# SIMULATION BASED POD EVALUATION OF NDI TECHNIQUES

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**Abstract.** The reliability of non destructive inspection techniques for specific applications can be assessed thru the determination of Probability of Detection (POD) curves. Such probabilistic approaches take into account the uncertainties that appear during inspections and that are responsible for the output variability. Usually, the determination of the POD curve requires a costly and time consuming process that is based on statistical analysis of inspection data obtained during dedicated round robin programs.
Over the years the role played by simulation in the NDI field has been continuously increasing. One important application of simulation tools is to contribute to the performance demonstration of inspection techniques to complement the validation experiments. Until recently, this contribution was limited to deterministic approaches where simulations are run for a set of nominal input values. The numerical performances of current modeling tools such as those proposed by the software CIVA make it now possible to perform intensive computational campaigns. Thus, a new trend consists in applying simulation in the context of probabilistic approaches in order to replace some of the experimental data required to determine the POD with simulation results. This paper describes the methodology that was adopted and the tools that were implemented in the software in order to determine simulation supported POD curves. Applications of the methodology to UT and ECT inspections are also described.

## Introduction

The qualification of non-destructive testing consists in assembling all the supporting evidence for inspection capability. Various methodologies are available to quantify inspection capability. Among these methodologies, the Probability Of Detection (POD) is a metric that has been extensively used in some industrial sectors such as air transportation. The purpose of the approach is to relate the POD with defect size.POD curves are obtained thru practical trials using representative defective test pieces. Such empirical studies are expensive and time consuming.
During the past decade, ways to reduce costs of POD curves assessment have been proposed, most notably by the MAPOD (Model Assisted POD) working group [1]. Various means to achieve this task have been proposed and explored. Roughly, they can be grouped into two categories: the transfer function approach and the full-model assisted approach. The transfer function approach consists in determining a POD curve for a complex case by applying a "transfer function" to an already known POD curve. The transfer function is assessed thru a specific empirical study that is performed on more simple specimens (for instance, simpler geometrical properties) than the one for which the POD curve is needed. The full model assisted approach (also named simulation-based POD) promotes the use of physics-based models to complement or replace empirical data with simulation results. This paper is a contribution to this approach.
A thee-year duration project funded by the French national research agency, named the SISTAE project, resulted in a methodology and an associated software module implemented in the software CIVA [2]. The proposed methodology uses the physics-based models that are developed in the framework of the software to simulate realistic inspection results which are in turn used to determine the POD curve. The idea here is to switch from the usual deterministic approach where simulations are run using perfectly known nominal

values for the model input parameters to a statistical approach were uncertainties for some input parameters are assumed and accounted for. Thus, the variability of the inspection response is modelled and the POD curve can be estimated.
This paper describes this methodology and gives first results for UT and ECT application cases.

## 1. Taking into account uncertainties in the simulation

### 1.1 Description of inspection parameters using statistical tools

When performing an inspection, the probe signal response due to a flaw will be affected by factors related to the NDI system (transducer, scan plan, electronic device), to the part (geometry, material properties, surface roughness) and to the flaw (size, shape, orientation, position). A factor can be though of as deterministic it can be controlled during the inspection, if its influence on inspection results is weak or if it is desired to estimate the POD as a function of the level factor (flaw size for instance). The factor is considered as random if there is insufficient knowledge related to it, if the factor is not well controlled or if the factor implies physical phenomena with inherent randomness. Factors related to detection recognition by human operators (and any other human related factors) are not addressed in this paper.
New tools have been added to the software CIVA in order to complement the framework dedicated to the computation of simulation-supported POD curves. Probabilistic tools have been connected to the software. These tools provide a mean to characterize uncertainty for a set of input parameters for which actual values are thought to be not precisely known. This is done using random number generators. Various statistical distributions are proposed in the software: Uniform, normal, Log-normal, Rayleigh and Exponential (see in Figure 1).

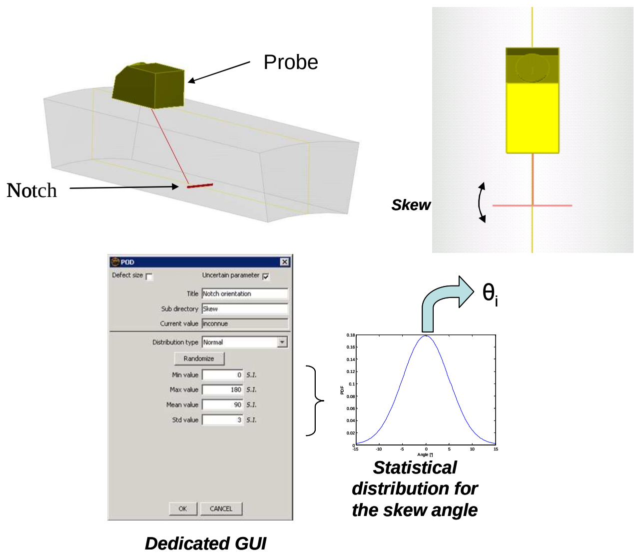


**Figure 1: Description of uncertainties using statistical distributions. Example of the notch skew**

### 1.2 Propagation of uncertainties thru the model using a Monte Carlo approach

Once the uncertain input parameters are selected and described, a numerical method is carried out to assess the inspection output variability. Typical UT inspection outputs are the maximum amplitude of the rectified signal or the peak-to-peak amplitude within a time gate. EC inspection results usually come in the form of the maximum amplitude of the impedance fluctuations over the scanned area. The idea here is to propagate uncertainties of the inputs through the model. For the time being, a simple Monte Carlo approach is proposed. The method consists in sampling the uncertain input parameters by randomly generating values from the selected statistical distributions. Then, the model is computed for each n-tuples of values of the uncertain inputs (in the case where n unknown inputs have been selected by the user). Once the execution of the model is achieved, the variable of interest is automatically extracted and displayed in a specific window for further post-processing (the POD curve computation). The approach is described in Figure 2.

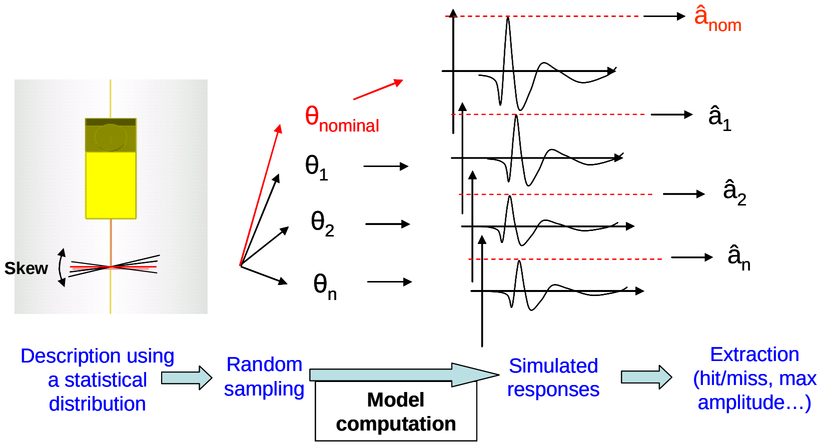


**Figure 2: Uncertainty propagation through a CIVA physics-based model using a sampling approach for simulation-based POD evaluation**

### 1.3 Description of the defect characteristic feature

A POD curve is defined as the variation of POD with respect to a characteristic quantity of the flaw. Often, it is the size of the flaw. Thus, this particular parameter needs to be selected and a set of possible values defined (Figure 3).

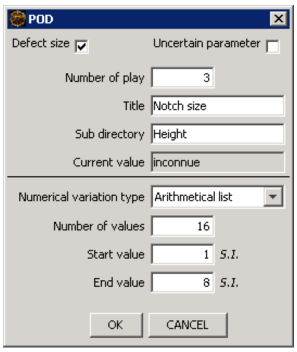


**Figure 3: Definition of the dependency parameter of the POD curve. Here, the notch height as been selected with values ranging from 1 to 8 mm.**

When performing the uncertainty propagation step, for each flaw size a set of random values for the uncertain input parameters is fixed. In the case of a POD curve estimated from hit/miss data, at least two simulations per flaw size are required since an average of the hits over the number of results for each flaw size is required (this is a sort of “averaged” POD curve which must be computed so that the parameters of the functional form can be estimated).

### 1.4 Determination of the POD curve using a parametric functional form: the Berens approach

For a specific inspection method the POD expresses the probability that a flaw of a certain size will be detected, if this flaw is actually present in the inspected component. The usual approach consists in assuming a functional form for the POD curve and in estimating the parameters of the function, as well as its associated confidence bound [3,4], from experimental data obtained during dedicated round-robin inspection programs.
Depending on the data format, different statistical analyses are performed. For hit/miss data, binary information is recorded by the inspection system, indicating whether or not a defect has been detected. The probability of detection is estimated for each defect size by computing the ratio of hits to the number of inspections for that defect size. A log-odds function is then fitted to the estimated detection probabilities. In the case of signal response data, the amplitude of the signal is recorded by the inspection system and thus, more information is available than for the hit/miss data format. The statistical analysis is first made by interpreting the system response to the presence of a defect. In the usual approach, it is assumed that the logarithm of the signal response amplitude is linearly correlated to the logarithm of the flaw size. The random error between the signal response amplitude predicted using the linear relationship and the measured one is supposed to be normally distributed with a standard deviation which does not depend on the flaw size. Based on these assumptions, it can be shown that the POD curve can be modeled using a cumulative log-normal distribution function. Since the POD model is estimated from a finite size data sample, there is a sampling uncertainty on the estimates of the model parameters. This uncertainty is usually characterized by placing confidence bounds on the POD function [5,6].

The data resulting from the uncertainty propagation step (in practice, the maximum amplitude of the inspection signal) are plotted against the defect size. A set of options proposes the user to:

- switch from the “signal response” data format to the “hit/miss” one,
- select between two different assumptions on the linearity between the signal response and the flaw size,
- select between two different assumptions on the linearity between the log of the odds of the probability of detection and the flaw size.

Depending on the selected assumption, the simulation results are displayed on a plot using the adequate scale (linear or logarithmic), thus giving the possibility to the user to qualitatively validate the linearity assumption. The POD curve is then automatically computed using the adequate model (based on the approach of Berens [4] as described previously in the paper) and plotted in the lower part of the window. An example is given in Figure 4.

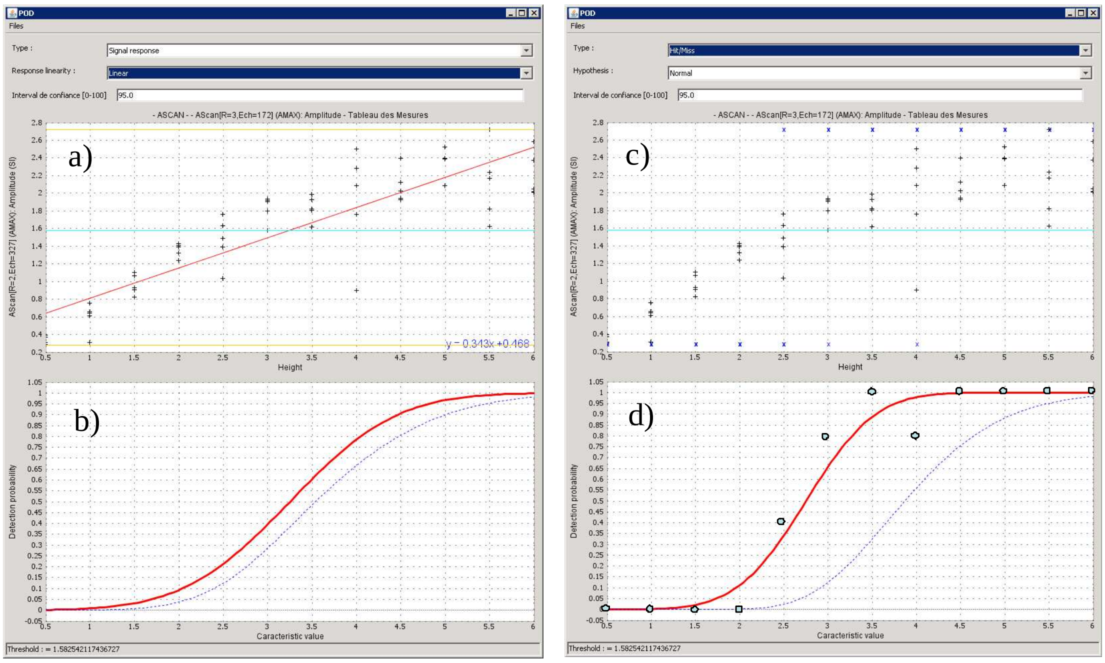


**Figure 4: Display of results: a) Simulated ultrasonic signal amplitudes (black marks) and b) corresponding computed POD curve (red curve) and the lower confidence bound (blue dotted curve). c) The same data converted in hit-miss format (blue marks) and d) the corresponding "averaged" POD (blue points), the POD curve and the confidence bound.**

On the example of Figure 4, 5 inspections per notch size were simulated. The height of the notches ranged from 0.50 mm to 10 mm with steps of 0.5 mm, giving a total of 20 x 5 = 100 values. The analysis can be also applied when certain values are censored at the recording threshold or at the saturation limit (the thresholds can be changed by moving the yellow lines on the upper right plot in Figure 4).

As it can be observed in the figure, another statistical analysis can be performed on the same data set when it is converted to a hit/miss format. The "averaged" POD curve obtained by calculating the ratio between the number of hits and the total number of simulated inspections per flaw size is also displayed (we have 5 inspections per notch size and thus, the mean POD can take 5 values: 0, 1/5, 2/5, 3/5, 4/5, 1).

## 2. Simulation-based POD results for representative application cases

### 2.1 Eddy current inspection of inconel plates

#### Simulation of lift-off and probe orientation fluctuations

In this example the EC signal is the impedance variation of the coil due to the flaw with respect to its impedance Z0 in a flaw-free region. The variation of Z0 due to the tilt and lift-off, which amplitude is actually much bigger than the EC signal, does not appear in Figure 6. The influence of these two parameters makes them particularly relevant for a study of perturbations occurring during an EC inspection. Small variation of the coil position and orientation may indeed occur when an operator manually scans a workpiece with an EC probe. As described below, such variations are taken into account in simulation-supported POD computation through random values.

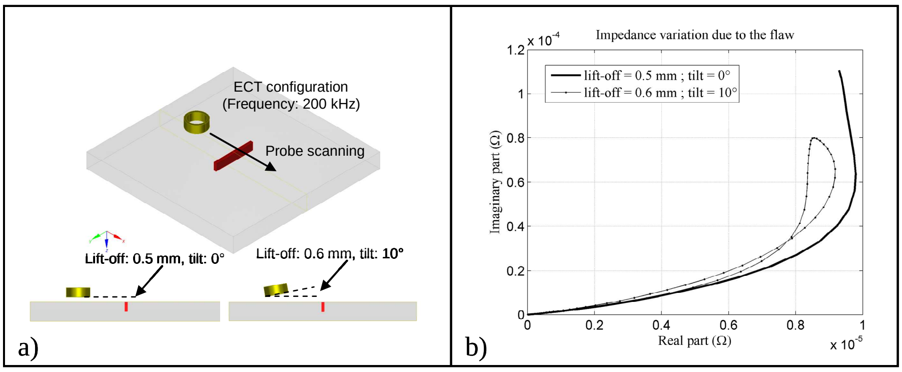


**Figure 8: Effect of a modification of the coil tilt and lift-off a) Simulated configuration, b) Results.**

## POD determination

POD tools have been applied in the purpose of simulating experimental POD campaign performed on a mockup by five operators. The mock-up contains 20 breaking notches of varying depths which are linearly distributed in the range [0.1 mm 2 mm]. The notches opening and length are respectively 0.3 mm and 5 mm. The mockup is successively inspected manually at the frequency of 200 kHz by the five operators, using the same surface riding probe. Therefore a set of five values has been simulated for each of the twenty flaws, taking into account the two perturbations occurring during the inspection (probe tilt and lift-off). The random variations of the input parameters are defined by normal statistical distributions centered about nominal values (a tilt of 0° and a lift-off of 0.5 mm). Chosen standard deviations for the tilt and lift off are 0.5° and 0.1 mm, respectively.

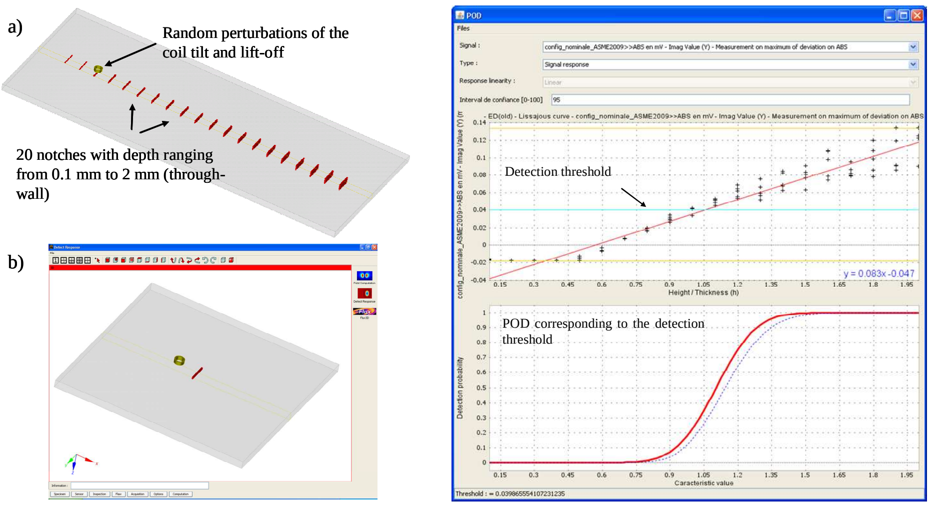


**Figure 9: a) Application of a POD study in an EC case. Twenty flaws are tested five times each with a coil, whose tilt and lift-off vary randomly about nominal values. b) Simulations with CIVA: only one configuration is defined, and a variation of the flaw depth as well as statistic distributions governing the tilt and lift-off perturbations are set up using POD tools. All Calculations are then carried out automatically. c) Simulated values of the imaginary part of the signal are plotted in the upper part of the window with respect to the flaw depth. Then, for a given detection threshold defined in this plot, a POD curve is plotted in the lower part of the window with respect to the characteristic value considered, here the flaw depth.**

The results are plotted in Figure 9. The imaginary part of the EC signal obtained after a phase rotation of 100° is extracted. This particular procedure aims at separating the EC signal due to the flaw from the one due to impedance variation Z0 in a flaw free region, which amplitude is several times bigger. The angle chosen for the phase rotation is such that most of the part due to Z0 is transferred in the real part of the signal, and the POD calculation is carried out using the imaginary part of the EC signal. For a given set of simulations, POD curves may be calculated for any detection threshold setup inside the data plot, located above the POD curve.

## 2.2 Ultrasonic inspection of cast stainless steel pipe

This example illustrates how the influence of the metallurgical properties on the reliability of the inspection may be accounted for. Statically and centrifugally Cast Stainless Steel (CSS) has been widely used in the primary loops of pressurized water reactors in France, USA and other countries. Due to their particular coarse grained structure, the ultrasonic inspection of CSS components is very challenging. Cast stainless steels are made of large equiaxed and/or columnar shaped grains with sizes that may exceed the ultrasonic wavelength at typical inspection frequencies. Thus, cast stainless steels are highly heterogeneous materials for the propagation of elastic waves. This results in beam distortions and disruptions and consequently to strong fluctuations of NDI signals even if those are generated by nominally identical flaws.

### Simulation of the macrostructure influence

Dealing with complex heterogeneous structures requires developing a dedicated physical model. Here, the heterogeneous material is defined using Voronoi diagrams [7]. This technique consists in subdividing the medium in convex cells with random geometrical properties. Example of such decompositions can be seen in Figure 6. The elastic properties of a single cell (which is thought to represent a macrograin) are supposed to be isotropic for numerical efficiency purposes. The velocity dispersion is taken into account by piquing random velocity values from a uniform distribution. The width of the distribution and thus the velocity dispersion characterizing the material is controlled by the input parameter $\Delta VL$. The wave propagation through this complex structure is computed by applying the pencil method.

Figure 5 illustrates the simulation of the back-wall echo in a cylindrical part of 68.5 mm thickness, inspected in pulse echo mode with a focused immersion probe at 1 MHz. A Voronoi diagram characterized by a mean cell size of 12 mm and various values of the parameter $\Delta VL$ has been used. The back wall has been computed for several transducer positions in order to display B-scan images. Fluctuations in amplitude and time of flight can be observed on the experimental data displayed in Figure 5. These fluctuations reflect the interaction between the ultrasonic wave and the metallurgical structure. The simulated back wall echo is perfectly coherent when the computation is performed in a homogeneous medium ($\Delta VL=0$). When the computation is performed in a medium with weak velocity fluctuations ($\Delta VL=3\%$ of the medium mean velocity), the experimental features can be qualitatively reproduced.

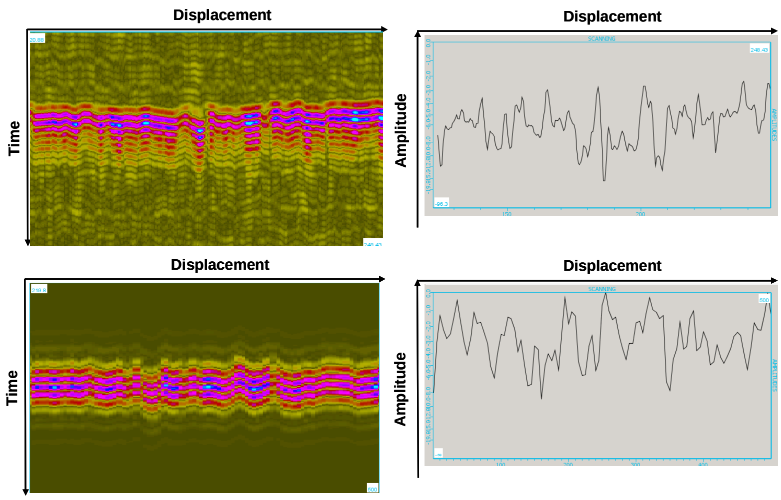


**Figure 5: Simulated (lower plots) and experimental (upper plots) Bscan images showing the fluctuation of amplitude and time of flight of the back wall echo.**

## POD determination

On this same example, the performance of the ultrasonic inspection is evaluated by computing the POD curve established as a function of side drilled holes diameters.

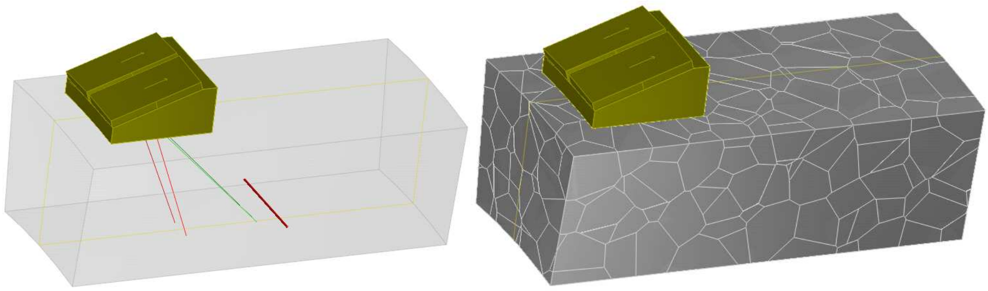

**Figure 6: Inspection of a cast stainless steel pipe containing a side-drilled hole. Simulated configuration: On the left, CAD representation showing the side drilled hole. On the right, one particular realization of the Voronoi description of the metallurgical structure**

The input parameters of the Voronoi diagram and the wave velocity fluctuations (i.e. the material properties of the CSS) have been settled according to the results of a previous study [7]. The mean grain size is approximately 10 mm and the mean velocity fluctuation is 1 %. Comparisons of simulated results to experimental data have proved that typical features such as phase and amplitude distortions of the transmitted beam were well reproduced with such values of the Voronoi diagram. Simulations are performed for various values of the hole diameter and for different realizations of the macrostructure.

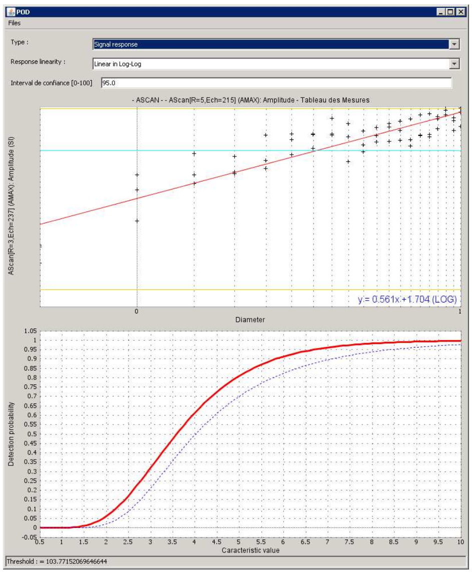

**Figure 7: Ultrasonic inspection of the cast pipe containing side-drilled holes Upper plot: Display of the simulation results (black marks); lower plot: Computed POD curve (red curve) and lower confidence bound (blue dotted curve).**

Figure 7 shows the results of the statistical study. The only source of signal fluctuation is the impact of the macrostructure on the transmitted beam.

## Conclusion

A methodology allowing the determination of simulation based POD curves is described in this paper. It consists in proposing statistical tools to describe uncertainties on the influential inspection parameters. Uncertainty is propagated thru the physics based model using a sampling technique (a Monte Carlo approach). For complex signal fluctuation sources such as the impact of a coarse grained metallurgical structure on elastic wave propagation, dedicated models are required. The POD curve is determined from the simulation results by performing a statistical estimation of the parameters of a functional form. Validation of the approach requires that simulation supported POD curves are compared to empirical ones for industrial application cases. First results for a high frequency eddy current inspection of titanium plates are presented during the conference [8]. Such validation studies and the development of new tools to complement the simulation supported approach that was initiated during the SISTAE project, are part of a European funded project called PICASSO that started in 2009.

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