Smart EMI monitoring of thin composites structures

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Overview

1. Goals of the SAPES project
2. Short focus on … our Multilevel approach and EMI experimental setup
3. Piezo properties identification by solving inverse problem
4. Damaged zone localisation (Probabilistic Neural Networks)
5. Conclusion and future works
1. Goals
Goals

Structural Health Monitoring (SHM) method for in-situ damage detection and localization in Carbon Fibre Reinforced Plates (CFRP).

Impact detection in composites thin structures: in aeronautic ➔
Problem of Birdstrike, ice etc...

The detection is achieved using the ElectroMechanical Impedance (EMI) technique employing piezoelectric transducers as high-frequency modal sensors.

Numerical simulations based on the Finite Element (FE) method are carried out so as to simulate more than 100 damage scenarios.

Simple damage model is used in order to limit computation time (high discretization, high frequency bandwith) and from exploring all domain with few points (100) we construct an approximation (surrogate model using ANN) of damage localization versus selected (pertinent) indicators from EMI analysis.

Damage metrics are then used to quantify and detect changes between the electromechanical impedance spectrum of a pristine and damaged structure
2. Short Focus on…
The main goal of his paper is to develop a multiscale localisation method that can be applied to a global structure (e.g. aircraft door), a subpart (composite plate) or a structural detail (stiffener).

The amount of data that needs to be generated to ensure a good generalization depends on the structure under study. For instance, if a global structure is considered, a large database of E/M impedance signatures relative to different localized single damage is ultimately required.

Simulations will be utilized so as to construct a significant database relative to the subpart problem in order that PNN well generalized (supervised approach).

Figure 1: Modeling principle of the EMI technique from global to details

(a) Aircraft door  (b) Composite plate  (c) Stiffener

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In order to generate a significant dataset relative to different damage localization, a coupled-field finite-element (FE) model of the EMI technique is developed in Abaqus [8].

The FE model permits to compute electrical reaction charges over each sensor electrode, which are then imported into Matlab [9] to derive the corresponding E/M impedance signature.

The resulting impedance spectrum is then processed to derive damage indicators. Finally, these damage metrics are used as inputs to train, validate and test the ANN.
Short focus on … EMI measurement

Experimental setup
- 3 PZT mounted on composite plate T700 M21 (PI : PIC 151) : 10x10x0.5 mm
- bi composants Epoxy/Argent (EPO-TEK® E4110) : thickness 0.3 mm

- Measurement system: Impedancemeter PsimetriQ N4L modèle 1700
  + Active Head (integrated shunt)

EMI principle:
→ Broadband excitation
  - voltage measurement PZT
  - voltage measurement shunt
  - PZT intensity :
  - Impedance estimation:

\[
I_{PZT}(\omega) = \frac{V_{shunt}(\omega)}{R_{shunt}}
\]

\[
Z_{PZT}(\omega) = \frac{V_{PZT}}{I_{PZT}(\omega)}
\]
3. Piezo updating
Piezoceramics properties exhibit statistical fluctuations within a given batch and a variance of the order of 5-20% in properties.

Therefore it becomes really important to accurately identify the behavior of the piezoelectric sensors as we solely depend upon these transducers to predict the mechanical impedance of the structure.

Identification of piezo material properties solving inverse problem:
→ From experimental data
→ Fit Analytical model (Bhalla & Soh, 2004 & 2008)

\[
\begin{align*}
& \text{Coef. diélectric} \\
& [\bar{\varepsilon}^T] = \begin{bmatrix}
\varepsilon_{11}^T & 0 & 0 \\
0 & \varepsilon_{11}^T & 0 \\
0 & 0 & \varepsilon_{33}^T
\end{bmatrix} \\
& \text{Coef. Dielectric loss} \\
& \bar{\varepsilon}_{33}^T = \varepsilon_{33}^T(1 - \delta i) \\
& \text{Constants piezo.} \\
& [d] = \begin{bmatrix}
0 & 0 & 0 & d_{15} & 0 \\
0 & 0 & d_{15} & 0 & 0 \\
d_{31} & d_{31} & d_{33} & 0 & 0
\end{bmatrix} \\
& \text{Structural Damping} \\
& \eta \\
& \text{Coef. correction} \\
& C
\end{align*}
\]

Low freq ID (<10kHz)

Around resonant frequency ID (≈200kHz)

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Impedance of a free PZT is:

\[ Y = \frac{I}{V} = 4\omega j \frac{l^2}{h} \left[ \epsilon_{33}^T + \frac{2d_{31}^2 Y^E (1 + \eta j)}{(1 - \nu)} \left( \frac{\tan(Ck)}{Ck} - 1 \right) \right] \]

Low Frequencies

\[ \tan(Ck)/Ck \to 1 \]

\[ Y_{bare} - G_{f,qs} + B_{f,qs} j - \left( \frac{8\pi d^2}{h} \right) \left( \epsilon_{11}^T \right) j + \left( \frac{8\pi d^2}{h} \right) \left( \epsilon_{33}^T \right) j \]

Exp measurements

2 linear functions of \( f \)

\[ B_{f,qs} = \frac{B_{f,qs} h}{8\pi d^2} - \epsilon_{33}^T f \]

\[ G_{f,qs} = \frac{G_{f,qs} h}{8\pi d^2 \epsilon_{33}^T} = \delta^* \]

\[ \rightarrow \text{Identification of: } \epsilon_{33}^T \text{ et } \delta \]
Piezo updating (2: results)

Example: PZT n°1

Résults for 3 PZT:

<table>
<thead>
<tr>
<th>$\varepsilon_{33}^T$ ($10^{-8}$ F/m)</th>
<th>PZT 1</th>
<th>PZT 2</th>
<th>PZT 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta$ fournisseur</td>
<td>6.7%</td>
<td>9.0%</td>
<td>7.7%</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.0203</td>
<td>0.0207</td>
<td>0.0204</td>
</tr>
</tbody>
</table>

$\rightarrow$ bias due to non implemented dielectric losses in abaqus

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Piezo updating (3)

Parameters to be identified: $d_{31}$, $\eta$ et $C$

\[
\bar{Y} = \frac{\bar{I}}{\bar{V}} = 4\omega^2 \frac{l^2}{h} \left[ \bar{E}_{33}^T + \frac{2d_{31}^2 Y^E (1 + \eta i)}{(1 - \nu)} \left( \frac{\tan(C \kappa d)}{C \kappa d} - 1 \right) \right]
\]

Nonlinear quadratic function to be minimized

\[
\min \sum (\bar{Y}(f, d_{31}, \eta, C) - \bar{Y}_{\text{exp}}(f))^2
\]

Analytic model

Exp measurements

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Piezo updating (3: results)

→ Excellent numerical experimental correlation

<table>
<thead>
<tr>
<th></th>
<th>(d_{31} \times 10^{-10})</th>
<th>(\Delta f_{\text{fournisseur}})</th>
<th>(\eta)</th>
<th>(C)</th>
<th>(C_1)</th>
<th>(C_2)</th>
<th>corrélation analytique/exp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>PZT 1</td>
<td>-1.8373</td>
<td>14.1%</td>
<td>0.0224</td>
<td>0.8681</td>
<td>-</td>
<td>-</td>
<td>0.998</td>
</tr>
<tr>
<td>PZT 2</td>
<td>-1.7718</td>
<td>17.2%</td>
<td>0.0185</td>
<td>-</td>
<td>0.8588</td>
<td>0.8909</td>
<td>0.976</td>
</tr>
<tr>
<td>PZT 3</td>
<td>-1.7716</td>
<td>17.2%</td>
<td>0.0219</td>
<td>-</td>
<td>0.8594</td>
<td>0.8787</td>
<td>0.992</td>
</tr>
</tbody>
</table>

→ It exists important difference between PZT manufacturer’s material data and identified data
4.0. The idea behind supervised ANN: generalization
Damaged zone identification

Generalization is the process of recognize unknown cases from database of indicators (inputs) versus damage localisation (outputs)

• Supevised ANN (previous studies) : discrete prediction \((x,y)\)  \(\Rightarrow\) induce sometimes large errors

• ICCS studies: Damaged zone prediction (classification problem well adapted to industrial constraints and multilevel approach)

Classification Problem  \(\Rightarrow\) PNN
PNN

A simple example: 1 database of 4 examples (learning vectors)

Plate divided in 4 zones

Weights=learning vectors

Radial Basis Layer

Competitive Layer

Unknown case
→ New inputs vector

Sensibility rules

Probability vector construction related to the input vector clustering (zone)

Max probability ➔ predicted zone

y=Z1
4.1. Parametric approach (The big Picture)
4.1. Parametric approach (The big Picture)

A finite-element model consisting of three piezoceramic patches (designation PIC151) of dimensions 10x10x0.5mm³ bonded onto a composite plate (200x290mm²).

The composite layup is composed of 12 plies of carbon/epoxy prepreg T700/M21 for a total thickness of 3mm.

Comparison of real part frequency response of impedance (experimental vs numerical model) for a pristine composite plate measured from PZT n°1.
Figure 6. Comparison of impedance spectra predicted by the FE model at the PZT n°1 terminals between undamaged (UD) and damaged (D80% or D90%) composite plates. (a) and (b) Plots corresponding to a damage surface of 225mm² and 600mm² respectively.
• 3 damage zone surfaces: 100, 225, 600mm² → 3 independent database
• 2 severities: decrease of 80% or 90% of $E_2/E_3/G_{12}/G_{13}/G_{23}$
• Border zones deleted from database
• Generation of database (learn 80%)
• Test of 100 networks (Results: mean of 5 best)
• Cross (random) validation 20%

Pertinent indicators

Damage localization (x,y or zone)
PNN Preliminary tests

Inputs choice is predominant in the classification results

→ Inputs are defined from comparison of impedance spectrums (2 successive states: damaged/pristine)

- Corrélation Coef. (Re(Z)) → 1
- Area substraction (Re(Z) & Im(Z)) → 2
- Quadratic mean (Re(Z) & Im(Z)) → 2
- Root mean square deviation (Re(Z) & Im(Z)) → 2

\[ RMSD = \sqrt{\frac{\sum_{i=1}^{N} [\text{Re}(Z_i) - \text{Re}(Z_i^0)]^2}{\sum_{i=1}^{N} [\text{Re}(Z_i^0)]^2}} \]

7 indicators from
Bibliography for each PZT
⇒ 21 indicators

Using only these indicators 47% of the networks are able to well classifiy 90% of the new damages

When we add 22 new indicators (frequency shifts)

85% of the networks are able to well classifiy 90% of the new damages

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As it can be expected, the higher the surface of damage, the higher the RMSD index is. The same conclusion can be drawn as regard the damage severity.

The other selected indicators more complex behavior that will help PNN to distinguish between damages having similar RMSD value but different localization.
4.2. Database creation from numerical analysis (Damage scenarios on Abaqus)
PNN

High damage area: 600mm²

Learning base 118 damages, no frequency shifts as input vectors
  - Test base 20 unlearned (new) cases

Random discrete location of damages

Histogram (X and Y)
69% of the networks can predict 90% of the unknown (new) damage location

90% of the networks can predict 80% of the unknown (new) damage location

10 new damages example

→ Very High variation of 21 indicators: can we reduce the input vector size ???
High damage area: 600mm²

\[
\begin{array}{cccccccc}
\text{Entrées considérées} & \text{Dim.} & \multicolumn{7}{c}{\text{Nombre de réseaux sur 100}} \\
\hline
\text{Toutes} & 21 & 30 & 39 & 21 & 10 & 0 & 0 & 0 \\
\text{RMSD Re(Z)} & 3 & 18 & 27 & 29 & 18 & 5 & 3 & 0 \\
\text{RMSD + Aire Re(Z)} & 6 & 27 & 39 & 26 & 4 & 3 & 1 & 0 \\
\end{array}
\]

→ PCA : reduced input vector containing RMSD Area difference of Re(Z) – dimension 6 – has the same performance than the all vector : For High damage area some indicators are correlated
Learning base 245 damages
Test base 20 unknown (new) cases

Random discrete location of damages

Histogram (X and Y)
85% of the networks are able to predict 80% of the 20 new unknown damages

61% of the networks are able to predict 90% of the 20 new unknown damages

Some examples

→ Due to computational time limits we did only hundred of scenari, not sufficient to
   generalized even adding frequency shifts indicators
PNN

Low damage area

**Damages 100mm²**

- Learning base 165 damages. Test base 20 unknown (new) cases

Random discrete location of damages

PCA answers that all indicators are needed …

→ lower performance of the networks only of 35% of the networks are able to localize

→ Indicators shifts are too small, database too small, local effects?
4.3. Experimental results (unknown cases)
4.3. Experimental EMI

- Plate n°3:

<table>
<thead>
<tr>
<th>Max</th>
<th>Déplacement (mm)</th>
<th>Effort (N)</th>
<th>Temps d'impact (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-5,63</td>
<td>6067,33</td>
<td>5,28</td>
<td></td>
</tr>
</tbody>
</table>

Données d’impact E=20J

- Amplitude

- Profondeur

US and : Cscan resolution 0.3mm

**RMSD**

8,46% 7,34% 3,93%

PZT1 PZT2 PZT3

**Shift in frequency**

20,00% 22,00% 21,00%

PZT1 PZT2 PZT3

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4.4. Final Results of classification

Experimental constraints: central zone for impact drop test machine

So we only have 5 experimental points (unknown cases) to be recognized by the PNN

<table>
<thead>
<tr>
<th>Plate n°</th>
<th>Damage center (x,y)</th>
<th>US Surface</th>
<th>Real zone</th>
<th>Predicted zone</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(150,145)</td>
<td>≈280mm²</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>(116,52)</td>
<td>≈381mm²</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>(110,87)</td>
<td>≈399mm²</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>(145,95)</td>
<td>≈380mm²</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>(177,105)</td>
<td>≈366mm²</td>
<td>2</td>
<td>4</td>
</tr>
</tbody>
</table>

D2 and D5 Problem of Border zones deleted from database...
5. Concluding remarks

EMI is able to detect and localize damage in composites plates. Our coupled FEM approach is interesting for exp/num EMI correlation.

Piezo updating is an important phase in the monitoring process.

3 surface of damages: 100, 225, 600 mm² → 3 different database, and 3 performances of PNN

Supervised ANN → x,y location prediction with reliability close to half damage size

PNN → Damaged zones localization (1/4 ou 1/8 of plate)

Ability to predict correct zone for all kind of damages

Good generalization for medium and large damage area

Futur works → Increase of damage scenarii for better generalization (small damage area)

Clustering of optimal zone (a priori information)

From ISO SURFACE NETWORKS to ISO ENERGY of IMPACT …

we need to know the predicted damage area versus location for each type of impact.

Pertinent indicators

Damage localization (x,y) couples or zones

Damage severities, numbers …