Pipe Wall Thinning Prediction Using Real Time Data of FAC Test Facility

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Carbon steel is mainly used for piping in the secondary cooling system of nuclear power plants. As a nuclear power plant operates for a long period of time, flow accelerated corrosion (FAC) occurs due to the flow of cooling water, and this is affected by the material of the pipe and water chemistry conditions [1]. In this study, we built a facility that can demonstrate the flow-accelerated corrosion under nuclear power plant operating conditions [2]. Using this test facility, we could generate the data of pipe wall thinning rate caused by FAC with the water chemistry conditions, such as the water temperature and pressure, flow rate, DO, pH, conductivity. It is expected that the machine learning (ML) approach could applied for FAC prediction, and proper regression results were not obtained because previous studies mainly used random forest, which is a limited ML technique. A real time FAC simulation data capable to improve the efficient train ML networks to predict FAC rate. In this study, the neural network based wall thinning rate prediction methodology is evaluated with these FAC datasets measured by on-line monitoring method.

2. Methods and Results

2.1 Test Conditions of FAC facility

The FAC demonstration test facility was constructed to test and evaluate the wall thinning rate of pipeline in a nuclear power plant secondary system environment. In order to demonstrate the pipe wall thinning phenomenon, the FAC test performed with a high temperature water at high fluid speed condition. The FAC facility consists of a main circulation loop connected with a test section, an injection water line and an extraction water line.

Fig. 1. FAC demonstration facility.

A purification system was added on the extraction water line in addition to a hydration system that was installed in the injection water line to ensure that the water chemical conditions, i.e., the DO and pH of the solution, could be controlled. An ion exchange resin, which is the purification system, was installed in the discharge water line, and a water chemistry control system was configured in the injection water line.

Using the FAC demonstration facility, pipe specimen is tested under 7~12 m/s flow rate, and pH 8~9.5 conditions in deaerated water condition.

2.2 Test specimen

The test specimen was prepared as pipeline using the commercial SA 106 Grade B carbon steel that has chemical compositions as shown in table 1. The test pipe is designed to have 2-inch diameter.

Table 1 Chemical composition of pipe materials (wt%)

Alloy	C	Si	Mn	Cu	Cr	Ni	Mo
SA106 Gr.B	0.19	0.24	0.98	0.02	0.04	0.02	0.01

2.3 FAC thickness monitoring methods

The thickness of pipeline is continuously monitored during the test period using a high-temperature ultrasonic transducers. The pipe wall thickness is measured by ultrasonic testing (UT). High-temperature FAC is monitored in real time using the shear horizontal (SH) waveguide transducer system as shown in Fig. 2. The results of pipe wall thickness are obtained with the conditions of different flow rates and pH environment by on-line monitoring method.

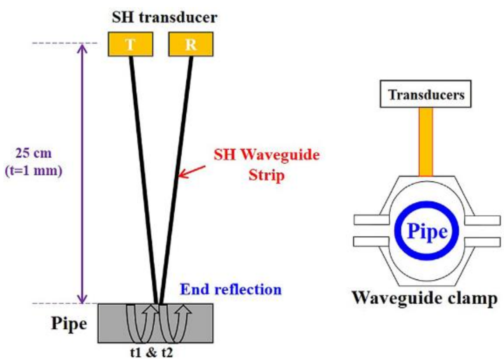

Fig. 2. Wall thickness monitoring transducers for a high temperature pipe, SH-UT system.

2.4 FAC prediction model and discussion

To predict the pipe wall thinning rate caused by FAC, a complex process is required to construct an empirical relationship based on understanding of the parameters affecting FAC. In this study, a ML-based prediction model to predict the thinning rate was evaluated using the FAC monitoring data (Fig. 3) as training law data. The test parameters (pH, Do etc.) were used as input data, and the thickness data was converted into wall-thinning rate per unit time and used as output data. The thickness value over time was adjusted as monotonically decreased by performing low-pass filtering.

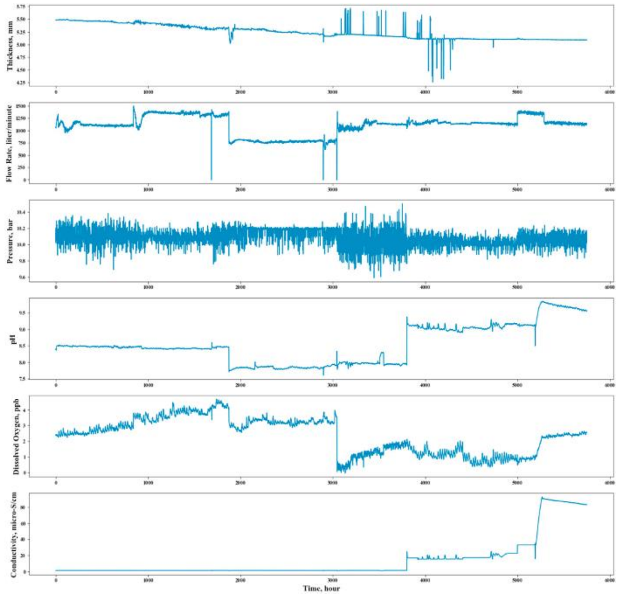

Fig. 3. On-line monitoring data from FAC facility.

ANNs and a CNN have been suggested to build pipe wall thinning rate prediction models. In this study, the FAC rate and test parameters were recorded as per hour, and it was assumed that the wall thinning rate was determined as a function of the test parameter values 1 hour before the thickness measurement or n[hour] before the thickness measurement. To construct the ML models, the input data were entered in the formats of (1×5) and (3×5), considering five types of parameters of 1 h and 3 h immediately before prediction to train the ANNs prediction models. ANN model evaluated with different input layers of 5 (ANN #1) and 15 (ANN #2), respectively. The CNN model is applied to the data of 3 h before prediction to train, and 20% of the data was randomly selected and used as validation data. The number of nodes in the output layer was set to one for the thinning rate, and it is normalized to values from 0 to 1 for the network training. The ANN and CNN for constructing the pipe wall-thinning rate prediction model was designed with KERAS open-source library. The filter size of the convolution layers was maintained (2, 1). The number of filters was gradually reduced from 256 to 32 as the layers became deeper, to extract the changed feature vectors from those layers. Because of the small size of the original input data, zero padding was applied to maintain the size of the data entered into the next layers, which is a way to apply the deep layers.

The average and standard deviation of the error were used as the performance evaluation indices. Error (e) is defined as follows.

$$e = \frac{y_{p,i} - y_{t,i}}{y_{t,i}}, i = 1, 2, \dots, n \tag{1}$$

Where $y_{p,i}$ and $y_{t,i}$ refer to the values calculated using the prediction model and the training data (i.e., the actual measured values), respectively, and n is the number of training data. The performance results of prediction models are shown in Table 2. The results indicate that all prediction models agreed well with the test results, and the performance among the models showed some difference.

Table 2 Performance indices of FAC rate prediction models

Model	Average Error (%)	Standard Deviation of Error (%)
ANN #1	1.1	8.9
ANN #2	0.5	8.2
CNN	2.3	9.6

3. Conclusions

FAC demonstration tests were performed on the pipe specimen of SA106 Gr. B carbon steel using a high-temperature and high-pressure flow rate test facility to demonstrate the wall thinning in the nuclear power plant secondary environment.

The performance of prediction models was validated using the test data from FAC simulating facility. It was concluded that the ML can be used for constructing pipe wall thinning rate prediction model under various FAC test conditions. This results provide important insights for developing a more precise FAC prediction model for actual power plant operation environment.

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