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Stability monitor for Boiling Water Reactors based on the Multivariate Empirical Mode Decomposition

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ABSTRACT

In this work a stability monitor based on a novel technique is presented. This monitor permits to launch general alarms indicating incipient high decay ratios (DR) and out-of-phase oscillations, in a simultaneous way time along. The implemented methodology to determine the estimations of DR and out-of-phase oscillations is based on the Multivariate Empirical Mode Decomposition (MEMD) processing the information obtained from all LPRMs located across the core of Boiling Water Reactor (BWR). The extracted modes with the MEMD, called the Intrinsic Mode Functions (IMFs), permit to tracking the oscillation associated to the density wave. The Case 9 (presenting high DRs and apparently out-of-phase oscillations simultaneously) from the Ringhals stability benchmark was used to show the effectiveness of the proposed methodology.

1. Introduction

In BWR instability events, two kinds of instabilities are found: in-phase (global, core-wide) oscillations, and out-of-phase (regional) oscillations. In-phase oscillations are caused by the lag introduced into the thermal–hydraulic system by the finite speed of propagation of density perturbation (Lahey and Podoswski, 1989). At high-core void fractions and low flow conditions, the feedback becomes so strong that it induces oscillations at frequency around 0.5 Hz. When this feedback increases, the oscillation becomes more pronounced, and oscillatory instability is reached. Additionally, the apparition of out-of-phase instabilities is relevant because of safety implications, i.e., large-amplitude out-phase power oscillation could be established in the core without resulting in an automatic scram. The term out-of-phase oscillation is applied to those instabilities in which different core zones show a considerable phase shift (180°) in neutron flux oscillation. March-Leuba and Blakeman (1991) examined the stability of subcritical higher harmonic neutronic modes which could result in out-of-phase power oscillations under certain conditions, even when the fundamental mode is stable and employed the subcritical reactivity of the spatial harmonic mode as another indication of the stability. In the out-of-phase instability, the usually first harmonic mode dominates the response of reactor (March-Leuba and Blakeman, 1991). The mechanism for the BWR out-of-phase stability has been explained as a phenomenon in which the neutron higher harmonic mode (the first azimuthal mode) is excited by the thermal–hydraulics feedback effect. Thus, the out-of-phase oscillation is dominated strongly by the momentum conservation among different in-core channel regions. In a large commercial BWR core, the first azimuthal harmonic mode usually appears as the first harmonic whose eigenvalue is the largest for all but the fundamental mode (Takeuchi et al., 1994). The reactivity feedback causes a spatial coupling that leads to a synthesized out-of-phase oscillation in the entire core.

Based on these facts, many efforts have been focused on the reactor safety, specially on core noise monitoring systems (Mori et al., 2003; Navarro-Esbrí et al., 2003; Ikeda et al., 2008; Lombardi et al., 2008). In this work we present a stability monitor based on a novel method to determine the instability parameters associated to the density wave (DRs and out-of-phase oscillations). In previous works, authors (Prieto-Guerrero and Espinosa-Paredes, 2014a,b) proposed two methods based on the classical empirical mode decomposition (EMD) and its bivariate version (BEMD) to estimate the DR (on a specific LPRM or APRM) and the phase between two specific LPRMs, respectively. The EMD algorithm 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 (HHT) it is possible to get the instantaneous frequency (IF) associated to each extracted

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IMF. By tracking this instantaneous frequency and the autocorrelation function (ACF) of the IMF associated to the BWR instability, the estimation of a DR local (o global) can be achieved. In the case of the phase estimation between the signals issued from two different LPRMs, in the same way that the DR estimation, the IF is obtained to track the modes associated to the instability; but the extracted modes (IMFs) are obtained considering the BEMD algorithm, showing a better performance than the classical EMD applied to each LPRM in an individual way. To estimate the phase from the considered IMFs, the cross-correlation function (CCF) is implemented. In another recent work, authors (Prieto-Guerrero et al., 2015) implemented the multivariate case of EMD (MEMD), testing it on the Case 4 of the Forsmark stability benchmark (Verdú et al., 2001). Results obtained were promising and they laid the foundations for the present work. Additionally, the EMD was applied (Prieto-Guerrero and Espinosa-Paredes, 2014c) on a real instability event occurred in Laguna Verde Power Plant (LV) on January 24, 1995 in the Unit 1 of a BWR-5. The instability event happened during a cycle 4 power ascension without fuel damage. The principal conclusion of this latter work was that it is possible, with the EMD technique, to detect an incipient oscillation due to the density wave long before that this one becomes clearly sustained. Based on all these results, in this work we present a new stability monitor that integrate the DR and out-of-phase estimations and decision rules permitting to raise an instability alarm based on the multivariate EMD (MEMD). MEMD takes the information issued from all the LPRMs (in a global way) to extract IMFs in each LPRM (in a local way). Considering the fact that an accurate prediction for the onset of BWR instability is indispensable for the safety of the BWR core, the proposed methodology was tested with the Case 9 of the Ringhals stability benchmark (Lefvert, 1996). This is a very interesting case to validate our algorithm because is a mixed case presenting high DR and apparently out-of-phase oscillations.

The rest of this paper is organized as follows: in Sections 2 and 3 the basic background to understand the Multivariate Empirical Mode Decomposition and the Hilbert–Huang transform, are presented. In Section 4 the methodology, integrating DR estimation, out-of-phase estimation and decision rules, is discussed. Then in Section 5, the validation of the methodology presented in this paper is performed doing experiments with real signals. Last, in Section 6, our conclusions are presented.

2. Multivariate Empirical Mode Decomposition (MEMD)

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.

Classical EMD is only suitable for univariate (real-valued) signals. In 2006 and 2007 were introduced extensions of EMD to the complex domain (Tanaka and Mandic, 2006; Rilling et al., 2007). Complex data are here considered as a bivariate quantity with a *mutual* dependence between real and imaginary parts. This proposed framework is called Bivariate EMD (BEMD). The most important contribution of this algorithm is to consider the mean of all partial envelope curves which were obtained through the projection over different directions in the complex plane. The set of directions vectors are chosen as equidistant points along the unit circle. Based on this idea, Rehman and Mandic (2010) proposed the Multivariate EMD (MEMD). They proposed to map an input multivariate signal into multiple real-valued projected signals, to generate multidimensional envelopes, obtaining N-dimensional rotational modes via the corresponding multivariate IMFs. These ideas are implemented in the next ***Algorithm*** suitable for operating on general nonlinear and non-stationary N-variate time series.

2.1. Algorithm

Consider an ensemble of vectors $\{\mathbf{v}(t)\} = \{v_1(t), v_2(t), v_3(t), \ldots, v_N(t)\}$ which represents a multivariate signal with N components, and $\mathbf{x}^{\theta_k}(t) = \{x_1^k, x_2^k, x_3^k, \ldots, x_N^k\}$ denoting a set of direction vectors along the directions given by angles $\theta^k = \{\theta_1^k, \theta_2^k, \theta_3^k, \ldots, \theta_{N-1}^k\}$ on a $(N-1)$ sphere (hypersphere). Then,

S1. Select an appropriate set of points for sampling over a $(N-1)$ sphere.
S2. Compute the projection, denoted by $p^{\theta_k}(t)$, of the input signal $\{\mathbf{v}(t)\}$ along the direction vector $\mathbf{x}^{\theta_k}(t)$, for all k (i.e., the whole set of direction vectors), resulting $p^{\theta_k}(t)\}_{k=1}^{K}$ as the complete set of projections.
S3. Determine the time instants $\left\{t_i^{\theta_k}\right\}$ corresponding to the maxima of the set of projected signals $p^{\theta_k}(t)\}_{k=1}^{K}$.
S4. Interpolate $[t_i^{\theta_k}, \mathbf{v}(t_i^{\theta_k})]$ to obtain multivariate envelope curves $\mathbf{e}^{\theta_k}(t)\}_{k=1}^{K}$.
S5. For a set of K direction vectors, the mean $\mathbf{m}(t)$ of the envelopes curves is calculated as: $\mathbf{m}(t) = \frac{1}{K}\sum_{k=1}^{K}\mathbf{e}^{\theta_k}(t)$.
S6. Obtain $d(t) = x(t) - m(t)$. If $d(t)$ meets the stop criterion for a multivariate IMF, apply again the procedure 1–5 to $x(t) - d(t)$, otherwise apply it to $d(t)$.

The multivariate EMD (MEMD) meets the main features of the standard method (EMD) and the bivariate decomposition (BEMD) into one, adding some improvements, including the alignment of the oscillation modes and the time alignment thereof. Additionally, it is worth mentioning that the EMD (standard, bivariate or multivariate) has an important feature of signal *denoising*. Indeed, the high frequency noise is automatically isolated in the first scale of the decomposition, then it is not necessary to perform any preprocessing of the signal.

These MEMD advantages over the standard and bivariate algorithms will be taken into account to decompose the LPRMs signals across the entire core of a BWR. Fig. 1 shows the IMFs extracted at scale 4, corresponding to the oscillation due to the density wave. These 36 IMFs correspond to the MEMD of a short time segment (15 s) of the 36 LPRMs of the Case 9 of the Ringhals stability benchmark. In this figure, the advantages before mentioned are clearly observed: perfect alignment of the IMFs in time-scale and, clearly out-of-phase oscillation. In Section 4, a methodology to determine the decay ratio and possible out-of-phase oscillations from an ensemble of N signals is proposed.

3. Hilbert–Huang transform

Applying the Hilbert transform (Delprat et al., 1992) to each obtained IMF to the corresponding real and imaginary parts, in the case of complex signals, the Hilbert–Huang Transform (HHT) of $x(t)$ is calculated according with Huang et al. (1998). Using this transformation, a distribution can be constructed from the instantaneous frequencies (IF) of each IMF considering real and imaginary parts in an independent way in the case of complex signals. This distribution is called the Hilbert–Huang Spectrum (HHS), (Huang et al., 1998). In this work we detect the instantaneous frequencies of each IMF to found the modes associated with the instability event.