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10th International Conference on Circulating Fluidized Beds and Fluidization Technology - CFB-10

Refereed Proceedings

Spring 5-5-2011

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DYNAMICS OF GAS-SOLID FLUIDIZED BEDS THROUGH PRESSURE FLUCTUATIONS: A BRIEF EXAMINATION OF METHODS OF ANALYSIS

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ABSTRACT

This paper revisits and critically examines a number of methods used for analysis of in-bed pressure signals recorded in gas-solid fluidized beds. The goal is to obtain information on the time scales of dominant phenomena present in the pressure time series of four fluidization regimes. It is demonstrated that the average cycle time represents an effective alternative to spectral analysis. In addition, we give evidence that the average cycle time yields equivalent information as some of the advanced methods of non-linear analysis (e.g. the Kolmogorov entropy). Finally, by using wavelets and wavelet packets, we show how to obtain an accurate time localization of the different frequency components present in the pressure signal.

INTRODUCTION

The dynamics of gas-solid fluidized beds are often characterized by investigating pressure fluctuations. A pressure measurement system is robust, cheap and non-intrusive, thus avoiding distortion of the flow around the point of measurement. In addition, pressure is easily measured, even in industrial conditions. The in-bed pressure fluctuations are predominantly related to bubble motion within the bed, but a more comprehensive explanation on the origin of the fluctuation has already been debated for a long time (e.g. Kage et al., (1); van der Schaaf et al., (2); Bi (3)). The pressure signal has an intrinsically non-local nature, and due to this fact, the interpretation of pressure measurements is far more complicated than of a more local measurement, such as local solids concentration measurements using optical probes. An important aspect of any interpretation is to evaluate available techniques of signal analysis, related to their ability to describe the dynamics of the bed. In general, the techniques can be grouped into three categories: (1) time domain methods, (2) frequency domain methods, and (3) state space methods. It is not feasible to analyse in this work all methods regularly used in the literature for the analysis of fluidized-bed pressure signals; a broader review has recently been published (4). In the current paper, our aim is to demonstrate how to most conveniently gain fundamental information on the dynamics of fluidized beds (e.g., the main time scales) by using some of the commonly employed methods of signal analysis. Furthermore, we will critically evaluate these techniques nowadays frequently used and show that often some very advanced methods do not give more insight into the system behaviour than do some considerably simpler ones. We will carry out the analysis by looking into data sets for four fluidization regimes investigated by Johnsson et al. (5). In summary, our goal is, by calculating the main time scales present in the signals, to provide important recommendations on the suitability of the use of the methods examined.

EXPERIMENTS

The data sets applied here are the same as those used in Johnsson et al. (5). In brief, the experiments were carried out in a CFB unit operated under ambient conditions. The riser has a cross-section of 0.12×0.7 m and a total height of 8.5 m. The bed material was silica sand with an average particle size of 0.32 mm and a particle density of 2600 kg/m^3, *i.e.*, Group B particles. In the riser, pressure fluctuations were measured at 0.2 m above the air distributor through a 50 mm long and 4 mm ID steel tube with a fine mesh net at the side facing the fluidized bed; these probe dimensions in combination with the transducer minimize the distortion of the pressure signal (van Ommen et al., 6). The pressure is measured “single ended”: the fluctuations are recorded and the signals were low-pass filtered at the Nyquist frequency. The sampling frequency was 400 Hz in all cases, with 33 minutes of total sampling time. The four fluidization regimes identified are: the multiple bubble regime, the single bubble regime, the exploding bubble regime and the transport regime. To obtain the multiple bubble regime, a distributor with a higher pressure drop was used (Johnsson et al., (5)). Note that, although the names of the identified regimes are not standard in the fluidization community, we have nevertheless used them in this work, in accordance with (5). The main conditions are presented in Table 1.

Table 1. Operating conditions for the four pressure time-series used in this paper

Regime condition	Multiple bubble	Single bubble	Exploding bubble	Transport conditions
gas velocity [m/s]	0.6	0.6	2.2	4.1
solids mass flux [kg m^{-2} s^{-1}]	0	0	~1	25
bottom bed height [m]	0.40	0.37	0.30	-
bottom bed voidage [-]	0.51	0.50	0.58	0.80*
bottom bed pressure drop [Pa]	4 960	4 730	3 310	1 120*
distributor pressure drop [Pa]	4 200	660	3 090	13 700

*No bottom bed present, values given over the lower 20 cm of the columns

THEORY

As indicated above, this paper is not a full review on all the methods employed in the literature when analyzing pressure signals in fluidized beds. Alternatively, we have chosen here to discuss only the techniques that are either a most straightforward choice when looking at time scales of the governing phenomena existing in a signal, or are at present extensively used (perhaps sometimes without justification, as we will show here).

The most common way to look at the time scales of a signal is to analyze the power spectrum (frequency domain analysis) and a brief explanation of the procedure is given here. Since the conclusions obtained by the spectral analysis may not be so clear in the case of non-periodic or non-smooth signals, an alternative in the form of the average cycle time or wavelets may be a suitable option. Finally, if we assume that a pressure signal from fluidized beds is non-linear in nature, it is of interest to characterize its unpredictability (i.e. the loss of information per unit of time). Accordingly, a concise description of those methods is given in this section.

Spectral Analysis

Fourier spectral analysis often aims at obtaining the dominant frequencies present in time series and assigning them to various physical phenomena (1). In the present paper we will use the Welch's method (7), where the variance is reduced by estimating the power spectra as an average of several sub-spectra. The number of sub-spectra is chosen to obtain a satisfactory trade-off between frequency resolution and variance. Therefore, the signal treated is divided into time segments and an estimate of the power spectrum of each segment is obtained. An important feature of the spectral analysis is that the energy of the signal is conserved in the frequency domain. Hence, summation of the power spectra over the range of interest yields the total energy of the signal in a given frequency range.

Average Cycle Time

A suitable alternative to spectral analysis is to look at the average cycle time of the signal. The method belongs to the time domain analysis. It is calculated as two times the pressure signal duration divided by the number of times the pressure signal crosses its average value (e.g. 8). The technique can be sensitive to the presence of noise in the data, but when a low-pass filtering of the signal is applied, the average cycle time yields useful information. A change in the trend of the average cycle time typically indicates a regime change.

Wavelets

Wavelets allow for the representation of a signal simultaneously in time and in frequency. In fluidization, wavelets are used to characterize the heterogeneous nature of fluidization, and for the study of short-time or transient phenomena. Since fluidization is a multiscale phenomenon, signals measured in fluidized beds typically contain components on at least three frequency scales: the high-frequency scale associated to particle motion, the medium-frequency scale related to particle clusters, and low-frequency scale related to voids. We use here the discrete version of the wavelet transform, which is based on a pair of digital filters. The latter decompose the signal into a low frequency component A_1 called the "approximation", and a high frequency component D_1 called the "detail". The operation is then repeated using the approximation A_1 as the input signal. By doing this operation recursively up to a desired level N, one obtains a hierarchical multiresolution representation of a signal f (Mallat, 9), such that each detail D_k contains frequency information in a range around $f_s/2^k$, where f_s is the sampling frequency, and k is an integer. The inverse wavelet transform allows for reconstruction of a signal without loss of information.

Entropy

Fluid dynamics in fluidized beds are governed equations of motion with a non-linear nature. It is then not surprising that numerous results have appeared so far in the literature from applying non-linear analysis to describe various aspects of performance of fluidized beds, such as behaviour of bubbles and information on flow regimes. The methods applied are based on the construction of an attractor representing the dynamic evolution of the system in the state space, defined as a multi-dimensional space containing all the variables governing the system. An attractor is a clearly identified structure in the state-space domain, and probably the most commonly applied method for its characterization is the Kolmogorov entropy (also called correlation entropy or just entropy). The latter is a measure of predictability of a system: it expresses the sensitivity to small changes in the initial conditions. Linear systems have an entropy of zero and are predictable at infinitum, whereas random systems have an infinite entropy and are thus unpredictable.

RESULTS AND DISCUSSION

Analysis in the frequency domain most often aims at characterizing fluidization regimes by finding the dominant frequency at which bubbles pass through the bed.

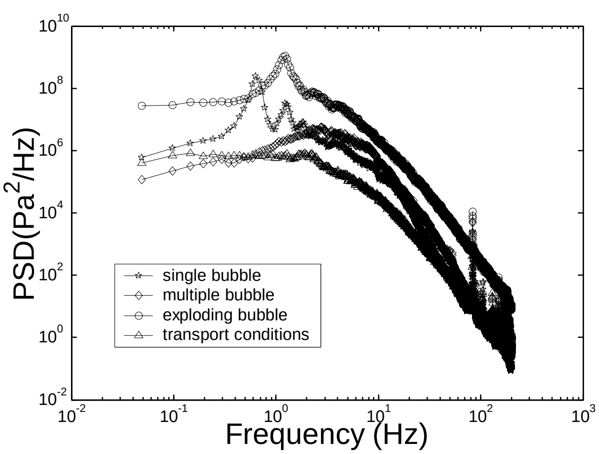

Figure 1: Power spectra of the four regimes treated in this work.

Fig. 1 shows power spectra of pressure fluctuations for the four regimes as obtained by the Welch method. The low frequency region is dominated by large structures (bubble flow), and, at higher frequencies, finer structures are represented. The relation between the two regions is still not clear, but it is often argued (5) that the fine structures are not primarily governed by the bubble flow. As for the analysis of the time scales of the signals, it is obvious that valuable information can be obtained from spectral analysis (e.g. the existence of the dominant frequency in the regimes studied). However, applying power spectral analysis to strongly non-periodic or non-smooth signals, such as those recorded in fluidized beds, may not always turn beneficial. In such a case, it is useful to look at alternatives in the time domain. As mentioned above, an easy-to-calculate characteristic is the average cycle time.

Figure 2 shows the average cycle time as the function of the gas velocity. It can be shown that, at least within the non-circulating fluidization regimes, the average cycle time is in effect independent of gas velocity, solid particles inventory and particle size. For the time series applied here, this would imply that the regime change, most likely from bubbling to turbulent fluidization, takes place at a gas velocity around 0.88 m/s.

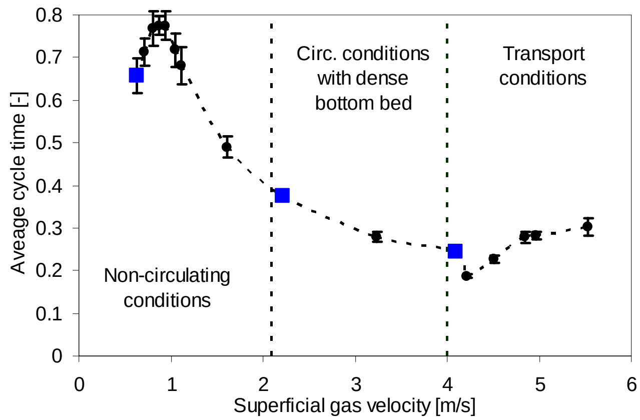

Figure 2: The average cycle times as a function of the fluidization velocity. The error bars give the standard deviation. The dashed vertical lines give the boundaries between the different regimes. The large squares indicate, from left to right, the values for the selected data sets for the single bubble, exploding bubble and transport conditions, respectively.

If we want to obtain a more detailed picture, we can plot the cycle time distribution instead of just calculating the average cycle time. Since fluidized-bed pressure signals are typically non-periodic signals, and in the same time contain information at multiple time scales, it may be a good idea to use wavelets in the analysis. In this work, we have decomposed the signals up to the 9th level, using the discrete version of the Meyer wavelet, implemented in the Matlab Wavelet Toolbox. For every level k of the decomposition, a reconstruction has been computed using only the detail coefficients D_K. The variance of the reconstruction is then proportional to the power of the signal in that particular frequency window. The resulting spectrum (Fig. 3) shows that the peaks at low frequencies, as well as power-law tails at higher frequencies, are nicely recovered.

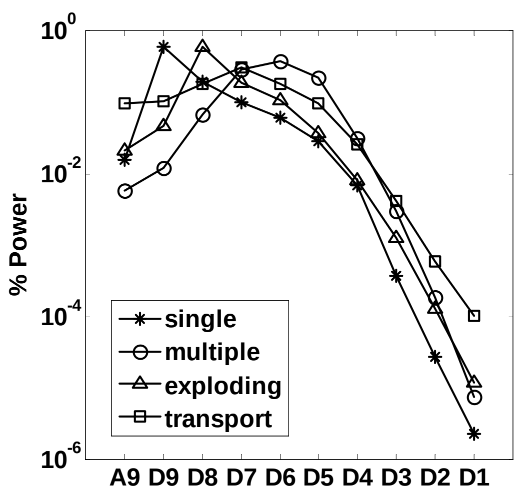

Figure 3: Representation of the wavelet power spectrum of the four signals. The x-axis corresponds to frequency, increasing from left to right.

However, with wavelets it can be difficult to interpret the results when the studied phenomenon does not reside exactly into one of the frequency bands of the wavelet decomposition. In such a case, wavelet packets may be used. With the latter, instead of decomposing only the approximation A_i at stage i, both A_i and D_i are passed through the low- and high-pass filters, thus producing four components: an approximation of the approximation, a detail of the approximation, an approximation of the detail and a detail of the detail. As an example, Fig.4 shows the results for the exploding bubble regime, with the logarithm of the coefficients plotted. Even with this representation, it is not straightforward to see a clear separation in frequency between different components of the signal. The frequencies seem to be mixed together, and we may even conclude that the broader bands of an ordinary wavelet analysis do a better job of separating them. Alternatively, if we choose to present the reconstructions of the signals from the coefficients plotted, we are in a position to recover the total time resolution. Fig. 5 exemplifies the result of the latter procedure, again for the exploding bubble regime.

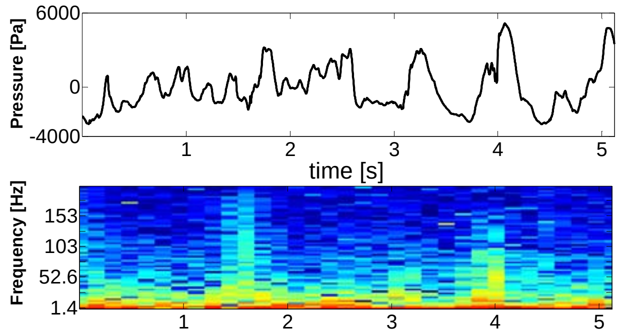

Figure 4: Logarithm of the wavelet packets coefficients for the exploding bubble regime.

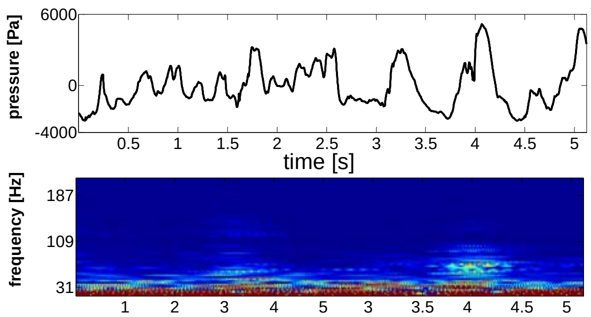

Figure 5: Reconstruction of the original signal from the wavelet packets coefficients for the exploding bubble regime.

The procedure may be summarized as follows: we set all but one of the coefficients of the terminal nodes to zero. Then, the signal is reconstructed from just the coefficients of that terminal node. It is now feasible to recognize the various components as shadows in the figure.

Finally, we will assess non-linear analysis (also called chaos analysis or state space analysis) in relation to the results obtained so far. State space analysis of pressure data in fluidized beds has been extensively used since the second half on the 1990s. In that period, the Kolmogorov entropy has been often used to characterize fluidized bed-hydrodynamics. For example, Schouten et al. (10) have suggested that the Kolmogorov entropy is proportional to the number of bubbles per unit of time, and to a bubble impact factor, defined in (10) as the ratio of the diameter of a bubble and that of a fluidized bed. This conclusion is more valid if the signal is recorded in the upper part of a riser, since these fluctuations reflect the local bubble behaviour more that if the signal is measured in the bottom of the bed. However, there is a potential problem when obtaining the Kolmogorov entropy. Namely, the entropy should be independent of the length scale at which it is calculated, if the latter is chosen small enough. Such a scaling region is very difficult, if possible, to find. This statement then implies that the entropy analysis does not prove that fluidized beds indeed exhibit low-dimensional chaotic behaviour. Furthermore, we will show on the data sets used in the present paper that there is a strong correlation between the Kolmogorov entropy calculated at a specific length scale and the average cycle frequency (the inverse of the average cycle time), see Fig. 6. Note that similar conclusions have already been suggested by Johnsson et al. (5) and van der Schaaf et al. (11). If we plot the entropy versus the average cycle frequency (Fig. 7), we see that the two are in fact linearly proportional. It can be demonstrated that the proportionality constant is directly related to the shape of the power spectrum. Since the average cycle frequency and the power spectrum are more easily correlated to physical phenomena, these characteristics should be preferred over the Kolmogorov entropy (or any similar feature from the state space analysis, such as the correlation dimension). The latter conclusion is further supported by the fact that the average frequency is not dependent on calculation parameters, whereas the Kolmogorov entropy clearly is. Since the application of non-linear analysis is typically more complicated, we recommend its use only if it yields information that is not obtainable by linear analysis, such as an early detection of non-stationarities in fluidized bed behaviour (12).

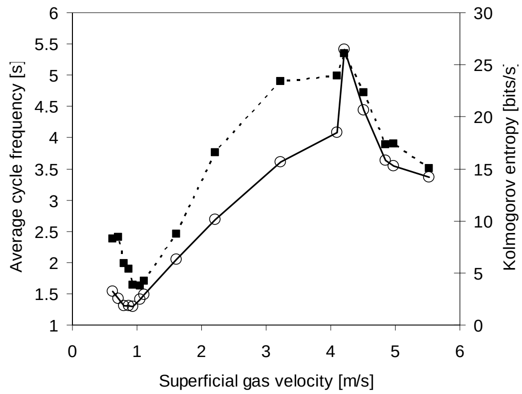

Figure 6: The maximum likelihood entropy and the average cycle frequency as functions of the gas velocity. The squares indicate the four data sets; the other markers represent the additional measurements at intermediate gas velocities.

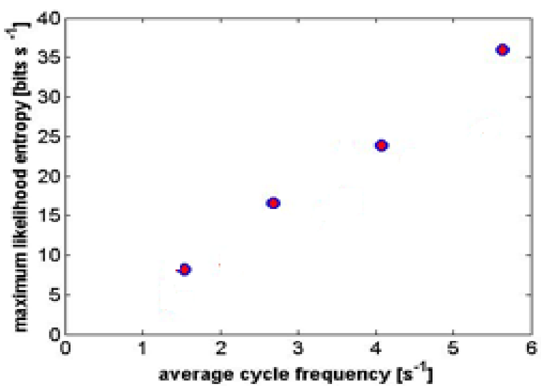

Figure 7: The maximum likelihood entropy versus the average cycle frequency for the four regimes investigated in the paper.

CONCLUSIONS

When pressure is recorded in a gas-solid fluidized bed, the obtained signal can yield significant information on the bed dynamics. The interpretation of signals is, however, not always straightforward. In this paper, we have revisited some of the most commonly used methods of analysis of the pressure time series. The work is not meant as a complete review paper. Instead, we have chosen to go through the techniques frequently used to obtain information on main time scales of the dominant phenomena present in the bed. We have shown that the cycle time and its distribution provide useful information on the dynamics of the bed. As such, they represent an easy-to-calculate alternative to frequency analysis. The latter, in general, provides essential information, but may be problematic when non-periodic and non-smooth signals are investigated.

To provide information on time localization of particular frequency components in a signal, we have carried out the analysis using wavelets and wavelet packets. We have seen that the main features of the spectral analysis are adequately reproduced by wavelet analysis. We have used wavelet packets to obtain an unambiguous separation in frequency between different components of the signals.

Finally, we have shown that the information given by the Kolmogorov entropy is entirely equivalent to that of the average cycle frequency, obtained by linear methods of analysis.

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