Model based inversion strategy dedicated to non-destructive testing applications

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***Abstract*—This paper presents a global strategy aiming at solving efficiently inverse problems classically faced in the community of non-destructive testing, like flaw characterization and sensors optimization, for instance. The approach is based on intensive use of simulation tools that are obtained from complex physical models developed at CEA LIST and dedicated to ultrasonic and electromagnetic testing applications. Results presented in different physical contexts show not only its efficiency to solve parametric estimation problems, but also its capability to account for variability due to uncertainty in some model parameters and to evaluate the so-called well-posedness of inverse problems considered.**

***Index Terms*—non-destructive testing, low frequency Electromagnetics, ultrasounds, flaw characterization, probe design.**

I. Introduction

The field of non-destructive testing (NDT) gathers a very large family of techniques used to inspect materials without affecting them in terms of usability [1], [2]. Most popular techniques are, in a similar way as in medical imaging, either based on Ultrasonics, Electromagnetics or X-ray. This paper focuses on two particular techniques, which are bulk waves Ultrasonic Testing (UT) and Eddy Current Testing (ECT), applied to inspection of metallic parts. These techniques are not limited to traditional detection and characterization of flaws in material, as they can also prove useful in a material characterization context, where they provide a macroscopic information, which is strongly correlated to the microscopic material state [3]. One of the main objective in NDT applications is, of course, to access to the largest amount of information about the material and possible unwanted inhomogeneities that affect it. This means that such methods are often required not only to detect inhomogeneities but also to characterize them in terms of geometry and/or physical properties [4]. A common way to regularize these ill-posed problems is to use physical models able to account for complex phenomena, and thus to transform them into a parametric estimation problem, the target being a subset of the models inputs. Numerous works have already been proposed to exploit, to this end, simulation tools in various ways [5]. The approach used in this paper uses mixed semi-analytical and numerical models developed by CEA LIST in the multi-physics platform CIVA [6]. In order to provide almost real time estimations, which are more and more required in the context of in-line diagnostic or even in-process diagnostic for additive manufacturing applications, accurate surrogate models [7] are built on top of the models, from adaptively designed databases of simulation results. Finally, sensitivity of the estimation process is evaluated through uncertainty propagation, in view of providing measures of results dispersion, like error bars, and give an indication about the well-posedness of the problem. After a succinct presentation of two particular applications cases in propagative and diffusive regime with corresponding physical models, the surrogate modelling approach used in this work will be introduced and estimation results will be discussed.

II. Physical application cases of interest

The two configurations of study are quite typical ones for ECT and UT. Signals to be dealt with are very different in nature and behaviour in each case: they are harmonic and diffusive in space for ET, which relies on the quasi-static phenomenon of induction, whereas they are oscillating in time and propagating in space for UT. Therefore, a particular care must be put in the comparison between signals, which is underlying the parameter estimation.

A. Eddy current testing of stratified plates

Eddy current testing is very popular for inspection of conductive materials as it is highly sensitive, contactless and very reproducible technique. It is, however, able to inspect the upper surface of materials only, due to the so-called skin effect. A classical use in Aeronautics consists in inspecting large areas, looking for small cracks that can be either breaking the surface or slightly buried below the surface. In the configuration considered (see Fig. 1), a signal coil is inspecting at a frequency of 1 kHz a stack of two plates separated by a thin insulating layer [8]. Each layer contains a through-wall crack and both cracks are tilted with respect to each other with an arbitrary angle. The characterisation of flaw parameters is made difficult in this case by the interaction between flaws and the buried location of one of them. From the modelling point of view, the forward problem is solved by means of a specific integral formulation [8] derived from the Volume Integral Method and adapted to narrow cracks. After the calculation with a modal approach [9] of the electric field induced in the flaw-free material, the two equivalent sources accounting for the flaws are calculated by solving an integral equation involving the Green dyadic function of the stratified material. Then, a reciprocity argument is exploited in order to directly derive, from these incident field and equivalent sources, the impedance variation of the coil as it scans the piece. As shown is Tab. I, parameters of interest are in this case geometrical parameters

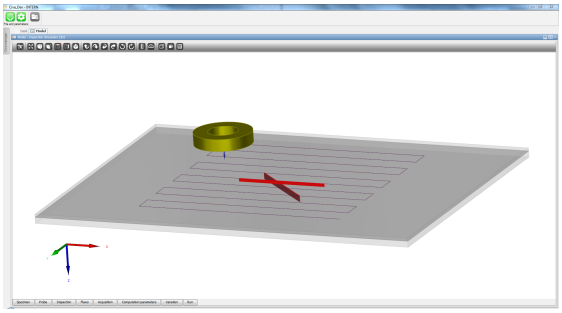


Fig. 1. ECT inspection configuration, as it can be described with the CIVA software. A stack of two aluminium sheets, affected by two narrow cracks, are inspected by a single coil.

Id.	Parameter		Range of variation
1	Coil lift-off	[mm]	$[0.025; 0.25]$
2	Crack 1 length	[mm]	$[25; 33]$
3	Crack 1 opening	[mm]	$[0.05; 0.5]$
4	Crack 2 opening	[mm]	$[0.05; 0.5]$
5	Crack 2 length	[mm]	$[25; 33]$
6	Crack 2 angle	[deg]	$[-15; 105]$
7	Coil Tilt	[deg]	$[-5; 5]$
8	Dielectric Thickness	[mm]	$[0.05; 0.5]$

TABLE I
PARAMETERS STUDIED IN THE ECT CONFIGURATION.

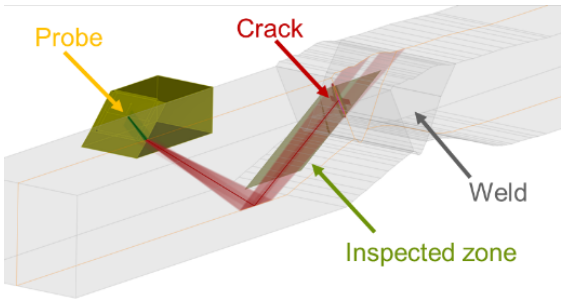


Fig. 2. UT inspection configuration, as it can be described with the CIVA software. the weld area joining two stainless steel plates is inspected using shear waves.

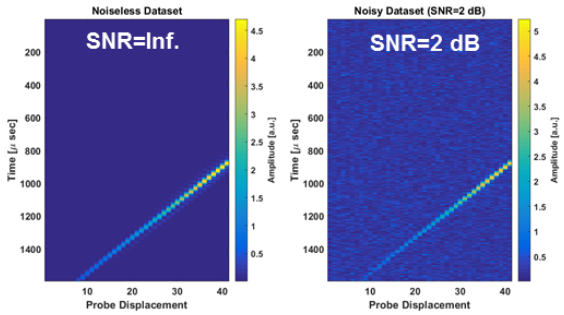


Fig. 3. Bscan representation of the UT signal, which has been used .

characterizing both flaws, namely their length and opening, as well as the angle between them. In addition, some parameters that are typical source of variability are also considered: the coil lift-off, which is certainly the main source of perturbation for such inspection configurations, its tilt angle and the thickness of the insulating layer separating the two Aluminium sheets. An interval of variation is set for each variable parameter studied.

B. Ultrasonic testing of welded parts

The second application case is related to welds inspection, which is a topic of great interest in several sectors of industry like the ones of Energy and Oil and Gas. In the configuration considered, described by Fig. 2 and Tab. II, a single probe with center frequency of 2 MHz scans a set of two welded plates made of stainless steel. The inspection angle is 45°, using shear waves. The so-called B-scan representation, consisting in a 2D map of the signal amplitude with respect to time and probe position, is used as input data, as shown in Fig. 3. The forward modelling of this problem is carried out using a ray-tracing formalism for the fast calculation of the ultrasonic field generated by the transducer, a Kirchhoff approximation for its interaction with the flaw, located in the immediate vicinity of the weld and, again, a reciprocity argument for the direct derivation of the signal of interest. Parameters to be estimated in this case are the crack height, length and position with respect to the weld, provided that it stays parallel to the weld bevel.

III. FAST MODEL APPROXIMATION BY MEANS OF ADAPTIVE DATABASES

In order to explore the space defined in both cases by the product of intervals of variation assigned to each parameter in Tab. I and II, corresponding forward models forward models need to be evaluated many times. Even with the fast formulations cite above, such an intensive use makes the estimation process so cumbersome that it prevents its deployment in contexts, where quick diagnostics are required.

Hence, these models have been approximated by surrogate models, based on databases of simulation results. A database $D = [(x_1, y_1), (x_2, y_2), ..., (x_N, y_N)]$ is defined as a collection of input/output couples. The outputs $y_i = \mathcal{F}(x_i)$ usually consist in a functional output, which can be real or complex-valued regardless of the considered NdT method and the associated inspection technique. In this work, the database is built based on functional complex valued signals in the case of ECT and functional real signals in the case of UT problems. Based on

Id.	Parameter		Range of variation
1	Crack height	[mm]	$[2; 6]$
2	Crack length	[mm]	$[8; 26]$
3	Crack position	[mm]	$[11; 25]$
4	Probe yaw	[deg]	$[0; 15]$
5	Shear waves velocity	[m.s^{-1}]	$[3180; 3280]$

TABLE II
PARAMETERS STUDIED IN THE UT CONFIGURATION.

the database training set, the surrogate model (M) is fitted by employing suitable kernel-based methods (e.g., kriging, radial basis function (RBF)) or sparse grid methods [10]. Thus predictions $\tilde{\mathbf{y}}$ are obtained by evaluating the surrogate model on a unseen test set such that $\tilde{\mathbf{y}} = M(\mathbf{x})$. In the ECT case, a database of 3544 simulated signals has been built adaptively using the output space filling method [11], then it was fitted by a RBF interpolator. The accuracy of th surrogate model obtained was checked with a 10-K fold Cross Validation (CV) with respect to the Mean Normalized L-2 Error (MNL2E) defined in eq. (1). The overall accuracy of the surrogate model according to this error is about 7%. In the UT case, the signals database contains 3500 samples and the surrogate model was built in a similar way.

$$MNL2E = \frac{1}{N}\sum_{n=1}^{N}\frac{\|\mathcal{F}\{\mathbf{x}_n\} - \mathcal{M}\{\mathbf{x}_n\}\|_2^2}{\|\mathcal{F}\{\mathbf{x}_n\}\|_2^2} \qquad (1)$$

IV. Estimation results and uncertainty propagation

Estimation of flaw parameters was carried out in this work using both local and global classical optimization algorithms, namely Sequential Quadratic Programming (QP) and Differential Evolution (DE), applied to the $MNL2E$ error function defined above. The investigation of other strategies based on learning methods are also investigated with great success in another context [12].

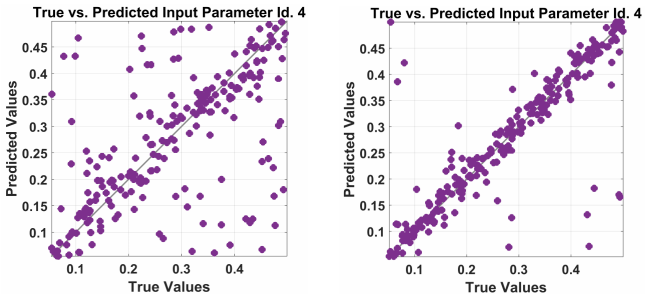
A. Robustness of estimation algorithms

A first comparison of results obtained with these algorithms has been performed in conditions, where the observations – which are synthetic in this work– are perturbed by additive white noise in such a way that the level of signal to noise ratio is decrease down to 20 dB. As expected, the local optimizer performance is affected by noise in a stronger way than that of the global one, as illustrated in Fig. 4 for the 'difficult' parameter to estimate: the opening of the buried flaw, as a single coil will have a lesser sensitivity to it than more complex probe arrangements and this flaw is shadowed by the upper crack. the DE algorithm is thus preferred, its high cost in terms of number of forward problems evaluation being overcome by the use of a surrogate model. It is worth noticing that learning by example techniques [12] show a very good robustness to noise, as they can integrate it in the learning phase.

B. Well-posedness of the inverse problem

It reduces, indeed, the unitary evaluation of the model (to a few milliseconds) drastically, which allows, in addition to carry almost real-time parameters estimations, to study the problem more in depth. For instance, it becomes possible to image the cost function, accounting for the distance between the observation and simulated signals, as shown in Fig. 5 for the ECT and UT case, respectively.

This function is represented in the input space, here three flaw parameters were chosen in each case. As one can see,



QUAD. PROG. DIFF. EVOL.

Fig. 4. Effect of additive white noise on the estimation of crack 2 opening (fourth parameter) in the ECT case. The signal to noise ratio is 20 dB.

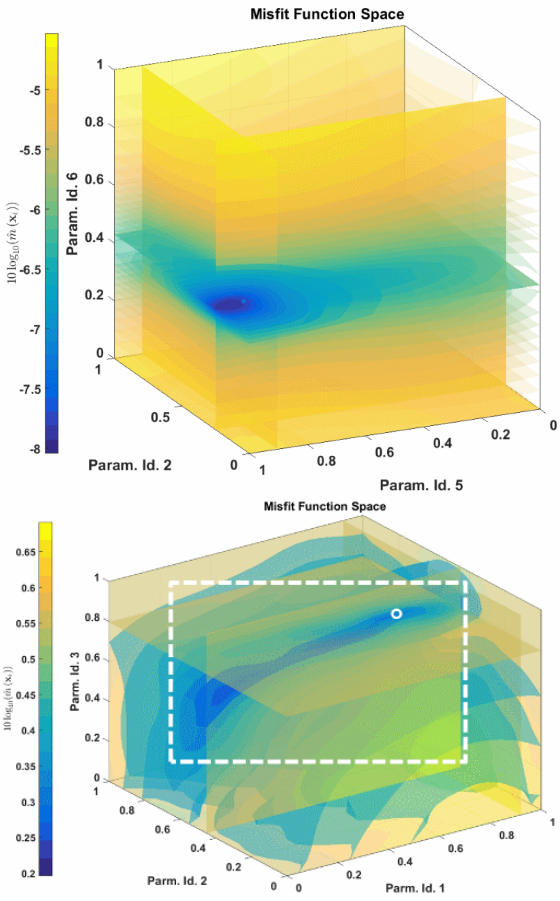


Fig. 5. Cost functions corresponding to the ECT (top) and UT (bottom) case, respectively. Each of them is depending on three flaw parameters: lengths of cracks 1 and 2 and angle separating them in the ECT case; height, length and vertial position in the UT case.

the cost function (its restriction to three parameters actually, as 5 parameters are estimated in this case) in the ECT case shows a clear minimum, whereas the one of the UT case is not clearly noticeable, which indicates that the ECT estimation problem is somewhat 'better posed' than the UT one. In order to quantify this, a strategy of uncertainty propagation was applied to the estimation process. Flaw parameters have been estimated assuming nominal values of probe or medium

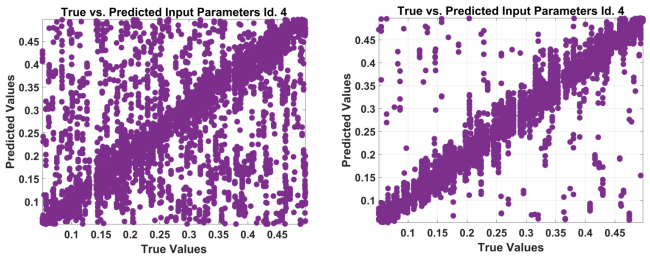


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Fig. 6. Estimation of crack 2 opening (fourth parameter) in the ECT case when applying uncertainty propagation.

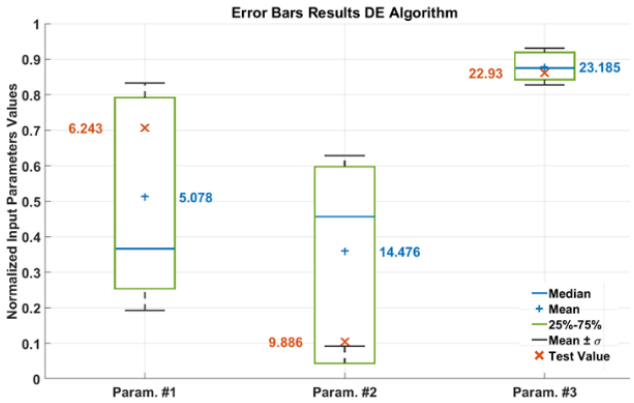

Fig. 7. Estimation results obtained in the UT case when applying uncertainty propagation.

parameters, but observations were generated with randomly taken values of these parameters. the dispersion of the obtained estimates gives, thus, a measure of the process robustness to this particular variability, which is commonly observed in the field of NDT. In the UT case, uncertain parameters, namely the probe yaw and the shear wave velocity, were sampled according to a normal distribution $\mathcal{N}(\mu, \sigma) = [7.5^\circ \ 0.5]$ and a uniform one in the range $[3219 \ 3241]$ m.s^{-1}. In the ECT case, the coil lift-off and tilt angle are described by normal laws $\mathcal{N}(\mu, \sigma) = [0.1125 \ 0.1]$ mm and $\mathcal{N}(\mu, \sigma) = [0 \ 0.1]^\circ$, respectively. The thickness of the insulating layer is described by an uniform law in the range $[0.185 \ 0.265]$ mm. Considering the same parameter as in Fig. 4, Fig. 6 illustrates the different behaviours of both QP and DE algorithms. The QP algorithm shows poor efficiency but the DE one still manages to estimate with good accuracy the crack opening. Similar results are observed with the two other flaw parameters. Hence we can conclude that the ECT case is quite well posed, in terms of flaw characterization. Now, if we look at the estimation results obtained in the UT case, represented as a box-plot in Fig. 7, then we can see that even with the DE algorithm, the first two parameters, corresponding to the flaw length and height, respectively, are determined with poor reliability. This indicates clearly that the inverse problem is very sensitive in this particular case.

V. Conclusions

A general strategy dedicated to parametric inversion in the field of NDT has been described and illustrated in two classical cases involving ultrasonic testing and eddy current testing. Limitations in terms of computation time are faced out by the use of surrogate models, built from adaptive database of results in order to ensure their accuracy with respect to physical models. This enables firstly to use more expensive optimization algorithms like genetic ones in order to improve robustness of estimation to measurement noise. Secondly, statistical studies based on uncertainty propagation through the modelling and estimation process can be carried out within minutes in order to check the estimation robustness to more realistic conditions, where some input parameters of the physical model are no known precisely. These tools can prove very useful in the context of online diagnostic, as they are able to provide almost real time estimation and associate a level of confidence to it. Perspectives of this work include comparing classical optimization techniques to other methods, which can also assimilate prior knowledge and enable the estimator to improve itself with time.

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