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Flow characterization of high-pressure dense-phase pneumatic conveying of coal powder using multi-scale signal analysis

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ABSTRACT

Flow characterization of high-pressure dense-phase pneumatic conveying of coal powder is not fully understood. To further reveal the dynamic behavior of coal particles in dense-phase pneumatic conveying pipelines, a method for the scale decomposition of particle motion based on empirical mode decomposition and Hurst analysis of experimental electrostatic signals is reported. This allows the multi-scale motion characteristics of single coal particles and particle clusters to be determined. Micro-, meso-, and macro-scale subsets were reconstructed, which reflected the different behaviors of the coal particles: specifically, dynamic features of the micro-scale subset represented features of single particle collisions and frictional interactions; dual fractal characteristics of the meso-scale subset described the motion of coal particle clusters; and features of the macro-scale subset reflected persistent dynamic behavior of the entire pneumatic conveying system. Motion behavior of single particles and particle clusters could be respectively investigated by considering the relative energies of the micro- and meso-scale contributions to the electrostatic signal. This was verified both by theoretical analysis and experiment.

Introduction

High-pressure dense-phase pneumatic conveying is a critical technique in entrained-flow pulverized coal gasification systems. In-depth insight into the motion of coal particles in the dense-phase gas–solid two-phase flow in pneumatic transport pipelines is significant for their optimized design and operation. Such knowledge is also important in the context of research into gas–solid two-phase flow.

The motion of pulverized particles in a dense-phase pneumatic conveying pipeline is an unsteady and complex non-linear dynamical process that has been studied by many non-linear methods, including fractal theory, information entropy, and chaos analysis (Cao, Wang, Liu, & Yang, 2009; Liang et al., 2007; Lu et al., 2013; Mittal, Mallick, & Wypych, 2014; Wu, Briens, & Zhu, 2006). These studies have made significant contributions to understanding particle motion in these gas–solid two-phase flow systems. It should, however, be noted that all of these studies were performed at a single scale.

Particles in a dense-phase gas–solid two-phase flow exist in several different states: as individual particles; particle clusters in the dense region; and particle clusters in the dilute region. To link these particle states with features of their dynamic movement, it is noted that individual particles and particle clusters have individual dynamic movement behaviors, which cannot be revealed through investigations at only a single scale. Furthermore, the dynamic features of dense-phase gas–solid two-phase flow are known to be multi-scale (Lu et al., 2013; Xu, Liang, Zhou, & Wang, 2010). There are three basic scales: micro-scale (representing dynamic behavior of discrete individual particles); meso-scale (representing dynamic behavior of clusters, involving interaction between dense-phase clusters and the dilute-phase broth); and macro-scale (representing dynamic behavior of the global gas–solid flow motion) (Li & Kwauk, 2003).

Various widely used analysis methods can reveal the multi-scale characteristics of signals. Many studies have shown that multi-scale dynamic behavior can be studied by wavelet transforms and empirical mode decomposition (EMD) (Zhao & Yang, 2003). For the application of the former, it is necessary to select the mother wavelet a priori; the resulting lack of self-adaptability of this method somewhat limits its ability to analyze non-linear and non-stationary signals. In contrast, EMD, as proposed by Huang

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et al. (1998), can be used to adaptively decompose signals based on their intrinsic features and is more suitable for analyzing such signals. EMD has therefore been used to decompose the electrostatic and pressure signals of dense-phase pneumatic conveying systems (Briongos, Aragón, & Palancar, 2006; Xu et al., 2010).

In this research, a method for the scale decomposition of particle motion based on EMD and Hurst analysis is proposed. EMD was adopted to analyze the time–frequency characteristics of particle motion; the Hurst analysis was then applied to evaluate the fractal characteristics of the resulting time–frequency components. The Hurst exponents were calculated to analyze the persistence or stochastics of these components. These time–frequency components, which represented stochastic tendencies, dual fractal structures, and strongly persistent tendencies, were then reconstructed into micro-, meso-, and macro-scale subsets, respectively. Finally, parameters related to the behavioral characteristics of these three scales were calculated to analyze individual dynamic movement behavior of single particles and particle clusters.

Particle charging in a pneumatic conveying pipeline is a comprehensive result of particle motion, so the electrostatic fluctuations obtained from gas–solid two-phase flow contain rich multi-scale information on particle movement. In this work, the three scales of particle motion were subjected to EMD and Hurst analysis to obtain the electrostatic fluctuations of the dense-phase gas–solid two-phase flow in a conveying pipeline. Theoretical and experimental analysis then verified that the relative energy contributions of the meso- and macro-scale subsets could be taken as the respective eigenvalues to investigate the movement behavior of single coal particles and particle clusters.

Signal processing methods

Empirical mode decomposition

EMD is based on the local characteristic time scale of the data and is applicable to non-linear and non-stationary processes. The purpose of EMD is to obtain the intrinsic mode functions (IMFs) that characterize the internal vibration modes of the data. Each IMF satisfies two conditions: (1) in the entire data set, the numbers of extrema and zero crossings must either be equal or differ, at most, by one; (2) at any point, the mean value of the envelopes defined by the local maxima and minima is zero. According to the above definition, the decomposition of the data $X(t)$ is carried out as follows (Huang et al., 1998).

First, the extrema of the data are identified and connected by a cubic spline to give the upper envelope. The same procedure is followed for the local minima to determine the lower envelope. All data should be contained within the upper and lower envelopes. The mean of the upper and low envelope values is denoted as m_1. The difference (h_1) between the data $X(t)$ and m_1 is the first component:

$$X(t) - m_1 = h_1. \tag{1}$$

Ideally, if h_1 is an IMF, then h_{11} is the first component of $X(t)$; however, if h_1 is not an IMF, h_1 is treated as a data point:

$$h_1 - m_{11} = h_{11}. \tag{2}$$

This sifting procedure is repeated k times until h_{1k} is an IMF, i.e.:

$$h_{1(k-1)} - m_{1k} = h_{1k}. \tag{3}$$

If c_1 is designated as $c_1 = h_{1k}$, then c_1 is separated from $X(t)$ and Eq. (4) can be obtained:

$$X(t) - c_1 = r_1, \tag{4}$$

where r_1 is treated as the data. The above procedures are repeated for all subsequent r_j ($j = 1, \ldots, n$) and Eq. (5) can be obtained:

$$r_1 - c_2 = r_2, \ldots, r_{n-1} - c_n = r_n. \tag{5}$$

This shifting process can be stopped when r_n is a monotonic function. By summing Eqs. (4) and (5), the final decomposition results of the data $X(t)$ can be expressed as:

$$X(t) = \sum_{i=1}^{n} c_i + r_n. \tag{6}$$

Hurst analysis

Hurst analysis, also known as R/S analysis and originally proposed by Hurst (1951), can be used to estimate the Hurst exponent H for a non-linear time series, which can then be used to analyze the stochastic behaviors of the signal. In this work, Hurst analysis was used to characterize the behaviors of different IMF components after EMD. For a given discrete time series, the Hurst exponent was calculated using the following steps: a time series of length of M was divided into W subseries, i.e., $WN = M$. The subseries are represented as I_w ($w = 1, 2, \ldots, W$), where the kth item in I_w is designated as $x_{k,w}$ ($k = 1, 2, \ldots, N$) and N is the time range of a subseries.

The statistical parameters of the subseries I_w ($w = 1, 2, \ldots, W$) can be calculated by:

$$e_w = \frac{1}{N}\sum_{k=1}^{N} x_{k,w} \quad w = 1, 2, \ldots, W; \tag{7}$$

$$S_w = \left[\frac{1}{N}\sum_{k=1}^{N}(x_{k,w} - e_w)^2\right]^{1/2}; \tag{8}$$

$$y_{k,w} = \sum_{i=1}^{k}(x_{i,w} - e_w) \quad k = 1, 2, \ldots, N; \tag{9}$$

$$R_w = \max_{1\le k\le N}\{y_{k,w}\} - \min_{1\le k\le N}\{y_{k,w}\}; \tag{10}$$

where e_w and S_w are the mean and standard deviation of the subseries I_w, respectively; $y_{k,w}$ is the cumulative time series of the subseries I_w; R_w is the range of I_w.

The mean value $(R/S)_N$ of the rescaled range for all subseries can be expressed as:

$$(R/S)_N = \frac{1}{W}\sum_{w=1}^{W}(R_w/S_w). \tag{11}$$

To compare different time series, Hurst established the following relation:

$$R(\tau)/S(\tau) \propto \tau^H, \tag{12}$$

or

$$\ln\left(R(\tau)/S(\tau)\right) \propto H \ln \tau, \tag{13}$$

where $N = \tau$. The value of H can be obtained by linear regression of Eq. (13).

H varies between 0 and 1. A Hurst exponent equal to 0.5 ($H = 0.5$) indicates that the series under examination behaves in a manner consistent with random-walk theory; a Hurst exponent greater than 0.5 indicates persistence, while an exponent of less than 0.5 means anti-persistence. For a persistent data set, if the trend or behavior in the data set is increasing or decreasing over a certain unit interval of time, it will continue to increase or decrease over such an interval.