CRITERIA FOR ASSESSING THE QUALITY OF SIGNAL PROCESSING TECHNIQUES FOR ACOUSTIC LEAK DETECTION

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1.0 INTRODUCTION

Early detection of water or steam leaks into sodium in the Steam Generator units of Liquid Metal Fast Breeder Reactors (LMFBRs) is an important requirement from economic and safety considerations and acoustic leak detection technique is considered to be a promising diagnostic method. This technique is being developed in most of the countries interested in LMFBR programme. In this method, acoustic noise emitted by the steam leak and the resulting sodium-water reaction is sensed by acoustic transducers and this signal is processed using signal analysis techniques to detect leak signal in the presence of background noise. From the view point of a plant operator, the detection technique must be reliable: a leak must not be missed; a spurious leak signal must not occur; a leak must be detected within a certain time and with good discrimination. Hence it becomes necessary to assess the quality of detection and signal processing (analysis) techniques with respect to meeting certain reliability criteria.

Sodium boiling noise detection is another important area in which acoustic detection technique is used as a diagnostic method. International Atomic Energy Agency (IAEA) organised a co-ordinated Research Programme (CRP) on signal processing techniques for sodium boiling noise detection during 1985-88. In this CRP participating Laboratories evaluated their analysis techniques against a set of criteria and the results are given in Ref.1. The second stage of this CRP titled "Acoustic signal processing for the detection of boiling or sodium\water reaction in LMFBR" commenced in June 1990.

In this paper the criteria used in the first CRP to assess the quality of signal processing techniques for sodium boling noise detection are highlighted. Signal processing techniques using new features sensitive to boiling and a new approach for achieving higher reliability of detection, which were developed at Indira Gandhi Centre for Atomic Research (IGCAR) are also presented. Similar criteria and methods would also be applicable for assessing the quality of acoustic leak detection techniques.

One of the aims of this presentation is to initiate a discussion among the specialists participating in this meeting, on the criteria to be set to assess the quality of acoustic leak detection techniques (and in turn the signal processing methods), based on their experience in failure and failure propogation in steam generators.

2.0 IAEA-CRP ON BOILING NOISE DETECTION [1]

Data for this CRP was made available from out of pile boiling experiments (KNS-I, KfK, FRG) [2] and from in-pile boiling experiments (BOR-60, USSR) [3]. Signal processing techniques were evaluated against the criteria discussed below.

2.1 Evaluation of the quality of signal processing techniques:

Quality or reliability of a detection method can be assessed in terms of its ability to detect boiling signal in the presence of background noise with low probabilities of false or spurious alarm (Ps) and missing a boiling signal (Pm). In United Kingdom, an integrated false trip rate of 0.1 per year (less than 10^{-8} per second decision time) is demanded together with a probability of missing a boiling signal of less than 10^{-3} per second decision time. It was decided to consider the same targets for the CRP also.

To calculate Ps and Pm, a large number of estimates of the feature of the signal (like RMS value, kurtosis, pulse counting etc.) under test were calculated for background and boiling noise signals and probability density function (PDF) of the estimates was determined. The fraction of area of the PDF curve above a given threshold for background noise and below that threshold for boiling noise was defined as Ps and Pm respectively (See Fig.1). Values of Ps and Pm depend on threshold level and averaging time. In the case of single features, the PDF of the feature estimates for background and boiling noise lie in a two dimensional space and the threshold is a line parallel to the vertical axis.

In multivariate pattern recognition techniques (4), multiple features of noise signals are evaluated and considered simultaneously for detecting the boiling. For N multiple features, the distribution of feature estimates would be in (N+1) dimensional space and boiling threshold level would be a surface in this space seperating the boiling and non-boiling regions. In general, various features considered may not be independent of each other and may have some correlation among them. Then if $\bar{z}$ is the threshold, Ps or Pm is given by,

$$P_s \text{ or } P_m = \frac{1}{(2\pi)^{N/2}(\Delta)^{1/2}} \int_{\bar{z}}^{\infty} d\bar{x}\, \exp\left[-\tfrac{1}{2}\left\{(\bar{x}-\bar{\mu})^T \Sigma^{-1} (\bar{x}-\bar{\mu})\right\}\right]$$

where the integrand represents the N-dimensional Gaussian distribution of the mean value of the features. For calculating Ps, features correspond to background noise and for calculating Pm, these correspond to boiling noise. In the above equation,

$\bar{\mu}$ - mean value of the feature

$\bar{x}$ - vector

T - transpose of the vector

Δ - determinant of the covariance matrix

Σ - Covariance matrix of the feature

Shifting of threshold to decrease Ps tends to increase Pm. An optimum value of threshold for a given feature was selected in the CRP by maximising the product (1-Ps).(1-Pm). Alternately, threshold giving a minimum of Ps+Pm could be considered as the optimum threshold. In fact an exercise done to check the two criteria, gave nearly the same result.

The other two criteria assessed were the minimum averaging time (detection time) and the level of discrimination between boiling and non boiling phases of the signal. For boiling noise detection, a method may be considered satisfactory, if it is able to detect boiling in a few seconds time, while achieving the targeted Ps and Pm. Level of discrimination is the ratio of the value of the feature in the boiling and background regions and is mainly of psychological significance.

As part of this CRP, a number of features were evaluated and asessed at IGCAR. Some of the major contributions from IGCAR, which also have relevance to leak detection are described in the following sections.

2.2 PDF features sensitive to boiling noise [5]

From an indepth analysis of PDFs of the signal in background and boiling regions, new features which are sensitive to boiling were identified by IGCAR. Fig.2 depicts the PDFs of background and boiling noise regions, with the background PDF more sharply peaked. It was observed that the area under the boiling PDF was more than the area under background curve, below a certain amplitude level (designated area A1) and also above a certain amplitude level (designated Area A3). In the intermediate amplitude range (Area A2), area under the background PDF was more. A large number of PDF estimates were evaluated to verify that statistically these segmented areas remain sensitive to boiling. From this analysis, Areas A1 and A3 emerged as new features which are sensitive to boiling noise. Table-I summarises the results obtained for different data.

Subsequently these features alongwith other well known features like RMS value, pulse counting etc. were used in multifeature pattern recognition techniques. Two techniques, namely the multivariate pattern recognition method with six features and a two generation adaptive learning network method with three features were evolved at IGCAR and successfully used for detecting the boiling signal. Results are described in Ref.6,7 and 8. Multifeature analysis was found to be superior to individual feature analysis.

The increase in segmented areas A1 and A3 of the PDF estimates during boiling is due to the impulsive nature of the boiling signal caused by bubble collapse. Similar trend can be expected in the case of a leak signal also due to increase in the standard deviation (or roughness) of the signal caused by different mechanisms like reaction noise, bubble noise and jet noise. A close examination of the background and leak PDFs estimated for the signal or its features like RMS value would confirm this behaviour. At IGCAR, such data is not available at present to verify this hypothesis. However it is interesting and encouraging to note that the PDF of RMS value plots for no leak and leak signals given in Ref.9 by E.Pridohl et al clearly indicate areas similar to A1, A2 and A3 which are sensitive to the leak.

The multifeature pattern recognition techniques evolved at IGCAR will find appliation in leak detection work also. In the analysis carried out, multiple features of the signal from one transducer were used. It is possible to extend this technique to signals (and their features) from different transducers mounted on the steam generator and improve the detection reliability.

2.3 <u>A new approach for achieving targeted Ps and Pm (6,7,8,10):</u>

In addition to the segmented areas, other features like RMS value, pulse counting, RMS value of squared data, area under power spectrum density plot etc. were evaluated at IGCAR as independent features and also as joint features in pattern recognition techniques to detect boiling signal. Analyses indicated that Ps and Pm values achieved for the optimum value of threshold were generally much higher than the targeted values. Increasing the averaging time, i.e. increasing the length of data used to calculate the feature, is generally expected to reduce Ps and Pm. Analyses carried out at IGCAR on the boiling noise data indicated that for data with good signal to noise ratio, Ps could be reduced to desired level by increasing the averaging time. But for data with poor signal to noise ratio, this approach was not possible. Above a certain averaging time, Ps did not continue to show a decreasing trend. Hence a new statistical approach was evolved at IGCAR to achieve the desired low levels of Ps and Pm.

2.3.1 <u>Principle of the new approach</u>:

The new method is based upon the criterion that decision to declare presence of boiling is not based upon a single estimate of the feature crossing the threshold. $\underline{N}o$ estimates are evaluated successively and boiling is detected by checking whether $\underline{n}o$ or more estimates indicate boiling. If Ps is the probability of spurious alarm for a single estimate crossing the threshold, the probability of spurious alarm when $\underline{n}o$ or more estimates indicate boiling is given by,

$$P'(s) = \sum_{n=no}^{No} \frac{No!\, Ps^{n}\, (1-Ps)^{No-n}}{(No-n)!\, n!}$$

Similarly if Pm is the probability of missing the boiling signal when a single estimate does not indicate boiling, the probability of missing boiling when (no-1) or less estimates out of No estimates do not indicate boiling, is given by,

$$P'(m) = \sum_{n=No-(no-1)}^{No} \frac{No!\, Pm^{n}\, (1-Pm)^{No-n}}{(No-n)!\, n!}$$

From the above approach, it is always possible to achieve target probability values by selecting appropriate no/No criterion for any values of Ps and Pm and is thus very attractive. Sampling, averaging and decision times relating to a digital processing system using no/No criterion are shown in Fig.3. Same approach can also be followed in multifeature pattern recognition methods.

This approach assumes that the successive estimates are statistically independent. If they are not independent, the estimated values of Ps and Pm will be lower than what they are in reality. In spite of this limitation, this approach offered an attractive solution for achieving higher levels of reliability in boiling detection.

2.3.2 Results from application of the new approach to BOR-60 data:

no/No criterion was applied to KNS-I data and BOR-60 data to detect successfully the onset of boiling with the targeted Ps and Pm satisfied. Results obtained from the wave guide transducer of BOR-60 data, for some of the features and for the multivariate pattern recognition technique are summarised in Table-II. The decision times shown in the Table also meet the target. (Decision time corresponds to the data length for No feature estimates and does not include the time required for feature estimation and other computations).

It is expected that a similar approach will find application in enhancing the reliability of acoustic leak detection in steam generators.

3.0 EVOLVING CRITERIA FOR ACOUSTIC LEAK DETECTION

If an acoustic leak detection system is to be incorporated into the plant protection system, its reliability must be established. Acoustic leak detection system is expected to play a supplementary role to hydrogen detectors and will be mainly contributing to detecting rapidly escalating leaks. It is desirable to detect the leak and isolate the steam generator unit before adjacent tubes fail due to wastage. If this criterion cannot be satisfied, the minimum requirement is to detect the leak and isolate the steam generator unit before rupture discs get activated, for most of the likely leaks. Time available for detection depends on the leak rate, design of steam generator and operating conditions. Detection time available is less at higher leak rates; but the signal level is expected to be more at higher leak rates. Better signal to noise ratio at higher leaks would require less processing time.

Probability of a spurious trip is governed by economic considerations. As assumed for sodium boiling detection, a value of Ps equal to 0.1 per year per secondary loop may be considered reasonable for acoustic leak detection also. The achievable value of Pm will depend on the type of distribution of features for background noise and leak signal. It is expected that information on this aspect will emerge during the second stage of CRP, when acoustic signal from steam generator leak experiments will be made available to the particpants.

4.0 CONCLUSIONS

In this presentation an effort has been made to highlight the criteria followed in the IAEA-CRP on sodium boiling noise detection for assessing the quality of signal processing techniques. Some of the contributions from IGCAR to this CRP, which also have relevance to leak detection have been presented. It is expected that the approach evolved to improve reliability of sodium boiling detection, will be effective in leak detection also.

5.0 ACKNOWLEDGEMENT

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6.0 REFERENCES

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TABLE - I

RESPONSE OF FEATURES A1, A2 AND A3 TO BOILING NOISE

Feature	KNSI: OdB SNR		KNSI:-17.5dBSNR		BOR 60:Wave Guide	
	Background	Boiling	Background	Boiling	Background	Boiling
A1 mean	0.74	44.2	0.11	1.22	200.7	227.5
A1 standard deviation	1.24	34.5	0.54	1.63	11.8	14.9
A2 mean	1405.6	1025.2	1027.5	1009.4	697.4	638
A2 standard deviation	37.9	89.2	27.4	27.2	17.8	19.6
A3 mean	188.8	498.6	433.1	495.3	94.8	123.3
A3 standard deviation	40.8	130.6	37.3	39.7	9.7	9.9

Note: a) SNR - Signal to noise ratio

b) Units are arbitrary; values may be compared only for the same data

TABLE - II

APPLICATION OF nO/NO CRITERION

Data : BOR-60; Wave guide transducer

Feature	Averaging time (ms)	Ps%	Pm%	no/NO	Decision time (s)
Area A1	6.4	14	17	18/30	0.192
Area A2	6.4	6	6	9/13	0.0832
Area A3	6.4	7	8	10/15	0.0960
RMS	32	14	18	19/40	1.280
RMS squared	32	16	17	18/40	1.280
Area under PSD	6.4	8	3	9/20	0.128
Multivariate pattern recognition	32	21	9	22/31	0.992

Note: a) Ps and Pm correspond to the probabilities for single threshold crossing

b) no/NO selected results in targeted Ps and Pm

c) For definition of averaging time and decision time, refer Fig.3

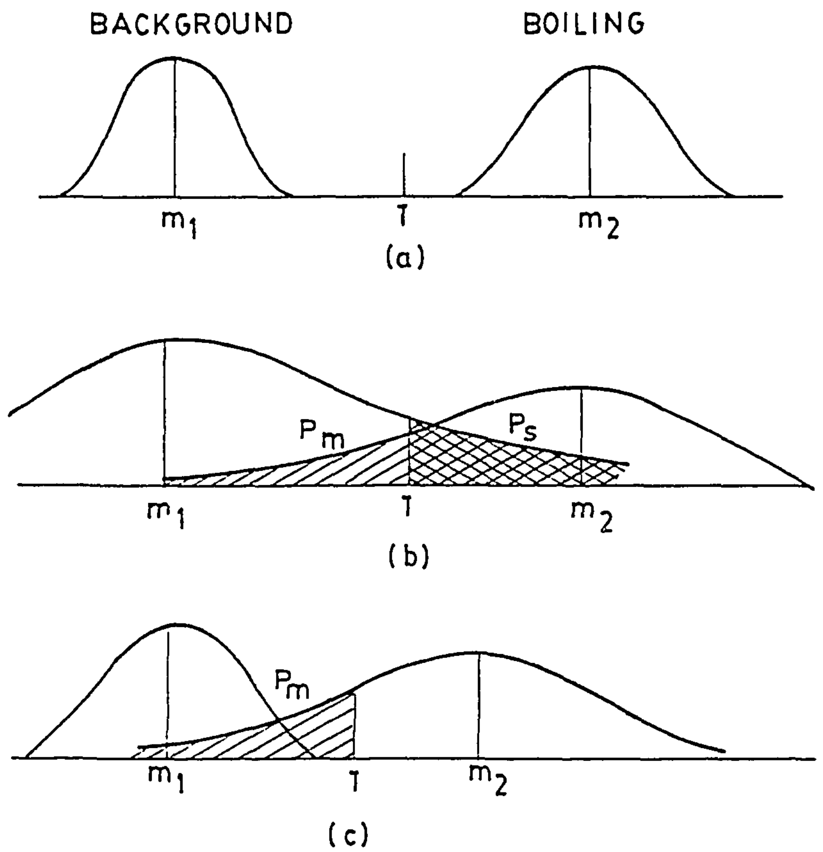

Fig-1. SCHEMATIC DISTRIBUTION OF FEATURES FOR BACKGROUND AND BOILING NOISE.

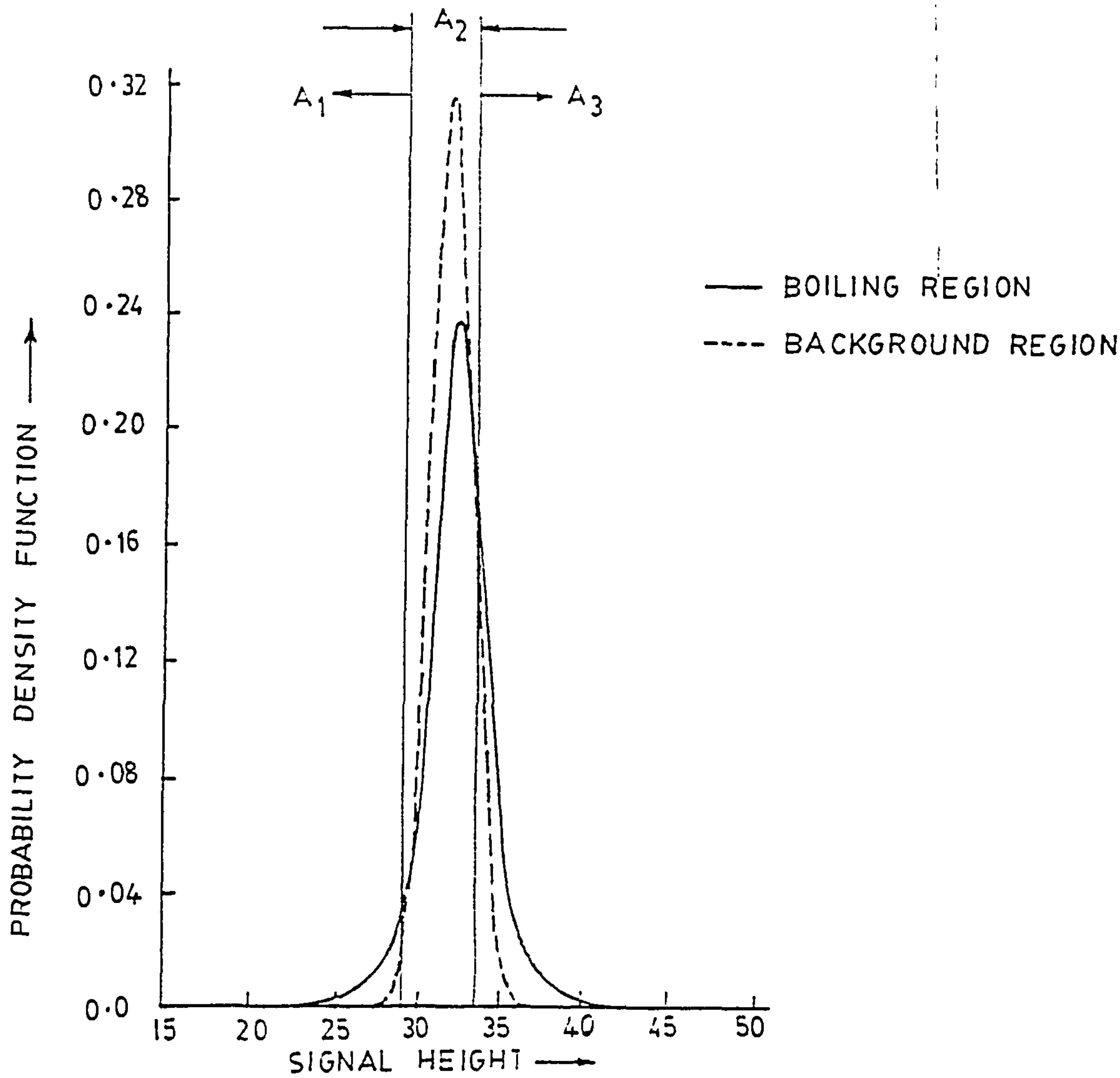

Fig-2. PROBABILITY DENSITY FUNCTION OF THE SIGNALS

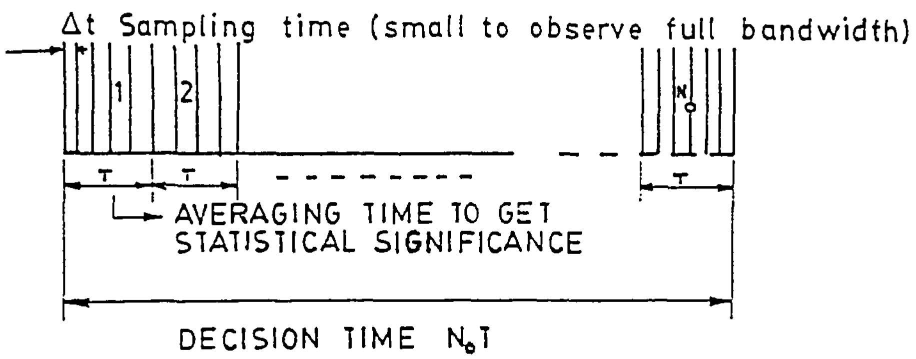

Fig-3. SAMPLING, AVERAGING/DETECTION AND DECISION TIMES