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Technical note

Cofrentes nuclear power plant instability analysis using ensemble empirical mode decomposition (EEMD)

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ABSTRACT

Several instability events have occurred in the world in various commercial BWRs since the 80s. The dynamics of these events has been studied for many years. Basically, the power in normal operating conditions is a noisy signal with no significant frequencies. When instability takes place, oscillations around 0.5 Hz and 1 Hz become more relevant in the reactor dynamics behaviour due to the void fraction feedback. In the last years, time frequency analysis has been used by several authors to study instability events so as to isolate certain harmonics. Among them, we can cite wavelets, Short Time Fourier Transform (STFT), Hurst exponent, Hilbert Huang Transform (HHT), etc. The latter consists of decomposing the original signal into a subseries (Empirical Mode Decomposition, EMD). The Hilbert transform is then applied to each mode to obtain the instantaneous amplitude and frequency. However, when a frequency component within the signal comes into existence or disappears from it entirely at a particular time scale, the EMD does not work properly and one mode can present more than one frequency component (mode mixing problem). In this work, a modification of the HHT methodology has been applied to Local Power Range Monitors (LPRM) signals during an instability event. A different signal decomposition method is used, the Ensemble Empirical Mode Decomposition (EEMD), and compared with the previous EMD. The EEMD produce Intrinsic Mode Functions (IMF) with no frequency mixing problem. The frequencies and modes extracted this way describe the instability dynamics more accurately.

1. Introduction

The BWR instability is a possible event in a nuclear power plant, typically in a BWR. (March-Leuba and Rey, 1993). In such a situation, significant core power oscillations may occur. The stability is of primary interest from the point of view of BWR operation, since the stability margin may be strongly reduced during plant maneuvering and transients (Gialdi et al., 1985). The average and local power range monitor (APRM and LPRM) signals contain more information than the natural frequency of the core, e.g., frequencies due to the actuation from the plant control system. Therefore, an accurate prediction for the onset of BWR instability is indispensable for the safety of BWR core design and operation (Ikeda et al., 2007). This is why in the last few decades a great effort has been devoted to the development of accurate BWR stability monitoring techniques (Blázquez and Ballestrín, 1995; Navarro-Esbrí et al., 2003).

The event shown in Fig. 1 occurred at Cofrentes Nuclear Power Plant in Valencia (Spain) on January 29th, 1991, during a normal startup sequence, right before the transfer to high speed of the recirculation pumps (Blázquez and Ballestrín, 1995). In that moment, reactor power was 42% with a core flow of 30.72%. Heater 6B was being put into service and feedwater temperature was increasing. Another operator was inserting control rods to adjust rod pattern to the recirculation pump transfer speed. Once the operator observed the oscillations, control rods were inserted to cancel them out and restore reactor stability.

In order to analyse the instability event, the neutron flux time series must be studied. Typically, the neutron flux time series that are recorded in an unstable process are neither linear nor stationary. This non linearity and non stationarity gives the idea that the Fourier Transform should be used carefully and with small subseries (Blázquez and Ruiz, 2000).

Another approach is a time-frequency analysis. In Gavilan-Moreno et al. (2015), two frequencies were identified, 0.93 Hz and 0.47 Hz for the Cofrentes case. Those frequencies confirmed the out-of-phase instability. The method used to identify the abovementioned frequencies is the Short Time Fourier Transform

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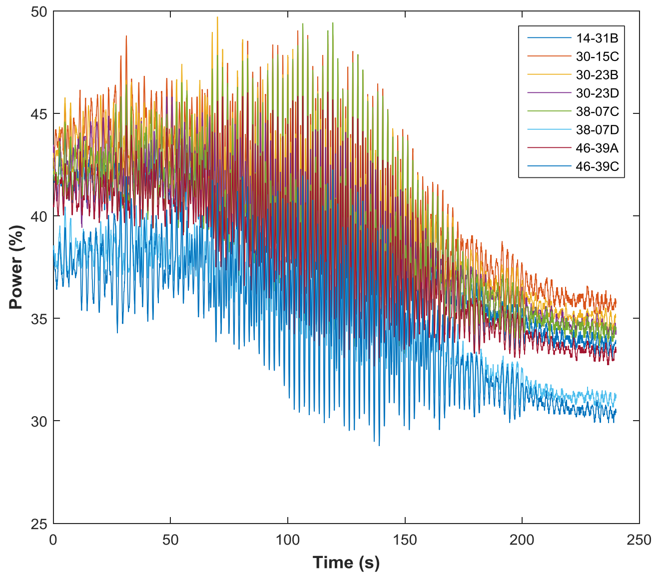

Fig. 1. LPRM signals at different core locations during the instability event at Cofrentes Nuclear Power Plant.

(STFT), using a rolling window technique which looks for short linear and stationary sub series, inside the nonlinear and non-stationary neutron flux time series. As was mentioned, the APRM and LPRM signals are very noisy signals, so an accurate instability monitor or analysis needs to isolate those frequencies associated to the instability and to eliminate the rest. One of the most used instability indicators is the Decay Ratio (DR), but the accuracy of its determination is rather noise dependent. So it is necessary to isolate the frequencies related with the instability to calculate it accurately.

For this purpose, the Hilbert-Huang Transform (HHT) is a very efficient tool. This method implies dividing the original time series into a set of IMFs by the so called Empirical Mode Decomposition, EMD (Huang et al., 1998). Each mode has symmetrical amplitudes and it is centred at a particular frequency or time scale. In the literature, one can find some researchers who have used the HHT as a filter, and they have utilized some individual vibration modes (Intrinsic Mode Function, IMF) to calculate the DR (Prieto-Guerrero et al., 2015; Montesinos et al., 2003; Blázquez et al., 2013). The problem with this methodology is that the IMFs do not always present a unique frequency, and different time scale components may appear in one mode. This is known as a mode mixing problem and it could lead to a lack of accuracy in the DR calculation.

Recently, EMD has been modified in order to avoid the frequency mode mixing problem (Wu and Huang, 2009). The result is the Ensemble Empirical Mode Decomposition based on adding white noise to the original data. This modified methodology has been applied in this work to LPRM signals during an instability event in order to improve the dynamics analysis. Specifically, this means that IMFs obtained by EEMD have a unique frequency and it could result in a more accurate DR estimation. Comparisons with previous methods are also included.

2. HHT, EMD and mode mixing problem

HHT was elaborated by Huang (Huang et al., 1998) to analyse non-stationary signals. It is an adaptive and empirical method which, prior to any frequency analysis, decomposes the signal in a series of IMFs. The different modes obtained contain normally one harmonic. The second part of the methodology consists on the application of the Hilbert transform to each IMF so that the instantaneous frequency and amplitude of the analytical signal can be obtained. The strength of the HHT compared to other signal processing techniques is the decomposition phase: the Hilbert transform extracts better the different local harmonics in simpler subseries.

The properties of IMFs are:

- They are centred at a frequency band which determines the time scale of such IMF.
- Symmetrical amplitudes.
- Between consecutive maximum and minimum there is a single zero.

The decomposition process is an iterative algorithm (sifting process) (Huang, 2014) which checks if these properties are fulfilled. The highest frequency IMF is the first mode; the last one corresponds to the lowest frequency mode. Once the decomposition of the data into n empirical modes is achieved, a residual is obtained which can be either the mean trend or a constant. Therefore the original time series $h(t)$ can be expressed as:

$$h(t) = \sum_{i=1}^{n} IMF_i(t) + r(t) \tag{1}$$

where n is the number of IMFs obtained and $r(t)$ is the residual.

As mentioned before, after the signal is divided into n modes, the Hilbert transform is applied to each IMF. The Hilbert transform is defined as follows:

$$H[h(t)] = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{h(\tau)}{t-\tau} d\tau \tag{2}$$

where P indicates the Cauchy principal value. Practical applications come from the analytical signal $g(t)$ defined as the complex function:

$$g(t) = h(t) + iH[h(t)] \tag{3}$$

The instantaneous amplitude and phase are defined as:

$$\begin{aligned} a(t) &= \sqrt{h^2 + H^2} \\ \phi(t) &= \tan^{-1}\left(\frac{H}{h}\right) \end{aligned} \tag{4}$$

So that the instantaneous frequency is the time derivative of the phase divided by 2π:

$$f = \frac{1}{2\pi} \frac{d\phi}{dt} \tag{5}$$

The instantaneous frequency and amplitude describe the frequency and the energy content of the signal. The Hilbert spectrum is a 3D colour map representation where the intensity of the colour is the instantaneous amplitude and the x and y axes are the time and instantaneous frequency respectively (Huang et al., 1999). The marginal spectrum of each IMF is a widely used plot to see the frequency content of each IMF (Huang, 2014).

The EMD algorithm does not work properly when certain harmonics disappear along the time span considered. In signal processing this phenomenon is known as intermittency (Huang et al., 1999). If that was the case, the IMFs obtained in the EMD contained more than one frequency, that is, modes of different time scales. Consequently, the task of determining when certain frequency content has appeared or disappeared becomes difficult. This is referred as a mode mixing problem. Mode mixing is defined as a single IMF including oscillations of dramatically disparate scales, or a component of a similar scale residing in different IMFs. It is a result of signal intermittency (Lei et al., 2009).