25th ABCM International Congress of Mechanical Engineering
October 20-25, 2019, Uberlândia, MG, Brazil

COB-2019-1612
A METHODOLOGY TO CLASSIFY COMPOSITE PLATES AFTER MANUFACTURING PROCESS USING KRIGING METAMODEL

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Abstract. *The manufacturing process of a composite material can introduce several defects and imperfection in the final component. This work aims to demonstrate a methodology to identify components out of design specifications using a Kriging Metamodeling. The base of the methodology is analysed a reference set of plates, and defining a baseline to the represent intact components, then it is compared the damaged plates or recently manufactured components to classify them accordingly to the design specifications. For this, a methodology that uses Kriging metamodeling to represent a set of composite plates and creates boundaries to a quick identification of damaged components. The results are analysed in order to evaluate the potentialities and limitations of the methodology. Therefore, the strategy presented can be helpful in the study of damage detection systems that uses Finite Element Method and dynamic analysis as part of its process.*

Keywords: *Composite materials, dynamic analysis, Kriging metamodeling, damage detection.*

1. INTRODUCTION

Differently, from metallic structures, properties of composites are not easy to control during manufacturing, and as a consequence, there is a level of uncertainty in the properties of these materials. These uncertainties make the design task difficult and increase the probability of errors in predicting the structure life cycle. Therefore, methodologies that take into account the materials properties and geometry uncertainties are very useful to support the engineering design process, and also the quality and control process of the composite industry (Jiang *et al*., 2008, Sriramula and Chryssanthopoulos, 2009, Chandrashekhar and Ganguli, 2009).

Kim and Sin (2001) proposed an algorithm to obtain the optimal design of composite laminated plates and observed that results for optimal thickness increases when elastic moduli uncertainties are considered, which indicates that such uncertainties should not be ignored at the design stage. Due to uncertainties, the repeatability of composite components, even in the same manufacturing process, is quite hard. Thus, it is not possible to define reference values to be used in the design phase, without experimental tests.

The Non-Destructive Testing (NDT) can be additionally applied to identify properties of a component during operation, which is known as damage detection methods. Successful damage detection in structures is essential for maintenance. Non Destructive Evaluation/Non-Destructive Testing, which can identify damage, may be used for this purpose. However, most of the non-destructive methods, such as ultrasonic methods, require the location of the damage and that location must be accessible. The methods based on vibration responses (VBM), usually do not show these limitations. The basis of vibration response methods is that damage changes the dynamic behaviour of the structure. Damage in a structure can alter the structural integrity, and therefore, the physics properties like stiffness, mass and/or damping may change, modifying the global structural dynamic response.

Dynamic analyses have shown high potential as NDT (Sinou, 2013). Different methods have been already presented in the literature using natural frequencies and the Frequency Response Function (FRF) to detect damages on composite structures (Montalvao, 2006). Several damage detection methods assume that damages cause changes in the mass and stiffness (Kessler *et al.*, 2002). However, to make this assumption, it is necessary to have a good definition of the intact state of the component. A usual methodology is to proceed non-destructive testing on all the components, just before and after the operation to verify its state (De Medeiros *et al.* 2018). This is required because, it is well known, that the characteristics of a composite component are not easy to control. The manufacturing process has several variables that can affect the final properties of the component. Therefore, depending on the manufacturing process and the design tolerances for the structure, it is possible to define a method to provide information about the acceptability of the components based on a set of specimens, reducing the time and cost of the non-destructive evaluations.

On the other hand, response surface methods have been used for a variety of applications. Echaabi *et al.* (1996) presented a review about the failures criteria such as Tsai-Wu, parametric formulations, maximal stress and strain, Hashin criterion, Hart-Smith criterion, and the method based on Kriging. The authors discuss their implementation for composite materials by pointing out the validity, advantages, and limitations of each one. Lanzi and Giavotto (2006) presented a multi-objective optimization procedure for the design of composite stiffened panels capable to operate in post-buckling. The procedure is based on Genetic Algorithms and three different methods of global optimization: Neural Networks, Radial Basis Functions and Kriging approximation. The obtained results prove the influence of the initial imperfections not only on the first-buckling load but also in the post-buckling range up to collapse. Jansson *et al.* (2007) evaluated approximation models used in conjunction with genetic algorithms by using a generic but industry relevant beam structure as an example problem. The accuracy of four different approximation methods was assessed, polynomial models with and without term selection, radial basis functions and Kriging. Lu *et al.* (2014) proposed a inverse procedure to identify the mechanical properties of both the carbon fibre and the interphase region based on computational micromechanics and kriging metamodel. Mukhopadhyay *et al.* (2017) showed a critical comparative assessment of Kriging model variants for surrogate based uncertainty propagation considering stochastic natural frequencies of composite doubly curved shells. The study reveals that Universal Kriging coupled with marginal likelihood estimate yields the most accurate results, followed by Co-Kriging and Blind Kriging.

Thus, considering the scenario pointed above, this work aims to contribute to the development of a methodology to identify the admissibility of the components, based on design characteristics and dynamic behaviour. Analysing the design variables most affected during the manufacturing process and the effects on the dynamic behaviour, aiming to define the tolerance limits of a set of components. To support this study, a numerical model is updated using a Kriging based methodology. Therefore, numerical and experimental results are used to compose a range of possibilities for the FRF that can be used to verify the state of other composite plates. Finally, there is a discussion on damage detection by VBM and metamodels.

2. METHODOLOGY

The structural dynamic response of composite plates is investigated evaluating the influence of the manufacturing process. Experimental and numerical tests are performed and compared to understand the variabilities of the component properties. To study the design variables influence in the dynamic response, a Design of Experiments method is applied in the structure. Furthermore, analysing the experimental data, it is possible to infer the frequency range of the composite plate set. Therefore, to obtain the numerical model that represents the frequency range bounds, a model update process is required. This is a very standard procedure to adjust numerical with experimental or analytical models presented in the literature. However, depending on the complexity of the problem, it can become computationally expensive. Some techniques, like metamodels, can be used to approximate the expensive computational model to an analytical solution, and solve the problem quickly. Therefore, the numerical FRFs, to represent the boundaries, can be calculated and used as a reference to evaluate the quality of the manufactured components. Figure 1 shows the methodology workflow.

More details about the design of experiments used in this work can be obtained in Souza *et al.* (2019). The influence of different parameters is evaluated and the four most important design variables are defined to study the dynamic behaviour of composite plates. The proposed methodology uses the Kriging metamodeling instead of finite element analysis to obtain the materials properties of a component. Then, these properties can be used in the finite element model to acquire the dynamic behaviour data. The experimental analyses were performed on 9 composite plates. Five plates are made of eight layers stacked in $[0]_8$ layup configuration, and the others are made of 12 layers stacked in $[0/15/-15/0/15/-15]_s$. The specimens are manufactured using filament-winding process.

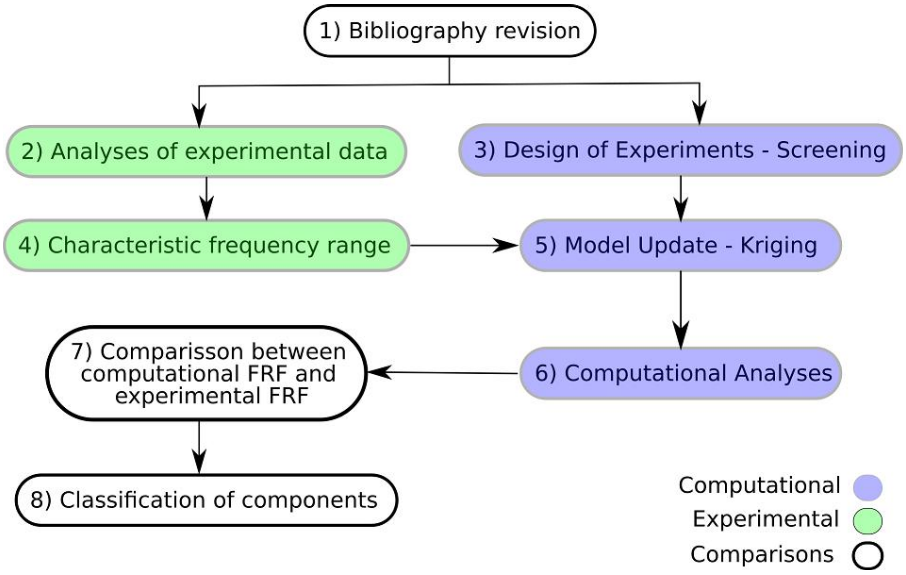

Figure 1. Methodology flowchart (Souza, (2018))

2.1 Kriging Metamodeling

Metamodels are known as response surfaces, surrogates, emulators, auxiliary model. According Kleijnen *et al.* (2009), a metamodel is an approximation of the Input/Output (I/O) function that is implied by the underlying simulation model. Surrogate models, as Kriging, are fitted to data that are obtained for larger experimental areas.

Kriging model is constructed based on the correlation function theory. Particularly, it is an exact interpolation of the given data and goes through all the sampling points. Therefore, the Kriging model usually has a higher approximation accuracy than traditional Root Mean Square (RSM). Jeong *et al.* (2005) applied the kriging-based genetic algorithm to aerodynamic design problems. The kriging model drastically reduces the computational time required for objective function evaluation in the optimization (optimum searching) process.

This technique considers the relationship between input and output as a black-box system, and other system information, such as the internal process of dynamic analysis is not required. It can create, for example, a fast running surrogate model to replace the exact FEA, and then the solving time of optimization will be reduced significantly. Thus, the potential of metamodel techniques is indisputable in model updating field. A comparison of the most commonly used metamodels is presented by Simpson *et al.* (2001a). In addition, Simpson *et al.* (2001b) investigated the use of kriging models as alternatives to traditional second-order polynomial response surfaces, for constructing global approximations to use in a real aerospace engineering application, namely, the design of an aerospike nozzle. They find that the kriging models yield global approximations that are slightly more accurate than the response surface models.

The best linear unbiased predictor, also known as Kriging, is a surrogate model, frequently used to represent a physic phenomenon or process, which is difficult to represent by numerical models or to measure experimentally. The name Kriging was introduced by Matheron (1963), in honour of the South African mining engineer Danie Krige, who first developed the method now called Kriging (Krige, 1951). Kriging made its way into engineering design following the work of Sacks *et al.* (1989), who applied the method to the approximation of computer experiments.

For a given set of samples data, $\boldsymbol{X} = \boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_n}^T$, and the observed responses, $\boldsymbol{Y} = \boldsymbol{y_1}, \boldsymbol{y_2}, ..., \boldsymbol{y_n}^T$, the expression of the Kriging model that reflects the relationship between them is,

$$y(\boldsymbol{x_i}) = \boldsymbol{f}^T(\boldsymbol{x_i})\boldsymbol{\beta} + z(\boldsymbol{x_i}), \tag{1}$$

where $\boldsymbol{f}(\boldsymbol{x})$ is a polynomial vector of the sample $\boldsymbol{x}$, $\boldsymbol{\beta}$ is the vector of the linear regression coefficients to be estimated, and $z(\boldsymbol{x_i})$ represents errors and is assumed to be a stochastic process that follows a normal distribution of $N(0, \sigma^2)$, with a zero mean and standard deviation σ.

The fundamental assumption of the Kriging model is that the same input will lead to an identical output. Therefore, the deviation between the output response and the polynomial regression part is only due to the modelling error itself, regardless of the measurement error and other random factors. This method does not depend on the simulated precision of the polynomial part to the response surface but focuses on constructing the appropriate surrogate model by the effective filling of the stochastic process part, which makes it more suitable for dealing with non-linearity. Thus, the polynomial part is often taken as a constant in some other references.

To estimate the stochastic process $z(\boldsymbol{x})$, the Kriging method assumes that the true response surface is continuous, any two points will tend to have the same value as the distance in between approaches zero, and it is the same for $z(\boldsymbol{x})$ of two points. Thus, the correlation between $z(\boldsymbol{x})$ of any two sample points can be expressed as a function of their spatial distance. The most widely used Gaussian correlation model is adapted as,

$$R(z(\boldsymbol{x_i}), z(\boldsymbol{x_j})) = exp\left(-\sum_{k=1}^{m} \theta_k |x_i^k - x_j^k|^2\right), \tag{2}$$

where x_i^k and x_j^k are the k^{th} components of the two sample points $\boldsymbol{x_i}$ and $\boldsymbol{x_j}$, m denotes the number of design variables, θ_k controls the decay rate of correlation on different dimensions. And, then the matrix of correlation functions between sample points is obtained as,

$$\boldsymbol{R} = \begin{Bmatrix} R(\boldsymbol{x}_1, \boldsymbol{x}_1) & \cdots & R(\boldsymbol{x}_1, \boldsymbol{x}_n) \\ \dots & \ddots & \dots \\ R(\boldsymbol{x}_n, \boldsymbol{x}_1) & \cdots & R(\boldsymbol{x}_n, \boldsymbol{x}_n) \end{Bmatrix}. \tag{3}$$

The likelihood function of the sample point can then be written as,

$$L = \frac{1}{(2\pi\sigma^2)^{\frac{m}{2}} |\boldsymbol{R}|^{\frac{1}{2}}} exp\left[-\frac{(\boldsymbol{Y} - \boldsymbol{F}\boldsymbol{\beta})^T \boldsymbol{R}^{-1} (\boldsymbol{Y} - \boldsymbol{F}\boldsymbol{\beta})}{2\sigma^2}\right], \tag{4}$$

where $\boldsymbol{F}$ is a matrix of vector $\boldsymbol{f}(\boldsymbol{x})$ for each sample point. $|\boldsymbol{R}|$ is the determinant of $\boldsymbol{R}$ which is a function of θ_k. According to the maximum likelihood function method, one can get,

$$\hat{\boldsymbol{\beta}} = \left(\frac{\boldsymbol{F^T}\boldsymbol{R}^{-1}\boldsymbol{Y}}{\boldsymbol{F^T}\boldsymbol{R}^{-1}\boldsymbol{F}}\right), \tag{5}$$

$$\hat{\sigma}^2 = \frac{((\boldsymbol{Y} - \boldsymbol{F}\boldsymbol{\beta})^T \boldsymbol{R}^{-1} (\boldsymbol{Y} - \boldsymbol{F}\boldsymbol{\beta}))}{n}. \tag{6}$$

Based on this, the logarithm form of the maximum likelihood function can be written as,

$$ln(L) \approx -\frac{m}{2} ln(\hat{\sigma}^2) - \frac{1}{2} ln|\boldsymbol{R}|. \tag{7}$$

The maximum value of the function above is solved by the genetic algorithm to determine the value of the decay rate θ_k on different dimensions. At this point, a Kriging model linking the sample point and the response is constructed. The next step is to predict the value of the new points. For any point $\boldsymbol{x}_0$, following the principle that the predicted value for the point continue to maximize the augmented likelihood function of both the sample point and the new point, the predicted response value can be obtained by,

$$\hat{y}(\boldsymbol{x}_0) = \boldsymbol{f^T}\hat{\boldsymbol{\beta}} + \boldsymbol{r^T}(\boldsymbol{x}_0)\boldsymbol{R}^{-1}(\boldsymbol{Y} - \boldsymbol{F}\hat{\boldsymbol{\beta}}). \tag{8}$$

And the mean squared error (MSE) of the predictor can also be calculated to estimate the accuracy of the predicted value, which is denoted by $\hat{s}^2(\boldsymbol{x})$,

$$\hat{s}^2(\boldsymbol{x}) = \sigma^2 \left[1 - \boldsymbol{f}^T\boldsymbol{x}, \boldsymbol{r}^T\boldsymbol{x} \begin{bmatrix} 0 & \boldsymbol{F^T} \\ \boldsymbol{F} & \boldsymbol{R} \end{bmatrix}^{-1} \begin{Bmatrix} \boldsymbol{f}(\boldsymbol{x}) \\ \boldsymbol{r}(\boldsymbol{x}) \end{Bmatrix}\right], \tag{9}$$

where $\boldsymbol{r}^T(\boldsymbol{x}_0)$ is a row vector of the correlation function between the new point and each sample point,

$$\boldsymbol{r}^T(\boldsymbol{x}_0) = [R(\boldsymbol{x}_0, \boldsymbol{x}_1), ..., R(\boldsymbol{x}_0, \boldsymbol{x}_n)]. \tag{10}$$

It is worth noting that when the value of the i^{th} sample point is predicted, since $\boldsymbol{r}^T(\boldsymbol{x_i})\boldsymbol{R}^{-1}$ equals the i^{th} order unit vector, therefore,

$$\hat{y}(\boldsymbol{x}_i) = \boldsymbol{f^T}(\boldsymbol{x}_i)\hat{\boldsymbol{\beta}} + y_i - \boldsymbol{f^T}(\boldsymbol{x}_i)\hat{\boldsymbol{\beta}} = y_i, \tag{11}$$

which shows that the Kriging model predicts the real response value at the sample point, that is why it can be considered an interpolation technique.

3. DAMAGE IDENTIFICATION ANALYSIS

Damage identification by vibration based methods is supported by the hypothesis that damages cause changes in mass and stiffness matrix. However, this results from the degradation of material properties or alteration of geometry characteristics. Therefore, using the methodology proposed in this work, two different results can be obtained. First, the indication of damage type can be done based on the correlation of the variation in natural frequencies and the effect of the design variable, presented during the screening analysis. Another result is to verify if the damage caused is enough to characterize the plate as out of specification, using the range of FRFs.

Figure 2 shows the experimental layout used to acquire the dynamic response of the system. The experimental methodology applied here is based on the use of a drop tower to imply impact damage on the composite plates, and after analysing the specimens with the C-Scan test to evaluate the damage extension. Cracks are observed on the damaged structures, and natural frequencies are obtained to evaluate the changes in the dynamic response (De Medeiros, (2016)). The intact natural frequency of the six natural modes of the composite plates is evaluated. Considering that is admissible a variation of one standard deviation to classify the component measured, it is possible to compare the damaged results against the limits calculated from the intact plates. To obtain the dynamic behaviour of the components that virtually represents the limits, a Kriging metamodel can be used.

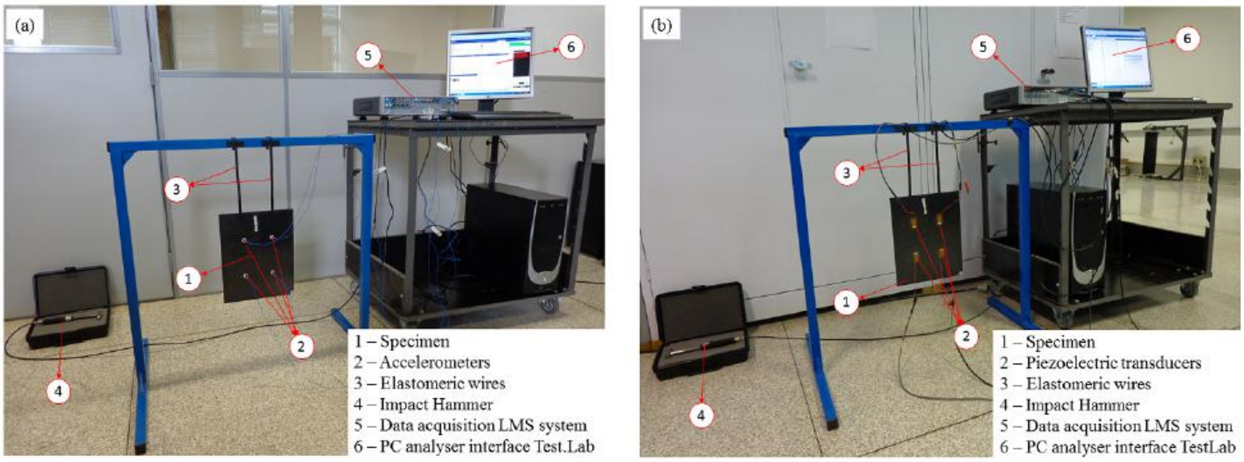

Figure 2. (a) Vibration tests: specimens with (a) accelerometers and (b) MFC sensors (De Medeiros, (2016)).

The natural frequencies and FRFs were obtained using accelerometers or PZT sensors. Figure 2 shows all data acquisition setups used in the experiments. The specimen is suspended using elastomeric wires to simulate 'free–free' boundary conditions. The accelerometers (Figure 2(a)) and MFC transducers (Figure 2(b)) and the hammer were connected to an LMS SCADAS Mobile equipment, which was controlled by the Test.Lab software (LMS Test.Lab). The excitation for both sets of vibration tests was applied using an impulse signal through an impact hammer PCB Model 0860C3 (Piezotronics). Each signal consists of 2048 points and sampling occurred from 0 to 512 Hz. It selected the frequency band of 512 Hz for the first five natural frequencies of the structure. The number of averaging individual time records was selected to be five in order to reduce the variation effects.

3.1 Results for plates with stacking sequence of $[0]_8$

Using the same experimental data presented by Souza *et al.* (2019), it is possible to calculate and graphically (Figure 3) represent to limits of the intact plates (lines) based on the set of specimens studied. Additionally, the frequency of the composite plates after the impact damage are represented as dots. In a quick evaluation, it is possible to see for each mode, which plate remains in the frequency limits and which ones are outside. This is a graphical tool that helps to evaluate how the damage has been changed the dynamic behaviour of the components.

It is clear that modes 2 and 3 are out of the bounds, indicating some difference in dynamic behaviour in relation to the reference set of plates (intact plates). Therefore, it is possible to state that the evaluated plates are not able to continue to be applied to future components. Additionally, cracks are observed on the impacted plates at $[0]_8$ by C-scan technique indicating a long crack in the fibre direction. The natural frequency analysis indicates a high difference between intact and damaged frequency in the 2^{nd} mode, which is strongly affected by changes in E_{22} (Young modulus normal to the fibre). Changes in E_{22} can characterize matrix cracks in a unidirectional laminate, and this is confirmed by the C-Scan results (Figure 4).

The image of the damaged plate shows a crack propagated on the transverse direction, which reduces the E_{22} of the material. This effect is remarked on the experimental results, where a reduction of 18% is observed (De Medeiros, (2016)).

Also, in the numerical results have been indicated the same behaviour, which shows that a reduction in the transversal Young's modulus results in a reduction in the natural frequency (Souza *et al.* (2019)).

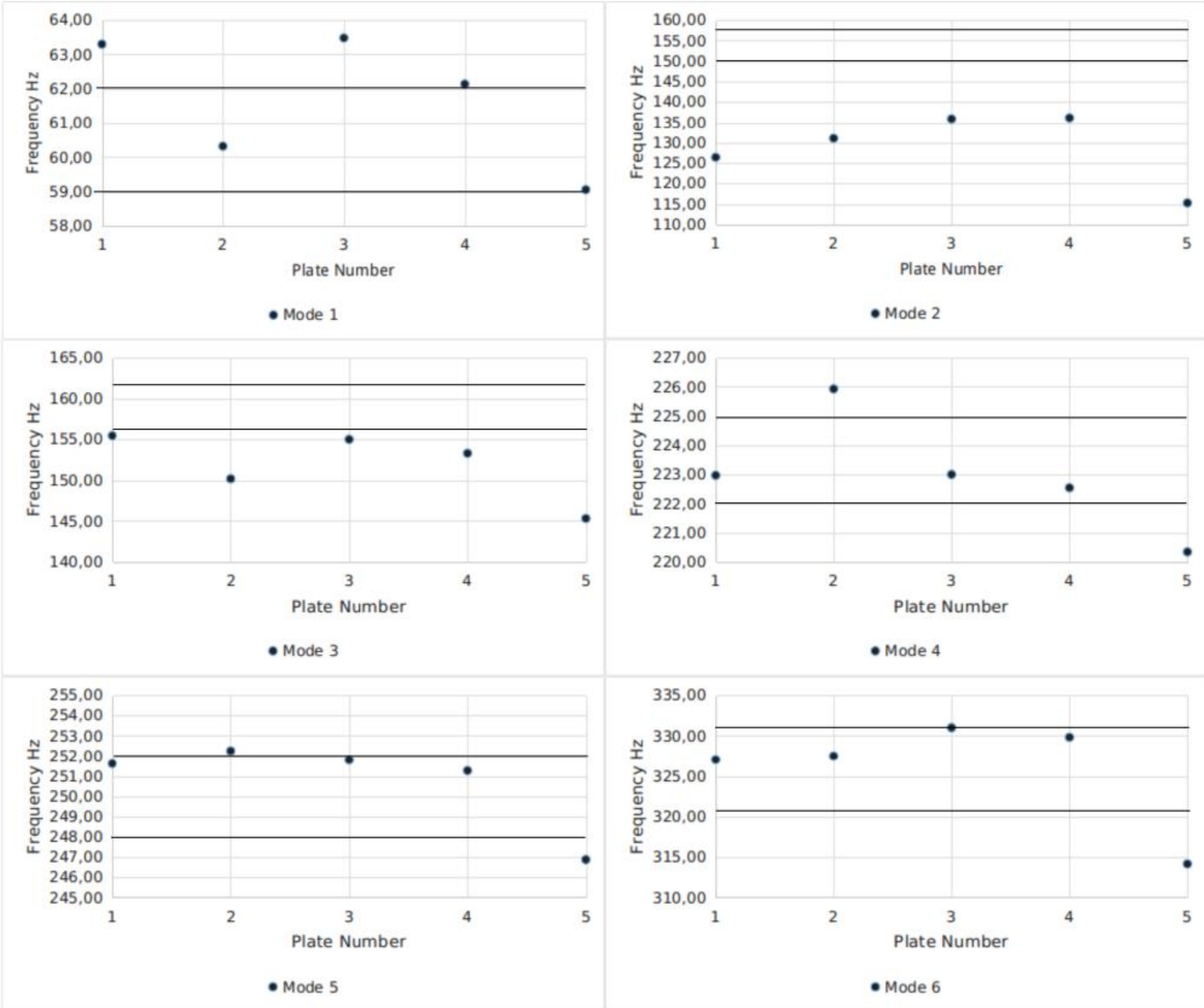

Figure 3. Maximum and minimum limits of the intact composite plates (lines) and damaged frequencies of composite plates (dots) with stack sequence of $[0]_8$.

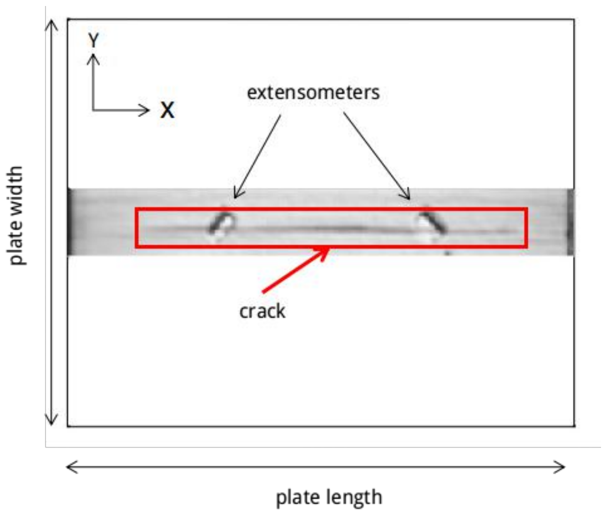

Figure 4. Damage observed by C-scan technique: $[0]_8$, red box highlights the crack on the plate.

3.2 Results for plates with stacking sequence of $[0/15/\text{-}15/0/5/\text{-}15]_s$

Considering the stacking sequence of $[0/15/\text{-}15/0/5/\text{-}15]_s$, the natural frequencies of the damaged plates do not differ much from the intact plates (Figure 5), because the extent of damage is much more restricted. The propagation of a crack in the unidirectional plates is not hindered, whereas the $\pm15°$ orientation of the fibres creates natural barriers for the extent of damages. The C-Scan evaluation (Figure 6) of the $[0/15/\text{-}15/0/5/\text{-}15]_s$ plates shows a combination of matrix and fibre cracks. Therefore, in the set of evaluated plates, it is possible to state that plates 11 and 12 are of bounds. These plates can be considered damaged by the implemented methodology. Plates 9 and 10 can be considered intact even after the intentional impact caused during the tests.

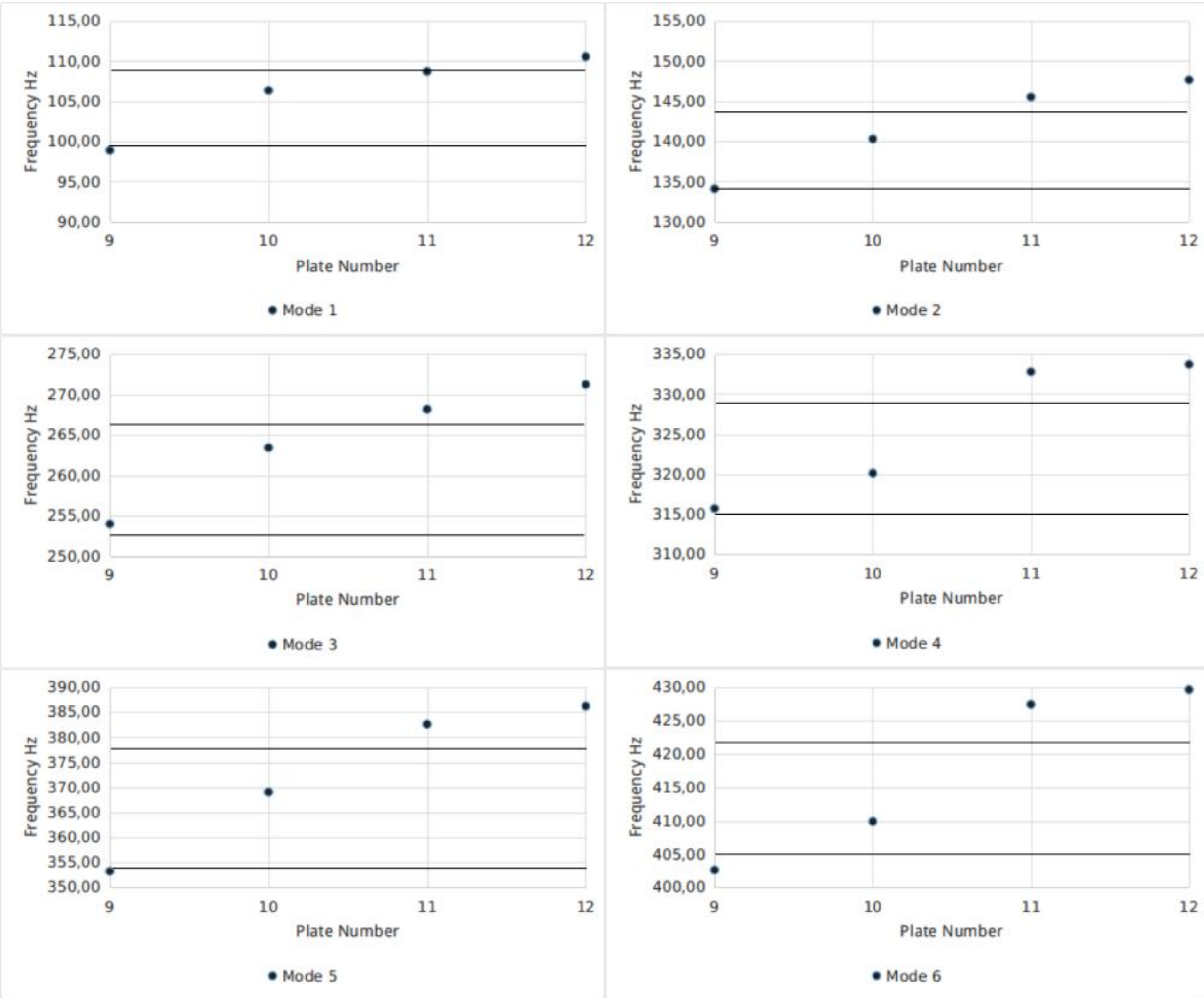

Figure 5. Maximum and minimum limits of the intact composite plates (lines) and damaged frequencies of composite plates (dots) with stack sequence of $[0/15/\text{-}15/0/5/\text{-}15]_s$.

For $[0/15/\text{-}15/0/5/\text{-}15]_s$ plates, it is observed a more significant effect of E_{11} on 4^{th} mode. Although the highest influence is provided by the thickness, as expected due to the greater number of layers, the 4^{th} mode remains more sensitive to changes in Young's modulus in longitudinal direction, but 2^{nd} and 6^{th} modes remain more sensitive to changes in Young's modulus in transverse direction. Differently from the $[0]_8$ plates, the 5^{th} mode has a lower effect, it is due to the fibre orientations and the mode shape. On the 5^{th} mode there are more nodal lines oriented at 15°, reducing the effect of the Young's modulus in longitudinal direction.

In addition, the image of the damaged plate shows a crack concentrated near the impact zone. This effect is remarked on the experimental results, where a maximum reduction is less than 4% is observed (De Medeiros, (2016)). Also, in the numerical results have been indicated the same behaviour, which shows that a reduction in the natural frequency (Souza *et al*. (2019)).

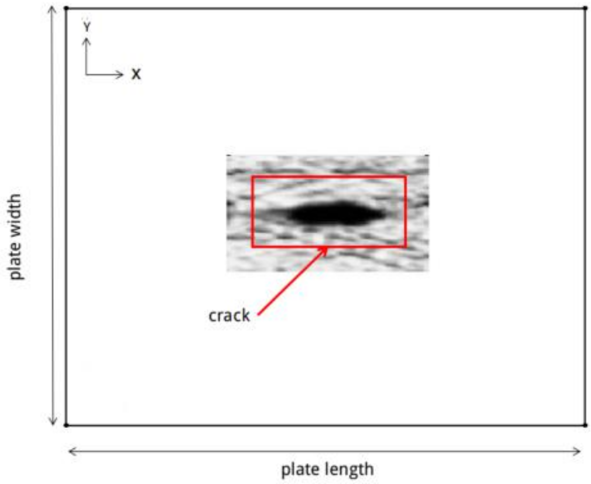

Figure 6. Damage observed by C-scan technique: $[0/15/\text{-}15/0/5/\text{-}15]_s$, red box highlights the crack on the plate.

4. CONCLUSION

Several uncertainties can be generated during the composite components manufacturing. It makes the design process complex and also difficulties the quality control process in the industry. This work presented a methodology to evaluate a restricted set of components, where allow to modelling computationally the behaviour of this set. Then, other manufactured components have its integrity evaluated against this reference model. This process allows a quality control based on the uncertainties of the manufacturing systems settled. The evaluated data presented in this work shows the applicability of the methodology and its potential for industrial usage.

Regarding the $[0]_8$ stacking orientation, it is possible to observe that the modes 2 and 3 are out of the bounds. This case study clearly shows the influence of matrix crack damage on 2^{nd} mode, which is directly related with E_{22} parameter. Regarding the the stacking sequence of $[0/15/\text{-}15/0/15/\text{-}15]_s$, the damage caused on plates have less effect on the dynamic behaviour when compared with the other ones. However, it is possible to note that plates 11 and 12 have almost all of its modes out of the bounds. Therefore following the methodology, these plates are not able to perform its functions as structural components.

Therefore, these results show that it is possible to identify components with the required specifications in terms of dynamic behaviour. In other words, there is a good perspective for the application of this methodology in Structural Health Monitoring (SHM) systems for composite structures.

5. AKNOWLEDGMENTS

The authors acknowledge the financial support of the Santa Catarina State Research and Innovation Funding Agency (FAPESC process number: 2017TR1747 and 2017TR784). As well as, Coordination for the Improvement of the Higher Level Personnel (CAPES process number: 011214/2013-09 and Finance Code 001), São Paulo State Research Foundation (FAPESP process number: 2012/01047-8 and 2015/15221-8), National Council for Scientific and Technological Development (CNPq process number: 401170/2014-4 and 310094/2015-1). The authors also would like to thank Navy Technological Centre (CTM – Brazil) for manufacturing specimens and Prof. Joel Martins Crichigno Filho (Santa Catarina State University – Brazil) for kindly providing the use of the ABAQUS^{TM} license.

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