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Decay Ratio estimation in boiling water reactors based on the empirical mode decomposition and the Hilbert–Huang transform

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ABSTRACT

In this paper a new method based on the empirical mode decomposition (EMD) to estimate a parameter associated with instability in boiling water reactors (BWR), is explored. This instability parameter is not exactly the classical Decay Ratio (DR), but it will be associated with this. The proposed method allows to decompose the analyzed signal in different levels or intrinsic mode functions (IMF). One or more of these different modes can be associated to the instability problem in BWRs. By tracking the instantaneous frequency (obtained through the Hilbert–Huang transform) and the autocorrelation function of the IMF associated to the instability of the BWR, the estimation of the proposed instability parameter can be achieved. The methodology was validated with two events reported in the Forsmark stability benchmark.

1. Introduction

In the last few decades, research has been devoted to the study of power oscillations and the mechanisms that generate them (e.g. Saha and Zuber, 1978; Peng et al., 1984; Lahey and Podoswki, 1989; March-Leuba, 1990; March-Leuba and Blakeman, 1991; March-Leuba and Rey, 1993; Cai et al., 2009). Several approaches have been taken to address the stability of BWRs, March-Leuba (1986) pioneered the study of reduced-order models for coupled thermal-neutron dynamics, followed by Turso et al. (1997) and Muñoz-Cobo et al. (2004), among others. Some of those works were developed to gain insights about the BWRs dynamics, while others were focused on a more complete description of the heat transfer process (e.g. Uehiro et al., 1996; Guido et al., 1997; Podowski and Pinheiro, 1997). The models presented in the mentioned works were able to describe, in a qualitative way, low-frequency oscillations and even instabilities, but neither sustained oscillations of relatively high frequency nor highly non-stationary behavior could be described accurately by such models (Verdu et al., 2001). When the signal is non-stationary Navarro-Esbri et al. (2003) studied the time dependence of the natural frequency using two different tools: the Short-Time Fourier Transform (STFT) and the Time Dependent Power Spectral Density (TDPSD). Both techniques split the signal in short segments with a high degree of overlapping. Their results show that the STFT provides better accuracy than the TDPSD despite the lower sensitivity to noisy neutronic signals of the TDPSD method. It is worth mentioning that an autoregressive method (AR) was used by those authors to estimate the Decay Ratio (DR). However one of the most important disadvantages in the methods above discussed is the large number of floating operations (multiplications and additions) needs to be implemented.

Recently, the wavelet theory has been used to explore new alternatives for transient instability analysis (Espinosa-Paredes et al., 2005, 2007). It has been shown that stability depends on several variables such as control rod patterns, void fraction, burnup, inlet mass flow, among others. A key point is that in general, BWR signals are non-stationary, therefore traditional methods such as the Fourier transform, might lead to biased stability parameters. Sunde and Pázsit (2007) proposed an original work using the wavelet transform in combination with the autocorrelation function (ACF) to estimate the DR. Prieto-Guerrero and Espinosa-Paredes (2008) propose the application of wavelet ridges to track the instantaneous frequency and determine the DR. Also recently (Torres-Fernández et al., 2010a,b, 2012), the idea of an *instantaneous* DR was introduced.

In this work, a new method based on empirical mode decomposition (EMD) to estimate a parameter associated to instability in BWRs is introduced. This instability parameter is not exactly the classical DR, but it will be associated with this. The methodology is based on the implementation of the empirical mode decomposition

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algorithm that allows the decomposition of the analyzed signal in different levels or intrinsic mode functions (IMF). One or more of these different modes can be associated to the instability problem in BWRs. Based on the Hilbert–Huang transform it is possible to get the instantaneous frequency (IF) associated to each IMF. By tracking this instantaneous frequency and the autocorrelation function of the IMF associated to the instability of the BWR, the estimation of the proposed instability parameter can be achieved, this is the main contribution in this work.

The effectiveness of EMD has been demonstrated before for processing biomedical signals (Wu and Huang, 2009), audio signals (Khaldi et al., 2009), mechanical signals (Peng et al., 2005), gravitational waves (Lin et al., 2009), geophysical signals (Huang and Wu, 2008), among others. In the nuclear signals domain, there had been a previous research effort on how to estimate the DR of BWRs using EMD (Montesinos et al., 2003). It is worth mentioning the differences between previous research and the present one. The research in of Montesinos et al. (2003) deals with estimating the DR of BWRs by also using EMD and IMF which, conceptually speaking, have no significantly difference from the method employed in the present paper as mentioned before. However, the proposed method is different in two important points: first, we consider the signal (from BWRs) in short segments of 15 s, tracking the estimated instantaneous frequency and second, the IMF associated to detected IF is processed in order to get a parameter similar to the DR along time. Montesinos et al. (2003) considers the complete signal of the IMF in order to estimate the impulse response of the system based on an autoregressive (AR) model. The classical global DR is then obtained based on this impulse response. In counterpart, in our method the proposed Decay Ratio is calculated directly on the autocorrelation function of the IMF associated to the instability phenomenon.

To validate our method, simulated and real neutronic signals were used. The methodology was validated with two cases (4 and 6) reported in the Forsmark stability benchmark (Verdu et al., 2001).

The rest of this paper is organized as follows: in Section 2 the basic background to understand our methodology is presented. In Section 3, the methodology to estimate the instantaneous frequency and the proposed DR is discussed, additionally a simulated case is proposed to validate our hypothesis. Then in Section 4, the validation of the methodology presented in this paper is performed doing experiments with real signals taken from the Forsmark stability benchmark. Last, in Section 5, our conclusions are presented.

2. Preliminaries

2.1. Empirical mode decomposition and intrinsic mode functions

The empirical mode decomposition (EMD) algorithm was proposed in Huang et al. (1998) in order to analyze non-stationary signals from non-linear processes. EMD extracts intrinsic oscillatory modes defined by the time scales of oscillation. The components that result from the EMD algorithm are called Intrinsic Mode Functions (IMFs). These obtained IMFs result in a composed AM–FM (Amplitude Modulation–Frequency Modulation) signal.

2.1.1. Sifting process

The fundamental step of the empirical mode decomposition (EMD) is the next iterative sifting process:

1. Consider a signal $x(t)$ with M maxima and L minima. The sifting process starts with identifying the extrema of the signal, $x(t)$, given by the sets $E^1_{\max} = \{x_{\max}(t_1), x_{\max}(t_2), x_{\max}(t_3), \ldots, x_{\max}(t_M)\}$, and $E^1_{\min} = \{x_{\min}(t_1), x_{\min}(t_2), x_{\min}(t_3), \ldots, x_{\min}(t_L)\}$. We also set $x(t) = s_0(t)$.
2. The set points of $E^1_{\max}$ are interpolated to form the upper envelope of the signal, $\hat{x}_U(t)$. Similarly, the set points of $E^1_{\min}$ are interpolated to form the minimum envelope, $\hat{x}_L(t)$.
3. The average envelope $\hat{x}_A(t) = \hat{x}_U(t) + \hat{x}_U(t)/2$, is computed.
4. This average envelope is subtracted from the original signal $x(t)$ resulting in a residue signal: $r^k(t) = x(t) - \hat{x}_A(t)$ with k indicating the iteration, and $k = 1$ for the first iteration. The iteration on k is continued until the scalar product $\langle r^k(t), r^k(t) \rangle = 0$ and the number of extreme (maxima and minima) and the number of zero-crossings of $r^k(t)$ may differ by no more than one. This sifting process produces the first IMF given by $\mathrm{IMF}_j(t) = r^k_j(t)$ with $j = 1$ obtained at the kth iteration.
5. Following this, the function with $s_1(t) = s_0(t) - \mathrm{IMF}_1(t)$ is created, and the sifting process is repeated (steps 1–4), resulting in the second IMF, i.e. $\mathrm{IMF}_2(t)$. Considering this procedure, the other IMFs are generated until the residue $r(t) = x(t) - \sum_{j=1}^{N} \mathrm{IMF}_j(t)$ is accomplished. The functions $\mathrm{IMF}_j(t), j = 1,2,\ldots,N$ decompose $x(t)$ and are nearly orthogonal to one another.

The schematic diagram of the EMD algorithm is given in Fig. 1. The sifting process essentially extracts scales of the signal. Since each IMF has only one extreme between any two successive zero crossings, the frequency of the signal can be directly inferred by measuring the distribution of the zero crossings of the signal. Further, the IMF has symmetric envelopes and a zero mean value. Due to these characteristics, the IMF is referred to as being *monocomponent*.

Since the residue is computed by successively subtracting the sifted functions from the original signal, the EMD algorithm is data driven and adaptive, i.e. the basis functions are derived from the signal itself in contrast to the traditional methods where the basis functions are fixed. Furthermore, interpolation is an inexact

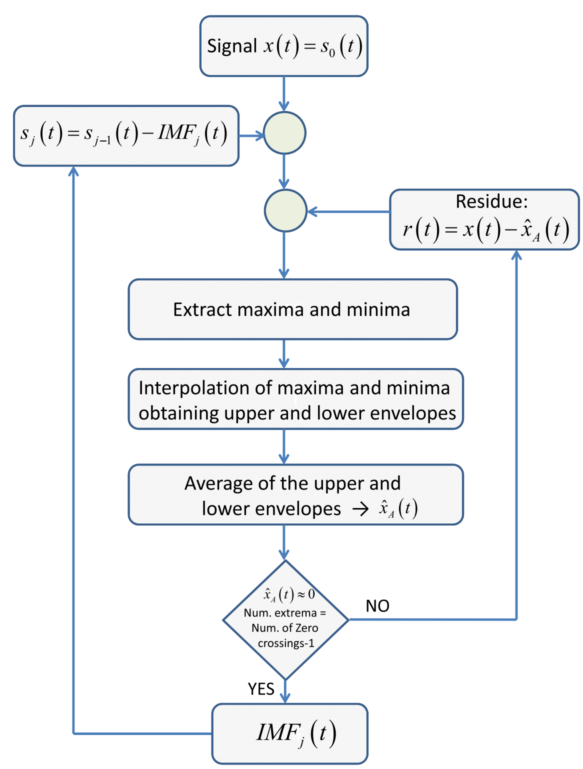

Fig. 1. Flowchart of the EMD method.