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Wall sheeting diagnosis in fluidized beds based on chaos analysis of acoustic emission signals*

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Abstract: A novel method, based on acoustic emission (AE) techniques, for detecting agglomeration in fluidized beds is presented. Particle size characteristics are determined based on the principle that AE signals with different frequency band energies are emitted when particles of different sizes impact an internal wall. By applying chaotic analysis to the AE signals, the malfunction coefficients are well defined. Agglomeration in the fluidized bed can then be detected by the sudden variation of malfunction coefficients. AE signals were investigated in a laboratory scale heated fluidized bed and an industrial polyethylene fluidized bed. Experimental data showed that the malfunction coefficients increased with the growth of agglomeration. The results indicated that agglomeration in fluidized beds can be predicted and diagnosed effectively and precisely using AE techniques based on chaotic analysis.

Key words: Acoustic emission (AE), Fluidized bed, Malfunction coefficient, Agglomeration, Chaos

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INTRODUCTION

In fluidized beds, the fluidization hydrodynamics are strongly dependent on particle size and density. The fine polymer particles tend to sinter to form clumps because the efficiency of heat transfer is lower in an ethylene gas polymerization fluidized bed reactor than in a slurry reactor. Unwanted particle agglomeration is a difficult problem, because it can affect the fluidization quality of a fluidized bed. Accumulation of the agglomerates may lead eventually to a loss of fluidization (defluidization) and the unscheduled shutdown of the plant (van Ommen *et al*., 2000). Therefore, it would be useful to be able to detect agglomeration as early as possible (Nijenhuis *et al*., 2007), so that appropriate measures could then be taken to prevent the condition of the bed worsening and to avoid economic loss. However, the diagnosis of malfunctions in fluidized beds has always been a very difficult task both in academic and industrial circles. At present, the main methods for detecting agglomeration include pressure fluctuation (van Ommen *et al*., 2000; Nijenhuis *et al*., 2007), optical fiber (Li *et al*., 1991; 1995) and γ-ray methods. Once a malfunction occurs in a fluidized bed, these physical variables reflecting the nature of multiphase flow might change greatly or abruptly. But some physical variables are insensitive to temporal and spatial changes. Pressure signals are not sensitive to temporal changes. When pressure signals change obviously, the fluidized quality of a fluidized bed reactor cannot be recovered by changing the operating conditions. Also, in the pressure fluctuation method, a probe needs to be intruded into the fluidized bed, and the probe can easily become plugged by polymer particles. Optic measurements are not suited to the rigorous fluidized conditions in factories though they may offer more accurate information about the shape and size of agglom-

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erations. The γ-ray is now being replaced by other methods because of the risk of harm to human health.

Compared with these methods, acoustic emission (AE) signals generated as a result of the collision between particles and the internal wall of the fluidized bed and sampled by accelerometers, give a wealth of information about the size and movement of fluidized particles (Terchi and Au, 2001). Technically, AE is the mechanical energy released in the form of characteristic mechanical vibrations (Mylvaganam, 2003). Any form of energy can cause these vibrations owing to deformations in a material under temporal and spatial variation in stress. Piezoelectric devices tuned to the frequency of the propagating wave can easily detect these characteristic waveforms due to AE. By having a direct or indirect path from the source of AE waves to the piezoelectric sensor, the mechanical vibrations can be converted to electrical signals. AE signals emanating from such activities carry revealing information about the behavior of the structures, materials or processes.

Recently, acoustic measurement techniques have been developed to monitor the state of equipment and the physicochemical changes within chemical engineering processes (Boyd and Varley, 2001). Cody *et al*.(1996; 2000) analyzed the AE signals from a fluidized bed and obtained a quantitative determination of the average particle granular temperature through independent measurement of the wall transfer function determining the coupling between the acoustic shot noise excitation at one location and the response of an accelerometer at another. Tsujimoto *et al*.(2000) found that there were direct correlations between the mean AE amplitude, dimensionless excess gas velocity, and dimensionless bed height. AE sensors can be applied to detect the onset of unstable fluidization due to an increase in moisture content in a fluidized bed. Boyd and Varley (2001) reviewed the use of passive measurement of AEs created by a process as a potentially non-invasive, real-time monitoring technique to be used in process control and fault detection within processes such as gas-liquid mixing, powder flow and mixing and chemical reactions.

Zhao *et al*.(2001) and Hou *et al*.(2005) showed that the change in the dominant frequency of an acoustic wave reflects the change in energy distribution of each scale (frequency band). The sum of acoustic energy from collisions of particles of various sizes leads to the difference of acoustic energy at each scale. We have predicted the particle size distribution successfully by multi-scale analysis of acoustic energy (Hou *et al*., 2005). Therefore, it is possible to monitor the growth of polymer particles and their agglomeration in a fluidized bed in real-time using AE technology.

Because a fluidized bed exhibits turbulent flow and irregular behavior, it is well known that chaos analysis is a valuable tool for improving the design and operation of fluidized bed reactors. The chaos analysis method (van den Bleek *et al*., 2002) includes strange attractors, Hurst analysis, correlation dimensions, the max-Lyapunov Index, the Kolmogorov entropy (K entropy), and so on. In this paper, correlations and K entropy calculated from AE signals collected in laboratory and pilot scale experiments were used to detect agglomeration in fluidized beds. Wavelet analysis (Zhen *et al*., 2002) was also used as a supplementary method.

EXPERIMENTAL SETUPS AND PROCEDURE

Laboratory scale experimental setup

The laboratory scale experimental setup included AE measuring apparatus and an externally heated fluidized bed (Fig.1). The UNILAB 2003, developed by the Unilab Research Center of Chemical Reaction Engineering of Zhejiang University (Yang *et al*., 2006), China, includes an AE sensor, a preamplifier, a main amplifier, a signal A/D conversion apparatus and a signal processing device. The diameter of the externally heated fluidized bed was 100 mm. Glass was used as the bed wall, which was coated with a thermal insulating layer and contained a heating cord. The temperature of the fluidized bed was controlled by a temperature controller (platinum resistance thermometer, ±0.1 K). A sintered plate with an aperture of 154 μm was used as the distributor. Hot air was used as the fluidizing agent, which was heated by the heating cord before entering the fluidized bed. The AE sensor was located 50 mm above the distribution plate. The frequency of sampling was set to 500 kHz for fitting the Nyquist Theorem by checking the power spectral density of the AE signals. The time series were divided into parts of three minutes for evaluation by the monitoring method.

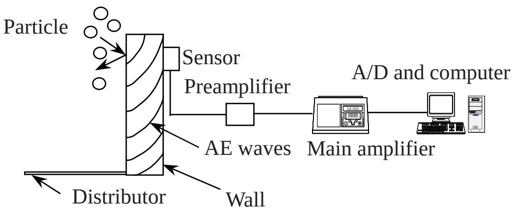


Fig.1 Schematic diagram of experimental apparatus

To investigate the effect of particle agglomeration on fluidization, experiments were carried out using bimodal polyethylene particles as the bulk solids because they are tacky and easy to agglomerate under heating. Agglomeration was controlled by raising the inlet temperature of fluidizing air to simulate the phenomenon of particle agglomeration in a fluidized bed. The velocity of fluidizing air was 0.25 m/s, and the air was heated from 30 to 80 °C. The AE signals were collected at each 10 °C increase in temperature, and at 3 min intervals after the air temperature reached 80 °C. Bimodal polyethylene particles readily self-agglomerate and form bigger agglomerates partly because of their low molecular weight.

Pilot scale experimental setup

The pilot scale experimental setup was an industrial fluidized bed, 420 mm in diameter. On the premise of not breakdown of the fluidized bed, excessive catalyst was added to agglomerate the polymer powder artificially in a short time. F catalyst was used which readily generates static electricity. High density polyethylene was produced at the reaction temperature of 93 °C, and the superficial gas velocity was set to 0.64 m/s. AE signals were collected to study the relationship between the agglomeration of polymer particles and the change in AE signals. The γ-radial system for warning of agglomeration worked from the beginning of the reaction, and all the original data was saved.

AE SIGNALS PROCESS METHOD

Analysis method

The basic idea behind AE signal analysis is to extract relevant information from the AE signal to gain some insight about the nature, location and severity of the sources. Here we introduce the characteristic parameters of chaos, including the classical correlation dimension (Ganz and Lenz, 1996) and *K* entropy (Grassberger and Procaccia, 1983), into the research on the effects of agglomeration on gas-particle fluidization. The regularity and essential mechanics of agglomeration affecting fluidization behavior were revealed, which might help us monitor fluidized beds much more effectively.

The character of AE signal is instantaneous and stochastic. In other words, AE signals are typically non-stationary in the sense that their frequency and statistical characteristics change with time. They consist of a series of often overlapping but sometimes separate, decaying transient bursts occurring at irregular intervals and with random amplitudes (Yang *et al*., 2005). During AE signals processing, a common problem is how to extract physical parameters of interest when these involve variations in time and frequency. It is important to obtain the AE signal and its character at every point in the time scale for analyzing the character of the acoustic source. The signal processing method should be able to analyze the signal synchronously in the time and frequency domains.

Applications of chaos analysis are based on examining the attractor shape and/or a characterization of the attractor by the *K* entropy (van den Bleek *et al*., 2002). The correlation dimension is a measure of the dimensionality of the space occupied by a set of random points. A high correlation dimension corresponds to a highly complex attractor with many degrees of freedom. The correlation dimension which indicates the complexity of the structure of the attractor in phase space can be calculated using the Grassberger and Procaccia algorithm (1983) with an embedding window length equal to the dominant cycle time. The *K* entropy is a number expressed in bit (s) that quantifies the unpredictability and, therefore, the degree of organization of the system, and is one of the characteristic numbers that quantifies the attractor (van den Bleek *et al*., 2002). The method of Zhao *et al*.(1999) was used to calculate the correlation dimension (D_2) and K entropy (K_2) at the same time, using a least square method. Details of the calculation procedures are given by Grassberger and Procaccia (1983) and Zhao *et al*.(1999).

The utility of the correlation dimension is in determining the (possibly fractional) dimensions of fractal objects. Thus, the correlation dimension could be considered as an indication (Grassberger and Procaccia, 1983) of the number of the control variables in a complicated system (e.g., a fluidized bed reactor). AE signals, which are highly affected by the particle size, might reflect parts of the hydrodynamic behaviors of the bed. When fine polymer particles agglomerate into big clumps which change the particle size distribution, the correlation dimension will increase accordingly. This can be explained by the growth in the number of the control variables. For example, before the agglomeration, AE signals are generated by the small particles; after the agglomeration, the signals are determined by not only the normal sized particles, but also the middle-sized ones and even by large clumps. The complexity of the system will increase as the formation of the agglomerates increases, which will greatly change the voidage and affect the breaking and coalescence of bubbles. As a consequence, *K* entropy will increase when agglomeration occurs.

Definition of malfunction coefficient

Generally, the factors affecting the signal system decrease with the decrease of the correlation dimension, which indicates that the complexity of system decreases and the relationships between each point in the system become more similar. In contrast, the complexity of the system increases when the correlation dimension increases. Thus, *K* entropy appears to be a good measure of the degree of disorder of dynamic systems. *K* entropy is zero for a regular system and infinite for a random system. It is a constant greater than zero if a system is classed as deterministic chaos. The information loss is faster and the level of system chaos is higher with increasing *K* entropy. The larger the *K* entropy, the more complex the system.

To determine the changes in chaos parameters during the process of agglomeration, we define the malfunction coefficients as follows:

$$C_{D_2}=\left|\frac{D_2-\tilde{D}_2}{\tilde{D}_2}\right|,\ \ C_{K_2}=\left|\frac{K_2-\tilde{K}_2}{\tilde{K}_2}\right|, \tag{1}$$

where C_{D_2}, C_{k_2} are malfunction coefficients; D_2, K_2 are the correlation dimension and *K* entropy of AE signal, respectively; $\tilde{D}_2$, $\tilde{K}_2$ are the correlation dimension and *K* entropy of AE signal under normal conditions. It is important to choose the right 'normal condition' for the malfunction coefficients. Clearly, the malfunction coefficients are sensitive to C_{D_2}, C_{K_2}, hence, the 'normal condition' should reflect the optimum or required fluidization state of the bed. Specifically, the state after normal start-up of the industrial plant and the state before heating the fine polymer particles in the laboratory scale fluidized bed will be preferred.

It is clear that the malfunction coefficients under agglomeration conditions are larger than those under normal conditions. Therefore, a malfunction threshold value α can be set: the malfunction of agglomeration occurs when the malfunction coefficient is larger than α; while the fluidized bed remains under normal conditions when the malfunction coefficient is smaller than α. It is easier and more convenient to judge the agglomeration using the malfunction coefficient than by analyzing the change of chaos characteristic parameters directly. In this research, the standard values of C_{D_2} and C_{K_2} were first determined by chaos characteristic parameters under normal conditions. Then the threshold value of malfunction was set. Finally, the malfunction coefficients were calculated under operating conditions.

RESULTS AND DICUSSION

Relationship between agglomeration and AE signals

We have found that the energy of AE signal is the function of particle size d_p, particle density ρ_s and analysis time T (Yang *et al*., 2005):

$$E=\int_0^T P_{AE}\Delta A v\mathrm{d}t=\int_0^T \frac{\pi}{3}\xi\eta\rho_s v^3 d_p \mathrm{d}t, \tag{2}$$

where ζ, η, v, P_{AE} and ΔA are particle porosity, effective conversion rate, particle velocity, sound pressure and impact area, respectively. Therefore, the energy of AE signals can be associated with particle size distribution. For a multi size composition particle mixture, the AE signals were studied using multi-scale wavelet analysis to obtain the particle size distribution data (Yang *et al*., 2005). In this research, the AE signals of granular fluidization are decomposed into seven scales by wavelet analysis, which not only ensures the accuracy of the analysis but also avoids complicated calculations (Serrano and Fabio, 1996). According to Yang *et al*.(2005), the relationship between each scale of wavelet and particle size is shown in Table 1. Each frequency divided by wavelet analysis corresponds to a range of particle size distribution (Hou *et al*., 2005; Yang *et al*., 2005), which provides theoretical support for diagnosing agglomeration in fluidized beds.

Table 1 Frequency and corresponding particle size of each scale of wavelet (Yang *et al*., 2005)

Scale	Frequency range (kHz)	Particle size of each scale (mm)
d_1	250~500	<0.14
d_2	125~250	0.18, 0.14
d_3	62.5~125	0.36, 0.18
d_4	31.25~62.50	0.50, 0.36
d_5	15.63~31.25	1.19, 0.71
d_6	7.82~15.63	2.00, <50.00 of agglomeration
d_7	3.91~7.82	>50.00 of agglomeration
a_7	0~3.91	Much bigger agglomeration

'*a*' and '*d*' represent approximation and detailed signals, respectively, and the subscripts 1~7 represent the levels of the wavelet

In laboratory scale experiments (Yang *et al*., 2005), linear low density polyethylene (LLDPE) powder was fluidized under the superficial gas velocity of 0.6 m/s. The AE signals were sampled after adding 1% (w/w) polymer agglomerate of sizes 10, 20, 40 and 60 mm. It was found that the energy of the sixth detailed level of wavelet d_6 increased markedly when adding 1% (w/w) polymer agglomeration with an equivalent diameter of less than 50 mm. The energy of the seventh detailed level of wavelet d_7 increased markedly when adding 1% (w/w) polymer agglomeration with an equivalent diameter larger than 50 mm. The energy of the seventh approximation level of wavelet a_7 increased markedly when adding greater polymer agglomeration. Therefore, the energy change of d_6 or d_7 can be used to diagnose the malfunction of agglomeration.

Analysis of agglomeration AE signal in a laboratory scale fluidized bed

The original AE signals of normal fluidization (T=30 °C) and malfunction fluidization (T=80 °C) are shown in Fig.2.

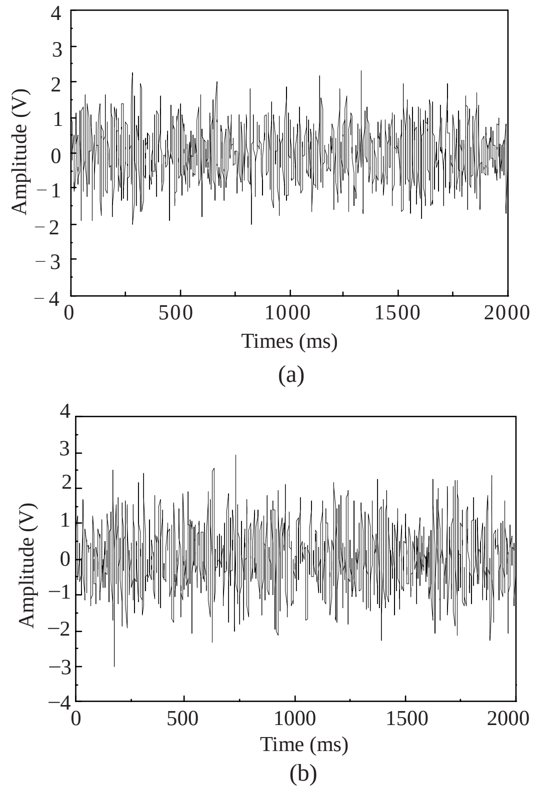


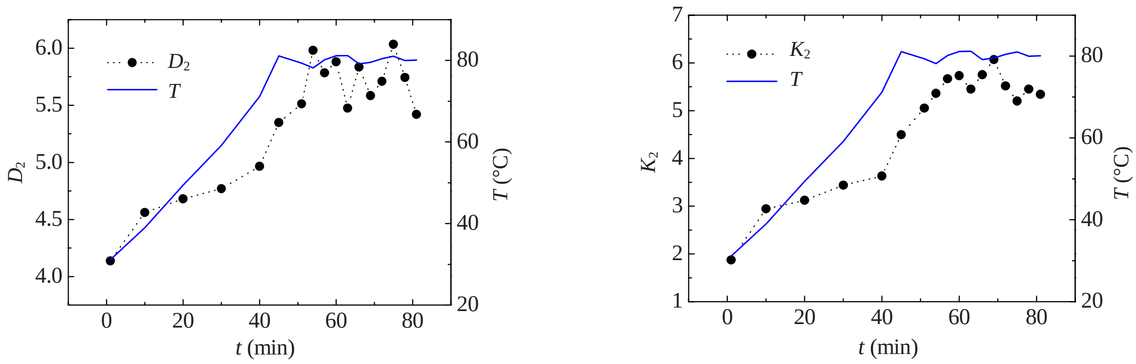
Fig.2 Original acoustic emission signals under (a) normal and (b) malfunctioned fluidization

Compared with the normal state, the amplitude of malfunction fluidization increases and is loosely distributed. With the increase in temperature, bimodal polyethylene particles agglomerate, causing an increase in the average particle diameter. The movement of particles in the fluidized bed becomes complicated because of the formation of the large clumps, thus the AE signals become more random. The processes of bubbles breaking and coalescing become more complicated after larger lumps or sheets are formed, and the irregularity of bubble motion and bubble size distribution is intensified. The mode and structure of AE signals generated by the collision of particles with the bed wall becomes more varied and changeable. Therefore, the randomness and complexity of the system increases greatly.

The correlation dimension and K entropy can be calculated from AE time series and then the malfunction coefficients can be obtained (Figs.3 and 4). The correlation dimension, K entropy and the degree of system complexity increase with the increase in temperature of the fluidized bed. As a consequence of the agglomeration, some fine particles agglomerate and form bigger particles, which changes the ratio of big particles to small particles. C_{D_2} and C_{K_2} increase as the temperature rises, and they are markedly increased compared with the normal condition. The most important information from these two figures is that during the temperature rise from 70 to 80 °C, the two corresponding malfunction coefficients of chaos characteristic parameters change distinctly, especially C_{K_2}. The system becomes more complex and the degree of chaos increases, which can be explained by the formation of agglomerates. When the temperature reaches 80 °C, the chaos characteristic parameters and malfunction coefficients are still increasing with time, which indicates the growth of agglomeration. The curves of malfunction coefficients also fluctuate continuously (Fig.4). Agglomeration can be broken at a certain level, but the general tendency of agglomerate development is growth. The clumps and sheets can be found in the fluidized bed or adhering to the bed wall after experiments which proves that the heating method causes the agglomeration. Although the chaos characteristic parameters change during the process of agglomeration, they have no uniform standards either for the same system or for different systems, so it is feasible to use malfunction coefficients to assess the unwanted events. While malfunction coefficients can clearly assess the form of agglomerates, it would be much more convenient to do this by setting a threshold value for α. Based on the careful observation of the experimental phenomenon, the agglomeration of the particles becomes irreversible when the temperature reaches 80 °C, therefore we will use threshold value of 0.3 for $\alpha_{C_{D_2}}$ and 1.2 for $\alpha_{C_{K_2}}$; higher values will give a warning and indicate that the state of the fluidized bed has changed and some appropriate strategies need to be implemented.

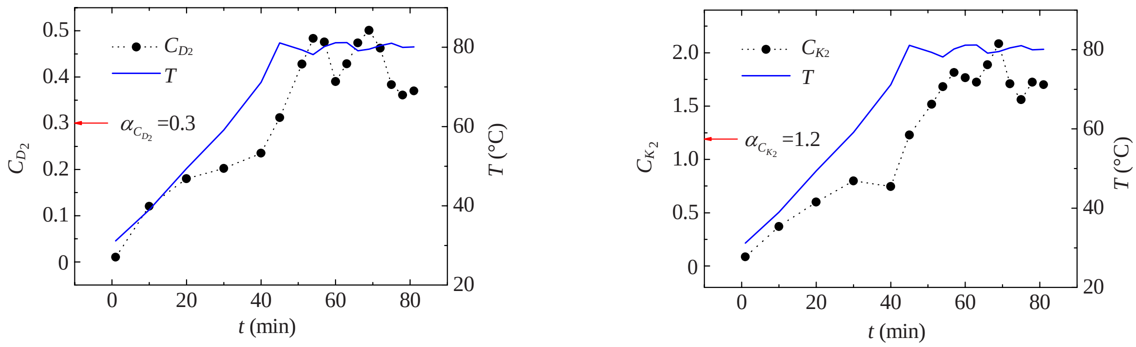
Analysis of AE signals of melting agglomeration in a pilot plant

For the purpose of revealing the mechanism of particle agglomeration, the experiments on agglomeration of polymer powder were also carried out in an industrial pilot plant fluidized bed (Φ420 mm). The criterion for agglomeration obtained in the laboratory



(a) (b)

Fig.3 Development of chaotic characteristic parameters in a heated fluidized bed of laboratory scale. (a) Correlation dimension; (b) *K* entropy



(a) (b)

Fig.4 Development of the malfunction coefficient in a heated fluidized bed of laboratory scale. (a) Malfunction coefficient based on correlation dimension; (b) Malfunction coefficient based on *K* entropy

scale fluidized bed was further verified, and more evidence was provided for early-warning signs of agglomeration in industrial reactors. On the premise of not breakdown of the fluidized bed, excessive catalyst was poured into the reactor to artificially cause agglomeration of the polymer powder. The AE signals were collected to investigate the relationship between AE signals and agglomeration.

1. Wavelet analysis

To examine the AE signals and find the differences between the normal state and the 'defluidization' state, the AE signals occurring during the agglomeration of polymer particles in the fluidized bed were decomposed into seven scales by wavelet analysis (Figs.5 and 6). In the first experiments, F catalyst was added excessively (5.9 g/h compared with the normal rate of 4.0 g/h), but the effect could not be seen immediately and the energy ratios of AE signals were unchanged. At time 17:50, the energy of the d_5 and d_6 levels of wavelet began to increase slowly, while the energy of the d_3 level of wavelet decreased continuously. The number of particles of sizes 0.71 and 2.00 mm (represented by levels d_5 and d_6 of the wavelet) started to increase, while the number of fine particles of 0.18 and 0.36 mm (represented by level d_3) decreased (Table 1). The variances of the energy ratios could be explained by the results of agglomeration of fine particles to form large particles, which changed the particle size distribution. At 17:47, there was a steep rise in the energy of levels d_5 and d_6, which meant that the mass fraction of particles of 0.71, 1.19 and 2.00 mm had increased greatly and polymer agglomerations with an equivalent diameter smaller than 50 mm had formed. At 18:15, the γ-radial warning system for agglomeration showed a response, but it was slower than the AE sensor.

At 18:51, the energy of the d_5 and d_6 levels of wavelet began to decrease, while the energy of d_7 and a_7 levels increased a little. This showed that agglomerations bigger than 50 and 100 mm had formed and the situation in the reactor deteriorated. At the same time, the γ-radial warning system finally detected the agglomeration in the fluidized bed.

At 19:50, the energy of the a_7 level of wavelet decreased and then stabilized. This indicated that the big agglomerations had begun to break up. After stopping the reactor, clumps and sheets with cracks were found in the discharge system. The dimensions of the agglomeration were 420 mm in length, 40 mm in width and 5 mm in thickness, with an equivalent diameter of 54.5 mm. There were lots of small fragments about 30~50 mm in size and 5 mm in thickness. Most fragments had a break mark, indicating the existence and break up of a larger agglomeration.

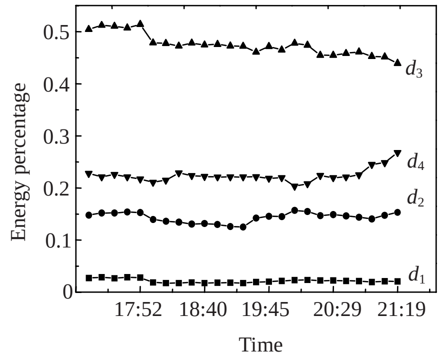


Fig.5 Development of AE at d_1~d_4 scales during agglomeration in a pilot plant

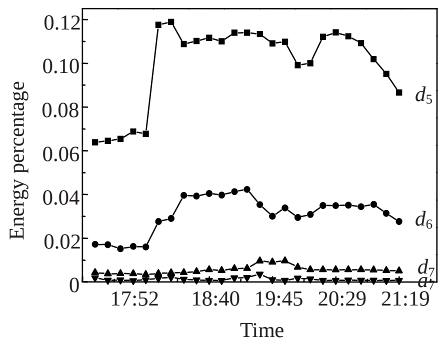


Fig.6 Development of AE at d_5~d_7 and a_7 scales during agglomeration in a pilot plant

2. Chaos analysis

The development of the energy of AE signals during the agglomeration process has been discussed. It seems that the energy ratio of different levels does change during the process of agglomeration of polymer particles, but it is difficult to give an alarm before the hydrodynamic behaviors develop into an undesirable situation. Therefore, it is worthwhile using the malfunction coefficients which were obtained in the Φ420 mm industrial pilot plant fluidized bed. The variation in the chaos characteristic parameters of AE signals and malfunction coefficients is shown in Figs.7 and 8. In the initial reaction stage, the correlation dimension and K entropy showed little fluctuation indicating that the effects of the catalyst had not emerged. To calculate the malfunction coefficients, the AE signals at 16:40 were chosen to represent the normal state ($\tilde{D}_2$ was 4.12 and $\tilde{K}_2$ was

1.92). The rapid increase in correlation dimension and K entropy occurred at 17:59. The system became more and more complex, and the malfunction coefficients rose sharply, indicating a large increase in big particle content and the formation of a few small agglomerations. According to the criteria obtained from the laboratory scale experiments, malfunction coefficients based on the AE signals would give an early warning of agglomeration at 18:10. Compared with the γ-radial warning system, chaos analysis of AE signals is an environmentally friendly method with fairly good efficiency.

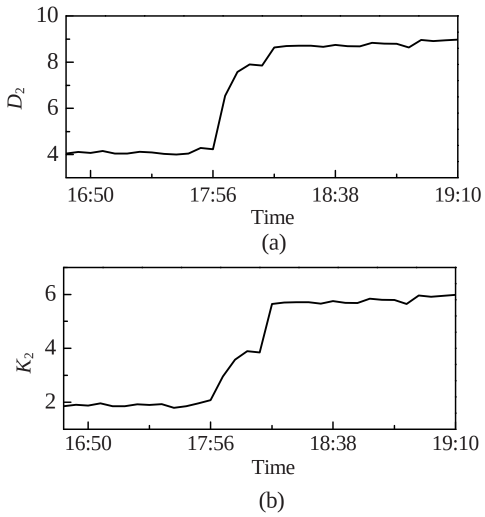


Fig.7 Variation of chaotic characteristic parameters in the agglomeration process. (a) Correlation dimension; (b) *K* entropy

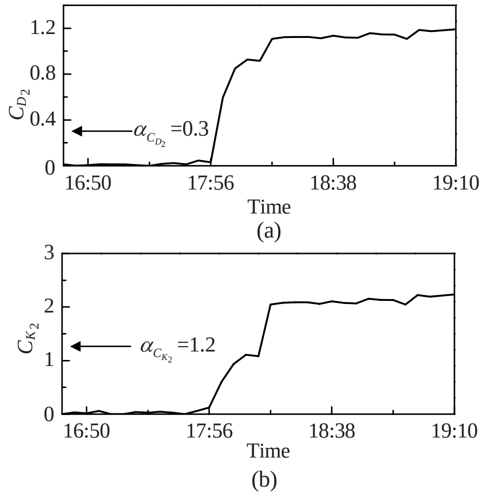


Fig.8 Variation of malfunction coefficient in the agglomeration process. (a) Malfunction coefficient based on correlation dimension; (b) Malfunction coefficient based on *K* entropy

Fig.9 shows the development of agglomeration of polymer particles in the pilot plant. The particles represented by levels d_1 to d_4 of the wavelet can agglomerate to form the big particles represented by levels d_5 and d_6. The particles represented by levels d_5 and d_6 of the wavelet can also break up into fine particles represented by levels d_1 to d_4. It is a dynamic equilibrium process of agglomeration and breaking, and the process is reversible. The particles represented by levels d_5 and d_6 of the wavelet can also grow to form the bigger particles represented by the d_7 level, and finally grow into great blocks of polymer. During the process of agglomeration, the AE energy increased gradually from a low level to a high level, and the dominant frequency of AE signal transfer was from high to low frequency. It is an irreversible process except that the energy of the d_1 to d_4 levels transfers to the d_5 and d_6 levels, thus the agglomeration alarm should be sent as early as possible (d_5, $d_6 \rightarrow d_7$). The abrupt change of AE energy within each level of wavelet can be used to diagnose the agglomeration accurately.

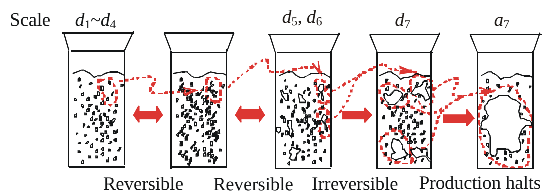


Fig.9 Development of agglmeration of polymer particles in the pilot plant

The malfunction coefficients C_{D_2} and C_{K_2} are sensitive to agglomeration and both of them had increased by 10 to 100 times after agglomeration (Fig.8). Therefore, they are useful parameters which can be used to detect the process of agglomeration by setting a malfunction threshold value α. The results from the pilot plant have proven that the criterion from the laboratory scale experiments can also be used in an industrial fluidized bed reactor which indicates that the method based on the chaos analysis of AE signals has the potential to be applied for agglomeration detection in large fluidized bed reactors.

CONCLUSION

A novel method based on AE signals generated by the random collision of particles with the reactor wall can be used to non-intrusively monitor the agglomeration of polymer particle in laboratory scale and pilot scale fluidized beds. The AE signals of granular fluidization are decomposed into seven scales by wavelet analysis. The characteristic of particle agglomeration in the fluidized bed is well described: when the AE energy gradually increases from low level to high level, the dominant frequency of AE signal transfer is from high to low frequency and the AE energy within a level changes abruptly, agglomerations will occur in the fluidized bed.

Furthermore, in this research, chaos analysis was applied to both laboratory scale and pilot scale experiments. The chaotic characteristic parameters of AE signals, correlation dimension and K entropy, were calculated based on experimental data, and their development was investigated. We defined the malfunction coefficient of particle agglomeration based on chaos analysis, which is more sensitive to agglomeration. A criterion for agglomeration in fluidized beds was presented: when the malfunction of $\alpha_{C_{D_2}}$ is larger than 0.3 or $\alpha_{C_{K_2}}$ is larger than 1.2, agglomeration occurs in the fluidized bed. It can predict and diagnose agglomeration in a fluidized bed reactor more effectively and accurately than other methods.

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