Annals of Nuclear Energy 80 (2015) 114–122

Contents lists available at ScienceDirect

Annals of Nuclear Energy

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

Improving the in situ measurement of RTD response times through Discrete Wavelet Transform in NPP

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ARTICLE INFO

Article history:
Received 4 July 2014
Received in revised form 2 February 2015
Accepted 3 February 2015
Available online 19 February 2015

Keywords:
Response time
Resistance Temperature Detectors
DWT
AR model

ABSTRACT

In Nuclear Power Plants (NPP) safety-related Resistance Temperature Detectors (RTDs) require of fast dynamic performance. In order to achieve dynamic performance sensor monitoring and diagnostics, response time can be estimated in situ by noise analysis techniques. Although plant conditions are steady state, measurement data are not always stationary and the sensor dynamics can be disguised by other processes. In this scenario, the noise analysis techniques get difficult to be applied, and consequently, in situ surveillance is not reliable. In this work, the use of the Discrete Wavelet Transform (DWT) is proposed. It decomposes the measurement signal in detail and approximated parts at a variety of scales (-time/frequency levels of resolution). Once the data is detrended, it becomes stationary and the sensor dynamics is separated from other processes. The response time is then computed as the ramp time delay of the autoregressive (AR) model of each sensor. Measurement data from two RTDs data of a commercial PWR in three different cycles are used to apply the proposed methodology. Comparison between the DWT based methodology and the standard one is presented. The results show that with the DWT methodology, the scatter of the estimated response times is significantly reduced, the data becomes Gaussian and the non stationary features such as trends and spikes are efficiently removed from the signals.

1. Introduction

Surveillance and diagnostics has always been relevant in Nuclear Power Plants (NPPs) to guarantee safety and control. Nowadays their importance is growing due to many license renewal applications. In US almost all 104 operating Nuclear Power Plants have applied to operate more than 60 years (Hashemian, 2010). As of December 2012, the Nuclear Regulatory Commission (NRC) had granted license renewals to 72 of the 104 operating US reactors, allowing them to operate for a total of 60 years (U.S. Department of Energy, Annual Energy Outlook, 2013).

One of the key variables to be monitored through the instrumentation is temperature. Most critical process temperatures are measured using Resistance Temperature Detectors (RTDs) and thermocouples (Hashemian and Jiang, 2009). Accuracy requirements are especially stringent for RTDs (Hashemian, 2006). There are around 16–32 RTDs in PWRs (Coble et al., 2012) and the ones located at the core inlet and outlet are used for calculating the thermal power (Hashemian and Jiang, 2009), a parameter that needs to be known accurately and depends on a reliable dynamic performance of the RTDs.

In NPPs, due to the harsh conditions, in situ surveillance is necessary for monitoring the dynamical state of the sensor without demounting it. In order to carry on this surveillance, response time can be estimated by noise analysis techniques (Montalvo et al., 2014; Hashemian et al., 1988).

Nevertheless, measured data from the sensors are not always as stationary as expected and certain problems arise; the measurement uncertainty increases and the noise analysis techniques get difficult to be applied, and consequently, in situ surveillance is not reliable. On the other hand, the sensor dynamics can be disguised by other processes preventing the sensor surveillance to be achieved (Balbas et al., 2012).

In this work, the use of the Discrete Wavelet Transform (DWT) is proposed. It decomposes the signal in different levels of detail (noise) and an approximated part (signal) (Mistry and Banerjee, 2013). By subtracting the latter from the original data, stationarity

Abbreviations: DWT, Discrete Wavelet Transform; RTD, Resistance Temperature Detector; PWR, Pressurized Water Reactor; AR, autoregressive ; NPP, Nuclear Power Plant; NRC, Nuclear Regulatory Commission; PSD, Power Spectral Density; MRA, Multi Resolution Analysis; STFT, Short Time Fourier Transform; HHT, Hilbert–Huang Transform ; CWT, Continuous Wavelet Transform; HPF, High Pass Filter; LPF, Low Pass Filer; BOC, Beginning of Cycle; MOC, Middle of Cycle; EOC, End of Cycle; AIC, Akaike Information Criterion.

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http://dx.doi.org/10.1016/j.anucene.2015.02.004
0306-4549/

is reached and the sensor dynamics is separated from other processes. By means of an AR model the response time is calculated (Montalvo et al., 2014).

Several RTDs data are analyzed to check this procedure. Measurements from a commercial PWR from three different cycles are utilized. The computed response times with the DWT based method are compared with those of a standard noise analysis procedure. Statistical descriptors of the resulting data after applying DWT are used to select the level of decomposition. These descriptors are also used for comparison with standard filtering.

2. RTD dynamics and noise analysis

RTDs are sensors which are used for measuring temperature by directly registering electrical resistance. The measurement is based on the fact that electrical resistance changes with temperature (Nicholas and White, 2001). Compared to thermocouples, they are more accurate and this is why they are used in the thermal power calculation (Hashemian, 2005). Their response times are in the range of 1–3 s depending if they are installed in a thermowell or not (Hashemian and Jiang, 2009).

From the dynamics point of view, they are equivalent to a first order system, that is, they are modeled by means of a transfer function with one pole. So, a time constant is representative of the sensor dynamics. Some authors consider that they cannot always be represented accurately by first order dynamics (Hashemian and Jiang, 2011) and others have found a second time constant in situ (Montalvo et al., 2014). However, in most cases, surveillance is based on estimating the response times from the Power Spectral Density (PSD) functions of the RTD noise signals by curve fitting techniques (Balbas et al., 2012; Glöckler, 2003).

The analysis of small fluctuations (noise) of the process variables around their stationary value is commonly referred to as noise analysis, noise diagnostics, or reactor diagnostics (Thie, 1981). This methodology can be used to estimate the sensor response time. The basic principle it is that sensors are driven by a white noise, so the PSD of the sensor output signal is a representation of the transmitter transfer function as a dynamical system (Newland, 2012). By taking the definition of the transfer function and then using Wiener–Khinchin theorem the following is obtained (Paez, 2006):

$$PSD_y(f) = |H(f)|^2 PSD_x(f) \tag{1}$$

f being the frequency, PSD_x, PSD_y the PSD of the input and the output respectively and $H(f)$ the transfer function of the sensor in Fourier domain.

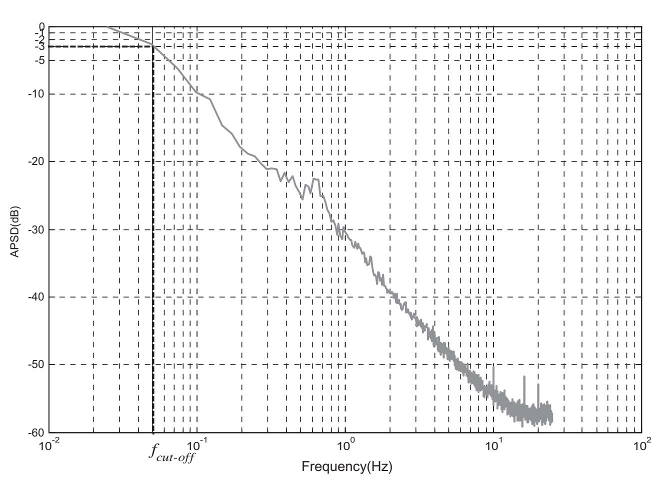

Fig. 1. PSD from a temperature sensor and the 3 dB cut-off frequency to obtain the response time.

For surveillance purposes, time or frequency domain methods can be used (Thie, 1981). In frequency domain, the response time is extracted from the spectra through 3 dB cut-off frequency (see Fig. 1).

Time domain methods such as AR models which can be inferred from the data, are very practical to reproduce sensor dynamics with a low number of coefficients.

3. Stationarity of RTDs data and problems to apply noise analysis

Noise is defined as a fluctuation around a mean value which is also known as the DC component (Hashemian, 2006). Noise analysis consists in removing the DC component and analyzing the fluctuating part which carries the dynamical information. Nevertheless if the records are not stationary, the analysis becomes more difficult and time domain methods like autoregressive modeling cannot be applied.

RTDs data from the cold legs are not always stationary. In many cases there are certain phenomena that influence the stationarity and make the surveillance difficult. Among these processes we can find thermal stratification in pipes, temperature inlet fluctuations, signal spikes induced by electrical effects, etc (Hashemian, 2006; Glöckler, 2003; Basu and Bruggeman, 1997).

In Fig. 2 two RTD signals are shown. They are not stationary, their inferred probability density functions from z-scores are not Gaussian and skewness is observed (Fig. 3).

Some authors have attributed the lack of stationarity to thermal stratification inside the pipe (Hashemian, 2006) and it is revealed through the skewness in the distribution of amplitudes (Basu and Bruggeman, 1997). By removing from the signal the processes not related to the sensor dynamics, more accurate measurements of the response time could be obtained. Nevertheless, this is not always possible just by standard filtering as it can be seen in Montalvo Martín et al. (2012). Non-stationary characteristics of signal restrict application of conventional linear filtering scheme (Singh and Tiwari, 2006).

4. Discrete wavelet transform

When the signals are not stationary and certain harmonic components can appear or disappear with time, it is necessary to use signal processing tools which provide information on amplitude, frequency and time simultaneously, that is, Multi Resolution Analysis (MRA).

There are several tools that can be used for this purpose, Short Time Fourier Transform (STFT), Hilbert–Huang Transform (HHT) and Continuous or Discrete Wavelet Transform (CWT or DWT, respectively) (Newland, 2012; Huang and Wu, 2008). In the present work, the wavelet transform will be used to remove from the measurement signal the process not related to the sensor dynamics.

The CWT is based on a scaling simple function $\psi(t)$ called wavelet (ondelette in French) that satisfies:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{2}$$

This function is dilated with a scale parameter a, and translated in time by a delay parameter b producing a collection of functions denoted by:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{3}$$

The CWT of a signal $x(t)$ is obtained by computing the correlation of $x(t)$ and the wavelet scaled and translated: