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RESEARCH ARTICLE OPEN ACCESS

NEURAL NETWORK EDDY CURRENT NON-DESTRUCTIVE EVALUATION OF CONDUCTIVE COATINGS THICKNESS

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ABSTRACT

The proposed study is a machine learning application using a Neural Network for the prediction and identification of the thickness of aluminum placed over a steel plate. Two thousand and five hundred datasets with the eddy current method of different aluminum plate thicknesses above a steel plate and working frequencies of EC-sensor were generated using experimentally validated analytical models in our previous research. The data has three input parameters (normalized resistance, normalized reactance, and frequency) and one output (thickness). The ANN architecture involves careful consideration of the number of hidden layers and neurons within the model. The acquired data was split into two sections: the first section was used to train and test the selected model, and the second section was used to test the model on untrained data to demonstrate its high accuracy. The results obtained, as mentioned in the article, prove the validity and sensibility of the chosen model.

I. INTRODUCTION

Industrial components commonly surface treated through the application of engineering coatings, conferring new functional properties to the material surface like hardness, electrical conductivity, and thermal insulation...etc. The material composition of coatings, and desired properties such as thickness and adhesion to substrates, is controlled by specific deposition techniques and processes, i.e., PVD, CVD, electroplating, thermal spray, and others. Regardless of the selected process, rigorous control over coating quality is essential to ensure that the treated surfaces meet specified standards. When the coating parameters such as thickness is out of required specifications; the performance will be then negatively altered. Hence, the ability of the assessment of coating properties by the mean of non-destructive method offers a crucial importance for many industrial sectors such as aerospace, energy. In fact, Non-destructive evaluation techniques are based on determining the inherent physical and mechanical characteristics of a material without damaging or affecting its intended functionality, and subsequently using the resulted data to decide and predict its performance in the suitable applications [1].

Eddy current testing (NDE-EC) among other is a highly sensitive and less costly non-destructive evaluation technique compared to other methods. It is widely used particularly to detect geometric defects of material. Several experimental works have established that NDE-EC is a robust and reproductible technique to measure and reveal cracks, corrosion failure and thickness of protective coatings [2–8] .

NDE-EC modeling is also an additional study that can aid to better understanding the corresponding electrical and magnetic phenomena. Many research efforts have focused on the modeling and simulation of NDE-EC. Commonly the modeling study is associated with an inversion problem analysis in order to characterize or identify either the physical or geometric properties of the materials, or to optimize the inspection process [9], [10]. Design, development, and optimization of eddy current as non-destructive evaluation (NDE-EC) have been successfully developed through analytical [2], [3], [6–8], [11], [12] and numerical modeling [4], [5], [10], [13–16] based on electromagnetic systems.

The principle of thickness measurement by NDE-EC, is based on induced voltage or impedance change in a coil which is positioned above the plate to be measured. When alternating current is added at different frequencies in the coil an eddy-current is generated at different depths of the conductive plate providing a beneficial electromagnetic parameter information to measure and evaluate the thickness [2],[4], [5–8],[11],[12],[14],[16],[17].

According to Huang et al, NDE-EC is a relevant experimental technique to determine thin coatings thickness by the placement of the impedance of a coil probe above a coated multilayered plate using the swept-frequency eddy current testing method [14]. The studied phenomenon was described theoretically by Dodd and Deeds in [18], [3], [19] being a solution of the analytical expression of the coil impedance. Whereas, the optimization can be conducted by some methods such as artificial intelligence optimization to iteratively determine the thickness of coating layer based on the coil impedance.

Several artificial intelligence algorithms such as artificial neural networks (ANN) have proven successfully a good capability of managing, modeling, forecasting [20], [21], and predicting various aspects in electromagnetic, mechanical, and geometrical characterization, [22], [23].

As a data-driven computational model, artificial neural networks (ANN) can learn from given examples and ascertain the relationship between inputs and outputs without passing by a physical model, which can decrease the strong need for further extensive research.

The present work is a complementary study to the previous one of [24]. Where, they had experimentally validated analytical models developed by Dodd and Deeds and Theodoulidis et al [19], [25]. In fact, the main objective is firstly modeling of eddy current sensor-based system that allows thickness measurement of an aluminum layer in multilayer material in accurate and fast way the thickness of the aluminum plate (coating) placed on steel substrate over a wide range of frequencies. Secondly, the investigation of future values prediction for an aluminum plate thickness by ANN model. Where, training and testing datasets were initially produced using the previously validated models [24].

An artificial neural network (ANN) model has been created using the acquired datasets. Our artificial neural network (ANN) design considers the optimum arrangement of hidden layers and neurons in the model. The obtained data was divided into two parts: the initial part was used for training and evaluating the selected model, while the next one was used to evaluate the model's performance on untrained data, demonstrating its accuracy in the forecast of thickness. The collected results demonstrate the selected model's accuracy and sensitivity.

II. DATASET PREPARATION

Our study assumes that the provided problem is an axisymmetric eddy current. We adapt the system utilized in previous works (Figure 1) [3], [24]. A cylindrical coil of rectangular cross-section serves as the excitation source, positioned above a two-layer material where the first layer is a conductive material (aluminum) and the bottom layer is a ferromagnetic material (steel). Once more, the computation of the coil impedance changes induced by eddy current in the multilayer conductor is of primary concern [3], [24].

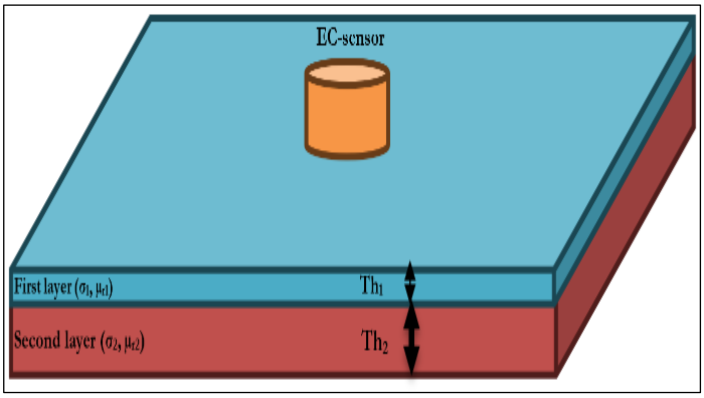

Figure1: Issue description.
Source: Authors, (2024).

The material to be evaluated has fixed physical parameters: two homogeneous layers of constant electric conductivity (σ) and relative magnetic permeability (μ_r). The distance between the coil and the material (lift-off) is fixed at 0.01 mm. It indicates how much the induced eddy currents alter the coil impedance and how much the coil is electromagnetically coupled to the material. The coil, top, and bottom layers extend to infinity in the third coordinate (z). The thickness of the first layer is changed from 0.01 to 0.25 mm, and the thickness of the steel layer is fixed to 5mm.

Tables 1 and 2 summarise the physical and geometrical properties of the material and coil used, respectively.

Table 1: The physical and geometrical properties of the material.

Multilayer material	**Electrical conductivity (MS/m)**	**Relative magnetic permeability**	**Thickness of plate (mm)**
First layer (Aluminum)	35.5	1	From 0.01 to 0.25
Second layer (Steel)	4.2	50	10

Source : Authors, (2024).

Table 2: Geometrical properties of the coil.

Coil parameter	
Outer diameter	19.4 mm
Inner diameter	10 mm
Height	4 mm
Lift-off	0.01 mm
Number of spires	406

Source: Authors, (2024).

Dodd and Deeds formulation [18] and the developed model by [3], [19] give an electromagnetic analytical solution to this problem. The magnetic vector potential *A* formulation in all regions satisfies the equation (1):

$$\left(\begin{array}{c}\frac{\partial^2 A}{\partial r^2}+\frac{1}{r}\frac{\partial A}{\partial r}-\frac{A}{r^2}+\frac{\partial^2 A}{\partial z^2}= \\ (j\omega\mu_r\mu_0\sigma)^2 A-\mu_0 I\delta(r_1 r_0)\delta(z_1 z_0)\end{array}\right) \quad (1)$$

δ is the penetration depth and I is the coil current, The total impedance of the coil is the sum of the individual coil impedance Z0 and the change in impedance Z produced by the conductive layer system. This change in impedance is a result of the presence of eddy currents within the system, which can be explained using the superposition principle. Having obtained the equation for Z0, equation (2) our task now is to calculate the value of ΔZ.

$$\begin{pmatrix} \Delta Z = \Delta R - j\Delta X = (R_c - R_0) + j(X_c - X_0) \\ = \dfrac{j2\pi\omega_{i0}}{r^2}\displaystyle\int_{r_1}^{r_2}\int_{z_1}^{z_2} A^{(ec)}\,(r_1 Z)drdz \end{pmatrix} \quad (2)$$

Equations (3) and (4) are used to compute the normalized resistance and reactance of the sensor for a range of frequencies and thicknesses of the aluminum layer as shown in Figure 2 and 3. Figure 4 illustrate the impedance normalised plane.

$$R_n = \frac{R_c - R_0}{X_0} \quad (3)$$

$$X_n = \frac{X_c}{X_0} \quad (4)$$

R_n and X_n are respectively the normalized resistance and normalized reactance. R_c and X_c are respectively the resistance and reactance of the eddy current sensor. R_0 and X_0 are respectively the sensor resistance and reactance sensor resistance without existence of material.

By varying the thickness of the first layer and the signal frequency by powering the sensor in an interval of 100 Hz up to 10 kHz with a step of 100 Hz, we obtained one hundred data points for each thickness. Furthermore, the thickness variation was from 0.01 mm to 0.25 mm with a step of 0.01 mm. In the end, we obtained data from 25 samples of the thickness of the first layer, and each one has 100 frequency calculations. At the end, three variables are in the input layer and a single output layer, each containing 2500 samples. The analytic model defined the normalized resistance and reactance, which proved the experimental solution to this problem in [24].

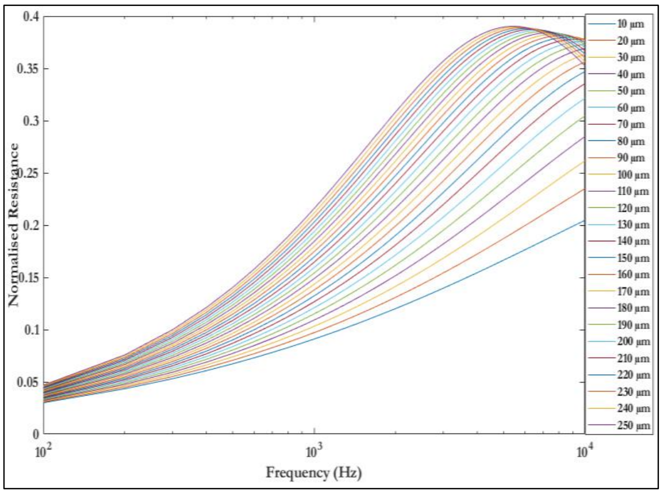

Figure 2: Normalized resistance.
Source: Authors, (2024).

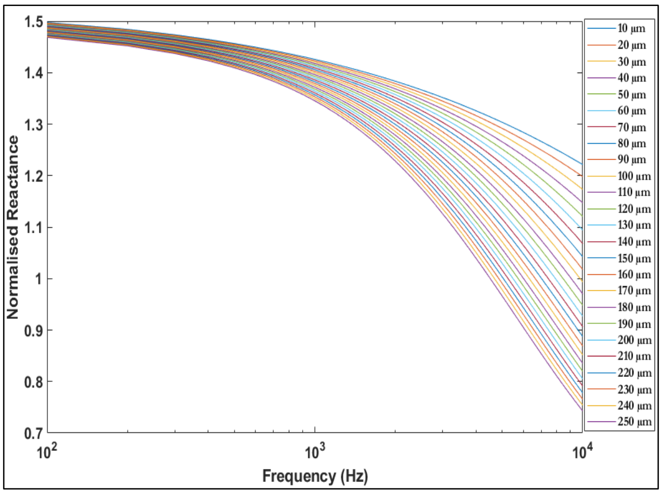

Figure 3: Normalized reactance.
Source: Authors, (2024).

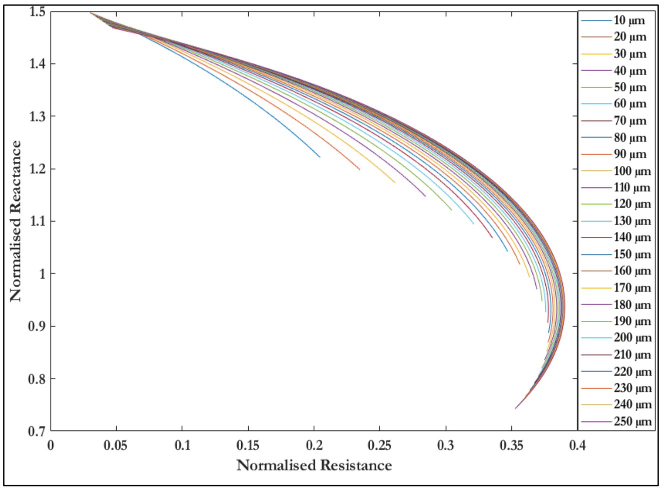

Figure 4: Impedance plane diagram.
Source: Authors, (2024).

III. ARTIFICIAL NEURAL NETWORK

This section delves into the development and training of an Artificial Neural Network (ANN) model for precise coating thickness prediction in eddy current testing scenarios. The ANN model is structured with an input layer, one or more hidden layers, and an output layer. The dataset is crucial for training the model to find relationships between input variables (normalized resistance, reactance, frequency) and output variables (thickness of the aluminum layer).

The ANN architecture involves careful consideration of the number of hidden layers and neurons within the model. Iterative testing determines that the optimal performance is achieved with 12 neurons in a hidden layer. The activation functions, specifically the sigmoid function in hidden layers and a linear function in the output layer, contribute to the model's capacity to learn complex relationships within the data. Figure (5) show the implemented ANN model's structure. The input layer of the Artificial Neural Network (ANN) is composed of essential parameters, including the responses of the coil at various frequencies. These variables play a pivotal role in providing the necessary input for the network to evaluate and predict the output layer, which presents the thickness of the coating layer. The ANN comprises 12 hidden layers, each contributing to the network's ability to capture intricate patterns inherent in structural responses. The activation functions are employed in these layers to introduce non-linearities crucial for accurate prediction. The training process involves using a neural fitting application, where 85% of the dataset is randomly selected for training the model. The iterative nature of this process allows the model to adjust its internal parameters to minimize the mean square error (MSE), optimizing its ability to predict coating thickness accurately.

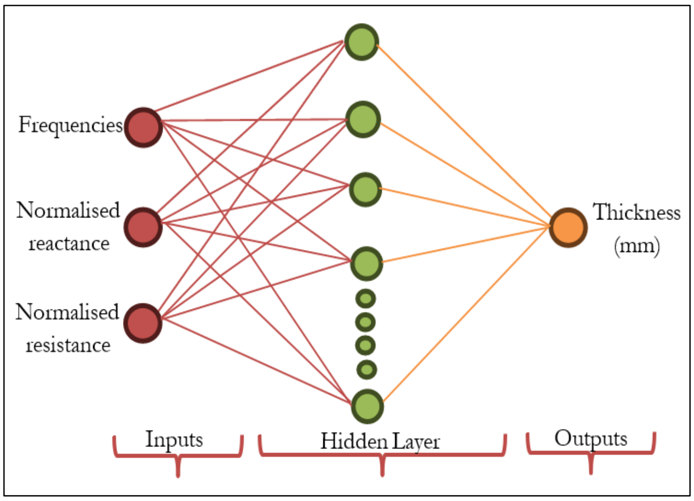

Figure 5: The implemented ANN model's structure.
Source: Authors, (2024).

Fine-tuning hyperparameters is a crucial step in enhancing the model's performance, including optimizing the learning rate and batch size to achieve the best convergence during training. After training, the model's performance is rigorously tested on the remaining 15% of the dataset. Evaluation metrics such as R-squared (R^2) and Mean Squared Error (MSE) provide insights into how well the model generalizes to new, unseen data.
The loss function of the regression ANN models was the mean square error (MSE), as expressed as follow:

$$Mse = \frac{1}{n}\sum_{1}^{n}(Th_s - Th_p)^2 \tag{5}$$

Were:

Th_s is simulated thickness values and Th_p is Predicted thickness values.

IV. RESULTS AND DISCUSSIONS

The regression ANN model was used to predict the thickness of the first layer of a multilayer material, which is an aluminum thin plate over a thick steel plate.
The network is a two-layer feedforward network with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The layer size value defines the number of hidden neurons, which have 12 neurons. You can see the network architecture in Figure 6. The network plot updates to reflect the input data. In this study, the data has three inputs (features) and one output. To show that it is feasible to apply a well-trained ANN model to untrained datasets, we only used the data from the thickness plate ranging from 0.01 mm to 0.2 mm for training and testing the selected ANN in our study. The remaining data was obtained for test the untrained data.

The training performance of our neural network model is displayed in Figure 7, which also shows the mean squared errors (MSE) for the training and test data throughout the epochs.

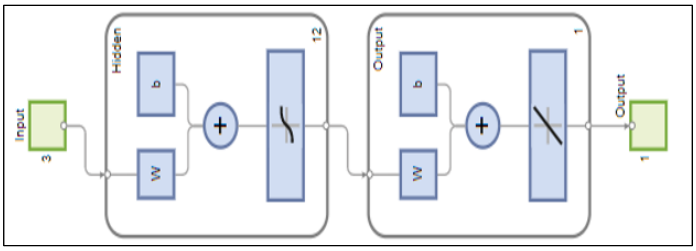

Figure 6: ANN Structure.
Source: Authors, (2024).

The vertical axis shows the mean square error, and the horizontal axis shows the number of epochs. The blue line, which rapidly decreases until stabilizing, represents the error on the training set. The red line represents the error on the test set. The black horizontal dotted line denotes the highest performance during training, and the blue circle denotes the optimal performance, which arrived at epoch 815 with an MSE of 5.2282e-10. This shows that the model performed exceedingly well on the test data, and the model has successfully learned the training dataset.

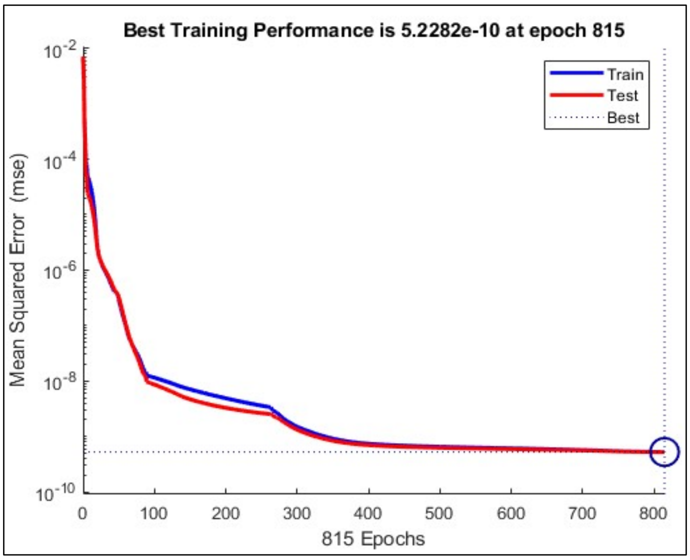

Figure 7: ANN performance.
Source: Authors, (2024).

To further substantiate the training performance, Figure 8 displays the error histogram plot for the training dataset. It displays data points known as outliers or those whose fits are noticeably poorer than those of the majority of the data. In our training model, there are no outliers in the data because the majority of the data lies on the zero-error line, and all errors fall between -5.1e-5 and 6.73e-5, which supports the performance results in Figure 7. The artificial neural network's performance is evaluated by calculating the variance between the test dataset's true values and the network's predicted values. The correlation between the first layer's anticipated and simulated thicknesses is displayed in Figure 9. The training and testing datasets had 1700 and 300 instances, respectively. For the training and testing datasets, the corresponding R^2 values were 1, and the regression lines had slopes of (1×Target+1.5e-7) and (1×Target+2.7e-6), respectively. Regression line slopes and R^2 values were both near 1.0, suggesting that the results that were predicted by the regression ANN model matched well with the analytical simulation results.

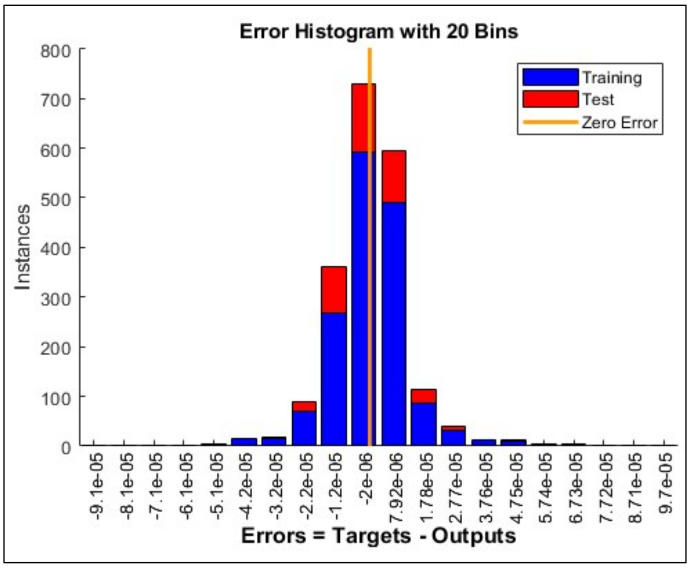

Figure 8: ANN histogram regression.
Source: Authors, (2024).

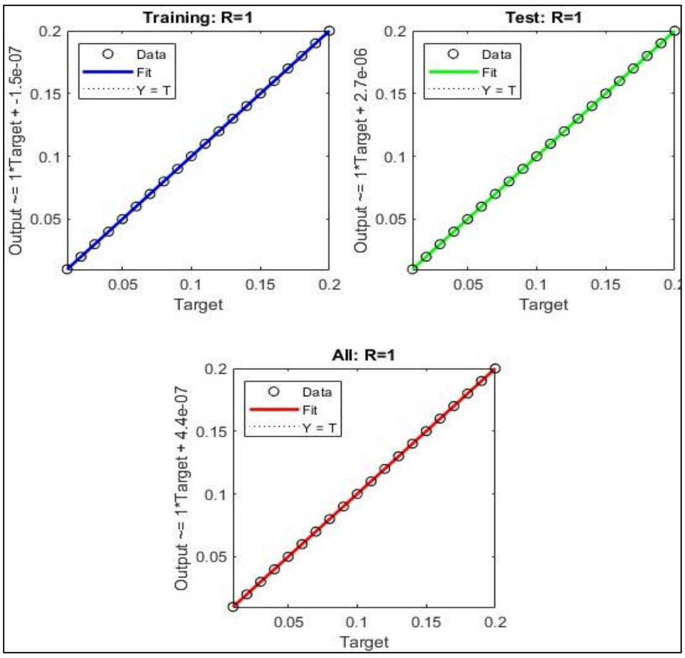

Figure 9: ANN regression.
Source: Authors, (2024).

After determining the most effective data processing approach, it became imperative to validate the applicability of the well-trained Artificial Neural Network (ANN) model to datasets that were not part of the initial training. All other input datasets that did not participate in the training and testing of the ANN model, which is the data obtained from the thicknesses of the first plate from 0.21 mm to 0.25 mm, were chosen. The simulated and predicted thicknesses of five cases of untrained inputs are illustrated in Figure 10 and Figure 11.

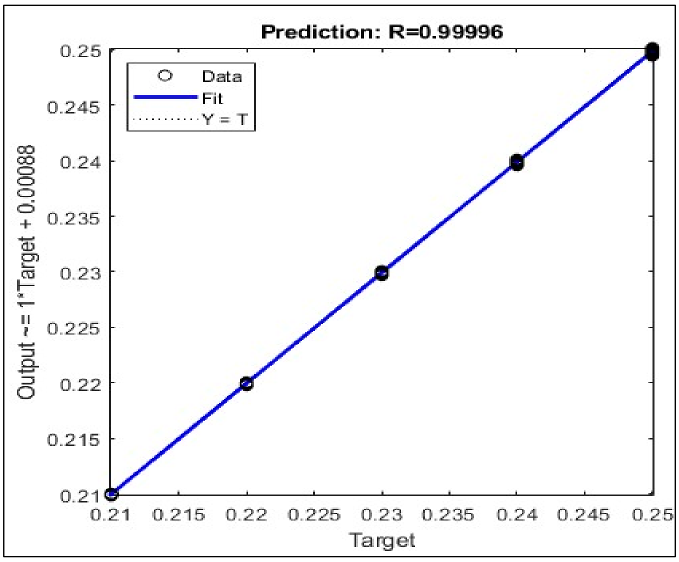

Figure 10: Regression of untrained predicted thicknesses.
Source: Authors, (2024).

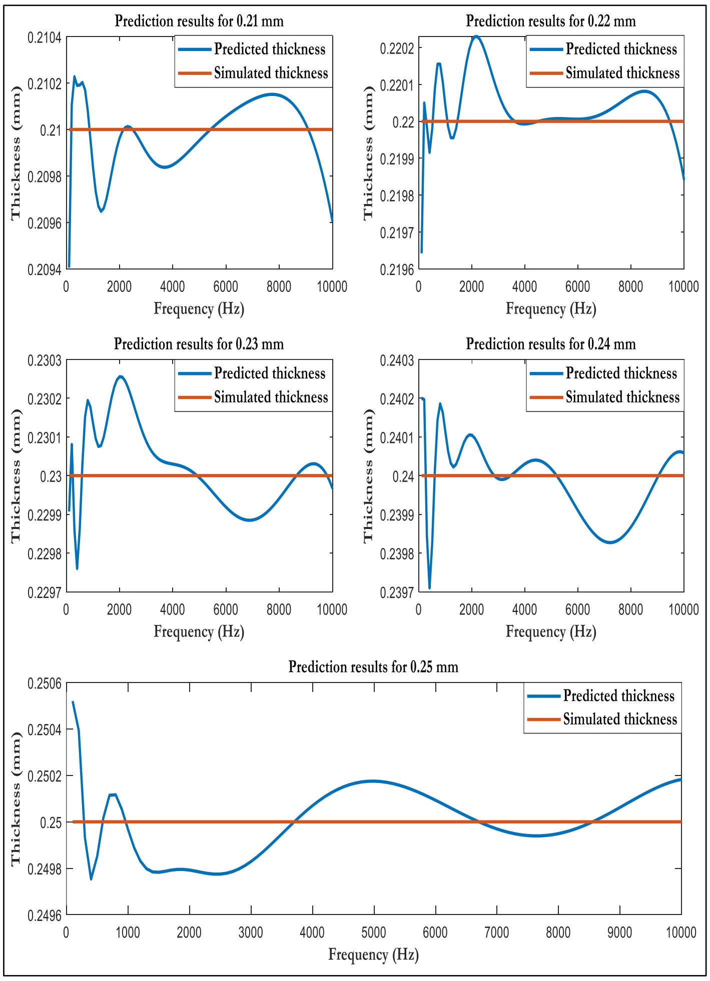

Figure 11: Results obtained for untrained data.
Source: Authors, (2024).

V. CONCLUSIONS

Two thousand and five hundred datasets with the eddy current method of different aluminum plate thicknesses above a steel plate and working frequencies of EC-sensor were generated using experimentally validated analytical models in our previous research. The values of the thickness measurement of the first layer predicted by the ANN model were almost identical with the simulated results.

Under the different thicknesses of the plate and working frequency of the sensor, the R^2 and MSE of the testing dataset were 1 and ,5.22e-10 respectively. The practicality of implementing the proficiently trained ANN model on untrained datasets was successfully demonstrated with R^2 equal to 0.99996. The model parameters, such as the number of neurons in the hidden layer and the choice of the activation function, have been systematically studied, and the developed ANN model gave quite good prediction results. In this study, we avoided those errors by searching for the optimal number of neurons and trying training with Bayesian regularization.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Islam Nacer Eddine El Ghoul, A. E. Lakhdari, S. Bensaid, A. Aissaoui, A.T. Ouamane.
Methodology: Islam Nacer Eddine El Ghoul, A. E. Lakhdari, S. Bensaid, A. Aissaoui, A.T. Ouamane.
Investigation : Islam Nacer Eddine El Ghoul, A. E. Lakhdari, S. Bensaid, A. Aissaoui, A.T. Ouamane.
Discussion of results: Islam Nacer Eddine El Ghoul, A. E. Lakhdari, S. Bensaid, A. Aissaoui, A.T. Ouamane.
Writing – Original Draft: Islam Nacer Eddine El Ghoul, A. E. Lakhdari, S. Bensaid, A. Aissaoui, A.T. Ouamane.
Writing – Review and Editing: Islam Nacer Eddine El Ghoul, A. E. Lakhdari, S. Bensaid, A. Aissaoui, A.T. Ouamane.
Supervision: Author Two and Author Three.
Approval of the final text: Islam Nacer Eddine El Ghoul, A. E. Lakhdari, S. Bensaid, A. Aissaoui, A.T. Ouamane.

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