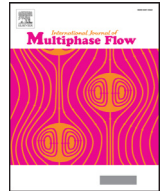




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Multiresolution analysis of gas fluidization by empirical mode decomposition and recurrence quantification analysis

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ABSTRACT

The dynamics of gas fluidization is investigated by means of multiresolution analysis. Empirical mode decomposition (EMD) and the Hilbert-Huang transform approach applied to the signals of pressure fluctuation of the bed have been used for this purpose, operating in bubbling and slugging regimes. To elucidate the different components of the different scales, recurrence plots (RP) and recurrence quantification analysis (RQA) have been used. These techniques can distinguish the three different scales of gas fluidization: micro-scale, meso-scale and macro-scale, and classify every mode on its scale. Three modes from the EMD have been related to each dynamic component: particle interaction, local bubble dynamics and bed oscillation, showing evidence of this relationship. To show that the complexity of the modes matches with their characteristics, two measures have been computed: the apparent entropy and Lempel-Ziv complexity.

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1. Introduction

Although gas fluidization has been industrially used for over a century, it remains a complex technique that still attracts researchers aiming to improve control and performance operation. It is recommended when good gas-solid contact is needed, improving mass and heat transfer. Also, its peculiar “fluid-like” dynamics greatly facilitates the handling and processing of solids in industrial processes. It is well known that particulate fluidization is desired for an optimal contact between the phases, but aggregative fluidization is quite common in industrial applications. Furthermore, for deep beds the bubbling fluidization can evolve to slugging fluidization, which is not convenient because then part of the gas bypasses the solid contact.

Gas fluidization is a complex dynamic system characterized by non-linearity and non-equilibrium. The complexity of its dynamics is due to the interaction of the phases involved at different scales in the heterogeneous flow structure. Complex systems are characterized by a multi-scale structure nature with respect to space and time, showing dissipative structures by non-linear and non-equilibrium interactions and exchanging energy, matter and information with their surroundings (Li, 2000; Li and Kwauk, 2003; Li et al., 2004).

Also, gas fluidization is a typical dissipative structure consisting of a non-equilibrium system with particle and fluid self-organization. A considerable amount of the total input energy is dissipated to maintain the two phase heterogeneous structure. Nevertheless, all the phenomena that take place in gas fluidization are the result of the nonlinear interaction between the particles and the fluid with their own individual movement tendencies. The dissipative structure in fluidized systems has been found to show multi-scale characteristics and the sum of individual processes does not properly reflect the dynamics of the system. Therefore, different scales must be considered for a detailed analysis. The system can be structured into three basic scales: micro-scale (individual particle and fluid scale), meso-scale (cluster and dilute phase scale, or “bubble and emulsion”) and macro-scale (effect of the equipment) (Li, 2000). This approach through different structures involving the fluidized bed is crucial to better understand the behavior of the bed dynamics and the influence of the different structures in the bed.

Among the techniques used to characterize the fluidization, the pressure fluctuations analysis is perhaps the most popular one because it is easy to implement and inexpensive, especially in industrial installations. Other techniques allow for more and better information, but their implementation is much more complex. In spite of the limited information provided by the pressure fluctuations of the fluidized bed, when properly treated, it may be a consistent and valuable source of information. It has even been considered to be the fingerprint of the system. The pres-

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sure fluctuations have been analyzed by means of time and frequency domain techniques (Fan et al., 1991; Johnsson et al., 2000; Llop and Jand, 2003; Sasic et al., 2007). However, given the complexity of multiphase flow and its nonlinear behavior, the analysis by nonlinear techniques has been introduced (van den Bleek and Schouten, 1993; Zijerveld et al., 1998, Johnsson et al., 2000; Llauro and Llop, 2006; Llop et al., 2012).

Several researchers have applied wavelet analysis to the experimental time series of pressure fluctuations for multiscale resolution (Lu and Li, 1999; Zhao and Yang, 2003; Shou and Leu, 2005; Wu et al., 2007; Tahmasebpour et al., 2015). To a lesser extent, Empirical Mode Decomposition (EMD) of the signal has been used to extract intrinsic mode functions (IMF) with different frequencies, which can be related to the different scales. The signal analysis approach has attracted the attention in several research fields. Briongos et al. (2006) used the multiresolution analysis EMD to study the hydrodynamics of a gas-solid fluidized bed.

Wavelets can handle non-stationary signals due to the nature of wavelet functions and, although they are basically suited for linear signals, they have been used successfully in non-linear systems. EMD is suitable for nonlinear and non-stationary systems and makes it possible to simultaneously obtain the real time and the instantaneous frequency and can classify time or frequency dependent information with more accuracy.

In this work the multiscale resolution of bubbling and slug-ging regimes has been studied, decomposing the pressure fluctuations in the bed by EMD while, using the Hilbert-Huang transform method, the intrinsic frequency has been extracted. With the aim to analyze the different modes obtained with EMD, Recurrence Plots (RP) and Recurrence Quantification Analysis (RQA) have been used. The modes extracted have been related with the particle, bubbles and bulk structures in the fluidized bed. To analyze the structure and to be able to discuss the behavior of the modes generated with the EMD two measures of the complexity have been used: approximate entropy (ApEn) and Lempel–Ziv (L-Z) complexity, which are very useful parameters to characterize spatiotemporal patterns.

2. Theoretical background

2.1. Empirical mode decomposition (EMD)

Wavelet analysis has been used for the decomposition of the pressure fluctuation signal in different levels of resolution, and related to the three scales associated to the fluidization dynamics: micro-scale, meso-scale and macro-scale. Zhao and Yang (2003) studied the fractal behavior of resulting levels from Daubechies wavelets with the Hurst exponent. Lu and Li (1999) used the discrete wavelet transform to analyze the pressure signal in a bubbling fluidized bed and related the bubble size with the average peak value of level 4 and the bubble frequency with the peak frequency of this level. Tahmasebpour et al. (2015) decomposed the pressure signals by means of Daubechies wavelets in three sub-signals representing the three scales of fluidized bed dynamics and analyzed them by means of Recurrence Plots and Recurrence Quantification Analysis.

Both the Fast Fourier Transform (FFT) and the Wavelet Transform (WT) can analyze nonstationary signals but have limited accuracy when used to classify time or frequency dependent information. The Hilbert-Huang Transform (HHT) is a time-frequency analysis method developed for the analysis of non-stationary and non-linear time series introduced by Huang et al. (1998), particularly suited for nonlinear processes. The result is a combination of an empirical approach with a theoretical tool, which has been successfully used in several fields of research like meteorology, seismology, multiphase flow, etc. The HHT is based on the Empirical

Mode Decomposition (EMD), which decomposes the signal in several oscillatory modes, named Intrinsic Mode Functions (IMF). The EMD is based on the sequential extraction of energy associated with the intrinsic mode functions of the signal, from finer temporal scales (high frequency modes) to coarser ones (low frequency modes).

The algorithm of extraction proposed by Huang et al. (1998) generates upper and lower smooth envelopes enclosing the signal. These envelopes are generated by the identification of all local extrema, which are connected by cubic spline lines. A new function is obtained by subtracting the running mean of the envelope from the original data signal. If this function has the same number of zero-crossing points and extrema, the first IMF is obtained, which contains the highest frequency oscillations in the signal. Otherwise, the process must continue until an acceptable tolerance is reached. To extract the following IMF, the previous IMF is subtracted from the original signal. The difference will be treated like the original data and the process is applied again until the above mentioned condition is fulfilled. The process of finding the several modes is carried out until the last mode (the residue) is found. The original signal is the sum of the different modes generated,

$$x(t) = \sum_{i=1}^n C_i(t) + r_n(t) \quad (1)$$

where C_i is every mode extracted and r_n is the residual part of the signal.

Once the modes have been extracted, a second process must be done. The instantaneous frequency is computed by applying the Hilbert transform to every mode so that the time-frequency distribution of the signal energy is obtained. Each mode function $C_i(t)$ is associated with its Hilbert Spectral Analysis $H_i(t)$:

$$H_i(t) = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{C_i(\tau)}{t - \tau} d(\tau) \quad (2)$$

and the combination of $C_i(t)$ and $H_i(t)$ gives the analytical signal $Z_i(t)$ with complex component:

$$Z_i(t) = C_i(t) + jH_i(t) \quad (3)$$

which can be expressed as:

$$Z_i(t) = A_i(t)e^{j\theta_i(t)} \quad (4)$$

where $A_i(t)$ is the amplitude of the signal and $\theta_i(t)$ is the phase of the oscillation mode “ i ”. Hence, the original time series, neglecting the residual part, can be expressed as:

$$x_i(t) = \text{Re} \sum_{i=1}^n A_i(t)e^{j\theta_i(t)} \quad (5)$$

Re meaning the real part. The amplitude $A_i(t)$ and the phase $\theta_i(t)$ times series can be computed by:

$$A_i(t) = \sqrt{C_i^2(t) + H_i^2(t)} \quad (6)$$

$$\theta_i(t) = \tan^{-1} \left(\frac{H_i(t)}{C_i(t)} \right) \quad (7)$$

The instantaneous frequency (f_i) can be obtained by differentiating the phase angle:

$$f_i(t) = \frac{d\theta_i(t)}{dt} \quad (8)$$

For each mode, the Hilbert spectrum can be defined as the square amplitude

$$H(f, t) = A^2(f, t) \quad (9)$$

The spectrum provides an intuitive visualization of the instantaneous frequencies of the signal in the time scale, showing where

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