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A Prediction Model for Natural Frequencies on Kevlar/Glass Hybrid Laminated Composite using Artificial Neural Networks (ANN)

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Abstract: This paper aims to develop a prediction model for the natural frequencies on Kevlar/Glass hybrid laminated composite plates using Artificial Neural Networks (ANN). Finite element simulations were performed to generate data for the natural frequencies under various lamination schemes and fibre angles. Rectangular symmetric and anti-symmetric hybrid laminated composite plates were modeled using commercial software, ANSYS, and meshed using shell elements. The Matlab-ANN tool was used to generate the prediction model, where the generated data (natural frequencies) from the finite element simulations were used for training and testing of the prediction model. The network adapted a two-layer feed-forward algorithm. The adequacy of using ANN in predicting natural frequencies was verified, where the coefficient of determination, R^2, was found to be over 0.995. The overall results proved that ANN could be a useful tool, where the prediction model produced an error of less than 5%, when compared to the simulated values of natural frequency of various hybrid laminated composites using finite element analysis. These findings concluded that the current study had contributed significant knowledge in understanding the prediction of natural frequency on hybrid laminated composite using the ANN model.

Keywords: Hybrid, laminated composite, natural frequencies, ANSYS, ANN

1. Introduction

Natural frequency is a dynamic characteristic that depends on mass, stiffness, and boundary conditions. When designing and analysing structures, it is critical to determine the natural frequencies to avoid resonance from occurring. Resonance will occur when the external vibrations coincide with one of the natural frequencies in the structures. Modern structures demand for composite and hybrid materials. A hybrid laminated composite is a laminate made of composite layers from different fibre materials to produce a laminate with optimum properties. Hybrid laminated composites are getting progressively famous as major auxiliary parts in essential aeroplane structures, automotive structures, marine structures, and some types of sports equipment. For example, recent attempts have been made to make a hybrid of Graphite epoxy layers with Glass epoxy layers for automotive panels with the aim of reducing the cost while maintaining the strength of the laminated panels [1]. The literature review shows that there is a lack of

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information related to the hybridization of Kevlar epoxy layer and Glass epoxy layer. In addition, it is critical to investigate the natural frequencies of such new types of Kevlar/Glass hybrid laminated composites before implementing these materials into structures or mechanical components. The success of Khanam et al [2] in using Artificial Neural Networks (ANN) in predicting the mechanical and thermal properties of nanocomposites has been the motivation to carry out this study to adapt a similar approach in predicting the natural frequency of Kevlar/Glass hybrid laminates with various lamination schemes and fibre angles.

2. Literature Review

Most of the previous studies have investigated the natural frequencies of the laminated composite plate using an analytical approach [3], [4] and numerical simulation software [5]. An example from Wu et al.[6] presented a new five-unknown higher-order theory to an analysis of natural frequencies on composite and sandwich plates using a non-polynomial zigzag theory [7], non-polynomial zigzag theories in line with C^0 finite element formulation [8], First-Order Shear Deformation Theory (FSDT) and Chebyshev collocation technique for the plate under a clamp or simply supported or free at the edge [9] and a modified FSDT was applied in an analysis of the free vibration on sandwich plates and shells such as a rectangular composite sandwich plate with symmetric cross-ply laminates with all edges simply-supported [10]. Famous FE software which has been used to analyse the free vibration of the composite plates are ANSYS Mechanical APDL [11], ABAQUS Software [12], [13] and MSC/NASTRAN [14].

The reason that the experimental method is not commonly used is because of the method being costly, time-consuming, and tedious in execution. Nevertheless, this method is important as it validates the results from the analytical approach with the numerical simulations. Rout et al. [5] presented a study which focused on both the experimental as well as the finite element method to investigate the natural frequencies of hybrid laminated composite beams. Erkliğ et al. [15] conducted a study on hybrid composites under the combination of boundary conditions of clamped, free, and simply supported conditions. In terms of experimental approach, a notable study has been conducted by Prashanth & Basava [16] to investigate the vibration of natural hybrid composites experimentally. Nevertheless, it is interesting to notice that recent approach adapts Artificial Neural Networks (ANN) to predict the mechanical properties and failure of materials and structures. The examples from previous research in composite using ANN are an optimized methodology for delamination identification of laminated composite plates [17], fibre-reinforced composite curved plates, damage in laminated fibre-reinforced polymer (FRP) composites [18] and predicting the natural frequencies of laminated composite plates with clamped boundary condition [19]. However, there currently has been a lack of study on the free vibration of the hybrid laminated composite plate and there is still ambiguity concerning various stacking angle effects on hybrid laminated composite. Therefore, this paper aims to develop a natural frequency prediction model using Artificial Neural Networks (ANN) and to investigate the effect of lay-ups and fibre angles on the natural frequencies of Kevlar/Glass hybrid laminated composite plates. The study to investigate the effect of natural frequencies on hybrid composite structures is critical in order to avoid resonance, especially those related to precision and high-speed applications such as pressure vessels, aerospace structures and race cars, where resonance could cause loss of lives. This study is novel as to date, no similar approach has been reported in literature pertaining to predicting the natural frequency of Kevlar/Glass hybrid laminates with various lamination schemes and fibre angles.

3. Methods

3.1 Generation of the Input Data for Training of ANNs using Finite Element Simulation

The minimum number of training data sets was determined by Eq. (1) [20]. This was important as this acted as a guide to determine the minimum number of data training sets needed for the specific ANN model. This approach also determined the number of training data sets based on the number of hidden layer nodes, input layer nodes and the number of output layer nodes. Moreover, the number of hidden layer nodes needed to be determined first. To perform the analysis of the ANN model, 101 criteria [21] with various hidden nodes were analysed to determine learning and generalization errors. It had been observed that the error values were less compared to other criteria using Eq. (2). The result for this case showed the minimum number of hidden nodes was 5 while the input was 8. As a result, the number of hidden networks for the ANN design for this problem had been chosen as 8, 9 and 10.

$$T_n = h_n\left(i_n + 1\right) + O_n\left(h_n + 1\right) \tag{1}$$

where T_n is the minimum number of training data sets, h_n is the number of hidden layer nodes, i_n is the number of input layer nodes and O_n is the number of nodes in output layers.

$$N_h = \frac{4n^2 + 3}{n^2 - 8} \tag{2}$$

where N_h is the number of hidden layer nodes and n is the number of input layer nodes.

Based on Eq. (1), the minimum number of data training sets needed was 123. The number of data training sets which had been generated using finite element simulation software (ANSYS APDL version 2021R1) was 150. The procedure had three steps namely Pre-Processing, Processing and Post-Processing. The finite element model was developed by incorporating the properties of laminated hybrid composite. In the present study, the symmetric and antisymmetric laminate lay-ups were used, where the detailed various configurations of lamination lay-ups have been shown in Table 1. The hybrid laminated plate was made of Kevlar/Epoxy and Glass/Epoxy with 4 plies respectively. The model of a rectangle hybrid composite laminated plate having dimensions 150mm (length) x 75mm (width) was used in ANSYS. The ply thickness for Kevlar/ Epoxy and Glass/Epoxy plate was measured as 0.15mm. The properties of Glass Epoxy and Kevlar Epoxy were as shown in Table 2. The plate was modelled as a plane area in ANSYS and then meshed using eight noded quadrilateral shell elements (SHELL 281). The plate boundary condition was modelled by constraining all degrees of freedom. In order to carry out the first five-mode shapes and natural frequencies, the Block Lanszoc mode extraction method was implemented. Finally, the problem was solved to obtain the primary unknown quantities.

Table 1 - Configuration of lamination lay-ups for symmetry and anti-symmetry

Lamination lay-up	Configuration
Symmetry	[0/0/0/0]s , [0/θ/0/θ]s , [θ/0/θ/0]s ,[0/θ3]s, [θ/03]s, [02/θ2]s , [θ2/02]s , [03/θ]s , [θ3/0]s, [-θ2/02]s , [-θ3/0]s, [0/-θ/0/-θ]s , [-θ/0/-θ/0]s ,[0/-θ3]s, [-θ/03]s, [02/-θ2]s
Anti-Symmetry	[0/θ/0/θ/0/θ/0/θ], [θ2/02/θ2/02], [02/θ2/02/θ2], [04/θ4], [θ4/04], [0/θ/03/θ/02], [0/-θ/0/-θ/0/-θ/0/-θ], [-θ2/02/-θ2/02], [02/-θ2/02/-θ2], [04/-θ4], [-θ4/04]

Table 2 - Material properties for Kevlar epoxy and S-Glass epoxy[15]

Mechanical Properties	S-Glass Epoxy	Kevlar Epoxy
E_1=E_2 (GPa)	19.5	26.5
v_{12}=v_{21}	0.15	0.09
G_{12}=G_{21} (GPa)	3.7	1.5
Density (kg/m^3)	1710	1250

3.2 ANN Modelling

Recently, Artificial Neural Network (ANN) has become a popular tool to predict the output based on input criteria. The ANN can be defined as the mathematical equivalent of the human brain function and will recognize complex patterns. The ANN model needs to be trained with the input data and target output. Around 150 sets of input data had been used to train the ANN model and had been divided into training, validation, and testing processes. The processing of input data was carried out in several functions:

(i) Training and Learning functions dealing with weights and biases in the network as well as in individual weights and biases for each hidden neuron.
(ii) Transfer function which strongly affects the neural network in the prediction model analysis. There are three types which consist of hyperbolic tangent or TANSIG, logistic sigmoidal or LOGSIG, and linear function or PURELIN.

3.3 Performance analysis of the developed ANNs models

The performance analysis of the prediction model using ANN was analysed by varying the number of neurons in the hidden layer with the hidden layer transfer function. The selected ANN model with suitable transfer function and the number of neurons in predicting natural frequencies of hybrid laminated composite had been determined. The ANN model had been selected based on the highest R^2 and lowest MSE values. The performance indicators (MSE and R^2) were mathematically expressed using equation (3).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right), R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{3}$$

where N is the number of observations, y_i is the observed data, $\hat{y}_i$ is the predicted data, and $\bar{y}$ is the mean of all values.

4. Results and Discussion

Table 3 depicts the error rate of the various train functions. There are various ways to evaluate network performance; one method is Mean Square Error (MSE). To get the maximum performance, the MSE should be the lowest value.

Table 3 - ANN training algorithm performance evaluation result

Algorithm	Hidden Neuron	Training Parameters			Error (%)
		Training	Validation	Testing	
LEVENBERG MARQUEDT	8	90%	5%	5%	4.200
		80%	10%	10%	3.379
		70%	15%	15%	2.063
		60%	20%	20%	6.486
		50%	25%	25%	8.970
	9	90%	5%	5%	2.740
		80%	10%	10%	1.478
		70%	15%	15%	2.794
		60%	20%	20%	3.501
		50%	25%	25%	6.840
	10	90%	5%	5%	5.471
		80%	10%	10%	0.698
		70%	15%	15%	7.066
		60%	20%	20%	0.710
		50%	25%	25%	0.908
BAYESIAN REGULARIZATION	8	90%	5%	5%	2.150
		80%	10%	10%	2.047
		70%	15%	15%	1.499
		60%	20%	20%	2.554
		50%	25%	25%	1.268
	9	90%	5%	5%	2.647
		80%	10%	10%	0.823
		70%	15%	15%	0.873
		60%	20%	20%	1.283
		50%	25%	25%	4.316
	10	90%	5%	5%	4.163
		80%	10%	10%	0.081
		70%	15%	15%	1.951
		60%	20%	20%	7.312
		50%	25%	25%	5.602
SCALED CONJUGATE GRADIENT	8	90%	5%	5%	4.794
		80%	10%	10%	4.978
		70%	15%	15%	2.010
		60%	20%	20%	0.660
		50%	25%	25%	12.090
	9	90%	5%	5%	7.597
		80%	10%	10%	3.826
		70%	15%	15%	2.204
		60%	20%	20%	7.807
		50%	25%	25%	3.902
	10	90%	5%	5%	6.832
		80%	10%	10%	6.323
		70%	15%	15%	3.785
		60%	20%	20%	2.741
		50%	25%	25%	6.466

4.1 Regression Analysis

Fig. 1 shows the regression analysis obtained from the training data for selected ANN models. The value of R^2 is required to approach 1 to get the best result of the analysis.

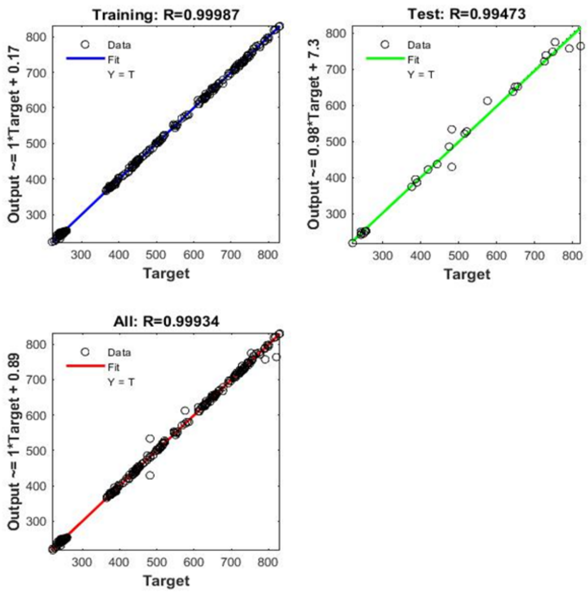


Fig. 1 - Regression analysis of neural network

4.2 Selection of the Best Training Algorithm

Table 4 shows the selected training function and hidden neuron for the performance analysis and validation. The hidden neuron had been chosen based on the lowest value of MSE. Fig. 2 shows the selected network architecture of ANN with eight input layers, three output layers and ten hidden neurons at the hidden layer. This architecture had been selected after identifying the best training algorithm.

Table 4 - Selected training function and hidden neuron

The number of data sets	150 data sets: 100 training, 30 validation, 20 testing
Input layer	8
The number of neurons in the hidden layer	10
Output layer	3
Network type	A two-layer feed-forward network
Training function	TRAINBR
Learning function	LEARNGDM
Output transfer function	Tangent sigmoid
Hidden transfer function	Tangent sigmoid
Performance function	MSE, R^2

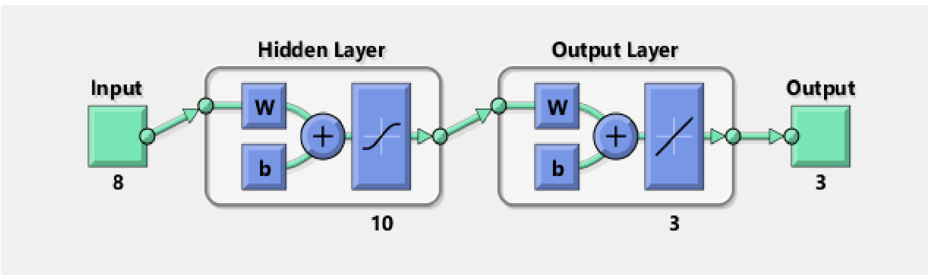
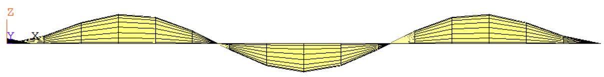


Fig. 2 - ANN network architecture

4.3 Prediction of Natural Frequencies for Laminated Hybrid Composite Plate

Initially, 150 data sets were created from the simulation using finite element software, ANSYS (v1, 2021). The data sets were then formatted and exported to MATLAB to be trained and tested for creating a neural network. Proper training algorithms were determined using the comparison of MSE and regression analysis (R^2). The developed neural network was used to predict the natural frequency of 8-plies symmetric and anti-symmetric Kevlar/Glass hybrid laminated composite plate with various lay-ups. The lay-ups considered were [-θ/0/-θ/0]s, [0/θ/0/θ/-θ/0/-θ/0], [θ/0/θ/0_2/-θ/0/-θ] and [$θ_2$/0_4/-$θ_2$]. For each lay-up, the fibre angle, θ, was varied as 15°,30°,45°,60° & 90°. The allowable tolerance rate was set to 5%. Fig. 3 shows the behaviour of the hybrid laminated plate due to the mode shape of vibrations. Fig. 4 until Fig. 6 present the results of predicted natural frequencies using ANN compared to the simulated results (ANSYS). The ANN prediction model was then used to predict the natural frequencies of hybrid laminated composite for the first three mode shapes of vibrations without repeating the process from determining the properties of the material to solving the problems. Fig. 4 shows the ability of the ANN prediction model for the first mode shape of a hybrid laminated composite plate. The prediction results for the second and third mode shape of vibrations have been shown in Figs. 5 and 6, respectively. It can be observed that the predicted results produced an error of less than 5% for the first three mode shapes of vibrations. Error bars have been presented for each graph to clearly highlight the small error (percentage error = ± 5%).

Mode Shape 1 and 2: First and second order bending



Mode Shape 3: Third order bending

Fig. 3 - Description of modes shape of vibrations

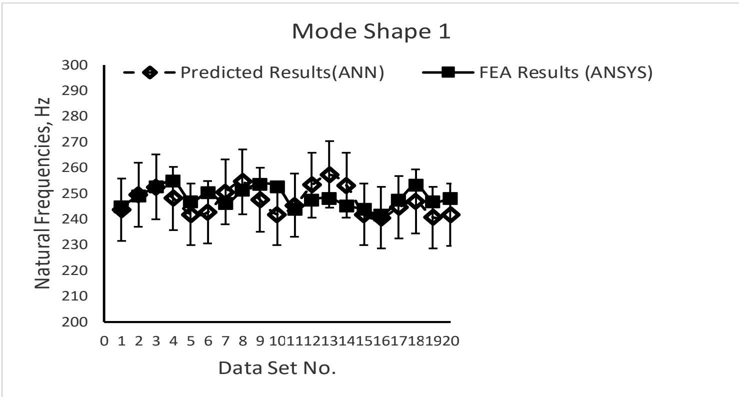


Fig. 4 - Natural frequencies of vibrations for first mode shape with various lamination lay-ups

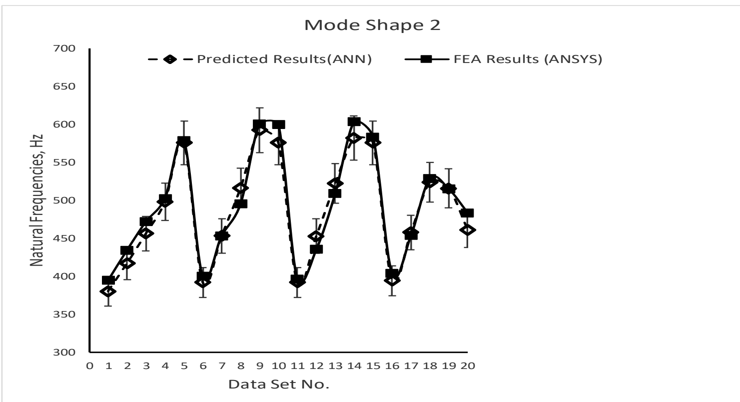


Fig. 5 - Natural Frequencies of vibrations for Second Mode Shape with various lamination lay-ups

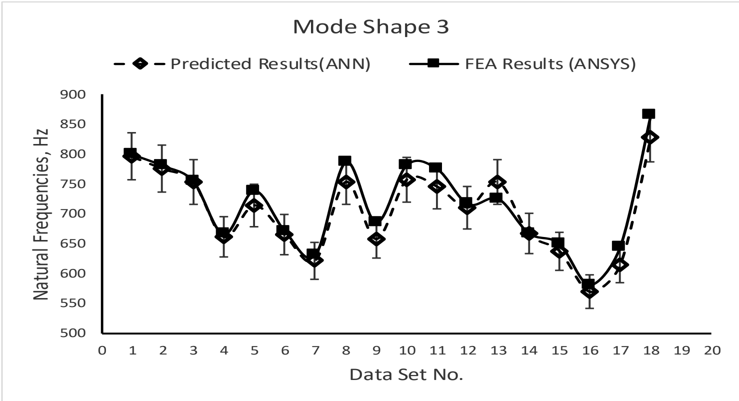


Fig. 6 - Natural Frequencies of vibrations for Third Mode Shape with various lamination lay-ups

5. Conclusion

This study presents the prediction of the natural frequencies using the ANN model on the Kevlar-Glass hybrid composite material. The various lay-ups and orientation angles which affect the natural frequency of the structure had been investigated. The ANN modelling had given a significantly good prediction of natural frequency using MATLAB software. The difference in error between prediction and simulation was less than 5% error. The artificial neural network model had been developed and trained by considering the lay-up angle as the input for predicting the natural frequency. The ANN results were in good agreement with the finite element results. The accuracy of the neural network relied solely on the number of data sets used for training. The higher the number of data sets, the higher the accuracy of prediction. These results show the importance of artificial neural networks in predicting the natural frequency of complex hybrid composites. This finding concludes that the current study is beneficial and has contributed to a more comprehensive understanding of the importance of predicting the natural frequency of hybrid composite materials using ANN. This neural network training will guide future researchers and manufacturers in predicting the natural frequency of hybrid laminated composite materials.

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