DESIGN OF AN OPTIMAL NEURAL NETWORK FOR EVALUATING THE THICKNESS AND CONDUCTIVITY OF THE METAL SHEET

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Abstract. : This paper presents the application of non-destructive evaluation by eddy currents for the determination of the geometrical and physical parameters of metal sheet, obedient to a sensor of a double coil (method of Adding-Opposing (A O)). The forward problem is solved by using an analytical model. The electrical impedance for coil is measured for two frequencies ranging from 1 kHz and 1 MHz. The inversion method is implemented using neural networks; it consists to introduce the real and imaginary parts of the impedance for the evaluated thickness and conductivity. The neural network (NN) implementation of this problem is determined by the split-sample method and the adjustment of the internal parameters of the neural networks so as to minimize the mean square error (MSE). The inversion results obtained with both NN (MLP and RBF) are presented and compared. The presented approach has permitted to achieve good parameters estimation in a very reasonable training time with respect to others approaches.

Keywords: Neural networks; Non-destructive evaluation; eddy current, Inverse problems, Electromagnetic

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1 Introduction

In the industry, the various methods of non destructive control (CND) are used currently for research and the qualification of defect in the pieces on the one share, and the characterization of the materials on the other share. This CND application is by eddy current; its flow in the part in a perpendicular direction to the flux is parallel to the winding and the part surface. In most eddy current instruments the exciter coil induces eddy currents in a test part. The objective of this work is the use of the method A-O [4], [5] who permits the determination of the physical and geometrical parameters of the immobile part simultaneously while using two identical solenoids, connected in series, placed face-to-face coaxialement, and disposed on the two sides of the sheet metal under control. The total impedance of the two coils when the current there passes in the same direction and in the opposite directions is measured. The difference of impedance between these two cases will be used as an intermediate value that permits to estimate these parameters of the sheet metal. With respect to the approaches proposed in [1], [2] based on the analytical model developed by Dodd & Deeds, our approach is based on the analytical model developed by Nonaka [4], [5]. For the evaluation of these parameters one uses the external inverse method at basis of neural networks, this method consists at finding the parameters of the corresponding target to the signals creative of the sensor, for that, it is simpler and faster to using the behavioural external modelling. The simplicity of the structure of an external model and the fast inversion that does not appeal to the successive iterations makes their use very interesting. The application of the neural networks to electromagnetic inversion is used in the case of impedance measurement by eddy currents of a metallic plan; the inversion method is investigated to estimate the metallic parameters, and its impedance is measured as a function of frequency [7]. The eddy current probe impedance is given as input to the neural network and the conductivity and thickness is evaluated continuously by output of the neuron. In our case the estimate of the sought parameters is carried out in a non iterative direct way by creating an inverse model by means of a NN. It's a matter of the behavioural modeling, by opposition to a physical model of method A-O.

2 STATEMENT OF PROBLEM DESCRIPTION AND THE FORWARD PROBLEM

The geometry of the problems considered is illustrated schematically in Figure 1. The two identical solenoids at an air-core circular coil of rectangular cross section, connected in series. The solenoids are placed coaxialement, face to face and they are disposed of on the two sides of the metal part under control, while the coils axis is perpendicular to the target surface. The coils parameters of importance are number of turns n, inner radius of the coil r1, and outer radius r2, L the length of the coil, lo the lift-off, s, e the conductivity, and the thickness respectively of the layer. The width and the length of sheet are supposed infinitely large. The surface upper and that lower of sheet are tf and tb. The forward problem was solved by Nonaka [4], [5] who consists in the determination of the winding impedance difference of the probe and the parameters of the metal sheet. The coil is excited by a constant alternative current of angular frequency; its impedance is measured as a function of frequency. So the probe impedance Z is theoretically given by. [1], [2]:

$$Z_{\pm} = jK \int_0^{\infty} \frac{D^2}{\alpha^6} \left(\alpha L + e^{-\alpha L} - 1 + (e^{-\alpha Z_b} - e^{-\alpha Z_t})\phi_{\pm}(\alpha)\right) d\alpha \tag{1}$$

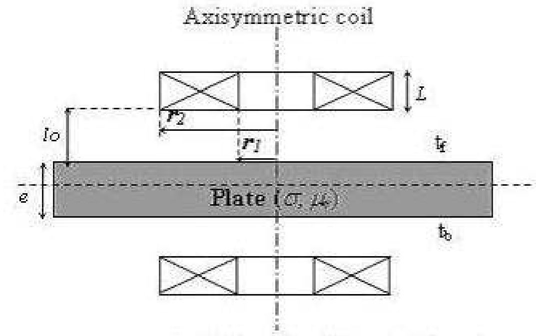

Figure 1: Geometry and dimensions of the solenoids used in method A-O for motionless sheets

Where

$$K = 4\pi w \mu_0 (\frac{n}{eL})^2 \tag{2}$$

The radial dimensions of the coil are incorporated via the function D, which is defined to be.

$$D = \int_{\alpha} x J_1(x) dx \tag{3}$$

Where $J_1(x)$ is a first-order Bessel function.
Finally,

$$\phi_{\pm}(\alpha) = \frac{\left(\mu_s^2 - \frac{\alpha_1^2}{\alpha^2}\right)\left(e^{\alpha_1 . e} - e^{-\alpha_1 . e}\right)\left(e^{2\alpha . t_f} + e^{-2\alpha . t_b}\right)}{4\left(\mu_s + \frac{\alpha_1}{\alpha}\right)^2 e^{\alpha_1 . e} - 4\left(\mu_s - \frac{\alpha_1}{\alpha}\right)^2 e^{-\alpha_1 . e}} \pm \frac{8\mu_s \frac{\alpha_1}{\alpha} e^{\alpha . e}}{4\left(\mu_s + \frac{\alpha_1}{\alpha}\right)^2 e^{\alpha_1 . e} - 4\left(\mu_s - \frac{\alpha_1}{\alpha}\right)^2 e^{-\alpha_1 . e}} \tag{4}$$

And

$$\alpha_1 = \sqrt{\alpha^2 + jw\mu_s\mu_0\sigma_1} \tag{5}$$

In this first application, the parameters of the sheet were set for this form (r1=5.35mm, r2=7.7mm, L=2.3mm), whereas s was allowed to vary from 15MS/m to 25MS/m, e from 0.5mm to 1mm and the lift-off equal at 0.5mm. The electrical impedance of the coil is measured at two excitation frequencies (f1=1 kHz and f2=1MHz). The signs + and - corresponding respectively to the cases where the current circulates in the solenoids in the same direction and in the opposite direction. The difference in the impedance, ΔZ, which is given by

$$\Delta Z = Z_+ - Z_- \tag{6}$$

Where

$$\Delta Z = \Delta R + j\Delta X \tag{7}$$

With an aim of evaluating the parameters of the plate, the real and imaginary parts of the complex impedance will be used like inputs of the neural networks. The diagram of the inversion model is illustrated schematically by Figure 2:

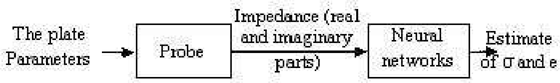

Figure 2: Diagram of the inversion with neuronal inverse model

The estimation is carried out starting from the impedance measurement at two fixed frequencies. The probe is simulated by means of an analytical model based on method A-O. The estimation of the sought parameters is carried out in a direct way (i.e. non iterative) by creating an inverse model by means of a neural network, thus, one observes the influence of the analytical model (calculation of the probe impedance) on the uncertainty estimate of the sought parameters.

3 INVERSION METHOD BY NEURAL NETWORK

The increasing interest to the neural network can be explained by their successful implementation in different areas [6]. 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 [2].

The application of NN to the inversion method of the probe coil impedance is trained and tested to identify and evaluated the conductivity and thickness of the metal sheet.

The NN input consists in the real and imaginary parts of probe impedance at the two frequencies f1 and f2 while its output provides the evaluated conductivity and thickness [1], [2].

The MIMO employed network has thus 4 inputs and 2 outputs, the input and output vectors were $[Re(f_1)\ \ Re(f_2)\ \ Im(f_1)\ \ Im(f_2)]^T$ and $[e\ \ \sigma]^T$respectively. The value relative error (RE) for each input signal is defined according to deviation of the real output signal value from the estimation value, which is defined to be [1].

$$RE(P) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\hat{P}_i - P_i}{P_i}\right)^2} \qquad (8)$$

Where

- N, the number of example in the test set,
- P_i, the parameters desired,
- $\hat{P}_i$, the parameters estimated by NN.

3.1 THE OPTIMAL NN DETERMINATION

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 split-sample method [9]. The data sets are created by data thanks to the problem of physical analytical model studying the electromagnetic interaction between the probe and the specimen of the method A-O. Every set contains the input-output data belonging to the evaluation range. These sets are training, validation and test sets.

The training set is constructed by estimating the output of the real system, when inputs are generated randomly in their corresponding specific intervals. The validation set is destined to select the NN structure, it is a sub set of the initial training one, but used only after the initial training process to select the final NN structure. The test set contains the data belonging to the same domain of training but are different from the training data. The test set is used to test the capacity of the NN to estimate the real system outputs when submitted to new inputs.

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 [1], [6].

The mean square error value is computed by:

$$MSE(w) = \frac{1}{N}\sum_{k=1}^{N}||D_k - S(E_k, w)||^2 \qquad (9)$$

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.

The training set for this application; contains 216 of input (e) and output (s), with $s = [e\ \ \sigma]^T$ and $e = [Re(f_1)\ Re(f_2)\ Im(f_1)\ Im(f_2)]^T$, where $Re(f)$ and $Im(f)$ are the real and imaginary part of the probe impedance at the frequency f , respectively.

3.2 INVERSION USING TO THE MULTILAYER PERCEPTRON NEURAL NETWORKS (MLP NN)

One of the most popular structures of artificial neural networks is the MLP NN. The input layer is given as an input vector, which thus constitutes the first layer of the network. Also, in a MLP-network there is at least one hidden layer and one output layer of nodes or neurons which enable the network to solve non-linear problems. The connections between the layers are represented by weight factors, which can initially be selected randomly.

In the first application one was interested in MLP network structure illustrates by Figure 3. The MLP structure which was used in the present study is constituted of one hidden layer having hyperbolic tangent activation functions and an output layer with linear activation functions. The training of the MLP-network is done by using Levenberg-Marquard algorithm of non-linear optimisation [8]. The number of the hidden layer has to be fixed, in this application; the number of neurons of the hidden layer is varied from 1 to 50 neurons. A typical neural network implementation of this problem is determined by the split-sample method, this range is determined heuristically and should be modified if it necessary. This method determined the optimal hidden layer of NN.

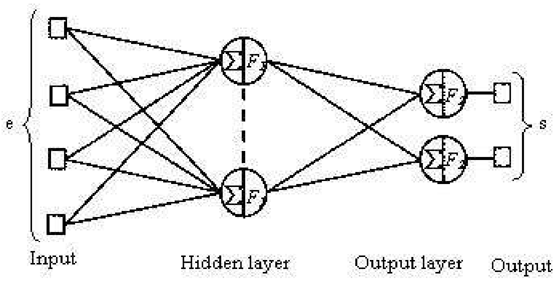

Figure 3: Structure of MLP NN

Where

- $F1$: hyperbolic tangent activation function
- $F2$: Linear activation function

When implementing the Split-sample method, several tests are realized for each structure of NN planned in order to try to avoid a bad initialization of the weights of the NN.

The adjustment of the weights of a MLP NN illustrated by Figure 4 is realized by means of an examples base (training bases) giving the desired output of the NN for a given input. In the case, the MLP NN is trained to identify the unknown conductivity and thickness of a metallic plate. Figure 5 shows the evolution of the MSE on training set and validation and test sets according to the optimal number of neurons in the impedance measurements. The optimal number of neurons in the hidden layer is 35.

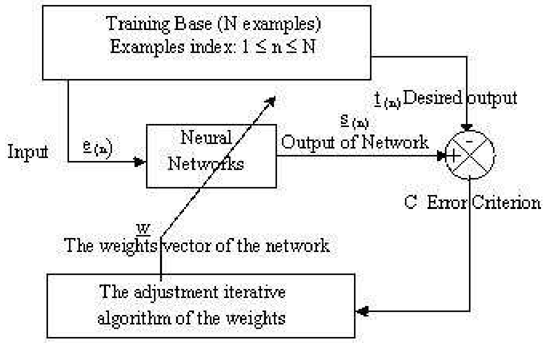

Figure 4: The weights adjustment of the MLP NN

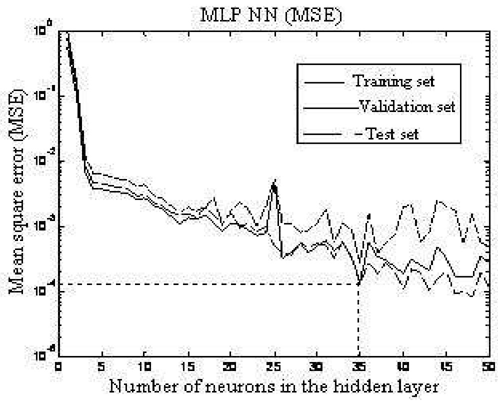

Figure 5: the evolution Mean Square Error on the tree sets for the MLP NN

3.3 INVERSION USING TO THE RADIAL BASIS FUNCTION NEURAL NETWORKS (RBF NN)

Radial-basis function RBF NN is 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. In the second application one was interested in RBF network structure illustrates by Figure 6, with a function of Gaussian activation on the hidden layer.

The number of neurons in the hidden layer is equal to the number of examples in the training set. The training is based on simulated data, involving the impedance

of the probe coil, which is measured by two excitation frequencies. Moreover, the hidden neurons centers are identical to the values of examples of input on the training set. The values of the widths of the Gaussian functions are identical for all the neurons of the hidden layer. This value of width is determined by the split-sample method, and for a variation of the width, one will choose that which corresponds to the lowest MSE on the validation set.
Finally, the output layer having linear activation functions while the training leads to linear system resolution. The training consists in the adjustment of the layer weights values for the output neural networks. The RBF NN is trained to identify the unknown conductivity and thickness of a metallic plate. In the case, Figure 7 shows the evolution of the MSE on training set and validation and test sets according to the width in the impedance measurements. The optimal value of the width is 1.618.

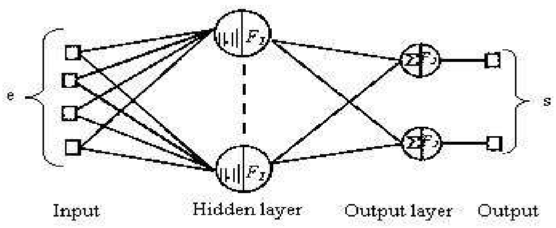

Figure 6: Structure of RBF NN

Where

- $F1$: Gaussian activation function
- $F2$: Linear activation function

4 INVERSION RESULTS

The results of inversion by NN for evaluation of the conductivity and the thickness of the metal sheet resulted to the following figures, this inversion is done by two types of neurons networks excited to their inputs by two frequencies one is small and the other is very big (1kHz and 1MHz).

These results show the effectiveness of the proposed NN inverse problem solution in the estimation of the parameters of the metal sheet by eddy current testing. The estimate offers the advantage of obtaining well-defined results of the parameters estimated with the real parameters. The evaluation of the real values of the thickness and conductivity by MLP and RBF one has given the values of the relative uncertainty errors for every parameter:

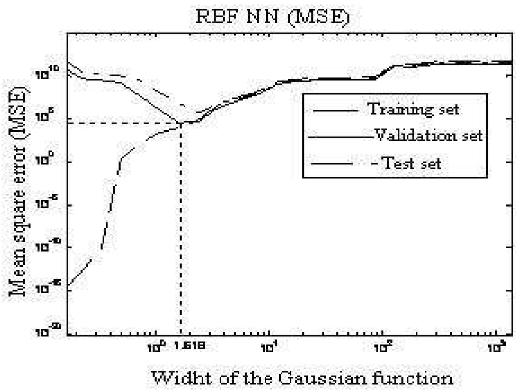

Figure 7: The evolution Mean Square Error on the tree sets for the RBF NN

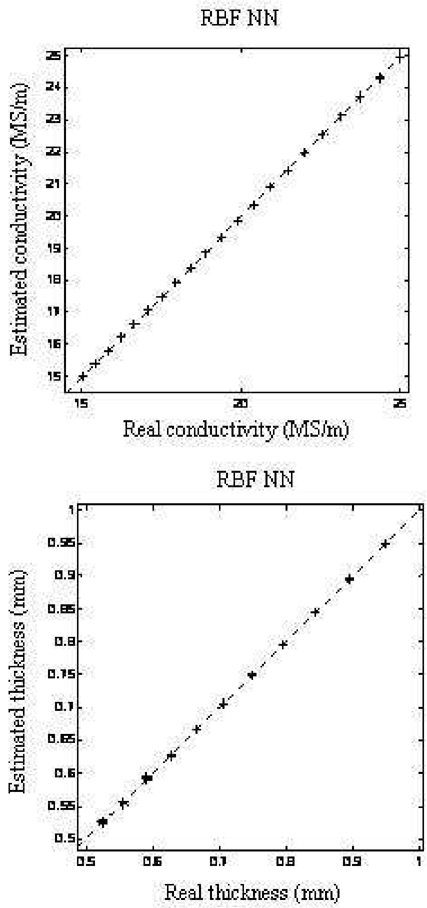

Figure 8: The evaluation vs real values of the conductivity and the thickness on the test set (+) per RBF NN

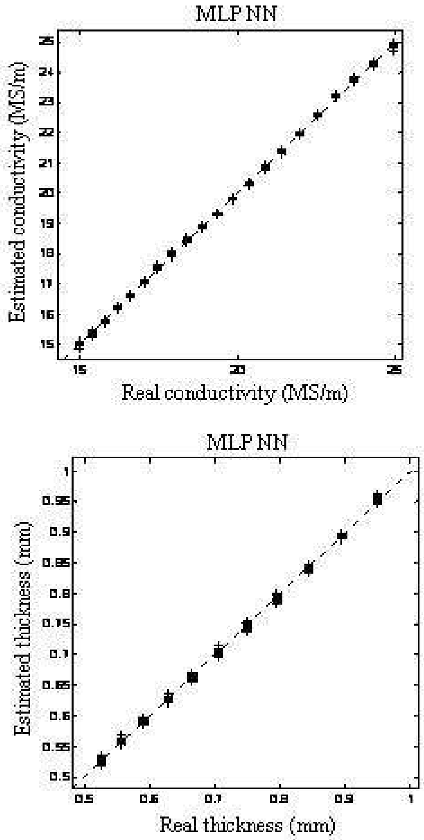

Figure 9: The evaluation vs real values of the conductivity and the thickness on the test set (+) per MLP NN

Using Network	Thickness	Conductivity
MLP NN	0.8774%	0.3096%
RBF NN	0.093%	0.0098%

Table 1. The indication of the relative uncertainty of the thickness and the conductivity for an application of the NN

5 Conclusion

In this paper we have presented the application of the neural networks for the evaluation of a metallic plate obedient at the use of the method A-O. This application has been achieved by the inversion method based on the networks of neurons MLP and RBF. We have used for the training, the validation and testing of the NN responses which estimate the conductivity and thickness obtained by the inverse model. The use of two excitation frequencies (1 kHz, 1 MHz) is input to the NN permitted to estimate with a good sought precision of the parameters.

The application of the neural network for evaluation of parameters has also some advantages:

- Simplicity and flexibility;
- Reliability of estimation.

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