

# Model Assisted Probability of Detection for Guided Wave Imaging Structural Health Monitoring

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Title: Model Assisted Probability of Detection for Guided Wave Imaging Structural Health Monitoring

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#### ABSTRACT

Guided Wave based Structural Health Monitoring has been studied in many laboratories in the last 20 years. In order to ensure industry adoption of this technology, a systematic performance demonstration of such systems is necessary. However, the cost of computing a Probability of Detection (POD) from experimental data is much higher in SHM than in classical nondestructive evaluation. 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 simplistic 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.

#### **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-

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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 is usually computed in "classical" Non Destructive Testing (NDT) and is an attractive approach for SHM too. This approach requires a large amount of data for a wide variety of configurations (sensors positions, flaw position/size, number of flaw...). Experiments can be substituted by simulation to generate this data, which corresponds to the MAPOD (Model Assisted POD) approach

The goal of this work is to illustrate, on a simplistic case study, the application of the MAPOD approach for GW-SHM performance demonstration. 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 and validate a meta-model, which in turns is able to generate several thousands of results to compute PODs as a function of input parameters.

### **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 of 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 dataset and is simulated with the elastic properties of aluminum at 20°C. Second, the responses of the sensors are degraded to represent an aging effect. Third, Gaussian noise is added to the signals to represent measurement noise. The imaging process is conducted at 40 kHz in a 400x400x3 mm<sup>3</sup> 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 blue 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.

## MODEL ASSISTED PROBABILITY OF DETECTION IN SHM

The POD approach in NDT consists of conducting an inspection procedure on multiple samples containing multiple 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 meaningful 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 inspections 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 this simplistic studied configuration, the following variabilities are taken into account:

- Position of the hole,
- Size of the hole,
- Temperature during the acquisition of the damaged 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 (and shape) of defect, therefore the specific POD that will now be computed 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 may represents the analysis realized by an operator attempting at classifying the results of at Figure 1 between pristine and damaged state. The contrast is defined as the ratio between the values of the highest pixels of the picture and the values of the lowest pixels. More refined detection approaches are not within the scope of this work.

### 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, 1 000 samples are evaluated using the metamodel. The POD is then computed using the hit-miss algorithm.

The 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 damaged state: from 0°C to 40°C with a uniform distribution,
- Additive white noise: Gaussian with a standard deviation equal to 10% of the amplitude of the signals

The degradation of the sensors is also taken into account using the following procedure:

- The amplitude measured by the sensor is multiplied by a degradation factor represented by a normal distribution centered on 1, with standard deviation of 0.1 and an upper bound at 1.
- If the sensor degradation is less than 0.9 then the sensor is removed (which significantly degrades the imaging results);
- If the sensor degradation is between 0.9 and 1, the amplitude of the signals measured by this sensor is multiplied by this sensor degradation factor;

These distributions are used to draw 1000 distinct configurations on which the imaging algorithm is applied. The contrast of each resulting image is represented in Figure 2 where each blue dot represents a configuration; the horizontal axis is the size of the defect and the vertical axis is the contrast of the image. As expected, it is observed that the overall value of the contrast increases with the defect size.



Figure 2: Contrast versus defect size dataset obtained with 1 000 samples. 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 12.0 mm.

The same process is replicated for the same distribution of the variable parameters but at a fixed temperature of 20°C. In this case, the POD curve obtained is in Figure 4 with a defect size yielding the POD<sub>90|95</sub> value equal to 9.5 mm.



Figure 3: POD versus defect size (blue) for the dataset with temperature variation  $[0^{\circ}-40^{\circ}]$ , with its 95% confidence bound (red).



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

This use case quantitatively illustrates how the temperature effect can influence the performance of a GW-SHM system. Even though the configuration studied in this paper is very simplistic, and some assumptions (for example concerning the representation of the sensor's degradation) must be consolidated to ensure the meaningfulness of the result produced by this procedure.

#### CONCLUSION

This work presents an 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, and therefore all the data are independent, 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 is built, large numbers of samples can quickly be computed for multiple distributions of the variable parameters. In this paper, the influence of temperature variations between 0 and 40°C was illustrated and compared to an inspection conducted at the nominal temperature of 20°C. A degradation from 9.5 mm to 12 mm of the defect size yielding the POD<sub>90|95</sub> value was observed, due to these variations.

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