Condition Monitoring of Check Valve Using Neural Network

Seung-Youn Lee*, Jeong-Seob Jeon*, and Joon Lyou*

* Department of Electronics Engineering, Chungnam National University, Daejeon, 305-764, Korea
(Tel : +82-42-821-7710; E-mail: lsyacts@cnu.ac.kr / mukkeby@cnu.ac.kr / jlyou@cnu.ac.kr)

Abstract: In this paper we have presented a condition monitoring method of check valve using neural network. The acoustic emission sensor was used to acquire the condition signals of check valve in direct vessel injection (DVI) test loop. The acquired sensor signal pass through a signal conditioning which are consisted of steps; rejection of background noise, amplification, analogue to digital conversion, extract of feature points. The extracted feature points which represent the condition of check valve was utilized input values of fault diagnosis algorithms using pre-learned neural network. The fault diagnosis algorithm proceeds fault detection, fault isolation and fault identification within limited ranges. The developed algorithm enables timely diagnosis of failure of check valve's degradation and service aging so that maintenance and replacement could be preformed prior to loss of the safety function. The overall process has been experimented and the results are given to show its effectiveness.

Keywords: check valve, acoustic emission sensor, neural network, fault diagnosis.

1. INTRODUCTION

Check valves play a vital role in the operations and protection of power plant components and systems. During one 10-year period of reporting, more than 5,000 check valve failures were recorded by the electric utility industry. A number of these failures resulted in damage to other plant components. In another words, check valve failures have been identified as important contributors to water hammer events, over-pressurization of low pressure systems. As with any other component, these valves must operate properly and reliably when called upon to perform their design function [1,2].

Check valves came in the forefront of utility attention in 1986. That year a number of check valve failures caused damages to important nuclear power plant systems at several plants. Swing check valves are self-contained, self-actuating valves that have no external operator to indicate their internal position or movement. There fore, a common practice followed widely in the nuclear industry consists of valve disassembly and inspection. It is very common in a nuclear plant for 10 to 30 valves to be disassembled per outage in 1980s. This particular preventive maintenance approach raises a number of serious questions such as, maintenance-induced failures, and prolonged outages. It becomes apparent that the introduction of nondestructive evaluation techniques will significantly reduce the cost of the preventive maintenance program[6,7].

Agostinelli suggests a diagnosis algorithm of check valve using acoustic emission sensor and magnetic flux sensor [3]. Yang suggests a diagnosis algorithm of check valve using ultra sonic sensor and acoustic emission sensor [5]. These three methods have been developed for check valve monitoring, namely: acoustic emission, ultrasonic inspection, and magnetic flux signature analysis. It have been developed as means of providing check valve condition related information such as disc position, disc motion, seat leakage, etc. The most of their research focus on whether fault or not. There has been lack of distinction of which fault occurs and how large it is.

To solve these problems, we have presented a condition monitoring method of check valve using neural network. The acoustic emission sensor was used to acquire the condition signals of check valve in direct injection vessel (DVI) test loop. The acquired sensor signal pass through a signal conditioning which are consisted of steps; rejection of background noise, amplification, analogue to digital conversion, extract of feature points. The extracted feature points which represent the condition of check valve was utilized input values of fault diagnosis algorithms using pre-learned neural network. The fault diagnosis algorithm proceeds fault detection, fault isolation and fault identification within limited ranges. The developed algorithm enables timely detection of check valve's degradation and service aging so that maintenance and replacement could be preformed prior to loss of the safety function. The overall process has been experimented and the results are given to show its effectiveness.

2. CHECK VALVE FAILURE MECHANISM AND EXPREIMENTAL SETUP

2.1 Check valve failure mechanism

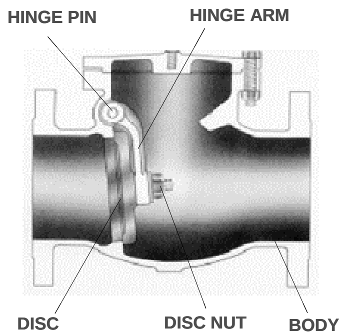

Fig. 1. The structure of swing type check valve.

The swing type check valve are consisted of a disc, a disc nut, a disc nut pin, a hinge arm, a hinge pin, a seat ring, a cap studs etc. The result of survey for nuclear power plant has operated over ten years reveals that the most frequently failure causes are "Disc/Seat wearing", "Hinge Pin wearing", "Foreign object intersection", "Improper Assembly" as shown in fig. 2.

Disk wear means the disk was worn to some flaw, so the backward leakage flows are induced through the flaws. When the foreign object is inserted, the disk is not fully closed. The backward leakage flows through the open section in the check valve. The result of experiment was shown that the case of "Hinge pin wear", "Improper Assembly" are improper in detection algorithm in advance. Therefore, the predictive case, "Disc/seat wear", "Foreign Object interface", are experimented. Figure 3 shows the picture of artificial failure of check valve[9,10].

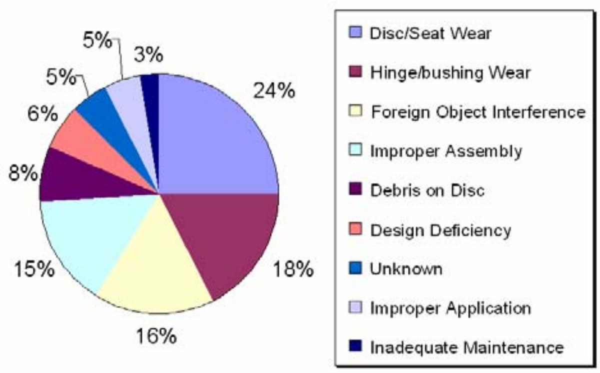

Fig. 2. A statistical chart of causes of fault.

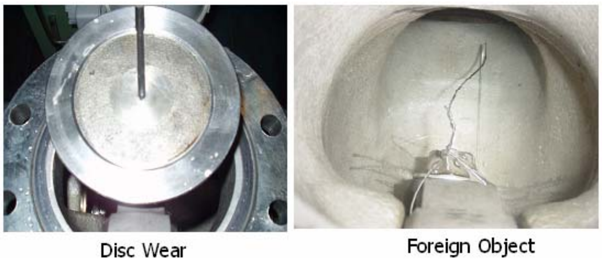

Fig. 3. The artificial defects of check valve.

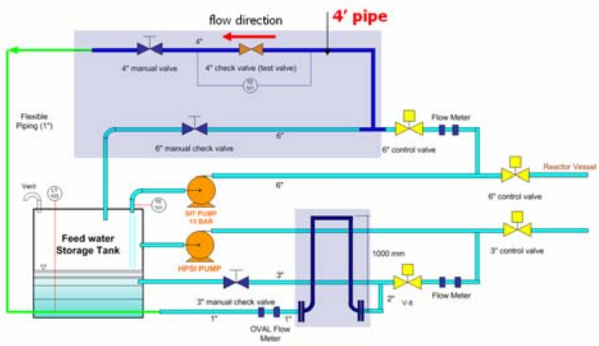

Fig. 4. Direct Vessel Injection (DVI) Test loop.

2.2 Experimental Setup

The test loop was manufactured and experimented to have information of the characteristic of signal when representative failures occur. Fig. 4 shows the DVI(Direct Vessel Injection) test loop. In DVI test loop, a check valve was installed to prevent the reverse flow from the high pressurized area (primary system) to the low pressurized area. The check valve can experience local degradation under operation in a number of ways.

Acoustic Emission (AE) refers to generation of transient elastic waves during rapid release of energy from localized sources within a material. In this experiment, the R6 AE sensor and R15 AE sensor are used for experiment. R6 sensor detects the frequency range about 30 to 100KHz. and the R15 sensor detects the frequency range about 100KHz to 1200KHz. The most sensitivity sensor for leakage was R15 AE sensor. Finite element analysis method is used for the analysis of pressure on check valve. The result shows that the most adaptive location of AE sensor on check valve is lower area because the pressure more powerful in lower area than upper area and the higher pressure means that the more leakages are exists. Therefore, the R15 sensor was attached on lower location of check valve as shown in figure 5. We use the coupling agent for higher sensitivity of AE sensor. Figure 6. show the 4 inch check valve(a) and experiment instruments(b).

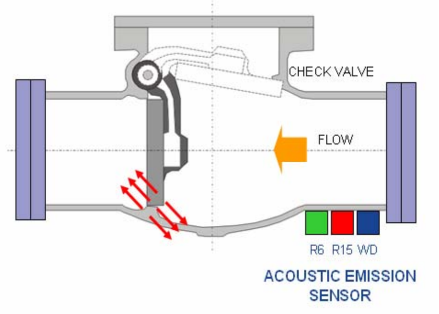

Fig. 5. The installation of acoustic emission sensor

Fig. 6. (a) A 4 inch check valve (b) Experiment instruments

The check valve monitoring by acoustic emission carried out as following check valve operation conditions with varying the pressure 3bar, 6bar, 9bar.

* Normal condition
* Disc Wear Failure: 1mm, 2mm, 3mm.
* Foreign Object : 0.5mm, 1.0mm, 1.2mm, 1.5mm, 2.0mm, 2.4mm

3. SIGNAL CONDITIONING

3.1 Sensor signal processing

The amplification of AE signals are essential for signal processing because the acquired signal level of AE sensor ranges from uV to mV. The amplification of signal processed between pre-amp and main amp. These AE signals detected from the sensors were amplified by a pre-amplifier, which had a fixed gain of 40dB. After passing through a band pass filter, to remove the electrical and mechanical background noise, the signals are amplified by the main amplifier (40dB)

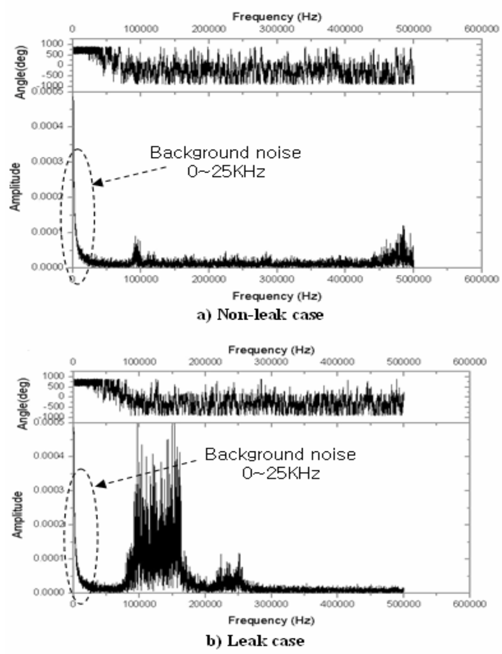

Fig. 7. The background noise of signal.

Table 1. Signal to noise ratio: Disc wear to Normal

Butterworth Filter			Chebyshev Filter		
SNR[dB]	P	σ^2	SNR[dB]	P	σ^2
12.5656	4.71^{-5}	2.61^{-6}	12.7683	4.54^{-5}	2.40^{-6}
Inverse Chebyshev Filter			Elliptic Filter		
SNR[dB]	P	σ^2	SNR[dB]	P	σ^2
7.4201	5.37^{-5}	9.72^{-6}	6.8033	4.32^{-5}	9.01^{-6}

Table 2. Signal to noise ratio: Foreign objective to Normal

Butterworth Filter			Chebyshev Filter		
SNR[dB]	P	σ^2	SNR[dB]	P	σ^2
46.1882	0.1086	2.61^{-6}	25.6142	0.1038	2.40^{-6}
Inverse Chebyshev Filter			Elliptic Filter		
SNR[dB]	P	σ^2	SNR[dB]	P	σ^2
40.4677	0.1082	9.72^{-6}	39.2531	0.0759	9.01^{-6}

As shown in Figure 7, we can find common background noises in every AE sensor data fewer than 25 KHz. The band pass filter designed for filtering which band-pass ranges from 25 KHz to 460 KHz.

To eliminate background noise various filter were used. (i.e. Butterworth filter, Chebyshev Filter, Inverse Chebyshev Filter, Elliptic Filter.) Table 1 and Table 2 show the results of signal to noise ratio (SNR) from each filter. Form the tables, a Butterworth filter is best fitting filter for the elimination of the background noise because it has a higher SNR than others.

The acoustic emission sensor signal was recorded at 1 M sample/sec rate. Each data contains approximately 60 seconds of data. The overall amplitude level of the signal varies just a little during this time that means the signal acquired stably and reliably.

3.2 Feature Extraction

The number of acoustic emission signals in general materials reach tens of thousands to hundreds of thousands. It is very time-consuming problem that processing the acquired AE signal data. So the characteristic points which extracted form raw acoustic emission data are used to signal processing and the commercial instrument extracts the variable directly. But the commercial instruments are inadequate for check valves because of their high price and large size.

In this experiment the developed instruments extracts the feature point directly from raw data. The feature points of AE sensor are RMS (root mean squire), Peak amplitude, AE energy, Feature Frequency, Pressure and the explanation of parameter is presented below.

(1) RMS valve

In mathematics, the root mean square or rms is a statistical measure of the magnitude of a varying quantity. It can be calculated for a series of discrete values. The name comes from the fact that it is the square root of the mean of the squares of the values. RMS is usually used in measuring signal power. The RMS for a collection of N values $\{V_1, V_2, \ldots, V_N\}$ is:

$$RMS = \sqrt{\left(\frac{1}{N}\sum_{i=0}^{N} V_i^2\right)} = \sqrt{\frac{V_1^2 + V_2^2 + \ldots + V_N^2}{N}} \quad (1)$$

N is number of acquisition data. (N = 65536)

Here, V_i is output of sensor and N is total number of data which is maximum size of buffer 2^{16}.

(2) Peak Amplitude

Amplitude is a nonnegative scalar measure of a wave's magnitude of oscillation. The amplitude of a wave is the measure of the magnitude of the maximum disturbance in the medium during one wave cycle. The form of the variation of amplitude is called the Envelope detector of the wave.

The Amplitude for a collection of N values $\{V_1, V_2, \ldots, V_N\}$ is:

$$V_P = \frac{\{Max(V_1 \sim V_m) + Max(V_{m+1} \sim V_{2m}) + \ldots + Max(V_{N-m} \sim V_N)\}}{N/m} \quad (2)$$

We select m = 8, because the small value is better than the large one. If we select less than eight, it is too small to calculate the exact Amplitude by experience.

(3) The Energy of acoustic emission (Signal Strength)

The signal strength is the measurement of how strong a signal is. Typically, this is measured as voltage per square area. Power uses the volts per square meter (V/m^2).

$$E_{AE} = \frac{1}{R}\sum_{i=0}^{N} V_i^2 \quad (3)$$

R is constant value. We select for "1" of R. It is simple and easy to handle the E_{AE}

(4) Characteristic Frequency

The name MUSIC is an acronym for MUltiple SIgnal Classification. The MUSIC algorithm estimates the pseudo-spectrum from a signal or a correlation matrix using Schmidt's eigen-space analysis method. The algorithm performs eigen-space analysis of the signal's correlation matrix in order to estimate the signal's frequency content. This algorithm is particularly suitable for signals that are the sum of sinusoids with additive white Gaussian noise.

$$MUSIC = \frac{1}{e^H(f)\left(\sum_{k=p+1}^{N} v_k v_k^H\right)e(f)} \quad (4)$$

Where N is the dimension of the eigen-vectors and vk is the k-th eigen-vector of the correlation matrix. The integer p is the dimension of the signal subspace, so the eigen-vectors vk used in the sum correspond to the smallest eigen-values and also span the noise subspace. The vector e(f) consists of complex exponential, so the inner product VkHe(f)amounts to a Fourier transform. This is used for computation of the pseudo-spectrum estimate. The FFT is computed for each v1 and then the squared magnitudes are summed. Freq1 is first peak value which was calculated by MUSIC algorithm. And Freq2 is second one. Fig. 8 shows to detect the Freq1 and Freq2 using Music algorithm.

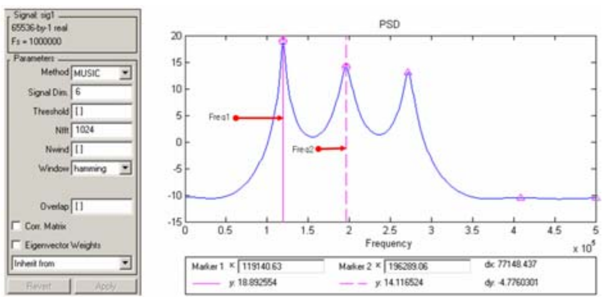

Fig. 8. Characteristic frequencies using MUSIC algorithm.

(5) Pressure

Pressure is a measure of force per unit area. The international system of units of pressure is the Pascal (Pa), which is one newton per square meter. The bar is a measurement unit of pressure, 1 bar is equal to 100,000 Pa. The bar is still widely used by the general public and in industry because 1 bar as close as atmospheric pressure. We put three cases 3bar, 6bar and 9bar into the input of diagnosis part.

$$p = \frac{F}{A} \tag{5}$$

Here, p is pressure and F is the force and A is the area.

4. FAILURE DAIGNOSIS ALGORITHM

4.1 Back propagation algorithm of neural network

An artificial neural network (ANN) can be defined as a computer processing system consisting of many simple processing elements joined together in a structure inspired by the cerebral cortex of the brain. These processing elements are usually organized in a sequence of layers, with full connections between layers. Typically, there are three (or more) layers: an input layer where data are presented to the network through an input buffer, an output layer with a buffer that holds the output response to a given input, and one or more intermediate or "hidden" layers

The mathematical basis for back-propagation training of ANNs is straight-forward but intricate. It is well documented in the literature and well known; hence, only a qualitative description of the process will be given here.

1) Set the weights to small random (both positive and negative) values to assure that the network training will not be overly influenced by large weight values.

2) From the training input-output pair, select a training input/output vector pair and apply it to the network as the input and the desired output.

3) Calculate the network output and the error (the difference between the network output and the desired output).

4) Adjust the weight of the network to minimize this error.

This process continues for each pair of input/output vectors in the whole training set (called an apoch) which is repeatedly applied until the error for the entire system is acceptably low.

4.2 Proposed algorithm

The neural net used in experiment is composed of three layers; input layers, hidden layers and output layers. The number of input layers is 6, and the number of hidden layers is 12 and the number of output layers is 1 or 2. When we used to the neural net, it is necessary to configure the initial parameters. In this algorithm, when we select that moment rate is 0.7, weight and threshold 0.2, learning rate 0.1, the decline of sigmoid function 0.7, and error rate 0.01, these parameters are the best connection weight.

It is necessary to make input data's range from "0" to "1" because of avoiding the saturation of sigmoid function and to have the identical weights of each data. The input data transformed to have a range from 0.1 to 0.9 by a numerical Eq. (6).

$$V_i = \frac{0.8}{v_{\max} - v_{\min}} v_i + \left(1 - \frac{0.8 v_{\min}}{v_{\max} - v_{\min}}\right) \tag{6}$$

The training data for neural net is mean valve of feature points. The error converge below 0.001 every case.

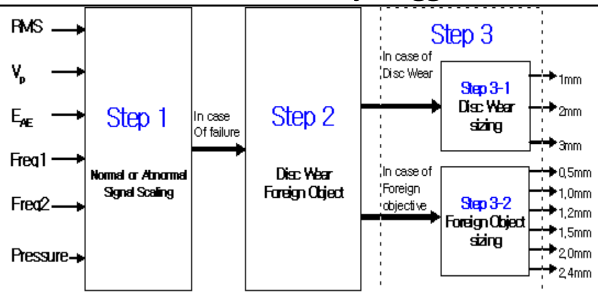

Fig. 9. Fault diagnosis algorithm.

Table 3. A data of acquired from acoustic emission sensor.

Condition of C.V.	3 Bar	6 Bar	9 Bar
Normal	100	100	100
Disc Wear 1mm	100	100	100
Disc Wear 2mm	100	100	100
Disc Wear 3mm	100	100	100
Foreign Object 0.5mm	100	100	100
Foreign Object 1.0mm	100	100	100
Foreign Object 1.2mm	100	100	100
Foreign Object 1.5mm	100	100	100
Foreign Object 2.0mm	100	100	100
Foreign Object 2.4mm	100	100	100

The Failure diagnosis algorithm consisted of three steps; fault detection, fault isolation and fault identification. The first is a fault detection step which distinguishes between normal and abnormal. In step 2, case of abnormal, the failure algorithm isolate of failure either disc wear or foreign object. The third is an identification step which performs a classification of failure's magnitude. In case of disc wear, the algorithm classified the magnitude of disc wear and in case of foreign object the algorithm classified the magnitude of a foreign object. Fault diagnosis algorithms are presented in figure 9.

Table 3 shows the experimented data which acquired form acoustic emission sensor for various conditions of failure type and pressure.

4.3 Result of experiments

Figure 10, 11, 12,13 shows the result of trained neural net output. The blue solid line represented the reference output and the red dots were the output. The numbers of input data and experiment modes are presented in x-axis. The diagonal line represents wrong decision in below figures.

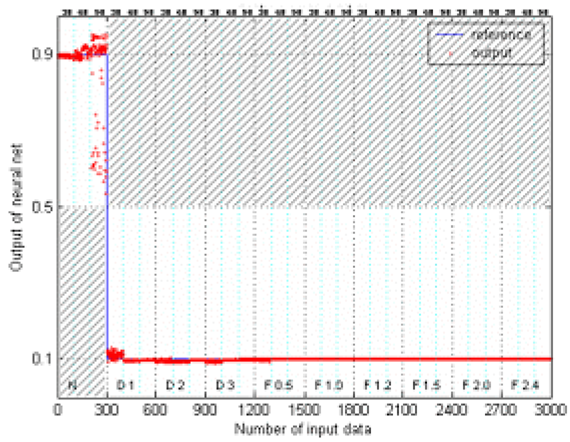

Fig. 10. Fault detection results of step 1.

The first output of neural net is presented left side and the second output is right side. The wrong decisions are 0% which was calculated by threshold value. The trained neural net perfectly distinguishes between normal and abnormal mode.

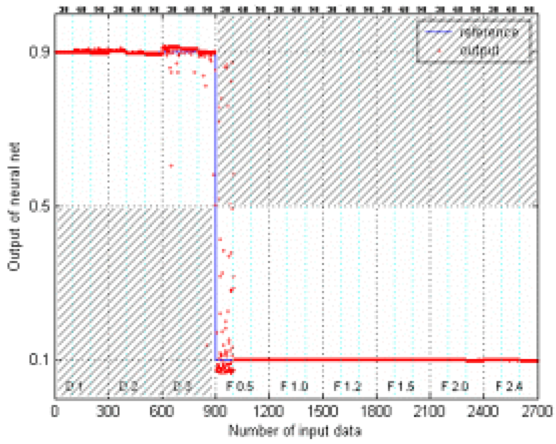

Fig. 11. Fault isolation results of step 2.

In second step, the results of neural net were perfectly distinguished between disc wear and foreign object except for the case of foreign object 0.5mm-3bar.

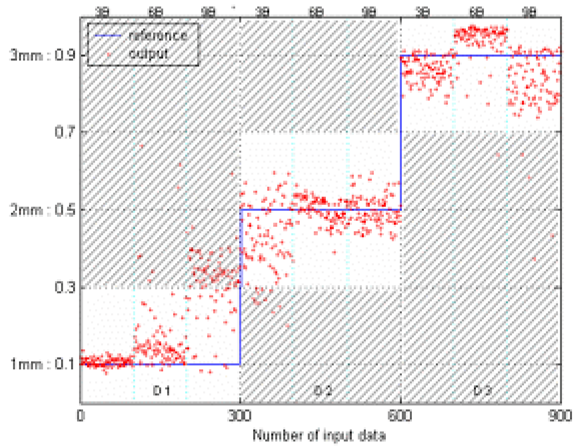

Fig. 12. Fault identification results of step 3-1 (DW).

The output of step 3-1 shows low error rate of 5.33%. The highest error occurred 1mm-9bar.

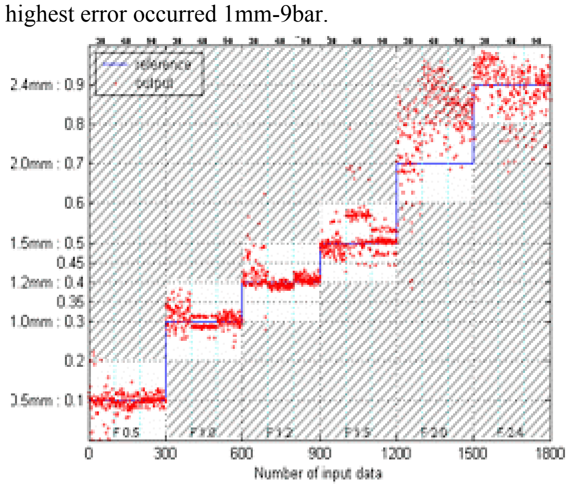

Fig. 13. Fault identification results of step 3-2 (FO).

The output of step 3-2 shows the error rate of 12.68%. The highest error occurred 2mm.

Above experiment, we can derive some conclusions. The first, step 1 (fault detection step) perfectly distinguishes between normal and abnormal. The second, step 2 (fault isolation step) distinguishes the cause of failures; which are disc wear, foreign object almost perfectly. The third (fault identification step), step 3-1, step 3-2 distinguish the size of failure perfectly except some specific range which is 1mm-9bar in disc wear and 2mm in foreign object.

5. CONCLUSIONS

In this paper we develop a condition monitoring system of check valves. The suggested condition monitoring method using neural network in this research seems to be a good solution capable of detecting and isolation of failure type and identifying the failed check valve in any physical conditions including power operation and the maintenance period. The developed system enables timely detection of failure of check valves before loss of safety function. The developed system seems to plays a vital role in the next generation nuclear power plant for monitoring of check valves.

ACKNOWLEDGMENTS

We would like to thank Jung-Teak Kim and Jung-Su Kim whom is the researcher of KAERI for their assistance in conducting this data collection and advices. This work was supported by the Nuclear R&D I-NERI program of the Ministry of Science and Technology, Republic of Korea.

REFERENCES

[1] D. S. Kupperman, D. Prine, "Application of Acoustic Leak Detection Technology for the Detection and Location of Leaks in Light Water Reactors," *U. S. Nuclear Regulatory Commission*, 1988.

[2] H. D. Hayes, "Evaluation of Check Valve Monitoring Methods," *Proceedings of the 17th Water Reactor Safety Meeting*, October 23-25, Rockville, MD, 1989.

[3] A. Agostinelli, "Check Valve Diagnostics Utilizing Acoustic and Magnetic Technologies," *Nuclear Plant Journal*, pp. 80-90, November, 1990.

[4] H. D. Haynes, et. al., "Aging and Service Wear of Check Valves Used in Engineered Safety-Feature system of Nuclear Power Plants," *NUREG/CR-4302*, vol. 2, 1991.

[5] M. K. Yang, "Acoustic and Ultrasonic Signals as Diagnostic Tools for Check Valves," *Journal of Reactor Vessel Technology*, vol. 115, pp. 135-141, May, 1993.

[6] R. E. Uhring et. al., "Using Neural Networks to Monitor the Operability of Check Valves," *Proc. of the Conf. on Expert System Application for the Electric Power Industry*, Phoenix, AZ, December 8-10. 1993.

[7] R. E. Uhring and L. H. Tsoukalas, "Application of Neural Networks," *EPRI/TR-103443-PI-2*, Knoxville, TN, January, 1994.

[8] C. Sim, H. Choi and H. K. Baik, "The Development of a Non-Intrusive Test of Check Valve Using Acoustic and Magnets," *Journal of Acoustic Society of Korea*, vol. 16 No. 1E, 1997.

[9] U. S. Nuclear Regulatory Commission, "Nuclear Plant Aging Research (NPAR) Program Plan," *NUREG-1144-Rev*. 2. NRC, June, 1991602-612, 1998.

[10] K. L. McElhaney, "An analysis of Check Valve Performance Characteristics based on valve design," *Nuclear Engineering and Design*, vol. 197, pp. 169-182, 2000.