

Artificial Intelligence Techniques for Enhancing Non-Destructive Eddy Current Testing

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This study explores the application of Machine Learning (ML) and Artificial Intelligence (AI) techniques to enhance non-destructive eddy current testing (ECT) for detecting and characterizing defects in conductive materials. COMSOL Multiphysics is employed to model the eddy current sensor and generate a comprehensive database of simulation data, representing various defect scenarios with different sizes and geometries. This dataset is used to train ML models designed to accurately predict defect dimensions and locations. The integration of ML and AI into ECT shows a significant improvement in the accuracy of defect size estimation compared to traditional methods, underscoring the potential of these advanced techniques to improve the reliability and efficiency of non-destructive evaluation in industrial applications

Index Terms— Eddy current testing, Finite element method, Artificial Intelligence, Non-Destructive testing, Machine Learning

I. INTRODUCTION

Non-Destructive Eddy Current Testing (ECT) is extensively utilized for evaluating the structural integrity of electrically conductive materials, with a primary focus on flaw detection. This method operates through the interaction between an inspection probe and the material under examination. The advancement of eddy current inversion methodologies is imperative for the accurate identification of cracks from ECT-detected signals. The process of reconstructing crack geometry from scanned data necessitates solving an inverse problem, which inherently involves the computation of a significant volume of forward problems. The Finite Element Method (FEM) is frequently utilized to simulate the forward process in eddy current testing. Despite their accuracy, iterative techniques based on numerical forward models are computationally demanding, and can be prohibitive for large-scale or real-time applications. In this context, artificial intelligence (AI) presents a promising alternative, as AI models demonstrate robust generalization capabilities and can significantly reduce computational costs while maintaining high accuracy in solving inverse problems

II. MEASUREMENT SETUP AND RESULTANT

The eddy current sensor used in this study comprised a single-coil wound around a cylindrically shaped ferrite core (Fig. 1.a). The coil has 110 turns, with an internal radius of 0.4 mm, an external radius of 0.6 mm, and a height of 1.4 mm. The ferrite core has a height of 4 mm. The lift-off distance was 100 μm and the sensor was operated at an excitation frequency of 2 MHz[1]. The conductive specimen under examination is a nickel-based rectangular sample, with a thickness of 3 mm, an electrical conductivity of 0.76 MS/m, and a relative magnetic permeability is almost 1.

Experiments were conducted on a previously presented specimen with a probe (Fig. 1.b). The probe was moved with a PC-controlled robot, and the impedance was measured using a 4192A low-frequency impedance analyzer [1].

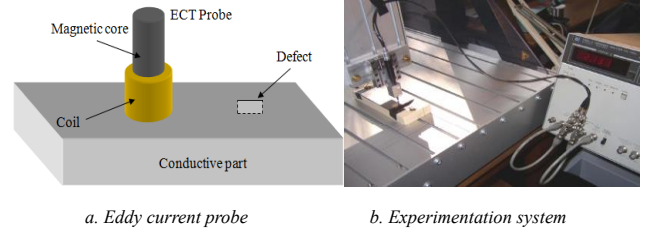


Fig.1. Geometry and experimental setup of the eddy current system

The eddy current problem can be mathematically formulated using the following partial differential equation expressed in terms of the magnetic vector potential

$$\left(\text{Rot} \left(\frac{1}{\mu} \text{Rot}(\vec{A}) \right) \right) + \sigma \left(\frac{\partial \vec{A}}{\partial t} \right) = \vec{J}_s \quad (1)$$

FEM is well fitted to the modeling of these kinds of problems because of its large flexibility which allows dealing with complex probe and part configurations. In this context, the COMSOL Multi-physics 3D resolution using a 3D electromagnetic formulation with Whitney edge elements.

After that, we compute the impedance at each displacement step of the probe. Fig.3 shows the comparison between calculated and experimental signals (complex impedance variation due to the presence of the defect) for two notch sizes with a scan according to the x line [2].

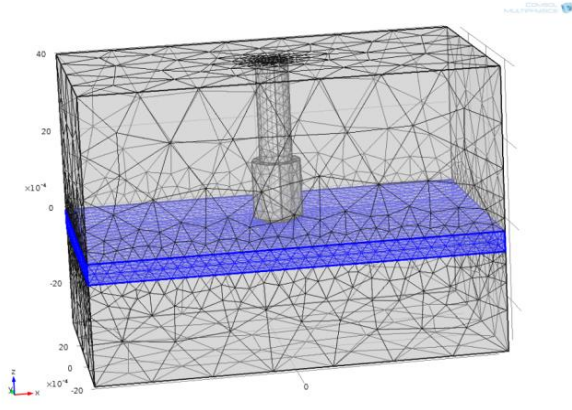


Fig.2. Mesh of geometry find by ComsolMultiphysic

with a notable alignment between the experimental observations and the theoretical predictions. This strong concordance validates the model's proficiency in accurately capturing the intricate impedance variations associated with material defects or discontinuities. The high degree of correlation underscores the robustness and reliability of the simulation framework in predicting the ECT signal's behavior in both the real and imaginary components, reinforcing its applicability in advanced non-destructive evaluation methodologies.

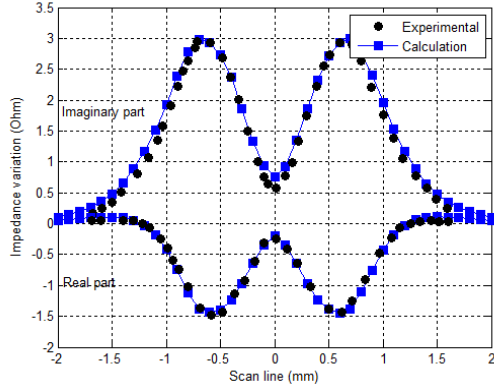


Fig.3. Real and imaginary parts of impedance variation ΔZ

III. INVERSE PROBLEM

To construct the database employed in the inversion procedure, an algorithm integrated with the Finite Element Method (FEM) was utilized to generate a systematically distributed dataset. The objective of this approach is to develop databases for training, ensuring regular distribution across the parameter space of interest, thereby enhancing the model's capability to accurately learn and generalize the desired parameter relationships.

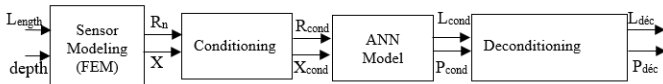


Fig.4: Inversion Procedure Using Neural Networks

Neural network inversion involves leveraging neural network-based methodologies to address inversion problems, wherein neural networks facilitate the reversal of complex input-output

relationships. In this study, the multi-layer perceptron (MLP) architecture has been employed for the inversion process due to its suitability for modelling nonlinear systems.

A neural network with two layers, comprising a hidden layer and an output layer, is deemed adequate for the identification of nonlinear, multi-variable dynamic systems characterized by multiple inputs and outputs. The number of neurons in the hidden layer will be determined through experimental evaluation to optimize the MLP's performance. Sigmoid activation functions are utilized in the hidden layer, while linear activation functions are generally applied to the output layer, producing the network's estimated outputs.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\frac{y_i - \hat{y}_i}{\hat{y}_i} \right)^2} \times 100\% \quad (4)$$

Where y_i denotes the actual value $\hat{y}_i$ denotes the regression value found by the ANN model.

TABLE I. PARAMETERS OF ANN MODEL WITH RMSE

Database	output	Time (PCU)	RMSE%
Training Set	Depth	0.147334 s	0.01183
	Length	0.307821 s	0.00697
Validation Set	Depth	0.121334 s	0.0144
	Length	0.204821 s	0.0090

According to this table, The parameters of an ANN model for Training and Validation datasets, showing execution time (PCU) and RMSE% for Depth and Length outputs. The Training Set has lower RMSE values (Depth: 0.01183%, Length: 0.00697%) compared to the Validation Set (Depth: 0.0144%, Length: 0.0090%), indicating better training accuracy. The model achieves efficient performance with low errors and reasonable execution times.

CONCLUSION

The results suggest that ANNs can be utilized to determine the defect size. The use of regular data during the training stage showcases their capability to accurately perform identification.

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