

Metamodel as Input of an Optimization Algorithm for Solving an Inverse Eddy-Current Testing Problem

Rémi DOUVENOT^{a,1}, Marc LAMBERT^a and Dominique LESSELIER^a

^a *Département de Recherche en Électromagnétisme,
Laboratoire des Signaux et Systèmes UMR 8506 (CNRS - SUPELEC - Univ Paris-Sud),
91192 Gif-sur-Yvette, France*

Abstract

A method to characterize defects by processing eddy-current testing (ECT) signals is presented. It works in a short time for generic defects and workpieces. To retrieve the dimensions of a defect, a metamodel-based Particle Swarm Optimization (PSO) is considered. Indeed, using a metamodel as an input of a stochastic method enables to significantly speed it up. The metamodel is generated using an adaptive database generation. Both tube and plate configurations, corresponding with either simulated or laboratory-controlled measured data are considered as illustration. Good accuracy and satisfactory speed of the method are exhibited, additional information besides the inversion results being provided as well, which highlights possibly indeterminate cases, making the method useful also for decision analysis.

Keywords. Eddy-current testing, Metamodel-based inversion, Particle swarm optimization, Decision analysis

Introduction

Eddy-current testing (ECT) is a well-known non-destructive technique for defect detection in metal parts. Yet ECT signals can be used also to characterize a defect, beyond mere detection. In the framework of the present study, a (quasi-)real-time method is aimed at. This implies that there is strong a priori information about the tested workpiece and the type of defects to be characterized. Previous efforts to reach this goal have focused on learning algorithms, with encouraging results as seen in [1,2]. To improve the learning step, adaptive databases have been introduced [3].

Here, the adaptive databases are employed to create a metamodel, which is used as an input of a Particle Swarm Optimization (PSO). A fast stochastic inverse method is then obtained. It is put to the test on a number of cases, involving synthetically generated data and laboratory-controlled measured data, in both tube and plate configurations.

To create the metamodel, an adaptive database is generated, refer to [4]. This database in practice concentrates a higher number of points where the output variations are the fastest ones, with respect to those of the inputs. In so doing, all the variations of

¹Corresponding author e-mail: remi.douvenot@lss.supelec.fr

the outputs with relatively few points can be encompassed. This being made, a classical radial basis function (RBF) interpolation [5] with a thin plate spline kernel function is applied. The adaptive database interpolated by RBF is the metamodel that is used to feed the stochastic inverse method.

The performances of the metamodel-based inversion method are illustrated for two configurations, each corresponding to one benchmark: a circular tube workpiece affected by groove defects (two parameters are to be retrieved) and a plate with parallelepiped defects (three parameters are to be retrieved). For each configuration, the method is applied on many simulated signals and a couple of measured data extracted from the benchmarks.

1. The metamodel-based PSO method

1.1. Forward problem solver

Let us assume that tests are performed on generic pieces. Constitutive materials and geometrical dimensions of both workpieces and probes are known, at a given frequency of operation. The input parameters are the ones describing the defect inside the workpiece. Then the response of the flawed piece to the probe is computed via an integral volume formulation (see for example [6]), and a variation of impedance is obtained as an output. The CIVA simulation software [7] is used for this purpose. If \mathbf{P} are the input parameters and \mathbf{y} is the measured or simulated output impedance, we denote $\mathbf{y} = \mathcal{L}(\mathbf{P})$. Other methods could obviously be preferred for carrying out the forward simulations. For our purpose, the forward simulations are only used to generate the database.

1.2. Generation of the adaptive database

The aim of the adaptive database is to get, at the end, input parameter sets with equivalent simulated output impedance variations, which are such that there exists a higher density of inputs where the output variations are faster.

The database is created iteratively in order to achieve this goal. This adaptive database generation is described in some more detail in [4]. First, a coarse mesh is generated. Then, at each edge of each simplex of the mesh, simulations are compared to linearly interpolated data. If the interpolation error ε , defined below, is larger than a prescribed stopping criterion, a node is added in the middle of the longest edge of the simplex. An example of a 2D mesh is shown in Figure 1. The interpolation error ε is expressed as

$$\varepsilon = \frac{\|\mathbf{y} - \hat{\mathbf{y}}\|_2^2}{\|\mathbf{y}\|_2^2} \quad (1)$$

where \mathbf{y} and $\hat{\mathbf{y}}$ are the exact and the interpolated data, respectively.

Once all calculations have been performed, the database is a set $(\mathbf{P}_i, \mathbf{y}_i)_{i=1, \dots, N}$ where N is the size of the database, each vector \mathbf{P} being of dimension D (number of parameters to describe a defect), and each vector \mathbf{y} being of dimension M (number of measurement points for one configuration).

The generation of the adaptive database certainly is a crucial step for metamodel-based optimization. Depending upon the formulation of the interpolation error, different

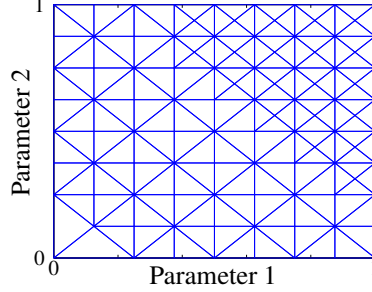


Figure 1. Example of a 2D adaptive database.

behaviors of the interpolated data can be observed (a better accuracy on low or high amplitude signals for instance) [8].

1.3. Interpolation of the database

The aim of interpolating the database is to create a metamodel. The operator \mathcal{L} is approached via an expression depending on the data in the database, this involving little computational effort compared to a forward ECT simulation.

Once the database has been created, an RBF interpolation is used to create the metamodel. That is, when an input \mathbf{P} is given, the output \mathbf{y} can be approximated by the quantity

$$\hat{\mathbf{y}} = \hat{\mathcal{L}}(\mathbf{P}) = \sum_{i=1}^N \mathbf{w}_i K(\mathbf{P}, \mathbf{P}_i), \quad (2)$$

where K is a so-called kernel function, and where the weights \mathbf{w}_i are computed during a training step. In the following, the thin plate spline kernel function [9], which is commonly used for interpolation, is chosen (Eq. 3). However, other kernels could be preferred without stringent differences being expected.

The thin plate spline kernel can be expressed as

$$K(\mathbf{P}_1, \mathbf{P}_2) = \begin{cases} \|\mathbf{P}_1 - \mathbf{P}_2\|_2^2 \ln(\|\mathbf{P}_1 - \mathbf{P}_2\|_2) & \text{if } \mathbf{P}_1 \neq \mathbf{P}_2 \\ 0 & \text{if } \mathbf{P}_1 = \mathbf{P}_2 \end{cases} \quad (3)$$

1.4. Stochastic optimization

The stochastic optimization is carried out by Balanced PSO [10] as a variant of the classical PSO method [11]. It is a metaheuristic based on swarm intelligence. Its principle is that particles moving in the input space while sharing information can find the global minimum.

Having an impedance data \mathbf{y} (the objective function), *particles* (usually about 20 [10]) are positioned in the input space with given initial speeds. For each one, a cost function is calculated, and the particles are moved towards likelier positions. The particles share information with some of them (generally 3 or 4) to know which particle has obtained the minimum cost function. Thus, the updated speeds of the particles depend

on their current speeds, weighted by an *inertia* w , on their best personal position, called *personal best* \mathbf{p} , and on the best position known by the particle, called *social best* \mathbf{s} .

At iteration k , and along each dimension $d \in [1, \dots, D]$, the positions \mathbf{x} of the particles are updated according to the formula:

$$\begin{aligned} v_d(k+1) &= w \times v_d(k) + r_1 c_1 (p_d(k) - x_d(k)) + r_2 c_2 (s_d(k) - x_d(k)) \\ x_d(k+1) &= x_d(k) + v_d(k+1) \end{aligned} \quad (4)$$

where r_1 and r_2 are uniformly chosen in $[0, 1]$ (independently on each dimension). w , c_1 , and c_2 are constants chosen following [11] ($w = 0.7$ or 1 , randomly; $c_1 = c_2 \approx 1.193$). The method is known to be relevant for solving nonlinear inverse problems [12], and its balanced version, which is consisting in sending a particle around a local minimum at each iteration, improves the compromise between exploration of the input space and exploitation of the interesting areas [10].

Stochastic methods as PSO are expensive since they require many simulations of the forward problem. With a metamodel to replace the simulation, the cost is significantly reduced and the method becomes relevant in view of almost real-time applications. Yet, consequently, the accuracy of the optimization is directly related to the accuracy of the metamodel.

One of the advantages of stochastic methods is also that the many cost function evaluations to be performed can be used in order to localize areas of large likelihood, which is useful to obtain a decision analysis tool.

2. Results on benchmark data

Results are discussed for two standard ECT configurations: a tube and a plate.

2.1. Tube workpiece

As first configuration, a circular cylindrical non-magnetic tube has been chosen. It is considered of infinite extent along the tube axis. Its internal diameter is 19.68 mm and the wall thickness is 1.27 mm. The test probe is made of a 70-wrapping emitting bobbin of internal diameter 15.66 mm, thickness 0.67 mm, and length 2 mm, and of an identical receiving bobbin which is placed at 0.5 mm of the emitting one. The impedance variation is collected on a distance of 19 mm. This configuration is extracted from the 2008 ECT benchmark that is discussed in [13].

To successfully apply the presented inversion method, strong a priori information is required. Here, the defect is assumed as being a circular notch with varying length and depth. Its depth is taken between 10 and 90 % of the wall thickness, and its length is taken between 0.1 and 10 mm. The defect can either open at the internal surface or the external surface of the tube.

First, two databases are generated, one database per type of defect. Then, two meta-models are generated. The inversion method is tested on 400 test cases randomly selected (defect parameters) and synthetically generated (impedance variations): 200 internal defects and 200 external defects. A metamodel-based PSO inversion is carried out on each generated impedance variation. The inverted parameters are the likeliest ones obtained with this inversion. The type of defect (internal or external) is assumed to be known, and

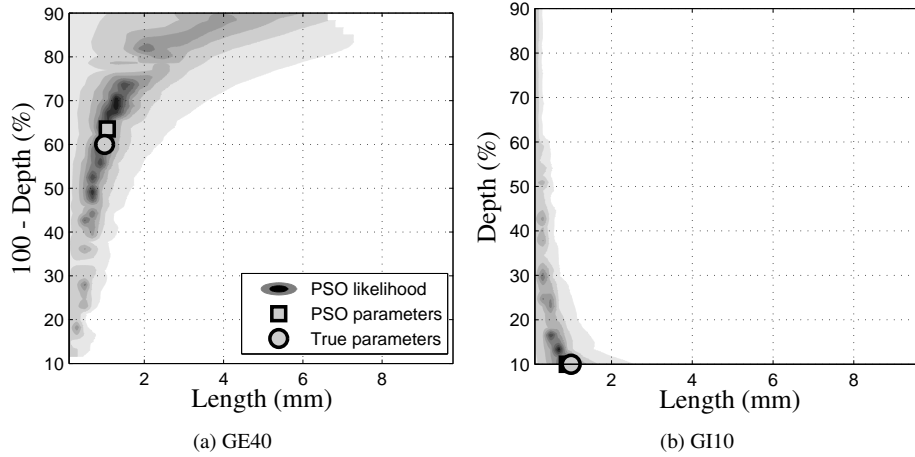


Figure 2. Results of the metamodel-based PSO inversion on measured data GE40 and GI10.

the inverse problem reduces to a regression on two continuous parameters. The normalized quadratic error $q = (P_d - \hat{P}_d)^2 / P_d^2$ is computed for each test case and is averaged on the 200 test cases.

For the internal defects, the average normalized quadratic error \bar{q} is 1.5 % for the depth and 1.9 % for the length. For the external ducts, the error \bar{q} is 0.6 % for the depth and 0.5 % for the length. Since the metamodel is used as the input of the optimization algorithm, these results are obtained in less than 2 seconds on a 3 GHz personal computer.

Two specific results are detailed. They are results on real data corresponding to this configuration and given in [13]. Measurements are available for two defects: GE40 is an external defect with a 40 % depth, and GI10 is an internal defect with a 10 % depth. Both have the same length of 1 mm. Figure 2 shows the results on these two sets of measured data. Darker areas correspond to the likeliest parameter values, the lighter ones to less likely parameter values. The circles correspond with the true parameters of the defects, and the squares give the likeliest ones retrieved by PSO.

The results obtained by the metamodel-based PSO inversion with this configuration appear very good in a reasonable time. The result obtained on GI10 is particularly promising because it is a very low signal, harder to invert. Comparisons of this method with support vector machines on this data can be found in [8].

2.2. Slab workpiece

As second configuration, a non-magnetic plate workpiece is considered, from the COFREND benchmark [14]. Its width and length are considered infinite, and its thickness is 1.55 mm. The probe is a 328-wrapping bobbin of internal diameter 2 mm, thickness 1.25 mm, and length 2 mm. The probe scans a 8 mm per 12 mm surface. The defect position is assumed to be known, at the center of the scanned zone.

The defect is a rectangular notch with varying length, width, and depth. Its depth is considered between 10 and 100 % of the tube thickness, its length is taken between 0.5 and 15 mm, and its width between 0.1 and 1 mm.

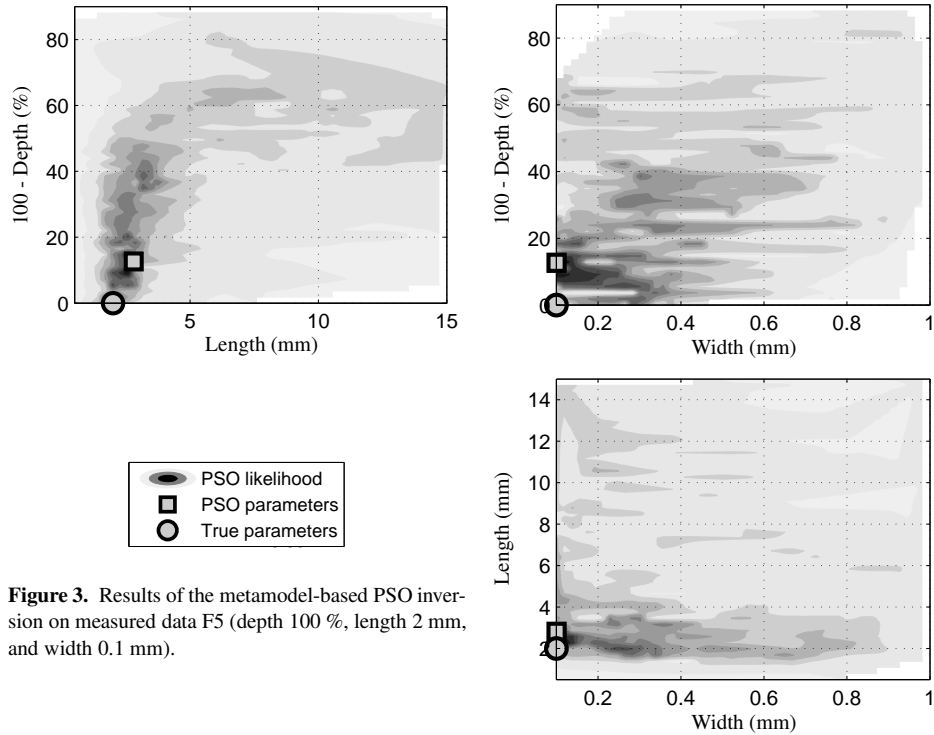


Figure 3. Results of the metamodel-based PSO inversion on measured data F5 (depth 100 %, length 2 mm, and width 0.1 mm).

The average normalized quadratic error \bar{q} is 0.6 % for the depth, 1.0 % for the width, and 3.2 % for the length of the defect. These results are obtained with an average time of 5.5 s on the same computer as in section 2.1.

So, in general, the accuracy of the inversion is good. Two measurements corresponding to this benchmark have been processed. F5 corresponds to a defect of depth 100 %, length 2 mm, and width 0.1 mm. F7 corresponds to a defect of depth 40 %, length 10 mm, and width 0.1 mm. The two inverted results are displayed in Figures 3 and 4, respectively. Both results are quite similar: the inverted parameters are acceptable yet not perfectly retrieved. However, the true parameters are inside the likeliest areas. In particular, it is difficult to precisely decide upon the depth of crack F5 or upon the width of the crack F7. These examples show how undetermined cases can be identified by the inversion method.

If other inversions were to be carried out on the same data, and since a stochastic inversion is non repeatable, slightly different results could be found (minimum of the cost function). However, the likeliest area should be approximately the same. So, the inversion tool is appropriate for decision analysis.

2.3. Conclusion

A metamodel-based optimization as a means to perform defect characterization by processing ECT signals has been presented. Interesting results on both simulated and measured data have been shown. This method requires strong a priori information (work-piece and global shape of the defect), but it can be applied to various problems. Defects

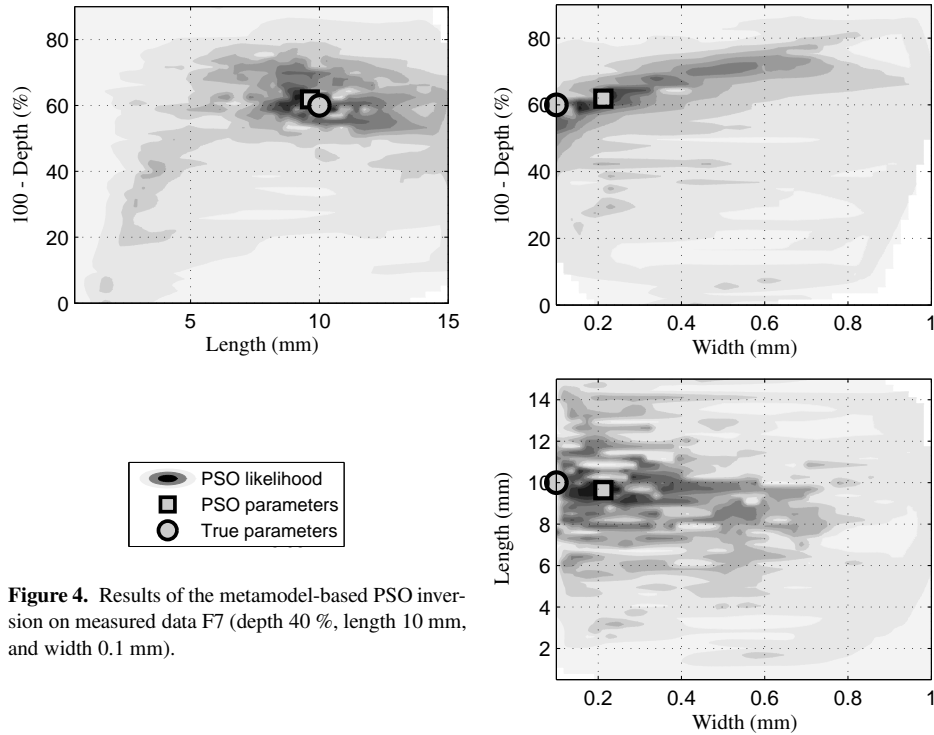


Figure 4. Results of the metamodel-based PSO inversion on measured data F7 (depth 40 %, length 10 mm, and width 0.1 mm).

in a tube and a plate have been retrieved successfully. Moreover, the time necessary to invert the data is reasonable and rather promising for on-site use. Let us note that this tool is also able to retrieve the local minima of the cost function, which makes it suited to decision analysis.

A representation of the data in a lower dimensional space (by principal component analysis for instance) could speed up the RBF interpolation. More forward simulations could then be performed in the stochastic method and the inversion could be improved. Indeed, the more time devoted to the stochastic inversion, the more accurate the inversion. But, the true challenge is to apply this type of methods to problems involving, say, 5 input parameters or more. Indeed, as the dimension is increased, the generation of an accurate database requires more and more forward simulations, possibly far too many for realistic use. In this case, other means in metamodel generations should be considered [15].

Acknowledgements

The authors thank CEA (Commissariat à l'Énergie Atomique) and the COFREND working group "Eddy current modelization" for providing the measured benchmark data.

References

- [1] L. Udpa and S. Udpa. Eddy current defect characterization using neural networks. *Mater. Eval.*, 48:342–347, 1990.
- [2] A. Bernieri, L. Ferrigno, M. Laracca, and M. Molinara. Crack shape reconstruction in eddy current testing using machine learning systems for regression. *IEEE Trans. Instrum. Meas.*, 57:1958–1968, 2008.
- [3] J. Pávó and S. Gyimóthy. Adaptive inversion database for electromagnetic nondestructive evaluation. *NDT & E Int.*, 40:192–202, April 2007.
- [4] G. Franceschini, M. Lambert, and D. Lesselier. Generation of adaptive database - results synthesis. Technical report, Laboratoire des Signaux et Systèmes, January 2009.
- [5] M. D. Buhmann. *Radial Basis Functions: Theory and Implementation*. Cambridge University Press, Cambridge, 2003.
- [6] J. R. Bowler, S. A. Jenkins, Sabbagh L. D., and Sabbagh H. A. Eddy-current probe impedance due to volumetric flaw. *J. Appl. Phys.*, 75:8128–8137, 1991.
- [7] CIVA: State of the art simulation platform for NDE. available at <http://www-civa.cea.fr>, accessed the 8th of June 2010.
- [8] R. Douvenot, M. Lambert, and D. Lesselier. Particle optimization with metamodel for crack characterization. In *Proceedings of the 2010 URSI Electromagnetic Theory Symposium (EMTS 2010)*, 2010. 4 pp., to appear.
- [9] F. L. Bookstein. Principal warps: Thin Plate Splines and the decomposition of deformations. *IEEE Trans. Pattern Anal. Mach. Intell.*, 11:567–585, 1989.
- [10] M. Clerc. The mythical balance or when Particle Swarm Optimisation does not exploit. Unpublished, 6 pp., available at http://clerc.maurice.free.fr/ps0/Balanced_PSO/Balanced_PSO.pdf, 2008.
- [11] M. Clerc. *Particle Swarm Optimization*. ISTE, London, 2006.
- [12] P. Rocca, M. Benedetti, M. Donelli, D. Franceschini, and A. Massa. Evolutionary optimization as applied to inverse scattering problems. *Inverse Problems*, 25:123003, 2009. 41pp.
- [13] C. Reboud, G. Pichenot, and S. Mahaut. 2008 ECT benchmark results: Modeling with CIVA of 3D flaws responses in planar and cylindrical workpieces. In *35th Annual Review of Progress in Quantitative Nondestructive Evaluation (QNDE - 2008)*, Chicago, 20-25 july 2008. 8 pp.
- [14] COFREND benchmark. available at http://www.cofrend.com/modelisationcf/GT_CF_COFREND_GB.html, accessed the 8th of June 2010.
- [15] R. R. Barton. Simulation optimization using metamodels. In *Proceedings of the 2009 Winter Simulation Conference*, pages 230–238, Austin, TX, December 13-16 2009.