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MULTI-MODAL PARAMETER BASED DELAMINATION DETECTION IN COMPOSITE STRUCTURES USING METHODS OF ARTIFICIAL INTELLIGENCE

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ABSTRACT

Vibration based delamination detection methods in composites, currently employed for structural health monitoring solutions uses Natural frequency as their basic damage indicator. Other indicators such as the mode shapes and damping parameters if used could enhance their capability of damage detection. Degradation of the structures due to delamination will reduce the strength of the material, i.e., its flexural stiffness, which will alter not only the natural frequencies but the mode shapes and damping parameters which could detect the presence of delamination, assessing its size, location and the interface.

The problem is basically divided into two parts, solving the forward problem of identifying the changes in natural frequencies and solving the inverse problem from the forward data. Artificial Neural networks like the Multi-Layer Perceptron has the ability to incorporate multiple damage indicators for producing the outputs. FE Models have been used along with the experiments to compare the data generated and validated against the simulated ones. FE models by themselves are computationally expensive, so surrogate models have been used to reduce the computational expense. This method is called Surrogate Assisted Optimization (SAO). In order to carry out SAO, Response Surface Models (RSM) has been developed to reduce the number of training data sets required for solving the inverse problem.

It has been seen that the algorithms are highly efficient in detection of damage in Composite beams and plates despite of the limited number of training datasets provided and the introduction of artificial errors and noise. Moreover the robustness of the algorithm were clearly evident when the errors where quantified using the experimental and simulated data. Thus the algorithms provide an efficient means of detecting the delamination parameters accurately from the vibration data.

Key words: Artificial Intelligence, Composite Materials, Damage Diagnosis.

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1. INTRODUCTION

Delamination is a potentially serious damage occurring in laminated polymer composites due to the poor inter-laminar fracture toughness of the matrix. Vibration based detection methods employ changes caused by loss of stiffness in dynamic parameters such as frequencies and mode shapes to detect and assess damage. One of the challenges of using frequency shift for damage detection is that while the presence of damage is easily identified through a shift in measured frequency, the determination of the location and the severity of the damage are not easy to accomplish. To determine the location and severity of damage from measured changes in frequency, it is necessary to solve the inverse problem, which requires the use of artificial intelligence tools such as artificial neural networks and surrogate assisted optimization techniques [1].

The problem is basically divided into three parts, firstly the generation of the forward data using the finite element modeling; Secondly Experiments are conducted to check the validity of the FE generated data, the model is updated in line with the experimental data. In the third phase the inverse problem is solved using artificial neural networks. The network model is trained using the change in natural frequencies and the mode shapes, then they are tested and the model is validated for unknown data.

2. FINITE ELEMENT MODELLING

A single delamination having a size 'l_1', at allocation 'X' from the fixed end of the beam occurred at an interface 'z' is considered in this study. The figure shows the analytical model of the beam. Composite beams of 4 layers with top interface and bottom interface symmetrical with reference to the mid-plane is taken for analysis. E-glass epoxy is having a quasi-isotropic layup having a fixed free boundary condition with through the width delamination have been studied.

The finite element solver namely ANSYS 14.5 is used to perform all the necessary computations. In the initialization phase, geometry and material parameters are specified. For the composite beam model with localized delamination, material parameters like modulus of elasticity, the modulus of rigidity, the Poissons ratio and the mass density of the composite beam material along with geometric parameters like dimensions of the composite beam, also the specifications of the delamination like size, location and the interface are supplied as input data into the preprocessor of the ANSYS 14.5 software. The beam is descritized with Solid 20 node 186 element. The model is then solved to obtain the natural frequencies for non-cracked and cracked composite beams.

Through the width delamination are assumed to occur in the three interfaces, ie, the top interface, middle interface and the bottom interface. The top and bottom interface are located at H/4 from the mid plane propagating uniformly towards the fixed end of the beam. The table below summarizes the material properties used for modeling the beam.

Table 1 Properties of E-Glass Reinforced Epoxy

Property	Notation	Value
Youngs Modulus of Fibre	E_f	72.4 Gpa
Youngs Modulus of Matrix	E_m	3.45Gpa
Poissons ratio of Fibre	ν_f	0.35
Poissons ratio of Matrix	ν_m	0.22
Modulus of Rigidity of Fibre	G_{12}	29.67 Gpa
Modulus of Rigidity of Matrix	G_{12}	1.277 Gpa
Density of Fibre	ρ_f	2600 Kg/m^3
Density of Matrix	ρ_m	330 Kg/m^3

The beam is assumed to be made of quasi-isotropic material. The analysis carried out here is linear in nature, which implies constitutive relations in generalized Hook's law for the materials are linear. The Euler–Bernoulli beam model considered here in the study. The damping properties of the beam are not considered for the sake of simplicity. The delamination is assumed to be an open and it extends through the width of the beam.

The first three bending natural frequencies of the healthy beam and delaminated composite beam has been obtained from the FEM analysis. The natural frequencies of composite beam with through the width delamination extending up to various positions (0.2, 0.4, 0.6, 0.8 times the length) along the top interface, middle interface of the E-Glass Epoxy beam are presented in Figure 1 to 2 respectively.

3. EXPERIMENTAL MODAL ANALYSIS

In order to validate the FEM Results in predicting delamination in structures, E Glass Epoxy beams with defects such as delamination and transverse open cracks at various locations and magnitude were manufactured and tested. They were fabricated with Owens corning® Thermopreg. Commingled Polypropylene Glass Fabric Woven Rowing(Corning & Composite Materials, n.d.). The size of the beams were 300mm x 27 mm with the stacking sequence [0,90,45,-45]s. Delamination were introduced by embedding waxed Teflon release films between the pre-preg layers at the desired locations during stacking to prevent them from bonding together. The specimens were cured at room temperature prescribed by the manufacturer. After curing, the laminate panel (405 mm x 70 mm) was cut into 30 beams of 300 mm long with clamping length of 50mm, six control specimens without any delamination or cracks and 18 beam specimens with delamination and 6 with cracks at various locations. The delamination in the above said beams are all located at the mid-plane and interfaces 2.5 mm above and below the mid-plane, but at different in-plane locations.

The specimen is clamped in a test rig and excited by Modal hammer (PCB Piezotronics, Type 086C03) which resembles an ordinary hammer. The vibration response is registered by a Triaxial ceramic shear Accelerometer (PCB Piezotronics Type 356A01) .The analog signals obtained from the transducer are amplified and converted to digital form by using the data acquisition unit (Data Translation, DT-9837) The results were obtained using the Vibration Measurement and Analysis Package (VMAP) version 4.5. The results of Experimental modal analysis were compared with Finite Element Analysis and found to be satisfactory.

Table # Specifications of Hardware used for dynamic measurement of composite structures

Sl.	Equipment	Make and Model	Hardware Specification
1.	Accelerometer	PCBPiezotronics 356A01	Triaxial ceramic shear Weight: 1.0 gm Sensitivity: 5 mV/g Dimension= 0.25" cube
2.	Modal hammer	PCB Piezotronics 086C03	Frequency range = 0.8 kHz Amplitude range = 500 lb Sensitivity = 10 mV/lb Hammer mass = 0.3 lb Head diameter = 0.6 inch
3.	Data acquisition unit	Data Transalation DT-9837	D/A converter = 24-bit Waveform Cap = 8,192 sampl Output = 46.875 k Samp /s Output range = 10 V
4.	Low Noise Coaxial Cable	PCB003	10-32 plug to BNC plug for ceramic shear
5.	Computing Workstation	Lenovo G 500	Type: 32 Bit, X86-based Processor: Intel i5-3230M Clock Speed= 2.60GHz Physical Memory= 4.00 GB

3.1.1. Modal Assurance Criterion (MAC) matrix

The Modal Assurance Criterion (MAC) matrix is a mathematical tool to compare two mode shape vectors to each other. It can be used to investigate the validity of estimated modes. The MAC between two mode shape vectors $\{\Psi\}_r$ and $\{\Psi\}_s$ is defined as, [cite]

$$MAC(\{\Psi\}_r, \{\Psi\}_s) = \frac{(\{\Psi\}_r^{*T}, \{\Psi\}_s)^2}{(\{\Psi\}_r^{*T}, \{\Psi\}_r)(\{\Psi\}_s^{*T}, \{\Psi\}_s)} \quad (1)$$

Here, the mode shape vector from finite element analysis is taken as $\{\Psi\}_r$ and the vector obtained from Experimental Modal analysis is taken as $\{\Psi\}_s$. The comparison is as represented in Figure 6 below.

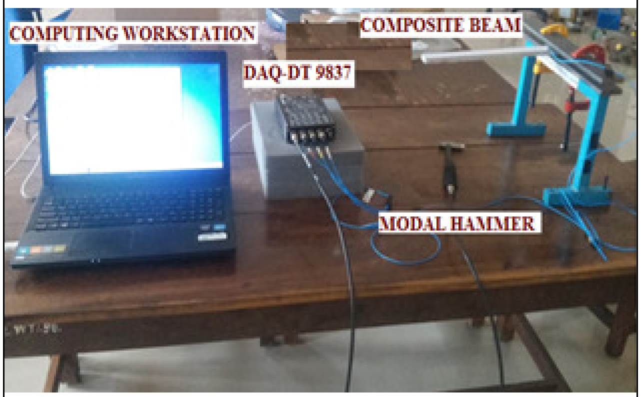


Figure 5 Setup for Experimental Modal Analysis

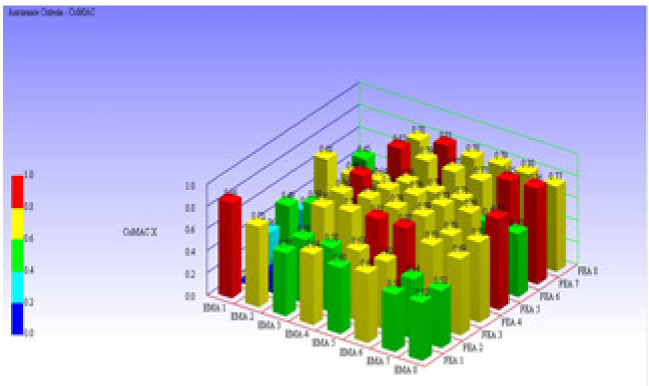


Figure 6 X-Co-ordinate Modal Assurance criteria (Co-MAC) of the first Eight Modes

4. SURROGATE ASSISTED OPTIMSATION USING ARTIFICIAL NEURAL NETWORKS

4.1. Application of Artificial Neural Networks in damage detection

Artificial neural networks are basically computational systems that have its working similar to that of the neurons inside the human brain. They are composed of parallel operating elements. The basic structure in a neural network is the neuron (or single-unit perceptron). A neuron performs an affine transformation followed by a nonlinear operation. If the inputs to a neuron are denoted as $x_1, \ldots, x_n$, the neuron output y is computed as..

$$y = \frac{1}{1+\exp(\frac{-\eta}{T})} \qquad (2)$$

Where, $\eta = w_1x_1 + \ldots + w_nx_n + \gamma$, with $w_1, \ldots, w_n$ being the regression coefficients.

Here, γ is the bias value of a neuron, and T is a user-defined (slope) parameter. Neurons can be combined in multiple ways. The most common neural network architecture is the multi-layer feed-forward network

The construction of a functional surrogate based on a neural network requires two main steps:

1. Architecture selection
2. Network training.

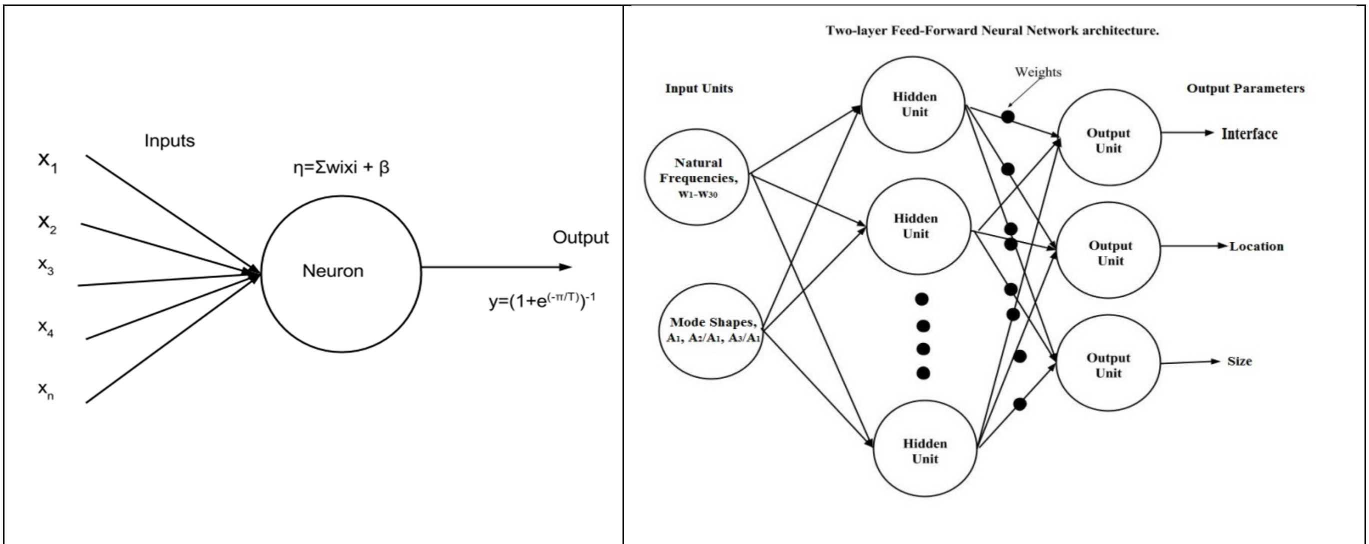
The network training can be established as a nonlinear least-squares regression problem for a number of training points. Since, the optimization cost function is nonlinear in all the optimization variables (neurons coefficients), the solution cannot be written using a closed-form expression. A very popular technique for solving this regression problem is the error back-propagation algorithm.

There is non-specific rule for choosing an optimum number of hidden layers. For the inverse algorithm using ANN in this paper, feed-forward back propagation neural networks (BPNN) were configured and trained by using Weka Machine Learning Toolbox, A feed-forward BPNN is named by the way it learns-by backpropagating the errors seen at the output nodes.

The training of BPNN involves three stages:

1. The feed forward of the input training pattern,
2. The calculation and back propagation of the associated error, and
3. The adjustment of the weights.

The database of frequency changes obtained from the FE model of delaminated beams are used to train the NN. The network consists of 60 inputs (corresponding to the thirty changes in frequency and thirty changes in mode shapes) and three outputs (size, Location and interface of the damage)



(a) Neuron basic structure

(b) Two-Layer Feed-Forward Neural Network architecture.

Figure 7 Artificial Neural networks[5]

4.2. Application of Surrogate assisted optimization for delamination prediction with SUMO Tool Box

The SUMO Toolbox is a flexible framework for surrogate modelling and adaptive sampling (active learning). This study was conducted using the SUMO Toolbox. The major steps in surrogate-based optimization process is described below,

1. The initial surrogate model is to generated
2. By optimising the surrogate obtain the approximate solution
3. Obtain the high-fidelity model at the approximate solution computed in Step 2.
4. Update the surrogate model using the new high-fidelity model data.
5. Stop if the termination condition is satisfied; otherwise go to Step 2.

Results indicate that there has been a consistent drop in natural frequencies occurs with the increase in extent of delamination. However the influence of location of interface on the natural frequency is marginal. Table 2 indicates that natural frequencies due to delamination at the top and bottom interface planes are same if the planes are symmetrically located and Figure 1. and Figure 2. represents the Mode shapes of vibration of the delaminated beams.

Table #. Natural frequency of delaminated E glass epoxy beam having different extent of damage.

Extent of Damage	Natural Frequency (Hertz) (Top-plane Interface at H/4)			Natural Frequency (Hertz) (middle plane Interface)			Natural Frequency (Hertz) (Bottom-plane Interface at H/4)		
	Mode 1	Mode 2	Mode 3	Mode 1	Mode 2	Mode 3	Mode 1	Mode 2	Mode 3
0*L	2.0057	12.465	34.719	2.0057	9.989	30.267	2.0057	12.465	34.719
0.2*L	2.0032	11.517	33.813	1.9837	9.125	29.636	2.0032	11.517	33.813
0.4*L	1.9161	11.256	31.436	1.9373	8.365	27.978	1.9161	11.256	31.436
0.6*L	1.3368	8.2526	30.302	1.7273	7.326	25.363	1.3368	8.2526	30.302
0.8*L	0.7970	4.9946	27.181	1.3713	6.653	24.214	0.7970	4.9946	27.181

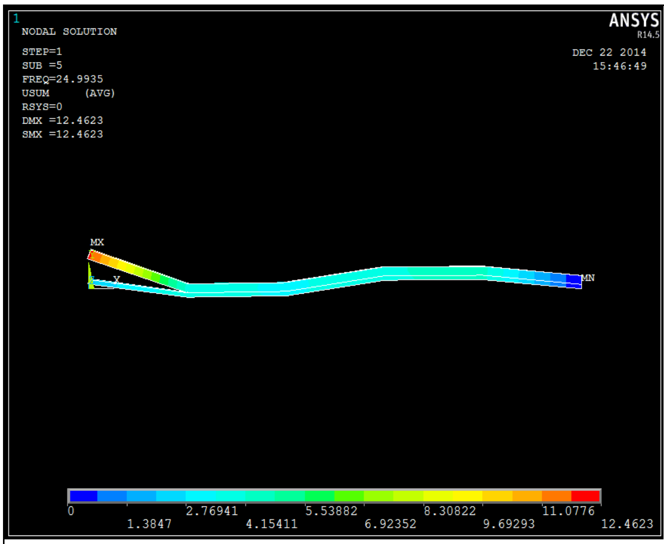


Figure #. Mode shape of E glass epoxy composite beam having delamination at bottom interface

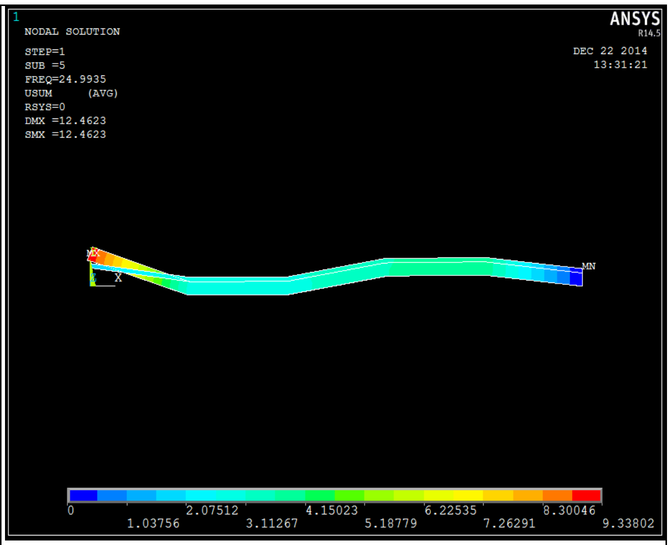


Figure #. Mode shape of E glass epoxy composite beam having delamination at top interface

4.3. Effect of artificial errors and noise

The objective of this analysis is to find the amount of errors and noise in the measured frequencies, the developed techniques can tolerate. The ANN model used for prediction is developed with 36 training datasets and the test cases are chosen from data not used during the network training. The surrogate models used for the optimization process are also developed with the same 36 training instances.

4.3.1. Effect of artificial errors

The error that was added artificially is the difference between computed percentage changes in natural frequencies (dFi) by FE model and the actual percentage changes in natural frequencies that were input as test cases into the inverse algorithm solvers to determine

$$\%E = \frac{dF_{Actual} - dF_{Simulated}}{dF_{Simulated}} = \frac{dF_{Mi} - dF_i}{dF_i} \qquad (3)$$

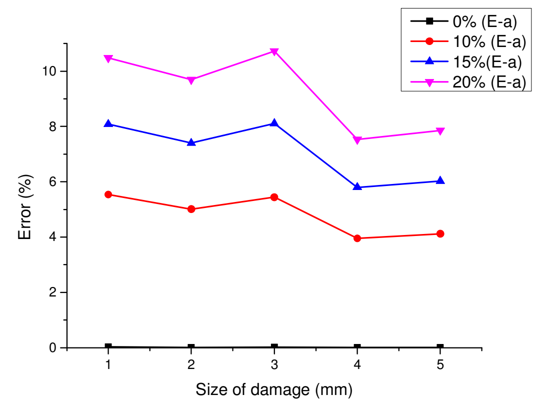


Figure 8 Prediction results of the size of damage using ANN with addition of artificial errors in the undamaged and damaged frequencies.

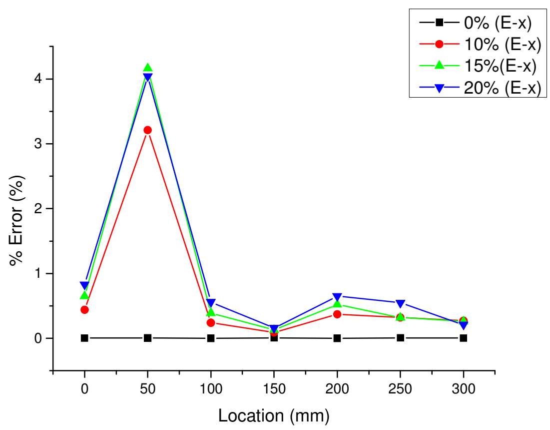


Figure 9 Prediction results of the location of damage using ANN with addition of artificial errors in the undamaged and damaged frequencies.

4.3.2. Effect of artificial noise

In experimental setups, noise in the function evaluation may be as a result of electrical fluctuations, changing environmental conditions or limited measuring precision. To induce noise in our simulated natural frequency data, a random number generator, randn is used to create random numbers with a normal distribution having zero mean and a variance and standard deviation of one. The natural frequencies of the undamaged composite beams (dF Muni) with a certain amount of noise (N) is given as;

$$dF_{M\,uni} = dF_{ui}[1 + N * randn(1, D)/100] \quad (4)$$

The natural frequencies of the damaged composite beams (dF_{Mdni}) with a certain amount of noise (N) are also given as;

$$dF_{M\,dni} = dF_{di}[1 + N * randn(1, D)/100] \quad (5)$$

Where; N = noise % ranging from 0….. 5; and D = number of datasets, the effect of noise is added on the natural frequencies of the undamaged and damaged composite beams. Actual percentage changes in natural frequencies with noise for the ith mode (dF_{Mni}) is given in,

$$dF_{Mni} = \frac{dF_{M\,uni} - dF_{M\,dni}}{dF_{M\,uni}} * 100 \quad (6)$$

The variation of percentage changes in natural frequencies of the first four modes of the delaminated beam relative to those of the undamaged composite beam in the presence and absence of noise in terms of the delamination size and location

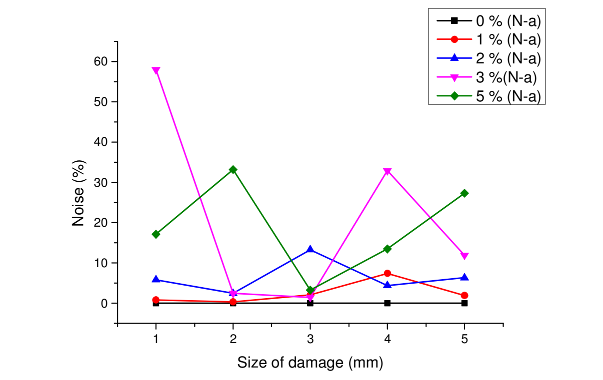
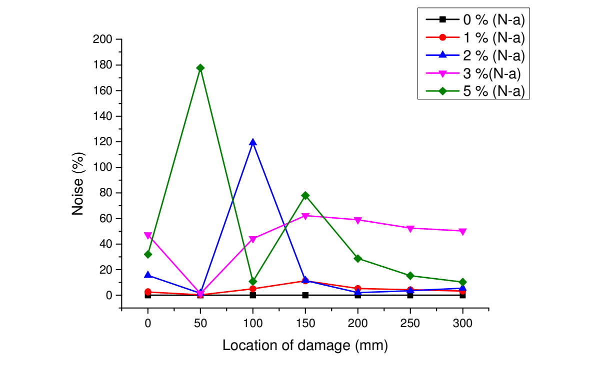
	

Figure 10 Prediction results of delamination size using ANN with addition of artificial random noise.	**Figure 11** Prediction results of delamination location using ANN with addition of artificial random noise.

5. CONCLUSION

1. The inverse problem to classify damage based on their severity, location and interface has been successfully carried out.
2. ANN is a powerful Machine learning tool which is primary used for inversion here. The best network architecture was obtained by trial and error and was selected based on highest number of correctly classified instances and the same was found to be 3-18-19-3 for the current problem.
3. The effect of artificial errors and noise could be easily accommodated in the current system and their response is found to be linear in nature, moreover their presence did not affect the percentage of correctly classified instances using this algorithm.
4. The implementation of Surrogate assisted optimization technique has reduced the training time considerably.
5. The use of mode shapes along with the natural frequencies as the input parameters improved the ability of the algorithm to detect the interface correctly.

6. In earlier works, when the changes in natural frequencies were used alone the detection of interface was a problem, since the delaminated area above and below the mid-plane tend to exhibit the same natural frequency.

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