Resolution of Structure Characteristics of Passive Acoustic Emission Signals in Multiphase Flow System

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Abstract. The underlying structure characteristics of acoustic emissions (AE) measured in a gas-solid fluidized bed was investigated detailedly by resorting to wavelet transform and rescaled range analysis. A general criterion was proposed to resolve AE signals into three characteristic scales, i.e. micro-, meso- and macro-scale, and a so-called “structure diagram” was introduced. Compared with the structure diagram of pressure signals, it was found that AE signals in micro-scale reflect mainly the particles motion while pressure signals in meso-scale reflect mainly the bubbles motion. Energy distribution analysis further revealed that the most energies in AE and pressure signals were distributed mainly by the micro-scale and meso-scale signals respectively. Moreover, the structure characteristics of AE signals collected from gas-solid fluidized bed and liquid-solid stirred tank were compared based on structure diagram and energy distribution analysis. The results indicated that although the same measurement technique was adopted, the structure characteristics of AE signals measured in gas-solid fluidized bed and liquid-solid stirred tank still exhibited larger difference. As an illustrative application of AE technique in process monitoring, a prediction model for particle size distribution was proposed and the satisfactory results were obtained both for laboratory scale and plant scale fluidized beds.

1. INTRODUCTION

Multiphase flow system exists widely in many industrial processes, such as chemical and petrochemical, metallurgy, piping transportation, pharmaceutical, and power engineering. Despite the wide usage of multiphase systems, the thorough understanding of the hydrodynamics of multiphase systems is also a challenging problem, because multiphase flows are almost always unstable and complex spatio-temporal patterns are observed ubiquitously. Advance in computer hardware technology as well as in numerical computation methods, study of the multiphase flow patterns by computational fluid dynamics (CFD) has thus received more and more attention in recent years. However, establishing the exact mathematical model of multiphase systems is usually still impossible, and the experimental validation of the results of CFD simulation is also difficult; on the other hand, CFD simulation is very time-consuming, and its application to large industrial multiphase systems is not yet feasible. Therefore, various measurement techniques, whether invasive or non-invasive, are needed both in academia and in industry, for understanding and analysis of the complex flow patterns, and for design, operation, control and scale-up purposes, respectively. Nevertheless, due to the non-linear, non-equilibrium and multi-scale characteristics of multiphase systems, as well as each
measurement technique has its own particular spatial and time resolution, none of the measurement techniques is capable of providing equally valid information over the complete spectrum of scales relevant to the complete characterization of multiphase flow systems. Hence, it is recommended that several techniques may be simultaneously derived to get complementary information (Boyer et al., 2002).

Fluctuation signals collected from various measurement techniques, such as pressure, optic fiber, capacitance, and radioactive, can usually reflect a wide spectrum of complex fluctuation phenomena in multiphase flow systems. However, due to the lack of more concrete knowledge of the underlying structure characteristics of fluctuation signals, how to mining useful information from these raw fluctuation signals is still a challenging problem. Statistical Characteristics (such as standard deviation, skewness, kurtosis and entropy), obtained by simple statistical analysis of raw signals, are in general directly used for predicting the properties of multiphase systems. Because fluctuation signals are commonly hybrid signals with multi-scale components, the most useful information is usually carried by some specific components at different scales with respect to a specific measurement task, such as particle size distribution, bubble size, and voidage. Therefore, prediction model, established based on the above statistical characteristics, not only has little physical sense, but also probably has poor generalization performance.

In recent years, multi-resolution methodology has been applied to reveal the underlying multi-scale characteristics of fluctuation signals. By resorting to advanced statistical tools, such as wavelet analysis and chaos theory, some efforts have been made to explore the relationship between the decomposed components at different scales and the corresponding physical phenomena, especially for the pressure fluctuation signals in gas-solid fluidized bed system. Lu et al. (1999) used wavelet analysis to pressure fluctuation signals in a bubbling fluidized bed and indicated that the scale 4 detail signal reflects the bubble behaviour. Zhao et al. (2003) adopted wavelet transform to decompose pressure fluctuation signals in a fluidized bed. Hurst analysis of the decomposed fluctuation signals showed that the measured pressure fluctuations can be resolved to three characteristic scales: meso-scale signals with two distinct Hurst exponents; micro- and macro-scale signals with only one characteristic Hurst exponent. Briongos et al. (2006) applied the Hilbert-Huang transform method to perform a multi-resolution analysis of pressure signals collected from a gas-solid fluidized bed, then the concept of averaged instantaneous frequency was used to identify three important dynamic components, such as local bubble, “bulk” and particle dynamics. Furthermore, the bulk dynamic component was used to estimate the bed expansion ratio and bed height. Yang et al. (2008) used wavelet transform to decompose the absolute pressure fluctuation signals into three scales corresponding to macro-scale, meso-scale and micro-scale in three circulating fluidized beds. A redefined variable, homogeneous index HI, obtained from the energy ratio of the micro-scale and meso-scale signals, was used to determine the transition velocities from bubbling to turbulent fluidization.

The passive acoustic emission (AE) technique has received more and more attention in recent years as a potential non-intrusive and real-time process monitoring technique to be used in multiphase flow systems. Due to AE signals are made up of emission from many acoustic sources at different scales, the interpretation of AE signals are often very complicated. Previous studies have demonstrated that AE signals contain rich information with respect to the motion of particles (Boyd et al., 2001; Ren et al., 2008). Multi-scale resolution of AE signals can be thus useful for separating the key feature information of particles motion from the original AE signals, which may help to establish physical meaningful prediction model with respect to specific measurement task. However, the underlying structure characteristics of AE signals is relatively poorly investigated.

In this study, wavelet transform and rescaled range analysis were applied to explore and understand the structure characteristics of AE signals in different multiphase systems. The different structure characteristics of AE signals and pressure fluctuation signals in gas-solid fluidized bed were firstly investigated. Secondly, the structure characteristics of AE signals collected from gas-solid fluidized
bed and liquid-solid stirred tank were compared. Finally, as an illustrative application example of AE technique in process monitoring, a prediction model for particle size distribution was proposed.

2. METHODS

2.1 Wavelet transform analysis

The wavelet transform (WT) analysis has become a very powerful time-frequency tool for analysis of non-stationary and transitory signals and has been widely applied in various fields, such as signal processing, image processing, data compression and financial time series. Contrary to the Fourier-related transform methods, WT provides a more flexible way of time-frequency representation of a signal by allowing the use of variable sized windows. In WT, at high frequencies (corresponding to small scales), narrow windows are used to get precise time resolution, whereas at low frequencies (corresponding to large scales), wide windows are used to get finer frequency resolution. Localization in both frequency and time domains is thus the greatest advantage of WT over Fourier-related transform methods. Moreover, WT is often regarded as a mathematical “microscope” that is able to examine different parts of the signal by automatically adjusting the focus.

WT uses the wavelet function and scaling function to perform simultaneously the multi-resolution analysis (MRA) decomposition and reconstruction of the measured signal. The wavelet function serving as a high-pass filter can generate the detailed version of the given signal, while the scaling function serving as a low-pass filter can generate the approximated version of the given signal. The discrete wavelet transform (DWT) can be regarded as an MRA technique, where the original signal can be decomposed into several signals with different scales or resolutions and can reconstruct the signals using inverse discrete wavelet transform. The detailed mathematical description of DWT should be referred to the literature (Zhao et al., 2003).

2.2 Rescaled range analysis

Rescaled range (R/S) analysis, originally developed by an Egyptian hydrologist Hurst (1951) to analyze Nile River’s overflows, can identify long-range dependence in highly non-gaussian time series and detect non-periodic cycles. Moreover, it also provides an effective way for studying the fractal characteristics of a time series. Recent years, R/S analysis has been applied by a number of groups to characterize the complex hydrodynamics of multiphase flow systems (Fan et al., 1991; Fan et al., 1993; Briens et al., 1997; Zhao et al., 2003; Ren et al., 2008). In this study, this type of analysis is adopted to analyze the decomposed AE signals on different levels, and a criterion is further established to resolve the AE signals into three characteristic scales in terms of different fractal characteristics. The detailed implementation of R/S analysis should be referred to the literature (Zhao et al., 2003).

By performing R/S analysis, the Hurst exponent, $H$, can be obtained. If the Hurst exponent equals to 0.5, the time series is random. If the Hurst exponent is greater than 0.5, the time series is persistent. Persistent implies that if the trend of the time series has increased or decreased, then the chances are that it will continue to increase or decrease in the future, respectively. Moreover, the strength of trend-reinforcing behaviour, or persistence, increases as the Hurst exponent approaches 1.0. Conversely, if the Hurst exponent is less than 0.5, the time series is anti-persistence. This means that, whenever the trend of the time series has increased, it is more likely that it will decrease in the close future. The strength of anti-persistent increase as the Hurst exponent approaches 0. It is important to note that persistent time series have little noise whereas anti-persistent time series show presence of high-frequency noise.

3. EXPERIMENTAL

3.1 Gas-solid fluidized bed

The gas-solid multiphase flow experiments were carried out in gas-solid fluidized beds both for cold mode in laboratory scale and hot model in plant scale. A schematic diagram of the laboratory scale cold mode experimental apparatus used in the present study is shown in Fig. 1. It consists of two parts:
a fluidized bed and an AE signal collection system. The fluidized bed assembly includes a plexiglass bed (150mm in ID and 1000mm in height) and a perforated-plate distributor (with a pore diameter of 2.0 mm and a fractional open area ratio of 2.6%). Three types of polyethylene (PE) particles: linear low-density polyethylene (LLDPE), high-density polyethylene (HDPE) and bi-mode polyethylene (BPE), were used as the fluidized particle. Seven different particle sizes of these three types of PE, 0.14, 0.18, 0.36, 0.50, 0.71, 1.19 and 2mm, were selected by sieving. The fluidized media is air at a velocity range of 0~1.1m/s. The AE signal collection and analysis system, developed by the UNILAB Research Center of Chemical Engineering at Zhejiang University, consists of an AE sensor, a preamplifier, a main amplifier and a control computer with an A/D conversion module. The AE sensor, which is made of a piezoelectric accelerometer, was attached close to the wall of the fluidized bed at a location 150mm above the gas distributor. Based on the Shannon sampling theory, a sampling frequency of 500kHz is determined.

The plant scale hot mode experiments were conducted in three industrial fluidized beds for production of LLDPE, HDPE and BPE. The ID and height of LLDPE, HDPE and BPE industrial fluidized beds are 3500mm and 12m, 3500mm and 15m, and 5000mm and 18m, respectively. The AE sensors were installed at a location 1000mm above the gas distributor for these three industrial fluidized beds, with a sampling frequency of 500kHz. The operating gas velocities for LLDPE, HDPE and BPE industrial fluidized beds are 0.6m/s, 0.6m/s and 0.4m/s, respectively.

3.2 Liquid-solid stirred tank

The liquid-solid multiphase flow experiments were carried out in a stirred tank. Figure 2 is a schematic diagram of the experimental apparatus used in the present study. It consists of two parts: a stirred tank and an AE signal collection system. The stirred tank assembly includes a tank (with a diameter of 105mm and a height of 150mm) and an impeller of 6 bladed disk turbine (with a diameter of 55mm). The impeller was installed at a height of 15mm above the bottom of the tank. The impeller speed was measured using an electronic constant agitator and is accurate to $\pm 10 \, \text{r} \cdot \text{min}^{-1}$. The stirred tank is charged with water with a density of 1000 kg·m$^{-3}$ as the liquid phase, and glass beads with a density of 2900 kg·m$^{-3}$ as the solid phase. The glass beads with three different diameters, 0.5 and 0.7mm, were investigated. A sampling frequency of 100kHz is determined in terms of the Shannon sampling theory.
RESULTS AND DISCUSSION

4.1 Structure characteristics comparison between AE signals and pressure signals

One type of PE particles, i.e. BPE, with four different particle sizes of 0.159, 0.365, 0.565 and 0.942mm, was investigated to study the structure characteristics of AE signals. Fluidization was performed in the laboratory scale cold mode fluidized bed at a superficial gas velocity of 0.103m·s⁻¹. The original AE signals from four different measurements, corresponding to four different particle sizes, were decomposed to 1-9 level detailed signals (D₁ – D₉) and level-9 approximated signal (A₉) using Daubechies 2nd order wavelet transform (Daubechies, 1988). The R/S analysis is further applied to the detailed signals D₁ – D₉, as well as the approximated signal A₉. Table 1 shows the Hurst exponents of decomposed signals for different particle sizes.

| Particle Size (mm) | Decomposed Signal |
|-------------------|-------------------|
|                   | D₁    | D₂    | D₃    | D₄    | D₅    | D₆    | D₇    | D₈    | A₉    |
| 0.159             |       |       |       |       |       |       |       |       |       |
| H₁                | [-]   | [-]   | [-]   | [-]   | [-]   | 0.984 | 0.989 | 0.998 | 0.992 | 0.995 |
| H₂                | 0.275 | 0.244 | 0.288 | 0.283 | 0.289 | 0.496 | 0.512 | 0.639 | 0.671 | 0.673 |
| H₃                | 0.105 | 0.133 | 0.195 | 0.178 | 0.184 | 0.168 | 0.195 | [-]   | [-]   | [-]   |
| 0.365             |       |       |       |       |       |       |       |       |       |       |
| H₁                | [-]   | [-]   | [-]   | [-]   | [-]   | 0.996 | 0.996 | 0.998 | 0.996 | 0.996 |
| H₂                | 0.217 | 0.238 | 0.275 | 0.249 | 0.289 | 0.494 | 0.529 | 0.616 | 0.666 | 0.661 |
| H₃                | 0.095 | 0.126 | 0.18  | 0.108 | 0.13  | 0.168 | 0.177 | [-]   | [-]   | [-]   |
| 0.565             |       |       |       |       |       |       |       |       |       |       |
| H₁                | [-]   | [-]   | [-]   | [-]   | [-]   | 0.995 | 0.995 | 0.995 | 0.996 | 0.995 |
| H₂                | 0.25  | 0.242 | 0.218 | 0.273 | 0.291 | 0.489 | 0.518 | 0.653 | 0.662 | 0.67  |
| H₃                | 0.145 | 0.215 | 0.165 | 0.171 | 0.187 | 0.191 | 0.197 | [-]   | [-]   | [-]   |
| 0.942             |       |       |       |       |       |       |       |       |       |       |
| H₁                | [-]   | [-]   | [-]   | [-]   | [-]   | 0.997 | 0.997 | 0.998 | 0.998 | 0.997 |
| H₂                | 0.27  | 0.252 | 0.316 | 0.281 | 0.295 | 0.488 | 0.518 | 0.553 | 0.662 | 0.67  |
| H₃                | 0.135 | 0.211 | 0.168 | 0.183 | 0.189 | 0.167 | 0.205 | [-]   | [-]   | [-]   |

It can be seen from Table 1 that two distinct Hurst exponents for the detailed signals D₁ – D₅ of all different particle sizes, H₂ from the slope at smaller τ and H₃ from the slope at larger τ, are found to be much less than 0.5. Both Hurst exponents less than 0.5 indicate that the detailed signals D₁ – D₅ are much irregular and represent an anti-persistence behaviour in the gas-solid fluidized bed. Because the mechanism of acoustic emissions generated in gas-solid fluidized bed mainly owe to the collisions between particles and wall, which reflects the micro-scale interaction behaviour among particles and between particles and fluid, the irregular and high-frequency detailed signals D₁ – D₃ can be considered to imply the complex micro-scale motion of solids phase. Moreover, according to the wavelet analysis, the frequency band of the detailed signals D₁ – D₃ lies within [15.63kHz, 500kHz].
being fair consistent with the main frequency band in a normal fluidized bed (Jiang et al., 2007), which further supports the above implication.

Three distinct Hurst exponents, $H_1$, $H_2$ and $H_3$ being the slopes at smaller, medium and larger $\tau$ respectively, are shown in Table 1 for the detailed signals $D_6 - D_7$ of all different particle sizes. It can be seen from Table 1 that (1) the Hurst exponent $H_1$ at smaller $\tau$ is much greater than 0.5 and almost approaches to 1.0, which indicates a highly persistent hydrodynamics feature of the gas-solid fluidized system, (2) the Hurst exponent $H_2$ at medium $\tau$ roughly equals to 0.5, which indicates a random hydrodynamics feature of the gas-solid fluidized system, and (3) the Hurst exponent $H_3$ at larger $\tau$ is much less than 0.5, which indicates a highly anti-persistent hydrodynamics feature of the gas-solid fluidized system. Generally, there are mainly two types of particles motions in gas-solid fluidized bed, particles motion along with solid phase and particles motion along with bubble phase respectively. Meanwhile, it is in general considered that the motion of bubble phase is more regular than that of solid phase. Therefore, the detailed signals $D_6 - D_7$ imply complex meso-scale interaction between solid phase and bubble phase, where the Hurst exponent $H_1$ at smaller $\tau$ represents a hydrodynamic feature of bubble phase and the Hurst exponent $H_2$ at larger $\tau$ represents a hydrodynamic feature of solid phase. It can also be seen from Table 1 that the Hurst exponent $H_2$ at medium $\tau$ is a little less than 0.5 for the detailed signal $D_6$ and that is a little greater than 0.5 for the detailed signal $D_7$. This implies that the detailed signals $D_6$ and $D_7$ can be seen as the meso-scale interaction in a fluidized bed mainly dominated by the motions of solid phase and bubble phase respectively.

Two distinct Hurst exponents, $H_1$ from the slope at smaller $\tau$ and $H_2$ from the slope at larger $\tau$, are shown in Table 1 for the detailed signals $D_8 - D_9$ and the approximated signal $A_9$ of all different particle sizes. Both Hurst exponents are found to be much greater 0.5, which indicates that the detailed signals $D_8 - D_9$ and the approximated signal $A_9$ are regular and represent a persistence behavior in the gas-solid fluidized bed. Therefore, the detailed signals $D_8 - D_9$ and the approximated signal $A_9$ can be considered to represent the whole macro-scale interaction of the fluidized bed.

According to the above R/S analysis of the decomposed AE signals, a complete characterization of hydrodynamics in gas-solid fluidized bed can be described. In the previous study of Zhao et al. (2003), a criterion was established to resolve the pressure fluctuation signals into three characteristic scales in terms of different numbers of Hurst exponents: meso-scale signals with two distinct Hurst exponents; micro- and macro-scale signals with only one Hurst exponent. However, the above criterion is no longer suitable for multi-scale resolution of AE signals. A more general criterion is thus established to resolve AE signals into three characteristic scales: micro-scale signals with all Hurst exponents less than 0.5; meso-scale signals with some Hurst exponents less than 0.5 and some Hurst exponents greater than 0.5; macro-scale signals with all Hurst exponents greater than 0.5.

In order to perform the structure characteristics comparison between AE signals and pressure fluctuation signals, a plot of Hurst exponent $H$ against level, called “structure diagram” in the present study, is adopted. Figs. 3 and 4 show the structure diagrams of AE signals and pressure signals respectively (for ease of explanation, level 10 in both Figs. 3 and 4 is actually a level 9 approximated signal), where the result of Figure 4 is derived and modified from the previous study of Zhao et al. (2003). It can be seen from Fig. 3 that (1) micro-scale signals consist of 1-5 level detailed signals, (2) meso-scale signals consist of 6-7 level detailed signals, and (3) macro-scale signals consist of 8-9 level detailed signals and level 10 approximated signals. It can be seen from Fig. 4 that (1) micro-scale signals consist of 1-2 level detailed signals, (2) meso-scale signals consist of 3-9 level detailed signals, and (3) macro-scale signals consist of level 10 approximated signals.

The energy percentages, $R_\%$, for micro-, meso- and macro-scale AE signals are shown in Table 2 for different particle sizes. It can be seen from Table 2 that the most energy is distributed mainly by micro-scale signals consisting of the level 1-5 detailed signals, and is over 95% of the total energy. It can also be seen that the energy percentage of meso-scale signals increases as the particle size increases, which may be caused by the fact that the effect of the motion of solid phase on the meso-scale interaction in a fluidized bed increases as the particle size increases. However, as Zhao et al.
(2003) stated, the most energy of pressure signals is distributed mainly by meso-scale signals consisting of the level 3-9 detailed signals, and is over 90% of the total energy.

Table 2. Energy Distribution for Multi-scale AE Signals

| Particle Size (mm) | Micro | Meso | Macro | Micro | Meso | Macro | Micro | Meso | Macro | Micro | Meso | Macro |
|--------------------|-------|------|-------|-------|------|-------|-------|------|-------|-------|------|-------|
| 0.159              | 98.96 | 1.02 | 0.02  | 97.95 | 2.03 | 0.02  | 97.65 | 2.33 | 0.02  | 97.36 | 2.62 | 0.02  |
| 0.365              |       |      |       |       |      |       |       |      |       |       |      |       |
| 0.565              |       |      |       |       |      |       |       |      |       |       |      |       |
| 0.942              |       |      |       |       |      |       |       |      |       |       |      |       |

Therefore, the structure characteristics difference between AE signals and pressure signals can thus be summarized that (1) the number of levels of meso-scale in AE signals is much less than that in pressure signals, and (2) the most energies of AE signals and pressure signals are distributed mainly by micro-scale signals and meso-scale signals respectively. These observations are consistent with the measuring principles of AE sensor and pressure probe. AE sensor, i.e. piezoelectric accelerometer, measures vibrations of the wall, originated mainly by collision between particles and wall. This also means that it is not a good way for applying directly AE sensor to measure the information about the bubbles motion. Therefore, signals collected from AE measurement technique represent the micro-scale dynamics of solid phase, which corresponds to the observation that the most energy of AE signals is distributed mainly by micro-scale signals. In contrast, pressure probe measures the fluctuations of pressure, which are generated mainly by the meso-scale motion of bubble phase. The most energy of pressure signals is, therefore, distributed mainly by meso-scale signals.

Based on the above thorough investigations of underlying structure characteristic of AE and pressure signals, it is, therefore, helpful not only to choose a more suitable measurement technique with respect to measurement requirement, but also to establish physical meaningful prediction model. AE measurement technique is more suitable for measuring granular properties (e.g. particle size, particle size distribution, and particle density etc.), whereas pressure measurement technique is more suitable for measuring bubble properties (e.g. bubble size, and wake vortex etc.).

4.2 Structure characteristics comparison of AE signals in gas-solid and liquid-solid systems

In view of the fact that the physical characteristics of different multiphase systems are in general different, the structure characteristics of AE signals collected from different multiphase systems could
exhibit larger difference. The structure characteristics of AE signals collected from gas-solid fluidized bed and liquid-solid stirred tank were compared in this section. Two experiments in liquid-solid stirred tank under complete suspension condition were conducted with the solid concentration of 0.13 g·mL⁻¹ and impeller speed of 8.33 r·s⁻¹ for two different glass bead diameters of 0.5mm and 0.7mm. The original AE signals from two different measurements with respect to two different glass bead sizes were decomposed into 1-9 level detailed signals and level-9 approximated signal using Daubechies 2nd order wavelet transform. Fig. 5 shows the structure diagram of AE signals by resorting to R/S analysis of the decomposed signals.

![Fig. 5 Structure diagram of AE signals in liquid-solid stirred tank. Glass bead size: 0.5mm(□); 0.7mm(△).](image)

Compared the structure diagram of AE signals in gas-solid fluidized bed shown in Fig. 3 with the structure diagram of AE signals in liquid-solid stirred tank shown in Fig. 5, it is indicated that (1) the micro-scale signals consisting of 1-2 level detailed signals in liquid-solid stirred tank is much narrower than the micro-scale signals consisting of 1-5 level detailed signals in gas-solid fluidized bed, and (2) the meso-scale signals consisting of 3-9 level detailed signals in liquid-solid stirred tank is much wider than the meso-scale signals consisting of 6-7 level detailed signals in gas-solid fluidized bed. Moreover, the energy percentages of AE signals in liquid-solid stirred tank are 45.5%, 53.2% and 1.3% for micro-, meso- and macro-scale signals respectively. This means that the energy of AE signals in liquid-solid stirred tank is roughly distributed equally by micro- and meso-scale signals, which is different from the AE signals in gas-solid fluidized bed whose most energy is distributed mainly by micro-scale signals. These observed structure characteristics differences between liquid-solid and gas-solid systems could be supported by the fact that (1) in gas-solid fluidized bed, acoustic emissions are generated mainly by the collisions between particles and wall, and (2) in liquid-solid stirred tank, acoustic emissions are generated not only by the collisions between particles and tank, but also by the collisions between liquids and tank. On the other hand, under the complete suspension condition, the most particles are suspended in liquid phase, and the frequency band of collisions between liquids and tank could be comparable to that of collisions between those particles and tank, which may cause the wide meso-scale signals in liquid-solid tank.

In a word, structure characteristics of AE signals measured in different multiphase systems could be distinguished by resorting to structure diagram and energy distribution analysis. Investigating the underlying structure characteristics of signals could provide primary information not only to judge whether this measurement technique is suitable for a particular application, but also to reveal possible difficulties encountered. Moreover, it could be helpful to extract the most characteristic features for a particular application based on structure characteristics of signals.

### 4.3 Measurement of particle size distribution

The average particle size and particle size distribution (PSD) have significant effects not only on the properties of final products, but also on the performance of gas-solid fluidized beds, especially with
respect to the polymerization of olefins in fluidized beds. Therefore, the developments of effective on-
line monitoring techniques for both average particle size and PSD measurements are very essential.
One of the most widely used methods to determine average particle size, as well as PSD, is manual
sieve analysis. However, sieve analysis can not satisfy the real-time requirement because of its long
sampling interval. Optical measurement technique can not be suitable for the stringent industrial
environment, and its applications in industrial fluidized beds are rarely reported in open literature.
Moreover, in view of the fact that the rays (e.g. χ-ray, and γ-ray etc.) are harmful to human health, it
hinders their applications as measurement techniques. Therefore, the invention of a novel on-line
measurement technique, not only health-friendly but also real-time, has become an urgently task.
Recent years, AE measurement technique, considered as a non-intrusive method, has attracted
considerable attentions and has been applied to measure average particle size (Halstensen et al., 2000;
Boyd et al., 2001; Jiang et al., 2007). However, its application to on-line measurement of PSD is rarely
reported.

The earlier analyses of structure characteristics of AE signals indicated that (1) micro-scale signals
consisting of 1-5 level detailed signals totally reflect the information about particles motion, and (2)
meso-scale signals consisting of 6-7 level detailed signals partially reflect the information about
particles motion. In contrast, there are only two levels detailed micro-scale signals of pressure signals
that totally represent the information about particles motion, while other seven levels detailed meso-
scale signals just partially or even not at all represent the information about particles motion. It could
thus be implied that AE technique is more suitable than pressure technique for measure average
particle size and PSD. Therefore, as an illustrative application example of AE technique, a prediction
model was established to measure PSD, as well as average particle size.

For \( n \) identical particles (with a diameter of \( d_p \) and a mass of \( m \)) impact on an area \( \Delta A \) of the wall of
a bed with the normal velocity of \( v \), the resultant average force \( <F(t)> \) in a time interval \( T \) is given by

\[
<F(t)> = \int_0^T F(t) dt = \frac{2mv}{T} \sum_{i=1}^{n} \delta(t-t_i)dt
\]  

where \( \delta(t) \) is Dirac delta function, and \( t_i \) is the arrival time of the \( i \)th particle on the wall. Let \( f_p \)
denote the average arrival frequency of the particles on the wall, the number of collisions between
particles and wall in a time interval \( T \) is \( f_p T \). Thus, the average force \( <F(t)> \) in an unit time interval
can be expressed as,

\[
<F(t)> = \frac{2mv}{T} \sum_{i=1}^{n} \delta(t-t_i)dt = \frac{2mvf_p T}{T} = 2mvf_p
\]  

Consequently, the acoustic pressure generated on an area \( \Delta A \) of the wall can be given by

\[
P_{AE} = \frac{\eta <F(t)>}{\Delta A} = \frac{2\eta mvf_p}{\Delta A}
\]  

where \( \eta \) is the transformation efficiency from the collision pressure to acoustic pressure detected by
AE sensor. There are several factors that can take significant effects on the transformation efficiency \( \eta \),
such as the distance between collision position and sampling position, and the operation conditions of
experimental apparatus. Let \( \rho_b \) and \( w \) denote the particle density near the wall and the mass fraction of
particles with a size of \( d_p \) respectively, then the number concentration \( C \) (number·m\(^{-3}\)) of particles with
a size of \( d_p \) can be expressed as \( C=\rho_b w/m \). Consequently, the average arrival frequency of the particles
on the wall, \( f_p \), can be given by

\[
f_p = C \cdot \frac{\Delta A}{\Delta A} = \frac{\rho_b w v}{m}
\]
Therefore, for particles (with \( d_p \) in diameter, \( m \) in mass, and \( w \) in mass fraction) impact on an area \( \Delta A \) of the wall, the energy of signals received by AE sensor, \( E \), during a time interval \( T \), can be calculated by

\[
E(d_p) = \int_0^T P_{d_p} \Delta A v dt = \int_0^T 2\eta \rho_b v^3 w dt
\]  
(5)

It can be seen from Eq. (5) that the signal energy \( E \) is a function of transformation efficiency \( \eta \), particle density near the wall \( \rho_b \), particle normal velocity \( v \) and particle mass fraction \( m \). By maintaining the operation conditions constant, such as superficial gas velocity and level of material, both the transformation efficiency \( \eta \) and the particle density near the wall \( \rho_b \) could be considered roughly to be constant. Meanwhile, under constant operation conditions, the normal velocity \( v \) is mainly related to the particle size distribution. It is, therefore, implied that the signal energy can be considered to be a function of PSD under specific operation conditions.

For particles with \( K \) different sizes jointly impact on the wall, the total mixed signal energy, \( E^{mix} \), can be calculated based on the linear superposition principle of acoustic energy as follows:

\[
E^{mix} = \sum_{k=1}^{K} E^k \cdot w_k
\]  
(6)

where \( E^k \) and \( w_k \) are the signal energy and mass fraction of \( k \)th type of particles with a size of \( d_{p,k} \) respectively. In view of the independent feature of acoustic propagation, different acoustic waves generated from particles with different sizes impact on the wall will maintain their own characteristics (e.g. frequency, and amplitude etc.). Hence, it can be further supposed that the energy of acoustic on different levels can be maintained constant under acoustic superposition. According to wavelet analysis, the conservation relationships of signals for mixed particle sizes and signals for single particle size at different detailed levels, as well as approximated level, can be given as follows:

\[
E^{mix}_{j,D} = \sum_{k=1}^{K} E^k_{j,D} \cdot w_k, \quad j = 1, \cdots, L
\]  
(7)

\[
E^{mix}_{L,A} = \sum_{k=1}^{K} E^k_{L,A} \cdot w_k
\]  
(8)

where \( L \) is the number of wavelet decomposed levels; \( E^k_{j,D} \) and \( E^k_{L,D} \) are the energies of detailed signal on the level of \( j \) and approximated signal on the level of \( L \) for the \( k \)th type of particles with a size of \( d_{p,k} \) respectively; and \( E^{mix}_{j,D} \) and \( E^{mix}_{L,A} \) are the energies of detailed signal on the level of \( j \) and approximated signal on the level of \( L \) for mixed particle sizes respectively. Let \( \lambda_k \) denote a ratio of signal energy for \( k \)th type of particles and signal energy for mixed particle sizes, which is defined as

\[
\lambda_k = \frac{E^k}{E^{mix}}, \quad k = 1, \cdots, K
\]  
(9)

Therefore, Eqs. (7) and (8) can be further transformed as follows:

\[
E P^k_{j,D} = \sum_{k=1}^{K} \lambda_k \cdot E P^k_{j,D} \cdot w_k, \quad j = 1, \cdots, L
\]  
(10)

\[
E P^{mix}_{L,A} = \sum_{k=1}^{K} \lambda_k \cdot E P^k_{L,A} \cdot w_k
\]  
(11)

where \( E P^k_{j,D} \) and \( E P^k_{L,D} \) are the energy percentages of detailed signal on the level of \( j \) and approximated signal on the level of \( L \) for the \( k \)th type of particles respectively; and \( E P^{mix}_{j,D} \) and \( E P^{mix}_{L,A} \) are the energy percentages of detailed signal on the level of \( j \) and approximated signal on the level of \( L \) for mixed particle sizes respectively. Hence, after calibrations of the values of \( \lambda_k \) \((k=1, \cdots, K)\), as well as the values of \( E P^k_{j,D} \) and \( E P^k_{L,D} \), where \( k=1, \cdots, K \) and \( j=1, \cdots, L \), the mass fractions of different types of
particles, \( w_k (k=1, \ldots, K) \), can be obtained by solving the linear equations shown in Eqs. (10) and (11). Because the earlier study on structure characteristics of AE signals has implied that the macro-signals consisting of the detailed signals on the levels of 8 and 9 and the approximated signals on the level of 9 do not reflect the information about particles motion at all, it is supposed that decomposing the AE signals into larger than 7 levels will not provide extra information for prediction of PSD, which has been demonstrated based on our experimental results. The number of decomposed levels, \( L \), is thus set equal to 7 in the present study.

To illustrate the effectiveness of the PSD prediction model, the on-line measurement experiments were carried out both in laboratory scale and plant scale gas-solid fluidized beds. Three types of PE particles collected from plant scale plant scale fluidized beds, i.e. LLDPE, HDPE and BPE, were used as the fluidized particle in laboratory scale fluidized beds. The model parameters in Eqs. (10) and (11) were calibrated based on the AE signals collected from laboratory scale apparatus. The results are shown in Table 3. It can be seen from Table 3 that the mass fractions of different particle sizes measured using AE method is consistent with that measured using sieve method. Define the average absolute deviation, \( AAD \), of PSD prediction between AE method and sieve method as

\[
AAD = \frac{1}{K} \sum_{k=1}^{K} |w_k^{\text{sieve}} - w_k^{\text{AE}}|
\]

where \( w_k^{\text{sieve}} \) and \( w_k^{\text{AE}} \) are the mass fractions of the \( k \)th type of particles measured by sieve method and AE method respectively; and \( K=7 \) is the number of types of particles. It can be calculated from Table 3 that (1) in the laboratory scale experiments, the values of \( AAD \) are 0.62%, 1.60% and 1.57% for LLDPE, HDPE and BPE respectively, and (2) in the plant scale experiments, the values of \( AAD \) are 1.26%, 1.86% and 2.14% for LLDPE, HDPE and BPE respectively.

### Table 3. Comparisons of Average Particle Size and Particle Size Distribution Measured Using AE Method and Sieve Method in Laboratory Scale and Plant Scale Apparatuses

| Type | Method         | Mass fractions for different particle sizes (%) | Average particle size (mm) |
|------|----------------|-----------------------------------------------|---------------------------|
|      |                | 2mm 1.19mm 0.71mm 0.5mm 0.36mm 0.18mm 0.14mm |                            |
| LLDPE| AE laboratory  | 0.50  5.60  4.00  27.70 42.60  9.90  9.30 | 0.4396                    |
|      | plant scale    | 0.39  8.40  4.40  25.70 40.10  11.00 10.10 | 0.4440                    |
|      | Sieve method   | 15.80 31.80 15.90 29.80 12.60  12.80  2.30 | 0.9758                    |
|      | AE laboratory  | 14.80 33.60 15.00 27.60 12.60  12.80  2.30 | 0.9604                    |
|      | plant scale    | 14.10 36.00 12.60 30.00 29.00  23.90  2.10 | 0.9674                    |
| HDPE | AE laboratory  | 4.53  9.50  19.74 20.47 32.89  12.87  2.30 | 0.9777                    |
|      | plant scale    | 4.80  11.60  16.80 19.90 30.90  13.00  3.00 | 0.5917                    |
|      | Sieve method   | 5.10  13.80  17.90 16.60 31.10  13.30  2.20 | 0.6153                    |

Moreover, because the average particle size can be calculated based on the measured PSD, the average particle size measured by AE method and sieve method are also compared and shown in Table 3. It can be calculated from Table 3 that (1) in the laboratory scale experiments, the relative deviation of average particle size between AE method and sieve method are 0.25%, 1.57% and 0.67% for LLDPE, HDPE and BPE respectively, and (2) in the plant scale experiments, the relative deviation of average particle size between AE method and sieve method are 0.99%, 0.86% and 4.69% for LLDPE, HDPE and BPE respectively. The results of plant scale experiments for the prediction of average particle size by the PSD prediction model proposed in this study show superior performance to the frequency model proposed by the Jiang et al.(2007). The superiority of PSD prediction model could be supported by the fact that wavelet transform analysis is more suitable to deal with non-stationary signals than Fourier transform analysis. In a word, the results illustrate that the AE measurement in combination with the PSD model provide an effective tool to on-line measurement of both average particle size and PSD.
5. CONCLUSIONS

This work investigated thoroughly the structure characteristics of AE signals measured in gas-solid fluidized bed and liquid-solid stirred tank by resorting to wavelet transform and R/S analysis. A general criterion was established to resolve AE signals to three characteristic scales based on the Hurst exponent characteristics: micro-scale signals with all Hurst exponents less than 0.5; meso-scale signals with some Hurst exponents less than 0.5 and some Hurst exponents greater than 0.5; macro-scale signals with all Hurst exponents greater than 0.5. Meanwhile, structure diagram, a plot of Hurst exponent against level, was introduced.

By the comparison of structure characteristics between AE and pressure signals in gas-solid fluidized bed, it was found that (1) AE signals in micro-scale consisting of 1-5 level detailed signals is much wider than pressure signals in micro-scale consisting of 1-2 level detailed signals, and (2) AE signals in meso-scale consisting of 6-7 level detailed signals is much narrower than pressure signals in meso-scale consisting of 3-9 level detailed signals. Further, energy distribution analysis revealed that the most energies in AE and pressure signals were distributed mainly by the micro-scale and meso-scale signals respectively. These observations imply that AE signals represent mainly micro-scale particles motion while pressure signals represent mainly meso-scale interaction dynamics between particles motion and bubbles motion. Therefore, AE technique could be considered as an effective tool to measure particle-related properties in gas-solid fluidized bed.

The structure characteristics of AE signals collected from gas-solid fluidized bed and liquid-solid stirred tank were also compared based on structure diagram and energy distribution analysis. The results indicated that although the same measurement technique was adopted, the structure characteristics of AE signals measured in gas-solid fluidized bed and liquid-solid stirred tank still exhibited larger difference. Compared with the structure diagram of AE signals in fluidized bed, it was found micro- and meso-scale of AE signals in liquid-solid stirred tank becomes narrow and broadens respectively. On the other hand, the energy of AE signals in liquid-solid stirred tank was roughly distributed equally by micro- and meso-scale signals, which was different from the AE signals in gas-solid fluidized bed whose most energy is distributed mainly by micro-scale signals.

Finally, as an illustrative application of AE technique in process monitoring, a prediction model was proposed to measure particle size distribution (PSD) and average particle size for three types of PE, i.e. LLDPE, HDPE and BPE. The on-line measurements of PSD and average particle size were performed both in laboratory scale and plant scale fluidized beds. The results showed that (1) average absolute deviation between AE method and manual sieve method were no more than 2.14% for PSD prediction, and (2) relative deviation between AE method and sieve method were no more than 4.69% for average particle size prediction.

However, the present study is preliminary and needs to be further investigated. On the one hand, analyses of structure characteristics based on structure diagram and energy distribution need to be further extended to other multiphase systems (e.g. gas-liquid, gas-solid-liquid, and gas-liquid-liquid etc.). On the other hand, it needs to further develop more effective on-line models for process monitoring with respect to AE technique based on the studies of structure characteristics, as well as advanced statistical and intelligent methods.

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