1Pa2-1

Quantitative evaluation of wall thinning of piping using deep neural network based on the frequency variation of the T(0,1) mode guided wave reflection coefficient

T(0,1) mode ガイド波の多周波反射率を利用した深層ニューラルネットワークを用いた配管減肉の定量評価法

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1. Introduction

A novel approach to determine the wall thinning of piping utilizing the deep neural network (DNN) with the frequency variation of guided wave reflection coefficients as vector data to the input layer of the DNN was presented. A huge number of training data, in general, is critical to building the supervised AI system. One of the specific features of the DNN proposed here is collecting a huge amount of training data by the mathematical model having an ability to calculate rapidly the reflection coefficients. The accuracy of the mathematical model which was evaluated in comparison with the FEM calculations was presented in the paper. Another important feature of the DNN propose here is to use the frequency variation of the reflection coefficients at a defect as the input layer for the AI, which includes informative clues for wall thickness, which were shown previously. Estimation results with the reflection coefficients of the artificial circular-shaped defects and actual defects that emerged in a chemical plant were shown. It was confirmed that the correct answer rate in ±0.5mm wall thicknesses was to be around 90%. The hyperparameters of the AI used in the estimations were also shown.

2. Deep Neural Network

Forty-six frequency variation (25~70 kHz) of the reflection coefficients for each wall thinning was used for the input layer of the DNN. Two hidden layers which are having 2000 units for each are installed. Multinominal classification for 0.5 mm step of wall thinnings using the softmax function is installed. Therefore the number of classifications is larger at a thicker wall thickness. **Table 1** shows the hyperparameters and the other conditions of the DNN used in the following evaluations. The coding language of the DNN is python with Keras (Tensor Flow) library.

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Table 1. Hyperparameters and the other conditions

Activation Function :	Relu,
Classification function :	Softmax
Optimizer :	Adam (a=0.0005, b1=0.1, b2=0.999, e=10^{-9})
Dropout rate :	0.3 at Input, 0.0 at hidden 1, 0.0 at hidden 2
Learning method :	Mini-batch stochastic gradient decent (n=350)

3. Mathematical model for the calculation of the reflection coefficients of T(0,1) mode guided wave

Collecting a huge number of training data is critical to building the DNN. Experiments and FEM calculations are the candidates for the collections; however, it takes too much time to complete enough training data. In our scheme, the mathematical model for calculating the reflection coefficients is used because of the fast calculation time. The detail of the calculation method is published elsewhere [1]. The reflection coefficients obtain ed both by the FEM and the mathematical model were shown in **Fig. 1**. Both calculations were carried out for the circular defect having defect curvature R50, R70, R90, and R110mm. The depth of all the circular defect d is 5 mm. The reflection coefficients obtained by the FEM have relatively complex structures but are similar outlines to those obtained by the mathematical model.

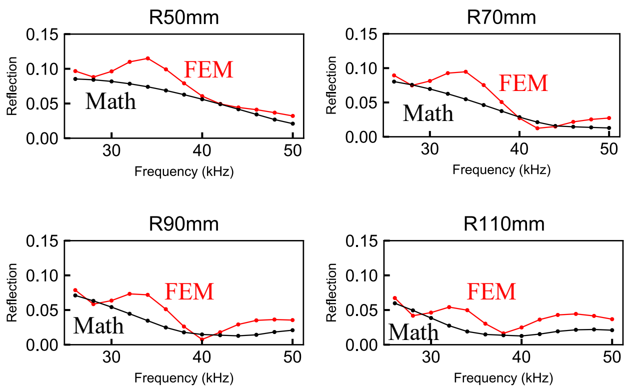

Fig.1 Reflection coefficients calculated both by the mathematical model and the FEM vs. frequency. The maximum depth of all the circular defect is 5 mm

4. Artificial wall thinnings and evaluation results

60-mm outer diameter and 4-mm thick aluminum pipes were prepared for the experiments. Three different original tools were used for making the artificial circular defects which are having radii of curvatures R50, R100, and R200 mm. The defects were deepened step by step 0.5 mm in depth. Reflection coefficients were measured for all the 21 individual artificial defects (3 different curvatures and 7 different depths) in 46 frequencies. Estimations of wall thinnings were carried out using the DNN, and a total of 3227 wall thinning data calculated by the mathematical model were used for the training data of the DNN. The estimation results for using the artificial defects having the curvature R200 were shown in **Fig. 2**. Blue arrows in all the graphs indicate the correct depths, respectively. More than 90% correct answer rate within ±0.5 mm accuracy could be obained in all the 21 cases. In Fig. 2(a), it was very interesting that the estimate was split; however, we have not understood the reason for the estimate.

5. Actual wall thinnings and evaluation results

The estimations for the two actual wall thinnings that emerged in one chemical plant were carried out using the AI. The frequency variations of the reflection coefficients for two wall thinnigs were obtained by the FEM calculations with the 3D distributions of the actual wall thinnings. The maximum depths of the two are 3.14 mm and 4.17 mm, respectively. **Figure 3** shows the estimation results. In this case, total 4610 wall thinning data calculated by the mathematical model were used for the training data of the DNN. The estimates were in good agreement with the actual maximum depths, respectively.

6. Conclusion

A multinominal classification of the wall thinning of piping using the frequency variation of the reflection coefficients obtained by the guided wave method along with a deep neural network (DNN) was presented. One of the features of the method is to use the frequency variation of the reflection coefficients for the input layer of the DNN, which includes important clues for the wall thinning. The other feature is to use the mathematical model for calculating the reflection coefficient, which can collect rapidly the huge number of training data. It was confirmed that the correct answer rate in ±0.5mm accuracy was to be around 90% in the artificial wall thinnings and that was 100% in the actual wall thinnings.

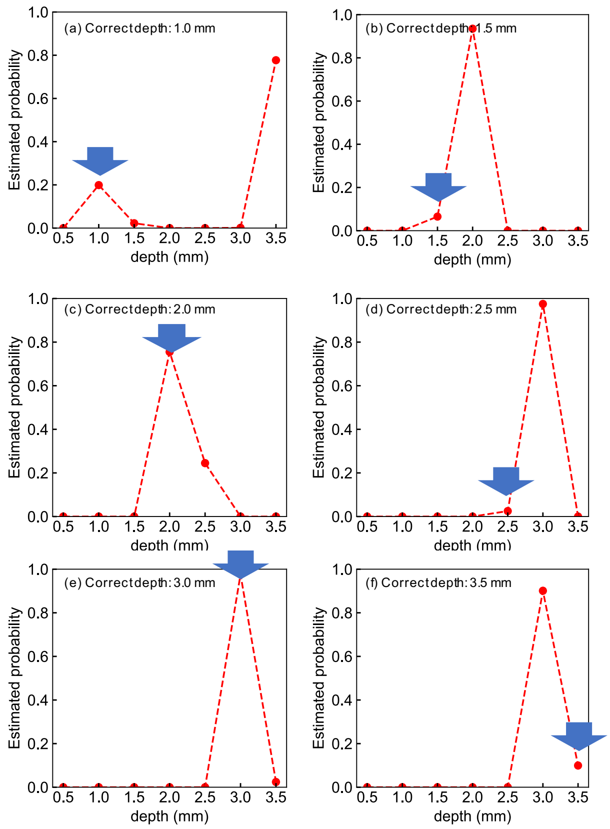

Fig. 2 Estimation results for six different depths of the artificial circular defects (radius of curvature: R200 mm). Red arrows indicate the correct answers.

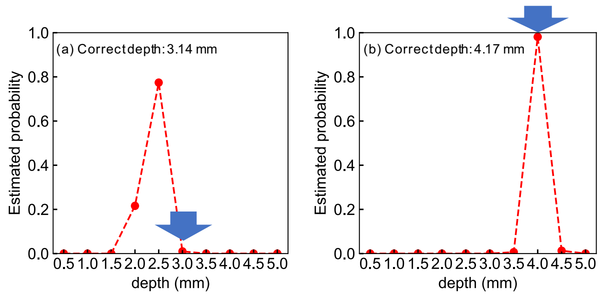

Fig. 3 Estimation results for two actual wall thinning that emerged in one chemical plant. Red arrows indicate the correct answers.

References

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