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Development of a Diagnostic Algorithm with Acoustic Emission Sensors and Neural Networks for Check Valves

Seung-Hwan Seong, Jung-Soo Kim, Seop Hur, Jung-Tak Kim, and Won-Man Park
Korea Atomic Energy Research Institute
150, Deokjin-dong, Yugeong-gu, Daejeon, 305-355, Korea
shseong@kaeri.re.kr

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Abstract

Check valve failure is one of the worst problems in nuclear power plants. Recently, many researches have been based on new technology using accelerometers and ultrasonic and magnetic flux detection have been carried out. Here, we have suggested a method that uses acoustic emission sensors for detecting the failures of check valves through measuring and analyzing backward leakage flow, a system that works without disassembling the check valve. For validating the suggested acoustic emission sensor methodology, we designed a hydraulic test loop with a check valve. We have assumed in this study that check valve failure is caused by disk wear or by the insertion of a foreign object. In addition, we have developed diagnostic algorithms by using a neural network model to identify the type and size of the failure in the check valve. Our results show that the proposed diagnostic algorithm with acoustic emission sensors is a good solution for identifying check valve failure without necessitating any disassembly work.

Key Words : check valve, diagnostic, neural network, acoustic emission sensor

1. Introduction

The failure of check valves to operate correctly in nuclear power plant safety systems could cause severe consequences because an unintended reverse flow through the failed check valves impacts the related hydraulic systems. Most conventional methods for examining the conditions of check valves are based on the movement of the disk under various conditions, as well as on detailed knowledge about the valve and an understanding of the potential modes of failure [1-4]. Often, it is necessary to open and close the check valve or to disassemble it entirely to examine its internal structure. Generally, such a test must be carried out while the plant is shut-down for refueling or maintenance.

Recently, many researches have been carried out in order to find ways to overcome the disadvantages of conventional valve check systems. These studies have been based on new technology using accelerometers, ultrasonic, magnetic flux, and so on [5-9]. Duke Power Company developed a method based on accelerometers that can detect pressure waves of flowing liquids [5]. This method utilizes acoustic measurements to determine when the valve reaches a fully open or fully closed position and can detect the failures of check valves, such as hinge pin or stud pin wear, using low frequency sound waves. Ultrasonic measurements, on the other hand, use high frequency sound waves [9]. The signals reflected through the check valve are dependent on the disk position, and the time record of the disk position can be used to identify the backstop and open/closed positions. Similar to these ultrasonic measurements, the magnetic flux method uses the Hall-effect to identify the disk motion [5,8,9]. Both the ultrasonic and magnetic flux methods have similar features and are able to detect disk motion and thus identify hinge or stud pin wear. In this study, we have suggested a method that uses acoustic emission sensors in order to detect the failures of check valves by measuring and analyzing the sound wave originating from the backward leakage flow through the failed section of the check valve. The acoustic emission sensor and the accelerometers detect sound waves originating from the flows through pipes in similar ways. However, the acoustic emission sensors can generally measure a wider-ranged sound wave than the widely used accelerometers. Also, a method using acoustic emission sensors has a simple architecture because the sensor does not require the source signal and the dedicated system that are required by methods that use ultrasonic sensors and magnetic sensors. Therefore, we have chosen acoustic emission sensors in our detecting device for failures of the check valve, for example, disk wear and foreign object insertion. For validating the suggested acoustic emission sensor methodology, we designed a hydraulic test loop that includes the typical four inches swing typed check valve widely used in the industry [4]. The test loop was designed to identify the mechanical failures of the check valve for a case in which the reverse backward leakage flows are induced through a failed section in a check valve with various failures. The causes of failure in swing typed check valves are hinge pin wear, back stop fail, disk wear, foreign object insertion, and so on. The failures of hinge pin and back stop have already been studied adequately [3,9]. Therefore, in this research, we have focused on disk wear (DW) during operation and the insertion of a foreign object (FO) during installation or maintenance.

We have experimented on the usefulness of the suggested technology through a hydraulic test loop composed of check valves that were artificially failed through disk wear of various sizes or foreign objects at various pressures and at room temperature. When failures due to foreign objects or disk wear occur, the disk cannot close fully, which causes backward leakage flows. Since backward flows produce a sound wave, the acoustic emission sensor is able to detect the wave and identify the characteristic response frequencies of the failed check valve through an analogy of test results. In addition, we have developed a diagnosis algorithm that uses neural network models to identify the type and size of the failure in the check valve [9]. Our results show that a diagnostic algorithm with acoustic emission sensors and a neural model is a good solution for identifying the failures of the check valves without any disassembly work.

2. Check Valve Test Configuration

For validating the suggested methodology, we designed a hydraulic test loop that included the typical four inches swing check valve through modifying the direct vessel injection test loop at KAERI. The test loop is designed to examine the mechanical failures of a check valve for a case in which reverse backward leakage flow is induced through a failed section in the check valve due to disk wear or the insertion of a foreign object. The pressure waves from the reverse flow in the failed check valve are detected by the attached acoustic emission sensors. The configuration of check valves for failure testing, including the location of the acoustic emission sensor, is shown in Figure 1. For detecting failure signals, four acoustic emission sensors are attached to both bottom sides of the check valve housing. The four acoustic emission sensors are categorized into two types according to their characteristic frequency sensitivities and covered frequency range. One type is a narrow range sensor that is highly sensitive to a frequency of about 150 kHz and covers a range of 50 kHz to 200kHz. The other type is a wide range sensor that covers a range of 100 kHz up to 500 kHz and is less sensitive to a particular frequency. Since the response frequency of the failed check valves was unknown, we used both types of acoustic emission sensors in order to obtain adequate information regarding the check valve failures. The sensor positions were determined by the analogy of the propagation of the backward leakage flow in the failed section of the target check valve. In Figure 1, AE1 and AE2 represent the wide range sensor (WD) while AE3 and AE4 are the narrow range sensor (R15).

3. Check Valve Test and Results

We have tested the usefulness of the suggested method through a hydraulic test loop comprising various disk wear (DW) sizes or a check valve with a foreign object inserted at various pressures and

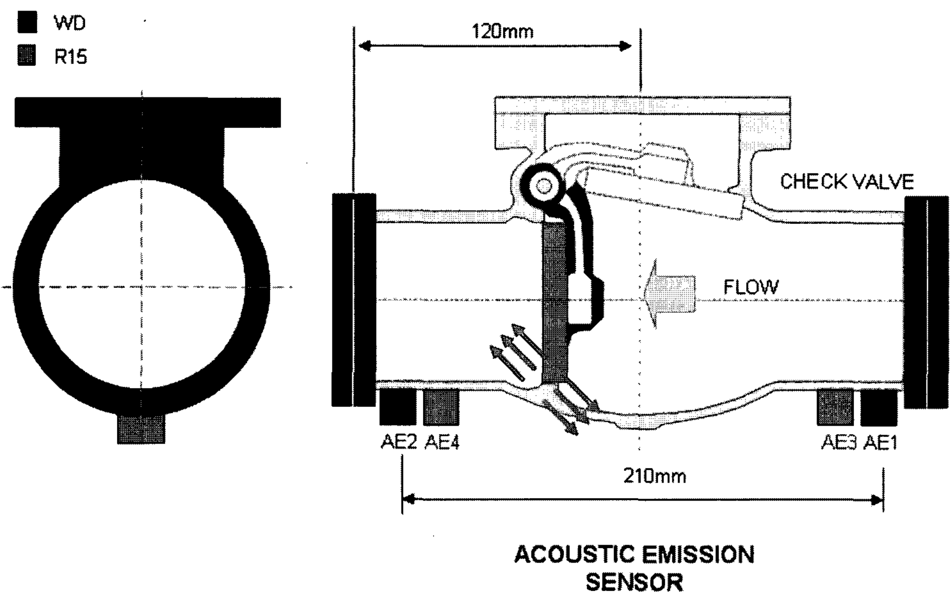
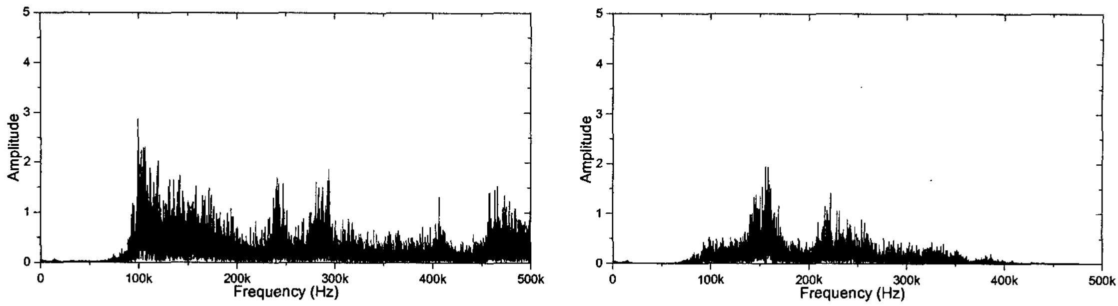
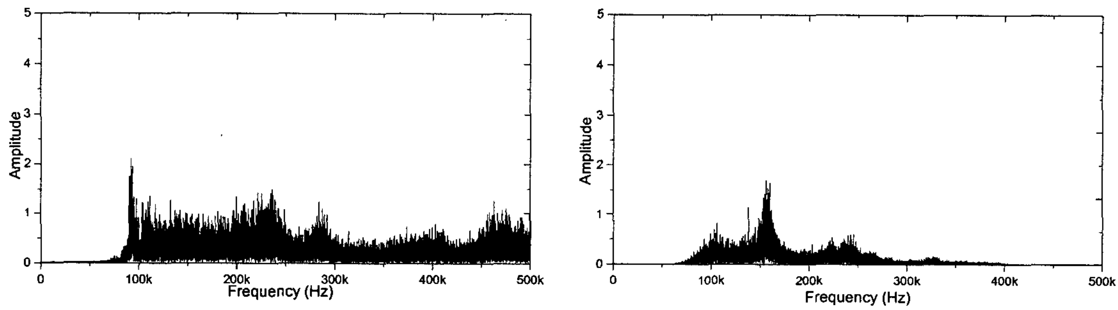


Fig. 1. Typical Check Valve Diagram Including the Sensor



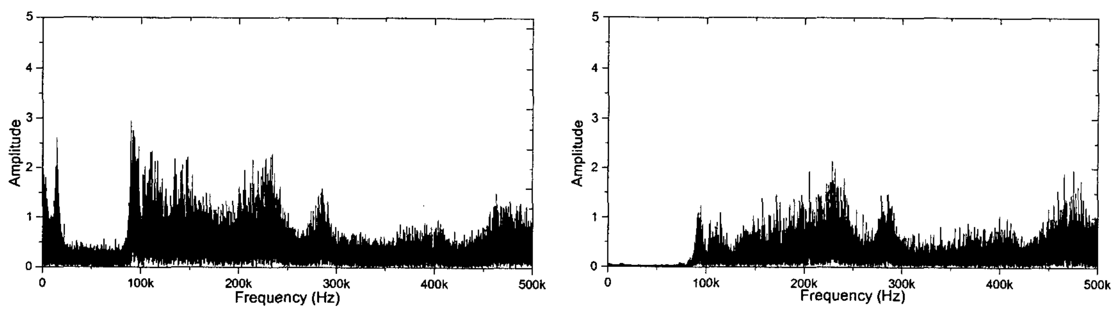
(a) wide range AE1 sensor **(b) narrow range AE3 sensor**

Fig. 2. Frequency Spectrum in Disk Wear 2mm Test at 3 Bar



(a) wide range AE1 sensor **(b) narrow range AE3 sensor**

Fig. 3. Frequency Spectrum in Foreign Object 1mm Test at 9 Bar



(a) foreign 1.2mm at 6 bar **(b) disk wear 1mm at 9 bar**

Fig. 4. Frequency Spectrum from AE1 Sensor

at room temperature. We have detected and analyzed a total of 20 test matrixes as follows. We defined the test of a good healthy check valve as a normal condition and used a weld rod as the foreign object (FO).

1. Pressure (3bar) : DW[1,2,3]mm FO[1.0, 1.2]mm and normal
2. Pressure (6bar) : DW[1,2,3]mm FO[1.0, 1.2]mm and normal
3. Pressure (9bar) : DW[1,2,3]mm FO[1.0,

1.2]mm and normal

We performed the Fast Fourier Transform (FFT) with a Hanning window to identify the characteristic frequencies in the measured data at various experimental conditions [10]. Some of the representative experiment results are shown in the frequency domain after the FFT analysis in the following Figures form 2 to 4. For gathering the background noise data, we tested a healthy check valve that did not have any failures for normal data. In the check valves with various sizes of disk wear, the analysis result of the acoustic signal sensors shows similar frequency characteristics at each experimental condition. Figure 2 shows the frequency spectrum of experiment results in which there is 2 mm disk wear at a pressure of 3 bar. Figure 2 (a) shows the frequencies spectrum as detected by the wide range acoustic emission sensor 3 (AE1), and Figure 2 (b) shows the result from the narrow range acoustic emission sensor 3 (AE3). Since the signals acquired from AE1 and AE3 are more sensitive than those from AE2 and AE4, the data from AE1 and AE3 are analyzed and represented in this paper. We represent the relative amplitudes in all the Figures in order to easily compare and analyze the test results. Figure 3 shows the frequency spectrum of experiment results for a case of failure due to foreign object insertion (1 mm weld rod). Figure 4 shows the other representative frequency spectrum of test results with the AE1 sensor. The results show that the mechanically failed check valves have frequencies higher than 50 kHz below the 9 bar in our experiments (~several hundreds of kHz). In Figures 2 and 3, the characteristic frequency patterns are somewhat different according to the type of sensors because the sensor characteristics are different. That is to say, the acquired patterns of a narrow range sensor are centered at 150 kHz because the sensor has a highly sensitive frequency at 150 kHz. However, a wide range sensor can acquire wide frequency patterns because it is less sensitive at center frequency. After analyzing the frequency spectrum of all test cases, we can conclude that the AE1 sensor has a better capability than other sensors to analyze the characteristic frequencies of various failure modes. Therefore, we chose the AE1 sensor to detect failures of the check valve.

From the analysis of the frequency spectrum, we have concluded that the characteristic frequencies from the AE1 sensor are independent of the size of the failures but are dependent on failure types such as disk wear or foreign object insertion. So, the failure types can be identified by the analysis of characteristic frequency analysis from the acquired acoustic data. As shown in the Figures, the peak frequency patterns in all DW failures are about 150 and 230 kHz, and all FO failures are 100 and 140 kHz.

4. Diagnostic Algorithm

Based on the experiment, we have developed a diagnostic algorithm using neural networks in order to identify the failures of check valves. We have adopted back propagation neural networks for the diagnostic algorithm, which is a widely used and well-known model [9, 11]. As shown in Figure 5, the diagnostic algorithm consists of a two-layered hierarchical architecture that includes three neural networks for monitoring the failures of the check valve. In the Figure, the BPN means the back propagation neural network model using the unipolar sigmoidal function as a processing element. The FAIL BPN is used to determine the failure status of the check valves: normal, disk wear (DW), or foreign object (FO). If the valve is determined to be healthy, the diagnostic algorithm is finished. If the valve is determined to have failed, the FAIL BPN distinguishes between disk wear failure and foreign object insertion failure.

The FAIL BPN has an average amplitude after the FFT analysis, loop pressure, and the two characteristic frequencies that have the first and second highest amplitude after the FFT act as input nodes. Since the acoustic magnitude in the failed case is larger than in normal cases where no failure occurs, the amplitude and pressure are selected as an input node[.4]. In addition, the two characteristic frequencies are selected as an input node in order to identify the failure type, as shown in the previous section. The FAIL BPN has two output nodes. The first of the two output nodes can determine disk wear failure, and the second can determine foreign object insertion failure. If both output nodes have a value below the threshold (0.5), the valve is determined to be healthy, or to have not failed. The FAIL BPN has a hidden layer that consists of 9 processing elements.

If the FAIL BPN identifies a disk wear failure, then the acquired data is sent to the DW BPN in order to estimate the failure size. The DW BPN has an average amplitude after the FFT analysis, acquired signal strength (detected energy magnitude), RMS (root mean square) of the acquired voltage input, and loop pressure. After analyzing various acoustic parameters such as RMS, amplitude, signal strength, duration, rise time, counts, and so on, the four inputs mentioned above are concluded to have a relation between the magnitude of the failure and the size of the disk wear. The output node determines the size of the disk wear failure (1mm, 2mm, or 3mm). The DW BPN has a hidden layer that consists of 9 processing elements. Finally, the FO BPN has the same features and the same input as the DW BPN, but the output, which is garnered in a similar fashion, indicates the size of the foreign object.

Each BPN has learned 30 training cases. After training, a total of 900 unlearned experimental data are estimated as test cases in order to validate the developed diagnostic algorithm. Figures 6 and

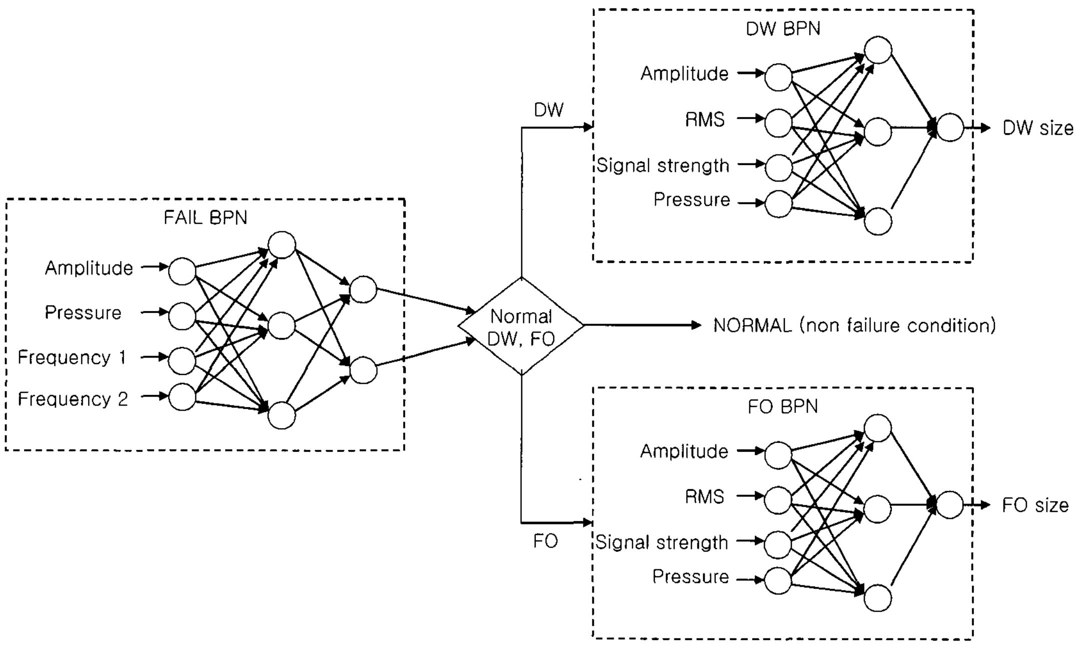
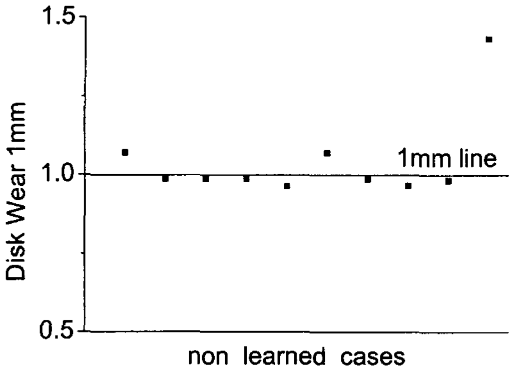
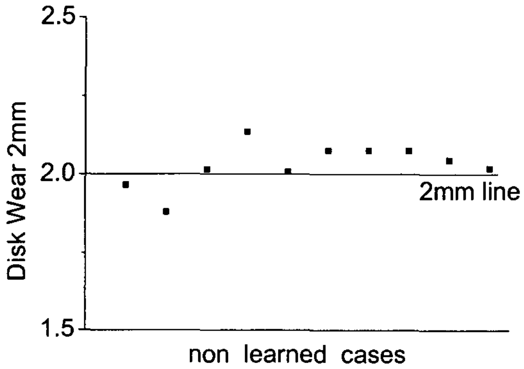


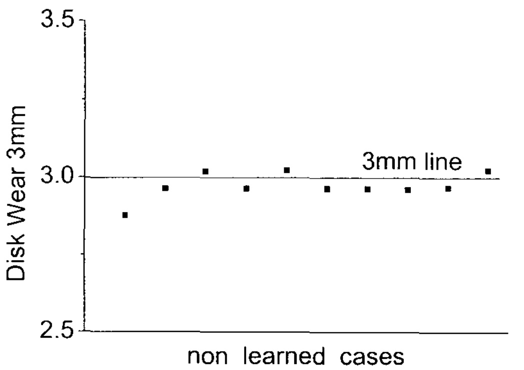
Fig. 5. Hierarchical Diagnostic Algorithm Using Neural Networks



(a) disk wear 1mm estimation results

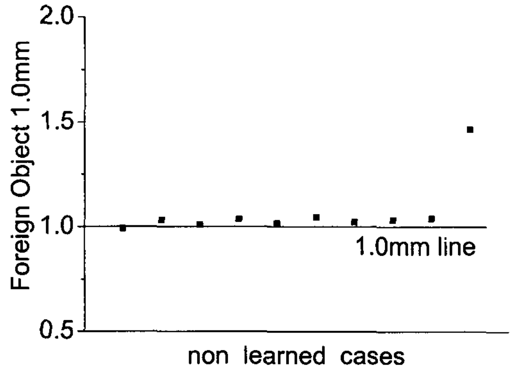


(b) disk wear 2mm estimation results

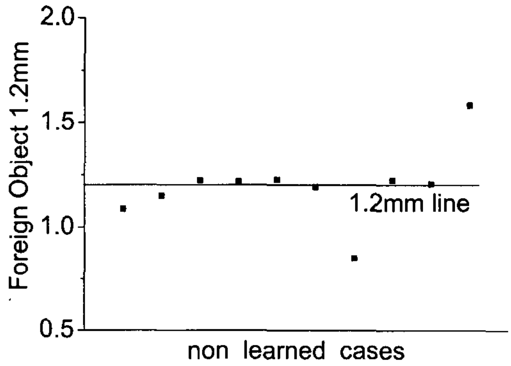


(c) disk wear 3mm estimation results

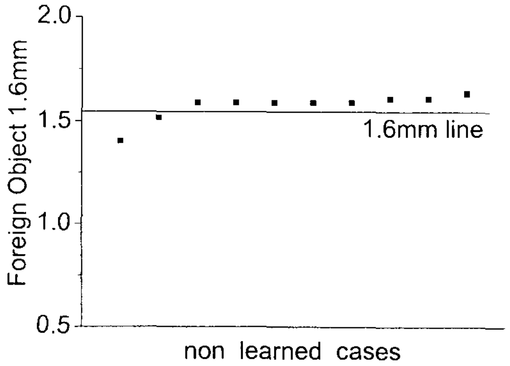
Fig. 6. Disk Wear Estimation Results



(a) foreign object 1.0mm estimation results



(b) foreign object 1.2mm estimation results



(b) foreign object 1.6mm estimation results

Fig. 7. Foreign Object Estimation Results

7 show estimation results where the Y axis means the failure size, the straight line means the actual failure size, and the points mean the estimated size. Firstly, the FAIL BPN is able to determine all 300 test cases as normal, disk failure, or foreign object without error. The DW BPN can estimate the disk wear size with an average error of 10%. However, 10 test cases have a 50% error between the estimated size and the actual size. For example, the DW BPN estimated a disk wear size of 1.5mm in a case where the actual disk wear failure was 1mm, as shown in Figure 6 (a). The FO BPN can estimate the foreign object size with an average error of 15%. However, 50 test cases have a 60% error between the estimated size and the actual size. For example, the FO BPN estimated the foreign object size at about 1.7mm in a case where the foreign object was actually 1.2mm, as shown in Figure 7 (b). Repeated experiments showed that the size of the foreign object changed due to the pressure of the test loop. So, the estimation error for foreign object cases is higher than for disk wear cases. Although some estimation error exists, we have concluded that the estimated error could be tolerable in real situations because the lowest FAIL BPN has the ability to identify the status of a check valve as being normal or suffering from disk wear failure or foreign object failure. Finally, the developed diagnostic algorithm has a good capability for identifying the failures of check valves and estimating the size of each failure mode.

5. Conclusions

In this study, we have found that the proposed diagnostic algorithm can identify check valve failures early. A wide range acoustic emission sensor attached to the backward leakage side can detect check valve failures without any disassembly work. In addition, the developed diagnostic algorithm with the neural network models can estimate the size and type of the failure. Although some diagnostic results were inaccurate in this respect, the algorithm of the developed method is able to detect the presence and type of failure, so errors in estimating the size of the failure are not considered critical.

To confirm our conclusions, future experiments involving high pressure and high temperatures, similar to physical conditions at a normal power operation, will be conducted. After we gather and analyze data pertaining to failure signals at the operating conditions, we can further improve the analysis techniques and diagnosis algorithm. The developed diagnostic technology using the acoustic emission sensor suggested in this research will be a good solution for detecting and identifying failed check valves without any disassembly work.

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