Eddy current nondestructive evaluation of metallic plates electrical conductivity using artificial neural networks based inverse problem

Avaliação não-destrutiva da condutividade elétrica de placas metálicas usando redes neurais artificiais com base no problema inverso

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ABSTRACT
The most used method and extensively studied in the literature for conductors’ characterization is Eddy Current Nondestructive Evaluation (ECNDE) due to its significant advantages, such as its ability to preserve the integrity of the structures or materials to be examined during manufacturing or a regular in-service nondestructive testing. Various approaches are developed for the Eddy Current
measurement of the electrical conductivity. In the present work, the evaluation of the electrical conductivity is treated as an inverse problem. In pursuit of this aim, a combination is established between Eddy currents evaluation and artificial neural networks (ANN) to evaluate the electrical conductivity of homogeneous metallic plates from eddy-current probe impedance measurements. For this purpose, an experimental setup is developed, including a bobbin-coil probe, metallic plates (target), data acquisition and signal processing systems. Finally, experimental conductivity values of various metallic plates using ANN are compared with those obtained using four-point measurements of direct current potential drop (DCPD) made on the same plates and very good agreement is obtained.

**Keywords:** Eddy Current Nondestructive Evaluation (ECNDE), Inverse Problem, Artificial Neural Networks (ANNs), Finite Element Method (FEM), COMSOL multiphysics.

**1 INTRODUCTION**

Since the first application of Eddy current technique (ECT) developed by David Hughes for material sorting in 1879 (Hughes 1879), then the appearance of the first Eddy current thickness-measurement equipment developed in 1926 in the steel industry, the use of Eddy current nondestructive evaluation (ECNDE) for conductive materials characterization is rising in different fields mainly in the aircraft industry due to its primary advantage of preserving the integrity of the structures or
materials to be examined either during manufacturing, or during a regular in-service nondestructive testing (Terekhin; Slavinskaya 2019). The nuclear industry's stringent requirements for heat exchanger tube inspection have played a significant role in advancing the development of ECT as a reliable and precise nondestructive testing technique (Krajčovič; Plášek 2006, Ida; Meyendorf 2019).

Many activities in the industry, like sorting metals, checking for proper heat treatment, and defect identification require information about the electrical parameters. The most important of those parameters for conductive materials is electrical conductivity ($\sigma$). Therefore, its evaluation is essential in inspection activities dealing with metallic elements.

For decays, various approaches are developed for the Eddy Current measurement of the electrical conductivity (Baird and Boyle 1953). Nowadays, ECNDE like all inspection techniques has evolved beyond its fundamental principles and methodologies by taking advantage of the developments in electronic devices, computing systems, and data analysis. Thus, precise high-efficiency results can be obtained using sophisticated, effortless post-inspection signal analysis (Hellier 2003).

In the proposed work, the evaluation of the electrical conductivity is treated as an inverse problem. For that, a benchmark for Eddy current Nondestructive Evaluation (Martinos, Theodoulidis et al. 2014) has been considered to validate the numerical model used for solving our forward problem and generate a database for solving our inverse problem.

In the inverse analysis, an artificial neural network model is employed to evaluate the electrical conductivity value.

An experimental setup is performed, includes the developed bobbin-coil probe, metallic plates, data acquisition, and signal processing systems. The acquired data are used to feed the developed ANN model, which subsequently evaluates the electrical conductivity value of the plate under test.

For results validation, an X-ray fluorescence (XRF) spectroscopy is performed for each plate for precise identification of their alloys. The evaluated values of electrical conductivity are compared with those obtained using four-point measurements of direct current potential drop (DCPD) done on the same plates.
The culmination of all the work mentioned above leads to the primary objective of the study, which is to assess the electrical conductivity of different homogeneous metallic plates by combining artificial neural networks (ANN) with eddy current evaluation.

2 FORWARD PROBLEM

In Eddy Current Testing (ECT), solving the inverse problem, i.e., determining a piece under test properties knowing measured data, is one of the main challenges (Bilicz, Lambert et al. 2010).

In order to get representative desired output from inverse analysis of a given system, a forward analysis is indispensable. In our application, the forward problem consists of the calculation of the probe impedance variation (ΔZ) in the presence of a conductor, in other words, the variation of the resistance (R) and reactance (X) of the probe due to the Eddy currents induced in the conductor with known parameters (electrical conductivity, magnetic permeability, thickness). To this end, the modeling of our ECT problem is presented below.

2.1 PROBLEM MODELING

In the present ECT problem the excitation is provided by a circular multi-turn stationary air-cored coil, a so-called probe, with rectangular cross-section, which is the most practical design in eddy current testing. The coil is located above a metallic test plate which has the physical properties capable of inducing modifications in the initial magnetic field.

The impact of the plate's electric and magnetic properties on the detection signal is evaluated by analyzing the measurements obtained. The analysis process is governed by the system of Maxwell's equations for the electromagnetic field. These equations, including Faraday's law of induction, Maxwell-Ampere's law, and Gauss's laws in electric and magnetic formats, are expressed in a differential form and explain the phenomena mathematically (Ida; Meyendorf 2019).

Typical NDE applications are usually low-frequency electromagnetic field problems employing excitation frequencies below 1 MHz. Under that assumption, the equation defining the Eddy currents flow is derived from Maxwell's equation and it is written in terms of the magnetic vector potential A (Dodd and Deeds 1968):
\[ \nabla^2 A - \mu \sigma \frac{\partial A}{\partial t} = -\mu J \quad (1) \]

Where \( \mu \) is the magnetic permeability (H/m), \( \sigma \) is the conductivity (S/m) of the medium, and \( J \) is the total current density (A/m²).

The magnetic vector potential \( A \) can be obtained by solving Eq (01) with appropriate boundary conditions imposed by the configuration being studied using either analytical or numerical methods. Upon obtaining the potentials, various other physical parameters, including the coil impedance, can be inferred from them.

Since the 1960s, there has been progress in numerical modeling of the EC method (Auld and Moulder 1999, Rosell 2012). As a mathematical model, the EC method is described using the finite element method (FEM), which is one of many techniques used to solve the governing equations that describe physical principles with the ability to incorporate complex geometries in order to predict configurations that are reasonably close to reality.

To simulate our NDE problem, a 3D numerical model based on FEM has been designed using COMSOL Multiphysics software. All of the calculations were done using the Magnetic Fields Physics option of the AC/DC module of COMSOL Multiphysics in the frequency domain.

2.1.1 Benchmark Used for Modeling

The agreement between numerical calculations and experimental measurements is the best way to verify the correct application of modeling methods. For that reason, many approaches have been proposed using different probes with various shapes and arrangements according to the application (JSAEM et al., 1996, Mayos et al., 2008). In this paper, a numerical model was implemented for precision impedance measurements Benchmark Proposal (Martinos et al. 2014) in order to validate the model used for solving our forward problem.

The system simulated was an AC driven pancake coil interacting with a multi layered structure (two aluminum plates) affected by holes and cracks. Measurements for four configurations have been performed:

1: only one plate was present with a hole and a notch,
2: two plates, with holes aligned, a notch in the upper one (the one closer to the coil).
3: two plates with holes, a notch in the lower plate.
4: one holed plate, no notch.

The coil and plate parameters are shown in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>Coil</th>
<th>Plate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inner radius</td>
<td>7.0 [mm]</td>
<td>Thickness 2 [mm]</td>
</tr>
<tr>
<td>Outer radius</td>
<td>12.0 [mm]</td>
<td>Conductivity 17.34 [MS/m]</td>
</tr>
<tr>
<td>Height</td>
<td>4.0 [mm]</td>
<td>Relative Permeability 1</td>
</tr>
<tr>
<td>Wire-turns</td>
<td>1650</td>
<td>Gap between 70 [μm]</td>
</tr>
<tr>
<td>Lift-off</td>
<td>1.082 [mm]</td>
<td>Hole radius 10.0 [mm]</td>
</tr>
<tr>
<td>L0 (measured)</td>
<td>53.655 [mH]</td>
<td>Crack length/width 9.8/0.234 [mm]</td>
</tr>
</tbody>
</table>

Source: Authors.

2.1.2 Validation of the Benchmark Numerical Model

For our application, only one configuration is considered (configuration 4). So, a single line scan was conducted by moving the coil above the hole. The resulting signals, which include normalized resistance and inductive reactance at 1 and 5 kHz, are depicted in Fig 1.a, as a function of the distance from the center of the hole, and Fig 1.b shows the signals in the normalized complex impedance plane.

The numerical results show a satisfying agreement with the benchmark experimental results.

Figure 1 – Comparison between the experimental and numerically computed coil Normalized impedance at 1 kHz and 5 kHz, a) Variation of the real and imaginary parts as a function of the distance from the hole center, b) Complex impedance plane.

Source: Authors.
3 INVERSE PROBLEM

Inverse problems in ECT are usually ill-posed, frequently exposed as an objective function minimization (Helifa, 2012). Many studies involving methods based on optimization procedures, such as downhill simplex algorithms, have been used for their solving (Chelouah et al., 2000).

Inversion methods that employ conventional optimization methods would suffer from being easily trapped into local minima (Hou et al., 2023); however, this issue can be solved by using new intelligent optimization methods.

Nowadays, the introduction of Artificial Intelligence (AI) techniques, which allows for solving the inverse problems in the Nondestructive evaluation, has shown effectiveness in data regression and prediction compared to the traditional statistical methods such as linear and non-linear regression (Shih et al., 2015). One of the increasingly used AI techniques is Artificial Neural Networks (ANN), simply known as neural networks.

In addition, ANN is widely accepted as a technology providing a different approach for solving complex problems due to its ability to learn and model non-linear and complex relationships.

Last decays, many ECT studies focused on the use of ANN especially when complex physical modeling is considered (Rao et al., 2002; Buck et al., 2016; Cui et al., 2018). In these studies, Neural Networks are mostly related to the inversion of Eddy Current NDE signals for cracks reconstruction and classification. This part of work consists of the evaluation of the electrical conductivity of metallic plates using an inverse analysis technique to interpret the ECT signals.

3.1 ARTIFICIAL NEURAL NETWORKS

One of the most used information-processing systems nowadays is the Artificial Neural Networks, which was inspired in the 1940s by the biological neural networks of the human body.

The comprehension of the neural networks in the brain has expanded possibilities for creating artificial neural networks and adaptive systems capable of learning from their experiences and adjusting in response to new information.
Figure 2 shows the strong similarity between the processing element’s structure and that of a biological neuron. The process of the basic elements in an ANN has been inspired by the transmission of the electric impulse signal across the following essential biological neuron parts (Haykin 2009):

1. **Dendrites**: which receive signals from other neurons,
2. **Synapses (connecting links)**: The received signals are modified and transmitted by means of a chemical process in a manner similar to the action of weights in an ANN,
3. **Cell body (Soma)**: This part of the neuron sums the weighted input signals then transmits the output to another neuron via its **Axon**.

As it is illustrated in Figure 2, ANNs combine artificial neurons in order to process information. For a given number of inputs, a corresponding number of neurons (input layer) receives and transmits data to the following layer without taking part in its modification. In the next layer (hidden layer) neuron computes a weighted sum of its input data and then applies mathematical function that determines the activation of the neuron. The number of neurons in the last layer (output layer) corresponds to the number of the output values of the neural network; they receive the desired output for specific inputs by adjusting the weights using a process called learning or training.

Artificial Neural Networks (ANNs) are employed, in this work, to estimate the electrical conductivity of metallic plates from ECs signals. This evaluation is
based on the prediction of the relationship between the required electrical conductivity and the probe output signals (Figure 3).

Figure 3 – Analogy between Artificial neural networks and biological neuron.

3.2 DATA PREPARATION AND ANN MODEL DEVELOPMENT

In order to get a well-trained ANN model to inverse problem solving, it is essential to use a database as big as possible in the training phase. In fact, the collection of data on all possible materials and Alloys is impossible, which makes the nondestructive valuation suffers from the difficulty of obtaining sufficient and relevant data to train algorithms. To overcome this limitation when working with small datasets, some considerations should be taken into account during the development of the ANN model:

- Use of a network as simple as possible with a reduced number of neurons,
- Ensure that training data include edge cases to ensure that our model can make accurate predictions on real data.

The ANN learning database, in our case, consists of two parts:

a) ANN desired output data: that contains electrical properties of conducting materials (esp. electrical conductivity). For that, some renowned references in literature have been consulted (Committee, 1992; Lide, 2004).

b) ANN input data: real and imaginary parts (R and X) of the probe impedance (Z).

In order to prepare the database, we used the ECT COMSOL model developed previously (section 2.2.1). The coil parameters in this model must be adapted to fit with the probe coil to be used in our experimental measurements (Table 2).
Table 2 – Coil parameters

<table>
<thead>
<tr>
<th><strong>Coil</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Inner radius</td>
<td>6.0 [mm]</td>
</tr>
<tr>
<td>Outer radius</td>
<td>11.0 [mm]</td>
</tr>
<tr>
<td>Height</td>
<td>5.0 [mm]</td>
</tr>
<tr>
<td>Wire-turns</td>
<td>1950</td>
</tr>
<tr>
<td>Wire-diameter</td>
<td>0.1 [mm]</td>
</tr>
<tr>
<td>Lift-off</td>
<td>1 [mm]</td>
</tr>
<tr>
<td>(L_0(\text{measured}))</td>
<td>59 [mH]</td>
</tr>
<tr>
<td>(R_0(\text{measured}))</td>
<td>249 [Ω]</td>
</tr>
</tbody>
</table>

Source: Authors.

3.2.1 Coil Excitation Signal Frequency

For the choose of an adequate coil excitation signal frequency, a sensitivity study must be carried out, and thence we obtain the optimal frequency at which the probe impedance is sensitive as possible to the change in the physical properties of the target (plate).

Figure 4 shows the variation of \(R_{\text{coil}}\) and \(L_{\text{coil}}\) as a function of the electrical conductivity of the plate at different frequencies.

Figure 4 – Variation of \(R_{\text{coil}}\) and \(L_{\text{coil}}\) as a function of the electrical conductivity of the plate.

![Graph showing the variation of \(R_{\text{coil}}\) and \(L_{\text{coil}}\) as a function of electrical conductivity.]

Among the previous results, we notice that a good sensitivity is reached at 1 kHz and 100 kHz (Figure 5)
Figure 5 – Variation of $R_{\text{coil}}$ and $L_{\text{coil}}$ as a function of the plate electrical conductivity at; a)1kHz, b)100kHz.

![Graphs showing variation of $R_{\text{coil}}$ and $L_{\text{coil}}$](image)

Source: Authors.

The other important factor for choosing the excitation signal frequency is the standard depth of penetration ($\delta$: electromagnetic skin depth). This last is defined as the depth at which the magnetic field intensity decreases by 37% of its value at the surface of the plate.

$$\delta = \frac{1}{\sqrt{\pi \mu \sigma f}}$$  \hspace{1cm} (2)

Where $\delta$ in meters, $f$ is the operating frequency in Hz, $\mu$ is the material magnetic permeability, and $\sigma$ is the electrical conductivity in S.m$^{-1}$.

In NDT, if the size of the test part is much larger than the skin depth, the result would probably not be useful, so it is generally recommended to operate with a depth less than three times the standard skin depth (Hellier 2003).

Taken into account the plate dimensions, our choice among the two frequencies is indeed 1 kHz which certainly corresponds to a skin depth greater...
than our plate thickness (2 mm). In this case, an air domain was added under the plate to avoid numerical problems due to the boundary conditions.

After adjustment of the ECT model parameters and the coil excitation signal frequency, a parametric sweep study is performed on the electrical conductivity to simulate the material changing of the plate under test.

As a result, we got the corresponding values of $R_{coil}$ and $L_{coil}$ for each plate material. Those last make up the learning database discussed earlier (section 3.2).

Figure 6 – Air domain containing a multi-turn coil placed over a metallic plate.

Figure 7 – 3D surface plot of the y-component of the induced current density, $J_y$ (A/m²) in the plate combined with the arrow volume plots of the coil current direction and the induced current density in the plate.

3.2.2 ANN Model

The key of a powerful ANN is finding the proper structure and the adjustment of internal parameters. Unfortunately, there are currently no well-defined rules for
doing this; rather, there are some procedures to follow in order to yield useful results (Haykin, 2009).

In this study, our network can be viewed as a nonlinear input-output mapping. For that kind of problems, a multi-layer feed-forward error-back propagation network is the most optimal structure (Figure 8).

Figure 8 – Schematic diagram of multi-layer feed-forward error-back propagation network.

After many sequences of training using the same learning database generated previously, we reached an appropriate net with two input neurons corresponding to real and imaginary parts of the probe impedance ($R_{probe}$ and $L_{probe}$), 20 hidden neurons in one hidden layer and one output layer of one neuron leading to electrical conductivity estimation. The network weights updating was performed through a Levenberg–Marquardt back-propagation training algorithm.

Figure 9 shows the fit of the training, validation and test data used for the ANN model development. The coefficients of determination ($R^2=1$) reveal how well the trained model fits the given data set.
Before testing the generalization of our ANN model, we tried to verify it with the data already used during its development. The superposition of the given values of $\sigma$ and their estimation is presented on Figure 10.a.

The corresponding error for each value is presented in Figure 10.b.
As described earlier, during the development of the ANN model a part of the database is already preserved to test its performance (Figure 10.c). In addition to this test, another generalization test was done using some data which have not been used in the training of the ANN model (Figure 11).
Looking to the magnitude of the error shown in Figure 11.b, we can clearly observe a very good performance in estimating the electrical conductivity values.

4 EXPERIMENTAL RESULTS DISCUSSION

4.1 EXPERIMENTAL SETUP

4.1.1 Plates (Figure 12.b)

Four metallic plates were studied (copper, 2 aluminum alloys and stainless steel). For precise identification of their alloys, an X-ray fluorescence (XRF) spectroscopy is performed for each plate. Plate thicknesses were measured using digital calipers at different points on the plates. Parameters and major elemental composition of the plates are given in Table 3.

![Figure 12 – a) Probe-coil, b) Studied metallic plates.](image)

Table 3 – Plate parameters: Chemical composition, conductivity, $\sigma$ (from literature); thickness, $T$; and lateral dimensions, $w \times l$.

<table>
<thead>
<tr>
<th>Alloy</th>
<th>Chemical elements (%)</th>
<th>$\sigma$ (MS/m)</th>
<th>$T \times w \times l$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C18100</td>
<td>99 Cu, (Cr+Zr+Mg&lt; 1)</td>
<td>46.1</td>
<td>(1.9x100 x100) ±0.01</td>
</tr>
<tr>
<td>Al1145</td>
<td>Al 99.4, Si 0.258, Cu 0.036</td>
<td>[3.48-3.54]</td>
<td>(1.75x100x100) ±0.01</td>
</tr>
<tr>
<td>SS304</td>
<td>Fe 68.18, Cr 18.35, Ni 10.15</td>
<td>1.38</td>
<td>(0.68x100x100) ±0.01</td>
</tr>
</tbody>
</table>

Source: Authors.

4.1.2 Probe

The probe is composed of a cylindrical coil with rectangular cross-section wound in regular layers (Fig 12.a); the coil was fitted in a support manufactured from a block of Teflon. A Bridge connector is mounted on the support block allowing a good connection of the coil to a signal conditioning circuit. The free space probe impedance real and imaginary parts ($R_0$ and $L_0$) at 1 kHz were measured using LCR meter. The coil parameters are given in Table 2.
4.1.3 Data Acquisition System:

In order to measure the current through the probe-coil, a signal conditioning circuit using TL081 operational amplifier is developed (Fig 13.a). Then, voltages across a probing resistor and the probe-coil were collected by a dynamic signal acquisition module NI9234 (Fig 13.b).

Figure 13 – a) Output signal conditioning circuit, b) Main elements of the experimental bench.

Acquired data from the probe were used to evaluate both resistance and inductance of the coil in presence of the target (metallic plate). The probe impedance and phase shifting ($\phi$) are given by:

$$Z_{\text{coil}} = \frac{V_{\text{coil}}}{I_{\text{coil}}} = R_{\text{coil}} + j\omega L_{\text{coil}}$$

(3)

Where, $\omega = 2\pi f$ is the angular frequency.

$$\cos \phi = \frac{R_{\text{coil}}}{Z_{\text{coil}}} \rightarrow R_{\text{coil}} = \cos \phi \cdot Z_{\text{coil}}$$

(4)

The current through the coil and the phase shifting ($\phi$) are evaluated from the waveform of the electrical signals picked up from a probing resistor $R_{\text{SH}}$ (Figure 13.a) connected in series with the coil-probe:

$$Z_{\text{coil}} = \frac{V_{\text{coil}}}{I_{\text{coil}}} = \sqrt{R_{\text{coil}}^2 + L_{\text{coil}}^2 \omega^2}$$

(5)
Combining (4) and (5) we have:

\[ R_{coil} = \frac{V_{coil}}{I_{coil}} \cos \varphi \]  

(6)

From (3) we obtain the coil-probe inductance:

\[ L_{coil} = \frac{1}{\omega} \sqrt{Z_{coil}^2 - R_{coil}^2} \]  

(7)

4.2 TEST AND VALIDATION OF EXPERIMENTAL RESULTS

Using SDG 5082 function/waveform generator, a sinusoidal waveform with 5V amplitude and a frequency of 1 kHz was used to drive the coil (Figure 14), while the current is deduced from the voltage read across a probing resistor in series with the coil. The liftoff was maintained at 1 mm throughout all measurement.

Figure 14 – Experimental bench of the ECNDE measurements.

Source: Authors.

For every measurement, the values of \( R_{coil} \) and \( L_{coil} \) were transferred directly via the data acquisition system to the neural networks based-application developed earlier by which corresponding electrical conductivity was evaluated.

Table 4 shows a comparison between the experimental values of the coil impedance and those obtained from ECT COMSOL model.
Table 4 – Simulated and measured values of different plate’s impedance.

<table>
<thead>
<tr>
<th>Plate</th>
<th>Measured</th>
<th>Simulated</th>
<th>Error rate [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>C18100</td>
<td>417.46</td>
<td>411.86</td>
<td>1.34</td>
</tr>
<tr>
<td>Al 1145</td>
<td>412.5065</td>
<td>410.93</td>
<td>0.38</td>
</tr>
<tr>
<td>SS 304</td>
<td>447.01</td>
<td>452.0737</td>
<td>1.13</td>
</tr>
</tbody>
</table>

Source: Authors.

4.2.1 Four-Point Direct Current Potential Drop (DCPD)

If the impedance of leads/connectors is comparable to that of the sample under test, the Two-point measurement method is not adapted for conducting electrical conductivity measurement. To overcome this issue, a high impedance precision voltmeter is used to measure the potential difference between two additional contact points. This approach ensures that the measurement circuit carries very little current, and the potential drop across the contact resistance of the measuring wires is negligible (Bowler and Huang 2005).

The four-point measurement arrangement employed for measuring the conductivity is illustrated in Figure 15.

Two measurements are required: the current passing through the plate, and the pickup probe voltage measured by a high-precision voltmeter.

![Figure 14 – Four-point probe in contact with metallic plate.](image)

Source: Authors.

Measured values of the voltage between the pick-up points as a function of the current passing through the plate are presented in Table 5.
Using the test plates dimensions, the applied current $I$, and the measured voltage $V$, the total conductivity $\sigma$ is calculated using Eq (8) (Heaney 1999, Pokrovskii and Khvostov 2013):

$$\sigma = \frac{I \cdot T}{w \cdot l \cdot V} \quad (8)$$

Where $T$ is the thickness and $w \times l$ are the lateral dimensions of the plate.

Experimental values of electrical conductivity for each of the plates obtained by the developed ANN are compared with those measured using four-point direct current potential drop (DCPD) method made on the same plates, the results are presented in Table 6.

<table>
<thead>
<tr>
<th>Plate</th>
<th>$\sigma$ (ECNDE) [MS/m]</th>
<th>$\sigma$ (DCPD) [MS/m]</th>
<th>$\sigma$ (literature) [MS/m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>C18100</td>
<td>45.7</td>
<td>46</td>
<td>46.1</td>
</tr>
<tr>
<td>Al 1145</td>
<td>33.5</td>
<td>33.8</td>
<td>[34.8-35.4]</td>
</tr>
<tr>
<td>SS304</td>
<td>1.39</td>
<td>1.36</td>
<td>1.38</td>
</tr>
</tbody>
</table>

Source: Authors.

It can be seen that, the conductivity values obtained by means of the ECNDE and DCPD methods agree, within experimental uncertainty.

5 CONCLUSION

In this work, the Eddy current evaluation of electrical conductivity was treated as an inverse problem solving. For this purpose, a combination was established...
between Eddy currents evaluation and artificial neural networks (ANN) in order to evaluate the electrical conductivity of various homogeneous metallic plates.

A FEM numerical model has been used for solving the forward problem in order to generate a learning database for the ANN. To solve the inverse problem, a well-trained Multilayer Perceptron Networks (MLP) was used.

Through the developed neural networks based-application, conductivity values were estimated from experimental measurements of eddy-current probe impedance. The estimated values were compared with those obtained using four-point measurements of direct current potential drop (DCPD).

The agreement observed between estimated and measured values shows the great promise of the approach and its capability to deal with the electrical conductivity estimation of conductive samples.

The samples studied in this work are non ferromagnetic materials. In order to enhance this application, in light of this research findings, more materials can be taken into account in future works including ferromagnetics to cover all materials.

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REFERENCES


HAYKIN, S. Neural Networks And Learning Machines, 3/E, Pearson Education India, 2009.


TEAM TESTING ELECTROMAGNETIC ANALYSIS METHODS (T.E.A.M.).
Workshop Benchmarks Problems (Nº8, Nº15).


WFNDE. World Federation Of Nde Centers.