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Extrapolation of Autoregressive Models for Structural Health Monitoring in Composite Structures

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This work presents a methodology for damage quantification in composite structures based on the extrapolation of autoregressive models (AR) that are applied to fit the time response signal of Lamb wave propagation in a carbon/epoxy composite plate. The proposed approach uses a damage index based on the residue of identified AR models, which is much more sensitive to the simulated progressive damage - mass increasing - than the temperature changes. An extrapolated learning is established between the damage severity and the damage index calculated from the identified AR models. The results obtained demonstrate the capability of the methodology to be applied for damage quantification in composite materials where we can observe a quantification of the level of damage and future extension of the damage when the severity is increasing.
Keywords: Autoregressive Models Extrapolation, Damage Quantification, Composite structures

1 INTRODUCTION

The use of composite materials has been widely explored recently in many industrial fields due to their capability to combine its strenght with a reduced mass(MECHBAL and REBILLAT, 2017). However, these materials can present more complex modes of failure and most of them occur internally and they are visibly undetectable (Adams and Cawley, 1988). In this scenario, the use of Structural Health Monitoring (SHM) methods has been receiving an special attention for composite structures. Among these methods, those using Lamb wave propagation excited with piezoelectric elements to interrogate the structure condition based on the modeling or direct analysis of the signal response have been largely explored in the level of damage detection and localization (Neerukatti et al., 2016; Yuan, 2016). These methods involves the comparison of an extracted feature from the measured signal due to the guided wave propagation with the same pre-stored feature in a baseline condition to classify the structure's health. However, there are some challenging problems to be overcome, as for example, to guarantee an efficient classification under the variation of environmental conditions and to quantify the damage severity (Lee et al., 2011). A method using a mathematical-physical model could be applied in order to address these problems, but, the complexity to obtain a representative wave propagation model in composite materials can becomes it an impractical solution. In this scenario the use of a data-driven model seems to be an adequate way to treat this problem and to reach a quantification and extrapolation of the damage scenario. Then, in this paper is proposed a methodology to damage quantification based on the extrapolation of autoregressive models (AR) models for guided wave propagation in composite structures. The use of AR models in SHM to composite materials have been little explored in rares works (Nardi et al., 2016; da Silva, 2018) and none of them have investigated yet the model extrapolation for damage quantification. In order to illustrate the procedure an experimental setup is employed with a progressive structural change in a composite plate with PZTs bonded. It is worth to note that it is not used the input signal to build the models.

DAMAGE DETECTION USING AR MODELS

An AR model can be used to describe the $j-$th PZT output signal $y_{ij}(k)$, $j = 1,\cdots,n_s$, when an excitation signal is applied in $i-$th PZT input, $i = 1,\cdots,n_u$ (Ljung, 1998):

$$A_{ij}(q)\,y_{ij}(k) = \varepsilon_{ij}(k) \tag{1}$$

where k is the sample number of the signal, $A_{ij}(q) = a_{0_{ij}} + a_{1_{ij}}q^{-1} + \cdots + a_{n_{ij}}q^{-n_{a_{ij}}}$ is the autoregressive polynomial in function of the AR coefficients $a_{1_{ij}},....,a_{n_{ij}}$ and the delay operator, for example : $a_{1_{ij}}q^{-1}y(k) = a_{1_{ij}}y(k-1)$, $\varepsilon_{ij}(k)$ is the residual error, n_{ij} is the order of the model, n_s is the total number of PZT used as sensors and n_u is the total number of PZTs used as actuator.

The use of AR models for SHM purposes have two common approaches: one by extracting the damage feature from the AR coefficients and another from the residual errors (ε_{ij}). The investigation about the two approaches in the application that will be presented in this work indicated that the adequate approach is that based on the residues of the AR model. This damage index(DI) represents the root mean square (RMS) value negative of the residues from the AR model described by Equation 1.

$$\mathscr{D}_{ij} = -\sqrt{\frac{1}{N}\sum_{k=1}^{N}\varepsilon_{ij}^{2}(k)} \tag{2}$$

where N is the size of the sampled signal used to fit the AR model.

The negative signal in the DI described by Eq. 2 is proposed just to reverse the slope of DI curve and obtain it increasing rather than decreasing, that is more intuitive and follows the classic form of data presentation in SHM.

Here it is proposed a novelty procedure using the extrapolation of AR model to obtain a future index if the damage is increasing. To our knowledge, it is the first time in the literature that someone use a procedure as this to SHM purpose. In order to extrapolated the model is used a cubic due to its efficiency and smooth approximation.

The methodology proposed for damage quantification based on the AR model extrapolation is summarized in the Fig. 1, and can be organized in five main steps:

- Step 1: Guided wave propagation under defined conditions;
- Step 2: AR model identification;
- Step 3: Damage feature extraction;
- Step 4: AR model extrapolation;
- Step 5: Damage quantification.

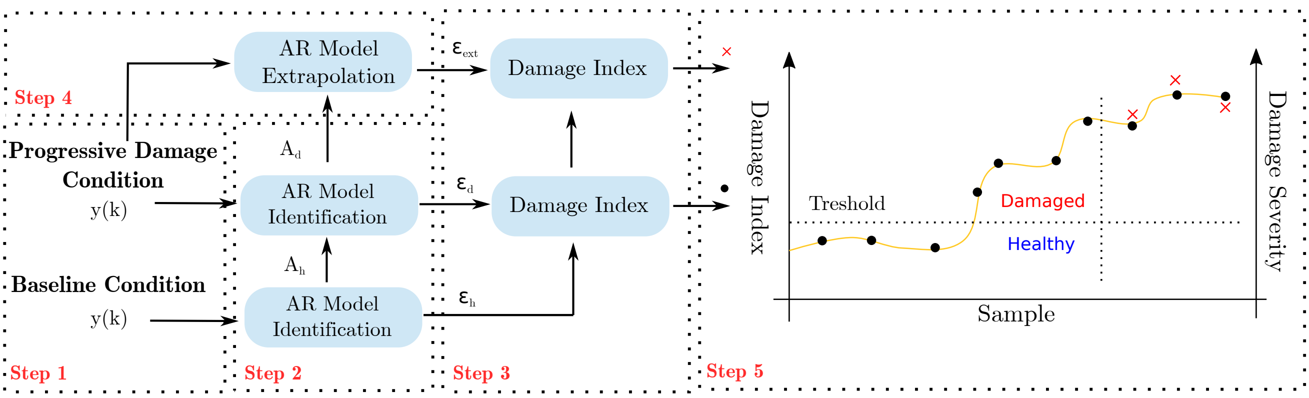
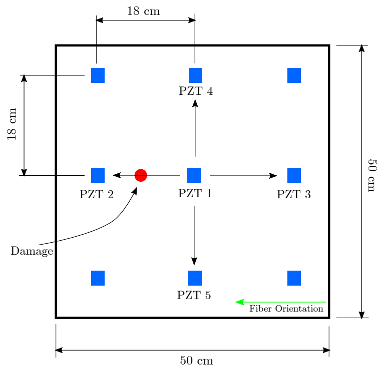


Figure 1 – Proposed methodology for damage quantification

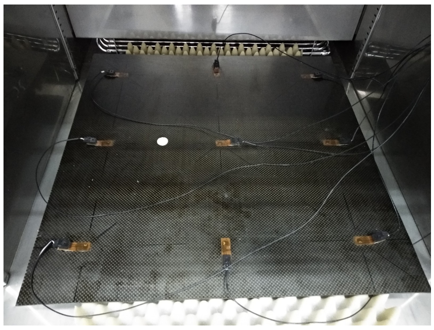
EXPERIMENTAL SETUP: A COMPOSITE PLATE

Figure 2(b) illustrates a composite plate of carbon fibers in a epoxy resin matrix with the lay-up containing 10 plies unidirectionally oriented along 0 °, which gives the structure quasi-isotropic properties. The composite was instrumented using an array of 9 PZTs with 0.254 mm thickness, manufactured by Accelent®. A burst-sine signal of 30 V, 10 cycles and central frequency of 300 kHz was generated to excite the PZT 1 to propagate the guided waves. Structure's response was saved with a sampling frequency of 3 MHz using the PZTs 2,3,4 and 5, placed as indicated in Fig. 2 (a). The excitation signal was generated using a National Instrument board model 6353 coupled with a power amplifier Mide QuickPack® model EL 1225 . The acquisition was made by using the oscilloscope Keysight® model DSO7034B. A Labview® program was developed to manage the signal generation and acquisition synchronously. A post processing step was performed to eliminate the noise from the measured signal by means of a discrete wavelet transform up to order 4 using a Daubechies 10 (db10) wavelet. A complete scheme of the experimental setup is described in Fig. 2(c).

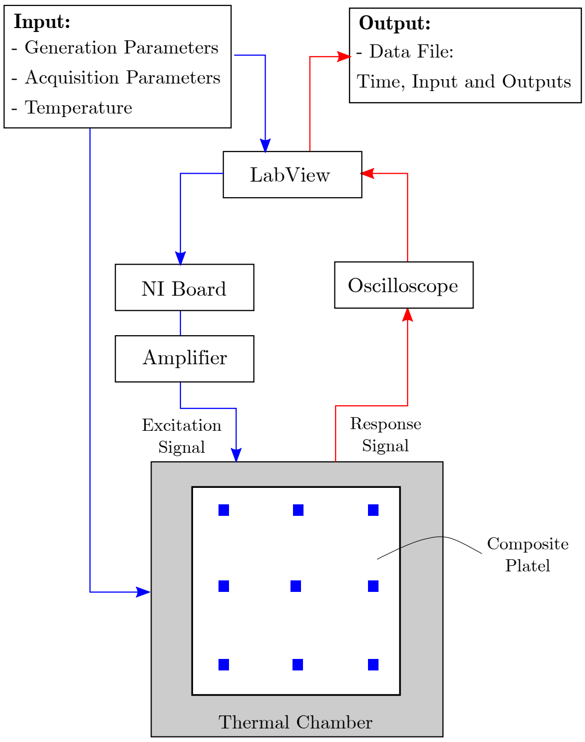
A damage in the structure was simulated using an adhesive putty bonded on the plate surface in the region indicated in Figure 2 (b). This mass increasing, changes locally the damping of the structure, an effect similar to delamination in composites (Lee et al., 2011). The damage severity was increased progressively by changing the area covered with the adhesive putty. Three damage stages were considered: 255 mm^2 (damage 1), 700 mm^2 (damage 2), and 1100 mm^2 (damage 3). In order to investigate the influence of temperature variability in the methodology applied, the experiments



(a) Composite Plate Scheme.



(b) Photo.



(c) Experimental Setup Scheme.

Figure 2 – Experimental Setup.

were performed inside a temperature chamber Thermotron® model SM-8. For each structure condition, 50 tests were performed in order to have enough data to statistic analysis. It should be noticed that the composite plate was placed inside the temperature chamber in a free-free boundary condition.

EXPERIMENTAL RESULTS

The first step of the methodology implementation is to define the baseline condition, that in this case was chosen as structure in the healthy state at 30 ^{o} C. The excitation signal applied in the PZT 1 to propagate the Lamb wave is shown in Figure 3 and the response signal acquired by the PZT 2 is shown in Figure 4. Besides the baseline condition, still in the healthy state, the structure was submitted at two different temperatures, -20 ^{o}C and 80 ^{o}, inside the temperature chamber. It is well know that the temperature have an important effects on the guided wave propagation due to the changes caused on the material properties and as can be seen in Fig. 4, it causes an attenuation in the amplitude and a time delay on the response signal when compared with the baseline condition.

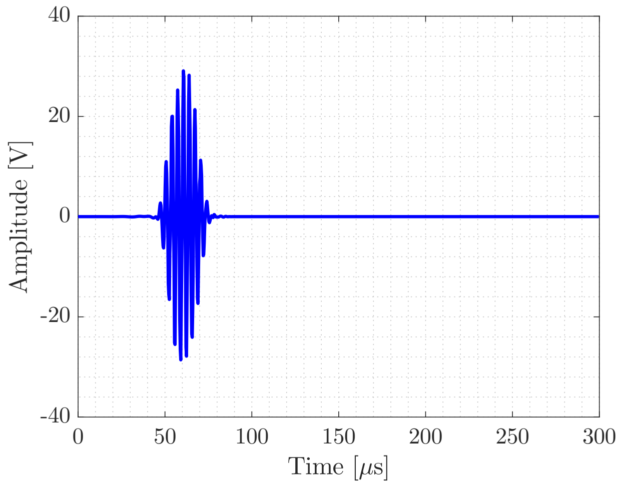


Figure 3 – Input signal applied to the PZT 1

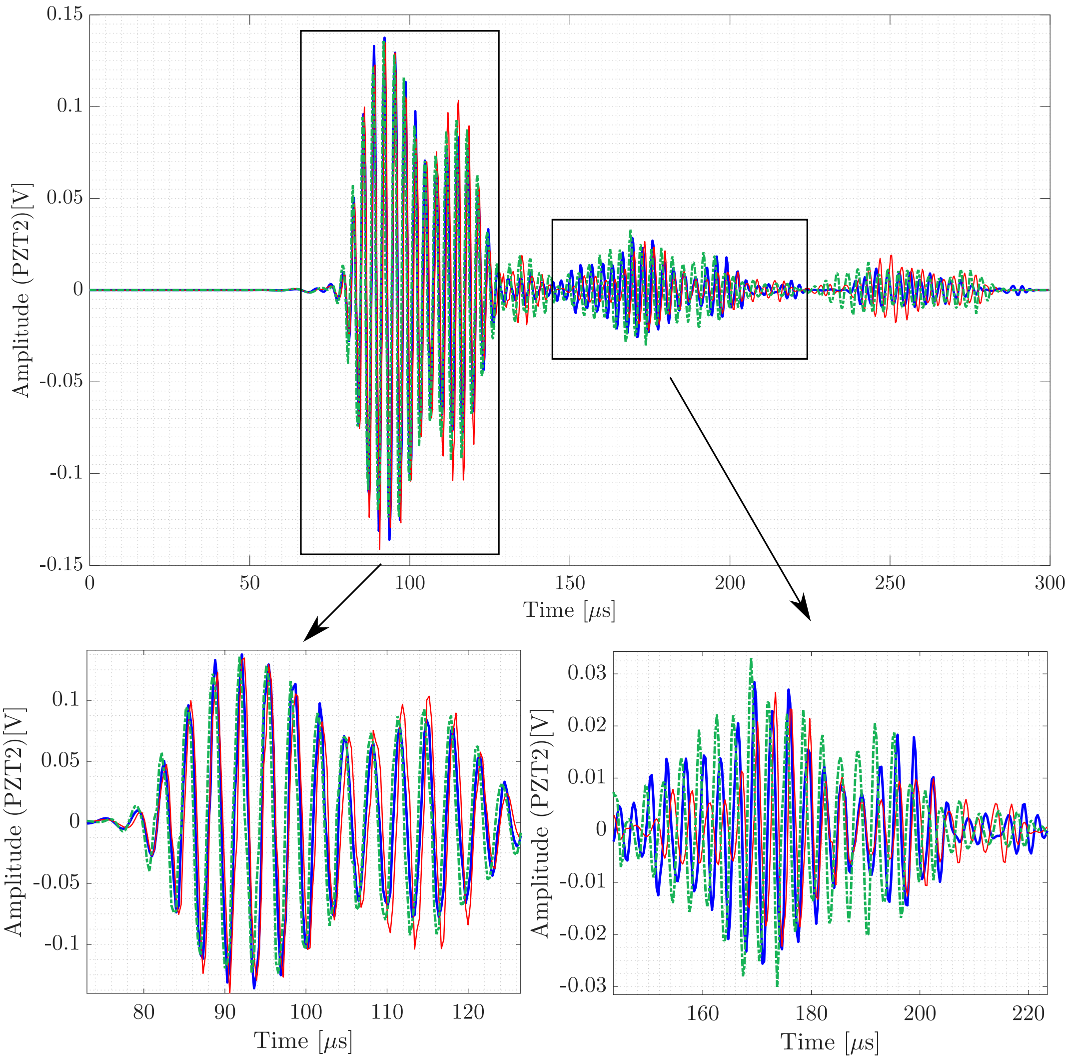


Figure 4 – Output signal of PZT 2 at different temperatures in the healthy state. is the healthy condition at 30° C (baseline), is the healthy condition at 80° C and is the healthy condition at -20° C.

The damage was introduced in the composite plate progressively in 3 steps using the adhesive putty to simulate different damage severities. In order to separate the effects caused by temperature changes from those by damage, the structure was kept at 30 °C. Figure 4 shows the response acquired by the PZT 2 for the three damaged conditions, where it can be noticed a reduction in the amplitude of the signal, proportional to the damage severity. This characteristic is reasonable due to the nature of damage, which increases damping locally in the structure and then causes the wave attenuation.

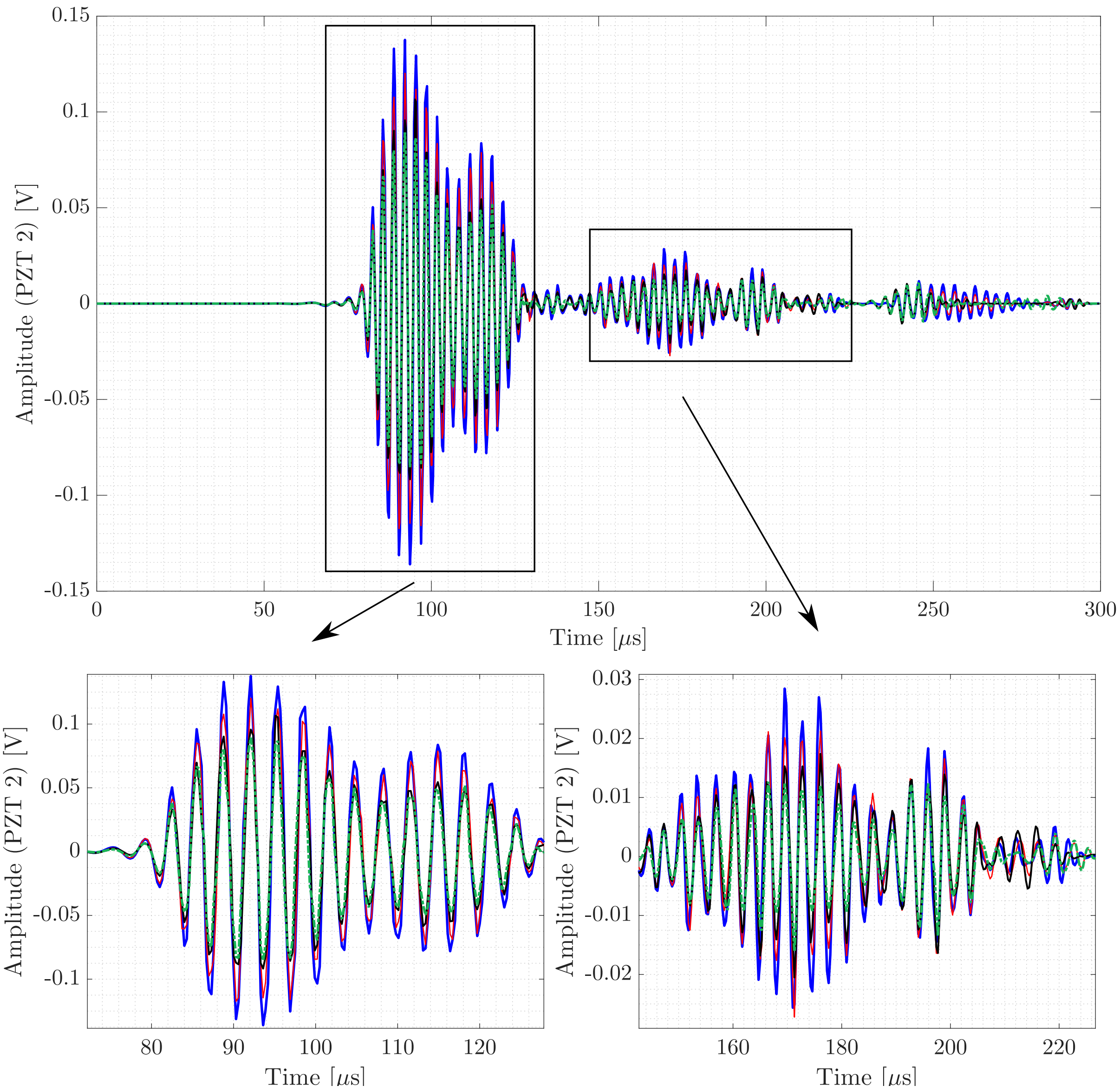


Figure 5 – Output signal of PZT 2 for baseline condition and progressive damage conditions. ▬ is the healthy condition at 30° C (baseline), ▬ is the damage condition 1 at 30° C, ▬ is the damage condition 2 at 30° C and - - - is the damage condition 3 at 30° C

Figure 6 shows the response measured by the PZT 3 when PZT1 is excited. In this case, the damage is not placed in the propagation wave path (PZT 1 to PZT 3) and consequently this one is less sensitive to the presence of damage, especially on the arrival modes, those who have the greatest influence in the damage index proposed. Output acquired by the PZTs 4 and 5 are even less sensitive than PZT 3, because, besides the fact, that the damage is not placed in these paths, the fiber orientation is perpendicular to this paths increasing even more the wave attenuation, making these PZTs almost insensitive to the damage.

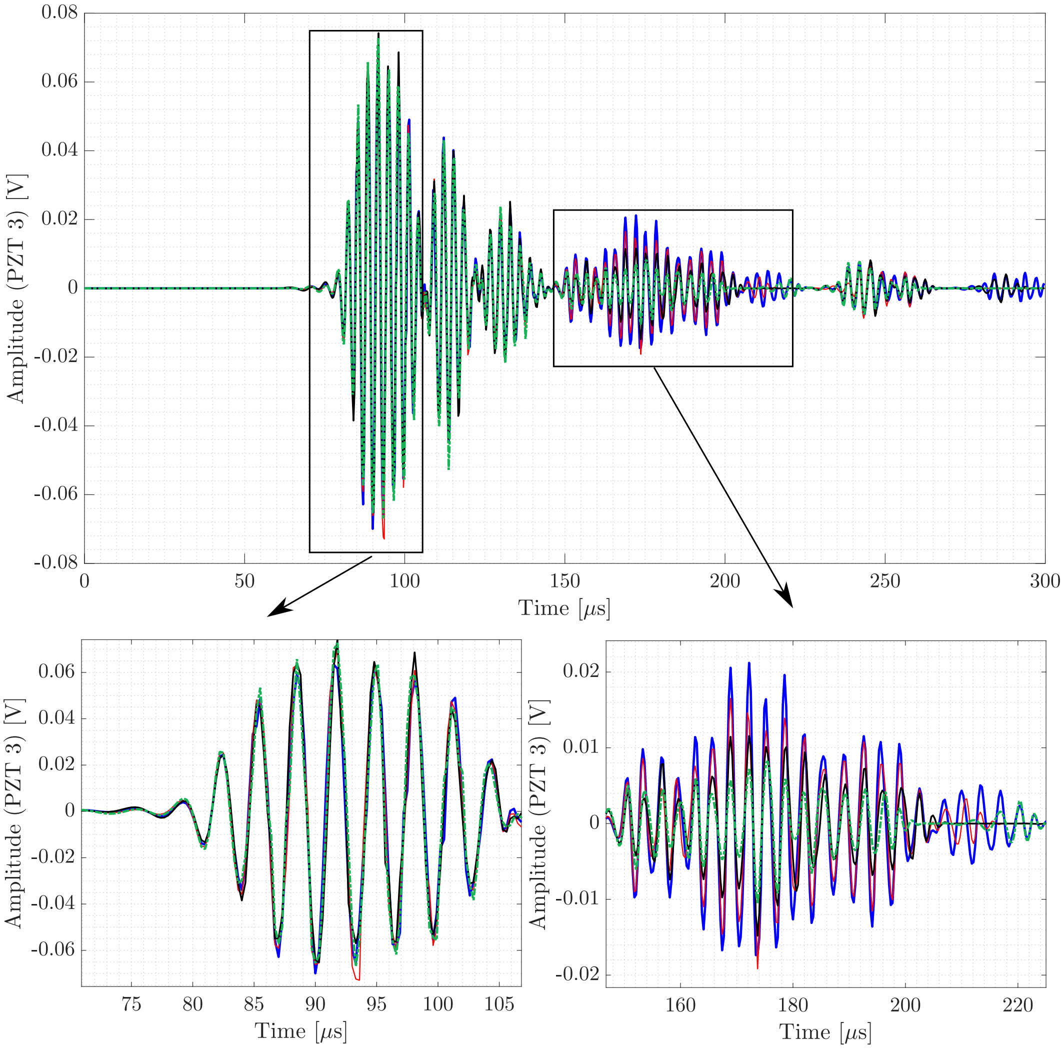


Figure 6 – Output signal of PZT 3 for baseline condition and progressive damage conditions. is the healthy condition at 30° C (baseline), is the damage condition 1 at 30° C, is the damage condition 2 at 30° C and is the damage condition 3 at 30° C

The second step of the methodology is the AR model identification for each condition. In order to fit an AR model to represent the response signals is necessary to define an adequate order. The model order was chosen based on the Bayesian Information Criterion (BIC) considering output signal at the baseline condition. Figure 7 shows the BIC considering the response acquired by the PZT 2 and PZT 3, where it is noticed that the order 10 represents an adequate candidate for model order in both paths.

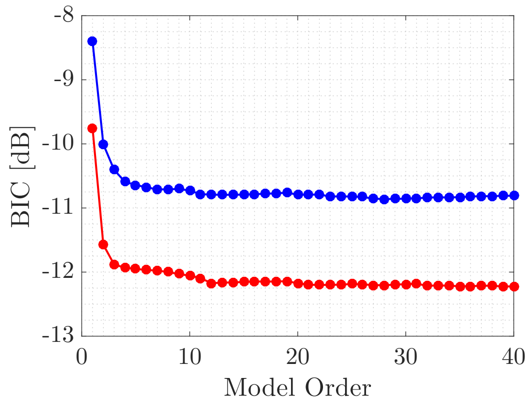


Figure 7 – Model order selection based on the BIC considering the output response on PZT 2 ( ) and PZT 3 ( )

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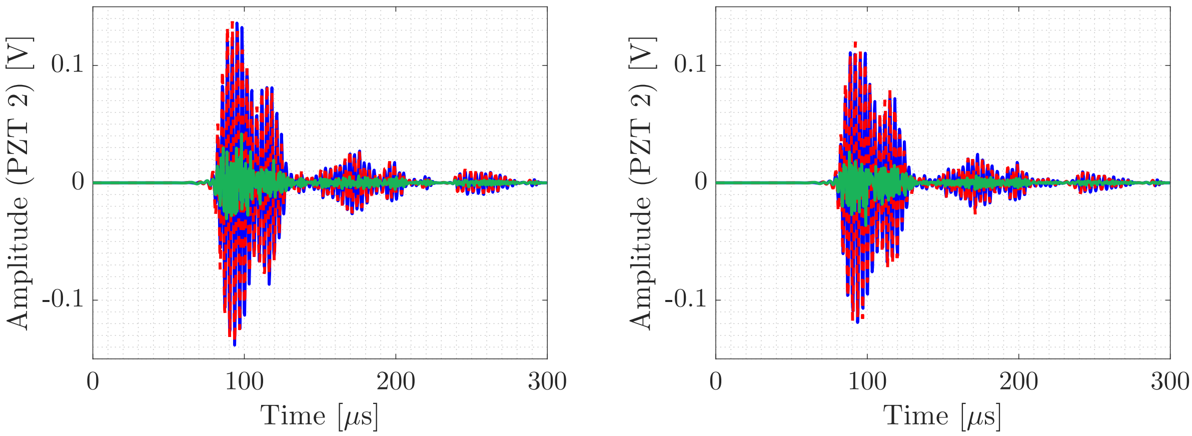
Figure 8 shows the response signal of PZT 2 in the baseline and damaged conditions from the fitted AR model compared with the measured response and the error between them (ε). The AR models obtained represent well the experimental signal as can be observed. The most significant part of the error occurs in the arrival propagation mode. As the damage feature proposed in the methodology is based on the error of AR model, it is observed that the sensitivity on arrival mode of wave propagation have the greatest influence in the damage detection methodology proposed.



(a) Baseline Condition

(b) Condition : Damage 1 and T=30°C

Figure 8 – Example of response signal measured by the PZT 2 ( ) and obtained by the fitted AR model ( ) compared to their respective residue ( ).

In order to interrogate the structural condition based on the obtained AR models it was used the damage index proposed by Eq. 2, the RMS value negative of the error (ε). As observed previously, the insertion of the damage causes an attenuation of amplitude for the measured signal in the path containing the damage. By computing the DI, it was observed that the RMS error decreases as more accented is the attenuation of the amplitude in the arrival modes, that means, as more severe is the damage. Another important fact observed is that the temperature variability has a small influence in this index, once, that amplitude attenuation caused by temperature change is much less pronounced. Figure 9 shows the DI calculated for all models under the different conditions tested, where is possible to distinguish very well the DI of damaged conditions from those of healthy even under a considerable temperature change.The dotted line represents the threshold used to classify the structure condition by the process of outliers detection and its value was calculated based on the statistic distribution of the DI for baseline condition models, a normal distribution, and considering an interval of confidence approximately 95% (2σ).

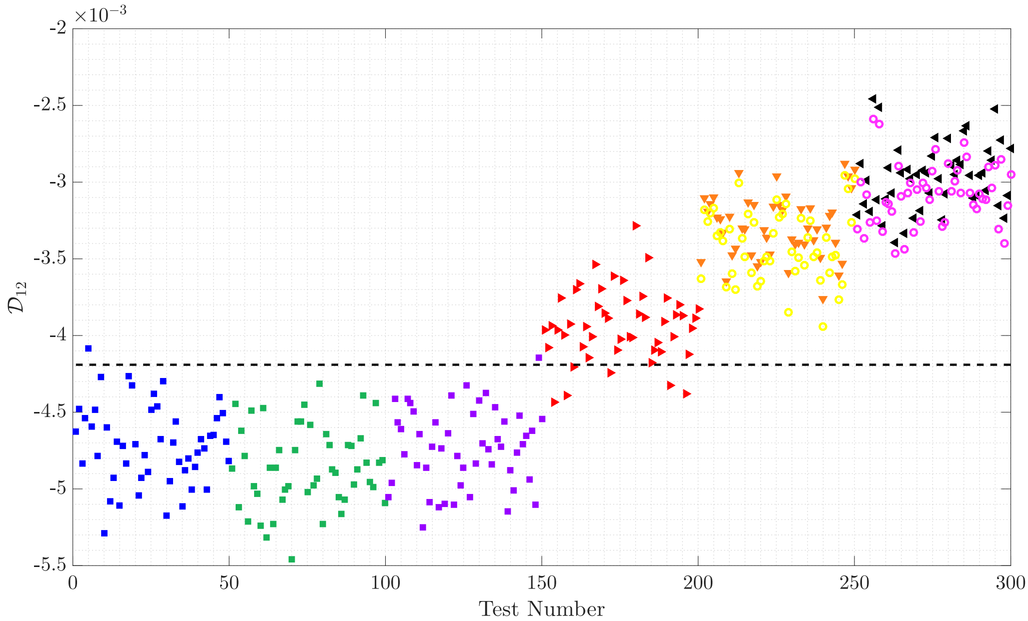


Figure 9 – Damage index calculated from extrapolated and identified AR model of PZT 2 output at different conditions. ■ is the healthy condition at 30 ° C, ■ is the healthy condition at 80 ° C, ■ is the healthy condition at -20 ° C, ▲ is the damaged condition 1 at 30 ° C, ▲ is the damaged condition 2 at 30 ° and ▲ is the damaged condition 3 at 30 ° C, ○ is the extrapolated damaged condition 2 at 30 ° C and ○ is the extrapolated damaged condition 3 at 30 ° C

Figure 10 shows DI with the damage severity, that in this case is represented by the area covered by the adhesive putty. The points in the graph were obtained by calculating the centroid of the cluster formed by the set of calculated DI in each structure condition shown in Fig. 9.

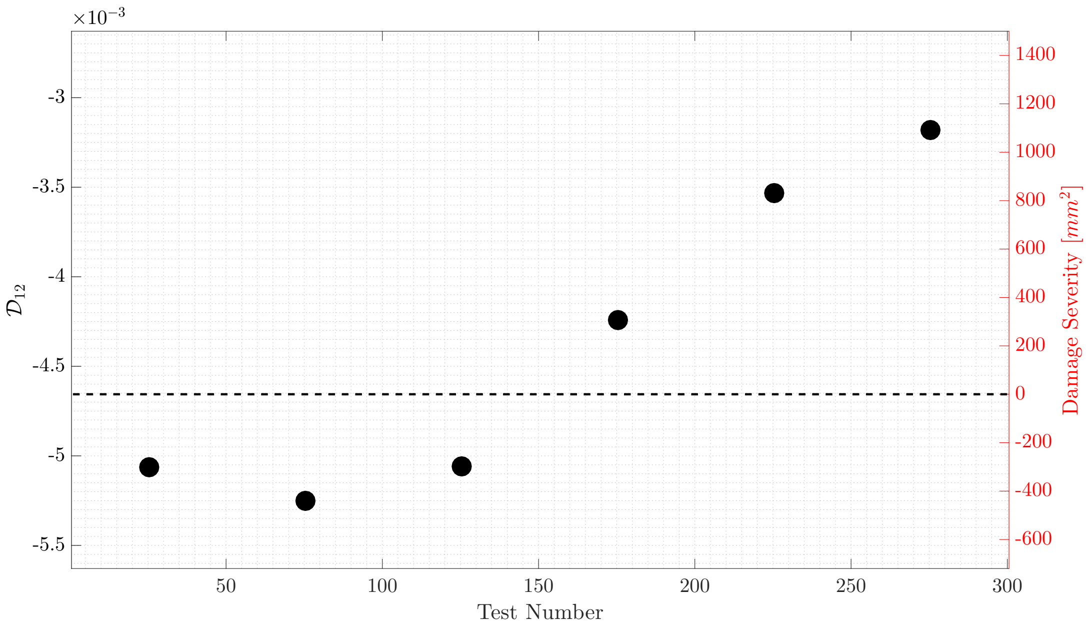


Figure 10 – Centroids of the damage index clusters computed for each structure condition related to their respective damage severity

2 FINAL REMARKS

A new approach to damage quantification using a data-driven model was presented and experimentally validated for a composite plate. The results obtained demonstrate the capability of damage detection and quantification of incipient simulated damage even as small as 0.1 % of the whole surface area of the composite plate. Besides that, the damage index proposed shows to be much less sensitive to the temperature changes than the damage increase. The methodology was validated just for the case of damage localized in a single spot in order to evaluate its potential in the quantification level. Therefore, to generalize its application is necessary to separate the effects of the damage location from its severity, that will be studied by the authors in future works. The results presented in this paper demonstrate the potentialities of application of a novelty methodology for damage quantification in composite materials employing a data-driven model, that represents an alternative approach to address some obstacles in the SHM techniques development for composite structures, such as, the difficulty in obtaining a representative model to be used in the damage quantification and the effects of environmental variability in the damage detection performance.

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