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Artificial neural network based multi-parameter inversion for the characterization of transversely isotropic composite lamina using velocity measurements of Lamb waves

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Abstract

Artificial neural network (ANN) based multi-parameter inversion method is proposed to characterize transversely isotropic composite lamina using Lamb wave group velocity measurements. The ANN is first trained using numerical simulations and known micromechanics based formulae before being deployed on experimental samples. The group velocities obtained from the experiments were fed to the trained network. The network so trained, predicted the elastic properties, fiber volume fraction, and density.

Keywords

Composite lamina, lamb wave, lamina properties, artificial neural network

Introduction

Specific strength and stiffness are the two important driving parameters, which paved the way for extensive usage of composite materials in load bearing structural applications. For design and analysis of any composite structure, an accurate and dependable knowledge of its elastic properties is a must. Conventionally, all data on the elastic properties of a composite structure is obtained by resorting to destructive testing as per ASTM test norms.[2]

Lamb waves[25] propagate long distances in thin plate and cylindrical structures. These waves provide information regarding the integrity of the structure along the line-of-sight. Hence, these waves can be used with great efficacy, for Non-destructive Evaluation (NDE) as well as structural health monitoring (SHM) of composite laminated structures.[20,21] Lamb waves are dispersive i.e., their velocity depends on the product of frequency and thickness. Depending on the relationship between the displacement profiles and thickness, these modes are classified into symmetric (S_n) and anti-symmetric (A_n) modes.

Elastic properties of a material can be measured using conventional destructive techniques as per ASTM standards. Ultrasonic wave based techniques for material characterization is undoubtedly more utilitarian than the conventional destructive techniques.[13,17–19,25] In ultrasonic testing, both bulk waves and Lamb waves can be used for evaluating the elastic properties of a given media.

Many authors[5,6,24] have heretofore, explored ways and means for determining elastic moduli using bulk waves. Some authors used Lamb waves for reconstruction of elastic moduli. Reference 23 described a method for the measurement of elastic moduli of isotropic plates using Rayleigh–Lamb waves produced by using a pair of variable-angle contact transducers in

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pitch-catch mode. From this technique, Young's modulus and Poisson's ratio were estimated. Reference 22 reconstructed the elastic moduli of a unidirectional composite by reducing the error between theoretical and experimental Lamb wave dispersion curves. Reference 29 attempted to reconstruct all nine unknown elastic moduli of orthotropic plates using a single-transmitter-multiple-receiver (STMR) compact SHM array. Phase velocities of fundamental symmetric and anti-symmetric Lamb waves were used in an inversion algorithm based on genetic algorithms. Reference 14 proposed an inversion scheme to invert Leaky Lamb wave (LLW) velocity data using simplex algorithm to approximate the elastic moduli and thickness of an adhesive layer between two aluminium plates and the elastic moduli of a unidirectional Glass Fiber Reinforced Plastic (GFRP) composite laminate.

With the rapid developments in the field of artificial intelligence, neural network (NN) methods have become all-pervasive in many areas of Science and Engineering. Artificial neural network (ANN) is currently used in various fields of Engineering, without undergoing any significant change in its basic methodology. ANN technique is also in use for damage detection and identification applications.[15,16,30] Reference 26 carries out a study to examine the fiber volume fraction variations of approximately 0.4 to 0.7 in composites employing Lamb waves. The Lamb wave measurements were compared with fiber volume fractions obtained from acid digestion test.

The velocity of Lamb waves in a laminate depends on its elastic properties and density. For a given fiber volume fraction, the elastic properties and density of a lamina can be estimated using established principles of micro-mechanics and semi-empirical relations. Any change in the fiber volume fraction alters the elastic properties and density of the lamina. These changes affect the Lamb wave velocities in a predictable and quantifiable manner. An attempt was made, in this paper, to envisage the elastic properties of a composite lamina by studying the transmuting velocities of the fundamental symmetric Lamb wave (S_o) along and across the direction of fibers in an ANN environment. The ANN was trained beforehand to identify various elastic properties for the given group velocities of S_o mode along and across the direction of fibers, using data obtained from numerical simulations. Experiments were carried out on glass/epoxy uni-directional (UD) laminates employing piezo patches as transmitters and receivers. The trained ANN could predict the elastic properties, fiber volume fraction, and density, when experimentally measured S_o mode velocities were fed.

The organisation of this paper is as follows. The Artificial Neural Network section deals with ANN and data generation for training the network. Estimation of elastic properties of lamina using rule of mixtures and semi-empirical relations is presented in Lamina Properties section. Generation of training data through numerical modelling is described in Group Velocities of S_o Mode section. Experimental work carried out on UD laminates is delineated in Experimental Work section. The predictions of ANN are presented in ANN Predictions section. Results and discussion and conclusions are presented in the last two sections, respectively.

Artificial neural network

ANNs are quite similar to the neurons in human brain—both in their structure and in the methodology of processing and restoring data. The learning mechanisms too are analogous. NN consists of interconnected processing elements called neurons operating in parallel to a set of input signals given to each. In an ANN model, there are essentially three parts, viz., neurons, weighted interconnections between neurons and an activation function that responds on the set of input signals at neurons to produce output signals. The NNs are trained to perform a particular function by adjusting the values of weights between elements.

Among many different types of ANN, the feed forward, multi-layered, supervised neural network with error back propagation algorithm, generally known as back propagation (BP)[27] network, is by far the most commonly applied ANN owing to its simplicity. The output of the network, $\boldsymbol{a}$, is a transferred sum of weighted inputs, $\boldsymbol{p}$, with added bias using the sigmoid or a linear function. A simple three layer ANN consists of an input layer, a hidden layer, interconnected by modifiable weights, and an output layer. Input vector is presented to the input layer and output of each input unit equals the corresponding component in the vector. Each hidden unit computes the weighted sum of its inputs to form its net scalar neural net activation. The neural net activation is the inner product of the input and the weights, at the hidden unit. Each hidden unit emits an output that is a non-linear function of its activation function. Each output unit similarly computes its net activation based on the signals from the hidden unit. Before an ANN can be applied, the network needs to be trained from an existing training set comprising pairs of input-output elements. An ANN with BP algorithm takes a long time to learn. Therefore, several different approaches were developed to enhance and hasten the learning performance of BP learning algorithm. Among them, the most popular are Scaled conjugate gradient (SCG), Quasi-Newton, and Levenberg-Marquardt (LM) algorithm.

In this work, S_o mode velocity along fibers ($V_{//}$) and across fibers ($V_{\perp}$) were used as input vectors in the network and the output vector consists of the five elastic properties, fiber volume fraction and density of the lamina as shown in Figure 1. The range of fiber volume fraction selected for the present study was from 0.30 to 0.78. For a given volume fraction, the elastic properties (lamina level) can be estimated using expressions from Equation (1) to (5) given hereafter. Using these elastic properties, S_o mode velocities along and across fibers were calculated through numerical simulations for fiber volume fraction ranging from 0.30 to 0.78 in steps of 0.04. A total number of thirteen data sets were generated for training the network.

Lamina properties

The lamina level properties can be ascertained using micromechanical analysis, if the properties of constituent materials, fiber and matrix, and fiber volume fraction are known. Once a micromechanical model that is in concord with the experimental results is developed, such a model can be used for estimation of elastic moduli, which will in turn be used in the design and analysis of laminated composite structures. If directions '1' and '2' are taken as in-plane ('1' is along the direction of the fiber), the direction '3' is out-of-plane. Longitudinal modulus of lamina in direction '1' is E_{11}. The following expression can be used to estimate E_{11} (Refs. 1 and 9).

$$E_{11} = E_{f1} v_f + E_m v_m, \tag{1}$$

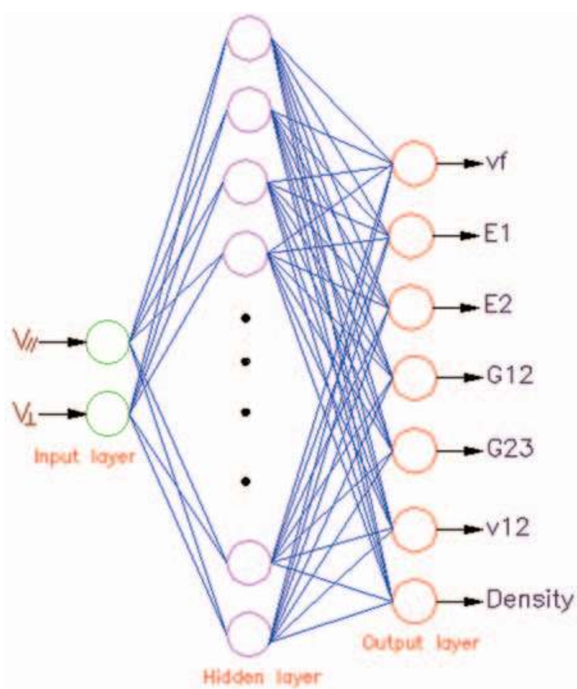

Figure 1. Neural network used for predicting elastic properties, fiber volume fraction, and density.

where, E_{11}, E_{f1}, and E_m are Young's moduli of lamina along fiber direction, longitudinal direction of fibers, and matrix respectively, v_f and v_m are fiber and matrix volume fraction, respectively.

The expression for in-plane Poisson's ratio,[9] ν_{12}, is given by the following:

$$\upsilon_{12} = \upsilon_{f12} v_f + \upsilon_m v_m, \tag{2}$$

where, ν_{f12} and ν_m are Poisson's ratio of fibers and matrix, respectively.

Reference 28 proposed a semi-empirical approach (SEA) to evaluate E_{22}. This approach was based on the fact that the stresses in the fibers and matrix are not equal under the corresponding loading condition. 'Stress-partitioning parameter' (η_2) was introduced in deriving the semi-empirical equation. The result of this derivation[28] is as follows:

$$\frac{1}{E_{22}} = \frac{1}{v_f + \eta_2 v_m}\left[\frac{v_f}{E_f} + \frac{\eta_2 v_m}{E_m}\right]. \tag{3}$$

If stress-partitioning parameter is taken as unity, it leads to the inverse rule of mixtures of E_{22} derived from micro-mechanics principles. It was shown in Ref. 28 that the stress-partitioning parameter $\eta_2 = 0.5$ was found to yield accurate predictions of E_{22} based on comparison with experimental data for the same laminate [11].

Reference 10 proposed the following expression for estimation of in-plane shear modulus (G_{12}).

$$\frac{G_{12}}{G_m} = \frac{1 + \xi\eta v_f}{1 - \eta v_f}, \tag{4a}$$

where

$$\eta = \frac{(G_f/G_m) - 1}{(G_f/G_m) + \xi}. \tag{4b}$$

Here, 'ξ' is the reinforcing factor, which depends on fiber geometry, packing geometry, and loading conditions. For circular fibers in a square array, $\xi = 1$ (Ref. 4). The value of $\xi = 1$ for circular fibers in a square array, provides reasonably good results.

In most composites because the fiber-packaging arrangement is statically random in nature, the properties are nearly same in any direction perpendicular to the fibers.[9] Such materials are 'Transversely isotropic'. Directions perpendicular to the fibers are along '2' and '3' directions. In UD laminate, plane 2-3 is assumed to be isotropic. For a transversely isotropic material, five elastic moduli are required for defining the stiffness matrix in entirety.[9]

Four in-plane elastic properties, E_{11}, E_{22}, ν_{12}, and G_{12} are sufficient for design and analysis of thin composite structures. In case of thick, transversely isotropic structures, one more elastic constant is required. In general, the value of Poisson's ratio in 2-3 plane, ν_{23}, is governed by matrix. For design purpose, this value was taken as the value of matrix.

As 2-3 plane was assumed to be isotropic, the following relation between E_{22}, G_{23}, and ν_{23} holds good:

$$G_{23} = \frac{E_{22}}{2(1+\upsilon_{23})}. \quad (5)$$

The density of the lamina can be obtained from rule of mixtures.[9] The following expression gives the density of the lamina:

$$\rho = \nu_f \rho_f + \nu_m \rho_m. \quad (6)$$

Equations (1)–(5) furnish the elastic moduli while Equation (6) gives density of the lamina.

If fiber volume fraction is known, Equations (1)–(6) can be used for estimation of elastic properties and density of the lamina.

Group velocities of S_o mode

As the input vector for training the neural network consists of S_o mode group velocities along fibers and across fibers, these were obtained from two dimensional numerical simulations carried out using Finite Element code, ANSYS [3]. The constituent materials used in this work were Chomarat 500 GSM glass fabric (8077/1F) and proprietary epoxy resin system capable of forming films. The properties of the constituent materials[9,12] are shown in Tables 1 and 2. The average thickness of each ply was 0.33 mm. The specifications of the model used in numerical simulations are shown in Figure 3. It was assumed that there are three unidirectional plies in the laminate. The corresponding thickness of the UD laminate was 0.99 mm thickness and the length was chosen as 300 mm. In Finite Element (FE) model, each ply of 0.33 mm thickness was modeled and its properties were attributed. The size of the element was 0.165 mm in the thickness direction and 0.25 mm in the length direction. There were more than 100 elements in one wavelength of S_o mode at 148 kHz frequency. The element used for analysis was higher order eight node plane element with four corner nodes and four mid-side nodes, belonging

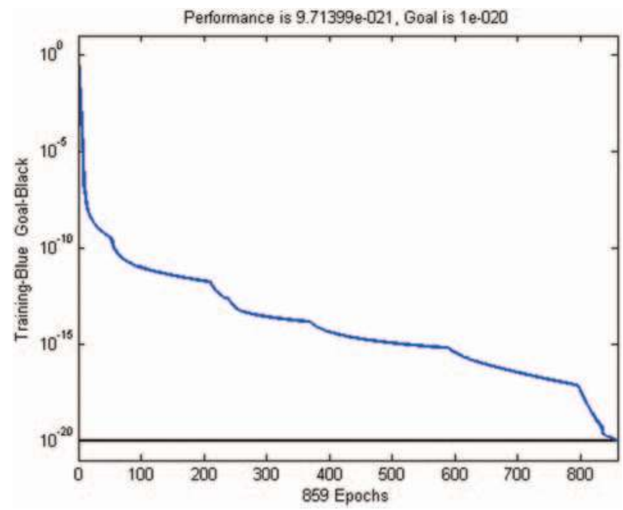

Figure 2. Convergence of ANN.

Table 1. Chomarat 500 GSM glass fiber properties

E_{f1} in GPa	E_{f2} in GPa	G_{f12} in GPa	G_{f23} in GPa	ν_{f12}	ρ_f in kg/m3
72.53	72.53	30.14	30.14	0.22	2540

Table 2. Epoxy

E_m in GPa	G_m in GPa	ν_m	ρ_m in kg/m^3
2.8	1.0	0.34	1170

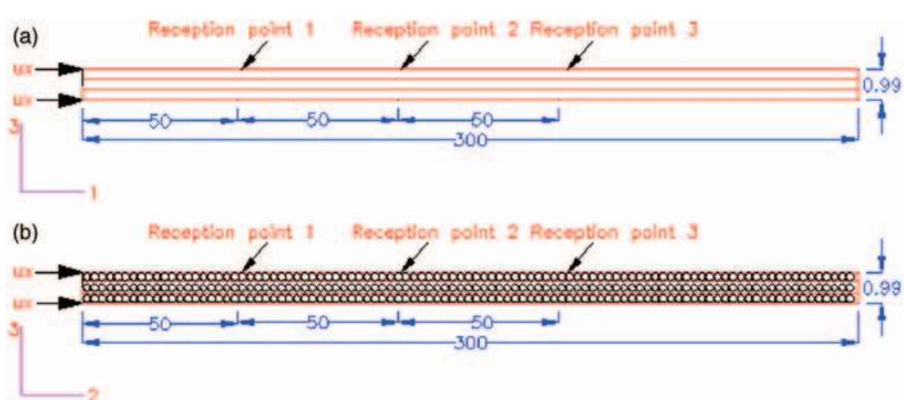

Figure 3. Specification of model used for FE simulations. Excitation of S_o mode (a) along fibers and (b) across fibers.

to serendipity family. Each node has two translatory Degree-of-Freedom (DoF) in 'x' and 'z' directions. It was assumed that plane strain conditions prevail. The excitation frequency and number cycles were 148 kHz tone-burst and three, respectively. Time marching was carried out using Newmark's time integration scheme (ANSYS) [3]. The time increment and total capturing time used in the simulations were 20.27 ns and 90 μs, respectively.

The location and direction of excitation were x = 0 and in-plane, respectively, as shown in Figure 3. There were two reception points in each direction. At all reception points, A-scans for in-plane displacement time history were plotted as shown in Figure 4. A video envelope, which is a smooth curve passes over all the peaks of the signal, was fitted over each signal. This video envelope looks like a rectified signal. The peak of the video envelop represents the arrival time of that wave group at that reception point. Knowing the distance between the two reception points and the difference in arrival times of a wave group (Time-of-Flight (ToF)) at these two reception points, the group velocity can be calculated as the ratio between the distance and ToF.

Experimental work

Fabrication of specimen

A Glass/epoxy cross-ply laminate of 0.99 mm thickness with $[0_3]$ lay up was prepared using resin film infusion (RFI) technique. A resin film was sandwiched between two fabric layers. Such sandwiches were placed one above the other till the desired thickness was reached. Sufficient bleeder was used to absorb any excess resin released during curing. A vacuum bag was placed on the top and sealed with a sealant tape. A thermocouple was placed on the top of the job to continuously monitor the temperature during curing. The job was heated at a rate of 2°C/min up to 80°C, soaked for 30 min followed by heating up to 120°C, and re-soaking for 60 min. After completion of heating cycle, the job was allowed to cool to room temperature. The edges were trimmed and the final dimensions of laminate were 300 × 300 × 0.99 mm.

Experimental set up

The schematic of experimental set up shown in Figure 4 consists of a signal generator, A/D card (PXI), power amplifier and a desk top computer. In this system, piezoelectric lead zirconate titanate (PZT) (ϕ14.5 mm, thickness: 1.25 mm) patches were used. As the diameter of PZT was chosen as 14.5 mm, the frequency of excitation estimated from diameter-frequency product was 148 kHz. At this frequency, S_o mode falls in non-dispersive region. The excitation given to patches was three cycle tone burst with Hanning window at a central frequency of 148 kHz. As the wave velocities are required along and across fiber directions, three patches in each direction were bonded as shown in Figure 5. There were one transmitter and two receivers placed in each direction. The "Receiver 1" position was marked at the center of the laminate. The locations of transmitter and "Receiver 2" were at a distance of 75 mm on either side of the "Receiver 1" as shown in Figure 5. But after bonding, the actual distances between the PZTs were found to be slightly more than 75 mm. In group velocity computations, the actual distance between the patches was taken.

A-scans from experiments. A-scans obtained from "Receiver 1" and "Receiver 2" along and across the fiber direction are shown in Figure 6 and 7,

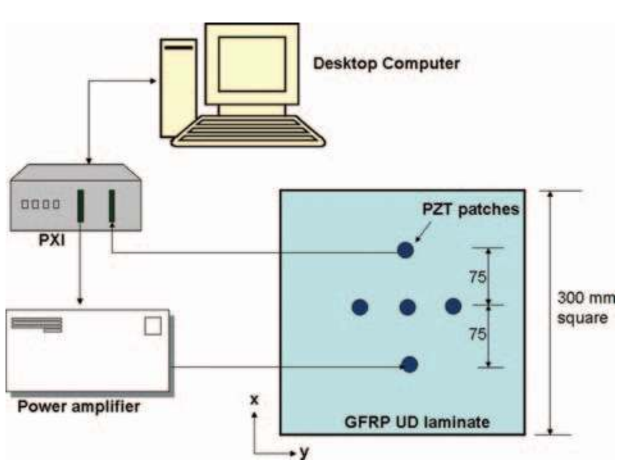

Figure 4. Schmatic of experimental set up.

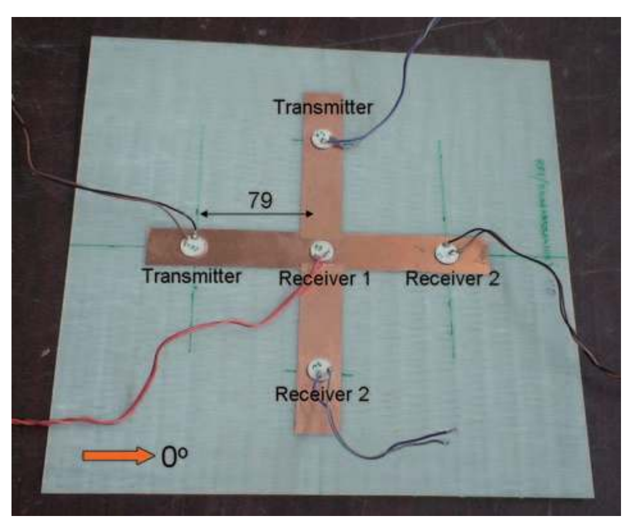

Figure 5. PZT patches bonded on glass/epoxy UD laminate.

respectively. The first wave group in each A-scan represents S_o mode. On each A-scan, a video envelope was fitted. The peak of this envelope represents the arrival time of that wave group at the receiver. Since the distance between the two receivers and the difference in arrival times were known, group velocity was computed as the ratio between the two.

Such A-scan were obtained for the other two laminates also. The group velocities, $V_{//}$ and $V_{\perp}$, of S_o modes in all three laminates are shown in Table 3.

Matrix burn-off test as per ASTM standard (ASTM D2584) was carried out on samples cut from all the laminates. This test gives fiber volume fraction, void fraction as well as the density. The values of these parameters obtained for all the laminates are shown in Table 4.

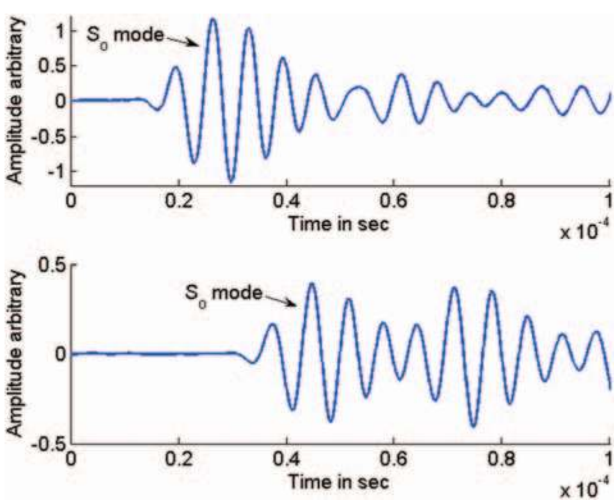

Figure 6. A-scans from experiments, taken at (a) "Receiver 1" and (b) "Receiver 2" along fiber direction.

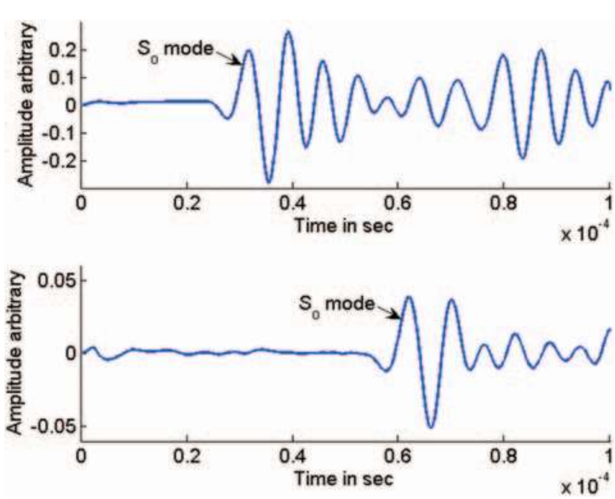

Figure 7. A-scans from experiments, taken at (a) "Receiver 1" and (b) "Receiver 2" across fiber direction.

Artificial neural network predictions

Each data set used for training ANN consists of an input vector and a corresponding output vector. There were two neurons in the input vector and seven linear neurons in the output vector. Sigmoid neurons were used in the hidden layers.[16] The variables in input vector were S_o mode velocities along and across the direction of fibers. The variables in output vector were five elastic moduli, the fiber volume fraction, and density. Training of ANN is referred to as the determination of weights in the model using training data. To train the network, SCG and LM algorithm[7] which are the standard functions available in Neural Network Toolbox of MATLAB [8], were used. The efficacy of trained network for mapping between the input and output depends on training data.

The convergence criterion of NN was mean square error (MSE), which minimises the averaged square error between the network output and the target value mentioned in the training data. The chosen convergence criterion (MSE) in this work was 1×10^{-20}. Figure 2 shows the convergence plot of ANN.

The group velocities of S_o mode along and across fibers obtained from experiments were fed in trained neural network. The prediction made by the network is shown in Table 4. As the fiber volume fractions of all three laminates were known from matrix burn-off test, the elastic properties and density were calculated using Equations (1)–(6). The properties thus obtained are shown in Table 5. Dynamic elastic property analyzer

Table 3. Lamb modes velocities in three laminates from experiments

Laminate	$V_{//}$	$V_{\perp}$
1	4787.8	2508.0
2	4593.0	2358.4
3	4477.9	2123.4

Table 4. Fiber volume fraction, density, and void fraction from matrix burn-off method

Laminate	Fiber volume fraction	Density in kg/m^3	Void
1	0.62	2014.3	1.9 %
2	0.51	1865.0	0.8%
3	0.44	1762.5	1.2 %

Table 5. Elastic properties predicted by ANN and estimated using Equations (1)–(6)

	Laminate–1		Laminate–2		Laminate–3	
Property	ANN	Equation (1)–(6)	ANN	Equation (1)–(6)	ANN	Equation (1)–(6)
v_f	0.60	—	0.52	—	0.44	—
E_1 (Gpa)	44.5	46.0	38.9	38.4	33.9	32.8
E_2 (Gpa)	10.1	10.6	8.8	8.0	7.3	6.6
G_{12} (GPa)	3.8	3.8	3.1	2.8	2.6	2.4
G_{23} (GPa)	3.9	3.9	3.2	3.0	2.7	2.5
v_{12}	0.29	0.27	0.29	0.28	0.32	0.29
ρ_m (kg/m^3)	1989.1	2019.4	1878.5	1868.7	1781.5	1759.1

(DEPA), which works on the principle of impulse excitation technique, was also used to predict the Young's moduli along and across fiber directions, as per ASTM standards. Table 6 lists the predictions from DEPA.

Table 6. Young's moduli from DEPA

	Laminate–1	Laminate–2	Laminate–3
E_{11} in GPa	44.7	36.7	33.1
E_{22} in GPa	11.5	9.8	7.8

Results and discussion

In the present study, an attempt has been made to estimate the five elastic moduli, the density and the fiber volume fraction in a UD laminate using Lamb waves in ANN environment. The required data for training ANN was generated through numerical simulations carried out using Finite Element Method (FEM). The parameters in the input vector of this neural network were selected in such a way that they change with elastic properties. It should also be ensured that the parameters in the input vector are measurable experimentally. Based on the aforementioned criterion, the selected parameters in the input vector were S_o mode group velocities along and across the direction of fibres. The other potential choices for selection as parameters in the input vector are group velocities of the fundamental anti-symmetric Lamb wave (A_o) or combination of S_o and A_o modes.

For experimental validation, PZT patches were deployed as transmitter and receivers to capture signals along and across the direction of fibres in all the three laminates, which were fabricated using RFI process. From the captured signals, group velocities of S_o mode were computed. These velocities were fed in the trained network. Table 5 shows the predictions made by the network for all the three laminates. Shear modulus, G_{23}, was obtained by assuming Poisson's ratio in 2-3 plane as equal to matrix Poisson's ratio, which is 0.34. As fiber volume fractions of all three laminates were known (from burn-off test), the elastic properties and density were also estimated using Equations (1)–(6). These values are found to be in good agreement with ANN predictions as shown in Table 5. Micromechanics and semi-empirical models, which are in good agreement with the experimental results, were selected for estimation of the elastic properties from fiber volume fraction. Elastic properties predicted by ANN are in good agreement with those obtained from Equations (1)–(6) (viz. micromechanics and semi-empirical models) and from the above-mentioned experiments. DEPA was used to measure the properties wherever possible. In all three laminates, Young's moduli along and across fiber direction were measured using DEPA. The elastic properties obtained from DEPA were found be in good agreement with ANN predictions as listed in Tables 5 and 6. Matrix burn-off test as per ASTM D2584 was carried out on all four laminates and the properties obtained from this test are shown in Table 5. The void fraction in all four laminates was found to be less than 2%. The density and fiber volume fraction obtained from matrix burn-off test were also found to be in good agreement with ANN predictions.

In a laminate, the fiber volume fraction may also change from point to point. In such cases, matrix burn-off test gives a local value of fiber volume fraction. When a Lamb wave propagates from a transmitter to a receiver, any variation in fiber volume fraction in its path of propagation influences the group velocity of this mode. As the wave propagates through regions of differing fiber volume fractions, the predictions made by ANN were based on the average group velocity of Lamb wave. In general, in the design and analysis of composite structures, the elastic properties based on average fiber volume fraction are used. To estimate average fiber volume fraction using ASTM burn-off test, many samples cut at various locations in the laminate are to be tested. In the present technique, the average fiber volume fraction can be obtained from a single experiment.

Determination of lamina properties from ASTM standards is very tedious, because, each property requires an individual test. The present technique based on Lamb wave velocities and ANN reduces experimentation a lot.

In this study, the network was trained to give seven parameters, viz. the five elastic moduli, the density and the fiber volume fraction. This can also be modified as following.

Group velocities of S_o mode along and across the direction of fibers depend on elastic properties. Elastic properties in turn depend on fiber volume fraction. The network can be trained for an input vector consisting of $V_{//}$ and $V_{\perp}$ and an output vector consisting of the fiber volume fraction. Once the fiber volume fraction is obtained from the neural network, Equations (1)–(5) can be used for estimating the elastic moduli and Equation (6) for estimation of density.

In this study, the thickness of laminate and frequency of excitation were 0.99 mm and 148 kHz, respectively. The frequency-thickness product was equal to 146.52 kHz.mm In a given media, velocities of Lamb waves depend on frequency-thickness product. Lamb waves velocities remain constant as long as frequency-thickness product does not change. While generating data for training the network, a particular thickness of UD laminate and central excitation frequency were selected. That means the network is trained for a particular frequency-thickness product. This trained network can be used to characterize a UD laminate of different thickness, but, fabricated from same constituent materials (fiber and matrix). In such a case, the central frequency of excitation of Lamb wave should be selected such that the frequency-thickness product is equal to the value for which the network is trained. If frequency-thickness product is changed, then the whole network has to be trained once again, since the group velocities change.

Conclusions

Use of Lamb waves and ANN for composite lamina characterisation was attempted. Experiments were carried out using PZT patches on three laminates. The predictions made by ANN are in good agreement with those obtained from DEPA and matrix burn-off test. The experimentation involved in this method based on Lamb waves is simple compared to ASTM, DEPA, and matrix burn-off method. The elastic properties obtained through this technique are averaged properties over a certain area through which Lamb waves propagated.

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References

1. Adams RD. Damping properties analysis of composites. In: Reinhart TJ and Halbert HF (eds) *Engineered materials hand book*. Vol 1, *Composites*. Materials Park, OH: ASM International, 1987, pp. 206–217.
2. Annual Book of ASTM standards 2004, Section 15, General products, chemical specialties and end use products, Volume: 15.03, D 3039/D 3039M, 2004.
3. ANSYS Inc. *User's manual R11*. Pittsburgh, PA: ANSYS Inc 2007.
4. Autar KK. *Mechanics of composite materials*. CRC press, 1997.
5. Balasubramaniam K and Rao NS. Inversion of composite materials elastic constants from ultrasonic bulk wave phase velocity data using genetic algorithms. *Composites Part B* 1998; 29: 1710–180.
6. Balasubramaniam K and Whitney SC. Ultrasonic through-transmission characterization of thick fiber-reinforced composites. *NDT & E Int* 1996; 29: 225–236.
7. Bishop C. *Neural networks for pattern recognition*. Oxford University Press, 1995.
8. Demuth H and Beale M. *Neural network toolbox user's guide version 4, for use with MATLAB 5.2-5.73*.
9. Gibson RF. *Principles of composite materials mechanics*. Mc Graw Hill International Edition, 1994.
10. Halphin JC and Tsai SW. *Effect of environment factors on composite materials*. Air force technical report, AFML–TR–67–423.
11. Hashin Z. *Experimental data from Hashin Z*. NASA technical report contract no. NAS1-8818, 1970.
12. Henry Lee and Kris Neville. *Hand book of epoxy resins*. McGraw Hill Book Company, 1967.
13. Jones RM. *Mechanics of composite materials*. New York: Hemisphere publications, 1975.
14. Karim MR, Mal AK and Bar-Cohen Y. Inversion of leaky Lamb wave data by simplex algorithm. *J. Acoust. Soc. Am*. 1990; 88(1): 482–491.
15. Kesavan A, Deivasigamani M, John S and Herszberg I. Damage detection in T – joint composite structures. *Compos Struct* 2006; 75: 313–320.
16. Kim YY and Kapania RK. Neural networks for inverse problems in damage identification and optical imaging. *AIAA J* 2003; 41(4): 732–740.
17. Kline RA. *Non-destructive characterisation of composite media*. PA: Technomic publications, Lancaster, 1992.
18. Liu GR and Xi ZC. *Elastic waves in anisotropic laminates*. CRC press: Boca Raton, 2002.
19. Nayfeh AH. Wave propagation in layered anisotropic media with applications to composites, Elsevier publications, Amsterdam.

20. Prasad Mahadev S, Balasubramaniam K and Krishnamurthy CV. Structural health monitoring of composite structures using Lamb wave tomography. *Smart Mater Struct* 2004; 13: N73–N79.
21. Rajagopalan J, Balasubramaniam K and Krishnamurthy CV. A phase reconstruction algorithm for Lamb wave based structural health monitoring of anisotropic multilayered composite plates. *J Acoust Soc Am* 2006; 119: 872–878.
22. Rao NS. *Inverse problems in ultrasonic non-destructive characterization of composite materials using genetic algorithm*. MS thesis, Mississippi State University, 1997.
23. Rogers WP. Elastic property measurement using Rayleigh-Lamb waves. *J Res Non-destruct Eval* 1995; 6: 185–208.
24. Rokhlin SI and Wang W. Double through-transmission bulk wave method for ultrasonic phase velocity measurement and determination of elastic constants of composite materials. *J Acoust Soc Am* 1992; 91: 3303–3312.
25. Rose JL. Ultrasonic waves in solid media. 1st edition. Cambridge University Press, 1999.
26. Seale DM, Smith TB, Prosser WH and Zalameda NJ. Lamb wave assessment of fiber volume fraction in composites. *J Acoust Soc Am* 1998; 104(3): 1399–1403.
27. Simon H. *Neural networks: a comprehensive foundation*. 2nd edition. Pearson Prentice Hall publications, 1998.
28. Tsai SW and Hahn HT. *Introduction to composite materials*. Lancaster, PA: Technomic publishing Co, 1980.
29. Vishnuvardhan J, Krishnamurthy CV and Krishnan B. Genetic algorithm based reconstruction of the elastic moduli of orthotropic plates using an ultrasonic guided wave single-transmitter-multiple-receiver SHM array. *Smart Mater Struct* 2007; 16: 1639–1650.
30. Wu X, Ghaboussi J and Garrett JH. Use of Neural Networks in Detection of Structural Damage. *Comput Struct* 1992; 42(4): 649–659.