Wall Thinning Diagnosis by using Accelerometer and Machine Learning Algorithms

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1. Introduction

Wall thinning occurs widely in the secondary loop of nuclear power plants. One of the major phenomena, which induces wall thinning, is flow accelerated corrosion. Flow accelerated corrosion (FAC) is the corrosion process that is especially enhanced by chemical dissolution and mass transfer. The operating condition of secondary loop of nuclear power plants have the characteristics that are vulnerable to FAC. FAC phenomena induces wall thinning effect, which may lead secondary loop tube rupture event. From 1970 to 2012, throughout the world, 1987 events occurred because of the FAC induced wall thinning effect.

Nuclear power plant utilities try to estimate the FAC induced wall thinning effect by using CHECWORKS code and nondestructive testing [1]. However, the code analysis method requires the pipes' empirical test result or pre-defined model. In reality, extracting the result of the whole test results from the secondary system is almost impossible. And also, the nondestructive testing has large measurement error and huge loss of time and expenses due to remove insulators.

Therefore, in this study, to minimize the cost and risk due to wall thinning effect, accelerometer and machine learning based wall thinning diagnosis is suggested.

2. Selection of Data Type and Machine Learning Algorithms to Diagnose Wall Thinning

In this section, several measurement data types and machine learning algorithms are reviewed and selected.

2.1 Selection of Data Type

In this study, followings are considered to select proper data type. 1) Measuring instrument should operate under the harsh condition. 2) Measuring instrument should monitor a component in the realtime. 3) Measuring instrument should be simple and not difficult to install.

Ultrasonic measure is commonly used to measure wall thickness. However to conduct ultrasonic measure in the nuclear power plant field, insulator of secondary loop of NPP should be removed first. Therefore, huge loss of time and expenses occur due to removing insulator.

Electromagnetic measures are accurate in the lab scale experiment. However, electromagnetic measures are vulnerable to disturbance.

Accelerometer can monitor the component in real time and easy to install. And also, J. T. Kim et al. [2] proved that vibration characteristic could change due to the pipes' thickness. Therefore, in this study, accelerometer measure is selected to diagnose pipe's thinning status.

2.2 Selection of Machine Learning Algorithm

Three different machine learning algorithms (Support vector machine, Convolutional neural network, and Long short term memory network) were reviewed. All three different machine learning techniques are good at classification.

2.2.1. Support Vector Machine

The support vector machine (SVM) had been the most promising machine learning algorithm before the deep learning stage. The SVM classifies data by using hyperplane concept that can maximize the distance (margin) between each group.

2.2.2. Convolutional Neural Network

The convolutional neural network (CNN) is a deep neural network architecture that is good at feature extraction and classification. The CNN has feature extraction part and classification part. The calculation in the classification part is same as basic neural network calculation. For feature extraction, convolution filter is attached before classification network. Convolution filter is used widely in image processing field. By using filter, various image can be made from a picture. In the same manner, by using various filter, neural network can be trained with various features from a limited dataset.

2.2.3. Long Short Term Memory Network

The long-short term memory network is a developed architecture of recurrent neural network (RNN). The basic structure of recurrent neural network is shown in figure 1. RNN uses previous cell's output as current cell's input. Therefore, this architecture can reflect the previous cell's change. Because of this architecture, RNN can consider time dependency. However, because the neural network calculation is based on multiply operation, the information from the first cell vanished as calculation goes on. This phenomenon is called as vanishing gradient problem.

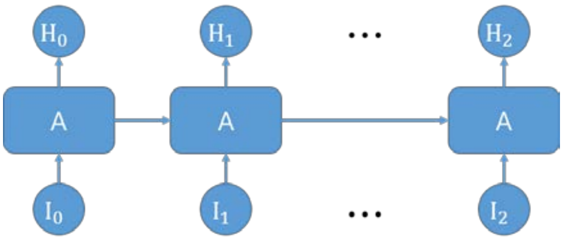

Figure 1. Recurrent Neural Network

To overcome this issue, long short term memory (LSTM) network architecture is suggested. The basic structure of LSTM network is shown in figure 2. LSTM has cell state. The information of cell state is updated by using forget gate and input gate. Forget gate decides how much information to keep. By using cell state, the information of previous cell consistently affect to the later cell. It means RNN can consider long-term dependencies.

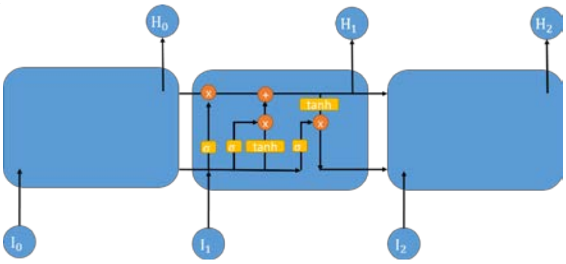
Figure 2. Recurrent Neural Network

3. Data Acquisition, Pre-processing to Train Machine Learning Algorithms

3.1 Flow Accelerated Corrosion (FAC) Test Loop

The analyzed data was acquired from I-NERI program test loop [3] which is a mock-up system to simulate the FAC phenomena at the secondary loop of the nuclear power plant.

The experiment was conducted in two different ways. The first experiment was conducted under a pure water condition. A Normal, 1mm artificially grinded, and 1.5mm artificially grinded pipes are used as test specimen. The objective of first experiment was to collect vibration characteristics of each grinded pipe. The second experiment was conducted under pH 4.5 condition. The test loop was operated for 2 weeks with a hydrogen added condition to accelerate corrosion phenomena. The objective of the second experiment was to collect the vibration characteristics of the pipe due to the corrosion. The vibration was measured every day at the same time.

3.2 Data Pre-processing

3.2.1. Trimming Outliers

When training artificial intelligence, outlier may distort the training process. Therefore, trimming the outliers is important to train artificial intelligence properly. In this study, Cook's distance is used to trim outliers. Generally, an observation with Cook's distance bigger than three times the mean Cook's distance might be an outlier.

3.2.1. Fourier Transform

Two different domain data are used to train artificial neural network. The one is time series data from the accelerometer. The other is frequency domain data. Frequency domain data is acquired by adopting Fourier transform to original time series data.

4. Wall Thinning Diagnosis Results

4.1 Artificially Grinded Pipe Diagnosis

For the artificially grinded pipe diagnosis, a Normal, 1mm artificially grinded, and 1.5mm artificially grinded pipes' vibration data are used. All of three different machine learning algorithm (Support vector machine, convolutional neural network, and long short term memory network) show good diagnosis result. The best algorithm was support vector machine. Support vector machine diagnosed pipe with 100% accuracy with short training time (below 3 seconds). Convolutional neural network and long short term memory network diagnosed with 96% and 100% accuracy. The training procedure (step-accuracy) of each neural network are shown in figure 3 and figure 4. The test result is listed in table 1.

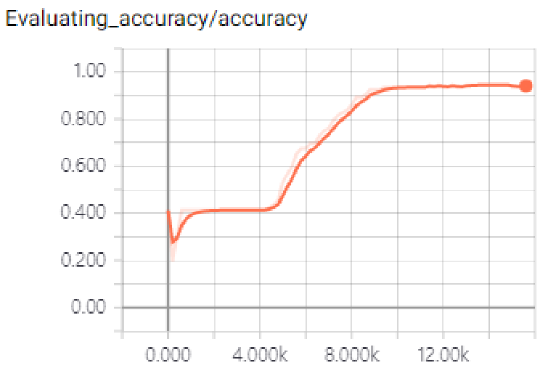

Figure 3. Tranining step - Accuracy (CNN) Test1

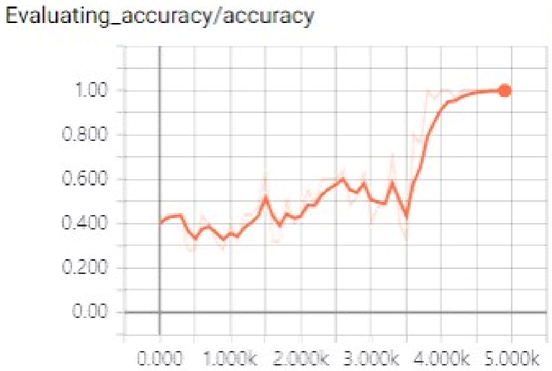

Figure 4. Tranining step - Accuraccy (LSTM) Test1

Table 1. Test Result of Artificially Grinded Pipe Classification

Algorithm	Performance (Accuracy)	Training Time
SVM	100%	<3sec
CNN	96%	<1hour
LSTM	100%	<1hour

4.2 Chemically Accelerated Thinned Pipe Diagnosis

For the chemically accelerated thinned pipe diagnosis, the vibration data from the experiment under pH 4.5 condition are used. The machine learning algorithms are trained to classify the experiment date [day1, day3, day5, day7, day9] with vibration data. During the test period, the thickness of the pipe decreased 0.2mm. The test result is listed in table 2. Support vector machine shows 40.3% accuracy and convolutional neural network shows 38% accuracy. However, long short term memory network shows 96% accuracy.

Result shows that long short term memory network successfully classify the subtle vibration change between each date. The training procedure (step-accuracy) of each neural network are shown in figure 5 and figure 6.

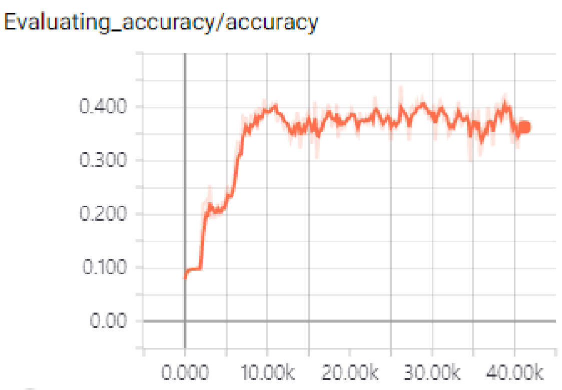

Figure 5. Tranining step - Accuracy (CNN) Test2

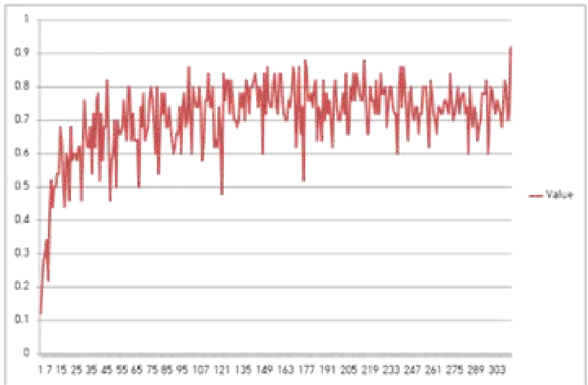

Figure 6. Tranining step - Accuracy (LSTM) Test2

Table 2. Test Result of Chemically Accelerated Thinned Pipe Diagnosis

Algorithm	Performance (Accuracy)	Training Time
SVM	40.3%	<5sec
CNN	38%	<3hours
LSTM	96%	<1hour

3. Conclusions

Many unexpected events occurred due to FAC induced pipe thinning. According to CODAP Topical Report [1], 1987 events were occurred since 1970. To prevent the event induced from FAC phenomena, current utility uses ultrasonic thickness gauge to measure pipe's thickness. However, ultrasonic thickness gauge has large measurement error and inefficiencies.

The accelerometer can operate under the harsh condition and Jung Taek Kim et.al [2] proved that vibration characteristic changes due to the pipe's thickness. However, the vibration signal change due to wall thinning is too subtle to diagnose.

Therefore, in this study vibration based pipe status diagnosis is conducted. To extract the characteristics from the subtle vibration change, three different machine learning algorithms (Support vector machine, convolutional neural network, and long short term memory network) are reviewed and designed.

For the grinded pipe classifying problem, all three machine learning techniques show good results. However, for the date classification problem, which has subtle difference, long short term memory network shows best result compared to others. Therefore, by combining vibration data and LSTM network, pipe's thinning status can be successfully diagnosed.

REFERENCES

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[3] V, K, Luk and J. T. Kim, “Condition Monitoring Through Advanced Sensor and Computational Technology Final Report”, SAND2005-3226 Sadia Report, USA (2005)