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Sodium boiling detection in a LMFBR using autoregressive models and SVM

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Abstract:
This paper deals with acoustic detection of sodium boiling in a Liquid Metal Fast Breeder Reactor (LMFBR) cooled by liquid sodium. As sodium boiling induces acoustic emission, the method consists in real time analysis of acoustic signals measured through wave guides. Auto Regressive (AR) models are estimated on sliding windows and are classified in boiling or non-boiling models using Support Vector Machines (SVM). One of the difficulties to cope with is disturbances due to the influence of some environment noises like the liquid coolant cavitation, vortex flow, shaft vibration and mechanical pump noise. These disturbances can generate false alarms or mask the boiling. The proposed method is designed to be robust toward these disturbances. Furthermore, the SVM are designed to be robust toward the operating mode changing. The application for online monitoring is made on data obtained from French nuclear power plant Phenix and boiling sound signals generated from laboratory experiments. Different acoustic boiling sound levels are used and the effectiveness of the method is shown by the good detection rate and its low false alarm rate even for low acoustic boiling sound level.

1. INTRODUCTION

Early fault detection systems are required to insure safety in every production plant. The earlier a fault is detected, the smaller are the damages for the plant. In a Liquid Metal Fast Breeder Reactor (LMFBR) cooled by liquid sodium, the reactor core is one of the main parts which requires monitoring. The fission reaction is produced inside the core by fuel assemblies and its rate is controlled by control rods. The heat produced during the fission reaction is carried outside by the coolant (here liquid sodium).

If the heat removal by the coolant decreases, the coolant temperature starts rising and it could lead to coolant boiling. This decreased heat removal can damage the fuel. For all these reasons, real time monitoring of the core temperature is needed. Some efficient methods based on temperature measurements are used for early detection of abnormal overheating. Since the early 1960s, various acoustical methods have been introduced to liquid-cooled fast reactors monitoring, mainly for the detection of liquid metal's boiling (see for instance Anderson et al. [1970], Macleod [1988]). A number of parametric methods are available for acoustic sound analysis. These include methods such as wavelet analysis, Power Spectral Density (PSD) and autoregressive (AR) modeling. In order to strengthen and diversify these detection methods, acoustic method based on ambient sound measured through waveguide is also proposed in this paper.

Hayashi et al. [1996] developed a twice-squaring method for real time sodium boiling detection which consists at enhancing the signal to noise ratio by non-linear amplification of a band limited signal. Band-pass frequency is selected from PSD graphs, focussing on pulsive nature of boiling signal. It consists of five steps: band-pass filtering, squaring, another band-pass filtering and squaring and integration. A low pass filter is afterwards applied to obtain the feature signal. The threshold for boiling detection is calculated from the mean and the standard deviation of the feature signal in non-boiling conditions. If the mean and the standard deviation change when the operating

conditions change, it sets up the problem of choosing an adequate value for the detection threshold.

Autoregressive model-based detection techniques are also proposed in the literature. Hayashi [1997] used an Auto Regressive (AR) model for sodium leak detection. Assuming that in normal functioning, the prediction error from the AR model follows a gaussian distribution, he showed that this prediction error deviates from gaussian distribution in non-normal functioning conditions. Inujima et al. [1982] also worked on boiling detection by analysing residual time series data of autoregressive model. The underlying assumption behind all these model-based fault detection strategies is that the occurrence of a fault changes the model structure (or caracteristics) of the received signal. An appropriate comparison between parameter estimates obtained under normal operating conditions and those obtained during any further operating conditions may indicate the onset of an anomaly. However, even in normal functioning conditions, the AR models may change with the operating modes of the LMFBR. And this can lead to wrong detection or false alarm.

In this paper, we present an improved approach for boiling detection using AR models. First, a filter is used in order to reduce the influence of the changing of the operating modes and the ambiance noise. And secondly, instead of estimating only one AR model, we propose to estimate several AR models using a sliding time window and then classify these AR models into boiling and non-boiling models by a strong classification method like Support Vectors Machines (SVM). Moreover, AR models low computational complexity may be useful in an online implementation of our proposed method.

The paper is organized in 5 sections. Section 2 presents the experimental data, deals with fault condition data generation and data preprocessing. In section 3 the proposed boiling detection method is presented. Section 4 provides the results of the method on the experimental data. At last, summary and conclusion are outlined in section 5.

2. PRESENTATION OF THE EXPERIMENTAL DATA

2.1 Acoustic background noise recording in non-boiling operating

These data are furnished by Commissariat l'Energie Atomique et aux énergies alternatives (CEA). They consist in records of the acoustic background noise of the Phenix nuclear plant (France) in 2009 made in normal functioning i.e. without any boiling. The two wave guides are called sensors 1 and 2 in this paper. The sampling frequency is 500 kHz. These records correspond to different operating modes whose parameters are presented in Table 1.

2.2 Data preprocessing

In non-boiling condition, the background signal can be made of noise from different sources like cavitation, vortex flow, shaft vibration and pumps. We assume the non-existence of cavitation, vortex and shaft vibrations in the LMFBR acoustic background noise during the experiments. The pump noises which are the most energetic part of the background noise are filtered using a 5th

Table 1. Parameters of the operating modes

Parameter	Unit
Power of the reactor	MW
Inlet temperature of the core	°C
Outlet temperature of the core	°C
Primary pump 1 speed	RPM
Primary pumps 2 and 3 speed	RPM
Secondary pumps speed	RPM
Overpressure	mB

order Butterworth filter with a 2 kHz cut-off frequency. By using this cut-off frequency, the filtering doesn't affect the sodium boiling acoustic noise frequencies (see Hayashi et al. [1996] for more details). The filtered signals are used in the rest of the paper.

2.3 Boiling data generation

Liquid metal boiling sound recording   Data supplied by CEA contain only records during normal functioning (non-boiling) of the power plant. To check the efficiency of the proposed method, background noise in boiling conditions is needed. As these data are not available, they could be generated by mixing non-boiling background noise with liquid sodium boiling sound. Sodium boiling experiment may be very complicated and very costly. Therefore, potential substitutes of liquid sodium for which the boiling experience will be simpler to perform are considered. Water is proposed by Bomeluberg [1968] as an efficient substitute of liquid metal when hydraulic characteristics are concerned. Prakash et al. [2011] have also used water instead of sodium for hydraulic experimental studies on a fast breeder reactor due to similar hydraulic characteristics of sodium and ease of testing. But one must be careful as far as the heat transfer is concerned.

Obviously, complete thermal hydraulic and acoustic scaling of a sodium boiling loop to a water boiling loop could not be assumed. However a partial transposition of the boiling source with a scale reduction factor and a power reduction factor can (see Vanderhaegen et al. [2013] for more details).

To generate the background noise in boiling conditions, water boiling sound has been recorded and afterwards injected into the background noise supplied by the CEA. The boiling sound has been recorded (with a 262 144 Hz sampling frequency) from boiling water in a steel container at four different stages described in Lienhard IV and Lienhard V [2000]: isolated bubbles regime, slug and columns regime, transitional boiling and film boiling.

Boiling condition background data generation   The non-boiling background signal frequency is reduced to 262 144 Hz to match those of the boiling sound. Consider a normalized (i.e. divided by its standard deviation) non-boiling signal s_s and a normalized boiling sound s_b of the same length M (number of samples) of common sampling frequency $F = 262\ 144$ Hz. Both signals have a duration of M/F seconds. Let t ($0 \leq t \leq M/F$) the onset boiling time. The number of points before t is $m = \lfloor F \times t \rfloor$ (i.e the integer part of $F \times t$). Assuming the acoustic effect of the boiling to be additive, the boiling condition signal is generated as:

$$s_{\beta,t}[n] = \begin{cases} \mathbf{s}_s[n] & \text{if} \quad n < m \\ (1-\beta)\mathbf{s}_s[n] + \beta\mathbf{s}_b[n-m+1] & \text{otherwise} \end{cases} \quad (1)$$

where $\beta \in [0,1]$ is the proportion of boiling noise injected.

The Signal to Noise Ratio (SNR) is calculated as:

$$\text{SNR} = 20\log_{10}\left(\frac{\beta}{1-\beta}\right)$$

3. PRESENTATION OF THE METHOD

Our proposed method is a supervised learning with two steps: learning and test. For a given SNR, the learning set is composed of AR models estimated on both boiling and non-boiling condition signals. To make this method robust, the non-boiling background signals are of different operating conditions. A Support Vector Machines (SVM) classifier (or decision rule) is built from this learning set.

In the test step, online supervision is done by applying the classifier to the current estimated AR model. The latter is classified into one of the boiling and non-boiling classes depending on the values of their components. In the remainder of this section, the AR models estimation method is proposed, afterwards the SVM classification method is introduced.

3.1 AR models estimation

Here we present the Autoregressive modelling used in this study. Autoregressive (AR) modelling (see Kay [1988] for example) belongs to a class of modern spectral analysis techniques generally known as autoregressive moving average (ARMA) time series modelling. The AR method is the preferred method for this class since it is the best compromise between temporal resolution and speed, efficiency and simplicity of algorithms.

Consider a $R \times N$ matrix $s_w = \left[s_w^1 \mid \cdots \mid s_w^R \right]^T$ of N-samples records by R sensors of the signal on time window N/F, where $\mid$ is the concatenation operator, w is the signal number, s_w^r is a vector of N samples recorded by sensor r ($r = 1, \cdots, R$) and F is the sampling frequency. Assuming s_w^r is stationary, the p_r-order AR model associated to s_w^r is the vector $a_w^r = \left(a_{w,1}^r, \cdots, a_{w,p_r}^r \right)$ such as the sample $s_w^r[n]$ can be estimated as described by Eq. (2):

$$\widehat{s_w^r}[n] = -a_w^r \, (s_w^r)_{[n-p_r:n-1]} \quad (2)$$

where

$$(s_w^r)_{[n-p_r:n-1]} = (s_w^r[n-p_r], \ldots, s_w^r[n-1])^T$$

Minimizing the total prediction error, it is proved (Makhoul [1975], O'Shaughnessy [1988]) that a_w^r is solution of the *Yule-Walker equations*:

$$\Phi_w^r a_w^r = -\phi_w^r \quad (3)$$

with ϕ_w^r a vector of p_r components calculated as:

$$\phi_w^r[i] = \sum_{k=i}^{N} s_w^r[k]s_w^r[k-i], \quad i = 1, \ldots, p_r \quad (4)$$

and Φ_w^r a $p_r \times p_r$ symmetrical matrix whose components are:

$$(\Phi_w^r)_{i,j} = \phi_w^r[i-j], \quad 1 \leqslant i,j \leqslant p_r \quad (5)$$

The R AR models thus obtained could be combined into a unique multi-sensor AR model as:

$$a_w = \left(a_{w,1}^1, \cdots, a_{w,p_1}^1, a_{w,1}^2, \cdots, a_{w,p_2}^2, \ldots a_{w,1}^R, \cdots, a_{w,p_R}^R \right)^T$$

In the rest of this paper, the multi-sensor model a_w is used instead of the R one-sensor models a_w^r ($r = 1, \ldots, R$) and its number of components is called p.

3.2 The monitoring method: Support Vectors Machines

Once a multi-sensor AR model is obtained, this latter should be classified as boiling model or non-boiling model. Support Vectors Machines (SVM), as described in Hamel [2009] and Schlkopf and Smola [2002], are used for this purpose. The SVM, which are one of the most popular classification methods, can be seen as a method for constructing a decision rule with theoretical guarantees of good predictive performance (i.e. good quality of classification on unseen data). They consist in finding a maximal margin hyperplane separating the two classes: boiling (say "+1" class) and non-boiling models (say "-1" class).

Let $\{a_1, a_2, \ldots, a_L\}$ a learning set composed of both boiling and non-boiling AR models and y a function of one multi-sensor model such as $y(a_w)$ equals +1 if a_w is a non-boiling multi-sensor model and -1 otherwise. Let K a two-variables function (called gaussian kernel) such as the image of two multi-sensor models $a_w = (a_{w,1}, \cdots, a_{w,p})^T$ and $a_v = (a_{v,1}, \cdots, a_{v,p})^T$ equals:

$$K(a_w, a_v) = \exp\left(-\frac{1}{2\rho^2}\|a_w - a_v\|^2\right) \quad (6)$$

where $\rho > 0$ is a parameter called the *bandwidth* of K.

The maximization of the margin is equivalent to the following constrained optimization problem:

$$\begin{cases} \max_{\alpha} \left[e^T\alpha - \frac{1}{2}\alpha^T H\alpha \right] \\ \\ \text{subject to} \quad (y_a)^T\alpha = 0 \\ \text{and} \quad 0 \leq \alpha \leq C \end{cases} \quad (7)$$

where $\alpha = (\alpha_1, \cdots, \alpha_L)^T$, $e = (1, \cdots, 1)^T$, $y_a = (y(a_1), \cdots, y(a_L))^T$ are vectors of length L, H is a $L \times L$ matrix of components:

$$H_{w,v} = \alpha_w\,\alpha_v\,y(a_w)\,y(a_v)\,K(a_w, a_v)$$

and C is a regularization constant for outliers.

Let $\alpha^* = (\alpha_1^*, \cdots, \alpha_L^*)^T$ the problem and b^* a real value calculated as:

$$b^* = \frac{1}{L}\sum_{w=1}^{L}\left(y(a_w) - \sum_{v=1}^{L} \alpha_v^* y(a_v)K(a_w, a_v) \right)$$

For a new time window signal s_w, the diagnosis with AR and SVM (AR-SVM) can be done in the following steps:

(1) Compute the multi-sensor model a_w associated to s_w.
(2) Compute the feature value:

$$f(a_w) = \sum_{v=1}^{L} \alpha_v^* y(a_v)\,K(a_v, a_w) + b^*$$

(3) a_w is classified as a boiling-condition model if $f(a_w) < 0$ and a non-boiling condition model otherwise.

The method was implemented using the MATLAB toolbox developed in Loosli et al. [2004].

4. RESULTS ON THE EXPERIMENTAL DATA

4.1 Determination of the appropriate AR order and sliding window duration

A key factor in the decision making process is the time taken to recognise a fault condition. This decision time is directly related to the number of samples used in any estimation scheme. One of the main points in the AR modelling process is to choose two correct orders p_1 and p_2 for the AR on the sensors 1 and 2 and also a correct duration ℓ for the sliding windows. In our study, the values $\ell = 100$ milliseconds and $p_1 = 12$ were chosen by minimizing the Akaike's Information Criterion for Finite samples (AICF) (see Mahmood [2007]). We also set the AR order on the sensor 2 to $p_2 = 12$ so that the number of components of the multi-sensor models is $p = 24$.

4.2 Boiling Detection by AR and SVM

After AR models estimation on the non-boiling data supplied by CEA and the boiling data obtained from injection of boiling sound, we get an overall 67 120 multi-sensor models (33 560 non-boiling models and 33 560 boiling models of the same SNR). This set is divided into learning set (50%) and test set (50%), each of these two sets contains both non-boiling and boiling models. Similar results are found for all types of boiling. Those presented in tables 2 and 3 correspond to film boiling. In table 3, the term *false alarm* corresponds to the rate of non-boiling models detected as boiling models by our method, *detection of boiling* corresponds to the rate of boiling models classified by our method as boiling models and *classification error* corresponds to the rate of misclassified models.

Table 2. Results of the SVM classifier on the test data for different values of the SNR (in dB).

SNR (dB)	Classified as non-boiling	
	Really non-boiling	Really boiling
-19	16773	12
-12	16779	3
-7	16779	0
⩾-3.5	16780	0

SNR (dB)	Classified as boiling	
	Really non-boiling	Really boiling
-19	7	16768
-12	1	16777
-7	1	16780
⩾-3.5	0	16780

It can be seen that the classification error and false alarms rates are almost zero. And the boiling detection rate is very close to 100%. These good results mean that the boiling models are detected even when the SNR is low and there is no false alarm generated even when the environment conditions change. Thus, our proposed method can be

Table 3. Error, false alarm and boiling detection rates on the test data

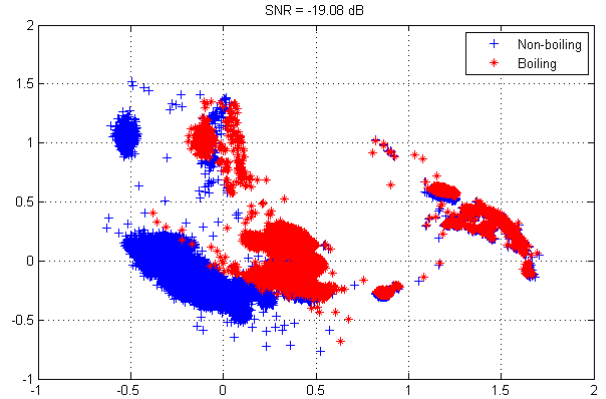| SNR (dB)	Classification error	False Alarms	Detection of boiling
-19 dB	0.06%	0.0004%	99.93 %
-12 dB	0.01%	0.00005%	99.98%
-7 dB	0.003%	0.003%	100%
⩾-3.5 dB	0%	0%	100%

Fig. 1. Projection of boiling models (red) for SNR=−19 dB in the principal plan of PCA performed on non-boiling models (blue) only.
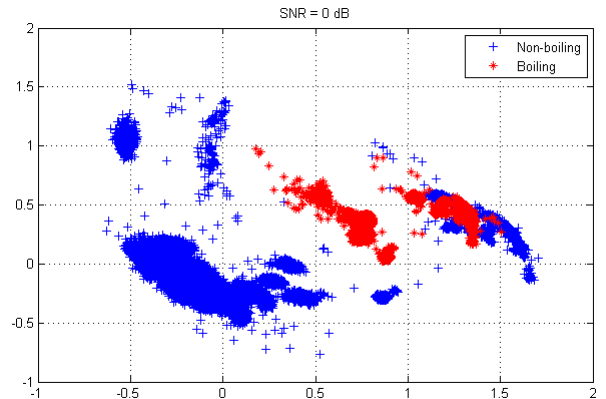

Fig. 2. Projection of boiling models (red) for SNR=0 dB in the principal plan of PCA performed on non-boiling models (blue) only.

considered robust towards the change in the environment conditions of the LMFBR.

Graphical illustrations of the boiling and non-boiling models for different values of SNR are given on figures 1 to 4. We performed a PCA on the 33 560 multi-sensor models in non-boiling conditions afterwards the 33 560 boiling multi-sensor models are projected in the principal plan of the PCA (i.e. the first two components). The first two principal components explain 73.68% of the total variance. It can be seen on figures 1 to 4 that with the increase of the SNR, the boiling multi-sensor models cluster at one point which means a better classification and thus a better boiling detection.
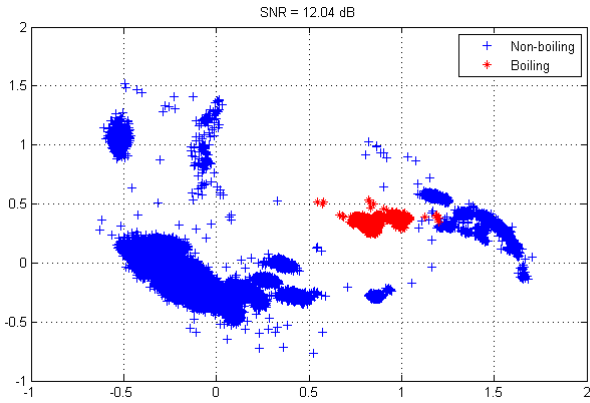
Fig. 3. Projection of boiling models (red) for SNR=12 dB in the principal plan of PCA performed on non-boiling models (blue) only.
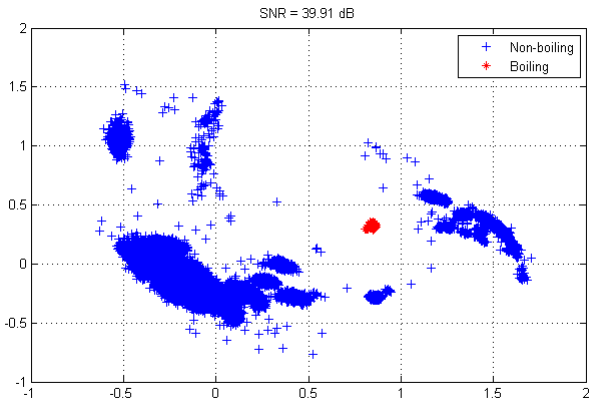

Fig. 4. Projection of boiling models (red) for SNR=40 dB in the principal plan of PCA performed on non-boiling models (blue) only.

5. CONCLUSION

In this paper, we proposed a new approach for acoustic boiling detection in a Liquid Metal Fast Breeder Reactor (LMFBR). Obviously, Auto Regressive Linear Predictive Coding has already been proposed for boiling detection by many researchers. The novelty in our approach is that, instead of estimating just one AR model for monitoring, we propose to estimate several AR models on a sliding time window. A learning database composed of both boiling and non-boiling models is used to built a Support Vector Machines classifier and then the current AR model can be classified into one of these two classes. The SVM are known as a robust classification method which separate the two classes with a maximal margin hyperplane. Given that both learning and test sets contain non-boiling sound from different environment conditions, and also that the false alarm rates obtained in our application of the proposed method are almost zero, the method can be considered as robust towards the change of environment conditions in the LMFBR. The high boiling detection rates even for low negative SNR prove that the proposed method is promising for acoustic boiling detection. Work is still in progress to obtain accurate sodium boiling modelling and test the proposed method. This will help to strengthen the monitoring of the Liquid Metal Fast Breeder Reactors.

REFERENCES

T. T. Anderson, T. P. Mulcahey, and C. Hsu. Survey and status report on application of acoustic-boiling detection techniques to liquid-metal-cooled reactors. Technical report, Argonne National Laboratory, 1970.

H. J. Bomeluberg. An evaluation of the applicability of water model testing to liquid metal engineering problems. Technical report, Liquid Metal Engineering Center, 1968.

Lutz Hamel. *Knowledge Discovery with Support Vector Machines.* Wiley Series on Methods and Applications in Data Mining. Wiley, 2009.

K. Hayashi. Autoregressive techniques for acoustic detection of in-sodium water leaks. In *Acoustic signal processing for the detection of sodium boiling or sodium-water reaction in LMFRs*, number IAEA-TECOOC-946, pages 179–202. International Atomic Energy Agency (IAEA), 1997.

K. Hayashi, Y. Shinohara, K. Watanabe, and K. Nabeshima. Twice squaring method: non-linear acoustic signal processing technique for real time detection of sodium boiling. *Ann. Nucl. Energy*, 23(10): 863–875, 1996.

H. Inujima, T. Ogino, K. Haga, and Y. Kikuchi. Detection of local sodium boiling in a simulated LMFBR fuel subassembly. *Progress in Nuclear Energy*, 9(0):107–121, 1982.

S. M. Kay. *Modern Spectral Estimation: Theory and Application.* Prentice Hall, 1988.

J. H. Lienhard IV and J. H. Lienhard V. *A heat transfer textbook.* J. H. Lienhard V, Cambridge, Massachusetts, USA, 3rd edition, 2000.

G. Loosli, S. Canu, S. V. N. Vishwanathan, A. Smola, and M. Chattopadhyay. Une boîte à outils rapide et simple pour les SVM. *Presses Universitaires de Grenoble*, pages 113–128, 2004.

I. D. Macleod. Signal processing techniques for the acoustic detection of boiling in LMFBRS: Preliminary results of an IAEA collaborative research programme. *Progress in Nuclear Energy*, 21(0):623–632, 1988.

K. Mahmood. Finite sample AIC for autoregressive model order selection. In *2007 IEEE International Conference on Signal Processing and Communications (ICSPC 2007)*, pages 1219–1222, Dubai, United Arab Emirates, November 2007.

J. Makhoul. Linear prediction : A tutorial review. *Proceedings of the IEEE*, 63(4):561–580, april 1975.

D. O'Shaughnessy. Linear predictive coding. *Potentials, IEEE*, 7(1):29–32, feb. 1988. ISSN 0278-6648. doi: 10.1109/45.1890.

V. Prakash, M. Thirumalai, M. Anandaraj, P. A. Kumar, D. Ramdasu, G. K. Pandey, G. Padmakumar, C. Anandbabu, and P. Kalyanasundaram. Experimental qualification of subassembly design for Prototype Fast Breeder Reactor. *Nuclear Engineering and Design*, 241 (8):3325–3332, 2011.

B. Schlkopf and A. J. Smola. *Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond.* Adaptive Computation and Machine Learning series. The MIT Press, 2002.

M. Vanderhaegen, A. Paumel, and A. Tourin. Acoustic emissions of a boiling liquid - an experimental survey in water and extrapolation to SFRs. Third International Conference on Advancements in Nuclear Instrumentation, Measurement Methods and their Applications (ANIMMA 2013), 2013. 23-27 June, Marseille, France.