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A Study on Loose Part Monitoring System in Nuclear Power Plant Based on Neural Network

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Abstract

The Loose Part Monitoring System(LPMS) has been designed to detect, locate and evaluate detached or loosened parts and foreign objects in the reactor coolant system. In this paper, at first, we presents an application of the back propagation neural network. At the preprocessing step, the moving window average filter is adopted to reject the low frequency background noise components. And then, extracting the acoustic signature such as Starting point of impact signal, Rising time, Half period, and Global time, they are used as the inputs to neural network. Secondly, we applied the neural network algorithm to LPMS in order to estimate the mass of loose parts. We trained the impact test data of YGN3 using the backpropagation method. The input parameter for training is Rising Time, Half Period, Maximum amplitude. The result showed that the neural network would be applied to LPMS. Also, applying the neural network to the practical false alarm data during startup and impact test signal at nuclear power plant, the false alarms are reduced effectively.

Key word : Loose Part, Impact Test Data, Neural Network, False Alarm, Diagnosis, Background Noise

Ⅰ. Introduction

LPMS is a diagnostic system that monitors the integrity of Nuclear Steam Supply System (NSSS) and analyzes the impact event caused by moving or loose parts. This system provides the necessary information for the operator's proper decision to maintain a reliable and safe Nuclear Power Plant. The loose parts, which are metal pieces, are produced by being parted from the structure of the reactor coolant system (RCS) due to corrosion, fatigue, and friction between components in RCS and also by coming into RCS from the outside during the period of reactor test operation, refueling, and maintenance in overhaul time. These loose parts are mixed with reactor coolant fluid, moved with high velocity along the RCS circuit, and generate collisions with RCS components. When a loose part strikes against the component within the pressure boundary, the acoustic impact wave is produced and propagates along the pressure boundary. For detecting the impact signal, the conventional LPMS uses the accelerometer sensor installed on the outer surface of the pressure boundary of RCS components and announces the alarm when the detected impact signal exceeds a certain level which is pre-set by the operator. The sensors are usually installed in the probable places where loose parts may be collected or existed such as the upper head of the reactor pressure vessel, hot chamber of the Steam Generator[1]. Fig.1 shows a typical arrangement of sensors mounted on the outer surface of the major components of the NSSS, where the sensor locations are marked with a block circle at YGN 3 & 4. In the existing LPMS, the alarm is triggered in the case where the signal threshold is exceeded by the measured signal and the detected signal is recorded on the magnetic tape. Later, the experienced operators analyze the recorded data and determine whether the detected signal is an impact signal by a loose part or noise signal. If their decision is concluded that loose parts caused the signal, they evaluate the characteristic parameters such as impact location, energy, and mass. After the above diagnosis process is completed, the proper procedure required for maintaining the safe and reliable operation is performed.

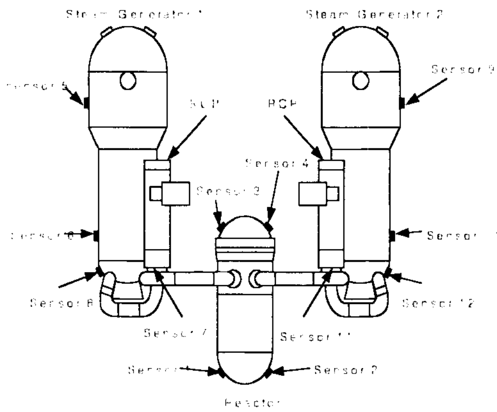

Fig.1 The general sensor position of NSSS at YGN 3&4

In the conventional diagnostic method in LPMS, the

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operators should have expert knowledge for diagnosing the impact signal in order to execute proper action. Moreover, it takes a long time to analyze the detected signal data and hence possibly fatal damage of components may occur during the analysis procedure. Therefore, it is very desirable that if the alarm is triggered by a loose parts impact, the detected signal is stored in the computer memory, the automatic diagnosis procedure is activated immediately, and displays the diagnostic results such as location, mass, and energy of loose part in the operator's monitors.

Various methods for improving conventional LPMS have been presented [2]-[4]. Some of them were implemented in the nuclear power plant monitoring system. Especially, finding out the impact location at YGN 3 & 4 used to compare reference signal with the impact signal. However, operator's diagnosis procedure for each impact signal is still required, and needs the experienced knowledge of the impact signals. Also, due to the high sensitivity of the accelerometer, the detection potential for impact occurrences is comparatively high. Therefore, too frequent false or unnecessary alarms can reduce the confidence to Loose Part Monitoring System. In this paper, at first, we present an application of the back propagation neural network to reduce the false alarm occurrence rate. At the preprocessing step, the moving average filter is adopted to reject the low frequency background noise components. And then, extracting the signature such as Starting point of impact signal, Rising Time, Half period, and Global Time, they are used as the input to the neural network. And, at second, we presents the neural network algorithm to LPMS in order to estimate the mass of the Loose Parts. We trained the impact test data of YGN 3 using BP. The input parameter for training is Rising Time, Half period, Maximum Amplitude. The experimental results show the good performance of the diagnosis algorithm is based on neural network. In the paper, Sec. 2 describes the Prefiltering method to reduce the background noise. Sec. 3 presents the false discrimination alarm and mass estimation algorithm based on neural networks. Sec 4 describes the experimental results applying to the YGN 3 impact test data and the practical false alarm data during startup. The last section is the conclusion and further research.

II. Prefiltering

In most LPMS, some type of signal filtering exists as part of a signal conditioning for the impact detection. Usually, band-pass filters are used to restrict the accelerometer signal to frequency bands so as to get an improved SNR (signal-to-noise ratio) for impact signals. This frequency band is typically in the range from 1,000 to 20,000 Hz as indicated by the theoretical and experimental results. High-pass filters may typically be set for 500 to 1,000 Hz as a means to reduce the level of the induced ac power line frequency signals, low-frequency flow and vibrations noise, and acoustics tones associated with reactor coolant pump. Band-Pass filters are typically set between 10,000 and 20,000 Hz. These bands include passing all of the acoustic signal while filtering high-frequency electrical noise, removing higher frequency acoustic or sensor resonance, or setting the filter to provide the best SNR for impact calibration signal. Since the lighter mass of a loose part produces higher frequency impact signals, band-pass filters limit the minimum of loose parts which can be detected. And frequency is more or less fixed because for elastic collisions the contact time is more or less independent of amplitude but is strongly influenced by mass. Also, to reduce the false alarm rate, variable alarm setpoint at each frequency band has been given. The minimum setpoint level is required to be no greater than 2 or 3 times that of background vibration noise from RCS. For reducing effects of the background noises effectively and improving the estimation accuracy, it is necessary to improve the existing filter at LPMS.

2.1 Design in the Time Domain

The moving average operation as eqn. (1) can reject a slow time varying offset or bias.

$$\hat{x}(t_i) = y(t_i) - \frac{1}{n}\sum_{j=1}^{n} y(t_{i-j}) \qquad (1)$$

where, $\hat{x}(t_i)$ is the filtered signal, $y(t_i)$ is the actual signal and n is the data window size. $\hat{x}(t_i)$ in (1) is then utilized as important information to estimate the impact location. $y(t_i)$ is the actual signal and n is the data window size. Note that the prefiltering algorithm (1) is very simple (practical) to use and turn out to be effective enough to remove the low frequency noise component. We also applied the other filters (for example, the Least-Square Method, Kalman Filter, FIR Filter/Smoother etc.) to reduce the background noise.

Fig. 2 shows a sample of the impact signal. We see that it is impossible to analyze the impact position from the signal. So, it is necessary to cancel the low frequency background noise effectively. Fig. 3 is the FFT of Fig.2. Considering the simple structure and reasonable performance (SNR), we choose the Moving average(MA) filter as the basic prefilter. Fig. 4 shows the impact signal after cancelling the noise using the MA filter. Also, Fig. 5 is the FFT of Fig. 4. From the figures, we observe that the low frequency noises are effectively rejected, while preserving the useful impact information.

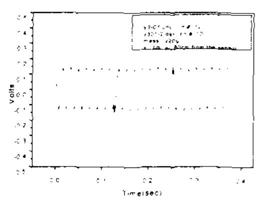


Fig.2 Actual Impact Signal

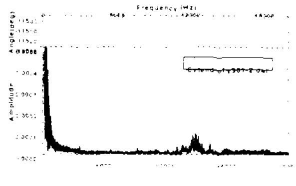


Fig 3. FFT of Fig 2

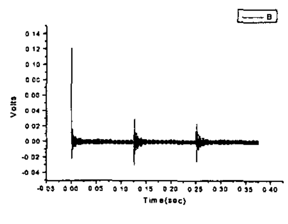


Fig. 4 The impact signal after prefiltering

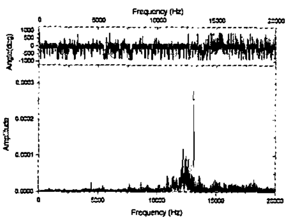


Fig. 5 FFT of Fig.4

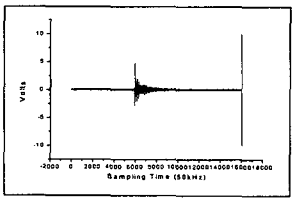
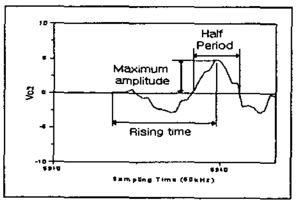


Fig 5.(a) impact signal



(b) Extended of (a)

III. False discrimination alarm and mass estimation algorithm

3.1 False Discrimination Alarm using neural network

The characteristic of impact signal is likely to the exponential function. Otherwise, the impact duration time of the false alarm is longer than that of the actual impact signal. The impact signal is divided into five parts; maximum amplitude, half period, rising time, global time, peak frequency. Fig 5. shows the maximum amplitude, half period, rising time.

The detection of Rising time used the eq. (2). The algorithm to find the impact starting point is :

$$T_S = SD_i > 10 \times SD_{background} \qquad (2)$$

where, $SD = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(\hat{x}_i - m)^2}$ and T_s is the starting impact time. From eq.(2), the maximum point minus the starting point is the rising time. The global time is defined from the starting time of the impact signal to the ending time of the impact signal. We are used to calculate the reverse standard deviation and compare with the forward standard deviation. If the Standard Deviation is equal point, then we chose the ending time of impact signal. Eq. (3) shows the algorithm of the global time.

$$\begin{aligned} T_e &= SD_{bw_i} \geq SD_{fw_{start}} \\ SD_{bw} &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{x}_{(n+1-i)} - m)^2} \end{aligned} \qquad (3)$$

where, SD_{bwi} is Standard deviation of backward, $SD_{fwstart}$ is Standard deviation of forward, Te is the ending time of impact signal and m is the meaning of background noise after impact. Eq (4) is the global time.

$$T_{Global} = T_e - T_s \qquad (4)$$

where, $Tg = global$ is the global time of impact signal. Fig. 6 represents the global time.

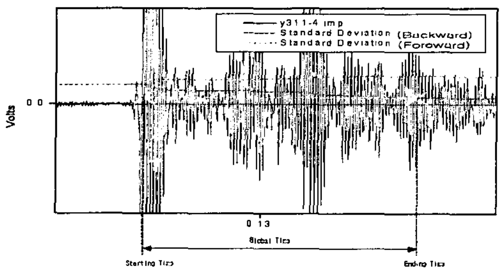
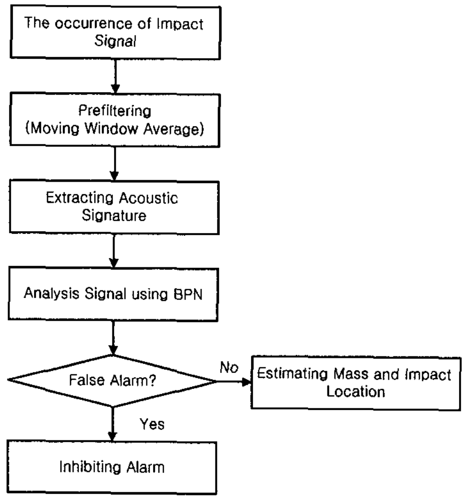


Fig. 6. Global Time

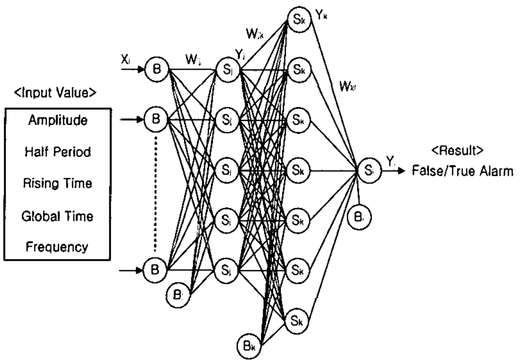
The Application of the neural network is the BP algorithm. The reason which used the BP is a simplified structure. As the input parameters are correct, then the output result is comparatively accurate. Fig. 7 shows the flowchart of BP and the structure of neural network.

3.2 Mass Estimation using a neural network

Generally, the impact signal of mass estimation used to Hertz Theory[5]. But the theory is not directly applicable to real plants because of violations of the basic assumptions. For instance, the structure of steam generator consists of two parts; the side is of cylindrical shape and upper & lower parts of hemisphere shape. The impact source is not the solid sphere. So, it is needed to modify the theory for applying to the real plant. However, the modification of theory includes the estimation error. We applied to the NN because NN is not used to the model and is not needed to the assumption. or estimating the Mass of impact signal, we choose the three parameters the same as the false alarm (Rising Time, Half period and Maximum amplitude). Also, the method of NN is BP. There is one hidden layer and five nodes. Fig. 8 shows the structure of NN for mass estimation.



(a)



(b)

Fig 7. (a) flowchart of BP (b) structure of the NN

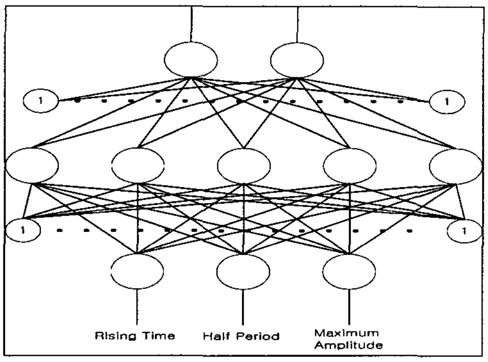


Fig 8. The structure of NN for Mass estimation

IV. Experiment Results

4.1 Test Environment

The impact test environment needs to be the same as that of normal operation. The reactor status must be more than hot standby. That is, RCP 1 was operating because temperature was fixed to 100℃. The number of impact tests at each sensor was six. The tool of the impact test was impact ball of 530 grams and 220 grams. The internal flow velocity within the S/G was 1.0844m/sec and the sensors sensitivity was 10pC/g through 50pC/g. The recorder used was TEAC RD-135T. The sampling time of the recorder was 512KHz (1/t=1.9539×10-5) and the SNR was 72dB, etc. And the false alarm data is collected twice : 5~30 % and 40~48 %(reactor power).

4.2 Application of NN

The input parameters used for false alarms to low power alarm and impact test data. All of the signal using the input at NN is normalized(0 ~ 1). The output value describes that "0" is false alarm and "1" is impact signal. The initial weighting factor is random -0.5 ~ +0.5 , learning rate is 0.6 (μ) and bias rate is 0.5(β). Momentum is 0.9. If error is less than 0.0001, then the execution is stop. Fig. 9 shows the result of the execution of the NN program.

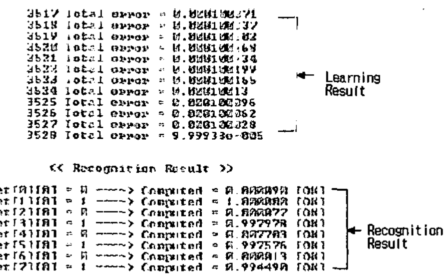


Fig. 9 The execution of NN program

The false alarm is 28 and impact is 205. Among false alarm, the error rate of false alarm is 28.8(%)(28/8) and the error rate of impact signal is 15.61(%)(205/32). And NN parameter of Mass estimation is that learning rate is 0.7(η), bias rate is 0.8(β) and Momentum is 0.9. If the error is less than 0.05, then the execution is stopped. The number of impact data is four(52g, 175g, 228g, 443g). The actual impact signal is 76.6 gram. We trained the impact data and actual signal is input to trained NN and compared with the trained result. Fig. 10 shows the trained result. In this Fig., 00 is 52 g and 01 is 175 gram and 10 is 288 gram and 11 is 433 gram. the actual signal is threes(the same gram: 76.6 gram). The result shows that "00" means the similar as 52 gram.

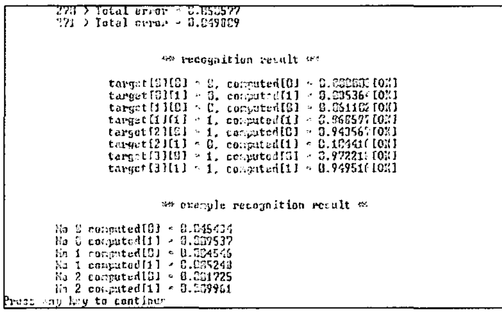


Fig. 10. The trained result of Mass estimation

V. Conclusion and Results

The Loose Part Monitoring System(LPMS) has been designed to detect, locate and evaluate detached or loosened parts and foreign objects in the reactor coolant system. It is known that loose parts in the reactor coolant systems (RCS) cause serious damage into the systems. In the existing LPMS, due to the high sensitivity of the acoustic monitoring, the detection potential for impact occurrences is comparatively high. But, too many false or unnecessary alarms can reduce the confidence of the LPMS. In the paper, firstly, we present an NN to reduce the false alarm. At the preprocessing step, the moving window average filter is adopted to reject the low frequency background noise components. And then, extracting the acoustic signature such as the Starting point of impact signal, Rising time, Half period, and Global time, they are used as the inputs to neural network. At second, we applied the NN to estimate the mass of loose part. We trained the impact test data of YGN3 using the backpropagation method. The input parameter for training is Rising Time, Half Period, Maximum amplitude. Applying the neural network to the practical false alarm data during startup and impact test signal at nuclear power plant, the false alarms are reduced to one fourth level. And the results of mass estimation showed that the NN would be applied to LPMS.

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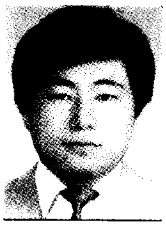

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