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Neural Network Approach to Automated Condition Classification of a Check Valve by Acoustic Emission Signals

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Abstract This paper presents new techniques under development for monitoring the health and vibration of the active components in nuclear power plants. The purpose of this study is to develop an automated system for condition classification of a check valve one of the components being used extensively in a safety system of a nuclear power plant. Acoustic emission testing for a check valve under controlled flow loop conditions was performed to detect and evaluate disc movement for valve failure such as wear and leakage due to foreign object interference in a check valve. It is clearly demonstrated that the evaluation of different types of failure types such as disc wear and check valve leakage were successful by systematically analyzing the characteristics of various AE parameters. It is also shown that the leak size can be determined with an artificial neural network.

Keywords: Active Component, Check Valve, Safety System, Acoustic Emission(AE), Leakage, Artificial Neural Network

1. Introduction

Check-valves are used extensively in safety systems of a nuclear power plant. Hence, the failure of a check-valve is a crucial event. It has been reported check-valve monitoring methods based on acoustic emission, ultrasonic, and magnetic flux techniques (Haynes, 1992). However, monitoring may not be sufficient since the check-valve failure can occur instantaneously during the loss of coolant accident accompanied by a water hammering or rapid impact of the valve disc on the valve seat.

Although there are many possible failure mechanisms for check valves, the most common problems are due to system flow oscillations or system piping vibrations that induce check valve component wear, and often component failure. Most failures induce additional vibration from the valve body. The common types of physical failures in check valves are disc separation from the hinge pins, stud pin breaks, disc nut loosening, disc being partially open, a disc caught on the outside of the seat ring, a cracked disc, a worn hinge pin, and a bent hinge pin, disc, or hinge arm. Among these failures we take special interest with disc and hinge pin wear (Pool and Porwit, 1982; Schwertzer, 1972; Lee, 2005).

The objective of this research is to demonstrate that a condition-monitoring system based on acoustic emission detection can provide timely detection of check valve failure and service aging so that maintenance or replacement can be preformed prior to the loss of safety function. This work is focused on the capability of the AE technique to provide diagnostic information useful in determining check valve aging and degradation, check valve failures, and undesirable operating modes. In addition, we considered an artificial neural network (ANN) as automated pattern classifier to distinguish check valve failures.

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A systematic approach to classifying the dynamic responses of AE signatures associated with typical failure modes of check valves is performed in this study. The characteristics of the AE signal responses of the internal parts of check valves due to local aging and degradation are analyzed by extracting the effective AE parameters.

2. Techniques for Check Valve Health Monitoring

The different types of failure check valves are prone to include disc wear, hinge pin wear/fracture, hinge arm wear/fracture, seal wear and erosion, corrosion. Thus check valve must be inspected or monitored to detect these failures before it become catastrophic. There are many techniques under investigation for detecting failures in check valve.

In this research, the concept of a condition monitoring of the check valve is to utilize of two or more monitoring techniques. Several commercially available check valve diagnostic-monitoring methods were evaluated, especially for the techniques based on measurements of acoustic emission, ultrasonic, and accelerometers. The methodology employed in this work is basically a three monitoring approach (Lee et al., 2004; Lee 2002).

This paper is focused on the analysis and understanding of the capability of the acoustic emission (AE) technique to provide diagnostic information on check valve failures.

Acoustic emission technique was used to detect a disc movement and to evaluate valve degradatioins including disc and hinge pin wear. The AE testing for a check valve under controlled flow loop conditions and with the introduction of various implanted defects that simulated severe aging and service wear was performed. In this paper, we have considered failures from disc wear and foreign object among various failure modes of the check valve. Disc wear mean a disc was worn due to some flaw on the surface, so the backward leakage is induced through the flaw. When the foreign object is, also, inserted between the disc and housing of a check valve, the disc is not fully closed. Therefore, the backward leakage occurs through the not fully closed section in the check valve. The idea of our research is based on the detection of the acoustic wave originating from those backward leakages with acoustic emission technique. Fig. 1 and 2 shows the typical configuration of swing type check valve and simplified depiction of condition monitoring for the check valve.

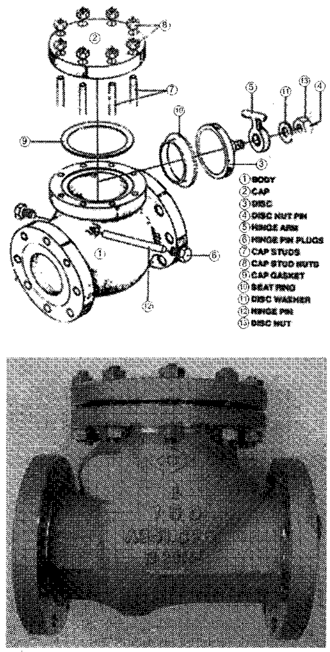


Fig. 1 Typical swing type check valve

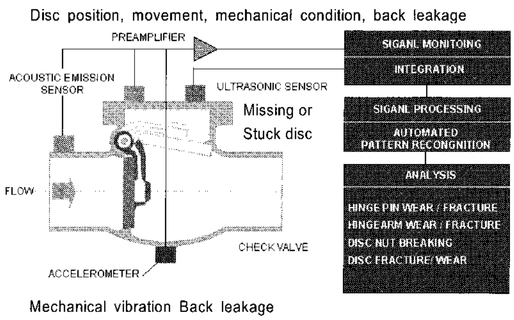


Fig. 2 Simplified depiction of the condition monitoring of the check valve

2.1 Development of Failure Classification Using a Neural Network

In this study, several artificial neural network models have been developed based on different architectures and modes of learning. However, probably the most popular among the artificial neural network(ANN) models is the layered feed-forward net, known as the multilayer perceptron (MLP) because of its wide applicability in pattern classification and function approximation(Roy et al., 1995). The MLP can trained by many algorithms out of back-propagation (BPN) is the most popular. The back propagation network is useful artificial neural network system in addressing problems requiring recognition of complex patterns and performing nontrivial mapping functions.

In this study, we have adopted the back propagation neural networks for the diagnosis algorithm to identify leak signals associated with different failures ('disc wear' and 'foreign object' failure mode).

When $i_l (l = 1,2,3...i)$ are the values of the input-layer unit and $y_n (n = 1,2,3...k)$ are the values of the output-layer unit, eqn. (1) represents the hidden-layer unit values, $x_m (m = 1,2,3...j)$, and eqn.(2) represents the output-layer unit values, $O_n (n = 1,2,3...k)$.

In these equations, w is the weight on the connection, θ is the bias weight, and function is $f(\ )$ the sigmoidal function. In eqn. (1), the input-layer unit values i_l project each weight onto the connections w^h_{ml}, then summations of these and bias θ^h_m will be hidden-layer unit values through the sigmoidal function, $f(\ )$:

$$net^h_m = \sum_{l=1}^{i} w^h_{ml} i_l + \theta^h_m \qquad (1)$$
$$x_m = f^h_m(net^h_m)$$

In the same way, the summation of bias θ^o_n and the values of the hidden-layer unit values x_m project each weight onto the connections w^o_{nm} will be the output layer unit values through the sigmoidal function $f(\ )$, as shown in eqn. (2). In this study, this sigmoidal function $f(\ )$ of the output layer generated the leak size as the output vector

$$net^o_n = \sum_{m=1}^{i} w^o_{nm} x_m + \theta^o_n \qquad (2)$$
$$O_n = f^o_n(net^o_n)$$

Eqn. (3) defines the error function E that represents the error value between real values and output unit values:

$$E = \frac{1}{2}\sum_{n=1}^{k}(y_n - o_n)^2 \qquad (3)$$

It is the training of a neural network that the weight on the connection, w values, are corrected so that the value of the error function E of eqn. (3) approaches zero. This means that the output-layer unit values approach real values through the back propagation algorithm.

The weights on the output-layer are updated by eqn. (4) during the training of the neural network. When α is the learning-rate parameter, (Freeman and David, 1991)

$$w^o_{nm}(t+1) = w^o_{nm}(t) - \alpha \frac{\partial E}{\partial w^o_{nm}(t)} (0 < \alpha < 0.25) \qquad (4)$$

The weights on the hidden-layer are updated by eqn. (5) during the training of the neural network:

$$w^h_{ml}(t+1) = w^h_{ml}(t) - \alpha \frac{\partial E}{\partial w^h_{ml}(t)} \qquad (5)$$

As shown in Fig. 3 the diagnosis algorithm consists of a three back-propagation neural networks in order to monitor the failures of the check valve. BPN means the back propagation neural network model using the unipolar sigmoidal function as a processing element.

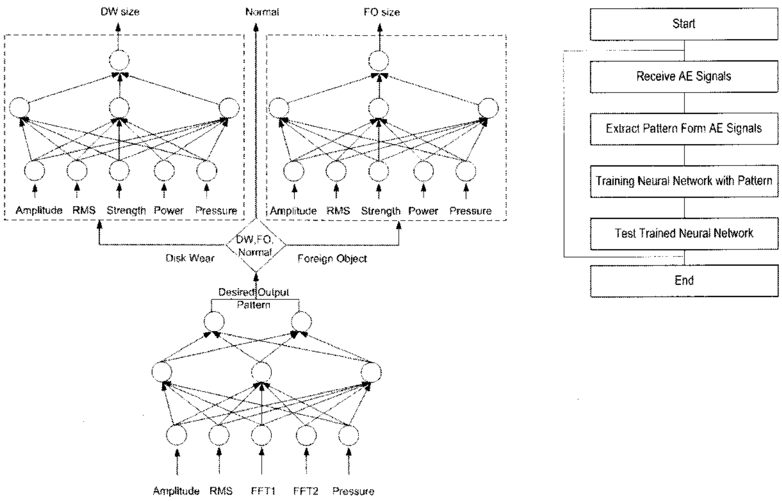


Fig. 3 Diagnosis algorithm using the neural network

We have developed a diagnosis algorithm using neural networks in order to identify the failures of the check valves. As above mentioned, we have adopted the back-propagation neural networks for the diagnosis algorithm. The diagnosis algorithm has two output nodes as shown in Fig. 3.

2.2 Experimental Set-Up

We have tested the usefulness of our method through the hydraulic tests including a check valve with various artificial disc wear sizes and a check valve inserted with various sized foreign objects at various pressures and at room temperature, respectively. In this experiment, the following check valve operational conditions were used to detect disc movement and to evaluate valve failures from disc/seat and hinge pin wear:

- Valve with new and artificially disc scratch: 1 mm, 2 mm, and 3 mm depth half-circle.
- Valve with new and artificially leakage: 0.5 mm, 1.0 mm, 1.2 mm, 1.5 mm, 2.0 mm, 2.4 mm foreign object interfered between body and disc.
- Valve with new and artificially hinge pin wear: 3 mm, 6 mm, and 9 mm depth hinge pin cutting.
- Valve with improper assembly: separating disc from disc arm by loosed disc pin.
- Loop operation condition (steady state, transient operation 0, 3, 6, 9 bar).

Fig. 4 shows an example of an artificially worn disc of the swing type check valve.

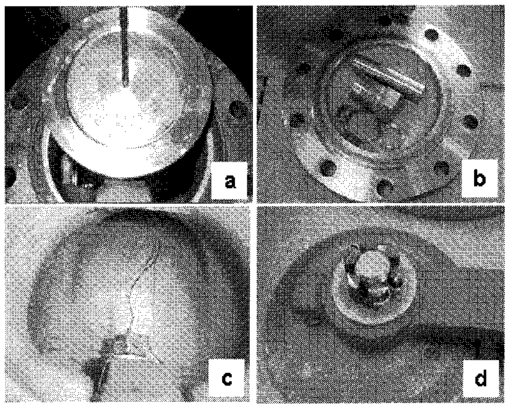
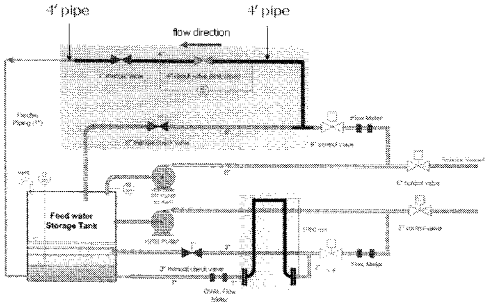


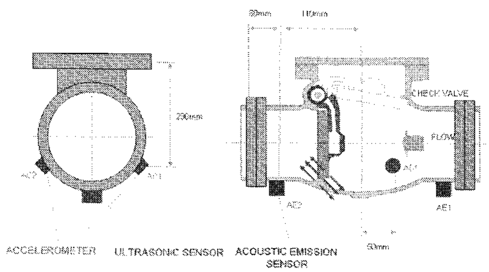
Fig. 4 Four different kind of artificial defects of the check valve (a)disc wear (b)hinge pin wear (c)foreign object (d)improper assembly

In this experiment, to obtain baseline data from typical wearing, condition monitoring tests were performed with the modified direct vessel injection (DVI) test loop at the Korea Atomic Energy Research Institute (KAERI) on selected wearing such as disc wear and foreign object interference. A schematic diagram and an actual installation of the check valve test loop were shown in Fig. 5. These tests were performed using water as the process fluid. Check valves were initially tested in a "good" condition and subsequently with one or more simulated degradations and operational failures.

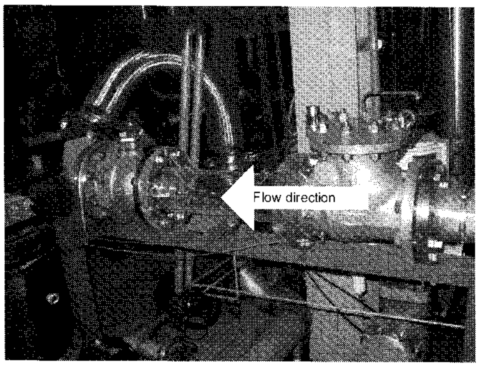
A schematic diagram of the sensor installation is shown in Fig. 5. The AE signals detected from the sensors were amplified by a preamplifier, which had a fixed gain of 40 dB. After passing through a band-pass filter of 100 to 300 kHz to remove the electrical and mechanical background noise, the signals were amplified by the main amplifier (40 dB). The AE parameters, such as RMS, energy, and frequency of AE signals, were analyzed in the AE system (Mistras 2001™). In addition, a digital oscilloscope (LeCroy 9310A) was used to analyze the AE signal waveform. AE data of the WD sensor was recorded at a 2 MHz sample/s rate, and AE data of the R15 sensor was recorded at a 1 MHz sample/s rate.



(a) a schematic diagram(DVI test loop)



(b) sensor position



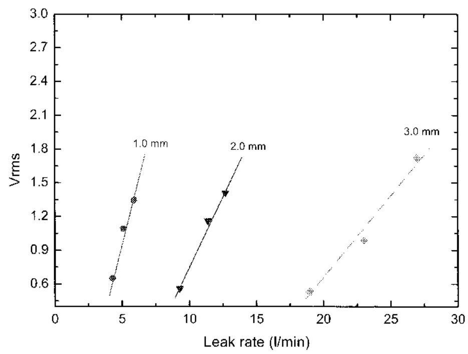
(c) an actual installation

Fig. 5 Check valve test loop

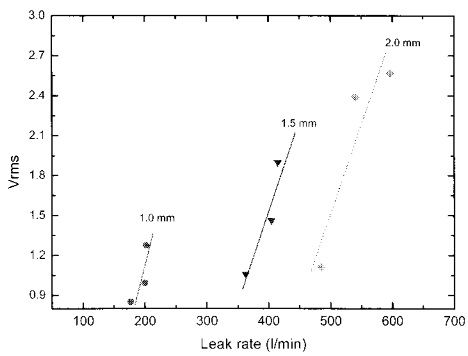
3. Experimental Results

3.1 Analysis of the Acoustic Emission Signals

Fig. 6 shows the results of actual measurement for comparing the intensity of AE



(a) disc wear failures



(b) foreign object failures

Fig. 6 AE RMS value vs. leak rate obtained from 'disc wear' and 'foreign object' failure

RMS value by a leak in the disc wear and foreign object failure modes. Fig. 6 shows the results between AE RMS value and flow rate obtained from the disc wear and foreign object failure modes. The leak flow rates were measured by means of an ultrasonic flow meter. As shown in Fig. 6 (a) and (b), a linear relationship is observed. The analyses of the results suggest that acoustic signals depend on leak rate.

The frequency spectrum of the check valve leakage is illustrated in Fig 7. Fig. 7 shows the frequency spectra for the 150 kHz transducers with each leak size of DW(disc wear) failure mode and FO(foreign object) failure mode. The frequency spectrum content on AE signals due to the leaks indicate no significant changes with the leak rate, pressure and leak size.

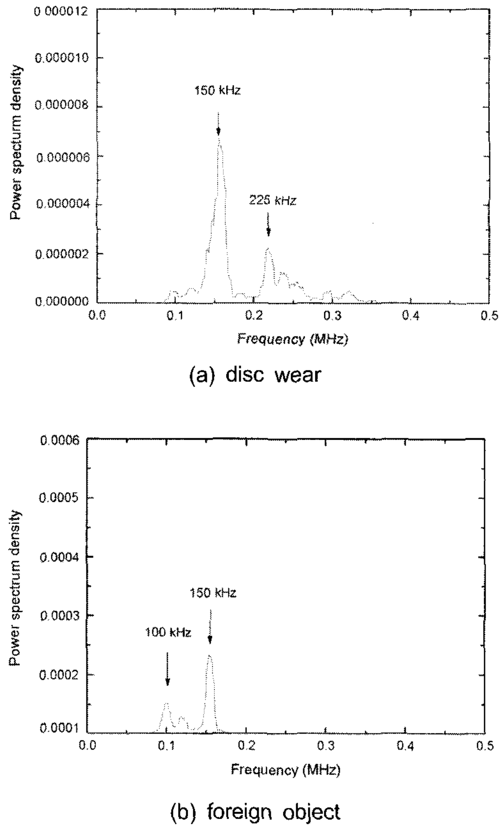
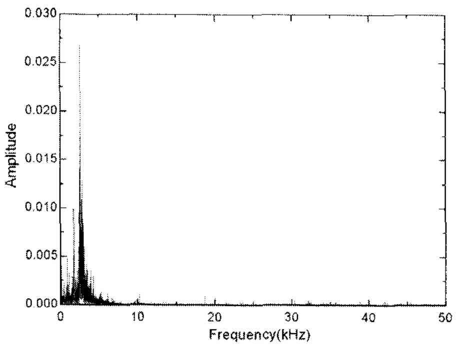


Fig. 7 Frequency spectrum of AE source signal

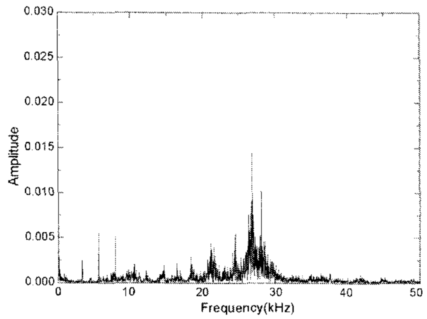
However, comparing the DW and FO failure modes (Fig. 7 (a) and (b)), the frequency range of the leak signals is significantly different. But, the frequency spectrum of the AE signals due to the leakage indicate no significant changes with the leak rate and pressure originating from the same source. These facts imply that the frequency spectrum profiles of the check valve leakage do not depend on the leak rate and the pressure, but that they are strongly dependent on the types of the failure modes. As shown in Fig. 7 (a) and (b), the peak frequencies in all the disc wear failures are about 150 and 225 kHz and those in all the foreign object failures are about 100 and 150 kHz. The peak frequency (150 kHz) is similar in any of the failure conditions. In addition, the peak frequency patterns in the normal cases are random and variable with low amplitude. So, the frequencies of 225 kHz and 100 kHz can be used as alternatives to distinguish failure modes such as a disc wear and a foreign object.

3.2 Analysis of the Accelerometer Signals

Several condition-monitoring tests were performed on a 4 in. check valve in normal condition and with simulated degradation. In particular, vibration signal were detected by accelerometers, which respond to pressure waves over a low-frequency range (<100 kHz). Fig. 8 shows the waveforms and corresponding spectra for the accelerometer output of initial background noise and leak signal. The resulting accelerometer signature (Fig. 8(a)) shows that the FFT is concentrated in the range of 2 to 3 kHz. Fig. 8(b), which shows the waveforms and corresponding spectra from the accelerometer for leak failure mode, involves detecting a leak flow signal that corresponds to a diameter of leak size of about 1 and 2 mm. When comparing normal signals (Fig. 8(a), with normal signals (Fig. 8(b)), their frequency characteristics could be clearly distinguished.



(a) normal condition



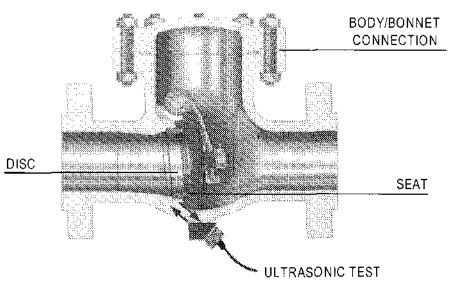
(b) leakage condition

Fig. 8 Frequency spectrum of accelerometer signal

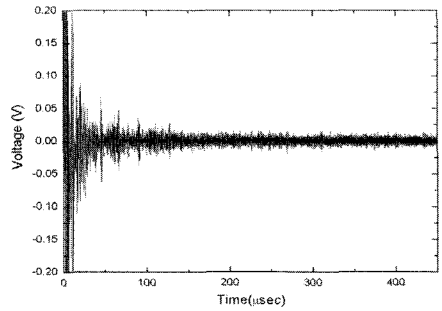
3.3 Analysis of the Ultrasonic Signals

Ultrasonic inspection techniques can be used to detect a missing or stuck disc. Typically, one (pulse-echo) or two (pitch-catch) ultrasonic transducers were used to detect internal part of the check valve. If the disc is missing, no signal will be reflected from the disc; however, if the hinge arm remains inside the valve, its position can be verified by ultrasonic inspection techniques.

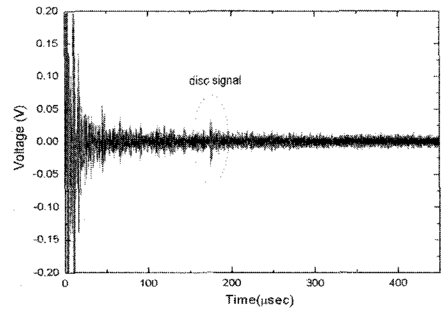
Fig. 9 shows ultrasonic signatures acquired from a check valve at two disc positions; fully open (b) and fully closed (c) from the worn hinge pin and the improper assembly of disc. It is noted that the no signal was returned from the disc in the open position and that echo signal was returned from the disc in the closed position.



(a) ultrasonic measurement



(b) disc open



(c) disc close

Fig. 9 The ultrasonic testing signals obtained from disc of check valve

3.4 Analysis of the Fusion Sensor Monitoring

The fusion sensor combines several sensors to identify and analyze the changes of frequency response for normal and degraded check valves. The AE sensor, accelerometer, and ultrasonic device have been selected for developing the fusion sensor methodology. It has been found that the AE sensor could directly detect a high frequency acoustic wave generated from the backward leakage flow. The accelerometer would be useful for high pressure and temperature environments. Ultrasonic devices would be used for detecting the disc locations when it fails to close or open, and measuring the leakage flows. The fusion sensor method provides a more comprehensive dataset than that from any single sensor technology, and this approach can be made non-intrusive, allowing check valves to be monitored and diagnosed without being disassembled from the piping system.

3.5 Failure Algorithm Development Using ANN Technique

This study, the failure algorithm has been developed for condition classification of check valve using an artificial neural network and waveforms processing method to distinguish the defect signals. The objective of an AE test is to detect the presence of emission sources and to characterize the source. The purpose of source characterization is to use the sensor output waveform to identify the sources and to evaluate their significance through qualitative and quantitative procedures. For quantitative leak evaluation, only six data features were used, including AE amplitude, RMS, pressure, signal strength (or energy), and FFT information collected from two different check valve failure modes as the input to the neural network. The AE data were in the form of analog signals that were filtered to remove the mean value and to prevent aliasing and then digitized into time series. These data were transformed into the frequency domain, where the signals were represented through their frequency components in FFT, using data sampling at 1 MHz sampling. The relationship between the FFT, signals amplitude, pressure, and RMS value is modeled with an ANN using time series data from a check valve. That is, the neural network was used to compute the corresponding AE parameters such as amplitude, RMS, pressure, and FFT.

The diagnosis algorithm has two output nodes as shown in Fig. 3. The first ('disc wear algorithm') node in the two output nodes can identify the disc wear failure, and the second ('foreign object algorithm') can identify the foreign object failure. The procedures for identifying the failure of a check valve are as follows: At first, main diagnosis algorithm is used to identify the failure status of the check

Table 1 The estimation error of each of failure modes identification.: neural network was trained to distinguish failure mode and the sizes of each failures. Error means the difference between real size of failure and result of classification through neural network.

Defect	Error(%)	Defect	Error(%)	Defect	Error(%)
Disc Wear (1.0mm)	1.3	Foreign Object (0.5mm)	2.7	Foreign Object (1.5mm)	0.2
	0.0		6.5		0.2
	0.8		0.2		0.2
	0.7		0.7		0.2
	0.1		0.3		0.2
	0.1		0.2		0.0
Disc Wear (2.0mm)	0.1	Foreign Object (1.0mm)	0.2	Foreign Object (2.0mm)	0.2
	0.2		0.2		0.2
	3.8		0.2		0.0
	4.0		0.2		0.0
	0.1		0.2		0.0
	0.2		0.2		0.0
Disc Wear (3.0mm)	0.0	Foreign Object (1.2mm)	0.2	Foreign Object (2.4mm)	0.2
	0.3		0.2		0.2
	1.5		0.2		0.0
	1.6		0.2		0.0
	0.1		0.2		0.0
	0.1		0.2		0.0

valves such as normal, disc wear and foreign object failure. If the valve is determined to be good state, the main diagnosis algorithm will be finished. If the valve is determined to be failed, the diagnosis algorithm can distinguish the failure modes such as a wear and a foreign object failure. If the main diagnosis algorithm identifies a disc wear failure, then the acquired and analyzed data should be sent to the 'disc wear algorithm' in order to estimate the failure size. The main diagnosis algorithm has input nodes with AE amplitude, RMS, pressure, signal strength (or energy), and two characteristic peak frequencies.

The architecture of the developed network is composed of 8 processing elements in the hidden layer. The main diagnosis algorithm learned 135 training cases and validated a total of 216 unlearned cases. The main diagnosis algorithm did not identify only three cases in the total 216 validation cases. That is, it is able to identify all the 216 test cases as normal, disc wear and foreign object failure within about 6.5% error.

The "disc wear algorithm' learned 135 training cases and validated a total of 216 unlearned cases. The unlearned cases for validation are 100 cases at each disc wear size, respectively. The "disc wear algorithm' can estimate the disc wear size with and averaged 3.26% error between the estimated and actual size. Table 2 shows the estimation error of each of failure size in each failure mode. The maximum error is about 26% in some test cased as shown in Table 2. For example, the 'disc wear algorithm' estimated as disc wear size of 0.74 mm in the case of an actual 1.0 mm disc wear failure.

The 'foreign object algorithm' learned 135 training cases and 216 case each foreign object size, respectively, similar to the case of disc wear size. The "foreign object algorithm' can estimate the disc wear size with and averaged 6.06% error between the estimated and actual size as shown in Table 2. In some test cases of the foreign object failures, the maximum error is about 39%. For example, the 'disc wear algorithm' estimated as disc wear size of 1.39 mm in the case of an actual 1.0 mm foreign object failure.

Table 2 The estimation error of each of failure size in each failure modes

DW Size	Pressure (bar)	Output (mm)	Error (%)
1.0mm	3bar	0.95	5
	6bar	1.08	8
	9bar	0.74	26
2.0mm	3bar	2.09	4.5
	6bar	2.02	1
	9bar	1.98	1
3.0mm	3bar	2.94	2
	6bar	3.09	3
	9bar	3.08	2.6

Foreign Object Size	Pressure (bar)	Output (mm)	Error (%)
0.5mm	3bar	0.49	2
		0.49	2
	6bar	0.51	2
		0.51	2
	9bar	0.51	2
		0.50	0
1.0mm	3bar	1.01	1
		1.00	0
	6bar	1.23	23
		1.39	39
	9bar	1.04	4
		1.07	7
1.2mm	3bar	1.32	10
		1.38	15
	6bar	1.13	5.8
		1.20	0
	9bar	1.15	4.1
		1.14	5
1.5mm	3bar	1.49	0.6
		1.60	6.6
	6bar	1.48	1.3
		1.47	2
	9bar	1.54	2.6
		1.53	2
2.0mm	3bar	2.54	27
		2.51	25.5
	6bar	2.06	3
		2.05	2.5
	9bar	2.27	13.5
		2.27	13.5
2.4mm	3bar	2.54	5.8
		2.50	4.1
	6bar	2.46	2.5
		2.44	1.6
	9bar	2.27	5.4
		2.27	5.4

However, although some estimation errors exist, it found that the developed algorithm could have a good capability for identifying the failures of check valves and estimating the size of each failure modes.

3.6 Automated System Development for Condition Classification of a Check Valve

To develop the automated condition monitoring system of check valve, 6 parameters (RMS, amplitude, signal strength, FFT1, FFT2, and pressure) were extracted to identify a characteristic of the experimental data.

The check valve failure diagnosis algorithms were processed in two steps. In step 1, the algorithms discriminated a normal condition from an abnormal condition. In step 2, the algorithms characterized failure types, such as disc wear and foreign object and failure sizes. Fig. 10 shows the two-step procedure of the failure diagnosis algorithms.

The neural network is composed of three layers; 6 input layers, 12 hidden layers, and 1 or 2 output layers. When applying the neural network, it is necessary to configure the initial parameters, and it was found that the best connection weight could be achieved with the following parameters: moment rate = 0.7, weight and threshold = 0.2, learning rate = 0.1, decline of sigmoid function = 0.7, and error rate = 0.01.

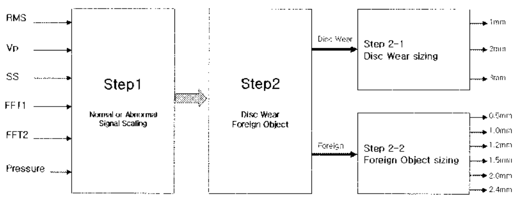


Fig. 10 Two-step procedure of classification of the failure diagnosis algorithms

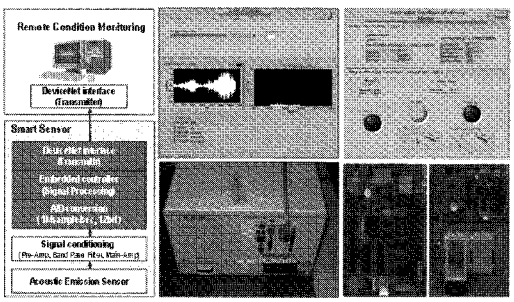


Fig. 11 A configuration of prototype using wired comminucation

To avoid the saturation of sigmoid function and obtain identical weights of each dataset, the following ranges were assigned: input data ("0" to "1"), RMS value (0.001 to 1.06), amplitude (0.007 to 1.31), signal strength divided by 100000 (2928 to 74125), FFT1 divided by 1000 (120 to 147), FFT2 divided by 100 (198 to 244), and pressure divided by 10 (3 to 9).

In this study, we developed a specially designed diagnostic system for condition classification of a check valve. This system consisted two operating programs (master and slave program). The master program took charge of the input/output communication as a DeviceNet™ master with a single slave device. Fig. 11 shows the Lab View™ display, which set the input value and displayed the output of block diagram for this task. This display comprised graphs and charts displaying the actual data. The DeviceNet communication setup and input data can be adjusted using switches, input windows, and buttons on the front panel.

The slave program performed the data acquisition from the sensor, displayed the acquisition data and the value of extracted parameters and filtering (Butterworth filter), and sent the extracted parameters to a master through a wired network.

4. Conclusions

In this study, an advanced condition monitoring technique based on acoustic emission detection and artificial neural networks has been applied to the check valves. The developed neural network algorithm has been shown that the proper use of an appropriate selection of parameters provide excellent classification results. That is, the developed diagnosis algorithm is proven to be a good solution, for detecting and identifying a failed check valves. It has been proved to be feasible to automate the condition classification without the intervention of human expert. The development of the specially designed system is essential for early warning of the structure condition degradation. The potential of this exciting technology for providing a new and cost-effective means of inspection and condition monitoring of structures is very high. This will include in future, the use of Expert systems resulting in a fully integrated control strategy, but in general, the inclusion of any additional feature such as condition monitoring, must be preceded by a comprehensive analysis of the overall reliability implications in terms of ultimate system safety.

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