Investigations Into the Use of the Finite Element Method and Artificial Neural Networks in the Non-destructive Analysis of Metallic Tubes

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Abstract : This work presents an investigation into the use of the finite element method and artificial neural networks in the identification of defects in industrial plants metallic tubes, due to the aggressive actions of the fluids contained by them, and/or atmospheric agents. The methodology used in this study consists of simulating a very large number of defects in a metallic tube, using the finite element method. Both variations in width and height of the defects are considered. Then, the obtained results are used to generate a set of vectors for the training of a perceptron multilayer artificial neural network. Finally, the obtained neural network is used to classify a group of new defects, simulated by the finite element method, but that do not belong to the original dataset. The reached results demonstrate the efficiency of the proposed approach, and encourage future works on this subject.

I. INTRODUCTION

Metallic tubes constitute important components of many kinds of industrial plants, such as gas pipelines, chemical pipelines, fuel vessels, sugar and alcohol plants etc. Generally, these walls are subject to the aggressive (corrosive) actions by fluids contained by them, or even by atmospheric agents. So, these equipments must be periodically evaluated in order to avoid operational interruptions and/or dangerous accidents. Usually, these evaluations are done using non-destructive techniques. Such techniques may involve the use of electromagnetic fields, which are induced in the metallic walls of the equipment under inspection.

More common techniques used in the inspection of metallic walls are based on eddy current systems. In this kind of analysis, the electreomagnetic devices are excited by an alternating current of a given frequency that induces a flow of eddy currents in the material beneath them. As the probe passes over the defect, variations occur in the flow of eddy currents. These variations are then detected by electronic sensors. The change in the flow of eddy currents as the probes pass over the defect is generally proportional to the depth of the defect, and makes possible to estimate the depth of the defect by proper electronic calibration. Relative motion between the test probe and the material being inspected is a requirement for this kind of analysis. Although the probe can be hand held as the piece under test is examined, this method is usually too slow and unreliable.

A very interesting alternative introduced by Low is the use of the Finite Element Method (FEM) in conjunction with Artificial Neural Networks (ANN) in the solution of this kind of inverse problem [1].

In this paper we present an investigation inton the use of FEM and ANN in the identifications of defects in metallic walls. The methodology consists of the following steps:

1. A large number of defects in a metallic tube is simulated using the finite element method.

2. The obtained results are then used to generate the training vectors of a multilayer perceptron artificial neural network.

3. The trained network is used to classify new defects in the tube, which do not belong to the original dataset.

4. The network weights can be embeded in an electronic device, and used to identify defects in real pieces, with similar characteristics to those of the simulated ones.

For the methodology presented here, the measured values are independent of the relative motion between the probe and the piece under test. In other words, the movement is necessary only to change the position of the probes, to acquire new field values, which are necessary for the identification of new defects. Furthermore, the use of neural networks in conjunction with the finite element method permits a very good determination of both, width and height of the defect.

The kind of defect we have investigated is corrosion on the inner surface of metallic tubes. For the purpose of the paper, the defects were classified in large, medium and small. The dataset was generated considering 30 variations in the width and 10 variations in the height, performing at least 300 finite elements simulations.

II. THE FINITE ELEMENT METHOD IN THE ELECTROMAGNETIC FIELD ANALYSIS

In this section we present a brief resume of the application of the finite element method in magnetostatic field problems.

Two-dimensional magnetostatic field problems are described by the quasi-Poisson equation :

$$\frac{\partial}{\partial x}\left(\nu\frac{\partial A}{\partial x}\right)+\frac{\partial}{\partial y}\left(\nu\frac{\partial A}{\partial y}\right)=-J \qquad (1)$$

where :

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A = magnetic potential vector, here presented as a scalar quantity, in A/m
J = density of current, in A/m^2.
ν is the inverse of the magnetic permeability, μ.

The magnetic potential vector $\vec{A}$ is a mathematical function, whose curl is the magnetic flux density $\vec{B}$, and has no physical meaning.

Equation (1) has no analytical solution. So, its solution must be numerical, and the most popular technique for this kind of solution is the finite element method (FEM).

In terms of calculus of variations, the magnetostatic field problem can be formulated in terms of a functional of energy :

$$F = \iint\left(\int \nu B dB - J.A\right)dxdy \tag{2}$$

where $B = \nabla \times \vec{A}$.

Minimization of (2) is done by proposing an approximating function for the magnetic potential vector, that is :

$$A(x,y) = \sum_{i=1}^{n} \phi_i . A_i \tag{3}$$

where A_i is the value of the magnetic potential at the nodes of the finite element, and ϕ_i are the shape functions. For the first order triangular element (the element used in this work, and shown in figure 1), ϕ_i is :

$$\phi_i = \frac{a_i x + b_i y + c}{2\Delta} \tag{4}$$

where the coefficients a_i, b_i and c_i are dependent of the node positions, and Δ is the area of the triangle.

The minimization is done substituting (3) in (2), and taking its derivatives in relation to the magnetic potential in the nodes.

For the magnetostatic case, after minimization, we have for each element the following 3x3 algebraic system of equations :

$$\frac{\nu}{4\Delta}\begin{pmatrix} b_1b_1+c_1c_1 & b_1b_2+c_1c_2 & b_1b_3+c_1c_3 \\ b_2b_1+c_2c_1 & b_2b_2+c_2c_2 & b_2b_3+c_2c_3 \\ b_3b_1+c_3c_1 & b_3b_2+c_3c_2 & b_3b_3+c_3c_3 \end{pmatrix}\begin{pmatrix} A_1 \\ A_2 \\ A_3 \end{pmatrix} = \frac{\Delta}{3}\begin{pmatrix} J \\ J \\ J \end{pmatrix} \tag{5}$$

Combining all the elementary matrices, we have the global system of equations :

$$(S)(A) = (R) \tag{4}$$

More details about the finite element theory can be found in references [2] and [3].

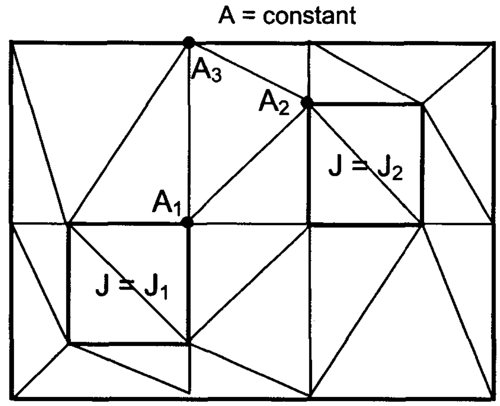

Figure 1 – Free representation of finite elements

III. THE METHODOLOGY FOR DEFECT IDENTIFICATION

First of all, an electromagnetic device was idealized to be used as an electromagnetic field exciter (Figure 2). In this paper, we have considered direct current in the coils. So, the material of the metallic wall must be ferromagnetic. Very low frequency currents in the coil must be used for non-ferromagnetic materials, and these will be studied in future works.

Deviations of the magnetic induction at equally stepped points in the region of the device are taken, on the external surface of the wall.

In order to generate the training vectors for the neural network, a large number of defect shapes must be simulated. In this work, 300 defects have been simulated, each one corresponding to one simulation with the finite element program.

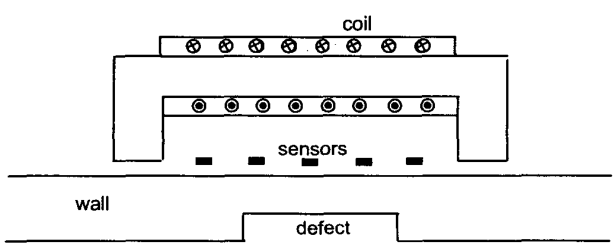

Figure 2 – Arrangement for the measurements

Figure 3 shows the steps of the methodology used in this work.

Steps 1-4 correspond to the finite element analysis of the defects. In this work we used a 2D finite element program to simulate the defects in a metallic wall.

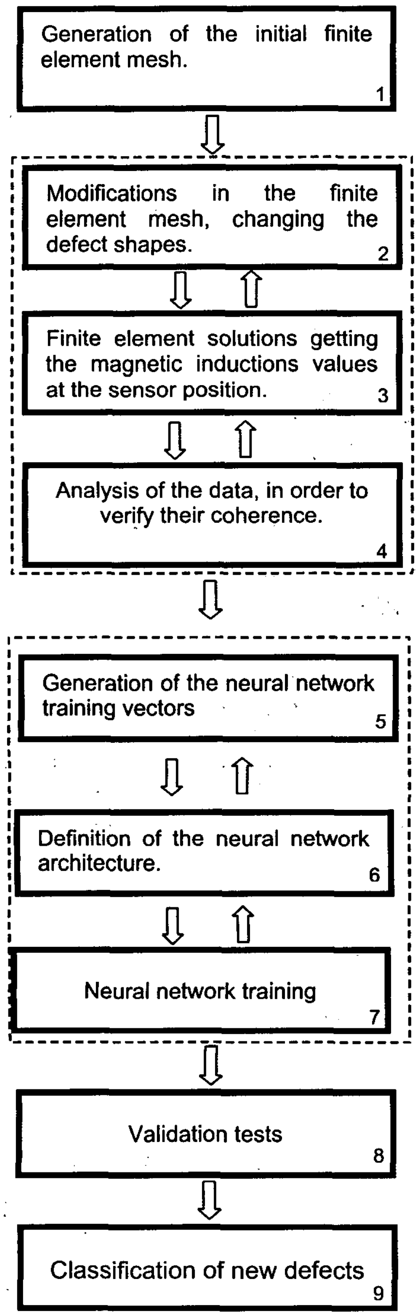

Figure 3 – Flowchart of the used methodology

The simulations were done for a hypothetic high pressure vessel, with 1500 mm of diameter and 10 mm thick. The material of the vessel is 1006 Steel (a magnetic material), and the permeability of the defects was set to the permeability of the air. Finite element meshes with 18000 elements and 9000 nodes, approximately, were used in the simulations. Figure 4 shows the flux density plot for two of these simulations.

Figure 4 – Density plot for two finite element simulation.

Due to the large number of finite element simulations, errors can occur during this phase. So, the results of the simulations must be carefully analyzed. This can be done, for instance, plotting in the same graphic the magnetic induction deviations for a set of defects. Figure 5 shows the deviation on the magnetic induction in the spanned by the device for four defects, having the same height (2.5 mm), and width ranging from 0.39 mm to 4.27 mm. A similar graphic, with height equal to 5 mm, is shown in figure 6. Figure 7 shows the graphics for a fixed width, 1.94 mm, and four different heights. Figure 8 shows a similar graphic, for the width equal to 3.88 mm.

The coherence of the curves in these graphics allows us to infer if there are or not errors in the dataset.

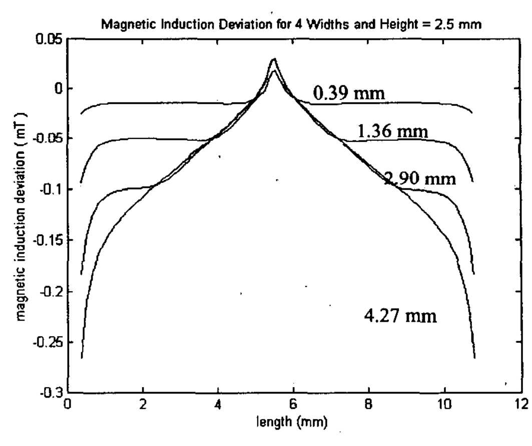

Figure 5 – Magnetic induction deviation for a set of defects with the same height

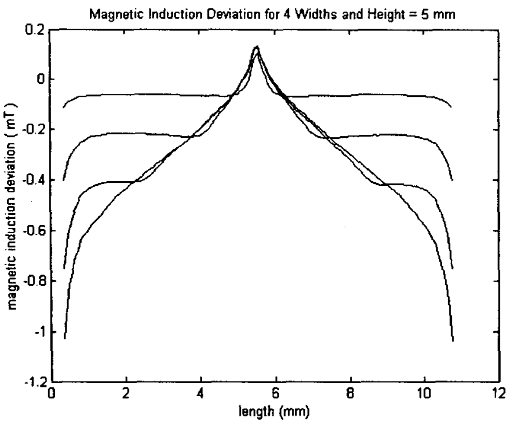

Figure 6 – Magnetic induction deviation for a set of defects with the same height

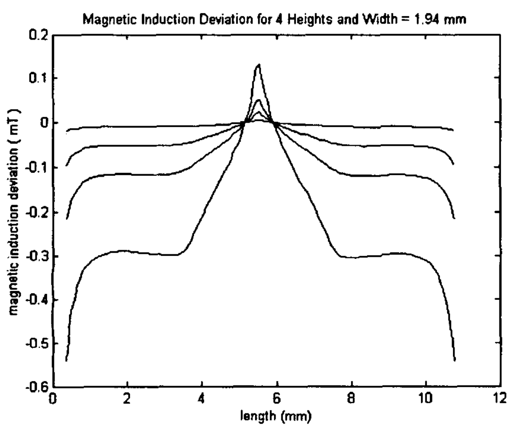

Figure 7 – Magnetic induction deviation for a set of defects with the same width

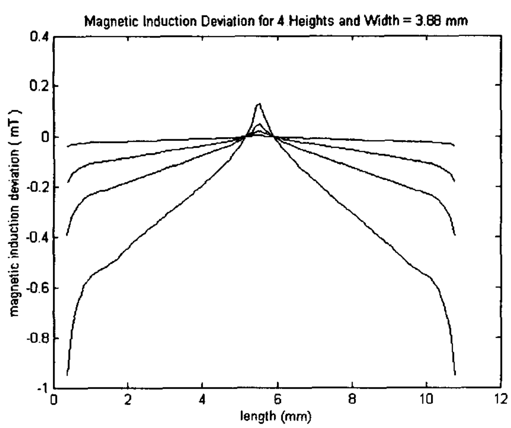

Figure 8 – Magnetic induction deviation for a set of defects with the same width

In the step 5, we generate the training vectors for the neural network. In this work, we have generated 300 vectors with 11 elements each one. For the purpose of training and classification, the defects were identified by height and width, in mm.

The architecture chosen for the neural network was a multilayer perceptron, trained with the Levemberg-Marquadt algorithm [4]. Several network configurations were tried, and better results have been obtained by a network constituted by four hidden layers with 24, 16, 8 and 4 neurons. From the original 300 vectors, 225 vectors were used in the network training, and 75 vectors were used in their validation.

Figure 8 shows the performance of a training session, and Table I shows some results for the validation of the network, for this session. As we can see, the results obtained in the validation are very close to the expected ones.

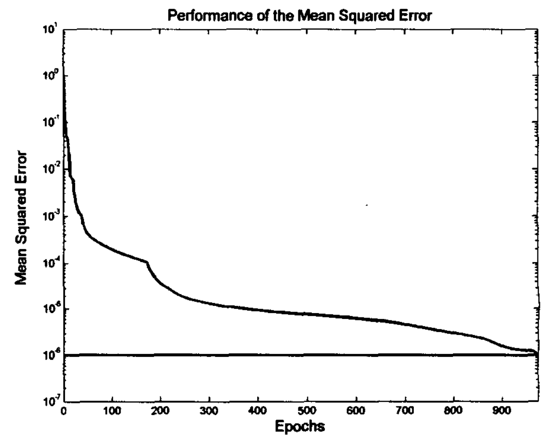

Figure 8 – Performance of the net, during a trainig session

TABLE I – EXPECTED AND OBTAINED VALUES DURING A TRAINIG SESSION

Heigth (mm)			Width (mm)		
expected	ANN	|error| %	expected	ANN	|error| %
0.0500	0.0500	-	2.3280	2.3267	0.055
0.1000	0.0999	0.100	3.4920	3.4922	0.006
0.1500	0.1497	0.200	5.4320	5.4313	0.013
0.2000	0.1998	0.100	2.7160	2.7154	0.022
0.2500	0.2501	0.100	3.8800	3.8779	0.054
0.3000	0.3002	0.067	4.2680	4.2664	0.037
0.3500	0.3503	0.086	3.1040	3.1038	0.006
0.4000	0.3997	0.075	1.9400	1.9402	0.010
0.4500	0.4508	0.178	4.6560	4.6369	0.410
0.5000	0.4999	0.020	5.0440	5.0481	0.081

IV. NEW CLASSIFICATIONS

After the neural network training and respective validations, new defects were simulated by the finite element method, for posteriori classification by the network. Table 2 shows the dimensions of the defects (height and width), and the obtained dimensions, by the neural network.

TABLE 2 – SIMULATION RESULTS, FOR NEW DEFECTS

Defect	Height (mm)		Width (mm)	
	expected	obtained	expected	obtained
1	0.0750	0.0749	2.910	2.909
2	0.1750	0.1752	4.462	4.460
3	0.3250	0.3247	4.850	4.853
4	0.5750	0.3247	2.522	2.521
5	0.7250	0.7246	4.080	4.078

As we can see, the results obtained in the identification of new defects, obtained by the neural network agree very well with the expected ones, demonstrating that the association of the finite element method and artificial neural networks is very powerful in the solution of inverse problems, like defect identification in metallic tubes.

CONCLUSIONS

In this paper we presented an investigation into the use of the finite element method and artificial neural networks for the identification of defects in metallic tubes, present in industrial plants. For a given metallic tube characteristics, defects can be simulated by the finite element method, and the magnetic field results are used in the preparation of the training vectors for artificial neural networks. The network can be embedded in electronic devices in order to identify defects in real metallic walls.

The association of FEM and ANN techniques seems to be an useful alternative for non destructive evaluations. Future works are intended to be done in this field, such as the use of more realistic finite element problems, computer parallel programming, in order to get quickly solutions.

References

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