

Delamination Monitoring of Composite Plates using Vibration-based Surrogate Assisted Optimisation

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Abstract

With the increasing applications of laminated composites in all kinds of industries, it becomes imperative to detect delamination, a frequently occurring damage which causes substantial stiffness loss in composite structures. This paper presents an approach to assess delaminations (in terms of their size, in-plane location and interface) in fibre reinforced laminated composite plates using natural frequencies as indicative parameters and surrogate assisted optimization as the inverse prediction tool. A 3D finite element model has been used to model eight-layer $[0/45/-45/90]_s$ graphite/epoxy plates having embedded delaminations at different interfaces. Contact elements are employed between the sub-laminates to prevent inter-penetration between them. Modal analysis was performed using the finite element simulation to generate a database of natural frequencies for up to 20 modes for various combinations of interface, X and Y locations and sizes of simulated delaminations in the fibre reinforced composite plate. This data was used to train a back propagation neural network to an acceptable level of accuracy. The trained neural network is then used as a surrogate model in the optimization routine for solving the inverse problem to predict the X, Y and Z locations and the dimensions of the delamination. The surrogate assisted optimisation is tested with numerically simulated data and validated experimentally with frequency shifts measured from graphite/epoxy and glass/epoxy plates with artificially induced delaminations. The results show that, the surrogate assisted optimization method, can determine the locations and sizes of delaminations in real plates from measured frequency shifts.

Keywords: Vibration, Delamination Detection, Simply supported, Structural Health Monitoring, Composite Laminate

Introduction

Fibre reinforced polymer (FRP) composites have wide applications in aeronautical, naval, and automobile industries due to their high strength to weight and stiffness to weight ratios. However, FRP laminates frequently suffer delamination damage due to low inter-laminar strength [1]. Delaminations may not be visible from surface but have a significant detrimental effect on bending stiffness and compressive load bearing capacity. Therefore, it is important to detect the presence of delaminations in composite structures at an early stage. While traditional non-destructive inspection (NDI) methods like ultrasonic, thermography and x-radiography are applied to detect such internal damage offline, recently considerable research effort has been put into developing Structural Health Monitoring (SHM) techniques which can detect delaminations in situ and in real time[2]. Vibration based methods through monitoring

dynamic response which can be extracted from the composite structures while in operation, is one of the most promising for SHM applications [3]. The principle behind vibration monitoring is that damage in a structure reduces the local stiffness which results in changes in dynamic parameters such as natural frequencies, mode shapes and damping ratios[4]. Therefore, by monitoring changes in these parameters damage can be detected and assessed. Among these parameters, frequency shift is preferable since it does not require data acquisition in more than one location and measurement of frequencies is more reliable and repeatable [5]. However, monitoring frequency shifts has the disadvantage that, while it easily indicates the existence of damage it does not readily identify the location or severity of the damage. This requires solution to the inverse problem, i.e. determination of the location and size of damage from measured frequency shifts in multiple modes.

Current methods for solution of the inverse problem include model updating and artificial intelligence techniques such as neural networks (NN) [6-8] and genetic algorithm (GA)[9]. Okafor et al [7] used the first four normalized frequencies obtained from a theoretical model of the delaminated beam to train a neural network to predict delamination size in delaminated composite cantilever beams. Valoor and Chandrashekhara [8] trained a back propagation neural network to predict both delamination size and location by using the natural frequencies obtained from an analytical thick beam model which incorporated shear deformation and Poisson effect. Su et al.[9] evaluated the efficiency of GA and artificial neural network (ANN) in quantitative damage identification. Both methods were validated using measured frequencies from glass fibre-reinforced epoxy composite beams using embedded fiber Bragg grating sensors for frequency measurement. While most previous studies have focused on delamination detection in composite beams, Chakraborty [10] used the first 10 modal frequencies generated from finite element model (FEM) of a delaminated composite plate to train a back propagation NN to predict the size, shape and in-plane location of damage. However, the interface location of delamination was not predicted. One of the disadvantages of NN is that it has difficulty in giving discrete outputs such as integral values of interface location. Direct optimization, on the other hand, requires a large database and can be quite time consuming, even though it can predict discrete Variables. In this paper, we have developed a surrogate assisted optimisation technique for detecting the x, y coordinates of the in-plane location, the dimensions "a" and "b" of the delamination along the length and width of the plate, and the interface (z) at which it is located, which takes on a discrete integral value. The surrogate is an approximation model which is a NN trained by data from FE simulation. The advantage of using a surrogate is that it considerably reduces the size of the data base and the time required to generate it as well as expediting the optimisation procedure which can now deal with discrete variables. The NN surrogate-assisted optimisation has been first validation using numerical test cases generated from the FE model. The method is then validated using experimental data from frequency measurements conducted on composite panels with embedded delaminations using a non-contact scanning laser vibrometer.

Finite element model

Three dimensional (3D) finite element modelling of undamaged and delaminated plates was performed using the commercial software ANSYS12. The dimensions and

material properties used in FE models are the same as those of the experimental samples: length=130mm, width=92mm and thickness=2.561mm for CFRP plates and 2.105mm for GFRP plates; $E_{11}=92.9\text{GPa}$, $E_{22}=8.1\text{GPa}$, $G_{12}=2.88\text{GPa}$, $\nu_{12}=0.328$, $\rho=1482\text{Kg/m}^3$ for carbon fibre reinforced epoxy laminates; and $E_1=30.9\text{GPa}$, $E_2=7.67\text{GPa}$, $G_1=2.86\text{GPa}$, $\nu_{12}=0.29$, $\rho=1787\text{Kg/m}^3$ for glass fibre reinforced epoxy specimens. The element type used is layered SOLID185, an eight-node layered structural solid element with three degrees of freedom at each node. For plates with delamination, the upper and lower sub-laminates are modelled separately and nodes at the interface are left unmerged. Due to symmetry in the lay-up, delaminations are simulated only in four of the eight interfaces, interface 1 (outermost interface) to interface 4 (mid-plane) as shown in Figure 1.

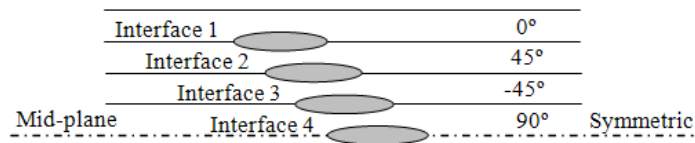


Fig. 1: Layup and designation of interfaces in the laminate

Contact elements (TARGE170/CONTAC173) were added between the mating surfaces of the delaminated area, which allow neither penetration nor separation between the sub-laminates. A mesh sensitivity study was first conducted to determine the optimum number of elements to be employed for the plate models. Eigen value modal analysis was carried out to extract first 20 natural frequencies of the flexural bending modes using the Block Lanczos method (in-plane bending modes are discarded). The percentage change in natural frequency $\Delta\omega$ for each mode is then calculated as follows:

$$\Delta\omega = \frac{\omega_u - \omega_d}{\omega_u} * 100\% \quad (1)$$

where ω_u is the natural frequency of the undamaged plate and ω_d is the natural frequency of the plate with delamination. The first nine modes of frequency change were used to train the surrogate NN model.

Surrogate assisted optimisation

For optimization problems involving computationally expensive simulations, the number of function evaluations one can afford is limited. Surrogate models are computationally cheaper alternatives to expensive simulations providing approximations to the responses in much shorter time. Genetic algorithms typically require large numbers of function evaluations to converge to the optimum. In an attempt to keep the computational cost of optimization affordable, surrogate models are used in lieu of the expensive analysis within GAs. In this paper, we use ANN to build approximation models to fit the datasets of frequency changes due to delaminations in composite laminates obtained from FE models. Two types of NN approximations were trialled: in the first instance, one ANN with the five delamination parameters as inputs and the first nine frequency changes as output; and second, nine separate ANN models each one approximating the frequency shift in each mode as a function of the five input parameters. Using test cases of input data, it was found that the latter method with a separate NN model for each mode gives a much better prediction of the frequency shifts. The number of hidden layers and neurons in each

layer of the NN model were determined by trial and error since there is no established rule for choosing the optimal number[8]. The final architecture for each of the nine ANNs is 5-20-20-1 (5 neurons in input layer indicating the five parameters, two hidden layers with 20 neurons in each, and one mode of frequency change in the output layer). The NN models were trained using data from the FE simulations until a mean square error (MSE) in the discrepancy between frequency changes obtained from NN model and FE model of 10^{-4} was achieved.

For problems in which the variables are a combination of discrete and continuous variables, it is difficult to use conventional optimization algorithms such as the gradient based method, since they rely on the use of continuous variables. To solve our inverse problem which has a combination of four continuous variables (x, y, a and b) and one discrete variable (the interface z) as outputs, we have employed a population based stochastic algorithm, the Non-dominated Sorting Genetic Algorithm (NSGA-II) [11]. The objective function for the GA optimization is formulated as follows:

$$\text{obj} = \frac{\sum_{i=1}^n \left(\frac{\Delta\omega_t - \Delta\omega_s}{\Delta\omega_t} \right)^2}{n} \quad (2)$$

where n is the number of modes considered, $\Delta\omega_t$ is the target frequency shift obtained either from measurements (in the case of experimental validation) or from FE test cases (numerical validation) and $\Delta\omega_s$ is frequency shift predicted by the surrogate model.

Experiments

Fabrication of composite plates with simulated delaminations

In order to validate the proposed surrogate assisted optimization in predicting delaminations in real structures, carbon fiber reinforced epoxy (CFRP) and glass fiber reinforced epoxy (GFRP) panels with various delaminations were manufactured and tested. The CFRP panels were fabricated with MTM57/PANEX35 prepreg tapes and the GFRP panels with MTM57/E-glass prepreg tapes. The size of both panels were 300mmx200mm and the stacking sequence $[0\ 45\ -45\ 90]_s$. Delaminations were simulated by embedding Teflon release films between the prepreg layers at the desired locations during stacking to prevent them from bonding together. The prepreps were cured in an autoclave using temperature and pressure setting prescribed by the manufacturer. The cured graphite epoxy panels had a nominal thickness of 2.561mm and the glass epoxy panels a nominal thickness of 2.105 mm. After curing, each of these laminate panels was cut into four plates (130mmx92mm), one control plate without any delaminations and three panels with delaminations. All the embedded delaminations were 40mmx40mm, occupying about 13% of the area of plates. The locations of the delaminations in the GFRP and CFRP panels are shown to scale schematically in Figure 2. The delaminations in the GFRP panels are all located at interface 4, the mid-plane, (indicated by magenta), but at different in-plane locations, viz, at x/L, y/L values of (0.85, 0.5), (0.35, 0.233), and (0.45, 0.5) respectively for GFRP 2, 3 and 4. The delaminations in the CFRP panels are all located at the same in-plane location (x/L = 0.85 and y/L = 0.5), but at different interface locations, interface 4 (magenta), interface 3 (green) and interface 2 (blue) in CFRP panels 2, 3 and 4, respectively.

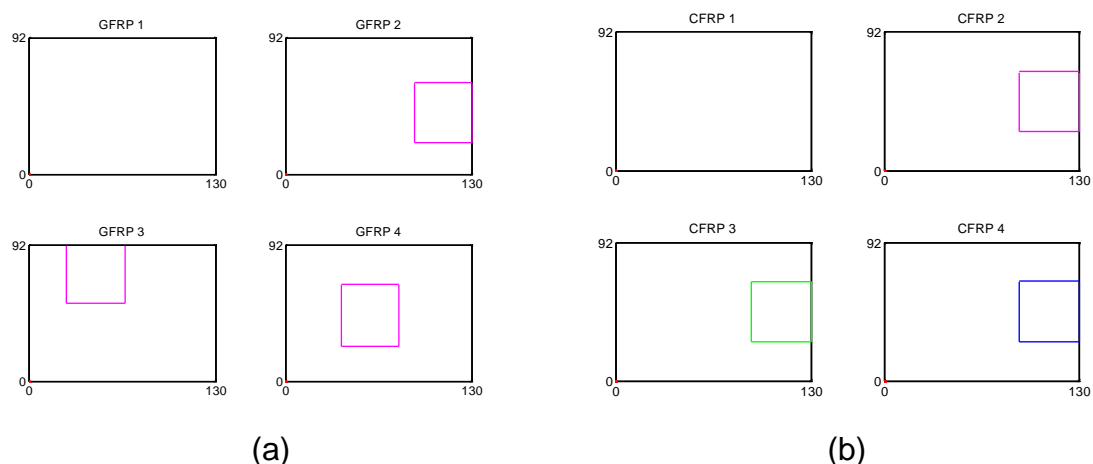


Fig. 2: Delamination locations in test specimens: (a) GFRP plates and (b) CFRP plates

Experimental Modal Analysis

The experimental modal analysis was conducted using a *Polytec PSV-400* scanning laser doppler vibrometer and the data was processed using the software PSV8.7 to extract the natural frequencies. The plates were clamped along the shorter edge without delamination left free on the other three sides to provide clamped-free-free-free (CFFF) boundary conditions. The clamping screws were tightened to the same consistency by using a torque wrench. The measurement area of the plate was set up to a grid of 13x9 to provide 117 measurement points. The response at each measurement point was averaged 15 times to improve the signal-to-noise ratio. A frequency range of 0 to 3200Hz was selected to cover the first nine modes. A grid of 6400 lines was selected over the frequency range for Fast Fourier Transform (FFT) providing a resolution of 0.5Hz. The excitation was provided with sound from a loudspeaker behind the plate with a sweep signal from 1Hz to 5000Hz in 0.5s. The frequencies were estimated by the PSV8.7 software within the bandwidths provided spanning the peaks in the frequency spectrum.

Comparison of frequencies from experiment and FE simulation

Table 1 shows the comparison of the frequencies measured in the tests with those predicted by the finite element simulation for the undamaged glass and carbon fiber reinforced plates. As can be seen, the maximum discrepancy between experimental and numerically predicted frequencies is only 4.52% for the undamaged GFRP plate and under 3.2% for the undamaged CFRP plate (both in mode 9), indicating very good agreement between FE and experiment. The measured frequencies of delaminated GFRP and CFRP panels also showed good agreement with those predicted by FE simulations, with discrepancies generally below 5%, except in mode 9, which again had discrepancies up to 9%. The larger discrepancies between FE and measurement for the highest mode may be attributed to larger inaccuracies in measurement as well as greater errors in FE prediction for higher modes. For illustration, the ratios of the measured modal frequencies to those predicted by FE simulation for two typical cases, delaminated panels GFRP3 and CFRP3, are plotted in Figures 3(a) and 3(b) respectively.

Table 1: Comparison of frequencies from experiment and FE model for undamaged panels

Mode No.	GFRP1 (undamaged)			CFRP 1 (undamaged)		
	Measured frequencies (Hz)	Frequencies from FE (Hz)	%Error	Measured frequencies (Hz)	Frequencies from FE (Hz)	%Error
1	69.92	71.06	1.61	156	160.11	2.57
2	188.09	188.63	0.29	384	377.15	-1.82
3	433.98	439.57	1.27	954	970.27	1.68
4	661.91	658.19	-0.57	1248	1226.52	-1.75
5	750.00	718.71	-4.35	1442	1421.20	-1.46
6	1216.02	1225.26	0.75	2390	2352.24	-1.61
7	1300.00	1275.67	-1.91	2748	2760.61	0.46
8	1441.99	1468.64	1.81	2970	2968.55	-0.05
9	1867.97	1787.16	-4.52	3146	3248.29	3.15

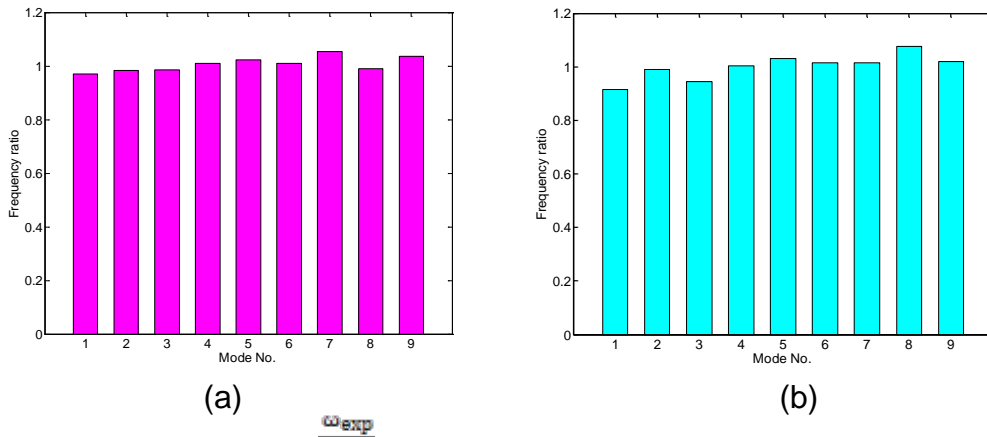


Fig. 3: Frequency ratio ($\frac{\omega_{exp}}{\omega_{FE}}$) for delaminated panels (a) GFRP3 (b) CFRP3

Delamination assessment using surrogate assisted optimization

Numerical validation

Eight different test cases of panels with delamination were generated using the FE model for validation of the proposed surrogate assisted optimisation technique for delamination assessment. The boundary conditions employed were CFFF, as in the tests. The test cases were chosen to cover different values of in-plane location, interface locations and lengths and widths of delamination, to cover all scenarios. The percentage frequency shifts due to the delamination in each case were input into the damage assessment algorithm to predict the in plane locations x , y , the interface location z , and the dimensions of the delaminations a and b along the length and width of the plate. The comparisons between the delamination parameters predicted by the damage assessment algorithm and the actual values are shown schematically in Figure 4 for the eight numerical test cases. In the figure, the delamination sizes and locations are shown to scale relative to the plate dimensions. The rectangles with solid edges indicate the actual delaminations modelled whereas the rectangles

with dashed edges indicate the predicted delaminations. The assessed and actual interface locations of the delamination are indicated by the colour code: red for interface 1, blue for interface 2, green for interface 3 and magenta for interface 4 (mid-plane). It can be seen that, in general the agreement between the predicted delamination parameters and the actual values is quite good. The interface is correctly predicted in all cases except case 6, in which the predicted interface is 4 while the actual one is interface 3. The largest error in prediction of in-plane location is in case 1, which has the delamination with the smallest size (only 4% of the plate area), suggesting that the delamination assessment technique using surrogate assisted optimisation may have its limitations when it comes to assessing small delaminations. A further sensitivity analysis will be conducted in the future to study the smallest delamination which can be detected by present optimisation method.

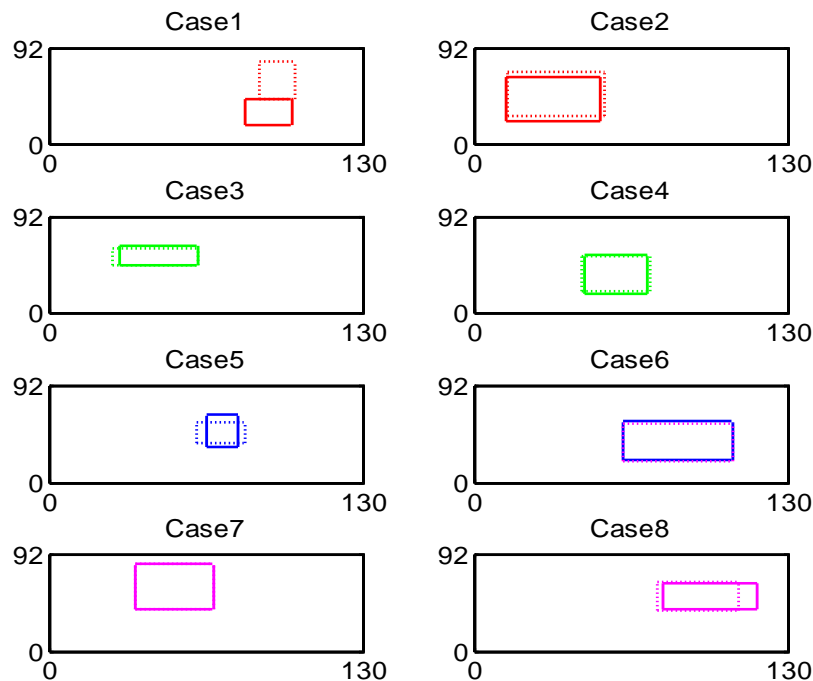


Fig. 4: Comparison of actual and predicted delaminations in numerical validation

Experimental validation

The delamination assessment technique using surrogate assisted optimisation was also validated using the frequency shifts measured in the experimental modal analysis. The predicted results are compared with the actual delaminations in the GFRP and CFRP test panels in Figure 5. Once again, the rectangles with solid edges indicate the actual delaminations and the rectangles with dashed edges indicate the predicted delaminations. The colour coding for the interface location is the same as that used in Figure 2. It is obvious that the prediction accuracy is much lower for the experimental test panels than the numerical tested cases. None of the interface locations of the delaminations in the CFRP plates has been predicted correctly, although the predictions of interface 4 for all the delaminations located in the mid-plane of the GFRP panels are correct. However, the delamination sizes have been predicted with good accuracy in most cases (except for GFRP4) and the in-plane locations have been predicted with reasonable accuracy (except for CFRP4) if note that in most cases the predicted delamination area has overlap to the actual one.

The greater inaccuracy in delamination assessment when applied to experimental test cases can be attributed to experimental errors and uncertainty in measurements which cause greater variance with the numerical simulation that is used to generate the database for the optimisation algorithm.

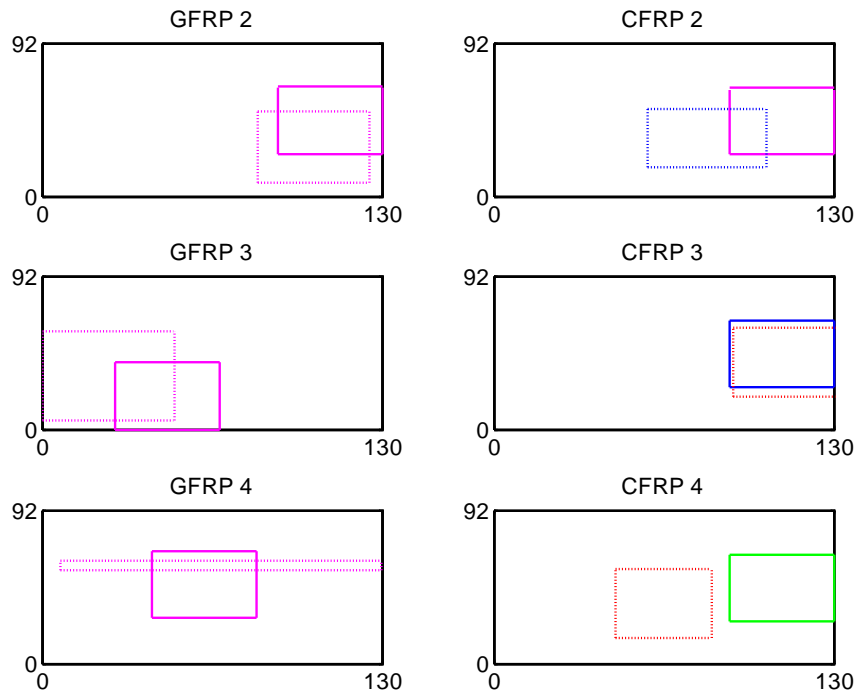


Fig. 5: Comparison of actual and predicted delaminations in experimental validation

Conclusion

A surrogate assisted optimisation method is proposed to predict delaminations in composite plates using changes in natural frequencies. The proposed method can predict both discrete and continuous variables at the same time with considerable savings in computational resources with the assistance of surrogate models. The method has been validated using numerical data from FE simulations with good accuracy. The experimental validation shows that the accuracy is not as good in real situations, especially in predicting the interface location of the delaminations, which can be attributed mainly to the greater discrepancy between the numerical model used to generate the database and the actual test panels. However, even in the experimental validation the in-plane locations and the sizes of the delaminations are assessed with sufficient accuracy, confirming that the method is useful in detecting and providing a reasonable estimate of the size and in-plane location of the damage. The accuracy may be improved by ensuring greater fidelity of the finite element simulation to the actual test cases (by model updating) and by using a larger data set to generate the surrogate models.

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