Annals of Nuclear Energy 85 (2015) 175–182

Contents lists available at ScienceDirect

Annals of Nuclear Energy

journal homepage: www.elsevier.com/locate/anucene

Technical note

Application of a new passive acoustic leak detection approach to recordings from the Dounreay prototype fast reactor

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ARTICLE INFO

Article history:
Received 4 December 2014
Received in revised form 28 April 2015
Accepted 2 May 2015

Keywords:
Acoustic anomaly detection
Sodium fast reactor
Signal processing
Noise analysis

ABSTRACT

A new approach for passive acoustic leak detection in sodium fast reactors without using a priori knowledge on the leak noise is introduced. The new approach is tested on recordings of argon and water injections from the Dounreay prototype fast reactor under digital mixing with two types of additional noise. It is estimated that the new approach is able to detect injection of argon into sodium in a stable background noise at signal to noise ratios between −9 and −17 dB with a low false alarm rate and with few free parameters in the signal processing. For detection of water into sodium injection the corresponding signal to noise ratios range from −9 to −18 dB.

1. Introduction

Sodium fast reactors (SFRs) represent one possibility for reaching Generation IV standards in nuclear power plants. The main objectives of Generation IV are to achieve better use of fuel resources, transmutation of long-lived radioactive waste and excellent plant safety (Generation IV International Forum). The latter objective demands reliable detection of all accident precursors that otherwise could lead to more serious events. One classic example for sodium fast reactors is a leak between the secondary and tertiary circuits, inside the steam generators. Acoustic detection methods have been studied for a relatively long time in this context, e.g. culminating in a joint research program summarized by the IAEA in International Atomic Energy Agency (1997).

Acoustic detection methods may be active or passive. In the former case, the detection system itself sends signals through the monitored system. Physical changes, such as gas inlet or temperature increase may then create a detectable difference in the received signal. A passive system on the other hand consists entirely of receivers and signal processing devices, monitoring the acoustic signal and searching for signatures of the events to be detected. Active methods have the advantage of transmitting at known points in time, whereas passive systems have to detect changes at any time.

Many earlier works on leak detection have assumed significant knowledge on the signal to be detected, e.g. through the use of experimental data. E.g. Srinivasan et al. (1993) suggested taking power spectral density (PSD) ratios to calculate frequencies where the leak noise is strong relative to the background. One may note that taking the ratio will give rapidly increasing weight to spectral regions where background noise is decreasing, without any regard to whether the leak noise spectrum has significant content in this region or not. Also, neural network methods such as the one used in Kim et al. (2010) have been popular in the literature. This approach however requires a substantial training database of labeled sounds. Also the twice-squaring method used in Hayashi et al. (1996) uses quite a lot of a priori information, in particular to define cut-off frequencies for its pass-band filters.

A common drawback of the above-mentioned methods is that acoustic signals in general are very dependent on their surrounding environment and difficult to model. The leak noise to be detected in a real reactor system might therefore have considerable variation since experiments closely imitating any incident situation in the real system is not possible. Therefore, methods that a priori look for any change in the signal are of interest, see for example the approach of Beauseroy et al. (2012) which used autoregressive-models of the signals. Some works such as Pridohl et al. (1984) recommended focusing on other basic time-domain features (as opposed to using spectral methods) such as root mean square (RMS) value and various pulse based statistics. Injections

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http://dx.doi.org/10.1016/j.anucene.2015.05.010
0306-4549/

were in this work indeed found to produce a more pulsative noise compared to the normal background which had a more stable output power. Signal-to-noise ratios were not estimated but seem to have been significantly higher than the −17 dB requirement given in International Atomic Energy Agency (1997). The authors of Pridohl et al. (1984) also based their recommendation of not using spectral methods on a viewpoint that leak specific resonances do not exist, but this seems very unlikely in the view of other and more recent works.

In order to combine some advantages of successful earlier methods and eliminate the dependency on prior knowledge of the signal to be detected, we propose and demonstrate that a detection approach originally based on pre-selecting frequency components of the PSD, can be modified to work also when the components are selected online by comparison to a background noise database. To avoid the problem of different weightings due to the spectral ratio mentioned above, the comparison is made using PSD differences, i.e. by spectral denoising.

The details of the new approach are given in Section 2. In Section 3 we describe an application of the proposed method to argon and water injection recordings from the Prototype Fast Reactor (PFR) in Scotland. The method's performance under mixing with two types of additional noise is investigated and compared to that of an approach where frequencies for detection are chosen a priori from an injection noise database. Results and discussion are presented in Sections 3.5 and 3.6 and the conclusions are given in Section 4.

2. Signal processing

2.1. Power spectral density

An estimate of the power spectral density $X(f)$ of a signal $x(t_n)$ sampled at f_s Hz during a time window of length N samples is given by

$$X(f) = \frac{1}{f_s N}\left|\sum_{n=0}^{N-1} h(t_n)x(t_n)e^{-j2\pi fn}\right|^2 \tag{1}$$

where $h(t_n)$ is some windowing function. $X(f)$ is a function which expresses the power density present in each frequency of the signal. By performing this transform in successive short time windows (sliding windows) of the studied signal, information of the current frequency content of the signal is extracted. The formula of Eq. (1) yields a quite noisy representation of the spectrum. To avoid this we use the Welch method, Welch (1967) which reduces this noise at the cost of lower spectral resolution. This method consists of averaging Eq. (1) over several shorter subwindows of length N_{sw} overlapping each other by N_{ol} samples. The result is a power spectral density estimate $X(f_i)$ defined on the discrete frequency bins f_i.

2.2. Using the PSD

The possibly simplest approach to signal change detection is the so-called *energy detection*, i.e. simply monitoring the generalized power carried by the signal, i.e.

$$P(m) = \sum_i X(f_i, N_m) \tag{2}$$

where m enumerates sliding windows of length N_m. Even if such a measure is not useful to perform automatic recognition of different sounds, the signal power may still be a relevant measure for detection under certain conditions.

For monitoring of changes located to selected frequencies or frequency bands $f_i, i \in I_{sel}$, e.g. the power spectral density sum or *PSDSUM* has been proposed (Srinivasan et al., 1993). It is defined by

$$PSDSUM(m) = \sum_{i \in I_{sel}}^{N} X(f_i, N_m) \tag{3}$$

The *PSDSUM* feature is a type of energy detection localized to the selected frequencies or frequency bands f_i.

The authors of Srinivasan et al. (1993) also showed that scalar functions of a covariance matrix for the same selected frequencies, such as the trace and determinant, yielded even better discrimination. The covariance matrix is given by

$$\mathbf{CM}(X(f_i, N_m), X(f_j, N_m)) = E[(X(f_i, N_m) - \mu_{X(f_i)})(X(f_j, N_m) - \mu_{X(f_j)})] \tag{4}$$

Note that discrimination was measured in terms of the detection margin, given by

$$DM = 20\log\left(\frac{\widetilde{D}_{det}}{\widetilde{D}_{non-det}}\right) \tag{5}$$

where $\widetilde{D}_{det}$ and $\widetilde{D}_{non-det}$ denote the mean level of the discriminating function D in a detection and a non-detection region of the signal respectively. It was also shown in Marklund and Dufek (2014) that features based on the covariance matrix with even higher detection margin than the trace and determinant could quite easily be created. Consequently, there exist powerful features for passive leak detection based on selected components of the PSD, but methods for performing this selection online without knowledge of the sounds to be detected have been missing.

2.3. A new approach for online frequency selection

In Srinivasan et al. (1993) and Marklund and Dufek (2014), frequencies for feature calculation were selected a priori by taking the ratio of a PSD of a detection region of the signal and a PSD of a pure background noise. The frequencies thus yielding the highest ratios were then used in the feature calculation. In a somewhat more realistic scenario, the best frequencies for detection should be selected by use of an injection noise database containing many background and leak recordings from experiments and/or the system to be monitored.

Both of these approaches might, however, turn out to be unrealistic for application to a real reactor system since recordings of leaks or experiments closely resembling the leak situation in the real system will probably never be available. Our suggested approach is instead to use only a background noise database and select frequencies online as the ones deviating the most from their level in this database. Precisely, we measure the deviation as a difference between spectra instead of a ratio and use the frequencies that produce the largest difference in the PSD.

More specifically, a long background noise recording $x_{bg}(t_n)$ is made and the PSD of this recording, $X_{ref}(f_i)$ is calculated. Then, during detection, the unknown signal $x(t_n)$ is analyzed by sliding time windows N_m and for each new time window, a PSD residual, XR is calculated according to

$$XR(f_i, N_m) = X(f_i, N_m) - X_{ref}(f_i) \tag{6}$$

where $X_{ref}(f_i)$ is normalized to have the same power as $X(f_i, N_m)$ when the detector is started.

For online frequency selection, an average residual over the past NTW time windows $N_{m-NTW,\dots,m}$ is repeatedly created, i.e.

$$\widetilde{XR}(f_i, N_m) = \frac{\sum_{k=m-NTW}^{m} XR(f_i, N_k)}{NTW} \tag{7}$$

and the K largest components of $\widetilde{XR}(f_i, N_m)$ are chosen as input to features such as the ones described in Section 2.2. The set of frequency indices selected online will be denoted $I_{max}(m)$, i.e.