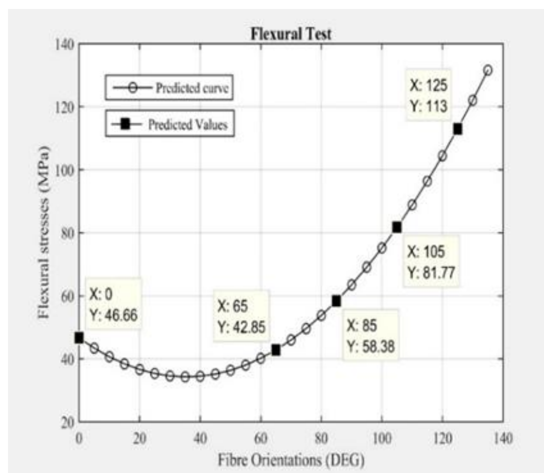

Figure 2. Flexural Test Stresses Prediction on Spline Interpolation

Hardness Test Prediction**:**

The prediction values of the tensile are generated by using the interpolation code written in MATLAB. The interpolation code written in the MATLAB gives the prediction values between the known values which are given as the inputs in the program from the FE analysis of the composites. The prediction values are plotted on the spline curve in the form of graphical representation as shown in the above Fig. 5.23. Here X axis represent the Fibre orientation and Y-axis represents the Hardness of the composite material with respect to orientation.

The predicted curve has numerous points which represent prediction values of the hardness.

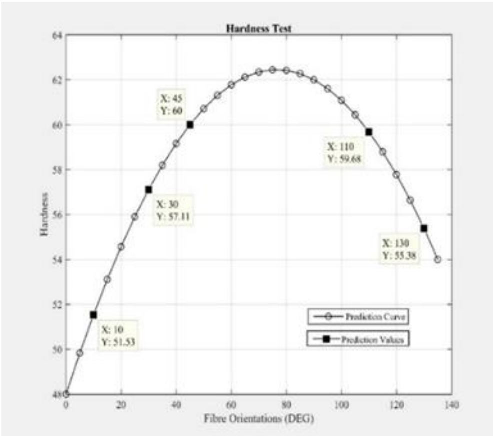

Figure 3. Hardness Values Prediction from the Spline Interpolation

Validation of the Prediction Values by using ANN Tools

Validation of Prediction Stresses for Tensile test:

This network consists Trainlm which is the training function where learning occurs in a training phase i.e., errors of target is back propagated from output to the inputs. Once the back propagation learns minimum error pattern it can be tested on second set of inputs. The performance of the neural network is determined by the mean squared error & data division is index. The overall Regression (R) is = 0.91

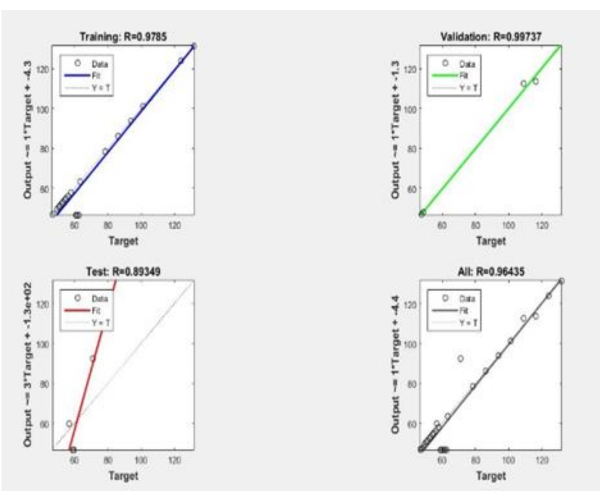

Figure 4. Validation of Prediction Stresses in ANNs TOOLBOX

Validation of Prediction Stresses for Flexural test:

This network consists Trainlm which is the training function where learning occurs in a training phase i.e., errors of target is back propagated from output to the inputs. Once the back propagation learns minimum error pattern it can be tested on second set of inputs. The performance of the neural network is determined by the mean squared error & data division is index. The overall Regression (R) is = 0.96

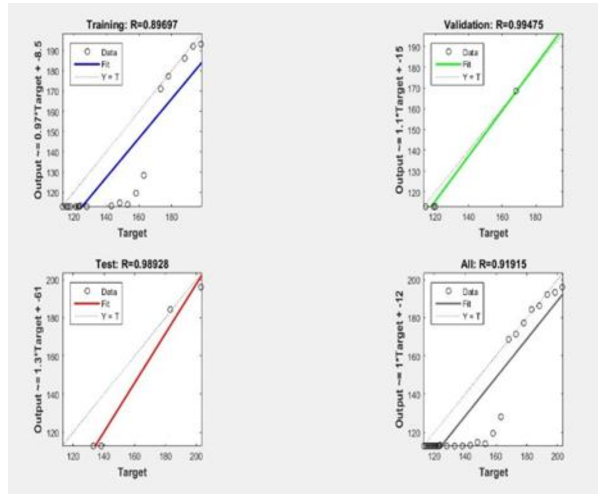

Figure 5. Validation of Prediction Stresses in ANNs TOOLBOX

Validation of Prediction values for Hardness Test:

This network consists Trainlm which is the training function where learning occurs in a training phase i.e., errors of target is back propagated from output to the inputs. Once the back propagation learns minimum error pattern it can be tested on second set of inputs. The performance of the neural network is determined by the mean squared error & data division is index. The overall Regression (R) is = 0.825

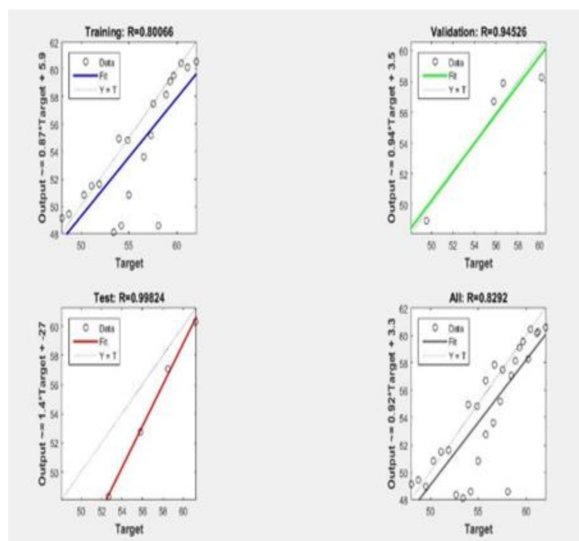

Figure 6. Validation of Prediction in ANNs TOOLBOX

5. CONCLUSION

We have presented a review of the current state of the use of artificial neural networks for prediction application. This review is comprehensive but by no means exhaustive, given the fast growing nature of the literature. The important findings are summarized as follows:

- The unique characteristics of ANNs adaptability, nonlinearity, arbitrary function, mapping ability make them quite suitable and useful for prediction. Overall, ANNs give satisfactory performance in forecasting.
- A considerable amount of research has been done in this area. The findings are inconclusive as whether and when ANNs are better than classical methods.
- It is concluded that there are no systematic investigations for the issues that affect the performance of ANNs.

ANNs offer a promising alternative approach to traditional linear methods. However, while ANNs provide a great deal of promises, they also embody a large degree of uncertainty. There are several unsolved mysteries in the prediction as well as forecasting of the values in program.

REFERENCES

[1] Adam,T.,Dickson,R.F.,Jones,C.J.,Reiter,H., Harris,B., 1986 A power law fatigue damage model for fiber reinforced plastic laminates, Proc Inst Mech Engrs: Mech Eng Sci, 2006 pp 155-166.

[2] Al-Assaf,Y., El Kadi,H.,2001 Fatigue life prediction of unidirectional glass fiber/epoxy composite laminate using neural networks, Composite Structures, 53, pp 65-71.

[3] Al-Assaf,Y., El Kadi,H.,2002 Prediction of the fatigue life of unidirectional glass fiber/epoxy composite laminate using different neural network paradigms, Composite Structures, 55, pp 239-246.

[4] Al-Assaf,Y., El Kadi,H.,2002 Energy-based fatigue life prediction of fiber glass/epoxy composite using modular neural networks, Composite Structures, 57, pp 85-89.

[5] Beheshty,M.H., Harris,B., 1998 A constant life model of fatigue behavior for carbon fiber composites: the effect of impact damage. Composite Science and Technology,58, pp 9-18.

[6] Caprino,G., Leone,C., de Iorio, I., 2005 Interpreting acoustic emission signals by artificial neural networks to predict the residual strength of pre-fatigued GFRP laminates, Composites Science and Technology.

[7] Dalvir Singh, 2005 A neural network model for predicting fatigue life of carbon steel, copper alloy and aluminum alloy under constant amplitude loading, M. Tech. Thesis Submitted to the Dept. of Mechanical Engineering, G.B.P.U.A.&T., Pantnagar.

[8] Fernando, G., Harris, B., Reiter, H., Adam, T., Dickson, R.F., 1990 Fatigue behavior of carbon fiber reinforced plastics, Composites,21, pp 232-242.

[9] Gathercole, N., Reiter, H., Adam, T., Harris, B., 1994 Life prediction for fatigue of T800/5245 carbon fiber composites: I Constant Amplitude Loading, International Journal of Fatigue ,16, pp 523-532.

[10] Harris,B., Gathercole,N. ,Lee,J.A., Reiter,H., Adam,T., 1997 Life prediction for constant stress fatigue in carbon fiber composites Phil Trans Roy Soc (Lond), A355, pp 1259-1294.

[11] Harris,B., Lee,J.A., Almond,D.P., 1999 The use of neural networks for the fatigue lives of composite materials, Composites Part A: Applied Science and Manufacturing, 30, pp1159-1169.

[12] Haykin,S., 1999 Neural Networks- A Comprehensive Foundation, Second Edition, Prentice-Hall, Inc., ISBN-81-203-2373-4.

[13] Aiken, M., Krosp, J., Vanjani, M., Govindarajulu, C., Sexton, R., 1995. A neural network for predicting total industrial production. Journal of End User Computing 7 (2), 19–23.