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Structural Damage Localization in Composite Plates Using Finite Element Method and Optimization Algorithm

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ABSTRACT

Damage detection techniques are tools of great importance in the mechanical and aeronautical engineering. The necessity to detect damage in complex structures has led the development of a vast range of techniques as well inverse problem based in optimization algorithms. In the present article, a numerical study is to assess damage detection techniques applied to composite materials, because the application of these materials in components and structures has replaced metallic materials due to their high mechanical performance and the most non-destructive inspection techniques (NDI) used in these materials needs a high level of technical expertise. We carried out the modeling by finite element method (FEM) and employed heuristic techniques of optimization (genetic algorithms) coupled to the numerical model, to minimize an objective function, written in terms of the natural frequencies of the analyzed structure, because vibration-based detection methods using dynamic parameters is one of the most promising in structural health monitoring (SHM). 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. Therefore, by monitoring changes in these parameters we can detect and assess damage. The structure studied is constituted of a damaged laminate of carbon fiber, and a local stiffness reduction is applied in a specific element as the damaged model. The main contribution of this paper is the development of a coding enhancement strategies designed specifically for the problem of damage detection using artificial intelligence. The effect of the two damage variables (damage location and severity) are studied. The results of numerical simulations as well optimization procedures using heuristics methods as shown a good performance to detect and identify the structural damage modeled as a local stiffness reduction.

INTRODUCTION

Detection, location and quantification of damage in structures via techniques that examine changes in measured structural vibration response is a very important topic of research, due to increasing demands for quality and reliability. Recent surveys on the technical literature, such as on Doebling*et al*. (1996) and Chang (1997), among others, show that extensive efforts have been developed to find reliable and efficient numerical and experimental models to identify damage in structures. The occurrence of damage in a structure modifies some of its mass, stiffness or damping properties, changing the vibrational response of the structure. Therefore, the knowledge of the vibrational behavior of a structure can be used to determine the existence as well as the location and the extent of damage. All themethods presented in the literature can be categorizedby the type of data or the techniques used to achieve thedamage identification purpose (Santos *et al.*, 2000).

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Lots of damage detection techniques have been proposedfor structural health monitoring (SHM) (Sun*et al.*, 2013; Sinou, 2009; MorassiandVestroni, 2008). However, according to Santos*et al.* (2000) they are somehow difficult to implement, andsome of them are impractical in many cases such as in-service aircraft testing and in situ space structures. Almost all of the above techniques require that the vicinity of the damage is known in advance and the portion of the structure being inspected is readily accessible.

The dynamics-based damage detection techniques using smart materials offer a viable and effective way to damage detection. Changes in the physical properties of the structures due to damage (e.g., delamination) may alter the dynamic responses such as natural frequencies, damping and mode shapes, and these physical parameter changes can be extracted to estimate damage information. (Qiao*et al.*, 2006). In addition, according to Qiao*et al.* (2006), delamination in composite structures is one of themajor failure modes, and it may cause structural failure leading to catastrophic consequences. Development of anearly damage detection method for delamination is one of the most important keys in maintaining the integrity and safety of composite structures.

An important class of damage identification methods is based on the updating or modification of structural matrices, namely the mass, stiffness and damping matrices (Friswell, 2008; CawleyandAdams, 1979). The models included in this class are theoretically analogous to some finite element model updating methods used to locate and quantify modeling errors. Typically, the updated matrices are determined by solving an optimization problem, based on the structural equations of motion, the initial matrices and measured data. By comparing the updated or modified matrices to the original matrices, it is possible to locate and quantify the damage (Santos *et al*., 2000).

Composite structures have an excellent performance, although this deteriorates significantly with damage. Unfortunately, damage, due to impact events for example, are difficult to detect visually, and hence some method of non-destructive testing of these structures is required. Zou *et al*. (2000) reviewed the vibration based methods that are available to monitor composite structures. Since this paper considers inverse methods for damage estimation, this section will only consider the parameterization of the damage in composite structures, and in particular the modelling of delaminations. Although composite structures have other modes of failure, such as matrix cracking, fiber breakage or fiber-matrix debonding (Ostachowicz and Krawczuk, 2001), these damage mechanisms produce similar changes in the vibration response to that obtained for damage in metallic structures. However, delamination is a serious problem in composite structures, and has no parallel to damage mechanisms in other materials. Once the damage is parameterized then inverse methods, such as sensitivity analysis, may be applied (Santos *et al*., 2000).

Supplementary, vibration-based detection methods using dynamic parameters is one of the most promising in SHM. 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. Therefore, by monitoring changes in these parameters we can detect and assess damage. The monitoring of mode shapes requires measurements at multiple locations, is time consuming and prone to noise. Damping parameters are notoriously difficult to measure, being sensitive to environmental conditions such as humidity and temperature. In comparison, natural frequencies require only single point measurement, and can be monitored with greater accuracy, ease and reliability (Zhang *et al.*, 2013).

Based on the brief review, it was proven that the damage detection is still a serious problem in composite structures, which requires more attentions. In this study, a numerical model, which allows the detection and identification of structural damage, is investigated using finite element analysis and genetic algorithm in laminated composite plate.This model allows the identification of local damage, with no need of previous knowledge of its localization. The model uses a discretization by finite elements to obtain a damage parameter in each finite element of the discretized structure. The damage parameter is directly related to the stiffness reduction of the damaged element. The model is applied to a laminated rectangular plate with free edges as boundary conditions. The optimization process using heuristic methods such as genetic algorithm (GA) are used in the inverse method procedure because heuristics methods, such as GA, are methods of zero-order, especially suitable for non-linear and multi-modal problems (Mitchell, 1999), since thedamage detection problem has a functional that is not convex with multiple local minima (Stavroulakisand Prior, 1998). Significant results were founds using this methodology.

Problem Formulation:

Direct Problem: Finite element model:

The direct problem was modeled on a square plate side. The structure is symmetrically laminated composite material consisting 12 layers in different orientations stacking symmetrically, i.e., $[0/90]_{3s}$ andthe layer thicknesses is$t$ = 0.18mm. Please note that this work is intended solely to the study of the damage detection method in laminated composite material using optimization algorithms, giving emphasis on geometric parameters and specific characteristics of the laminate material.

Thus, mapped shell elements were employed in the FE modeling. Figure 1 shows the results of the meshed geometry in 100 elements, generated on the surface of the structure studied and the material properties are shown in the Table 1.

Table 1: Material properties.

Material Properties	Value
E_1	83.02 MPa
E_2	5.13 MPa
G_{12}	8.37 MPa
v_{12}	0.32
ρ	1408.1 kg/m³

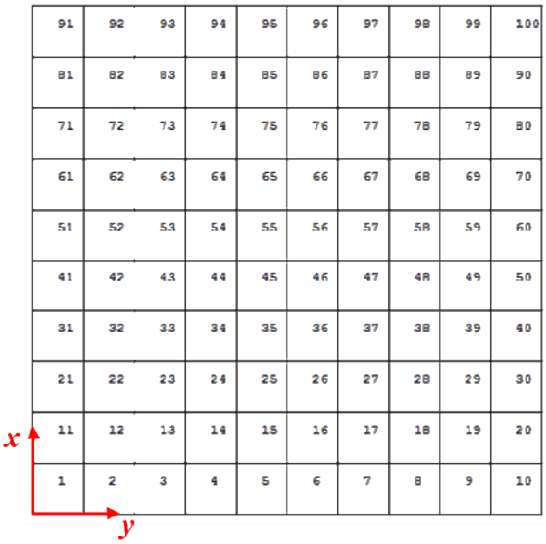


Fig.1: Element numbering sequence of the discretized plate.

Damaged Model:

It is known that the occurrence of damage in a structure modifies some of its mass, stiffness or damping properties, changing the vibrational response of the structure. So the damaged model used in this study will be based in local stiffness reduction which results in changes in dynamic parameters such as natural frequencies, mode shapes and damping ratios. The background of this model, for the discretized undamaged structure, according to Santos *et al.* (2000), the eigenvalue equation can be written as

$$Kq_i = \lambda_i M q_i \text{ for } i = 1, \ldots, n. \tag{1}$$

where K and M are the stiffness and mass matrices, respectively, $\lambda_i$is the *i*theigen value, q_i is the *i*th eigenvector an *n* is the computed or experimentally available number of mode shapes of the undamaged structure.If the structure undergoes some kind of damage, which reduces its stiffness, Eq. (1) is rewritten as

$$K^* q_j^* = \lambda_j^* M q_j^* \text{ for } j = 1, \ldots, m. \tag{2}$$

where $\tilde{K}$ is the stiffness matrix, $\lambda^*_j$the *j*th eigenvalue, $q^*_j$the *j*th eigenvector and *m* is the computed or experimentally available number of mode shapes of the damaged structure. The mass matrix of the damaged structure is assumed equal to the mass matrix of the undamaged structure. Matrices K and M are assumed symmetric positive definite and therefore the eigenvaluesλ_i are positive and the eigenvectors q_i can be taken as K-orthogonal. Similar conditions apply to K^*, λ^*_j and q^*_j.

Considering the mass normalization of the modeshapes, the orthogonality conditions are defined by

$$q_i^{*T} K^* q_j^* = \delta_{ij} \lambda_i^* \text{ with } \begin{cases} \delta_{ij} = 0 & \text{for } i \neq j \\ \delta_{ij} = 1 & \text{for } i = j \end{cases} \tag{3}$$

Since the damage stiffness matrix is given by$K^* = K - \delta K$ and on element *e* the corresponding perturbedmatrix is $\delta K_e = \delta b_e K_e$, where $\delta b_e \epsilon [0, 1[$ is thedamage parameter, expression (3) yields

$$\sum_{e=1}^{N} q_{ie}^{*T} K_e q_{je}^* \delta b_e = q_i^{*T} K q_j^* - \delta_{ij} \lambda_{ij}^* \tag{4}$$

Then, to simplify those notations, we consider $\boldsymbol{\alpha} = \boldsymbol{\delta b_e}$as the multiplier parameter in the element. So, the total stiffness reduction can be introduced as β such as:

$$\beta = 1 - \alpha \qquad (5)$$

The structure chosen for this study is a symmetriccross-ply plate free in space. The layershave equal thickness and the material properties of eachlayer are presented in Table 1.The plate is discretized in 10x10first-order shear deformation plate elements. Hence, there are 100 unknown damage parameters (Fig. 1). Each element has8 nodes with 6 degrees of freedom (3 translation and 3 rotations). Damage is simulated in element *e* by a reduction in itsstiffness matrix K_e. Thedamage is simulated in element number 45, with a damage parameter α of 0.20, 0.50 and 0.80, respectively as shown in the Figure 2 and 3.

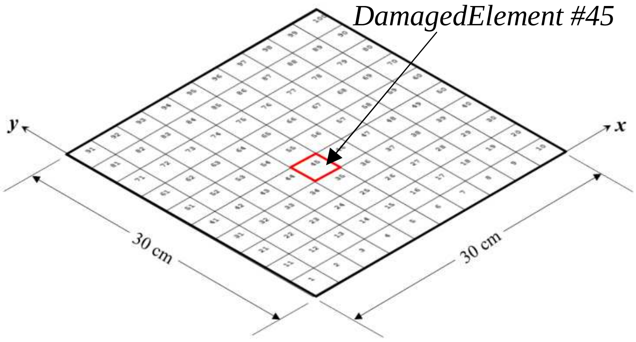
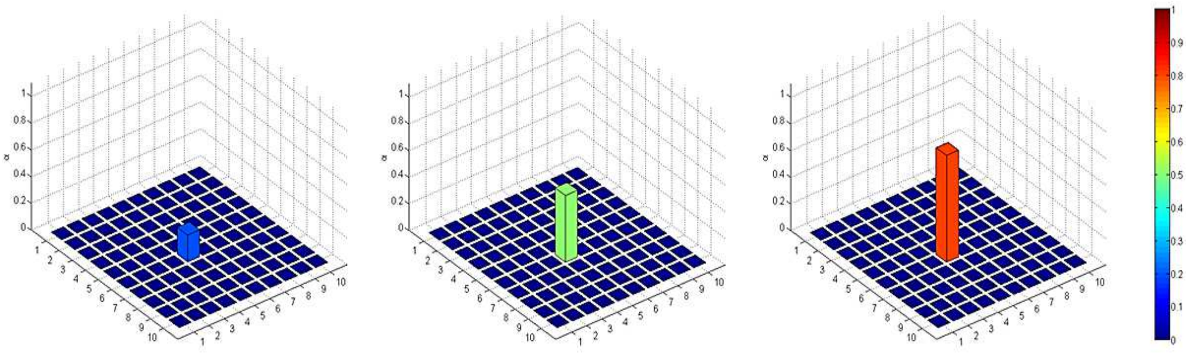


Fig.2: The finite element model of the laminated plate and the damaged element number 45.



(a) (b) (c)

Fig.3: Factor scale of α in three different caseson the laminated plate: α = 0.2 (a), α = 0.5 (b) and α = 0.8 (c).

Inverse Problem: Genetic algorithm optimization:

The main goal of the optimization procedure is to adjust the fractional order α and the damaged element number N_{elem} in order to obtain he best properties of the damage identification algorithm.Hence, the optimization problem can be written asfollows:

$$\text{Minimize} \quad J = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{\omega_i^{\text{damaged}}}{\omega_i(\vec{X})^{\text{calculated}}}\right)^2} \qquad (6)$$

$$\text{Subject to} \quad 1 < N_{elem} < 100, 0 < \alpha < 1 \qquad (7)$$

whereω^{damaged} is the target frequency shift obtained either from measurements (in the case of experimental validation) or from FE test cases (numerical validation) and $\omega^{\text{calculated}}$is frequency shift obtained from the surrogate model. Here,$X = \{N_{elem}, \alpha\}$ is called the design vector.

Genetic Algorithms (GA) represent an intelligent exploitation of a random search used to solve optimization problems (Santhanam and Padmavathi, 2015) .The GA procedure uses random initial populationsand through selection, crossover rand mutation in GA, better offspring are fed into the surrogatemodel for the next iteration. This iterative procedure continues untilconvergence to the set precision criteria is achieved or the numberof generations reaches the maximum set value. The parametersettings used for the GA are listed in Table 2.Every solution in the population is called as an individual and every individual is represented as a chromosome for making it suitable for the genetic operations. The user defined value is used as the initial population of meta heuristic which encode candidate solutions to an optimization problem and evolves better solutions (Sudha and Sukumaran, 2015).

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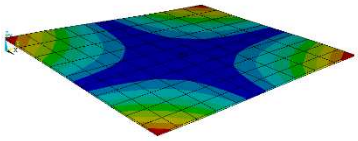
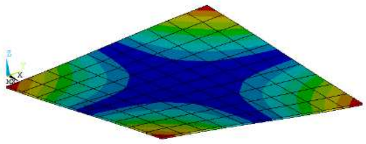
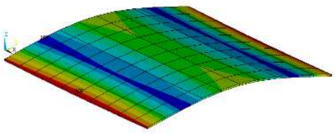
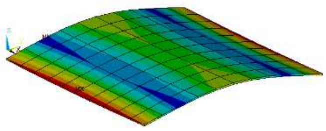
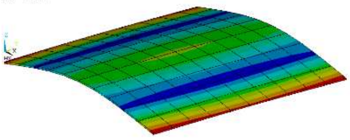
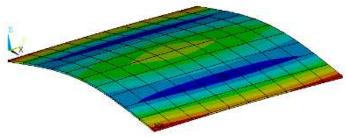
Table 2: Genetic algorithm operators.

Genetic Operator	Value
Population size	40
Crossover	60%
Mutation	2%
Elitism	2
Generations	100

Numerical Results:

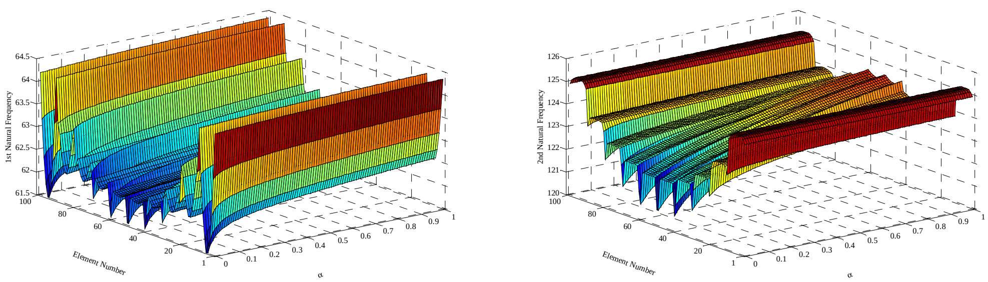
The initial analysis demonstrates that the stiffness reduction as induced damage changes the dynamic response of the plate. In order to further investigate the relationship between the stiffness reduction and the mode-dependent variations of natural frequencies in the plate, numerical simulation using FEM is employed (Table 3).

Table 3: Natural frequencies of undamaged and damaged plate considering α = 0.2.

Mode	Undamaged	Damaged
1st	 62.5436 Hz	 62.1774 Hz
2nd	 123.6100 Hz	 122.7640 Hz
3rd	 154.9480 Hz	 154.0170 Hz

It can be observed that the natural frequencies variations were quite small (Table 3), however, this stiffness reduction model behaves in a very approximate character, as addressed by Gomes (2016), in which structural damage lead to small dynamic variations in experimental modal testing in real structures. Therefore, the induced damagehas a total area of 9 cm² (3x3cm²), corresponding to 1% of the total area of the plate (900cm²).

In a preliminary stage, was varied the level of damage (α) in all discretized elements of the plate. In response of this variation, we obtained the first six natural frequencies. The results of this study are shown in Figure 4. It can be seen that the position of the damage (N_{elem}) has far more significance on the variation of the natural frequencies (sensitivity) than the rate of reduction.It is further, that for more α values than 0.2, there is no significant variation in the response. However, for a high reduction (0 <α<0.2), the reduction ratio affects the results significantly.



(a) (b)

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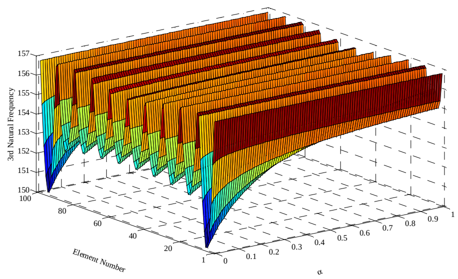
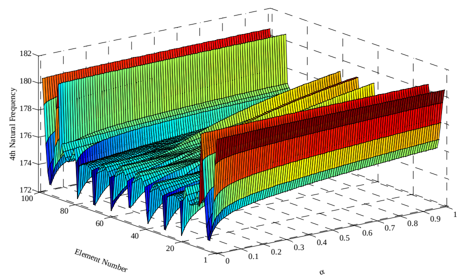
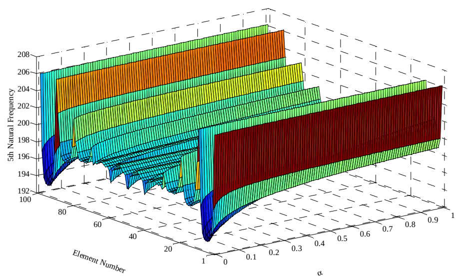


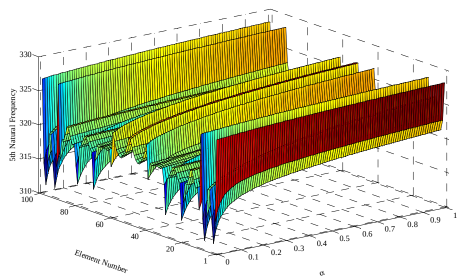
(c)



(d)



(e)



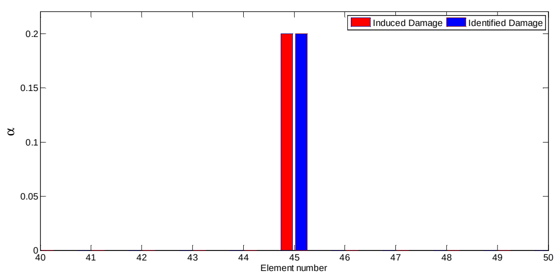
(f)

Fig.3: Natural frequency variation in function of the position of the damage (element number) and its severity (α) for the 1st (a), 2nd (b), 3rd (c), 4th (d), 5th (e) and 6th (f) natural frequency.

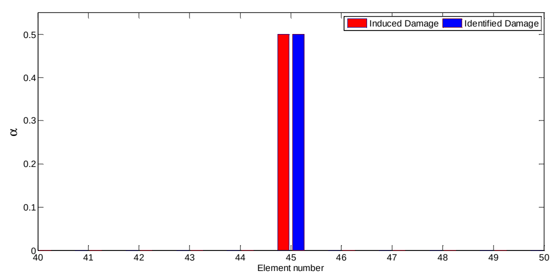
The key results from the optimization procedureare shown inFigure 4. This plot presents the intensity of the damaged region of the induced damage and the obtained by the present employed method.The values of behavioral parameters for these caseswere included in Table 4. It should be noted, that the genetic algorithm found precisely the damage on the composite plate with small errors and for the case 3, that represents the small damaged structural case, the algorithm obtained the smaller tendency to convergence to the induced damage (error around 0.0825%).

Table 4: Results of damage detection by stiffness reduction.

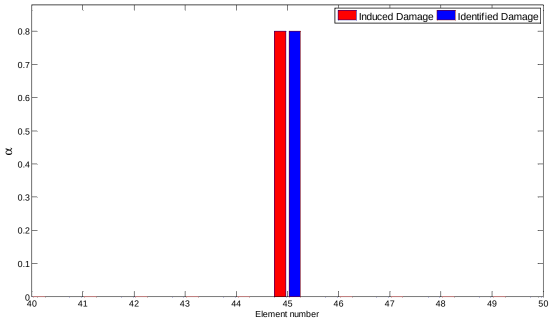
	Case 1		Case 2		Case 3	
	N_{elem}	α	N_{elem}	α	N_{elem}	α
Objective	45	0.2000	45	0.5000	45	0.8000
	45	0.1999	45	0.5002	45	0.8001
	45	0.1997	45	0.5001	45	0.8008
Stochastic Search	45	0.1999	45	0.4999	45	0.8009
	45	0.1996	45	0.4997	45	0.8009
	45	0.2001	45	0.4997	45	0.8006
Mean	45	0.1998	45	0.4999	45	0.8007
Deviation	0	0.0002	0	0.0002	0	0.0003
Error (%)	0	0.080	0	0.016	0	0.0825



(a)



(b)



(c)

Fig.5: Damaged laminated plate, detected damages applying the first six natural frequencies after 100generations for 20% (a), 50% (b) and 80% (c) of stiffness reduction.

Conclusions:

A numerical technique for the damage identification on composite structures, which considers the vibration-based damage detection, has been applied. The model does not requirethe previous knowledge of the damaged area or areaslocation and allows the identification of structural damage.

The results of numerical simulations as well optimization procedures using heuristics methods (GA) as shown a good performance to detect and identify the structural damage modeled as a local stiffness reduction. This local stiffness reduction concept can be treated as a delamination behavior in composite structures, since this damage model produce a local reduction of stiffness without mass loss. Due to the finite elementformulation, damage detection and identification on arbitrary structurescan be carried out.

It can be seen that the local stiffness reduction method, the position of the damage (element number) has more impact on the system response (natural frequencies) than its severity (α). The severity of local damage becomes important to over 80% in local stiffness reductions.

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