Visual Abstract

Natural Frequency based delamination estimation in GFRP beams using RSM and ANN

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ABSTRACT. The importance of delamination detection can be understood from aircraft components like Vertical Stabilizer, which is subjected to heavy vibration during the flight movement and it may lead to delamination and finally even flight crash can happen because of that. Any solid structure's vibration behaviour discloses specific dynamic characteristics and property parameters of that structure. This research investigates the detection of delamination in composites using a method based on vibration signals. The composite material's flexural stiffness and strength are reduced as a result of delaminations, and vibration properties such as natural frequency responses are altered. In inverse problems involving vibration response, the response signals such as natural frequencies are utilized to find the location and magnitude of delaminations. For different delaminated beams with varying position and size, inverse approaches such as Response Surface Methodology (RSM) and Artificial Neural Network (ANN) are utilized to address the inverse problem, which aids in the prediction of delamination size and location.

KEYWORDS. Natural frequency; Delaminations; GFRP; ANN; RSM.

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INTRODUCTION

Composites are replacing traditional metals in a variety of applications, including aerospace, automotive, and marine structures, due to their high particular strength, corrosion opposition, specific stiffness, and fatigue qualities. Laminated fibre reinforced polymers (FRPs) are one of the most popular composite configurations, and it is relatively easier to tune their properties in different orientations. However, matrix cracking, ply/fibre breaking, delaminations, and other failure modes can occur in such composites in its service period. These failures mostly occur because of static overloading, impact and fatigue loads, design/manufacturing errors, etc.

Delamination, also known as interlaminar damage, is the separating of the laminate plies and is one of the most serious flaws in composites as it can quickly spread across the entire laminate when subjected to repetitive loads, resulting in costly and devastating failures if not noticed. For example, a vertical stabilizer is a structure composed of composites that is designed to avoid aerodynamic side slip and offer directional steadiness in aircraft and cars. It may be subjected to heavy vibration during the flight movement and it may lead to delamination between different layers and even finally tends to flight crash. In such cases if there is a system developed to predict magnitude of delamination may help us to save human lives and cost.

Visual inspection, thermography, radiography, ultrasonic testing, and other nondestructive testing (NDT) and structural health monitoring (SHM) methods such as acoustic emission technique, vibration-based processes, fibre bragg grating, and others are the delaminations review techniques currently used in practice [1]. Most of these approaches involve either transporting the composite structure to the test centre or transporting major testing equipment to the structure site to conduct the test [2]. Researchers have recently concentrate their research on creating Structural Health Monitoring (SHM) approaches that may detect damages in situ, with vibration-based techniques being one example [3,4].

Damages like delaminations diminish the stiffness of composite structures and create local flexibility in the damaged area, changing the dynamic performance of the composite structure. As a result of the change in natural frequencies, mode shapes, frequency response functions, impulsive reaction, and so on, vibration study can be a useful technique for estimating delaminations [5,6]. The existence of damages such as delaminations can be easily recognized by monitoring changes in natural frequencies but determining the location and size of these delaminations is not possible straight-forward. But by solving the inverse problem using artificial intelligence tools, location and size of these delaminations can be evaluated [7,8]. Methods based on changes in natural frequencies will come under either of the forward problem or the inverse problem. Determining the natural frequency changes due to known damage cases is performed during the forward problem and assessment of damage from natural frequencies variation is achieved during the inverse problem [9]. Based on this literature review, it was found that relatively little work has been done in the area of composite health monitoring utilising AI techniques. Many study works on homogeneous materials can be found internationally, and some researchers are now attempting to use this as a preliminary step for their composite materials research. As a result, it is clear that there is enough room for research into the health monitoring of composites using AI technologies.

Vibration based monitoring of composites structure health by observing natural frequencies variations of the structures is the research work performed in this work. Glass fiber reinforced polymer composite (GFRP) is considered for this study as it is widely used in aircraft and automotive components like stabilizers. Vertical Stabilizer part will be subjected to heavy vibration during the flight movement and it may lead to delamination in the material. Delamination in these like structures may spread quickly throughout the structure when acted upon by fatigue loading which may leads to costly and disastrous failures when not detected priory. The objective of this research is to estimate severity/size and location of these delaminations accurately so that loses due to failures can be avoided. To establish a relationship between input elements and output responses, an inverse technique is used. Damage detection based on vibration is an inverse problem for which causes are effectively deduced from effects. Damage detection is basically the inverse problem's solution. This problem is separated into two phases for this purpose. Following the validation of the experimental results, the initial phase entails training the neural networks, for which a dataset consisting of the first five natural frequencies for various delamination scenarios is constructed using finite element (FE) modeling. In the second step, ANN and RSM are used to solve the inverse problem (RSM).

EXPERIMENTATION

GFRP beams with and exclusive of delaminations were made to validate the FE model findings. Composites investigated in this study are composed of bidirectional woven E-glass fibers. Epoxy resin was used as resin because of its high mechanical strength. For curing reasons, a 1:10 ratio of epoxy hardener was applied to the epoxy resin and curing was done in room temperature for a period of 48 hours. The first layer is placed on the plastic sheet, and the mixed resin is carefully applied with a brush over the face of the first layer. The second layer is then piled on top of the first layer, and is pressed with rollers ensuring uniform thickness throughout the area. The procedure is repeated for the remaining layers.

The ASTM D3039 is the standard used to fix the dimensions of the beam as it is the standard used to obtain the mechanical properties of composite. The 16-layer $[0/45/90/-45]_{2S}$ composite beam employed in the experimental and numerical vibration study has a final dimension of 250×25×4 mm. Hand layup technique was used for fabrication of plates which were later cut into beams, and delaminations in the beams were created using Teflon tapes of 0.09 mm thickness as shown in Fig. 1. For experimental validation of numerical results, delaminations were made on beams at four random axial locations and layers with different areas in each location as shown in Tab. 1. Fig. 2 shows the delamination of specimen 2 alone for better comprehension. Width of the delamination was same for all the beams and length of the delaminations is varied to get different sizes of delaminations.

Figure 1: Fabrication of composite

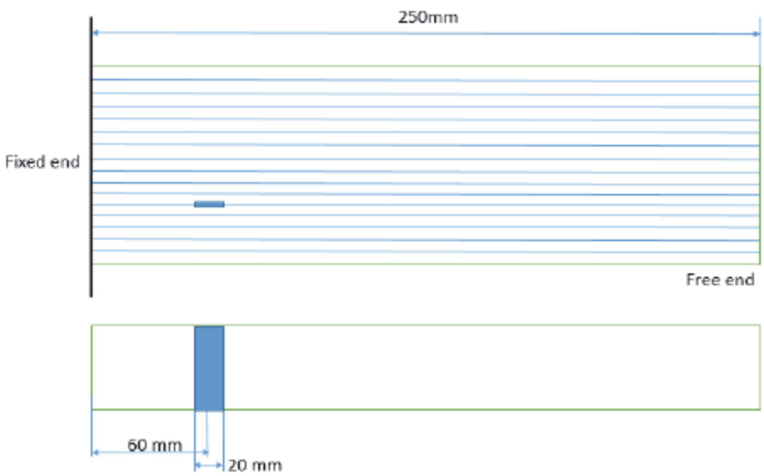

Figure 2: Delamination in Specimen 2.

Specimen	Delamination size (mm^2)	Layer of delamination	Position of delamination from the fixed end ('X', mm)
1	0	Nil	Nil
2	200	8	60
3	400	11	120
4	500	14	220

Table 1: Delamination size and location

Vibration testing setup consists of Data acquisition system which converts the analog wave forms into digital values for processing, impact hammer, Tri-axial accelerometer with 5 mV/g and LabVIEW software installed in the personal computer as shown in Fig. 3. Finally the series of impact force was given in the beam by using the impact hammer. The software gives the graph of amplitude (y axis) vs frequency (x axis). The objective of the testing's were to obtain first five natural frequencies for each of the specimen. Two beams with the specimen dimensions were made for the experiments and each beam is clamped to act as a cantilever beam. Three trials of experiments were performed on both beam cases and the average values of each of the first five natural frequencies were obtained for comparing with numerical results.

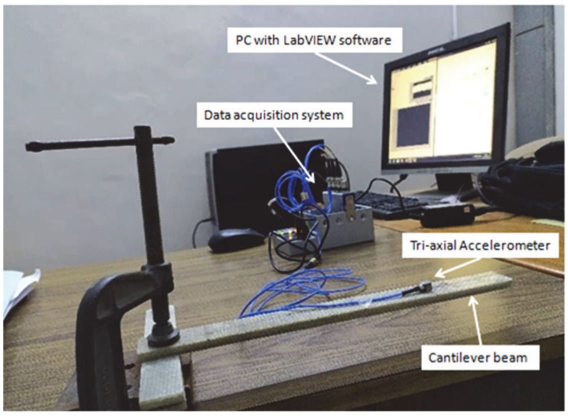

Figure 3: Experimental setup.

Finite Element Analysis

ANSYS software was used to construct a FE model of the 3D cantilever composite beams with and exclusive of damages, as illustrated in Fig. 4. There are sixteen layers in the $[0/45/90/-45]_{2S}$ laminate used in this beam type. The material property of the composite beam is determined using the rule of mixture. Poisson's ratio (v_{13}, v_{23} = 0.29, v_{12} =0.25, Young's modulus (E_1, E_2 = 42.1 GPa, E_3= 19 GPa), Shear modulus (G_{13}, G_{23} = 2.4 GPa, G_{12}= 1.6 GPa), and density 1764 kg/m^3. The layered Solid 185 element was utilized to model the beams. Only one element was examined for each layer along the thickness. To establish a balance among computational time and model bound accuracy, a mesh sensitivity analysis was performed to determine the ideal number of elements. It was observed that when the number of elements increases, the accuracy was improved but on the other hand computational time increased largely. Modal validation was done by comparing the results from experimental analysis.

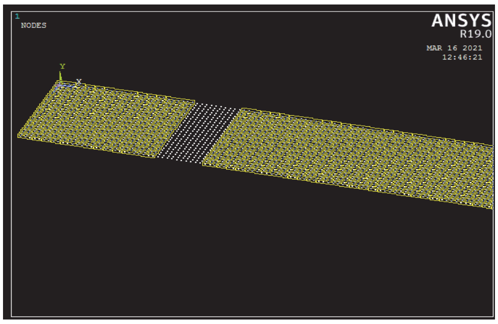

Figure 4: Delamination Creation in Ansys.

Natural frequencies for each of the specimen cases were obtained using FEA. Percentage errors of natural frequencies for each of the specimens were calculated. The first five frequencies were compared to the experimental results for undamaged and delaminated composite beam. It was observed that the FE model was able to predict the first five natural frequencies with just an error of less than 8%, showing that FE modeling is sufficient for constructing the dataset rather than the labor-intensive, time-consuming, and pricey experimental method. The main reason for deviations in results may be because of manufacturing difficulties in achieving uniform thickness of layers and errors occurred in noting natural frequencies experimentally.

Database for training the Inverse Algorithm

A database of variations in natural frequencies owing to delaminations is needed for training the inverse algorithm. Due to the lack of a well-defined analytical equation for vibration of the delaminated composite beams and the high expense of conducting experiments, the appropriate database is generated using a finite element tool and validated using experimental data. Ansys was used to simulate a big number of composite beams with various sizes and positions of delaminations. The database size required to train ANN is important for accurately determining delaminations (location and severity). For this research, 200 delamination scenarios were numerically created by combining delaminations at eight distinct locations along the length, five layer interfaces, and five areas of delaminations. A sample of bending modes 3 and 5 for dataset X=220, Layer-3 with delamination size of 250mm² is shown in Fig. 5 (a) and (b) respectively.

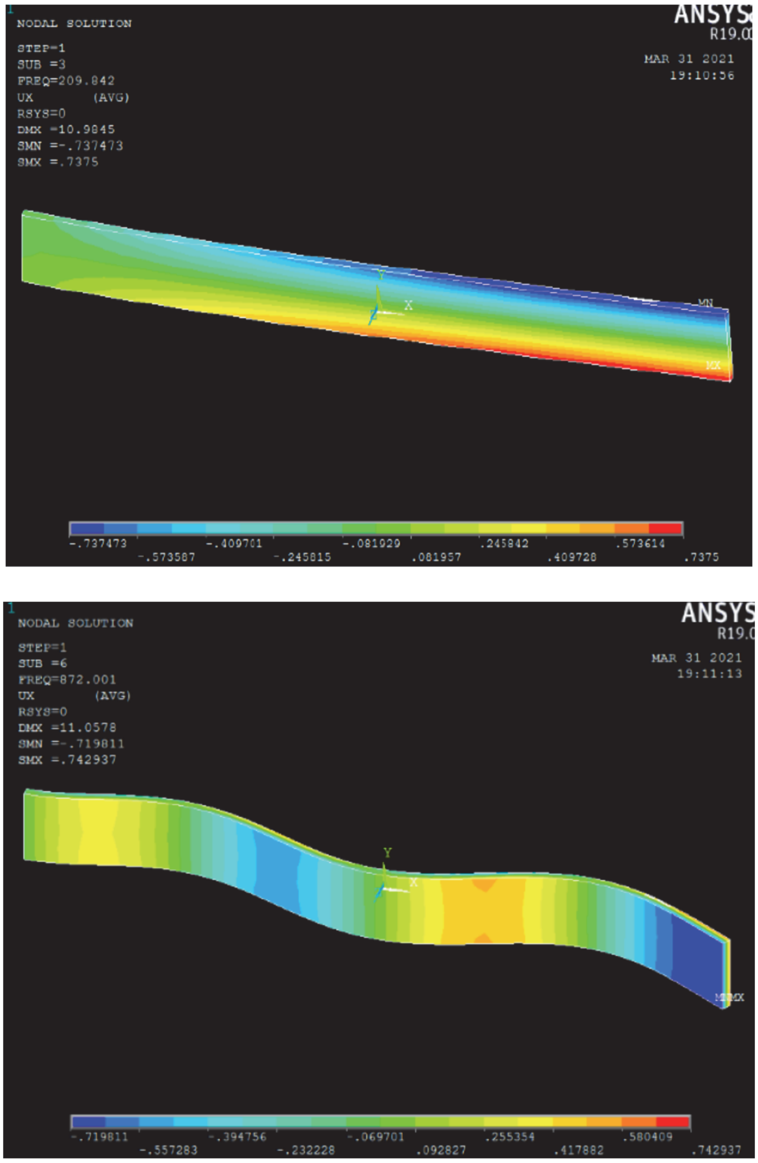

Figure 5 (a): Bending Mode 3, (b): Bending Mode 5, for delamination location at X=220, Layer-3 with delamination size of 250mm².

The first five natural frequencies were acquired and utilised as input to Artificial Neural Network for each delamination scenario, while delamination size and position were used as output. The ANN received a total of 192 input–output datasets for training, with the remainder being utilized for validation. Tab. 2 shows an example dataset for a position 30 mm from the fixed end of the beam with various delamination layers and areas, and similar data is generated for the other linear positions also. All these data indicates that the value of natural frequencies changes with location and areas of delaminations. As it is difficult to interpret this relation with human brain, utilizing AI tools is the solution here to relate relation between delaminations and natural frequency.

Delamination location X axis (mm)	Delamination location Layer No.	Delamination Area (mm^2)	BM1 (Hz)	BM2 (Hz)	BM3 (Hz)	BM4 (Hz)	BM5 (Hz)
30	3	250	25.41	159.7	207.91	447.12	874.2
30	3	500	25.32	159.52	207.28	446.9	872.5
30	3	750	25.28	159.87	206.5	444.2	868.64
30	3	1000	25.18	159.25	206.3	441.8	857.65
30	3	1250	25.01	156.8	205.4	435.6	857
30	6	25	25.51	159.65	207.7	445.91	870.85
30	6	50	25.46	158.8	206.97	441.23	857.22
30	6	75	25.41	157.6	206.35	431.29	835.84
30	6	100	25.33	153.9	205.7	417.57	818.26
30	6	125	25.24	149.62	205.3	404.93	807.08
30	8	25	25.548	159.77	207.94	446.4	873.58
30	8	50	25.533	158.9	207.34	442.59	869.54
30	8	75	25.492	156.69	206.8	435.27	866.48
30	8	100	25.427	153.09	206.39	427.88	867.81
30	8	125	25.317	148.32	206.03	422.8	861.22
30	11	25	25.517	159.77	207.94	446.62	873.87
30	11	50	25.484	159.16	207.32	444.01	871.19
30	11	75	25.44	157.69	206.82	438.98	868.76
30	11	100	25.372	155.21	206.36	433.38	866.92
30	11	125	25.286	151.88	206.01	429.08	852.71
30	14	25	25.391	159.73	207.92	447.24	874.35
30	14	50	25.254	159.57	207.28	446.58	872.32
30	14	75	25.132	159.24	206.76	444.96	868.71
30	14	100	25.025	158.66	206.32	441.91	810.61
30	14	125	25.932	157.73	205.97	432.65	852.7

Table 2: Dataset for delaminations located 30 mm away from the fixed end.

INVERSION USING ARTIFICIAL NEURAL NETWORK

To improve the model and test the hypothesis, inverse methods typically use both the original model of the structure (here, a delaminated beam) and observed data (natural frequencies). The Artificial Neural Network (ANN) is a strong interpolator that may be used to map functions and determine a relationship between input parameters and output responses. It's comparable to the brain's biological neural networks. Artificial neurons, which receive and process impulses, are the heart of ANN. ANN was performed using MATLAB. ANN is utilised here to predict the damage characteristics as neural networks are now being employed as universal function approximators for difficult problems. The ANN size is critical since smaller networks cannot accurately represent the system, while bigger networks overtrain it. Therefore, trial and error method is used to establish the network design. This is accomplished by repeatedly increasing the number of neurons and retraining the neural network. As shown in Fig. 6, Five input natural frequencies, three outputs (position, interface, and area), and one hidden layer with 13 neurons make up the ANN.

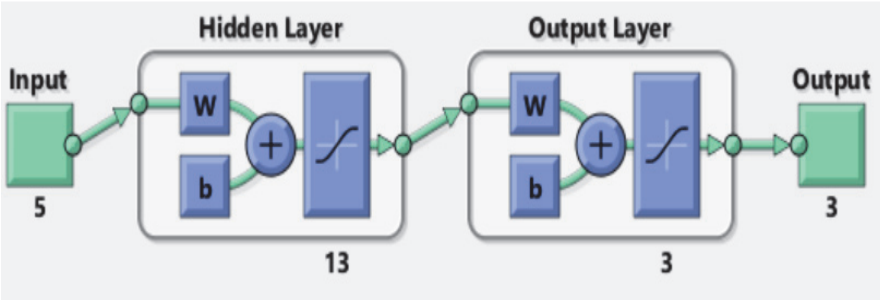

Figure 6: Neural Network framed for Delamination estimation.

Mean square error (MSE) is used as a performance metric for ANNs, and training is performed employing gradient descent plus momentum and adaptive LR. MLP-based ANNs are trained using the back propagation neural network (BPNN) methodology. The linear regression analysis of the target (defect dimensions) and anticipated values is shown in Fig. 7. For training, validating, testing, and all data, Pearson's correlation coefficients (R-values) are 0.97, 0.99, 0.98, and 0.97, respectively. This suggests that the ANN-based prediction model is reasonably accurate in predicting the experimental results.

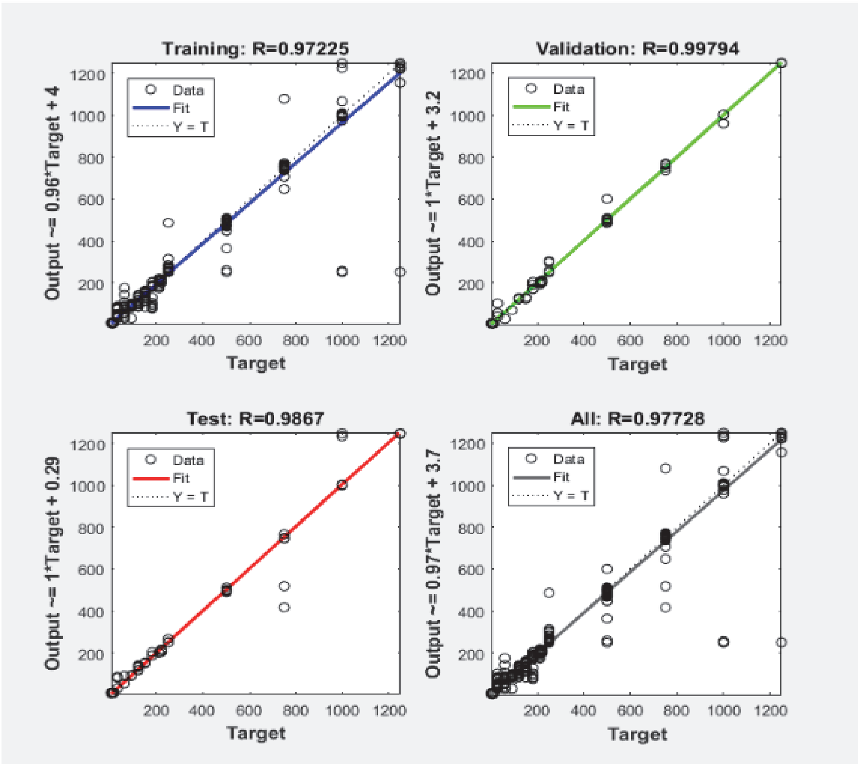

Figure 7: Regression Analyses results of Data Predicted by the ANN Model

Inversion using Response Surface Method

RSM is the development of analytical and statistical approaches utilized in the modeling and analysis of engineering issues in which the output of interest is driven by some input variables and the major purpose is to optimize this output response. RSM is a statistical approach for determining and solving multivariate equations concurrently

using quantitative data from appropriate simulations or experiments. The least squares approach makes fitting response surfaces to data in a simpler way. Because of their versatility and ease of use, RSM models are commonly used in polynomial approximation systems. The response surface model in the polynomial approximation approach is a polynomial of n^{th} degree whose coefficients are obtained from a linear system of equations. The linear system is solved by minimizing the error between the predicted and actual values using least square minimization.
RSM is used here to evaluatet the location and size of the delamination for the given change in frequency. RSM uses surface plots to identify the location and size of the delamination. The Response surface plots indicate the variation in the frequency modes with respect to the layer number and the delamination size. For a given change in frequency of a particular mode, RSM is used to anticipate the location and extent of the delamination. RSM was performed using Minitab. The location, size, and variation in frequency are all provided. The input factor is the frequency, and the responses are the matching location and size as it is an inverse problem. The RSM plots the location, size, and change in frequencies as a surface plot. The Response surface plots indicates the variation in the frequency modes with respect to the layer number and the delamination size It is shown in Fig. 8 for X=30mm Layer 3. When the test frequency is specified, the data in the surface plot is fitted, and the corresponding range of position and size is displayed.

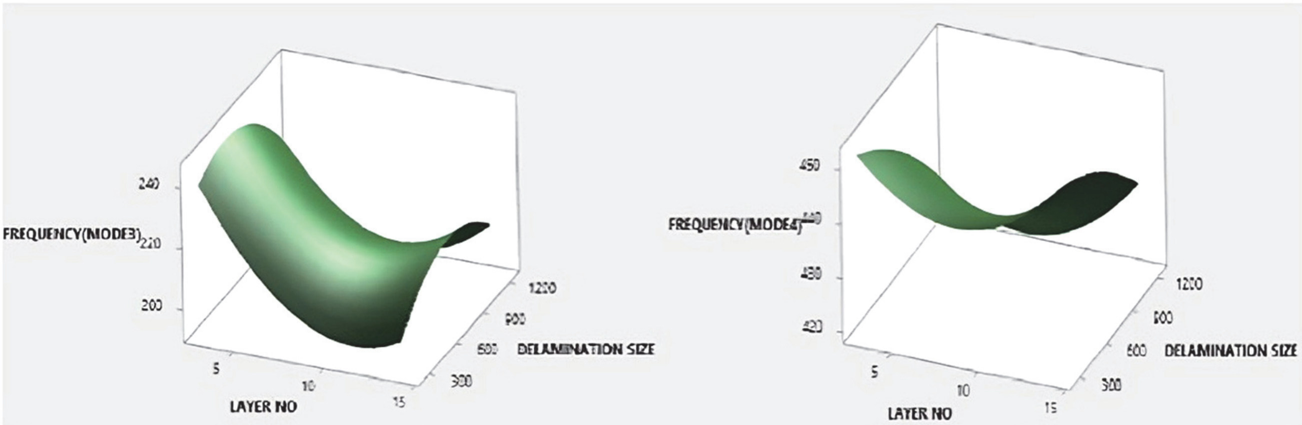

Figure 8: Response surface plots for modes 3 and 4, for delamination location at X=30mm Layer 3

COMPARISON OF ANN AND RSM RESULTS

The location and size of delamination obtained from RSM is compared with the actual location and size of delamination given in finite element analysis as shown in Tab. 3. Delamination layer prediction was found to be accurate using both the technique. It is observed that the predicted results obtained from ANN are comparatively more accurate than RSM. The RSM, on the other hand, quickly solves the inverse problem and provides an appropriate mathematical equation for forecasting delamination. In comparison to RSM, an ANN is a better and more precise modelling method since it better reflects nonlinearities.

CONCLUSIONS

This method uses natural frequencies in delamination structures to locate the damaged interface, as well as its size and position. The changes of frequency with various delamination location and size were obtained using experimentation and finite element techniques. The ANN and RSM inversion techniques were compared and ANN was found to be more accurate, but time consuming technique. The noteworthy delamination estimation results confirm the algorithms' and approach's robustness and accuracy. However, unlike RSM, which gives physical mathematical models that are simple to compute and analyse, one key drawback of ANN is the output weights of the network are not easy to infer. The future scopes of this research is using the mode shapes, damping or combination of all these vibration parameters, instead of frequencies alone to detect delamination.

S.NO	Actual [X, a]	ANN [X, a]	RSM [X, a]	%Error (ANN)	%Error (RSM)
1.	(60,500)	(59.36, 478.29)	(65.93, 552.41)	(-1.05, -4.34)	(9.88, 10.48)
2.	(90,750)	(89.16, 717.11)	(79.91, 780.32)	(-0.92, -4.38)	(-11.20, 4.04)
3.	(120,750)	(122.51, 771.12)	(128.96, 767.40)	(2.09, 2.81)	(7.47, 2.32)
4.	(150,1000)	(152.23, 1001.31)	(156.95, 1009.04)	(1.49, 0.13)	(4.63, 0.90)
5.	(180,1250)	(175.73, 1247.62)	(184.43, 1254.34)	(-2.36, -0.18)	(2.46, 0.34)
6.	(210,500)	(207.52, 501.34)	(208.48, 512.85)	(-1.17, 0.26)	(-0.72, 2.57)
7.	(220,750)	(210.13, 763.81)	(227.37, 762.51)	(-4.48, 1.84)	(3.35, 1.66)

Table 3: Comparison of actual and predicted delamination parameters using ANN and RSM results

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