Inverse Problem Approach for Electrical Conductivity Measurement using Eddy Current NDE and Artificial Neural Networks: Modeling and Experimental Validation

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Received: 9 March 2025 | Revised: 4 April 2025 and 20 April 2025 | Accepted: 22 April 2025

ABSTRACT

Conductors serve as essential components in various electrical and electronic applications (steel, aircraft, and nuclear industries). Therefore, an accurate evaluation of their electrical parameters, in particular their electrical conductivity (σ), remains critical for assessing their performance in industrial processes. Although numerous eddy current based methods exist for conductivity measurement, this study approaches the problem through inverse problem solving. A novel approach integrating Eddy Current Testing (ECT) with Artificial Neural Networks (ANNs) is proposed to determine electrical conductivity from probe impedance measurements. An experimental setup has been developed that includes a custom-designed bobbin coil probe used in conjunction with metal plate samples (targets) and data acquisition and signal processing systems. To validate the introduced approach, conductivity values predicted by the ANN model were rigorously compared with reference measurements obtained using the four-point Direct Current Potential Drop (DCPD) technique. This comparative analysis demonstrates the robustness and measurement fidelity of the proposed approach.

Keywords-Artificial Neural Networks (ANNs); Direct Current Potential Drop (DCPD); Eddy Current Nondestructive Evaluation (ECNDE); electrical conductivity; FEM

I. INTRODUCTION

Since the first application of ECT developed by David Hughes for material sorting in 1879 [1], the use of Eddy Current Nondestructive Evaluation (ECNDE) for the characterization of conductive materials is increasing in various fields. In industrial applications, such as metal sorting, heat treatment verification, and defect detection, the knowledge of electrical parameters is critical. For conductive materials, electrical conductivity (σ) is the most important parameter, making its accurate estimation essential for the inspection of metallic components. For decays, several approaches have been developed for eddy current measurement of electrical conductivity. Today, like all inspection techniques, ECNDE has evolved beyond its basic principles and methods, taking advantage of the developments in electronic devices, computer systems, and data analysis [2]. While most recent papers examining the properties of metallic materials rely on simplified solutions derived from the classical Dodd-Deeds analytical formulation [3-5], this paper proposes a novel approach by reformulating the problem as an inverse problem and introducing a hybrid methodology. The latter combines eddy current evaluation with ANNs to assess conductivity, exploiting ANN capabilities to overcome the limitations of conventional approximations. The novelty of this research lies in the use of a benchmark for ECNDE [6] to validate the numerical model for the forward problem, allowing the formation of a database to solve the inverse problem. An experimental setup is created that includes the developed bobbin coil probe, metal 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. To validate the results, X-ray Fluorescence (XRF) spectroscopy is performed on each plate to accurately identify its alloys. The evaluated electrical conductivity values are compared with those obtained from four-point DCPD measurements performed on the same plates.

II. FORWARD PROBLEM

In the context of ECT, one of the primary challenges lies in resolving the inverse problem, namely, ascertaining the properties of a component under evaluation solely based on the available measured data [7]. In order to obtain the desired output from the inverse analysis of a given system, it is indispensable to conduct a forward analysis beforehand. In this application, the forward problem is defined as the calculation of probe impedance variation (ΔZ) in the presence of a conductor. The variation of the probe's resistance (R) and reactance (X) is due to the eddy currents induced in the conductor, and the known parameters (electrical conductivity, magnetic permeability, and thickness) are taken into account.

A. *Problem Modeling*

In the present ECT problem, the excitation is provided by a circular multi-turn stationary air-cored coil, also known as a probe, with a rectangular cross-section. This probe is the most practical design in ECT. The coil is positioned above a metallic test plate, which possesses the physical properties necessary to induce modifications in the initial magnetic field. To simulate the aforementioned Nondestructive Evaluation (NDE) problem, a 3D numerical model based on FEM has been designed using COMSOL Multiphysics software. All calculations were executed within the frequency domain utilizing the Magnetic Fields Physics option of the AC/DC module of COMSOL Multiphysics.

1) *Benchmatk Used for Modeling*

A plethora of approaches have been proposed, using diverse probes with varying shapes and configurations, contingent upon the specific application [8, 9]. In this paper, a numerical model was developed for precision impedance measurements to validate the model used for solving the forward problem. The system under consideration was a model of an AC-driven pancake coil in interaction with a multi-layered structure (two aluminum plates) affected by holes and cracks. The coil and plate parameters are presented in Table I.

TABLE I. TEST SETUP PARAMETERS

Coil	Plate
Inner radius 7.0 (mm)	Thickness 2 (mm)
Outer radius 12.0 (mm)	Conductivity 17.34 (MS/m)
Height 4.0 (mm)	Relative permeability 1
Wire-turns 1650	Gap between 70 (μm)
Lift-off 1.082 (mm)	Hole radius 10 (mm)
L0 (measured) 53.655 (mH)	Crack length/width 9.8/0.234 (mm)

2) *Validation of the Benchmark Numerical Model*

In the current study, a single configuration is under consideration. Therefore, 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 kHz and 5 kHz, are shown in Figure 1(a) as a function of the distance from the center of the hole, while Figure 1(b) displays the signals in the normalized complex impedance plane. The numerical results demonstrate a satisfactory degree of concordance with the benchmark experimental results.

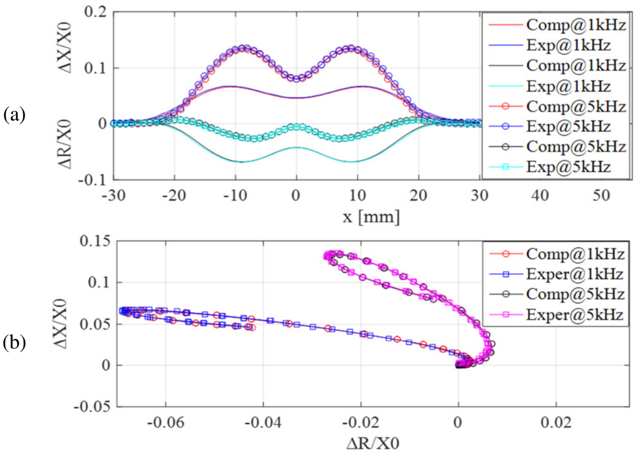

Fig. 1. Comparison between the experimental and numerically computed coil with normalized impedance at 1 kHz and 5 kHz: (a) variation of the real and imaginary parts as a function of the distance from the hole center, (b) complex impedance plane.

III. INVERSE PROBLEM

Inverse problems in ECT are generally ill-posed and are often exposed as an objective function minimization [10]. Many studies have employed optimization procedures, including downhill simplex algorithms [11]. Conventional inversion methods that deploy traditional optimization techniques are susceptible to being trapped in local minima [12]. However, this challenge can be addressed by employing advanced intelligent optimization methods. Currently, the use of Artificial Intelligence (AI) techniques has proven effective in addressing inverse problems in the field of NDE, particularly in data regression and prediction. This observation stands in contrast to conventional statistical methods, such as linear and non-linear regression, which have historically been employed in this context [13]. One of the increasingly prominent AI techniques is ANNs that provides a different approach for solving complex problems due to its ability to learn and model non-linear and complex relationships [14]. A significant number of studies on ECT have focused in the application of ANNs, particularly in the context of complex physical modeling [15-17]. The usage of neural networks has been examined in various studies, particularly in the context of inverting eddy current NDE signals for the purpose of crack reconstruction and classification. The central objective of this study is to assess the electrical conductivity of metallic plates by employing an inverse analysis technique to interpret the ECT signals.

A. Artificial Neural Networks

In this study, ANNs are used to estimate the electrical conductivity of metallic plates from Electrostatic Capacitance (EC) signals. This evaluation is based on the prediction of the relationship between the required electrical conductivity and the probe output signals, as depicted in Figure 2.

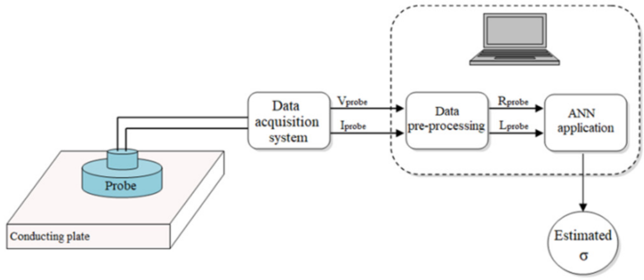

Fig. 2. Main steps of the electrical conductivity evaluation by inversion using ANN.

B. Data Preparation and ANN Model Development

In order to successfully train a well-tuned ANN model to solve inverse problems, it is important to use a database that is as extensive as possible during the training phase. The prospect of acquiring sufficient data on all conceivable materials and alloys is impractical and complicates the undertaking of non-destructive evaluation due to the difficulty of obtaining sufficient and pertinent data to train algorithms. In order to overcome the limitation that arises when working with small datasets, it is necessary to take certain considerations into account during the development of the ANN model:

- The usage of a network should be kept at a minimum, with a reduced number of neurons.
- It must be ensured that the training data will include edge cases so that the model is capable of making accurate predictions on real data.

The ANN learning database under consideration consists of two parts:

- The desired output data from the ANN consists of the electrical properties of conducting materials, with a particular emphasis on electrical conductivity [17, 19].
- The data provided by the ANN comprise the real and imaginary parts (R and X, respectively) of the probe impedance (Z).

In order to prepare the database, the ECT COMSOL model was used and the coil parameters must be adapted to ensure compatibility with the customized coil utilized in this study's experimental measurements, as illustrated in Table II.

TABLE II. COIL PARAMETERS

Coil
Inner radius 6.0 (mm)
Outer radius 11.0 (mm)
Height 5.0 (mm)
Wire-turns 1950
Wire-diameter 0.1 (mm)
Lift-off 1 (mm)
L_0 (measured) 59 (mH)
R_0 (measured) 249 (Ω)

1) Coil Excitation Signal Frequency

In order to select an adequate coil excitation signal frequency, it is necessary to conduct a sensitivity study that will yield the optimal frequency at which the probe impedance is sensitive to changes in the physical properties of the target (plate). As shown in Figure 3, the R_{coil} and L_{coil} exhibit a variation in accordance with the electrical conductivity of the plate across a range of frequencies.

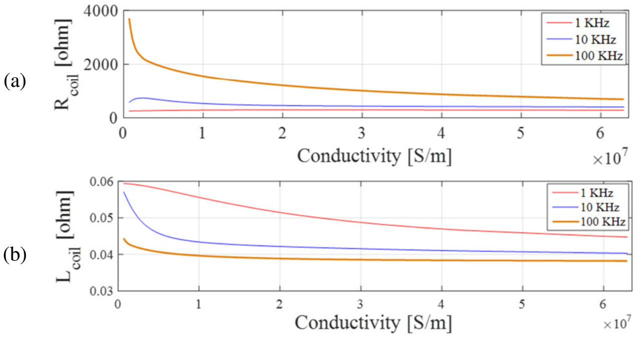

Fig. 3. Variation of: (a) R_{coil} and (b) L_{coil} as a function of the electrical conductivity of the plate at different frequencies.

A satisfactory level of sensitivity is at 1 kHz and 100 kHz. The selection of the excitation signal frequency is further influenced by the standard depth of penetration (δ: electromagnetic skin depth). In the context of NDE, if the dimensions of the test specimen exceed the skin depth, the result is unlikely to be useful. Consequently, it is generally proposed to operate with a depth less than three times the standard skin depth [3]. Given the dimensions of the plate, it can be concluded that the optimal choice among the two frequencies is 1 kHz. This frequency corresponds to a skin depth greater than the plate's thickness, which is 2 mm. In this case, an air domain was added under the plate to circumvent numerical problems arising from the boundary conditions. Subsequent to the 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 change of the plate under test.

2) *ANN Model*

The critical factor in the design of a powerful ANN is the identification of an appropriate structural configuration and the adjustment of internal parameters. Regrettably, there is an absence of well-defined guidelines for this procedure. Nevertheless, there is a set of procedures that, when followed, will yield useful results [20]. In this study, the network under examination is considered to be a nonlinear input-output mapping. In the context of such issues, the usage of a multi-layer feed-forward error-back propagation network has been identified as the optimal structural configuration [21]. Following the application of numerous training sequences employing the same learning database that had been previously generated, an appropriate net was obtained, comprising two input neurons corresponding to the real and imaginary parts of the probe impedance (R_{probe} and L_{probe}), 20 hidden neurons in a single hidden layer, and one output neuron that results in the estimation of electrical conductivity. The adjustment of network weights was executed through the use of a Levenberg–Marquardt back-propagation training algorithm. Prior to assessing the generalizability of the ANN model, an effort was made to verify its validity using the data utilized during its development. Figure 4 (a) portrays the superposition of the given values of σ and their estimation, and Figure 4 (b) presents the corresponding error for each value.

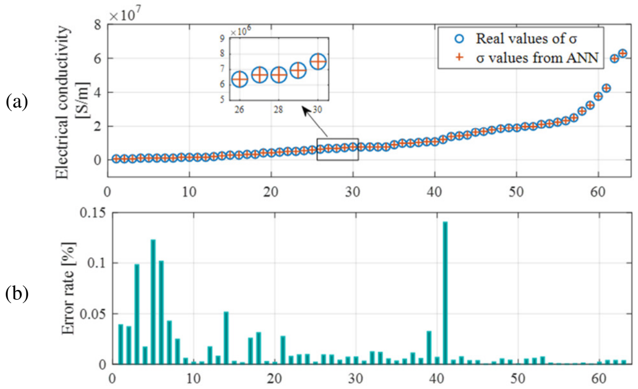

Fig. 4. (a) Electrical conductivity values used for the ANN training and their estimated values, (b) corresponding error rates.

During the development of the ANN model, a part of the database is kept in order to test its performance. In addition to this test, another generalization test was performed using some data that were not utilized to train the ANN model, as illustrated in Figure 5. Looking at the magnitude of the error displayed in Figure 5 (b), a very good performance in estimating the electrical conductivity values can be clearly observed.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. *Experimental Setup*

1) *Plates*

Four metal sheets were studied (copper, 2 aluminum alloys and stainless steel). XRF spectroscopy was performed on each plate to accurately identify the alloy. Plate thicknesses were measured using digital calipers at different points on the plates. The parameters and main elemental composition of the plates are given in Table III.

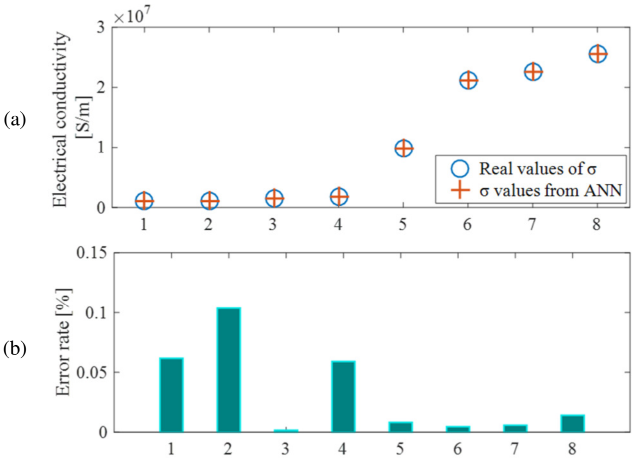

Fig. 5. ANN generalization test: (a) electrical conductivity and their estimated values, (b) corresponding error rates.

TABLE III. PLATE PARAMETERS: CHEMICAL COMPOSITION, CONDUCTIVITY σ (FROM LITTERATURE), THIKNESS T, AND LATERAL DIMENSIONS $W\times L$

Alloys	Chemical elements (%)	σ (MS/m)	Txwxl (mm)
C18100	99 Cu, (Cr+Zr+Mg< 1)	46.1	(1.9x100 x100) ±0.01
Al1145	Al 99.4, Si 0.258, Cu 0.036	[3.48-3.54]	(1.75x100x100) ±0.01
SS304	Fe 68.18, Cr 18.35, Ni 10.15	1.38	(0.68x100x100) ±0..01

2) *Probe*

The probe consists of a cylindrical coil of rectangular cross-section wound in regular layers, as exhibited in Figure 6 (a); the coil is mounted in a support made of a block of Teflon. A bridge connector is mounted on the support block to allow good connection of the coil to a signal conditioning circuit. The real and imaginary parts (R_0 and L_0) of the free-space probe impedance at 1 kHz were measured using an LCR meter.

3) *Data Acquisition*

To measure the current through the probe coil, a signal conditioning circuit was developed employing a TL081 operational amplifier. The voltages across a probe resistor and the probe coil were then collected by a NI9234 dynamic signal acquisition module. The acquired data from the probe were used to evaluate both the resistance and inductance of the coil in the presence of the target (metal plate). The probe impedance and phase shifting (φ) are given by:

$$\overline{Z_{coil}}=\frac{\overline{V_{coil}}}{\overline{I_{coil}}}=R_{coil}+j\omega L_{coil} \tag{1}$$

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

$$\cos\varphi = \frac{R_{coil}}{Z_{coil}} \quad \rightarrow R_{coil} = \cos\varphi \,.Z_{coil} \qquad (2)$$

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

$$Z_{coil} = \frac{V_{coil}}{I_{coil}} = \sqrt{{R_{coil}}^2 + {L_{coil}}^2\omega^2} \qquad (3)$$

Combining (2) and (3) we have:

$$R_{coil} = \frac{V_{coil}}{I_{coil}}.\cos\varphi \qquad (4)$$

From (1), the coil-probe inductance is obtained:

$$L_{coil} = \frac{1}{\omega}\sqrt{{Z_{coil}}^2 - {R_{coil}}^2} \qquad (5)$$

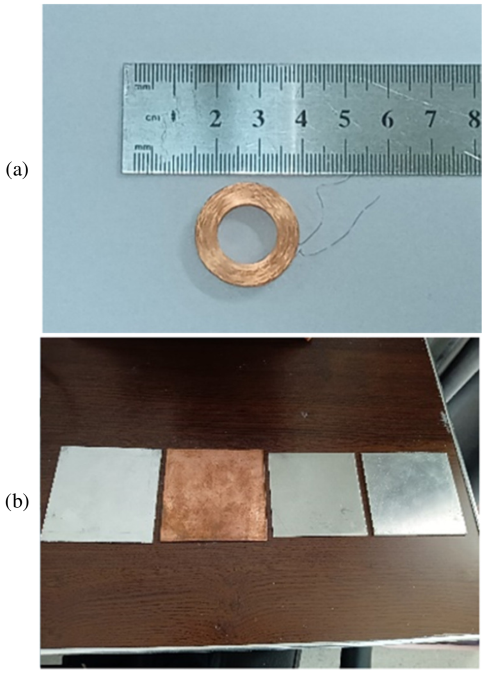

Fig. 6. (a) Probe-coil, (b) studied metallic plates.

B. Test and Validation of Experimental Results

Using the SDG 5082 function/waveform generator, a sinusoidal waveform with an amplitude of 5 V and a frequency of 1 kHz was utilized to drive the coil, as depicted in Figure 7, while the current was derived from the voltage read across a probe resistor in series with the coil. The liftoff was maintained at 1 mm throughout the measurement. For each measurement, the values of R_{coil} and L_{coil} were directly transferred through the data acquisition system to the previously developed neural network-based application, which evaluated the corresponding electrical conductivity. Table IV presents a comparison between the experimental coil impedance values and those obtained from the ECT COMSOL model.

C. Four-Point Direct Current Potential Drop

The conductivity of each plate is measured deploying a four-point method. Two measurements are required: the current passing through the plate and the voltage at the pick-up probe. The voltage between the pick-up points as a function of the current passing through the plate is measured using a high precision voltmeter, as shown in Table V.

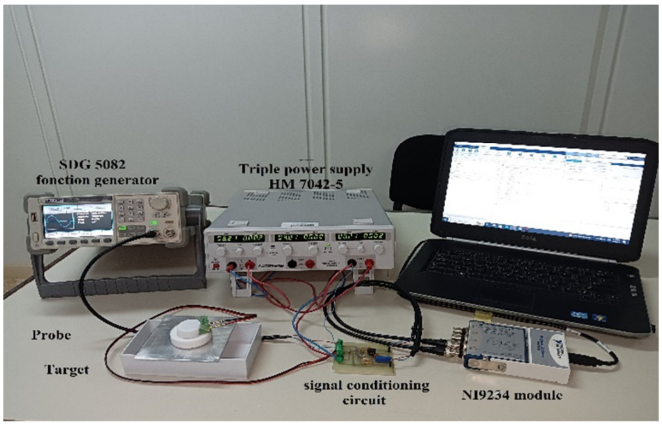

Fig. 7. Experimental bench of the ECNDE measurements.

TABLE IV. SIMULATED AND MEASURED VALUES OF DIFFERENT PLATE'S IMPEDANCE

Plate	Measured $\lvert Z_{coil}\rvert$ (Ω)	Simulated $\lvert Z_{coil}\rvert$ (Ω)	Error
C18100	417.46	411.86	1.34
Al1145	412.50	410.93	0.38
SS304	447.01	452.07	1.13

TABLE V. EXPERIMENTAL (I,V) VALUES ACQUIRED USING DCPD

Plates		Measurements										Mean
		1	2	3	4	5	6	7	8	9	10	
C18100	I (A)	0.51	0.766	1.07	1.3	1.58	1.84	-	-	-	-	1.19
	V (μV)	2	3	4	5	6	7	-	-	-	-	4.5
Al1145	I (A)	0.524	0.715	0.898	1.1	1.295	1.438	1.653	1.834	2.029	-	1.28
	V (μV)	3	4	5	6	7	8	9	10	11	-	7
SS304	I (A)	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6	1.8	2	1.1
	V (μV)	85	174	256	341	427	512	598	683	769	854	469.9

The total conductivity σ is calculated using the test plate dimensions, the applied current I, and the measured voltage V [22]:

$$\sigma = \frac{l}{w.T}\frac{I}{V} \qquad (6)$$

where T is the thickness and $w\times l$ are the lateral dimensions of the plate. The xperimental values of electrical conductivity for each of the plates obtained by the developed ANN are compared with those measured using the Four-Point DCPD method made on the same plates, with the results being presented in Table VI. It can be seen that the conductivity values obtained by the ECNDE and DCPD methods are in agreement within the experimental uncertainty.

TABLE VI. PLATE CONDUCTIVITIES MEASURED USING THE EDDY-CURRENT METHOD, FOUR-POINT DCPD METHOD, AND THOSE PUBLISHED IN THE LITERATURE

Plate	σ (ECNDE) (MS/m)	σ (DCDP) (MS/m)	σ (literature) (MS/m)
C18100	417.46	411.86	1.34
Al1145	412.50	410.93	0.38
SS304	447.01	452.07	1.13

V. CONCLUSIONS

Contrary to the majority of studies that use simplified classical models to analyze metallic materials, this work proposes a novel hybrid approach that reformulates the task as an inverse problem. The proposed methodology integrates the Eddy Current Evaluation (ECE) with Artificial Neural Networks (ANNs) to facilitate the precise determination of material conductivity, thereby circumventing the constraints imposed by conventional approximation methods. A significant innovation involves the usage of a benchmark to validate the numerical forward model, hence enabling the generation of a reliable dataset for solving the inverse problem through analysis based on ANNs. A Finite Element Method (FEM) numerical model was employed to solve the forward problem, generating a training database comprising probe impedance values across diverse target materials. Subsequently, the inverse problem was efficiently addressed using a well-trained Multilayer Perceptron (MLP) network. The application, which is based on ANNs, successfully estimated conductivity values from experimental probe impedance measurements. These estimations were meticulously validated against four-point direct Current Potential Drop (DCPD) measurements, which furnished the reference conductivity values. The findings indicated a substantial degree of concordance between the ANN-estimated and DCPD-measured values, along with an acceptable relative error in conductivity estimation. The primary cause of these error rates was identified as noise in the experimental probe data. Notwithstanding these minor discrepancies, the method demonstrates considerable potential for nondestructive conductivity evaluation, offering a robust alternative to conventional techniques. The present ANN model has been successfully developed and validated for nonmagnetic materials. The extension of the application to all metallic materials is a critical research direction. Subsequent research should concentrate on three primary domains: first, the augmentation of the training dataset to encompass a range of metallic properties, second, the optimization of ANN architectures to enhance their generalizability and third, the incorporation of magnetic material parameters into the model framework. These enhancements would significantly improve the model's precision and broaden its applicability to encompass the entire spectrum of conductive materials.

ACKNOWLEDGMENT

The authors would like to thank the stuff of the supercomputing unit (UCI), at the University of Médéa-Algeria, for allowing us to use their software and resources.

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