# ニューラルネットワークを用いた渦電流探傷試験における欠陥信号の 検出とサイジング

Detection and sizing of defects in eddy current testing using artificial neural network

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This paper proposes backpropagation neural network models which are based on artificial intelligence technology to detect the defect signals and to discern the measurements of defects according to the eddy current testing (ECT) results even under the probe lift-off and probe wobble noise effects. In this paper, a stainless plate with three different depth slits is tested by ECT to collect defect signals. And during the scanning process, the noise which is mentioned above is added. All the collected data are used to analyze and to figure out the differences between defect signals and noise and the relationships of different depth signals. The established neural network models are trained by the collected data and extracted features to achieve the desired functions, such as the detection and qthe sizing of defects. The verification experiment is carried out to confirm the trained neural network. It is evident that the trained neural networks can find out the defect existence and output the depth of defects accurately.

Keywords: Eddy current testing, Neural network, NDT, Defect detection, Defect sizing

## **1**. Introduction

In the broad field of nondestructive testing (NDT), eddy current testing (ECT) technique, which is based on electromagnetic principle, has been developed to be widely used for defect detection and sizing to characterize the structural health of conductive materials. However, ECT is sometimes carried out by an inspector who manually moves an EC-probe on the specimen. This leads to the inevitable noise such as probe lift-off and probe wobble which may affect the accuracy of defect detection and sizing. Additionally, the noise will reduce detection efficiency seriously because the ECT signal analysis is carried out by a trained, experienced person. Thus, reliability enhancement by automated, systematic signal interpretation tools is strongly desired.

Artificial neural networks are ideally suited to implement defect detection and sizing under the influence of noise since they can automatically learn the mapping between inputs and outputs through various examples. They can use the limited training data to fit a more accurate mapping function <sup>[1]</sup>. D'Angelo <sup>[2]</sup> proposed to analyze Lissajous figures to do defect

連絡先: 高木 敏行 E-mail: takagi@wert.ifs.tohoku.ac.jp 〒980-8577 宮城県仙台市青葉区片平 2-1-1 東北大学流体科学研究所未到エネルギー研究センター classification according to three kinds of artificial intelligence techniques, but he did not pay attention to the influence of noise and did not classify the unknown defects.

The purpose of this study is to accurately check for defects and to discern the depth of flaws in test materials according to the amplitude and phase even under the noise effect. This paper shows the theory of neural networks and data collection and analysis experiment. At the same time, the verification experiment and results are described.

## **2**. Theory

Artificial neural networks (ANN) are usually composed of several separated layers including an input layer, an output layer, and hidden layers which are shown in Fig.1. In each layer, some nodes receive inputs from nodes in lower layers, and the transform functions are applied to their inputs to produce a signal output.

ANN can judge weights and biases of neurons to learn the mapping between inputs and outputs according to the training process using many training samples and designed algorithm rules. The learning algorithm involves repeated



Fig.1 Structure map of neural networks

adjustment of weights for minimizing the errors and the outputs and the weight adjustment process is repeated for many training samples until the errors reach a sufficiently low level.

# 3. Experiment

#### 3.1 Data collection

The specimen (AISI 316) with three different depth rectangular slits and an ECT probe shown in Fig.2 is used to collect data. The electrical resistivity of the specimen is  $1.39 \times 10^6$  S/m, and the width of slits is 0.3 mm, which are fabricated by electrical discharge machining. The experiment is implemented under the frequencies of 50~100 kHz by an ECT system (ASWAN ASSORT-PC). During the scanning process, the probe is scanned perpendicularly to the three depth slits length directions and passes through the center of the slits. And the noise is added in random position during the scanning condition shown as Fig. 3.





Fig.3 Schematic diagram of noise

#### 3.2 Data analysis and feature selection

It is necessary to analyze the collected data to find out the differences between defect signals and noise, and the logical relationship of different depth slits. To understand the results easily, all data are processed by setting the maximum amplitude



Fig.4 1 mm slit signal with tilting (Left) and 1 mm slit with lift-off (Right)

of the Lissajous waveform of a 1 mm slit to 1 V and the phase to 90° in each frequency. According to Fig.4, it's evident that there are apparent differences in amplitude and phase among signals and noise.

## 3.3 Neural networks

Two backpropagation neural networks are established to determine noise existence and to discern the depth, respectively. All collected data are used to train two established neural networks as training data. And the target data is that 0/1 which means the existence of the noise, and the depths of slits, respectively.

## 4. Verification results and summary

The verification experiment is implemented using 30 different groups of training data to find out whether the trained neural networks work accurately or not. For depth determination, if the error is smaller than 0.2 mm, it can be regarded as a success. Table 1 shows the verification results of two neural networks. It is evident that the trained neural networks can identify the noise accurately, but there are some errors for the discernment of the depth of slits.

Table 1	Verification	of neural	networks
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Signals	Noise existence	Defect depth
Accuracy	100% (30/30)	86.7% (26/30)

## References

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