Deep Learning-based Thickness Measurement With Pulse Eddy Current Testing

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***Abstract*—The Pulse Eddy Current (PEC) technique represents an innovative approach within the field of eddy current testing (ECT), primarily employed to assess the structural integrity of engineering components. However, this method typically encounters challenges stemming from variations in lift-off distances and necessitates a manual calibration procedure prior to operation. In this research paper, we introduce a novel approach for thickness measurement that leverages deep learning techniques to enable automatic and highly precise thickness assessment. Our proposed solution encompasses an Auto-Encoder model, incorporating convolutional layers and long short-term memory layers, designed for effectively learning raw PEC signals and predicting thickness values across varying lift-off conditions. To validate this approach, we conducted experiments focusing on the measurement of thickness in a Mild Carbon Steel specimen. Our results demonstrate that the PEC system successfully predicts thickness values within the range of 1 mm to 10 mm, exhibiting a mean and standard deviation error of the thickness of 0.026 and 0.038 mm, respectively, even when confronted with lift-off variations ranging from 0.5 mm to 2.0 mm.**

Keywords*—*Pulse Eddy Current, Deep learning, Real-time Recognition, Non-Destructive Testing

I. INTRODUCTION

In industrial production, the monitoring of steel pipe corrosion is crucial, and metal thickness detection plays a significant role in this process. PEC has emerged as a widely used and well-established technique for corrosion-related applications. Ongoing research and development efforts by researchers globally continue to enhance and refine this technology. PEC offers an efficient screening method, enabling the detection of corrosion without the need to remove coatings or insulating materials from the samples [1]. Over the past few years, numerous studies have focused on investigating the lift-off effect and the inverse problem of PEC [2]–[5]. However, these studies have rarely addressed the issue of automatic thickness recognition algorithms. Conventional thickness distinguishing methods typically demand calibration prior to testing and struggle to eliminate the influence of weather jackets, insulation, and lift-off effects.

Several studies have addressed the issue of preventing the lift-off effect in thickness measurement. Fan et al. presented a thickness evaluation approach using the phase of spectral PEC response to eliminate the lift-off effect [6]. Wang et al. explored the intersection point of lift-off to identify thickness-related features in the frequency domain [7]. Zhang et al. introduced a time-to-rising point method for the PEC instrument, achieving coating thickness measurement accuracy of 0.02 mm [8]. However, most of this research relies on simulation models and cannot be directly integrated into the instrument for real-time thickness recognition. On the other hand, Eddyfi has developed a commercial PEC instrument called Lyft, which incorporates built-in software for thickness recognition [9]. This built-in recognition method offers practical and real-time thickness measurement capabilities. However, the precision is significantly contingent upon the calibration state of insulation and weather jacket thickness, demanding recalibration whenever measurement conditions undergo changes.

Recently, Deep learning (DL) is flourishing and has attained remarkable achievements across various fields, including but not limited to computer vision [10], natural language processing [11], speech recognition, recommendation systems [12], control applications [13], Auto-detection of hidden corrosion [14] and so on. In fact, deep learning techniques are extensively applied within the industrial sector to enhance productivity and efficiency. Notably, non-destructive testing (NDT) stands out as a pivotal industrial domain that can directly leverage the advantages of deep learning algorithms. Several studies on the amalgamation of PEC with DL for defect detection in materials and automatic thickness recognition have been published. For example, a Gaussian Process based machine learning technique

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is used to estimate various thicknesses of ageing water pipes [15], 1-D convolutional based deep learning models are utilized to achieve automatic thickness recognition with high accuracy [16], the pipe thickness estimation from pulsed eddy current signal using deep learning based on time series data [17] or automatically detect third-layer cracks at rivet sites in aircraft structures using the response signals collected by GMR sensors [18].

In this paper, we propose a thickness measurement method using deep learning technique for automatic and accurate measurement of thickness under different lift-offs. A PEC system was developed using an exciting coil and a Hall sensor element for sensing the induced magnetic field. The raw PEC signal was then analyzed by an Auto-Encoder model for predicting the thickness and lift-off at once. The proposed Auto-Encoder model was developed based on the integration of convolutional layers and long short-term memory layers for efficient learning the PEC signal and predicting thickness under different lift-offs. The proposed PEC system investigated measuring thickness of a Mild Carbon Steel specimen (C45).

II. System Design

A. Physical Principle

A simulation of electromagnetic field which includes excitation current, excitation magnetic field, eddy current on specimen and secondary magnetic field (induced by eddy current) of the PEC probe is simulated by COMSOL software, as shown in Fig. 1. A magnetic Hall sensor is strategically located at the center of the circular excitation coil to capture magnetic field fluctuations. This positioning is chosen for its excellent accuracy and stability within the low-frequency range. The magnetic field data recorded by this sensor comprises the primary magnetic field produced by the excitation coil, along with the secondary magnetic field induced by eddy currents within the test piece.

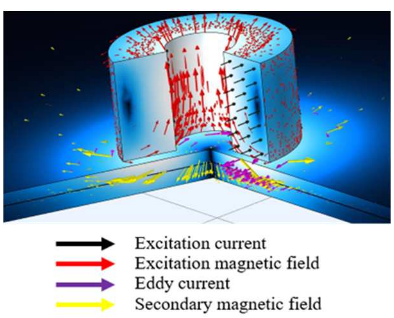

Fig. 1 Simulation of electromagnetic field distribution in PEC probe on the thickness measurement

The coil of the PEC probe is supplied by a square waveform signal. As applying Fourier transformation, the spectrum of the square wave can be defined as follows:

$$F(\omega) = \frac{2\sin\left(\frac{\omega T}{2}\right)}{\omega} \quad (1)$$

where T is the pulse width and ω is the angular frequency (rad/s) of the excitation signal. Being an eddy current inspection technique, PEC adheres to the skin depth effect, which is defined by:

$$\delta = \sqrt{\frac{2}{\omega\mu\sigma}} \quad (2)$$

where δ is the skin depth (m), μ is the magnetic permeability (H/m), σ is the electrical conductivity (S/m) and ω is the angular frequency (rad/s). By referring to equations (1) and (2), it becomes evident that the excitation waveform of PEC encompasses a series of frequency components. This characteristic empowers the technique to simultaneously assess properties at various depths within a single test, thereby offering a richer set of information compared to conventional methods using sine wave excitation signal (single frequency). The PEC signal with a square wave excitation signal of the exciting coil is shown in Fig. 2.

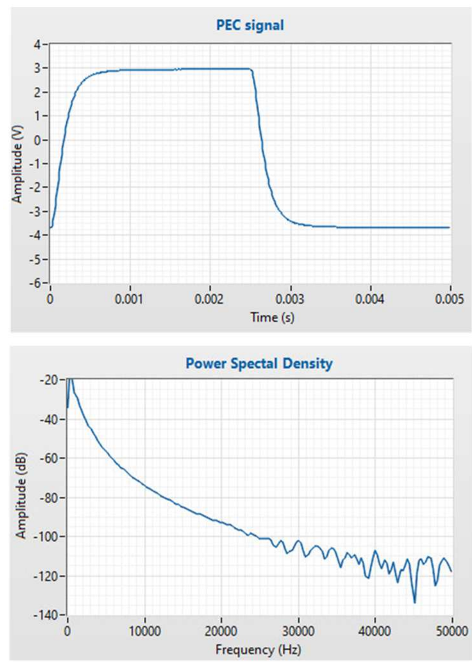

Fig. 2 Example of PEC signal in time and frequency domain

B. Hardware Design

The hardware configuration consisted of four main components: a sensor probe, a Signal Preprocessing board (Low-pass filter and Pre-Amplifier), a Data Acquisition Device (NI 6351), Pulse generation (NI 6351 + Power amplifier), and a PC with LabVIEW software. Fig. 3 illustrates the system's hardware architecture.

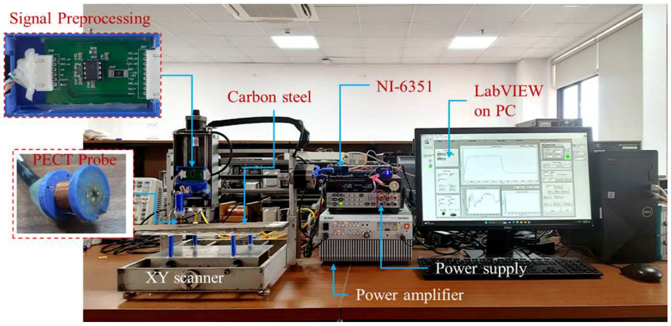

Fig. 3 Hardware structure of the PEC system

Regarding the sensor probe, it is outfitted with an excitation coil and a magnetic sensor for conducting PEC inspections. The excitation coil takes the form of a circular coil, characterized by three parameters: coil width (*W*), coil radius (*R*), and coil height (*H*). The parameters of the coil are shown in Table I. A Hall sensor is located at the lower center of the excitation coil. The sensor is installed vertically with respect to the sample, capturing the vertical magnetic field signal that carries the most pertinent information during PEC testing. The PEC probe is shown in Fig. 4.

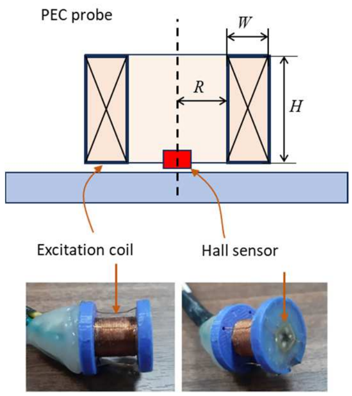

Fig. 4 PEC probe with an excitation coil and Hall sensor in the middle

TABLE I. PARAMETERS OF THE EXCITATION COIL

Turns	Wire diameters	Width *W*	Height *H*	Radius *R*
600	0.2 mm	2.65 mm	9.87 mm	3 mm

The Signal Preprocessing Board is designed for receiving and processing the signal from the magnetic sensor, the signal is passed through a low-pass filter before being amplified by a differential amplifier and then converted into a single-end signal, making it readable by the integrated 16-bit Analog-to-Digital Converter (ADC) within the NI-DAQ connect to PC.

For the DAQ device, the system is equipped with the USB-6351, a DAQ device produced by NI which offers various analog and digital I/O capabilities for measurement and control applications. In this experiment, the DAQ device is responsible for receiving analog data collected from the sensor after passing through the preprocessor circuit and converting them to digital signals for transmission to the computer. Simultaneously, this device is also used to transmit a square pulse signal programmed and generated by LabVIEW software from the PC to the excitation coil. This signal is also amplified before being fed into the excitation coil.

All sensor data will be collected and stored on PC by LabVIEW software and then data will be processed by AI algorithms and returned results on PC. On the other hand, LabVIEW will perform control of the scanner system and generate a square pulse signal with a frequency of 200 Hz to supply to the excitation coil.

The specimen used in the experiment are C45 mild steel plates machined with different thicknesses, continuously varying from 1-10 mm as shown in Fig. 5.

Fig. 5 Carbon Mild Steel (C45) specimen having different thickness from 1 to 10 mm used in experiment.

III. EXPERIMENTS WITH DEEP LEARNING

A. Dataset

To collect our dataset, we utilized C45 mild steel plates (Fig. 5) as our specimens. Our data collection procedure involved obtaining measurements from metal surfaces with varying thicknesses, ranging from 1 to 10 mm. To ensure the robustness of our dataset and minimize potential sources of measurement error, we adopted a strategic approach. Specifically, we concentrated our data collection efforts within a central region measuring 15×61 mm on each specimen. The rationale behind this approach is to effectively mitigate the potential impact of edge effects on our dataset. By focusing our data collection within the central region of each specimen, we aim to reduce the influence of these edge effects on our experimental results. In our experimentation, we systematically gathered data for each thickness value within the 1-to-10-millimeter range. To comprehensively investigate the role of lift-off, a critical parameter that significantly affects measurement accuracy, we considered three distinct lift-off values: 0.5 mm, 1 millimeter, and 2 mm. Lift-off, defined as the distance between the sensor and the specimen's surface, plays a pivotal role in determining the accuracy of our measurements. Our deliberate variation of lift-off distances allowed us to explore its impact thoroughly. After finishing created the dataset, we spilt 70% of the dataset for training process and 30% of the dataset for testing process.

Detailed information of our dataset is shown in Table II. This table provides an overview of the thickness values, corresponding lift-off distances, and other relevant variables within our dataset. To further enhance the accessibility of our findings, we have incorporated visualizations to illustrate the distinctions between various signals of different thickness values (Fig. 6) and the influence of different lift-off values (Fig. 7). These visual aids offer valuable perspectives on the interplay between thickness, lift-off, and sensor measurements.

TABLE II. DATASET INFORMATION

Thickness (mm)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
Lift-off (mm)	0.5, 1.0, 2.0
Material	C45 Carbon mild steel
Datapoints	15×61×3×10= 27.450

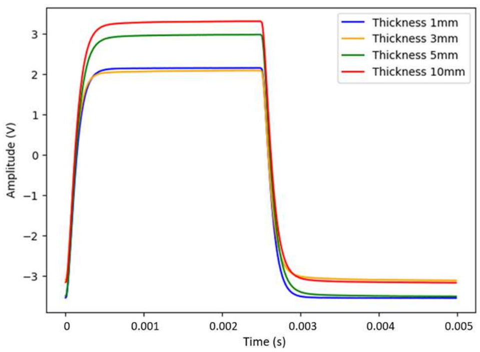

Fig. 6. Signals with different thickness.

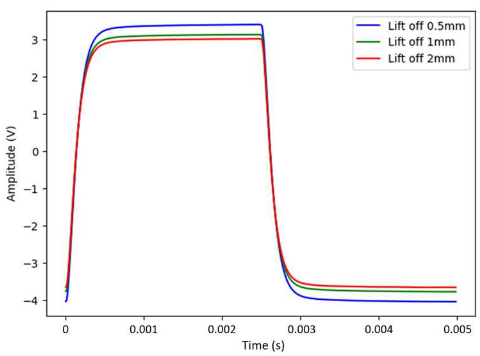

Fig. 7. Signals with different lift-off.

B. *Model Architecture and Hyper-parameters Setting*

In our research, we embark on a comprehensive exploration of different model architectures aimed at predicting both metal thickness and lift-off values. Our dataset comprises 1D-time series data, which has led us to some consider model selection. Our initial solution is used two fundamental architectures: Convolutional Neural Networks 1D (Conv1D) and Long-Short Term Memory (LSTM) networks. Both architectures have exhibited remarkable effectiveness in accommodating the specific characteristics of our dataset. Conv1D models are well-suited for capturing local patterns within sequential data. The application of convolutional filters allows them to efficiently detect intricate features, making them an ideal choice for our 1D-time series dataset. Additionally, LSTM networks excel at modeling sequential dependencies over varying time spans. Their ability to capture long-range correlations makes them another compelling candidate for our task.

However, recognizing that each model architecture has its own set of strengths and limitations, we embarked on a second approach that aimed to leverage the complementary capabilities of both CNN and LSTM networks. By combining these architectures, we created a model based on Auto-Encoder structure, as visually represented in Fig. 8. The model is structured by comprising three LSTM layers three Conv1D layers to facilitate the encoding process. Subsequently, we employ three Transpose Conv1D layers to recreate the original dimensions of the data, an effective decoding process. This intricate architecture is then followed by three LSTM layers for decoding. The last layer of the model is a Fully Connected layer (Dense) with two outputs of thickness and lift-off. This model architecture combines the strengths of CNN for feature extraction and LSTM for grasping complex temporal relationships. This combination provides a comprehensive grasp of the subtleties in our 1D-time series data.

To prepare for the training of the models, we applied standard-normalization on the dataset, a crucial preprocessing step that ensures data compatibility and stability across various models. The task of thickness and lift-off prediction is a regression problem, where our objective is to minimize the Mean Squared Error (MSE) as the primary component of our loss function. The MSE equation is as follows:

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2 \tag{3}$$

where y_i is the actual value for the i^{th} sample and y_i' is the predicted value for the i^{th} value. The Adam Optimization function is used to find the best parameters that yield the lowest MSE loss values.

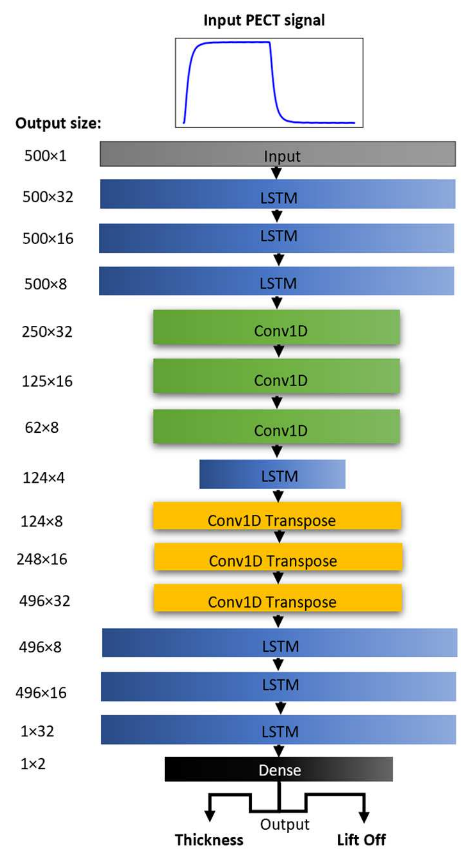

Fig. 8 Auto-Encoder Model Architecture

C. Model Evaluation

All three models underwent training for 300 epochs, employing a batch size of 128. Before training model, we split the training set, 60% for training and 40% for validating to avoid overfitting. These training sessions were conducted within the Google Colab environment. The training results have been graphically presented in Fig. 9.

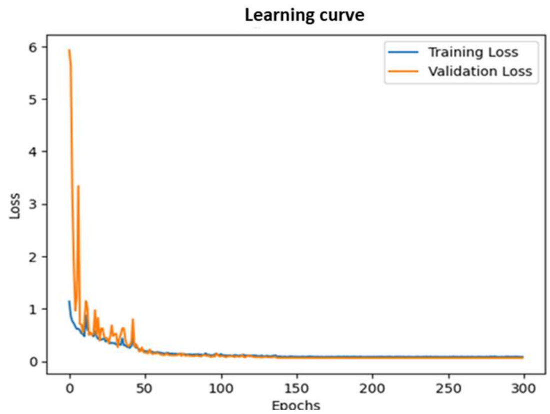

Fig. 9 Learning curve while training Auto-Encoder

The results unequivocally demonstrate that the Auto-Encoder model delivered the most favorable outcomes. Both training and validation losses converged to an impressive minimal value of approximately 0.04, underscoring the model's exceptional performance.

In contrast, the Conv1D model displayed promising results, achieving a validation loss of approximately 0.11. However, there remains a noticeable discrepancy when compared to the Auto-Encoder model. The LSTM model, on the other hand, exhibited comparatively less satisfactory performance, with the loss value only reducing to approximately 4.3 after training. This discrepancy can be primarily attributed to the inherent challenge posed by the minimal differences between our thickness and lift-off label values, which rendered the problem particularly complex for the LSTM model to address. The comparison of these models is shown in Table III. The proposed model has a higher number of parameters but provides excellent prediction results.

TABLE III. COMPARISON OF DIFFERENT DEEP LEARNING MODEL

Model	Model's Parameters	MSE
Conv1D	16.498	0.1128
LSTM	17.914	4.2987
Proposed Auto-Encoder	23.010	**0.0403**

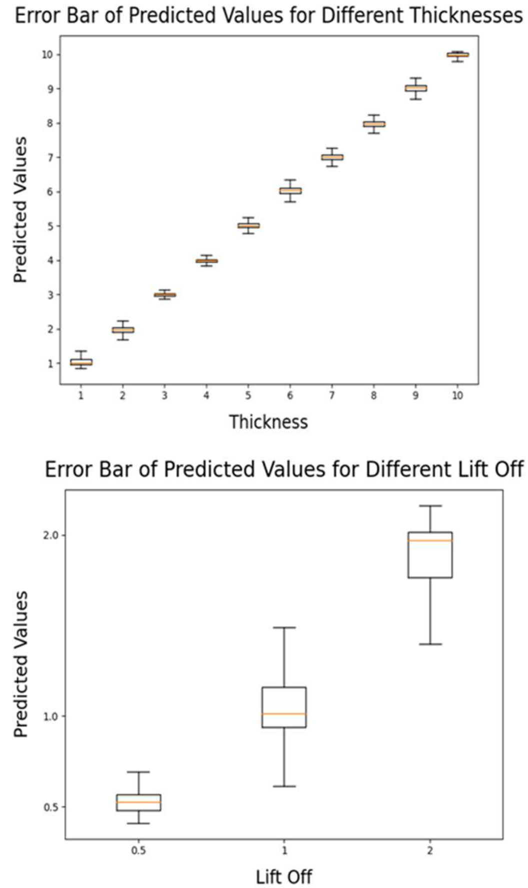

Fig. 10 Prediction results of the proposed model on test set

Auto-Encoder model prediction results of thickness and lift-off are shown in Fig.10. The proposed model excels at predicting various thicknesses with good precision, even when the thicknesses differ by only 1 millimeter. Moreover, our model exhibits the capability to simultaneously predict lift-off values, representing the distance between metal plates. The predicted results exhibit a high level of accuracy, indicating their potential applicability in real-time scenarios. The prediction results for each thickness and lift-off are shown in Table IV. The mean and standard deviation error of the thickness are 0.026 and 0.038 mm, respectively; and those of the Lift-off are 0.083 and 0.091 mm, respectively.

TABLE IV. PREDICTION RESULTS OF THE PROPOSED MODEL ON TEST SET

Size	Real [mm]	Prediction **Mean** [mm]	Prediction **Std** [mm]
	1	1.075	0.197
	2	1.958	0.185
	3	2.988	0.075
Thickness	4	4.012	0.192
	5	5.043	0.262
	6	6.018	0.208
	7	7.010	0.149

	8	7.955	0.131
	9	8.970	0.445
	10	9.959	0.102
Average thickness error		**0.026**	**0.038**
Lift-off	0.5	0.539197	0.086867
	1	1.097011	0.259574
	2	1.881674	0.186796
Average Lift-off error		**0.083**	**0.091**

IV. CONCLUSIONS

In this study, we introduce a Pulse Eddy Current (PEC) system designed for thickness measurement, employing a deep learning model. The model's architecture is based on the structure of an Auto-Encoder, enriched with the incorporation of both convolutional and Long Short-Term Memory (LSTM) layers. This model operates using an end-to-end approach, simplifying the process by directly inputting raw PEC signals, eliminating the need for additional signal processing or feature extraction steps. Remarkably, the model simultaneously predicts both thickness and lift-off values. Our investigation centered on applying the proposed PEC system to measure the thickness of Mild Carbon Steel specimens, ranging from 1 to 10 mm in thickness, with lift-off variations spanning from 0.5 to 2.0 mm. Encouragingly, the results indicate that the model achieves a remarkable level of precision in estimating thickness, yielding a mean and standard deviation error of the thickness are 0.026 and 0.038 mm, respectively. This innovative approach shows significant promise for practical applications, obviating the need for a calibration process while still delivering accurate results in the presence of lift-off variations.

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