DETECTION OF TRANSVERSE CRACKS IN A COMPOSITE BEAM USING COMBINED FEATURES OF LAMB WAVE AND VIBRATION TECHNIQUES IN ANN ENVIRONMENT

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Abstract - The detection, location and sizing of transverse cracks in a composite beam, by combining damage features of Lamb wave and vibration based techniques in artificial neural network (ANN) environment, using numerical finite element model, is discussed. Four damage features, time of flight (TOF) and amplitude ratio, which are Lamb wave based features and first and second natural frequencies, which are vibration based features were used as input to ANN. The output of ANN was crack location and depth. It was demonstrated that through the simultaneous employment of features from the two modalities in an ANN environment, the sizing could be done more effectively.

Index terms: Lamb wave, vibration, ANN, damage detection, crack, SHM, NDE

I. INTRODUCTION

Composites as structural material are being used in aerospace, military and civilian applications because of their tailor made properties. Composites are prone to damages like transverse cracking, fiber breakage, delaminations, matrix cracking and fiber-matrix debonding when subjected to service conditions. Transverse cracks can occur when a single ply in a multi-ply laminate fails. This leads to additional loads on the other plies and also increased stress concentrations at the edges of the cracks. This leads to further growth of the transverse crack size leading to reduce the stiffness and stability of the structures.

In the past, Lamb (guided) waves have shown the greater potential for damage detection. Lamb waves have characteristics of multimode propagation and dispersion [1]. When a Lamb mode interacts with a typical damage; reflection, transmission and mode conversion takes place.

Because of complexity of the received signals that sometimes may also overlap on each other it is difficult to interpret the signals and characterize the damages using Lamb waves. When Lamb waves are used for damage detection applications, there are no guidelines available on what feature(s) of Lamb waves should be used. Time of Flight (TOF) [2], amplitude, mode conversion, etc., are some of the features, which may be used for damage detection using Lamb waves. Some times damage detection using all of the above ultrasonic features may also become challenging due to difficulties in extracting these features from complex overlapped signals. For an effective NDE and SHM, various techniques of damage detection like guided waves, strain and vibration based techniques may be combined. Under some circumstances, a particular technique works well as an accurate damage detection technique. Vibration based damage assessment methods [3-7] aim at detecting, locating and quantifying the presence of structural damage, utilizing specific features of dynamic response of the structure. These features include changes in the classical model parameters such as frequency, strain energy mode shapes and damping ratios. Local damage in a structure will cause reduction of structural stiffness, so as to lead to change of strain under same loading and boundary condition. As strain measurement at different location of a structure is simple, it is convenient to use strain based damage detection using static strain data.

Lamb wave propagation based quantitative identification scheme for delamination in CF/EP composite structures using Artificial Neural Network (ANN) algorithm [8]. A multilayered ANN supervised by error-back propagation was used. The network was trained using spectrographic characteristics of acquired Lamb wave signals. Validation was done by on CF/EP quasi-isotropic laminates, assisted by an active actuator/sensor network and an online structural health monitoring system. Damage parameters like presence, location, geometry and orientation were found.

In this paper we attempted to find out the transverse crack location and depth in a composite beam combining features of Lamb wave and vibration based techniques in an ANN environment. ANN has been previously employed for damage detection using strain [9] and vibration based [10-11] techniques by several researchers.

The first part of this paper deals with damage detection strategy using Lamb wave and vibration based technique. It has been explained when each individual technique fails in the present cantilever beam example. The second part of the paper deals with generation of data for training the ANN. In the third part, a trained network was used for effective detection of the transverse crack depth and location. The predictions of network were compared with actual values.

II. DAMAGE DETECTION STRATEGY

The aim of the work is to find out the location and depth of a transverse crack in composite beam combining various features of Lamb wave and vibration based damage detection techniques that were simulated using analytical models. In this work, we selected a cross-ply composite, cantilevered beam with a lay up sequence of $[(0_2/90)_s]$. The thickness of each ply is 0.5mm. The material is carbon/epoxy (CFRP) with material properties given in the Table – 1. The length, depth and width are 300 mm, 3 mm and 12 mm respectively as shown in Fig. 1.

Table 1: Material properties

Material	E_{11} (GPa)	E_{22} (GPa)	υ_{13}	υ_{23}	G_{13} (GPa)	ρ kg/m^3
Carbon/Epoxy	155	12.10	0.248	0.458	4.40	1700

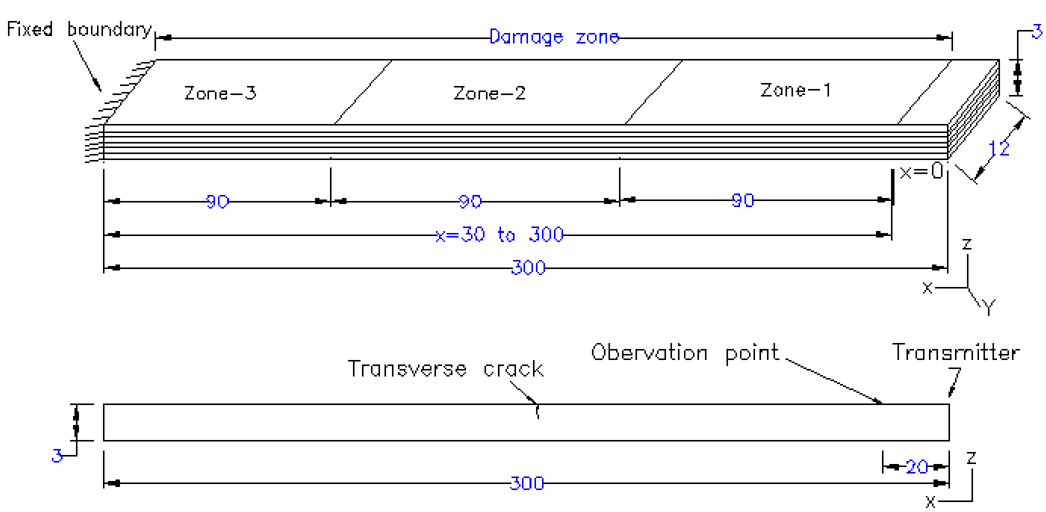

Fig 1 Composite beam with various damage zones

The crack can be anywhere in the beam from x = 30 to 300 mm, we call this domain of damage. It is assumed that the depth of the crack is equal to number of plies failed multiplied by thickness of each ply. Five different depths of cracks of 0.5 mm, 1.0 mm, 1.5 mm, 2.0 mm and 2.5 mm deep, which correspond to one, two, three, four and five plies failure respectively, have been considered for damage detection. It is assumed that the crack extends throughout the width of the beam. This is because, in general, the beams in structural applications are loaded whole width. This induces uniform stress along the width. So, the lamina can fail completely along the width of the beam.

For complete characterization of vertical crack in the beam, we need to find out the location of crack from reference position, $x = 0$, and the depth of the crack. Two features of Lamb wave, TOF and amplitude ratio of the reflected wave from the crack can be used for characterization of the crack. If the depth of the crack increases the amplitude of the reflected wave also increases. So, amplitude ratio feature can be used for predicting the depth of the crack. The arrival time of the reflected wave group is linearly proportional to the location of the crack. So, TOF feature can be used for predicting the location of the crack. If the crack is located away from the boundary, the reflected wave is purely from the crack. In such cases, the above two features can be used for predicting accurately, the location and depth of the crack.

If the crack tip location is close to the boundary, the reflected waves from the crack and boundary interfere. The amplitude of this interference wave will be higher than the reflected wave from the crack. In such cases, amplitude based damage detection gives a wrong interpretation about depth of the crack. When TOF is used for predicting the location of the damage, we look for the time of arrival of the reflected wave group from the crack. Here also, if the damage is close to the boundary, it is difficult to find out the arrival time of the reflected wave group because of interference between the boundary reflection and the reflection from the crack. So, when the crack location is approaching the boundary, the accuracy of prediction using amplitude ratio and TOF will come down. In such cases, we have to use some other technique for prediction.

When there is damage, the stiffness of the structure will change, in general it reduces. Since the natural frequencies of a structure depend on stiffness, the natural frequencies will also change when there is damage. In the present problem, we proposed to use first two natural frequencies along with damage feature of Lamb wave technique for damage detection in the beam. In complex structures, the changes in some of the natural frequencies may be less without and with damage. In such cases, we may have to look for some high frequencies and/or strain energy mode shapes [3-7], which will change with respect to damage. The sensitiveness of a particular feature for a particular type of damage can be better understood by performing numerical simulations. The prior knowledge or understanding of the structure's dynamic behaviour helps in selection of certain features for damage detection.

We made an attempt to use TOF, amplitude ratio and first and second natural frequencies in ANN environment for damage detection in a beam. The input to the neural network is TOF, amplitude ratio, first and second natural frequencies. The output is location and depth of the damage. The network is shown in Fig. 8.

III. TRAINING ANN

In Fig. 1, the domain of damage is from x = 30mm to 300mm. This domain has been subdivided into three zones, zone-1, zone-2 and zone-3. In each zone three locations have been chosen. In each location, the depth of the crack varies from 0.5mm to 2.5mm in steps of 0.5mm. The step size, 0.5mm, has been chosen to simulate the failure of each ply.

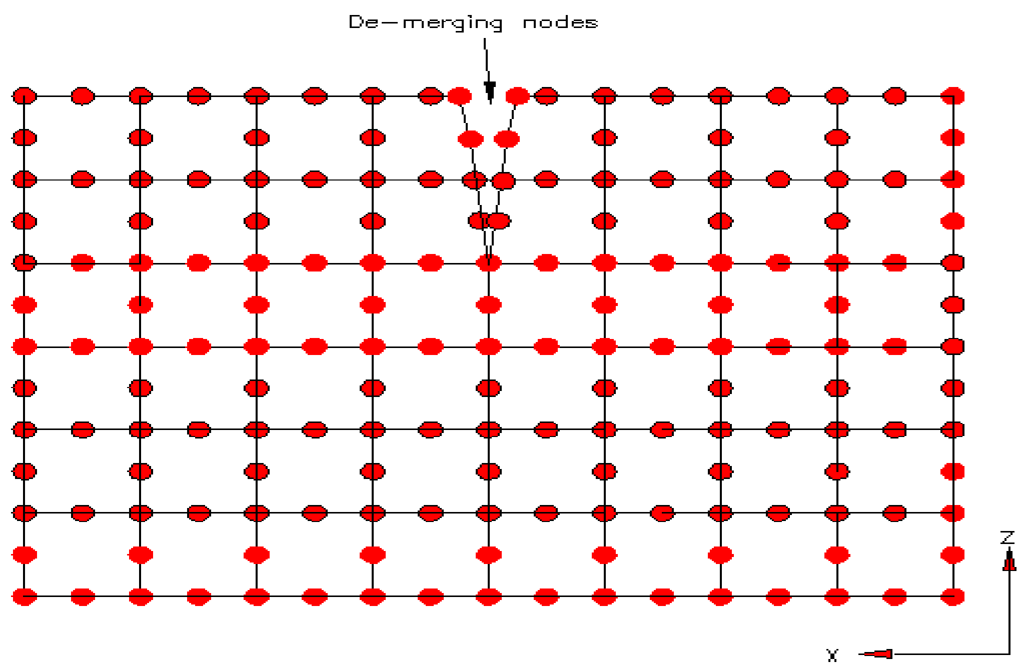

Fig 2 Modeling of crack

The transmitter is located at the free end of the beam and receiver or observation point at x = 20mm. The mode of excitation is primary anti-symmetric Lamb mode, A_0. The excitation frequency and number of cycles are 200 kHz and five respectively. The numerical simulations have been carried out using finite element (FE) method. The element selected is an eight node element with two degrees of freedom, translations in x and z directions, at each node. The size of the element chosen is 0.5 mm. The transverse crack has been modeled by de-merging the nodes as shown in Fig. 2. Anti-symmetric Lamb mode predominantly has out of plane displacements. So, this mode is excited by giving displacements in z – direction at transmitter. At receiver also displacement in z – direction is captured.

A typical signal obtained at observation point is shown in Fig. 3. The first wave group is a forward traveling wave and the second wave group is a reflection from the crack, third wave group is reflection from the free edge and the fourth wave group is reflection from fixed boundary.

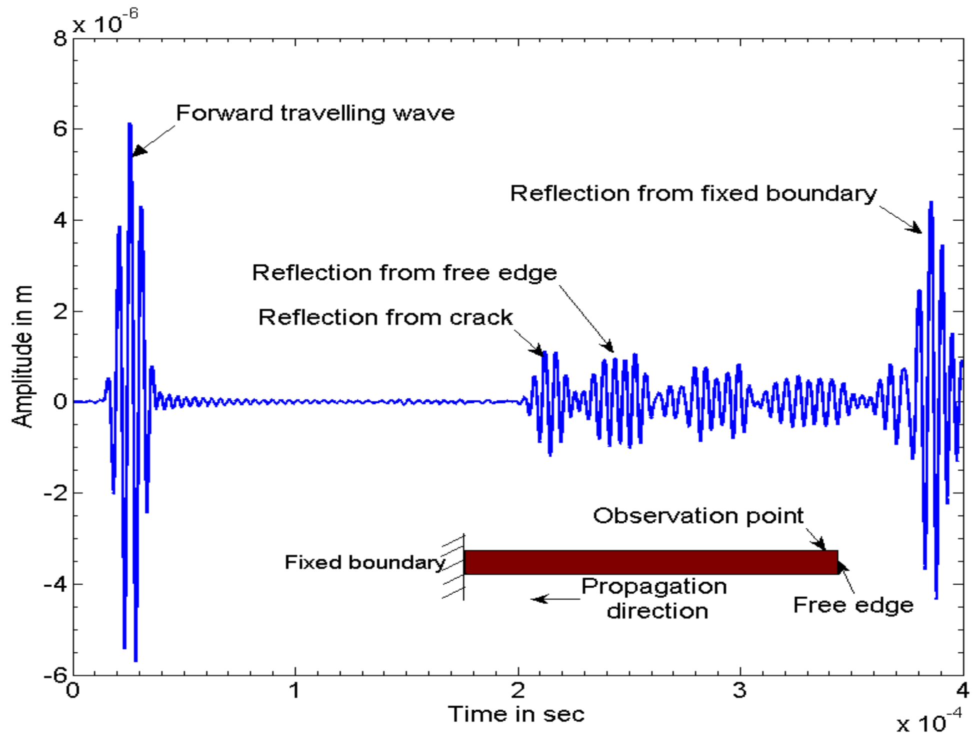

Fig 3 Typical signal obtained at observation point

Fit a video envelope on this signal as shown in Fig. 4. The peak of the video envelope on the reflected wave group is taken as the representative TOF for the whole wave group, which is shown in Fig. 4. The amplitudes of the forward traveling wave and reflected wave are measured in frequency domain using a standard Fast Fourier Transform (FFT) technique. The duration of the signal on which FFT has to be carried out has been decided as following. The peak time of the wave group can be obtained by fitting an envelope as stated above. Since the actual duration of the excited signal is 25 µs, a time window of width 25 µs, 12.5 µs on both sides of the peak, was applied on both the incident and reflected wave groups as shown in Fig. 4.

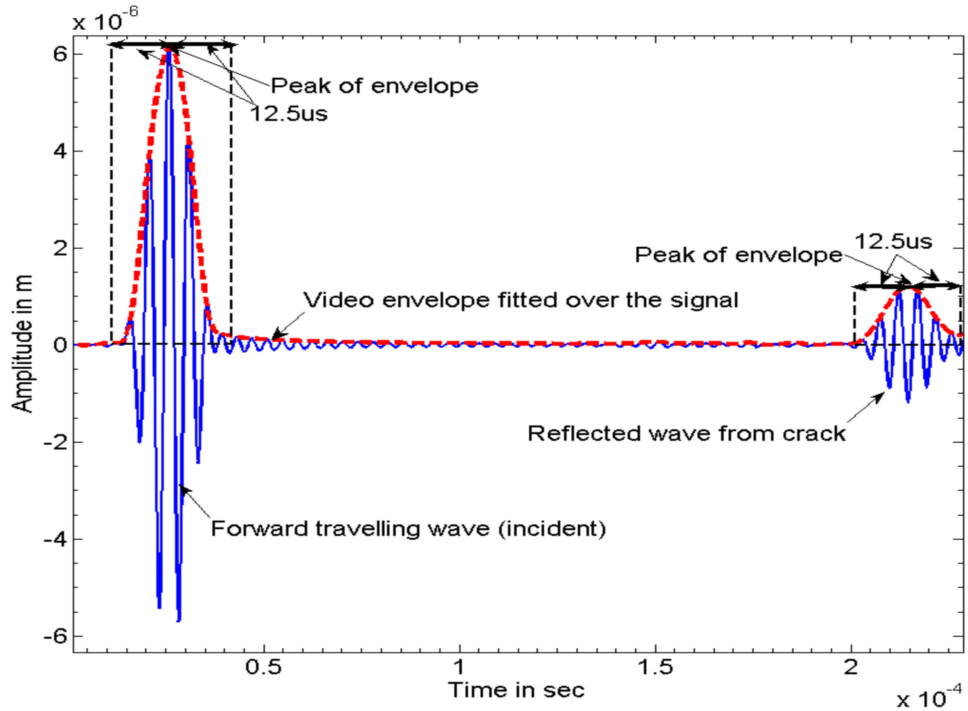

Fig 4 Video envelope & gates showing duration of signal for FFT

In the frequency domain, it is observed that peaks are obtained at nearly 200 kHz as shown in Fig. 5. The damage feature, amplitude ratio, (percentage of reflection of the wave mode) is calculated as the ratio between the amplitude of the reflected wave group and incident wave group.

In real structures, the natural frequencies can be obtained using an initial impulse perturbation and obtaining the peaks in the frequency domain corresponds to the natural frequencies of the structure.

The first two natural frequencies of the beam are also obtained as stated above. The tip of the beam is pulled down and left. This introduces a non-zero initial displacement and zero initial velocity. The beam starts vibrating. The dominating mode of vibration is first mode. At the tip of the beam, displacement in z – direction and time history has been obtained. This time domain data has been converted to frequency domain using FFT. The typical frequency response curve obtained as shown in Fig. 6.

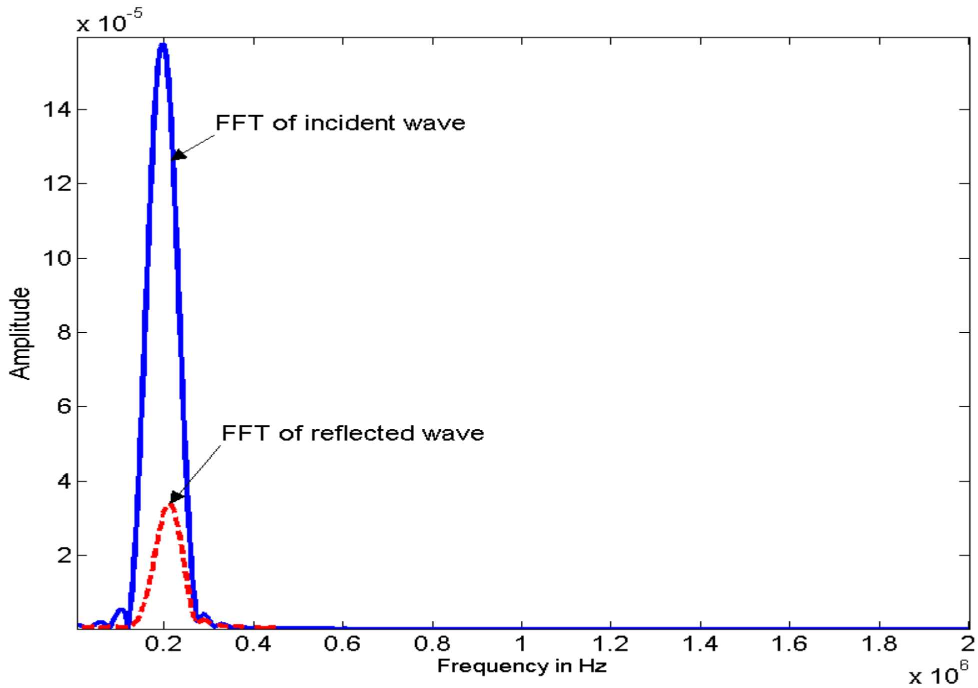

Fig 5 FFT of incident and reflected wave groups

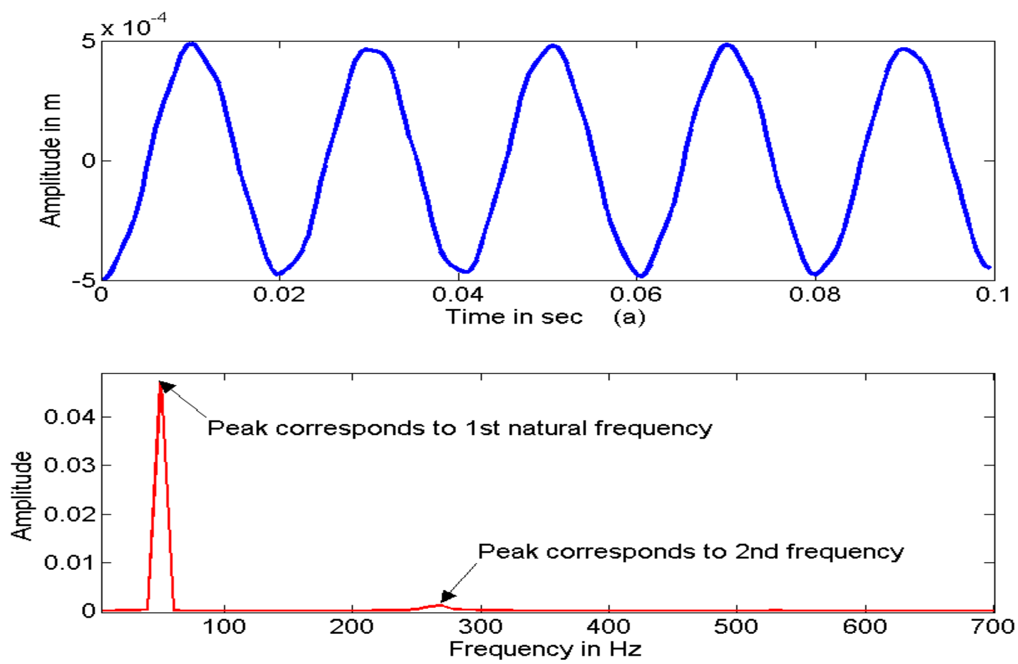

Fig 6 (a) Displacement time history at free end of freely vibrating beam, (b) FFT of signal in (a)

There are two peaks in this curve. The first and second peaks correspond to first and second natural frequencies of the beam respectively. These two natural frequencies with TOF and amplitude ratio are taken as the input.

When the crack is located away from the fixed boundary, the change in natural frequencies with and without crack is less. If a damage detection technique based on only vibration signature is devised, it fails to detect the transverse crack location and depth when the crack is located away from the fixed boundary. But, the damage detection based on Lamb wave technique, which uses amplitude ratio and TOF as damage features, estimates the crack location and depth in such cases. When the crack is close to the fixed boundary, the signal is shown in Fig. 7.

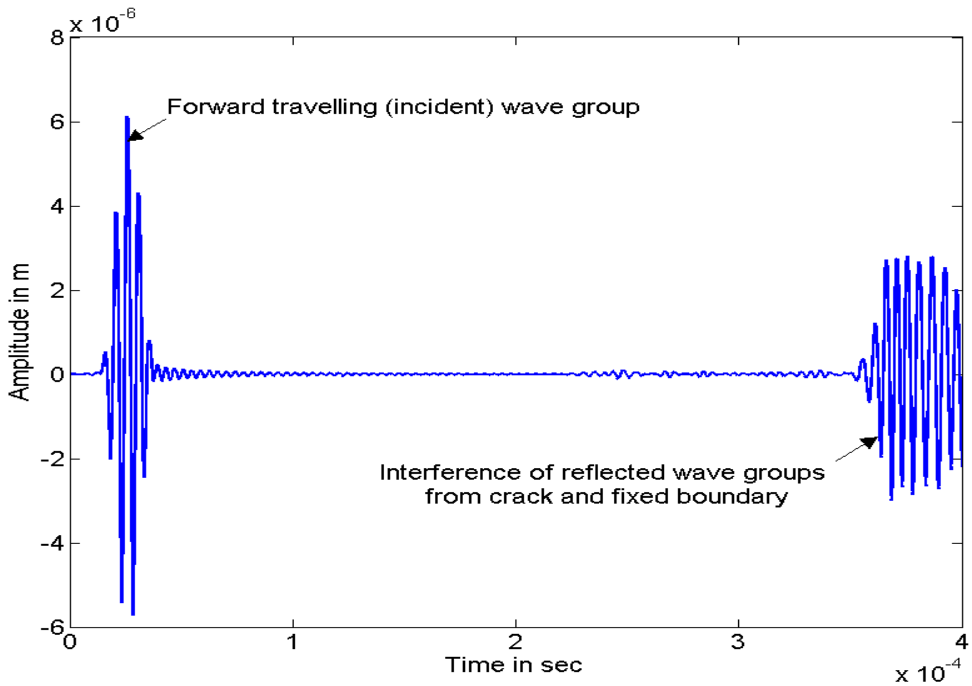

Fig 7 Interference of reflected wave groups from crack and fixed boundary

In this signal, the reflected wave group from the crack and fixed boundary are interfering. In such a case, it is difficult to identify the reflected wave group alone from the crack. Since, there is an interference of the reflected wave groups; we can predict that the damage is close to the boundary. Amplitude ratio of this signal can't be used for predicting the depth of the damage. When the damage is close to the fixed boundary, the change in natural frequencies is high. The natural frequencies are more sensitive to the depth of the crack when it is close to the fixed boundary. Combining two or more techniques of damage detection like Lamb waves and vibration based techniques; we can devise an efficient technique of damage detection than solely depending on either Lamb wave or vibration based technique.

IV. DAMAGE DETECTION USING ANN

In recent years there has been increasing interest in using neural networks to estimate and predict extent and location of damage in complex structures. ANN consists of interconnected processing elements called neurons operating in parallel to a set of input signals given to each. ANN maps the relationship between the input and output. In damage detection, ANN is used for mapping relationships between measured features and structural damage/physical parameters. In order to use ANN for damage detection, it has to be trained for known damage features and their corresponding physical parameters. The most common neural network in use is the multi-layer perceptron (MLP) trained by back propagation (BP) [12]. The back propagation learning algorithm is a way of adjusting weights and biases by minimizing error between predicted and measured outputs. A multi-layered feed forward network typically consists of input layer, one or more hidden layers, interconnected by modifiable weights, and an output layer. Among many different types of ANN, the feed forward, multi-layered, supervised neural network with error back propagation algorithm, generally known as back propagation network, is by far the most commonly applied ANN owing to its simplicity. In the present study, we selected feed forward back propagation neural network [12]. The training of this network is a two stage process. In the first stage, an input vector comprising of the measured/simulated features (TOF, amplitude ratio, first and second natural frequencies) is fed to the input layer. This input produces a set of output. In the forward pass, the weights are fixed. The difference between the output and the target output is error. The error is propagated through the network in backward direction. During this process, the weights are adjusted in such a way that, the mean square error (MSE) is minimized, so that the output of ANN is close to the target output. The training process is terminated when the error is sufficiently small for all training sample. In our network, which is shown in Fig. 8, there were three hidden layer, each having ten neurons and output layer has two neurons. Tan-sigmoid functions were used in all hidden layers and pure linear function in output layer. The performance function was mean square error.

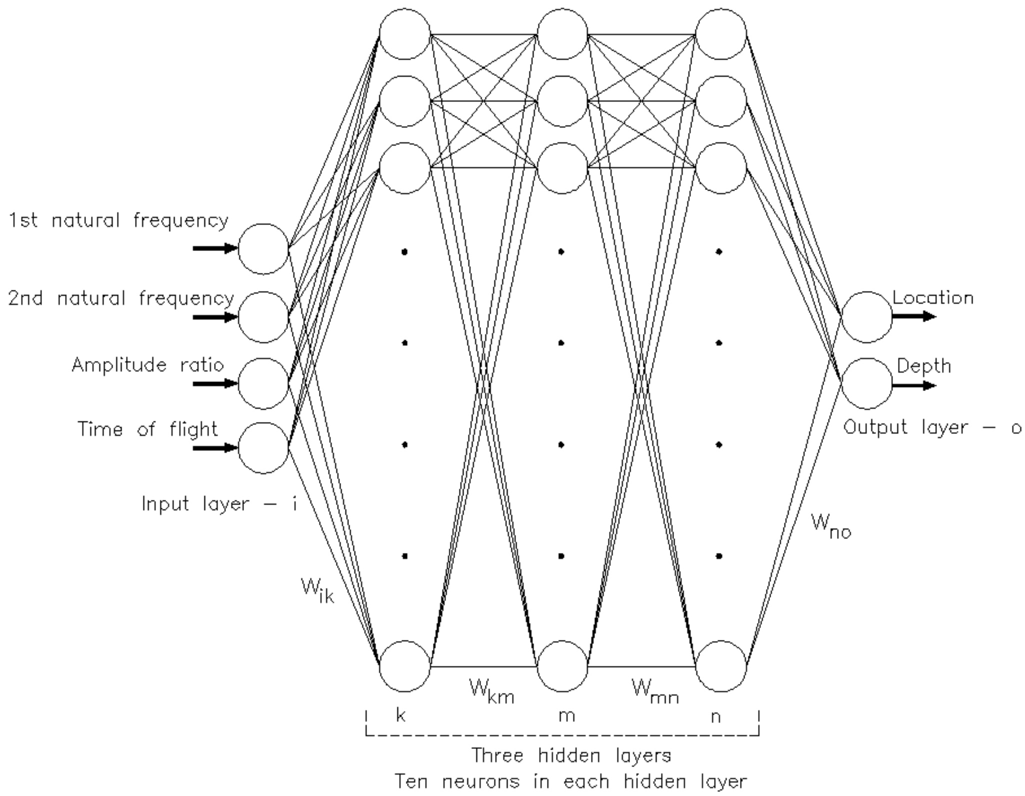

Fig. 8: ANN used for damage detection

The accuracy of prediction by ANN depends on the training. A properly trained ANN gives good predictions when an untrained data set is given as input. For training ANN, the training data sets have been generated using FEM. The input parameters of ANN are TOF, amplitude ratio, first and second natural frequencies. The output parameters of ANN is crack location from x = 0 and depth of the crack. The training data has been generated, using FE simulations, for crack depths varying from 0.5mm to 2.5mm in steps of 0.5mm, three locations in each zone, and total three zones as show in Fig. 1. When the crack is at third location in zone – 3, the typical signal is shown in Fig. 7. Since the reflected signal from crack cannot be clearly identified (due to interference from the signal reflected from the plate end), the amplitude ratio and TOF cannot reliably be calculated. In the training data, when the crack is at third location and zone – 3, the amplitude ratio is taken as 100% and TOF feature is obtained by computing the arrival time of the peak of the wave group considered. The network has been trained using the 'trainlm' function in MATLAB [13]. The convergence goal (error) was set at $1x10^{-20}$. Once the network is trained using training data, it is ready for predicting crack location and depth.

Twenty different damages cases, which are at different locations with various depths, have been simulated. For each of the damage case, all four damage features, such as TOF, amplitude ratio, first and second natural frequencies are calculated. These damage features are fed to ANN. The output parameters of ANN are crack location and depth. The predictions made by ANN for twenty different damage cases are shown in Table – 2.

Table 2 Comparison of actual and predicted crack sizes, locations and zones.

Actual		ANN prediction	
Location (mm)	Depth (mm)	Location (mm)	Depth (mm)
60	0.5	60.53	0.49
	1.0	61.61	0.89
	1.5	59.32	1.41
	2.0	65.36	2.04
	2.5	57.52	2.51
200	0.5	200.94	0.53
	1.0	199.38	1.10
	1.5	196.68	1.42
	2.0	196.73	2.00
	2.5	201.39	2.58
280	0.5	284.35	0.50
	1.0	284.14	1.06
	1.5	286.35	1.46
	2.0	283.29	2.11
	2.5	280.87	2.51
290	0.5	286.51	0.51
	1.0	292.26	1.13
	1.5	286.16	1.51
	2.0	289.25	2.09
	2.5	287.22	2.56

V. RESULTS AND DISCUSSION

In the present study, detection of transverse crack, at location closed to the fixed end and far from the fixed end has been considered. The reduction in flexural stiffness of the beam is more if the crack is close to fixed boundary. The features based on vibration are expected to be more effective, than ultrasonic Lamb wave based features, when the crack is close to fixed boundary. When the crack is located away from the fixed boundary, the reduction in flexural stiffness is small, so, there is relatively small change in natural frequencies of the beam. In this case, vibration based technique is expected to be less efficient. However, the reflected ultrasonic Lamb wave signals from the crack and fixed boundary are well separated and are expected to provide the required sensitivity for crack detection. Numerical simulations help to understand or study the sensitiveness of a feature for a particular type of damage when employed a specific technique.

The reconstructions made by ANN are given in Table – 2, which also lists the actual location and depth of the crack. The ANN predicts the damage location and depth with an accuracy of 95.8% and 89% respectively.

In an experimental scenario, sensors such as small footprint accelerometer or piezo-wafer may be placed at observation point for the measurement of both ultrasonic and vibration based features of the composite beam, without the need for two sensing system.

VI. CONCLUSIONS

An attempt has been made to combine damage detection features of ultrasonic Lamb wave (TOF and amplitude ratio) with vibration based technique features (first and second natural frequencies) in an ANN environment with a probability of detection of 89 %. It was studied that when damage features of more than one technique are combined, the damage could be identified more effectively than using damage features of each technique individually. If techniques like Lamb wave and vibration are employed individually for sizing of transverse cracks, Lamb wave technique fails when the damage zone is close to fixed boundary and vibration technique fails when the damage zone is close to free edge. By combining these two techniques the domain of damage detection is enhanced, which covers almost the whole sample. This study showed that ANN could form an efficient tool in detecting the damage location and depth.

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