DAMAGE INDEXES COMPARISON FOR THE STRUCTURAL HEALTH MONITORING OF A STIFFENED COMPOSITE PLATE

N. MECHBAL* & M. REBILLAT*

*PIMM – ENSAM/CNAM/CNRS,
151, Bd de l'Hôpital, 75013 Paris, France
e-mail: nazih.mechbal@ensam.eu & marc.rebillat@ensam.eu

Keywords: Structural Health Monitoring, Smart Structures, Composite Materials, Stiffener, Damage Detection, Lamb Waves, Performance Assessment, Robustness.

Abstract: Stiffened composite structures are very appealing in aeronautic applications due to their unique stiffness to mass ratio. However, they are also prone to various and complex damage scenario (stiffener debonding, impact damage...) and to complex wave propagation phenomena due to the presence of the stiffener. Consequently, autonomous monitoring of such structure is still a real issue. The process of monitoring in real-time a structure is referred to structural health monitoring (SHM) and consists of several steps: damage detection, localization, classification, and quantification. The focus is put here on the damage detection step of SHM. To detect damages, stiffened composite structures are equipped with piezoelectric elements that act both as sensors and actuators. A database at the unknown (and possibly damaged state) is then compared to a healthy reference database. Several damage indexes (DIs) designed for detection are extracted from this comparison. The SHM process classically relies on four sequential steps: damage detection, localization, classification, and quantification. The most critical step of such process is the damage detection step since it is the first one and because performances of the following steps depend on it. A common method to design such a detector consists in relying on a statistical characterization of the damage indexes available in the healthy behavior of the structure. On the basis of this information, a decision threshold can then be computed in order to achieve a desired probability of false alarm (PFA). In this paper, the performances of these DIs with respect to damage detection in a stiffened composite plate are studied. Results show that DIs based on energy consideration perform better than the ones based on cross-correlation. Furthermore Fourier-transform based DIs appear to be insensitive to the presence of damage in such structure.

1. INTRODUCTION

In aeronautic industry, composite materials are increasingly used due to their high strength properties. Because of their multilayer structure, they are inherently suitable to host smart materials. Indeed, embedded sensors and actuators (like piezoelectric transducers) can be permanently incorporated during the manufacturing process into the composite [1]. They can then be used to collect information about the structure through the analysis of guided waves signals in order provide a diagnosis of its current health and a prognosis of its remaining life [2]. This approach is called Structural Health Monitoring (SHM) and offers a new approach to interrogate the integrity of structures in real-time, unlike traditional techniques such as Non-Destructive Testing (NDT) which require operators to perform the inspection [3, 4].

However, fiber reinforced materials are more complex than traditional materials such as metals. Their structural anisotropy and the fact that they contain different phases of material (fibers and matrix) generally results in various types of damage with different evolution characteristics. Damage detection and determination of the remaining strength and life of the structure remains a challenging task in that context. This is particularly the case when dealing with composite structures with complex geometry and co-bonded stiffeners as frequently applied in aircraft components. In this case, attenuation and dispersion of Lamb waves induced by reinforced stiffeners must be evaluated [5] in order to enhance the probability of detection (PoD) and to ensure a given probability of false alarm (PFA) in the context of the detection step of a SHM process [6, 7, 8].

To detect damages, smart-structures are equipped with piezoelectric elements that act both as sensors and actuators. A database at the unknown (and possibly damaged state) is then compared to a healthy reference database. Several damage indexes (DIs) designed for detection are extracted from this comparison. To date, most service life predictions are based on measurements of DIs and their growth towards criticality or failure, e.g. fatigue crack length, material loss due to corrosion or wear, etc… However, the dissemination of instrumentation technologies, complex structures, harsh environments, and operational variability has led to the development of a large variety of DIs [6].

The aim of the present paper is to compare the performances of several families of classical DIs for the challenging task of damage detection in a stiffened composite plate. The paper is organized as follows: the experimental setup is first presented in Section 2, before in traducing the proposed damage detection methodology in Section **Erreur ! Source du renvoi introuvable.**. Results are then presented in Section 0 and discussed in Section **Erreur ! Source du renvoi introuvable.**.

2. EXPERIMENTAL SETUP

The composite structure we are interested in is a composite stiffened plate (see Figure 1). This structure is geometrically complex and is made of composite monolithic carbon epoxy. It is a multilayered structure consisting of 4-plies oriented along $[0°/\,45°/-45°/\,0°]$. This structure is 400 mm in width for a height of 300 mm.

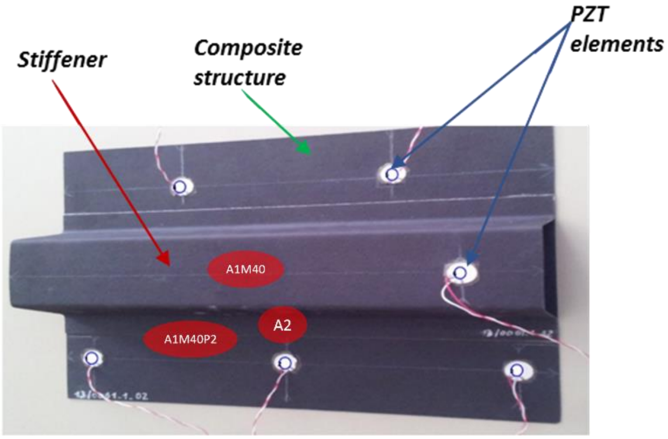

Figure 1: Stiffened composite plate under study

A network of 6 piezoelectric elements used as actuators and sensors has been bonded to the surface of the stiffened plate and is used to emit and collect signals. The PZT elements used are numbered from 1 to 6 and mounted at specific positions on the composite plate's surface as shown in Figure 1. The PZT elements have a diameter of 20 mm, a thickness of $0.1\,mm$ and have been manufactured by Noliac.

Three types of damage are considered in the present study. The first two damages are made using Neodymium magnets placed on both sides of the composite: one is located on the monolithic part of the composite plate (A1M40) and the other one is located on the stiffener (A1M40P2). Finally, damage 3 corresponds to a real debonding on the center of the bottom part of the stiffener (A2).

3. DAMAGE DETECTION METHODOLOGY

The methodology proposed for the detection of the damage appearing on the stiffened composite structure is summarized in Figure 2.

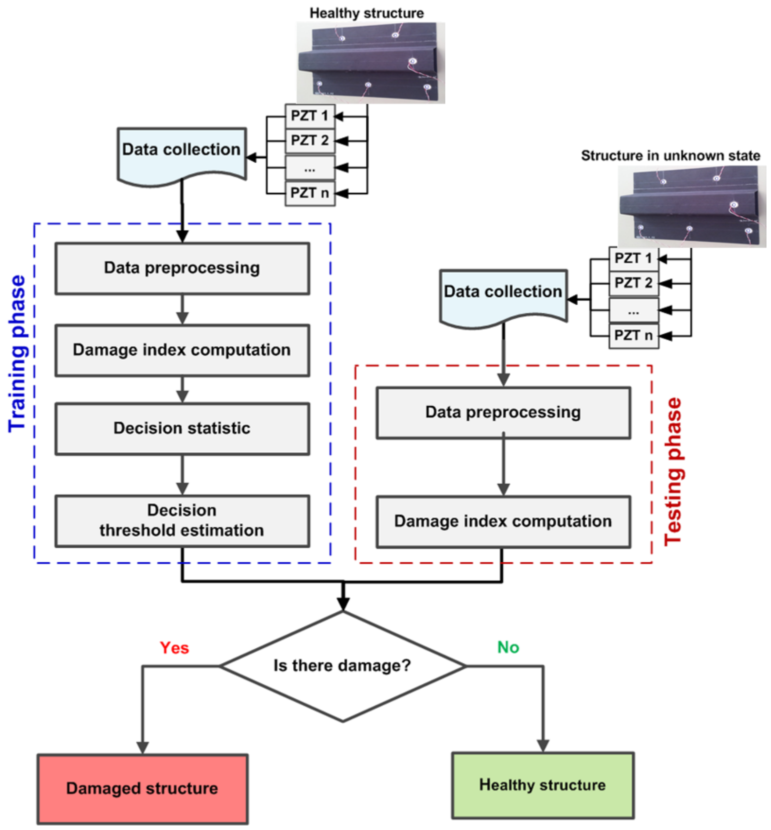

Figure 2: Damage detection methodology.

a. Data preprocessing

Structural health monitoring is achieved here by means of Lamb waves [9, 10]. This method is based on the principle that Lamb waves can propagate in the structure and will thus necessarily interact with damage. Information is then extracted from the waves diffracted by the damage for detection purposes. The excitation signal sent to the PZT element is a 5 cycles *"burst"* with a central frequency of $200\ kHz$ and with an amplitude of $10\ V$. In each phase of the experimental procedure, one PZT is selected as the actuator and the other act as sensors. All the PZTs act sequentially as actuators. Resulting signals are then simultaneously recorded by the others piezoelectric element and consist of 1000 data points sampled at $1\ MHz$. For all configurations 100 repetitions are performed to have enough data for a statistical approach.

As pre-processing steps, the measured signals are first denoised by means of a discrete wavelet transform up to the order 4 using the *"db40"* wavelet. Those signals are then filtered around their center frequency using a continuous wavelet transformation based on *"morlet"* wavelets and with a scale resolution equals to 20. The diaphonic part present in the measured signals (*i.e.* the copy of the input signals that appears on the measured signal due to electromagnetic coupling in wires) has been previously eliminated on the basis of the knowledge of the geometrical positions of the PZT and of the waves propagation speed in the material.

b. Damage Index (DI) computation

The damage index represents a crucial step for the design of the detector as this feature must correctly reflect the effect of the damage on the structure. The DIs chosen for this study are obtained as follows given a reference healthy signal $x_{ij}(t)$ and a signal $y_{ij}(t)$ corresponding to an unknown state for the path from actuator i to sensor j are given in Figure 3.

DI name	Comments	Definition
CCA	MATLAB based implementation of the maximum of the correlation	$1 - \max\left(xcorr\left[x_{ij}(t), y_{ij}(t)\right]\right)$
CC0	MATLAB based implementation of the zero-lag correlation	$1 - xcorr\left[x_{ij}(t), y_{ij}(t)\right](0)$
CRC	MATLAB-based implementation of the correlation coefficient	$1 - corrcoeff\left[x_{ij}(t), y_{ij}(t)\right]$
NRE	Normalized residual energy	$\int_0^T \left(x_{ij}(t) - y_{ij}(t)\right)^2 dt$
MA	Maximum amplitude of the difference	$\max\left[x_{ij}(t) - y_{ij}(t)\right]$
FFT	FFT of the difference signal at f_0	$\max\left[x_{ij}(t) - y_{ij}(t)\right]$
ENV	Maximum envelope of the difference	$\max\left[ENV(x_{ij}(t) - y_{ij}(t))\right]$

Figure 3: Implemented damage indexes

These DIs belong to three families. DIs CC, CCA, CC0 and CR are all based on the notion of correlation. DIs NRE, MA and ENV are all based on an energy based processing of the difference signal. The last one, FFT, is based on a frequency analysis of the signals around the center frequency.

The damage indexes DI_{ij} computed for each path “actuator i to sensor j” are then integrated together. This leads to a global damage index DI_G defined as follows:

$$DI_G = \sum_{i=1}^{N_{act}=6} \sum_{j=1}^{N_{sen}=6} DI_{ij}$$

By rotating the reference healthy signal and the signal corresponding to an unknown state (healthy or damaged), important DI-databases are obtained. Among these different databases, the one obtained by comparing the healthy set to itself is very interesting as it allows characterizing the healthy behavior of the structure and to compute the decision thresholds. This database will be the input of the detector design methodologies presented in the next section.

c. Damage detector design using Parzen window estimator

We considered the decision thresholds estimated based on a nonparametric Parzen window estimator [10] as reference. The Parzen window adjustment is a nonparametric mean to estimate the probability density function of a random variable x known on N samples. It is commonly referred to as “kernel density estimator” because kernel functions are used to estimate the probability density function [11]. The analytical expression of the nonparametric Parzen window probability density function is [12]:

$$\hat{f}_{N,h}(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{x - x_i}{h}\right) \quad (1)$$

where $K(.)$ and h are the kernel function and the window width respectively. The idea behind the Parzen window is to estimate the density probability function on N sample values thanks to a kernel function $K(.)$ which is most of the time a probability density function. The closer the observation x is to training samples x_i the larger is the contribution to $\hat{f}_{N,h}$ of the kernel function centered on x_i. Conversely, training observations x that are far from x_i have a negligible contribution to $\hat{f}_{N,h}$. This estimator of the probability density function is formed by averaging of the kernel function values (see Figure 4).

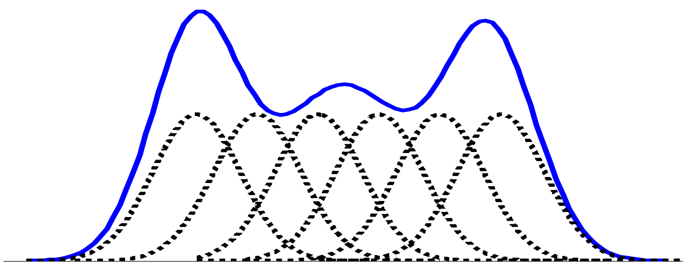

Figure 4: Probability density function of a random variable and some Gaussian kernels

This estimator is governed by the smoothing parameter h called window width. Under some non-binding restrictions on h, the Parzen window estimator is consistent. It exists several kernel functions (Gaussian, box, triangle…) but the Parzen window performances depend mainly on the choice of the window width h. It exists several methods to choose h. In this study, a Gaussian kernel has been used according to Eq. (*2*). Silverman [13] has determined an optimal window width value used a so-called "rule of thumb" when the distribution is Gaussian. This window width depends on an estimation of the variance $\hat{\sigma}$ and the learning data set size N according to Eq. (3).

$$K(x) = \frac{1}{\sqrt{2\pi}} \times e^{\left(\frac{x^2}{2}\right)} \tag{2}$$

$$h = \hat{\sigma}\left(\frac{4}{3\times N}\right)^{\frac{1}{3}} \tag{3}$$

According to the nonparametric Parzen window probability density function, $\hat{f}_{N,h}$, presented above in Eq. (*1*), and after the choice of the window width h using Eq. (3), the decision threshold, S, may be determined according to a requested probability of false alarm (PFA) and given a learning sample size N using Eq.(4).

$$S = \left\{ S \text{ such that} \int_{S}^{+\infty} \hat{f}_{N,h}(x)dx = \frac{1}{Nh}\sum_{i=1}^{N}\int_{S}^{+\infty} K\left(\frac{x-x_i}{x}\right)dx = \text{PFA} \right\} \tag{4}$$

4. RESULTS

This section presents the results obtained when computing the DIs defined in Figure 3 for the different damage cases depicted in Section 2. Their performances are assessed with respect to a decision threshold determined accordingly with the procedure described in Section **Erreur ! Source du renvoi introuvable.**.

a. Normalized probability density functions

The normalized probability functions (PDF) for the different DIs described in Figure 3 for different damage scenario are presented in Figure 5. From this figure, the behavior of the three DIs families previously mentioned can be clearly identified. The correlation based DIs all provide PDF that are above the decision threshold for the case A2 but that are very close or below it for the two other cases. The energy based ones all perform very well for each case. Finally, the frequency based one do not perform well at all as the PDFs corresponding to the different damage cases are not separated at all.

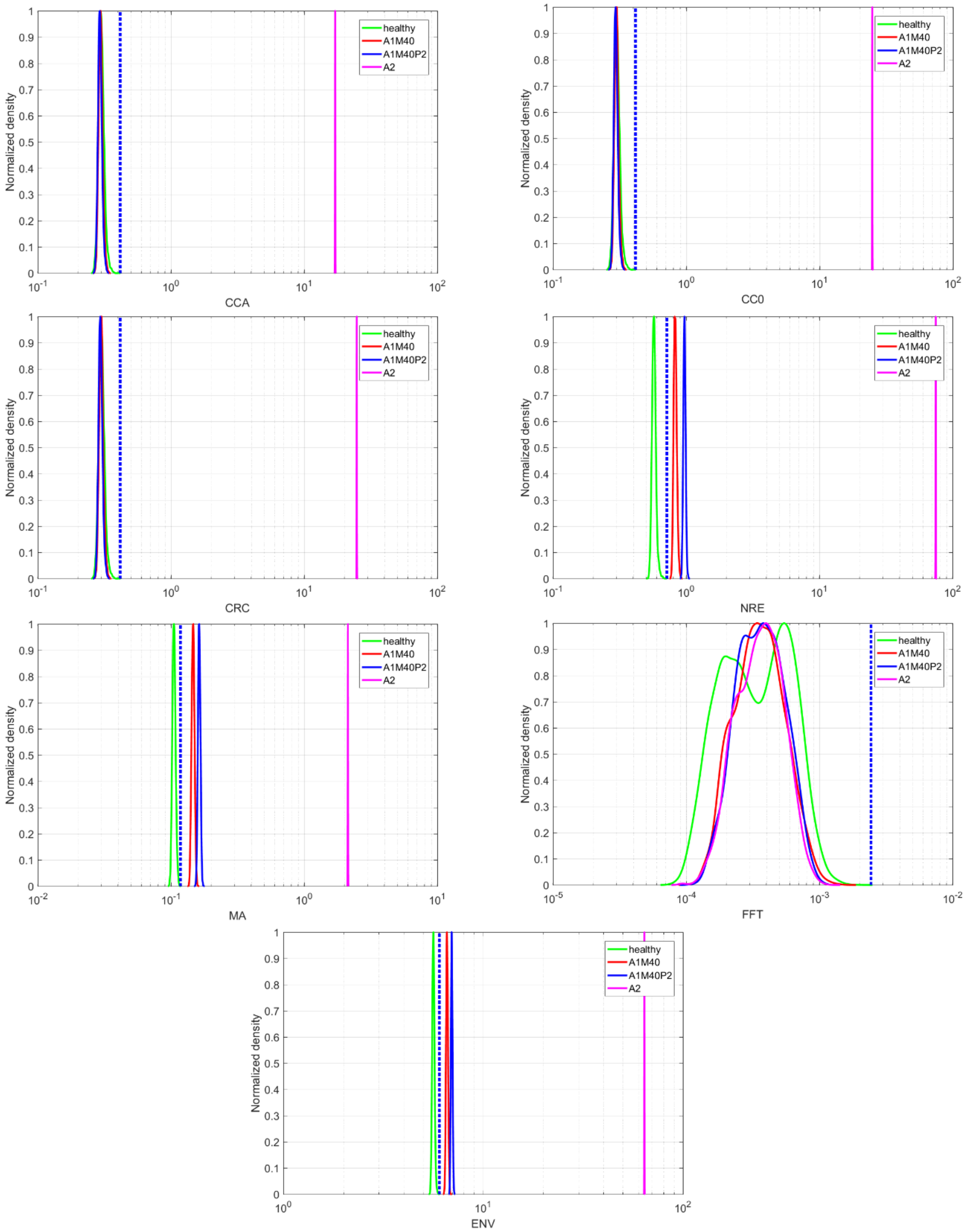

Figure 5: Normalized probability density functions for the different DIs and for the different damage cases.

b. Receiver Operating Characteristic

The Receiving Operator Characteristic (ROC) for the different DIs described in Figure 3 for different damage scenario are presented in Figure 6. From this figure, the performances of the three DIs families previously mentioned can again clearly be stated. The correlation based DIs all provide ROC curves that highlight good performances for the case A2 but poor ones for the two other cases. The energy based ones all perform very well for each case. Finally, the frequency based one do not perform well at all as the ROC corresponding to the different damage cases are close to the diagonal.

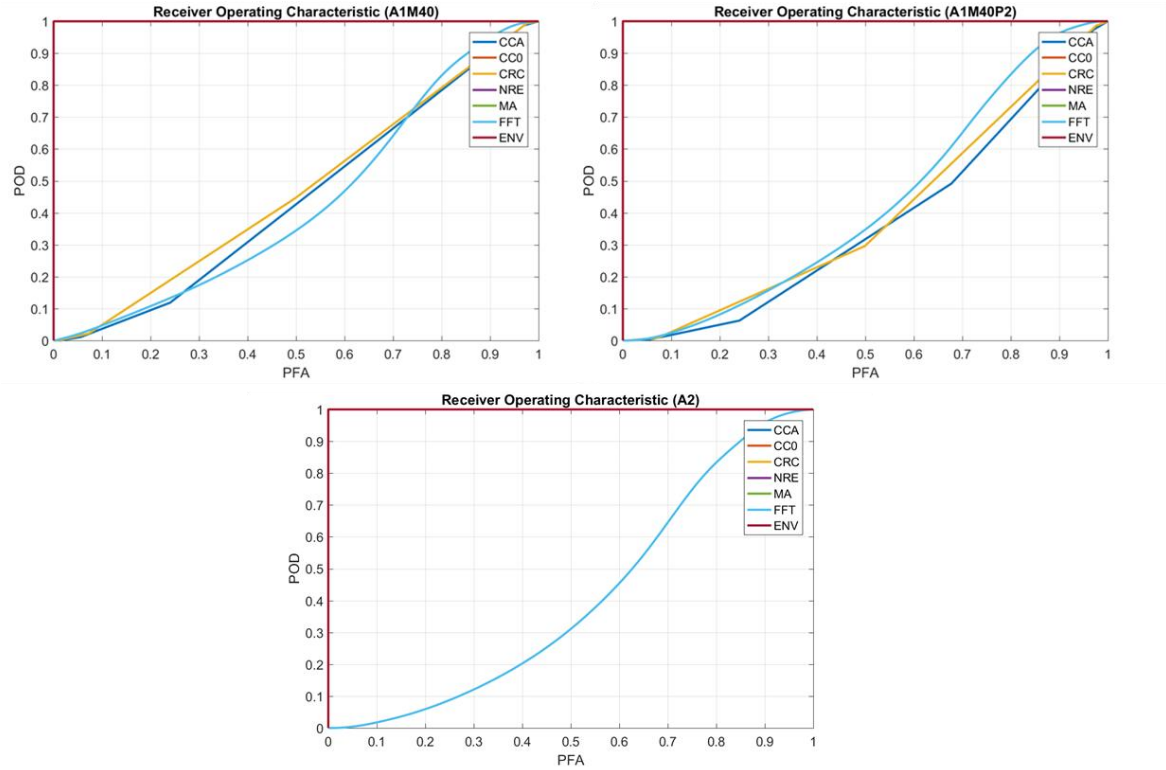

Figure 6: Receiving Operator Characteristic for the different DIs and for the different damage cases.

5. CONCLUSION

The aim of the present paper is to compare the performances of several families of classical DIs for the challenging task of damage detection in a stiffened composite plate. It appears that the correlation based DIs all provide good performances for the case A2 which corresponds to a real debonding of the stiffener but poor ones for the two other cases which correspond to a simulated damage case using magnets as damages. The energy based ones all perform very well for each case, real as well as simulated ones. Finally, the frequency based one do not perform well at all. Results provided here can thus help in designing an efficient SHM process for stiffened composite structures.

6. REFERENCES

[1] I. Chopra and J. Sirohi, Smart Structures Theory, New York: Cambridge University Press, 2013, p. 905.

[2] Z. Su and L. Ye, Identification of Damage Using Lamb Waves, Springer-Verlag London, 2009.

[3] K. Worden, C. R. Farrar, G. Manson and G. Park, "The fundamental axioms of structural health monitoring.," *Proceeding of the Royal Society,* vol. 463, pp. 1639-1664, 2007.

[4] W. Ostachowicz and A. Guemes, New Trends in Structural Health Monitoring,, I. 978-3-7091-1389-9, Ed., Springer,, 2013.

[5] Y. Lu, L. Ye, D. Wang and Z. Zhong, "Time-domain Analyses and Correlations of Lamb Wave Signals for Damage Detection in a Composite Panel of Multiple Stiffeners," *Journal of Composite Materials,* vol. 43, no. 26, 2009.

[6] O. Hmad, C. Fendzi, N. Mechbal and M. Rebillat, "Verification and Validation of Structural Health Monitoring Algorithms: A Maturation Procedure.," in *9th IFAC Symposium SAFEPROCESS'15,* Paris, 2015.

[7] O. Hmad, N. Mechbal and M. Rebillat, "Peaks Over Threshold Method for Structural Health Monitoring Detector Design," in *International Workshop on Structural Health Monitoring, IWSHM,* Standford, 2015.

[8] M. Rébillat, O. Hmad, F. Kadri and N. Mechbal, "Peaks Over Threshold Based Detector Design for Structural Health Monitoring: application to aerospace structures," *Structural Health Monitoring an international journal,* 2017.

[9] Z. Su and L. Ye, Identification of damage using Lamb waves: from fundamentals to applications, vol. 48, Springer Science & Business Media, 2009.

[10] H. Sohn, D. W. Allen, K. Worden and C. R. Farrar, "Structural damage classification using extreme value statistics," 2005.

[11] L. De Haan and H. Rootzén, "On the estimation of high quantiles," *Journal of Statistical Planning and Inference,* vol. 35, no. 1, pp. 1-13, 1993.

[12] E. Parzen, "On estimation of a probability density function and mode," *The Annals of Mathematical Statistics,* vol. 33, no. 3, pp. 1065-1076, 1962.

[13] B. W. Silverman, Density estimation for statistics and data analysis, vol. 26, CRC press, 1986.

[14] C. Fendzi, N. Mechbal, M. Rebillat and M. Guskov, "A General Bayesian Framework for Ellipse-based and Hyperbola-based Damage Localisation in Anisotropic Composite Plates," *Journal of Intelligent Material Systems and Structures,* vol. 27, no. 3, pp. 350-374, 2016a.