Agglomeration detection in Gas-Phase Ethylene polymerization based on the Gaussian of acoustic signal

Wu Haiyan, Wang Zhe, Lin Weiguo, Wang Jing, Li Dongdong

College of Information Science and Technology, Beijing University of Chemical Technology, Beijing 100029, China
E-mail: wuhy@mail.buct.edu.cn

Abstract: An agglomeration detection method based on the Gaussian of acoustic signal is proposed for the gas-phase Ethylene polymerization. The forming mechanism of acoustic pressure in Fluid Bed Reactor (FBR) is analyzed first. Based on the analysis, the kurtosis of the acoustic signal is extracted as the feature to predict the changing in particle size distribution (PSD) of polymer within FBR. To avoid the repeated false alarms due to the repeatability of agglomeration, the distribution parameter of kurtosis is introduced as the output of detection method. The alarm threshold is determined based on the physical characteristic of kurtosis that is not absolutely empirical. The availability of the proposed method is testified in a pilot plant producing polyethylene by gas-phase method, and the comparisons with the other time-domain characteristics of acoustic signal and with the other measurement variables show that the Gaussian detection of acoustic signal is more sensitive to agglomeration.

Key Words: Agglomeration detection, polymerization, Gaussian detection, acoustic method, FBR, PSD

1 INTRODUCTION

As an important polymer product, Polyethylene is widely used in the fields of industry, agriculture and national defense. The Polyethylene production by gas-phase ethylene polymerization has a high efficiency in heat and mass transfer, an even temperature distribution leading to an easier polymer quality controlling, a compact reactor structure, meanwhile the continuous production is easier to realize by gas-phase method. The Fluid Bed Reactor (FBR) is utilized as the kernel reactor in the gas-phase production of polyethylene. Compared with fixed bed reactor, the controlling of temperature in FBR is easier, and the stay time of reaction mass in FBR can be controlled which lead to the controlling of the molecular weight distribution (MWD) of polymers. However, in actual polymerization practice, the hydrodynamics may be changed drastically due to static electricity and the low heat exchange capacity, which will lead to particle melting, sheeting, aggregation, and even unscheduled shutdown of the plant. Therefore, the early-warning approach of gas-solid fluidized bed agglomeration has always been a research topic of great interest.

Several methods for the detection of agglomeration in FBRs have been proposed, such as pressure fluctuations [1], temperature [2], electrostaticity [3] and acoustic method [4-5]. Among these methods mentioned, the acoustic method has been considered as an attractive technique due to its non-intrusiveness, timeliness and safety. G.D.Cody et al. [6] introduced an accelerometer acoustic sensor as a novel non-intrusive probe of the average kinetic energy of a gas fluidized bed to obtain the average particle granular temperature. Yang Yongrong et al. [7] studied the early-warning method of the fluidized bed agglomeration based on multi-scale decomposition analysis of acoustic emission signals, and proposed the Hou-Yang Model to describe the particle size distribution (PSD) based on the frequency characteristic of acoustic signals. Sanni Materoa et al. [8] introduced a method for the implementation of real-time water content and granule size determination during granulation in FBR from acoustic emission spectra. N.Salehi-Nik et al. [9] processed the acoustic emission signals by statistical analysis, and demonstrated that the acoustic emission measurement is highly feasible as a practical method for monitoring the hydrodynamics of gas-solid beds. D. Vervloet et al. [10] investigated the potential of both passive acoustic emission and vibration measurements for monitoring gradual process changes in comparison to pressure fluctuation measurements, and the results demonstrate that one type of microphone and the accelerometer have some potential as non-intrusive alternatives for the purpose of monitoring transient processes compared to pressure fluctuation measurements in FBRs. Garret Book et al. [11] investigated a passive acoustic method for the detection of changes in bed fluidity in a large scale gas–solid fluidized bed after liquid injection. Zhou YeFeng et al. [12] measured the particle motion and bubble size variations with liquid action in FBR by acoustic and pressure fluctuation techniques. In our previous study [13], the time-frequency characteristic of acoustic signal is extracted by wavelet packet decomposition, and then the Principal Component Analysis was introduced to reduce the dimensionality of the feature vector. An agglomeration warning model is created by Support Vector Data Description.

This work is supported by the State Key Laboratory of NBC Protection for Civilian (SKLNBC2014-10); the National Natural Science Foundation of China (61403017, 61573050); and the Fundamental Research Funds for the Central Universities (YS0104).

In these studies, the important variables or conditions of FBRs (such as the regime transition, the particle fluidization, the granulation end-point and the agglomeration in FBR) are gained based on the extracted feature vectors from the time-domain or frequency-domain analysis of acoustic signals. Furthermore, the availabilities of proposed methods are testified by the experiments. Different frequency acoustic signals (including ultrasound, audible sound and infrasound) were used to detect the different scales and usages of FBRs (including granulation, drying et al.). Thus, there are many different ways in extracting the information from the acoustic signal. This also reflects that difficulties in extracting the information from the acoustic signal have been one possible reason why acoustic monitoring method is not more widespread.

This paper focuses on the agglomeration detection in pilot plant of FBR used for gas-phase Ethylene polymerization by the audible acoustic signal. The generation mechanism of sound source within FBR used for Polythene production is analyzed first, meanwhile the internal relation between the acoustic pressure and particles size distribution (PSD) of polymer within the FBR is gained. Then, based on the analysis, an agglomeration detection method based on the Gaussian of acoustic signal is proposed, in which the kurtosis is extracted as the feature variable to warn the agglomeration early during polymerization. The feature used for fault prediction have a clear physical meaning which can ensure the effectiveness in mechanism. Since the mechanism of polymerization is complicated as well as the movement law of the particles within FBRs, the abnormal particle gathering may disappear with the continuation of the reaction or by the particles collision that make a repetitive agglomeration. To avoid the continual false alarms caused by the repetitive agglomeration, the distribution parameter is introduced to the agglomeration discrimination function. The feature extraction is simple and effective and the proposed method provides a probability solution on the PSD measurement of polymerization.

2 THEORY

2.1 Relationship between PSD of Polythene and acoustic pressure in FBR

There are three kinds of sound sources within the FBRs: the friction between particles, the friction between particles and the vessel wall; the colliding between particles, the colliding between particles and the vessel wall and the fluid turbulence. The non-intrusive acoustic method lays an acoustic sensor out of the wall of FBR. Thus, the acoustic signals inside the reactor have too serious an attenuation to be sensed, therefore, the sound of colliding between particles and the vessel wall composes the main acoustic signals sensed by the acoustic sensor out of the vessel wall. G.D. Cody et al. [6] have analyzed the physics of acoustic shot noise of FBRs. The particle was regarded as elastic. For random elastic particle impacts on an area ΔA of the internal wall of a cylinder, the time average of the resultant force $\bar{F}(t)$ is thus given by [6]:

$$\begin{aligned}\bar{F}(t) &= 2mv\gamma \\ &= \frac{\pi}{3}D^3\rho_s v\gamma\end{aligned} \tag{1}$$

where m is the particle mass, v is the velocity of mass, D is the diameter of particle and ρ_s is density. $\gamma\ (1/s)$ is the mean rate of the arrival of the particles on area ΔA that can be given by:

$$\gamma = \rho_n v\Delta A \tag{2}$$

where $\rho_n (1/m^3)$ is the particle density within FBRs that means the quantity of particles per unit volume. Since the volumes of particles within FBR is disperse, the average of ρ_n can be estimated by:

$$\bar{\rho}_n = \frac{\varepsilon}{\bar{D}^3} \tag{3}$$

where ε is coefficient, $\bar{D}$ is the average diameter of particles within the FBR. $\bar{\rho}_n$, instead of ρ_n , is used to estimate the time average of force.

From Eq.1, the time average of pressure can be given by Eq.4 [7]:

$$\bar{P}_A(t) = \frac{\eta\bar{F}(t)}{\Delta A} \tag{4}$$

where η is the conversion efficiency from impact force to acoustic pressure.

Then, the time average of acoustic pressure due to the mass m particles colliding with the wall of FBR is given by:

$$\bar{P}_A(D,t) = \frac{\pi D^3 v^2\eta\varepsilon\rho_s}{3\bar{D}^3} = \frac{\pi\eta\varepsilon\rho_s}{3}\left(\frac{D}{\bar{D}}\right)^3 v^2 \tag{5}$$

In Eq.5, η and ε are coefficient that are determined by the characteristics of FBR, the polymer and the operating conditions. The velocity of particles is reflected by the gas velocity which is one of the important operating conditions during the continuous production.

From Eq.5, the average pressure by the colliding between particles and the vessel wall has a direct relationship with the size of the particle and its average. The sensed pressure is the overlapping of the acoustic pressures caused by a mount of different mass particles, and then has a direct relationship with the PSD within FBR. So the change of the acoustic pressure can reflect the changing in PSD. From Eq.5, the effective acoustic pressure will rise if particles of large size appear. From the Landau's research [14] , in the language of power spectrum analysis, the power spectrum due to random particle impact of these particles is white noise for frequencies below 300KHz. Therefore, if PSD changed, the frequency distribution of acoustic pressure will not be a white noise (Gaussian distribution). A conclusion can be concluded:

【Conclusion 1】The acoustic pressure fluctuation is directly correlated to the change in the size distribution of polythene particles within the FBR. If agglomeration happens, the Gaussianity of PSD will change. Thus the change in the Gaussianity of acoustic pressure can be utilized to detect the agglomeration in polymerization.

2.2 Time-domain characteristic of acoustic signal

In practice, the acoustic pressure is detected by the acoustic sensor and transmitted into electric signal. The characteristic of acoustic pressure fluctuation is indicated in the acoustic signals sampled by the acoustic transducer. Two of the time-domain characteristics of acoustic signal are introduced here.

1) Energy of acoustic signal

The energy of acoustic wave can be given by:

$$E = \frac{p_e^2}{2\rho c^2} \tag{6}$$

where p_e is effective acoustic pressure, ρ is the density of the medium of acoustic wave, and c is acoustic spread velocity in the transfer medium. From the definition in Eq.6, the energy of acoustic wave is proportional to the effective acoustic pressure. Then, in this paper, the average of square of amplitude is utilized to represent the energy of one acoustic signal sample:

$$\tilde{E} = \sum_{i=1}^{n} x^2(i) / n \tag{7}$$

where $x(i), i = 1, 2, \ldots n$ is the amplitude of a frame of signal sample, and n is the quantity of the data point in a signal frame.

2) Kurtosis

Kurtosis is a descriptor of the shape of a probability distribution of a real-valued random variable. The kurtosis is based on a scaled version of the fourth moment of the data. Kurtosis is calculated by:

$$K = \frac{\sum_{i=1}^{n} (x(i) - \overline{x})^4}{(n-1)\sigma^4} - 3 \tag{8}$$

where $\overline{x}$ is the signal average of a signal frame, and σ is the signal variance of the signal frame. Kurtosis is the mensuration of the Gaussianity of signals, and the kurtosis calculated by Eq.8 is equal to 0 if the signal follows Gaussian distribution. If K>0, the distribution of signal is more concentrate, and K<0 represents a decentralized signal distribution. Kurtosis is sensitive to the impulse signal, and is usually used for fault diagnosis of mechanical equipment.

2.3 Agglomeration detection method based on Gaussianity of the acoustic signal

Based on the conclusion 1, the kurtosis of one acoustic signal sample is selected as the feature to predict the agglomeration in FBRs during polymerization. The mechanism of polymerization is complicated, the random agglomeration may disappear with the reaction proceed or because of the impacts. To avoid false alarms caused by the repeatability of the agglomeration, the alarm function is given by Eq.9.

$$f(k) = \sum_{i=k-l}^{k} K(x_i(n)) / L \tag{9}$$

where $f(k)$ is the alarm function of detection system, which is the time average of $K(\cdot)$. L is the length of time window and is usually determined empirically. From the definition of kurtosis, the output is nearly equal to 0 while the signal distribution follows the Gaussian distribution. But in actual practice, because of the disturbance, the measurement error or the acoustic filtering, the kurtosis precise equaling 0 is impossible. Therefore, the threshold of $f(k)$ is set to 0.05. Then discrimination function is given by:

$$\begin{cases} |f(k)| \le 0.05, normal \\ otherwise, agglomeration \end{cases} \tag{10}$$

It should be note that the setting of threshold is based on the physical characteristic of the extracted feature, which is not absolutely empirical.

3 EXPERIMENTS

3.1 Experimental apparatus and control system

The experimental apparatus and control system has been described detailed in [13]. In this paper, a brief description is given.

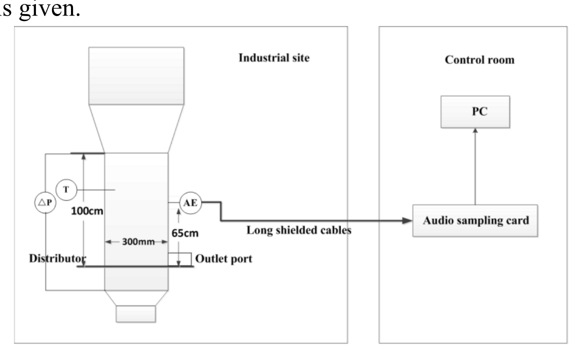

Figure 1. Schematic diagram of the experimental apparatus

Fig. 1 shows the schematic diagram of the acoustic agglomeration monitoring system in an FBR. There are two main parts: a pilot plant of the polyethylene fluidized bed and an acoustic signal acquisition system. The characteristics of the experimental apparatus and control system are shown in Tab1.

Table 1. The characteristics of the apparatus and control system

Characteristic	Value
Material of kettle	Carbon steel
Temperature	85℃
Pressure	1.9±0.5MPa
Main chemical reaction equation	$nCH_2{=}CH_2 \xrightarrow{catalyst} (\text{-}CH_2\text{-}CH_2\text{-})_n$
gas speed of the empty tower	0.5m/s
yield	≥2.0kg/hr

3.2 Acoustic sampling system

The acoustic system consisted of an acoustic sensor, a long shielding cable, a soundcard sampling system and a PC. The acoustic sensor used here is a piezoelectric ceramic sensor, which is pasted on the upper wall of the outlet port covered by silicone rubber. As silicone rubber has the property of sound insulation, it can prevent the influence of external interference on the measurement results. The sampling frequency is 44.1 KHz, and the sampling precision is 16 bits. The sampling duration is 1.486 s. In one sample, the sampling system collects 65536 points of data continuously and then stores them once the sampling is complete. So the n in Eq.7 and Eq.8 is 65536. The sampling and storage interval is 9 s.

4 EXPERIMENT RESULTS and DISCUSSION

The pilot plant described in section 3.1 is utilized to test the effectiveness of the proposed method.

4.1 Agglomeration detection based on the kurtosis of acoustic signal

There are five agglomeration records during a 2months-long experiment. The existing alarm in this plant is based on the signals of the material level and the temperature. If the material level does not drop or the temperature increases sharply, the system alarm. The 5 alarms are recorded in Tab.2.

Tab.2 Alarm Records

Alarms	Temperature	Material level	Alarm time
1	Keep invariant nearly	Do not drop	8:25
2	Keep invariant nearly	Do not drop	22:30
3	Keep invariant nearly	Do not drop	5:45
4	Keep invariant nearly	Do not drop	19:30
5	Keep invariant nearly	Do not drop	18:45

The acoustic signal is sampled and the alarm function is calculated by Eq.9. The alarm results are shown in Fig.2, where $W(\cdot)$ in Eq.9 is kurtosis.

From Fig.2, the proposed method can alarm accurately for every agglomeration records. In the first 4 alarms, the acoustic method alarm earlier than the material level signal ranging 6 minutes to about 50 minutes. But in the last alarm, the material level is earlier. In alarm1 and alarm 4, there are all 2 alarms which may indicate the forming of agglomeration, and the drops in the alarm curve are probably caused by the changing in the impact location.

There are two problems need to be avoid in fault detection: false alarm and missing alarm. Fig.2 shows that the detection system has no missing alarms. Furthermore, Fig.3 shows the output curves from a random selection of acoustic signal records to test the problem of false alarm of the acoustic method.

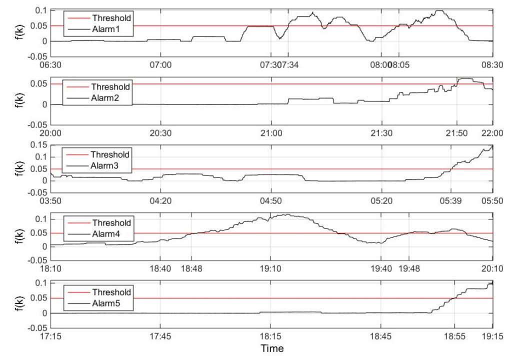

Fig.2 Alarm Results during Agglomeration

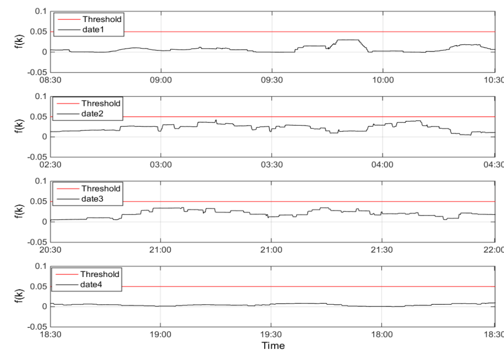

Fig.3 The output curve during normal condition

Fig.3 shows that, there is no fault alarm too based on proposed acoustic method. For the signal of date1, the original kurtosis is shown in Fig.4.

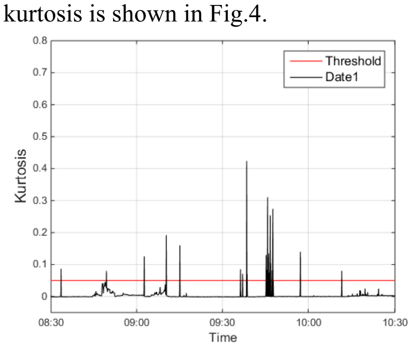

Fig.4 The kurtosis output

There are many repeated changes in the original kurtosis which are probably caused by the repetitiveness of agglomeration. The comparison between Fig.4 and Fig.3 shows that the calculation of Eq.9 decreased the false alarms and improved the reliability of the acoustic system.

4.2 Agglomeration detection based on the energy of acoustic signal

N.Salehi-Nik et al. [9] have proved that the hydrodynamic state of the gas-solid fluidized bed can be determined by statistical analysis (including energy, skewness and kurtosis) of the acoustic emission signals measured by a microphone based on a cold mode experiment. In this paper, the energy is selected to make a comparison with the kurtosis. The alarm results for the same dates of Fig. 2 are shown in Fig.5 where $W(\cdot)$ is energy calculated by Eq.7. The threshold is determined empirically.

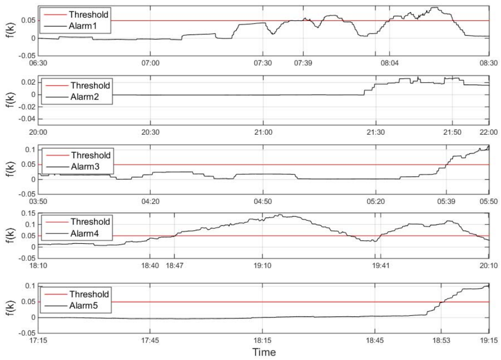

Fig.5 Output curve based on the energy of signal during agglomeration

Fig.5 shows that there is a missing alarm in alarm 2. It should be note that the skewness of acoustic signal is also tested and has similar results with the energy which testified that the kurtosis within the time-domain characteristics of acoustic signal has the best accuracy in agglomeration detection. The missing alarm in energy or skewness tells us that the acoustic signal caused by the agglomeration is probably a sudden change in wave shape which is like an impulse signal, and kurtosis is sensitive to the impulse signal lead to a more sensitiveness to agglomeration than other time-domain characteristics.

5 CONCLUSIONS

The mechanism of acoustic source of polymers within FBRs is analyzed first, based on the results, an agglomeration detection method is proposed based on the Gaussian of acoustic signal. The extracted feature is simple and has a clear physical meaning which has no need in the training between feature spaces to fault spaces, and the determination of threshold has a clear basis which is not empirical absolutely. The experiment results in pilot plant testified that the proposed method can get an earlier alarm than the temperature and material level based method in most cases, but there is still an exception which needs a further study. The proposed method gives a new probability for the prediction of PSD of polymers of FBR.

REFERENCES

[1] Chirone R,Miccio,F.Scala F. Mechanism and prediction of bed agglomeration during fluidized bed combustion of a biomass fuel: effect of the reactor scale[J], Chem Eng J 2006,123,71-80.

[2] Werther J. Measurement tehniques in fluidized beds [J]. Powder Technology, 1999, 102, 1-36.

[3] Aihua Chen, Hsiaotao T. Bi, John R.Grace. Charge distribution around a rising bubble in a two-dimensional fluidized bed by signal reconstruction[J]. Powder Technology, 2007, 177, 113-124.

[4] Malte Bartels, WeiGang Lin, John Nijenhuis, Freek Kapteijn, J.Ruud Van Ommen. Agglomeration in fluidized bdes at high temperatures: mechanisms, detection and prevention [J], Progress in Energy and Combustion Science, 2008, 34, 633-666.

[5] Halstensen M, de Bakker P, Esbensen KH. Acoustic chemometric monitoring of an industrial granulation production process- a PAT feasibility study[J], Chemometr Intell Lab Systems. 2006, 84, 88-97.

[6] G.D. Cody, D.J.Goldfarb, G.V.Storch.Jr, A.N.Norris. Particle granular temperature in gas fluidized beds [J], Powder Technology, 1996, 87, 211-232.

[7] Hou Linxi, Wang Jingdai, Yang Yongrong, Hu Xiaoping. Frequency analysis of acoustic emission and application in gas-solid fluidized bed[J]. Journal of Chemical Industry and Engineering (Chinese), 2005, 15, 380-384.

[8] Sanni Matero,Sami Poutiainen,Jari Leskinen,Kristiina Järvinen,Jarkko Ketolainen, Satu-Pia Reinikainen, Mikko Hakulinen, Reijo Lappalainen, Antti Poso. The feasibility of using acoustic emissions for monitoring of fluidized bed granulation [J], Chemometrics and Intelligent Laboratory Systems, 2009,97,75-81.

[9] N.Salehi-Nik,R.Sotudeh-Gharebagh,N.Mostoufi,R.Zarghami,M.J.Mahjoob. Determination of hydrodynamic behavior of gas-solid fluidized beds suing statistical analysis of acoustic emissions [J]. International Journal of Multiphase Flow. 2009, 35, 1011-1016.

[10] D. Vervloet, J. Nijenhuis, J.R. van Ommen. Monitoring a lab-scale fluidized bed dryer: A comparison between pressure transducers, passive acoustic emissions and vibration measurements [J]. Powder Technology, 2010, 197, 36-48.

[11] Garret Booka, Katherine Albionb, Lauren Briensa, Cedric Briensa, Franco Berrutia. On-line detection of bed fluidity in gas–solid fluidized beds with liquid injection by passive acoustic and vibrometric methods[J], Powder Technology, 2011, 205, 126-136.

[12] Kezeng Dong, Yefeng Zhou, Zhengliang Huang, Jingdai Wang, Yongrong Yang. Gas bubble behaviors in a gas–solid fluidized bed with an arch agitator [J], Powder Technology, 2014,266,38-44.

[13] LinWeiguo, Wang Xiaodong, Wang Weifen, Wu Haiyan. Feature extraction and early warning of agglomeration in fluidized bed reactors based on an acoustic approach [J], Powder Technology, 2015, 279, 185-195.

[14] L.D. Landau, E.M.Lifshitz, Theory of Elasticity [M], Pergamon, Oxford, 2nd edn., 1970.