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Towards Selective Agglomeration Detection in Fluidized Beds Using Advanced Signal Analysis Methods

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TOWARDS SELECTIVE AGGLOMERATION DETECTION IN FLUIDIZED BEDS USING ADVANCED SIGNAL ANALYSIS METHODS

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ABSTRACT

A new methodology of assessing large amounts of fluidized bed pressure fluctuation data with various signal analysis methods in combination with signal pre-treatment methods is presented. This approach can be used to find certain combinations that are selectively sensitive to certain physical effects in fluidized beds, such as agglomeration.

INTRODUCTION

Fluidized beds are utilized for a variety of applications in the process industry, such as fluidized catalytic cracking (FCC), drying, solid fuel utilization and gas-phase polymer production. The combustion and gasification of solid fuel, mostly coal, is an example that has been used in fluidized bed applications for a relatively long time. In light of the increasing world energy demand, coupled with a developing greenhouse effect as well as increasing fossil fuel prices, other fuel sources are currently considered and used. Biomass, although having a lower energy density than fossil fuels, is available in many parts of the world. It is neutral in terms of CO_2-emissions and therefore does not further contribute to the greenhouse effect. Also other fuel sources like sewage sludge or many kinds of solid wastes are an interesting option. Fluidized beds are specifically considered for alternative feedstocks because they are very suitable for a variety of fuels and changing fuel properties (e.g. (1)).

The utilization of alternative fuel such as biomass has, however, also introduced new operational problems. The main concern is agglomeration of bed particles resulting in partial or total defluidization, and a time consuming and expensive temporary shutdown of the plant. In the case of biomass conversion the agglomeration phenomenon stems from the formation of a sticky layer around the bed particles (2), which consecutively form larger entities (agglomerates). The stickiness of this layer originates from the formation of eutectic mixtures (mixtures of two or more components which melting temperatures lie below the pure component melting temperatures), in this case the silica from the sand and alkali components from the biomass (2,3). The timely recognition of this phenomenon is crucial for taking appropriate measures to avoid a potential shutdown.

Such a recognition should be carried out online and be as simple and reliable as possible. Moreover, it should result in as little as possible false alarms. Although the

need for suitable monitoring techniques is motivated by the application of conversion of biomass here, it is not limited to this process. Agglomeration problems are also encountered in several other fluidized bed processes, for example gas-phase polymerization and drying.
Our group has successfully applied the “attractor comparison” method in detection of particle size change and agglomeration in fluidized beds of different scales (4,5,6). Despite that we think that the pressure fluctuations contain more information from which one can distinguish different sources of hydrodynamic changes with the help of additional signal pre-treatment and analysis methods.

APPROACH & METHODS

This work is investigating the application of different signal analysis methods on pressure fluctuation data of bubbling fluidized beds with the goal of unambiguously detecting agglomeration. More specifically, the goal of this approach is to identify *selective methods* which are sensitive for certain distinct operational changes but not towards others. In the ideal case, such a selective method would only be sensitive towards the onset of agglomeration and not towards other changes in the process. However, a method that is only sensitive towards specific other irrelevant process changes, could potentially also be useful to serve as a countercheck in order to prevent false alarms.
In order to assess the effect of certain distinct changes on the outcome of different analysis methods, several data sets with controlled step changes hereof have been used. In this work we restrict ourselves to measurements in an 80 cm bubbling fluidized bed. In this setup we carried out step-changes in the superficial gas velocity and we simulated agglomeration by replacing fractions of the initial bed of fine sand (d_{10}=356μm, d_{50}=532μm, d_{90}=760μm) with coarse sand (d_{10}=1070μm, d_{50}=1280μm, d_{90}=1510μm). This resulted in mixtures of increasing average particle size with a bimodal distribution. Table 1 gives an overview of the imposed changes.

Table 1: Measurements in an 80 cm bubbling fluidized bed (total bed height ~90 cm)

Imposed change*	Steps	Measurement position height
Superficial gas velocity	0.21 / 0.23 / 0.24 / 0.25 / 0.31 / 0.33 / 0.34 [m/s]	23 cm
Replacing fractions of fine sand with coarse sand	0 / 6 / 24 / 36 [%] (coarse sand fraction in total bed mass)	24 cm

* For changes in superficial gas velocity the fine sand was used, for replacing fractions of the bed with coarse sand a velocity of 0.40 m/s was utilized.

Pressure fluctuations have been measured at the inner wall of the bed, consecutively being low-pass filtered at 60 Hz and sampled at 200 Hz.

In total, 37 different signal analysis methods have been investigated in this approach; three out of those are presented as illustrative examples in this paper.
The **standard deviation** (second moment of the distribution of the measured pressure fluctuations) is utilized as an analysis method. The standard deviation of a sample is a measure of the mean distance of values in a data set from their mean (Equation 1).

$$\textit{standard deviation} = \frac{1}{N-1}\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (1)$$

The **attractor comparison method** consists of an attractor reconstruction followed by attractor comparison. During attractor reconstruction high-frequent (typically a few hundred Hz) pressure fluctuation data of a certain time window are projected into a multidimensional state-space. This yields an attractor, a characteristic fingerprint of the system (4,7). The actual attractor comparison is based on comparing a reference attractor, taken from a well-fluidized state, with the current state of the fluidized bed online. This comparison is based on a statistical test developed by Diks *et al.* (8), which evaluates the dimensionless distance S between both attractors. An S-value larger than 3 refers to a 95% confidence interval of the two attractors being generated by a different mechanism. In a fluidized bed reactor, this indicates a change in the hydrodynamic behaviour, as induced by agglomeration. For details of the attractor comparison method the reader is referred to van Ommen *et al.* (4).
The **Kolmogorov-Smirnov (KS) test** (e.g. (9)) for similarity of underlying probability distributions is based on the maximum distance (one-sided or two-sided) between two cumulative distribution functions (CDF). The two-sided distance is incorporated in the presented approach. In the calculation of the two-sided KS distance, the empirical cumulative distribution function (CDF) of a sample of pressure fluctuation data, $F_n(x)$, is compared with the CDF of a reference sample, $F_1(x)$, at the beginning of the data set. The two-sided distance between the two functions is then defined as:

$$D_{CDF} = \max\left|F_n(y) - F_1(y)\right| \qquad (2)$$

These signal analysis methods are not only applied to raw (i.e., untreated) signals, but also to signals that are pre-treated with frequency filtering with different cut-off frequencies, principal component analysis or wavelet decomposition on different detail- & approximation levels using a Daubechies-5 wavelet (e.g. (10)). The choice to apply certain pre-treatment methods is motivated by the fact that different physical phenomena (individual particle collisions, bubble phenomena & flow/circulation patterns) manifest themselves at different frequencies in the pressure fluctuation measurements. Assuming that the effect of different changes on the hydrodynamics of the bed will not be evenly distributed throughout the whole frequency range, separating those effects can therefore help to better identify those changes.

Pressure fluctuation data of fluidized beds of different scales and at different measuring positions have been utilized in this approach and are currently under investigation. In this paper, however, we restrict ourselves at the data sets as presented in Table 1. With a large number of signal analysis methods, signal pre-treatment techniques, fluidized beds and measuring positions one arrives at a large amount of possible combinations for the resulting analysis. To handle these large amounts of results we have used a characteristic number to quantify the sensitivity of a method towards the imposed change. This quantification first takes the mean value of the analysis variable along all of the steps of the imposed change and requires a continuously increasing or decreasing value thereof. Besides the continuous trend in the mean value, it is also important to relate the *variation* of the analysis variable in each step to its average in order to assess whether the different steps can actually be distinguished from each other. This “quality of trend” has been quantified by:

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$$f = \frac{\sum_i (z_i - \bar{z})^2}{\sum_i (z_i - \bar{z})^2 + \sum_i \sigma_i^2} \tag{3}$$

In essence this measure for quality of trend assesses the extent to which the analysis parameter results (z_i) in a homogenous in- or decrease, at the same time taking into account the standard deviation (σ_i) of the variable. This measure will yield a value between zero and one, where one refers to a perfect trend and zero to no trend. If the average value of the analysis variable exhibits local maxima or minima, a value of zero is assigned. The quality of trend, in this case with respect to changes in particle size, is visualized in a matrix (Figure 1).

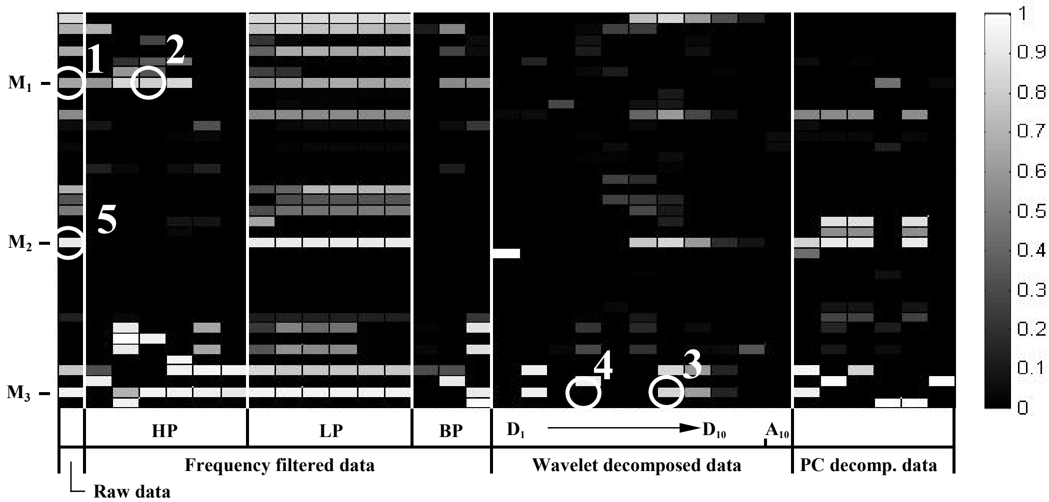

Figure 1: Matrix with the "quality of trend" for all signal analysis methods on the vertical axis (*M1=Attractor Comparison, M2=Standard Deviation, M3=Kolmogorov-Smirnov test*) & pre-treatment techniques on the horizontal axis *(HP=High-pass, LP=Low-pass, BP=Band-pass, D_i/A_i=Detail/Approximation level, PC=principal decompositions (various))*. The combinations marked by circles are used for illustrating different results in the remainder of the paper.

From this matrix one can quickly see that certain groups of analysis methods and signal pre-treatment methods are visually emerging in form of horizontal light bands. It also becomes clear which combinations are not yielding clear trends and can be disregarded.

RESULTS & DISCUSSION

In order to illustrate the potential of this approach, the trends for five examples in Figure 1 are chosen to be illustrated in Figures 2-6. Base case for the particle size is only fine sand (0% fraction of coarse sand) and for the superficial gas velocity a velocity of 0.21m/s (0% relative gas velocity increase); the presented consecutive step-changes in each case refer to increasing bed mass fractions of coarse sand as well as the relative gas velocity increase with respect to the base case.

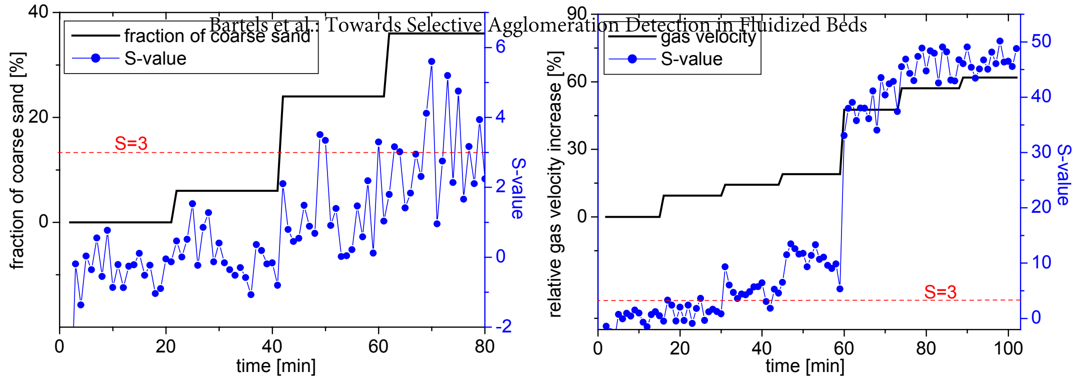

Figure 2: Attractor comparison based on raw data
for changes in particle size (left) and superficial gas velocity (right)

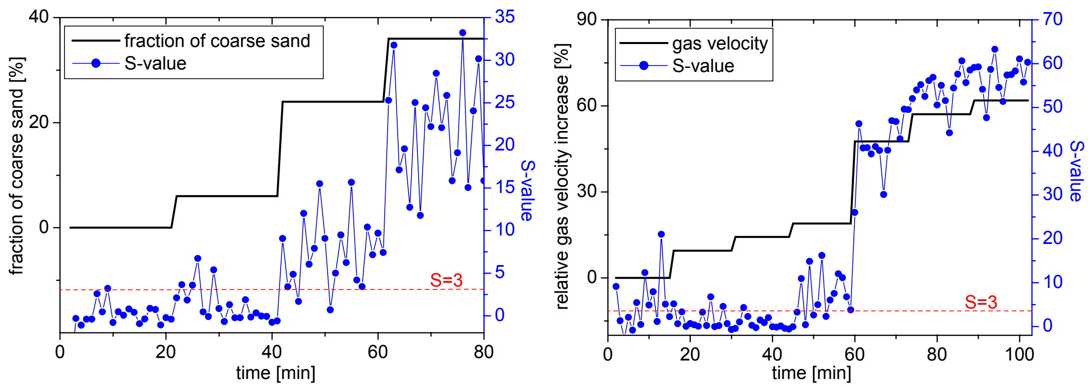

Figure 3: Attractor comparison based on frequency filtered data (high-pass, cut-off=15Hz) for changes in particle size (left) and superficial gas velocity (right)

Figure 2 (left) is a "reference case" in relation to earlier published work on agglomeration detection (e.g. 4,5,6), confirming that attractor comparison is sensitive towards particle size changes. Pre-treatment of the raw data with a high-pass filter (cut-off frequency 15 Hz) increases the sensitivity towards the particle size changes significantly, as observed in higher *S*-values in Figure 3 (left).

Towards superficial gas velocity changes attractor comparison is in principle also sensitive, however, not with certain limits (~10%), as observed in Figure 2 (right). Pre-treatment of the raw data with a high-pass filter (cut-off frequency 15Hz) further increases the sensitivity towards gas velocity as seen in Figure 3 (right); however, the method also gets less robust as the *S*-value frequently increases the value of 3 even for an unchanged gas velocity (0%). It has to be remarked that the method uses the same parameterization as for the un-treated data. When it will be optimized for the application with pre-treated data, better results are expected.

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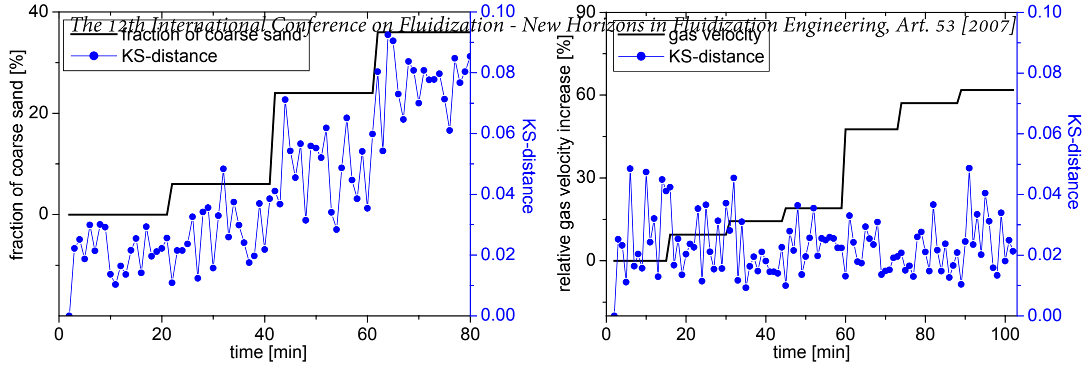

Figure 4: Kolmogorov-Smirnov test based on wavelet decomposition (detail level 7) for changes in particle size (left) and superficial gas velocity (right)

Looking for a good "quality of fit" within the matrix above (Figure 1), one can see that the KS-test in combination with a wavelet decomposition pre-treated signal on detail level 7 is sensitive towards changes in particle size, as seen in Figure 4 (left). The method is not sensitive towards even large changes in superficial gas velocity, as seen in Figure 4 (right), which makes it robust in terms of varying gas velocities in industrial practice.

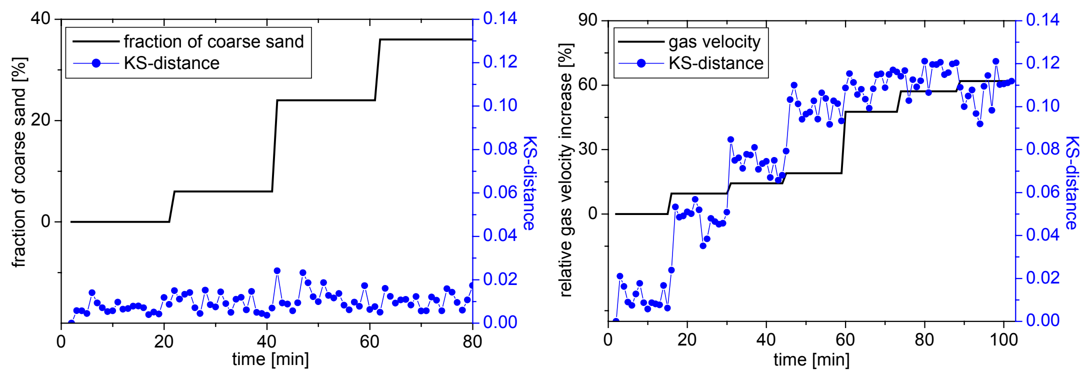

Figure 5: Kolmogorov-Smirnov test based on wavelet decomposition (detail level 4) for changes in particle size (left) and superficial gas velocity (right)

Choosing the detail level 4 in the wavelet decomposition in combination with the KS-test, a very different picture as compared to detail level 7 arises. In Figure 5 one can observe that the method in this case is not sensitive towards particle size changes (left) but indeed sensitive towards superficial gas velocity changes (right). This method can consecutively serve as a "countercheck" for a changing superficial gas velocity.

It should be remarked that the previous two examples (wavelet detail level 7 & 4) are not just "accidentally" good trends, but one can indeed observe a gradual overall trend in the sensitivity of the KS test as a function of the applied detail level (10 in total) in the wavelet decomposition.

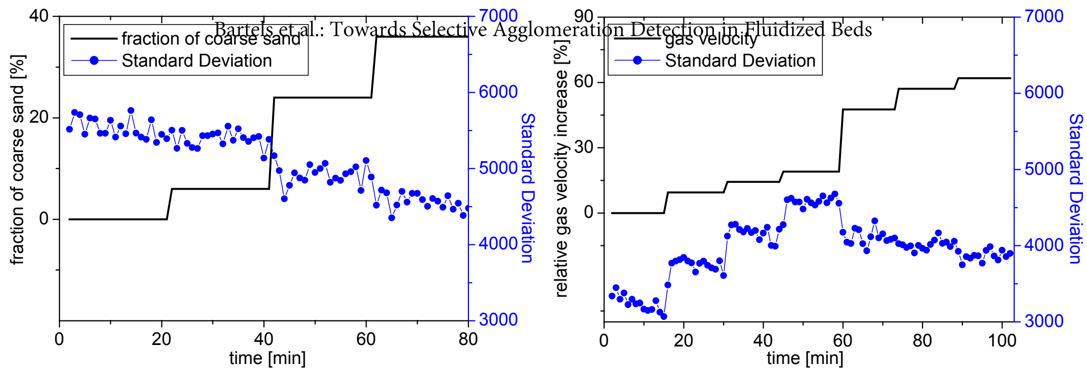

Figure 6: Standard deviation based on raw data for changes in particle size (left) and superficial gas velocity (right)

An example of how one can be mislead by simply looking at a single matrix, as presented in Figure 1, is shown in Figure 6: A good trend is observed for changes in particle size, but an even larger, not continuous in one direction, trend in superficial gas velocity changes. This effect is not desired since one obviously cannot determine whether changes in particle size or superficial gas velocity are responsible for the resulting trend in this case.

CONCLUSIONS & OUTLOOK

Aiming at distinguishing different sources for hydrodynamic changes in fluidized beds, we have presented a new methodology of screening large amounts of various signal analysis methods (37 in total) in combination with signal pre-treatment methods (33 in total). This methodology has been applied to pressure fluctuation measurements of a bubbling fluidized bed with distinct changes in only one of the operating parameters at a time: fluidization velocity and particle size. Assessing the "quality of trend" of an analysis variable as a function of an imposed step-change has been realized by a generic measure. With help of this measure one can see potentially useful combinations emerging from a matrix of all possible combinations; a few examples herein were highlighted. The examples given indicate the potential of this new methodology for developing a suitable early detection system for hydrodynamic changes, selective for the origin of this change.

We are currently investigating a large number of pressure fluctuation sets from different reactor scales and measurement positions in order to investigate how robust a method is in terms of those parameters. Circulating fluidized beds (CFB) are also part of this research, as attractor comparison has been shown to be sensitive towards particle size in lab-scale CFBs (11). Moreover, the measure for the quality of trend is subject to further optimization in terms of robustness.

NOTATION

d_{xx}	Cumulative volume fraction smaller than xx μm
D_{CDF}	Distance (two-sided) between cumulative distribution functions
f	Quality of fit (as defined in equation 4)
F_i	Cumulative distribution function (i=1 reference sample)
N	Number of samples
y_i	Pressure fluctuation data points
$\bar{y}$	Mean of y
z_i	Individual results of the analysis method
σ	Standard deviation

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