Crack Estimation using Adaptive Inversion Database With Multi Output Support Vector Machine for Eddy Current Testing

M. Chelabi[1] ,T. Hacib[1], Y. Le Bihan[2] and H, Boughedda[1]

[1] Laboratoire d'études et de modélisation en électrotechnique, Faculté des sciences et de la technologie, Univ. Jijel, Algérie

[2]Laboratoire LGEP, Supélec, UMR 8507 CNRS, Univ. Paris 06, Univ. Paris-Sud, France

***Abstract*- This paper considers the inverse problem of estimating the size of an unknown defect from the measurement of the impedance variations, By the novel combination of the multi output support vector machines (MO-SVM), and finite element modeling for eddy current flaw Characterization of a defect size in a conductive nonmagnetic plate.The finite element method (FEM) is used to create the database, In this context, the cylindrical sensor have been considered to validate a COMSOL-Multi physics 3D-resolution using a 3D electromagnetic formulation , A good agreement is obtained between the numerical results and the experimental ones. The database required to train the MO-SVM , Several method are used to find the parameters of MO-SVM.* the Particle Swarm Optimization (PSO) ,Genetic Algorithm GA are proposed.**

***Index Terms*—Eddy current testing, Finite element method, Multi output support vector machine, Particle Swarm Optimization. Genetic Algorithm**

I. Introduction

Eddy current testing (ECT) is widely used to check the integrity of electrically conducting parts and notably to detect flaws. It is based on the interaction between a probe and the part under testing. The development of eddy current inversion techniques is required to identify cracks from detected eddy current testing (ECT) signals. Reconstruction of crack shape from scanned signals requires the solution of an inverse problem and involves the calculation of a large number of forward problems.

Finite element method (FEM) can be used to represent the forward process. However, iterative methods using a numerically based forward model are computationally expensive, in this situation the multi output support vector machines (MO-SVM) are a good alternative to iterative methods and that they exhibit good generalization capability [1].

II. Measurement Setup and Resultant

The eddy current sensor involved in this study consists one coil wound around each end of a cylinder shaped ferrite core (Fig. 1), coil turn number (N = 110), The radius of the core is 0.4 mm and its height is 4 mm. The external radius and the length of the coil are 0.6 mm and 1.2 mm, respectively. lift-off = 20 µm, frequency = 2 MHz Its characteristics are as follows: conductivity: 0.76 MS/m, relative permeability: 1, thickness: 3 mm.

We use the FEM to solve the magneto-dynamic problem of system. After that we compute the impedance variation ΔZ of the sensor from equations (1)and (2).

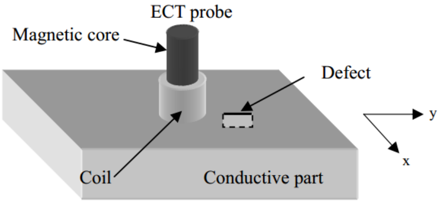

Fig. 1. Structure of the ECT probe and of the specimen

$$\mathrm{Re}(Z) = \frac{1}{I^2}\int_{\Omega}\frac{1}{\sigma}\left(\left|J_f\right|^2 - \left|J\right|^2\right)d\Omega \qquad (1)$$

$$\mathrm{Im}(Z) = \frac{\omega}{I^2}\int_{\Omega}\frac{1}{\mu}\left(\left|B_f\right|^2 - \left|B\right|^2\right)d\Omega \qquad (2)$$

where I is the current feeding the probe.

J_f, J, B_f, B are the current density field in the conductive media and the current density field in the whole meshed domain respectively calculated with and without the defect.

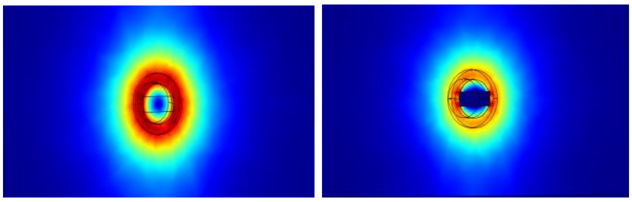

Fig. 2 and 3 Map of the eddy currents in the plate Without and with defect

The sensor is displaced along the y-axis (Figure1). The impedance variation is computed as a function of the position of the coil center. Figures 2 and 3 show a good behavior of the current density. The Figures 4 show a good agreement of the impedance variation results in comparison with the results obtain in references [2].

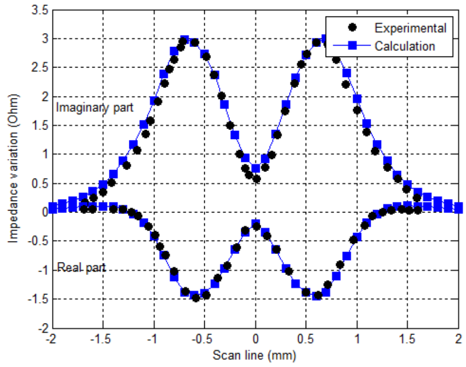

Fig. 4. Real and imaginary parts of impedance variation ΔZ

III. SVM FOR FUNCTION ESTIMATION

Let us consider the problem of approximating the data set $D = (x_k, y_k)_{k=1}^{N}$, $x_k \in R^n$, $y_k \in R$, with the nonlinear function,

$$y(x) = w^T \varphi(x) + b \qquad (3)$$

where $w \in R^n$ is a weight vector, $\varphi(.) : R^n \to R^{n_k}$ is a nonlinear function that maps the input space to a higher dimension feature space, b is a bias term. The optimization problem is given by:

$$\min \frac{1}{2} w^T w + C \sum_{k=1}^{N} (\xi_k + \xi_k^*) \qquad (4)$$

$$\text{Subject to} \begin{cases} y_k - w^T \varphi(x_k) - b \le \varepsilon + \xi_k \\ w^T \varphi(x_k) + b - y_k \le \varepsilon + \xi_k^* \\ \xi_k, \xi_k^* \ge 0 \end{cases}$$

where ε is the approximation accuracy that can be violated by means of the slack variables ξ, ξ^*. The constant $C > 0$ determines the trade-off between the flatness of y and the amount up to which deviations larger than ε are tolerated. This optimization problem leads to a solution,

$$y(x) = \sum_{k=1}^{N} (\alpha_k - \alpha_k^*) K(x, x_k) + b \qquad (5)$$

where α_k, α_k^*, b comprise the solution to the system obtained by constructing the Lagrangian of (2) and $K(\boldsymbol{x}, x_i) = \varphi^T(\boldsymbol{x})\, \varphi(x_i)$ is a kernel function. In this study, radial basis function (RBF) kernels are used,

$$K(\boldsymbol{x}, x_{\boldsymbol{k}}) = exp\left(-\frac{\| \boldsymbol{x} - x_{\boldsymbol{k}} \|}{\sigma^2} \right) \qquad (6)$$

where $\sigma > 0$ is a constant defining the kernel width.

In this case the observable output is a vector $y \in R^Q$, we need to solve a multi output regression estimation problem in which we have to find a regressor w^j and b^j for every output finally we find a linear system (5) [3].

$$\begin{bmatrix} K + D_a^{-1} & 1 \\ a^T K & 1^T a \end{bmatrix} \begin{bmatrix} B^j \\ b^j \end{bmatrix} = \begin{bmatrix} y^j \\ a^T y^j \end{bmatrix} \qquad (7)$$

where $j = 1 \ldots Q$, $y^j = [y_{1j}, y_{2j}, \ldots, y_{nj}]^T$, $(D_a)_{i,j} = a_i \delta(i - j)$,

$B^j = w^j \cdot (\phi^{-1})^T$ and $a_i = 2 \cdot C$ ($\varepsilon = 0$, least square)

If $\varepsilon \ne 0$

$$a_i = \begin{cases} 0 & u_i^k < \varepsilon \\ \dfrac{2 \cdot C(u_i^k - \varepsilon)}{u_i^k} & u_i^k \ge \varepsilon \end{cases} \qquad (8)$$

u_i^k that is, the square error between every dimension of y_i and all the regressors.

IV. INVERSE PROBLEM

The FEM provides the optimal data set required for the training of MO-SVM. A data set is constituted of input (impedance signal (8 component)) and output (size of defect) then normalize the initial data, the above 1116 groups (randomly and normalised) of data were divided into three sets. The first 558 groups were used to train the MO-SVM model, the second 279 groups were used for valid the model and the third 279 groups were used for test the model.MO-SVM algorithm (least square),is used to modeling, and the RBF kernel function is selected. The PSO and GA algorithm are used to tune the hyper-parameters of SVM. In this paper, we obtain $\sigma^2 = 649$,$C = 2.8939 \cdot 10^9$,for PSO and $\sigma^2 = 780$,$C = 4.2486 \cdot 10^9$, for GA The Root Mean Square Error (*RMSE*) is equal to 2.6866 10^{-4} for larger and 5.2251 $10^{-4}$for depth. The Root Mean Square Error (*RMSE*) is equal to 2.8766 10^{-4} for larger and 4.6231 $10^{-4}$for depth. The real data together with estimated one obtained by MO-SVM model are shown in Fig.5 .

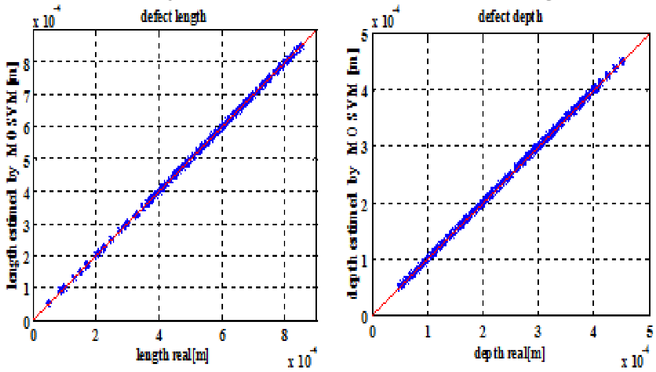

Fig. 5. Comparison between the defect provided by the MO-SVM and the defect contained in the testing datasets (PSO)

The results show that most of the points distribute along the diagonal line, which means the MO-SVM model can predict the values of defect accurately.

CONCLUSION

The results indicate that MO SVM could be used to determine the size of defect. The applied data set at the testing stage of the MO SVM demonstrates their abilities to perform identification with good accuracy.

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