

Solution of Inverse Problems in Electromagnetic NDT Using Neural Networks

Abstract. This paper presents a technique for solving inverse problems in electromagnetic nondestructive testing (NDT), using neural networks (NN). They are trained to approximate the mapping from the signal to the defect space. A crucial problem is signal inversion, wherein the defects profiles must be recovered from calculated signals by using finite element method (FEM), this method give good results by using the refinement mesh but in very long time. The idea of this paper is the exploitation of the FEM but with a middle mesh where the results are approached in short time. This signal was exploited in the inversion problem, where the maps represent the defects in the plate. The inversion results obtained with the NN are presented. The presented approach has permitted to realize good maps in a very reasonable training time with respect to others approaches.

Streszczenie. Przedstawiono metodę rozwiązania odwrotnego z wykorzystaniem sieci neuronowych stosowanego w defektoskopii. Sieć jest trenowana na podstawie próbek z defektami. Pozwala to na stosowanie metody FEM ze znacznie mniejszą liczbą oczek. (Rozwiązanie problemu odwrotnego w defektoskopii elektromagnetycznej przy wykorzystaniu sieci neuronowych)

Keywords: Eddy current, Finite element method, Defect characterization, Neural networks, Inverse problems.

Słowa kluczowe: metoda prądów wirowych, defektoskopia, sieci neuronowe.

Introduction

In recent years the artificial neural network was to use in the nondestructive testing (NDT) where it's interviewee to inverse problem. But, the NDT requires the use of the numerical analysis methods, among these methods, the finite element method (FEM). It appears to be very powerful because of its large flexibility which allows taking into consideration complex configurations [1]. Their application is widely used to detect cracks in metallic structures by using the Eddy currents [2].

This paper describes the inversion problem by using the neural Networks (NN) for the approximation the mapping from the signal to the defect space. A very crucial problem is signal inversion, wherein the defect profiles must be recovered from measured signals by using finite element method. A finite element model is solved on a PC using the ANSYS finite element analysis package [6, 8]. The responses of the probe coil for inspecting different types of defects in different shapes and at different locations by scanning the structures are calculated. The displacement of the sensor is simulated with the sliding mesh technique [9].

The application of the NN to electromagnetic inversion is used in the case of impedance measurement by eddy currents of the probe; the inversion method is investigated to estimate the map of defect [7]. The eddy current probe impedance is given as input to the neural network and the form of crack is evaluated continuously by output of the NN.

plate. The coils parameters of importance are number of turn's n, inner radius of the coil r1, and outer radius r2, h the coil height, lo the lift-off, σ , t the conductivity, and the thickness respectively of the plate. The width and the length of the plate are supposed infinitely large [10].

The forward problem consists in the determination of the crack in the plate by the variation of the probe impedance. The impedance change of the coil reflects the change in permeability distribution in a test specimen in the presence of defects. The coil is excited by a constant alternative current of angular frequency ω ; its impedance is measured as a function of frequency in scanning positions.

The eddy current problem can be described mathematically by the following partial differential equation in terms of the magnetic vector potential [1, 3].

$$(1) \quad \text{rot}\left(\frac{1}{\mu} \text{rot}(A)\right) = -j\sigma\omega A + J_s$$

where, A represents the magnetic vector potential, j is the imaginary unit, ω is the angular frequency of the excitation current (rad/s), μ is the magnetic permeability of the media involved (H/m), σ is the electrical conductivity (S/m), and J current density (A/m^2).

Finite element modelling

The finite element formulation for the 2D axisymmetric eddy current phenomena was developed in many works. For axisymmetric geometries equation (1) reduces to the 2D form [1, 4, 5].

$$(2) \quad \frac{1}{\mu} \left(\frac{\partial^2 A}{\partial r^2} + \frac{1}{r} \frac{\partial A}{\partial r} + \frac{\partial^2 A}{\partial z^2} - \frac{A}{r^2} \right) = j\sigma\omega A - J_s$$

This equation describes the problem shown in Fig. 1. The finite element approaches provide a solution to (2) by minimizing the variation of a functional, which is derived from (2) applying boundary condition.

The simulation of this problem is using the ANSYS Parametric Design Language (APDL) software, where it's based on the finite element analyses (FEA) method. The APDL is used to develop the simulation program so that the impedance of the scanning coil at different positions can be calculated automatically [8].

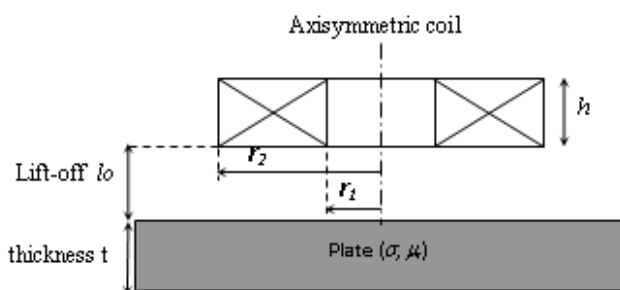


Fig.1. Geometry and dimensions of the 2D model (coil with plate)

Description of the problem

The geometry of the problems considered is illustrated schematically in Fig.1. An axisymmetric air-core coil of rectangular cross-section is placed above the evaluated

A. Calculation of the Eddy Current Probe Impedance

Once the magnetic vector potential values at all the nodes in the mesh region are determined, the probe impedance which is our parameter of interest can be computed.

The real and imaginary parts of the probe impedance are determined by using the magnetic energy and the power losses, respectively [3].

$$(3) \quad p = RI_{eff}^2$$

$$(4) \quad W = \frac{1}{2} LI_{eff}^2$$

(5) Hence, we can obtain the inductance and the resistance of the probe.

And the source impedance can be written as:

$$(6) \quad Z = R + jL\omega = \frac{1}{I^2} (P + j2\omega W)$$

Inversion method by neural network

The increasing interest to the neural network can be explained by their successful implementation in different areas [7]. These methods are also widely used in non-destructive testing by eddy currents. The artificial NN proved to be effective because of their well known non linear function approximation and system identification capabilities.

The aim of inversion techniques is to estimate the set of parameters allowing the model operator to explain the available measures in the best way [3].

The application of NN to the inversion method of the probe coil impedance is trained and tested to identify and evaluated the form of the cracks. The NN input consists in the probe impedance while its output provides evaluated cracks with different shapes.

An important problem in the NN inversion process is the selection of the network structure and the adjustment of the internal parameters. The determination of the optimal NN structure and the test are realized by the improbability method. The data sets are created by data thanks to the problem of the electromagnetic interaction between the probe and plate by using the FEA. Every set contains the input-output data belonging to the evaluation range.

The training set allows to train the NN, i.e. the adjust of internal parameters of the neural networks is performed by minimizing the mean square error (MSE) which is used as a cost function, and measured between the output of the network and the desired solution when the corresponding inputs are presented to the NN [5, 11]. The mean square error value is computed by:

$$(7) \quad MSE(w) = \frac{1}{N} \sum_{k=1}^N \|D_k - S(E_k, w)\|^2$$

where: $\{E_k\}$: The Input Vector, $\{D_k\}$: The desired output vector, $\{w\}$: The constituted column Vector of the set of the weights and bias of the network, S: The realised function by NN, N: The number of samples in the training set.

A. feed-forward back propagation neural networks

FFBPNNs are a class of networks that are widely used for solving multivariate function approximation problems

and it is used for the resolution of the nonlinear problems. FFBPNNs are composed of separate layers including an input layer, an output layer and hidden layers. The training is based on simulated data, involving the impedance of the probe coil, which is determined by the finite elements method.

The training consists in the adjustment of the layer weights values for the output neural networks. This weight adjustment process is repeated for many training samples, and is stopped when the errors at the output layer reach a sufficiently low level [12].

The input layer of the proposed neural network contains 95 units and the output of the FFBPNN predicts the flaw profile.

Simulation Work and inversion results

In this paper different shapes of crack are presented in fig. 2 and the different parameters of problem are listed in table 1.

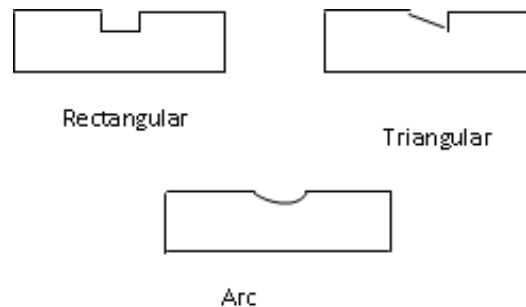


Fig.2. Defects in different shapes

Table 1. The Probe, Plate and Flaws Dimension

Probe	Inner radius (r_1)	0mm
	Outer radius (r_2)	10mm
	Length (h)	10mm
	Number of turns	500
Plate	Frequency	0.6kHz
	Thickness t	1mm
	Conductivity (σ)	1MS/m
	Permeability	1
Flaws	Lift-off (l_0)	0.5mm
	Length	80mm

The simulation work is approved out for defects in different shapes, using the developed APDL program. The scanning range of the probe is 190 mm. The coil impedance responses due to defects in different shapes (rectangular, triangular and arc) are calculated, respectively, using the APDL program and the simulation results shown in Fig. 3.

In this application the FEM analysis, exploiting the system symmetry, only half geometry has been discredited, in order to reduce memory requirements.

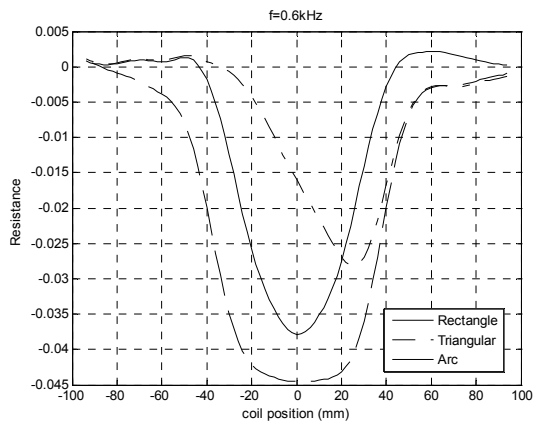
For Simulation the total CPU calculating time is about 600 s.

To check the validity of the implemented finite element model (APDL), we have calculated the variation of impedances for different shape defects at frequency 0.6 kHz. The probe displacement is made using the sliding method with 2mm step

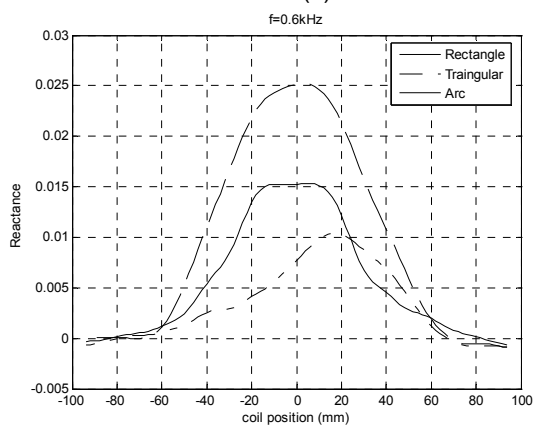
In the first application, the change impedance, resistance and reactance plane for the considered shape defects is given by the following Fig. 3 at 0.6 kHz frequency.

These results are exploited for the inversion problem where are used like the input of the NN.

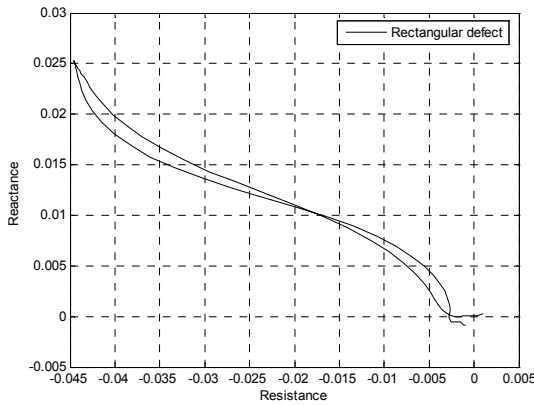
A. FEM results



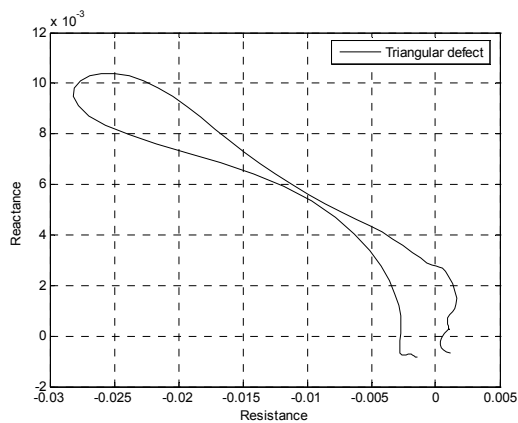
(a)



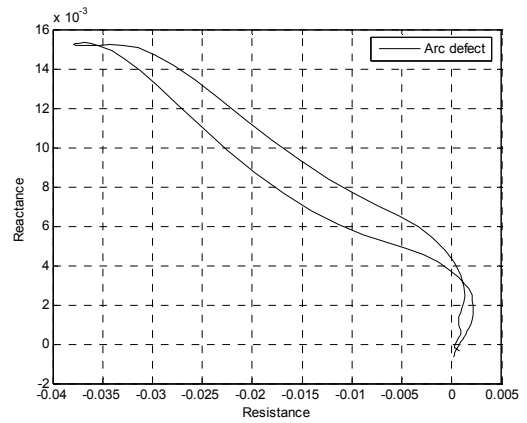
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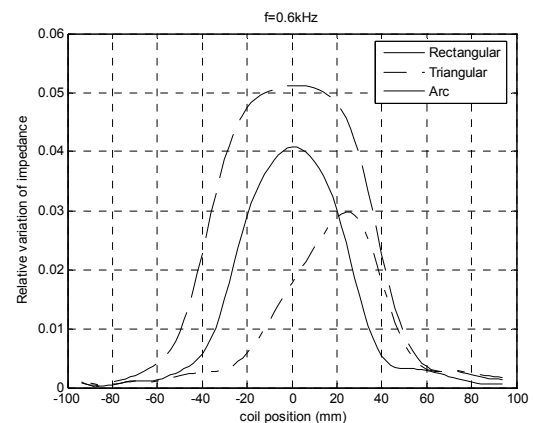
(c)



(d)



(e)



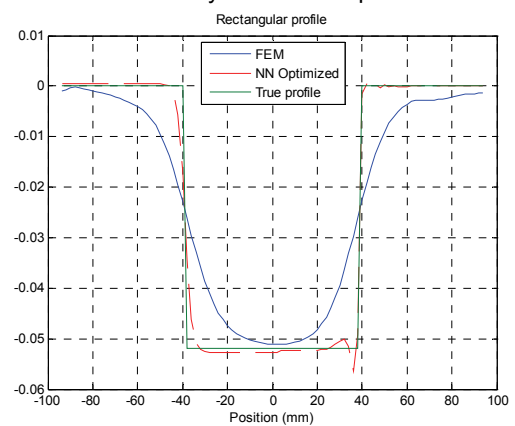
(f)

Fig. 3. Reconstruction results obtained with different defect shapes at 0.6 kHz frequency.

B. Inversion results

In these results the presentation of the FEM results for every figure have inverted for the compare with the NN Optimization and the true profile of the shape crack.

The comparisons results shown in the fig 4 give a good maps representing by the NN in very short time. However, the approach described in the paper manages to identify the problem fairly effectively by constraining the set of admissible solutions by different shapes



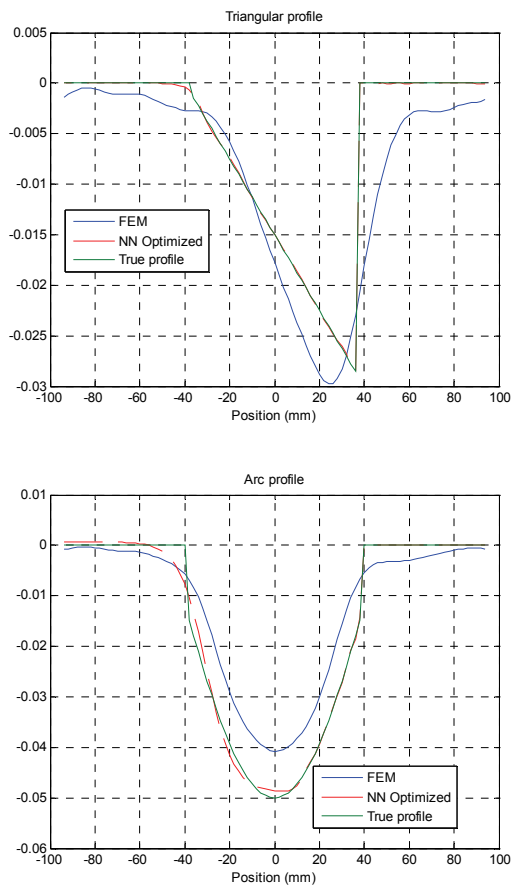


Fig. 4. Comparison results from the NN Optimized, FEM and true profile.

Conclusion

This paper presents the application of the neural networks for the evaluation of the form of cracks with different shapes. The simulation results obtained using a finite element model is presented in the first part. The use of the impedance for different forms of crack by using the FEM is used which the input to the NN permitted to estimate with good results of the maps of cracks. This application has been achieved by the inversion method based on the neural networks.

The NN responses which estimate the forms of crack are obtained by the inverse model in very short time. The

results also show that it is reasonable and feasible. The developed program involves a dramatic reduction of computing time requirements compared to other techniques.

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