Evaluation of the Signal Processing Techniques for a Sodium-Water Reaction Monitoring in a Liquid Metal Reactor

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1. Introduction

As a coolant for a Liquid Metal Reactor (LMR), liquid sodium is considered to be ideal, and at the present time most of the fast breeder reactors now in operation have sodium as a coolant. It is necessary to detect precisely and immediately a leakage of water from the tubes of the steam generator in order to prevent a propagation of the sodium-water reaction.[1],[2] For the detection of a leakage from a steam generator into a sodium loop, traditionally, pressure sensors and hydrogen meters have been used. Hydrogen sensors take a long time for detection. Even though the response time of the pressure sensor itself is prompt, this sensor can not detect a micro or small leakage due to a slow build-up of pressure in the large process system. The IAEA Coordinate Program concluded that a minimum detectable leak size was about 1 gram/sec, and, in the case of less than this value, it is possible to detect the leak if the physical phenomena are well-defined. [3],[4] This paper deals with the signal processing techniques for the detection of a small size leakage, which meets the performance requirements such as the response time and leak detection sensitivity.

2. Evaluation of Signal Processing Techniques

The test data consists of two data sets. One is the argon injection data into the water space from the sodium experimental facility at KAERI. The other is the background data from the PFR Loop. The SNR of the two data sets was started about at -7 dB which is the reference value of the IAEA data. To evaluate the detection sensitivity according to the SNR change, this data was combined with a SNR set at one of the values from a maximum of 0 dB to a minimum of -20 dB.

2.1 Spectral Estimation by the AR Model

The power spectral density of the acoustic signals including the background noises has been evaluated by using the periodogram and autoregressive (AR) spectral estimation methods. Figure 3 represents the power spectral density by the periodogram. In the case of the leak signals (Figure3), the major peaks of the spectrum are 1.50 and 17.8 kHz. These bands provide an interesting insight for detecting the water leak into the sodium boundary in the case of a spectral estimation. Figure 4 represents the property change of the characteristic frequency due to the variation of the SNRs. When SNR is lower than -3 dB, the power change is very small, while if the SNR is larger than -3dB the power change is relatively large. Therefore, in the case of a high SNR of above -3 dB, the leakage could be detectable using the power spectral density.

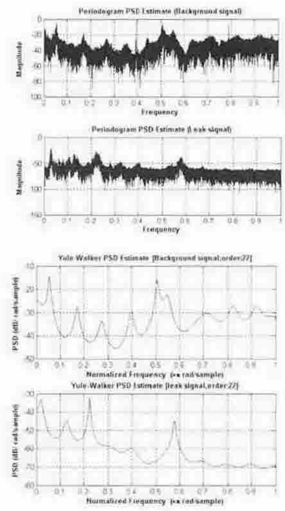

Figure 3. PSD using Periodogram(left) and AR Yule-Walker equation(right) of background signals(top) and injection signals(bottom).

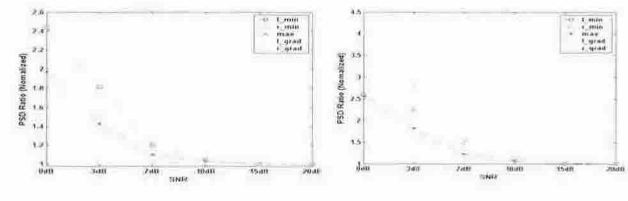

Figure 4 Change of properties of characteristic frequency due to the SNR ; PSD of normal condition (left), PSD with band-stop filter (right).

2.2 Estimation Error Method of the linear estimator

The underlying assumption with all the fault detection strategies that employ any form of modeling is that an occurrence of a fault changes the model structure of the received signal. The main idea of this method is to perform a direct comparison between the parameter estimates obtained under normal operating conditions which only generated the background noises and those obtained during the transient conditions which generated the background noise as well as the noises by the sodium-water reactions. It is expected that this error variance will be larger during fault conditions than during normal operating conditions. The mean square prediction error (MSPE) averaged over the N samples is given as

$$MSPE = \frac{1}{N}\sum_{j=1}^{N}\left|x_j - \hat{x}_j\right|, \quad (1)$$

where $\{x_j : j = 1,2,\ldots N\}$ is the actual signal value, $\{\hat{x}_j : j = 1,2,\ldots N\}$ is the predicted value, N is the total number of signals, and the error term at any value of n is given by the difference between the observed and predicted values. The ratio of the mean prediction errors of the background noise and those of the combined signals is shown in Figure 7. As this figure shows the mean square prediction error ratio eventually increases when the signal-to-noise ratio is increased. In the case of the SNR of below -10 dB, it is not possible to identify the fault condition using the mean square prediction error.

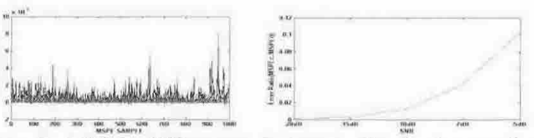

Figure 5. MSPE differences between the background and combined signals; (left) difference due to SNR change, (right) the ratio of the mean value of the MSPE differences.

Another estimation error approach is the adaptive convergence error method. Using the recursive least square algorithm, a variation of the convergence error was investigated due to an addition of the leak signals (transient state). In the case of the steady state condition, the computational result showed a good convergence within 5(five) iterations. When the leak signals were added to the background noises, the convergence of the system was worse than those of the steady state condition.(fig. 6) In the case of the SNR of below -10 dB, it is not possible to identify the fault condition using an adaptive algorithm, while we note that the leak could be detectable when the SNR is higher than -10 dB(fig. 6).

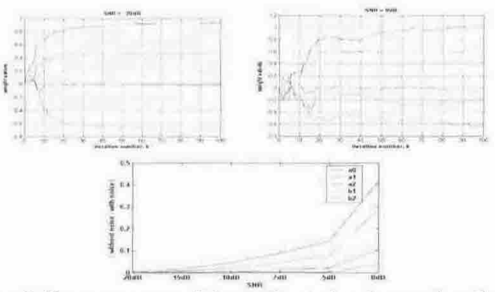

Figure 6. Convergence of the estimated values using the RLS algorithm; -20dB(top-left), 0 dB(top right), and change of the estimation errors of each parameter due to the SNR change(bottom).

3. Detection Probability by the Neural Network

To estimate the detection probability of various methods (above mentioned), neural networks (NN) have been used. Figure 7 shows the NN simulation results. As shown in the figure, the spectral estimation method without any filter has the poorest detection performance (less than -3 dB). While the modeling approaches and adaptive filtering method have a better performance than the spectral estimation method including the band stopped filtering PSD.

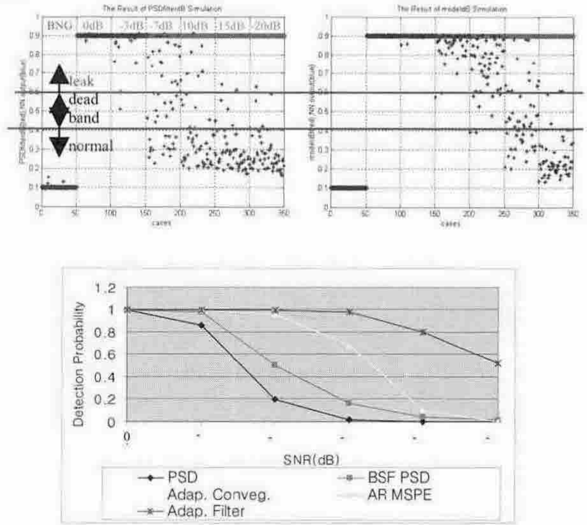

Figure 7. Fault detection probability by NN simulations; Case of PSD method with band stop filtering (top-left), adaptive convergence method(top-right), and detection probability of all evaluation methods(bottom).

4. Conclusion

Several signal processing techniques for an acoustic monitoring system have been reviewed. In the case of the signal characteristics which have a relatively high signal-to-noise ratio of the acoustic noises the spectral estimation method could be used to detect the sodium water reaction. In the case of a low SNR within -3 dB to -15 dB, the system modeling and identification methods using an autoregressive and an adaptive algorithm could be used to detect the sodium-water reaction. In the case of a SNR less than -15 dB, it is necessary that an alternative approach which combines the various signal processing techniques such as the system modeling method, adaptive method, time-frequency analysis, and a correlation method between the multi-channels be used.

Acknowledgements

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