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MODEL ASSISTED PROBABILITY OF DETECTION APPLIED TO GUIDED WAVE IMAGING FOR STRUCTURAL HEALTH MONITORING

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ABSTRACT

In Guided Wave Structural Health Monitoring (GW-SHM), reliability and performance demonstration is one of the main challenge to overcome to ensure industry adoption. However, the cost of computing a Probability of Detection (POD) from experimental data is much higher in SHM than in NDE. In addition, performance demonstration metrics must be rethought for SHM because of data dependency between the successive acquisitions. This work presents the computation of a POD metric of a GW-SHM system, using a Model-Assisted POD (MAPOD) approach. The use of simulation enables in particular a large coverage of possible configurations and the creation of independent datasets.

The studied application case is the inspection of an aluminum panel instrumented by 8 piezoelectric transducers for Guided Wave Imaging (GWI). The defect is a circular through hole. The POD is computed as a function of the defect size, taking into account the following variabilities: defect position and morphology, temperature of inspection, degradation of the sensors and measurement noise. In order to quickly compute the POD for various input parameter distributions, a meta-model of the configuration is built from simulation results obtained with the CIVA software.

Keywords: Model-Assisted Probability of Detection, Structural Health Monitoring, Guided Wave imaging

1. INTRODUCTION

In Structural Health Monitoring (SHM), sensors are permanently installed to monitor the integrity of a structure throughout its lifetime. Demonstrations of damage detection, localization and sometimes sizing of flaws using Guided Wave (GW) based SHM techniques can be found in the literature [1]. The GW-SHM technique used in this article is Guided Wave Imaging (GWI), which relies on the placement of a sparse sensor array on the inspected structure. Each sensor sequentially generates and receives GWs, thus a scan of the structure between every pair of sensors is obtained. By comparing this scan to a reference one taken in a pristine state, a cartography representing the health of the structure is generated. The GWI process used in this paper, the so-called Delay-And-Sum (DAS) [1], allows both detection and localization of the defect.

However, to reach sufficient maturity of GW-SHM techniques, the performance of such techniques must be demonstrated and certified. The Probability of Detection (POD) metric usually computed in Non Destructive Testing (NDT) but cannot directly be transposed in SHM. This is due to the fact that the sensors are permanently installed in SHM and that the GW-SHM inspection is a global process, meaning that one sample would only lead to one data point in the POD computation, while in NDT one experimental sample may yield dozens or hundreds of data points if it contains multiple defects and it is repeatedly inspected. One way to generate a large amount of data for a wide variety of configurations (sensors positions, flaw position/size, number of flaw…) in GW-SHM is to use simulation, which corresponds to the MAPOD (Model Assisted POD) approach. It requires a model describing the inspection process reliably and efficiently.

The goal of this work is to define the appropriate tools to demonstrate the application of the MAPOD approach in a GWI setup for GW-SHM. A GWI experiment is conducted with a sparse array of piezoelectric transducers placed on an aluminum panel. A meta-model is built to ensure that the influence of every variable is taken into account, including the combined influence of multiple variables. The forward model is provided by the CIVA [2] software with full 3D computations. Hundreds of simulations are required to build the meta-model, which in turns is able to generate several thousands of results to compute PODs as a function of input parameters. Multiple POD computational tools are discussed and compared.

2. Guided Wave Imaging

The GWI process used in this work is called Delay-And-Sum (DAS) [1] and relies on delaying and summing the residual signals by the theoretical time of flight for every pair of sensor. Data is generated by a spectral finite element code available in CIVA [3]. In order to produce simulated data representative experimental variabilities, imaging results obtained from simulations are degraded by the following factors. First, the elastic properties of the material are modified to represent a change of temperature between the reference and the baseline state. The baseline measurement is the same for every data set and is simulated with the elastic properties of aluminum at 20°C. Second, the frequency responses of sensors are degraded to represent an aging effect. Third, Gaussian noise is added to the signal to represent measurement noise. The imaging process is conducted at 40 kHz in a 400x400x3 mm aluminum panel affected with a circular through-hole and instrumented by 8 piezoelectric transducers. Two examples of imaging results of a 5 mm hole and 15 mm hole are represented in Figure 1. The 5 mm hole is not detected while the 15 mm is both detected and located.

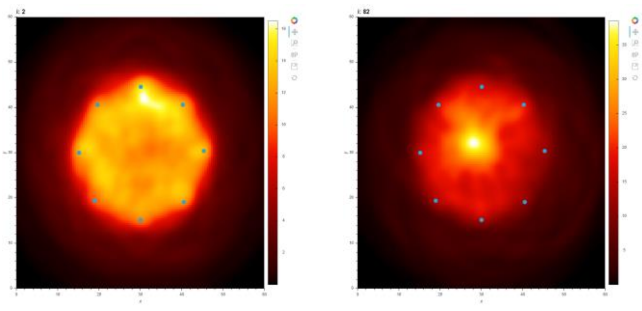

FIGURE 1: Example of GWI result, the white circles represent the sensors while the color map represents the results of the DAS imaging: (a): failed imaging of a 5 mm diameter flaw and (b): successful imaging of a 15 mm diameter flaw

3. Model Assisted probability of detection in SHM

The POD approach in NDT consist of conducting an inspection procedure on multiple samples containing multiple defects (or one sample with many defects). By repeating the inspection multiple times, possibly by multiple operators, variability intrinsic to the inspection is added to the measurement because each inspection is independent. A POD is then computed with various algorithms for example hit-miss or signal response [4, 5]. The POD curve is finally plotted as a function of the characteristic parameter, typically the defect size. This curve is correct only if the variability of every parameter influencing the result of the inspection is properly captured.

In SHM, because the sensors are permanently integrated, successive inspection are dependent. Moreover in GW-SHM, since long range and highly sensitive GW are used, the sample can only contain a unique defect, otherwise the detection of one defect will interact with that of others. This leads to doable but extremely costly experimental campaigns to compute a POD in a GW-SHM setup [6].

The MAPOD approach allows to carry out the computation of a POD using simulated experiments, and thus to study a much wider range of configurations at a reasonable cost. MAPOD is mainly limited by the requirement of having reliable models capturing all the relevant variabilities.

In the studied configuration, the following variabilities are identified:

- Position of the hole,
- Size of the hole,
- Temperature during the acquisition of the damage state (through the change of the elastic properties),
- Degradation state of the sensors,
- Standard variation of the added measurement noise.

Note that this list does not include the type of defect, therefore this specific POD is only relevant for a through-hole, and is irrelevant for a crack for example.

Even though GWI provides both detection and localization, the POD is a metric for the detection aspect only, and probability of localization is not treated in this work. From each image, a scalar value representing the success of the detection must be extracted. In this work, the contrast of the image is used as the detection metric, as it represents the analysis realized by an operator looking at Figure 1 appropriately. The contrast is defined as the ratio between the values of the highest pixels of the picture and the values lowest pixels.

The POD computed will be highly dependent on the following aspects:

- The studied configuration (number and position of sensors, geometry, and type of flaw…),
- The variabilities of the influent parameters,
- The post processing technique (in this work DAS imaging) and the detection approach,

4. Results

A metamodel of the previously described configuration is generated using CIVA. This metamodel fully describes the imaging results obtained in the studied configuration for all the variable parameters within a predefined range. For every variability of the input parameters, 10 000 samples are evaluated using the metamodel. The POD is then computed using the hit-miss algorithm.

First, 10 000 samples are computed for the following input variable distributions:

- Position of the hole: anywhere within the sensor circle with a uniform distribution,
- Size of the hole: from 5 to 15 mm with a uniform distribution,
- Temperature during the acquisition of the damage state: from 15°C to 25°C with a Gaussian distribution centered at 20°C,
- Degradation state of the sensors: amplitude degradation of the measured signals up to 10% for every sensor with a Gaussian distribution,
- Standard variation of the measurement noise: up to 10% of the amplitude of the signal with a log-normal distribution.

This dataset is used to produce the amplitude versus defect size plot represented in Figure 2.

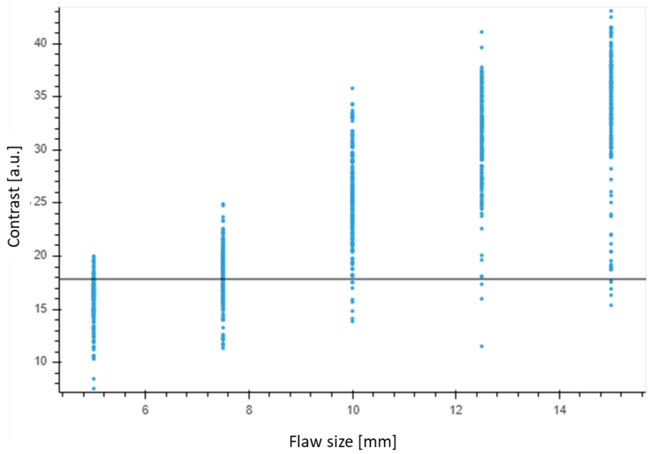

FIGURE 2: Contrast versus defect size dataset obtained with 10 000 samples as described in Section 4. The grey line denotes the detection threshold.

Then, by application of the hit-miss algorithm, the POD curve represented in Figure 3 is obtained. The defect size yielding the $POD_{90|95}$ value is equal in this case to 9.7 mm.

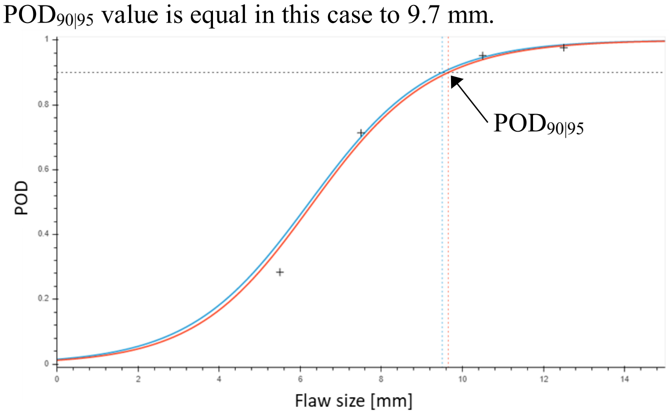

FIGURE 3: POD versus defect size (blue) for the dataset described in Section 4 with temperature variation, with its 95% confidence bound (red).

The same process can be replicated for the same sampling of variable parameters but at a given temperature. In this case, the POD curve obtained is in Figure 4 with a defect size yielding the $POD_{90|95}$ value equal to 9.3 mm.

This use case quantitatively illustrates how the temperature effect can influence the performance of a GW-SHM system. The very small variations in POD compared to the centimetric wavelength means that the temperature variation within this range have very little influence over the imaging results.

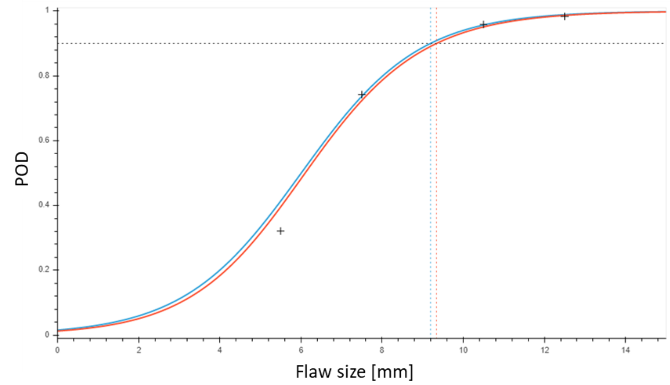

FIGURE 4: POD versus defect size (blue) for the dataset described in Section 4 but without temperature variation, with its 95% confidence bound (red).

5. Conclusion

This work presents the first application of the MAPOD methodology to a GWI experiment in a GW-SHM setup. It is enabled by the availability of efficient and accurate numerical models. Because simulation is used, POD metrics used in NDT can directly be used. A significant effort must be accomplished to ensure that the variability of all the influencing parameters is properly captured. Once a meta-model built, large numbers of samples can quickly be computed for multiple arrangement of the variable parameters. In this paper, the influence of a small variation of temperature between 15 to 25°C was illustrated and compared to an inspection conducted at the nominal temperature of 20°C. A degradation from 9.7 to 9.3 mm of the defect size yielding the $POD_{90|95}$ value was observed, due to these variations.

REFERENCES

[1] Michaels, J. E., Detection, localization and characterization of damage in plates with an in situ array of spatially distributed ultrasonic sensors, Smart Materials and Structures, IOP Publishing, 2008, 17, 035035.

[2] http://www.extende.com

[3] Mesnil, O.; Imperiale, A.; Demaldent, E. & Chapuis, B. Validation of Spectral Finite Element Simulation Tools dedicated to Guided Wave Based Structure Health Monitoring AIP Conference Proceedings, 2019

[4]: Knopp, Jeremy S., and Li Zeng. "Statistical analysis of hit/miss data." Materials Evaluation 71.3 (2013).

[5]: Jenson, F., E. Iakovleva, and N. Dominguez. "Simulation supported POD: methodology and HFET validation case." AIP Conference Proceedings. Vol. 1335. No. 1. AIP, 2011.

[6]: Schubert Kabban, Christine M., et al. "The probability of detection for structural health monitoring systems: Repeated measures data." Structural Health Monitoring 14.3 (2015): 252-264.

