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Direct numerical simulations and experiments of a pseudo-2D gas-fluidized bed

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HIGHLIGHTS

- Detailed comparison is conducted between DNS and experiments of gas fluidization.
- Direct numerical simulations are performed using an immersed boundary method.
- Experimental measurements are conducted using extended PIV and DIA techniques.
- Good agreement is obtained on pressure fluctuations and mean solids flux.
- The granular temperature is analyzed in detail from DNS and experimental results.

GRAPHICAL ABSTRACT

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ABSTRACT

This paper reports our study on fluidization of 5000 spherical particles in a pseudo-2D gas-fluidized bed by direct numerical simulations (DNS) and experiments as well. Simulations are performed using an immersed boundary method, together with the methodology developed in our earlier work for accurate prediction of gas–solid interactions at relatively low grid resolutions. This modelling approach provides detailed information on the gas flow and the motion of individual particles, which allows for a priori calculation of the bed hydrodynamics. Experimental measurements of solids mean motion are conducted using a combined technique of Particle Image Velocimetry (PIV) and Digital Image Analysis (DIA). Further, the PIV technique is extended and applied for instantaneous measurements of the particle granular temperature, which is the key characteristics of particle velocity fluctuations.

For the first time, this paper reports a direct comparison in great detail between DNS results and experimental data for realistic gas fluidization. The detailed comparison reveals a reasonably good agreement with respect to the time-averaged solids motion and the pressure fluctuations. In addition, the granular temperatures calculated from the simulations agree well with the experimental data, but provide more details with respect to the variations corresponding to bubble formation and eruption. From our investigation, it also becomes clear that attention should be paid on the measurement and interpretation of the granular temperature.

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1. Introduction

Gas-fluidized beds are widely applied in the chemical and process industries for mixing, coating, drying, catalytic and non-catalytic
reactions, and many other applications. The best known application of fluidized beds is probably in the fluid catalytic cracking process, which is the heart of almost any oil refinery. A typical gas-fluidized bed (Davidson et al., 1985; Geldart, 1986) consists of a vertical vessel closed at the bottom by a gas distributor such as a porous plate, a bed of randomly arranged granular particles that are subject to a gas flow supplied from the bottom. At sufficiently high gas velocity (minimum fluidization velocity), the gas drag acting on the particles can outbalance gravity and the particles start fluidizing, hence the bed expands in an interval of apparent uniform fluidization. As the gas velocity increases, the excess gas will form fast-rising bubbles and the bed enters the bubbling fluidization regime. When the gas velocity is further increased beyond a critical value, the bed might display turbulence-like structures, hence it is named turbulent fluidization. At extremely high flow rates, the fast fluidization regime is entered and finally at still higher gas velocities the dilute pneumatic conveying regime prevails. In the past, a lot of studies have been reported for dense bubbling beds in view of their relevance for many industrial processes. In dense gas-fluidized beds the solids mixing is intense and results from the vertical movement of particles carried in the wake region behind the rising bubbles. Consequently, excellent heat/mass transfer characteristics prevail. Because of these favorable characteristics, gas-fluidized beds have been the subject of extensive research campaigns. However, at present, the design and scale-up of fluidized beds is mostly an empirical process, owing to limited insight into the fundamentals of dense gas–solid flows. In order to improve the state-of-the-art, a sound understanding of the transport phenomena in these systems is vital.

There exists a vast amount of literature on experimental investigation of transport phenomena in gas-fluidized beds. Over the years, many techniques (van Ommen and Mudde, 2008) have been developed to perform measurements in such systems. These techniques basically fall into two broad categories: invasive and non-invasive techniques. The invasive techniques, such as optical probes and capacitance probes, can to some extent locally interfere with the bed dynamics and thereby influence the outcome of the measurements. Conversely, the non-invasive techniques, by definition, do not disturb the bed behavior. For example, X-ray tomography is a non-invasive technique frequently used to obtain the voidage distribution in a horizontal cross-section of the bed. Particle Image Velocimetry (PIV) and Digital Image Analysis (DIA) are two of the most common non-invasive techniques applied to analyze the instantaneous solids motion and to study gas bubbles’ behavior, respectively. Note that the application of these two techniques is limited to flat and pseudo-2D fluidized beds, due to the requirement of visual accessibility. Laverman et al. (2008) combined PIV and DIA techniques to correct for the influence of particles raining through the roof of the bubbles on the measured time-averaged solids velocity profiles. These measuring techniques (Bokkers et al., 2004; Link et al., 2004; Lim et al., 2007; van Buijtenen et al., 2011; de Jong et al., 2012) have been extensively applied to dense gas-fluidized beds to obtain the time-averaged solids circulation patterns, bubble size, velocity and hold-up distribution, which are used to validate or compare with numerical models. Recently reported work (Dang et al., 2013; Patil et al., 2015) have combined PIV and DIA with infrared thermography to study the mass and heat transfer characteristics in gas-fluidized beds. In addition, a very important parameter to characterize dense gas–solid flows is the granular temperature, which is the kinetic energy associated with the random particle velocities. Holland et al. (2008) and Müller et al. (2008) reported time-averaged measurements of the granular temperature in gas-fluidized beds using a magnetic resonance (MR) technique, and found fair agreement to their simulation results. Dijkstra et al. (2007) extended the PIV technique to enable simultaneous measurements of instantaneous velocity and granular temperature fields in dense gas-fluidized beds. This extended PIV technique was demonstrated for a bubble forming and rising in the bed and a freely bubbling fluidized bed. So far, no further work has been reported with respect to the utilization of this technique.

Despite numerous experimental investigation, quantitative understanding of the flow behavior in gas-fluidized beds remains challenging. In this respect, computational fluid dynamics (CFD) simulations can, in many cases, complement experimental studies by providing detailed information that is difficult to obtain otherwise. Researchers have developed a variety of CFD models that describe gas–solid flows at different levels of details (van der Hoef et al., 2008). The numerical prediction of fluidization in engineering-scale equipment can, in practice, only be achieved with continuum models such as the Two-Fluid Model (TFM) (Gidaspow, 1994; Panneerselvam et al., 2009; Verma and Deen, 2013). Such models are typically based on averaged conservation equations for mass and momentum for both gas and solids phases. In recent years, the Discrete Element Model (DEM) has become increasingly popular for modelling dense gas–solid flows in fluidized beds (Deen et al., 2007; Oevermann et al., 2009; Guo et al., 2013; Dietiker et al., 2013; Tsuji et al., 2014). In this model, the gas phase is described as a continuous phase like in TFM, while the solids phase is described by the Newtonian equations of motion for each individual particle. However, the predictive capability of all these models depends largely on the accuracy of the closures adopted for describing the gas–solid interactions and the particle–particle interactions. For instance, the average interphase momentum transfer between gas and particles in these models is described by a drag correlation, the development and improvement of which remains a continuing area of research (Beestra et al., 2007; Tang et al., 2015). Furthermore, the internal momentum transport in the solids phase in continuum models is commonly based on the kinetic theory of granular flow (KTGF), which at present still challenges the community of granular flows. Conversely, in Direct Numerical Simulations (DNS) the incompressible Navier–Stokes (NS) equations are solved for the gas phase whereas for each individual particle the Newtonian equations of motion are solved, coupled with appropriate (i.e., no-slip) boundary conditions imposed at the particle surface. In this way, information implicit in the equations of motion can be extracted without approximation. This feature makes DNS the most popular tool for developing the closure relations required in the averaged models like TFM and DEM (Deen and Peters, 2014). Naturally, DNS is also the most accurate model to study fluid dynamics in fluidized beds, from which the results can be used to improve the larger-scale models. However, owing to the complexity of particle–flow interactions, direct numerical simulations of inertial particulate flow with finite-size particles have often been restricted to a small number of particles. This means that DNS of fluidization is prohibitively expensive even for fluidized beds at lab scale, where the number of particles is in the order of thousands.

Together with the rapid increase of computing power, parallel implementation of DNS-type methods opens an interesting option to study gas–solid suspensions with a relatively large number of particles. Albeit at relatively low Reynolds number (Re ≤ 20), Höller and Schwarz (2000) first managed to simulate O(10,000) particles in a fluid. Later, the lattice-Boltzmann method (LBM) was used to perform DNS of 8000 spheres settling in a periodic cubic box (Yin and Koch, 2007) and low-Re fluid flow in bidisperse fixed beds with up to 5207 particles (Yin and Sundaresan, 2009). Furthermore, Jin et al. (2009) simulated the separation of 21,336 particles of two different densities in a viscous fluid using a fictitious domain method. Apart from those, large-scale DNS of particulate flow were conducted by Xiong et al. (2012) for a 3D suspension of 129,024 particles (75 μm) driven by gravity in a periodic domain. Also, Liu (2011) has numerically demonstrated the capability of the PHYSALIS method to simulate the electric field with the order of one million particles. To investigate the segregation of particle suspensions, the
largest simulation based on a fully resolved fluid-structure interaction performed at the Jülich Supercomputing center contains 264 million spherical objects (Götz et al., 2010). Nevertheless, direct numerical simulations of fluidization in realistic systems are very rarely reported, due to the complex gas–solid interactions in comparison with sedimentation or segregation of particles by gravity. Pan et al. (2002) did simulate the fluidization of 1024 spheres in liquids at finite Reynolds numbers of $O(1000)$, and compared the results with an experiment. Also, Deen et al. (2012) performed DNS of liquid fluidization of 1296 spheres to study the fluid-particle heat transfer characteristics. Fluidization of 400 spheres in a gas-fluidized bed was simulated by Kuwagi et al. (2010) using a volumetric-type immersed boundary (IB) method, in which inhomogeneous gas flow was observed in the particle bed. Kriebitzsch et al. (2013) compared DNS with DEM simulations of a small gas-fluidized bed consisting of 2000 particles, which showed some discrepancy of the computed gas–solid interaction force. Finally, the latest DNS of fluidization reported in the literature was a study of the heat transfer of 225 heated spheres in a gas-fluidized bed (Feng and Musong, 2014).

With respect to the DNS-type IB method, Tang et al. (2014) have developed a methodology that allows for highly accurate simulations of dense gas–solid flows at relatively low resolutions. This can efficiently reduce the computational cost of simulations and accordingly make it feasible for, e.g., modelling fluidization in a realistic system with $O(1000)$ particles. Consequently, a direct comparison between DNS and experiments of fluidized beds is possible. This will be demonstrated in this work for DNS of fluidization of 5000 spherical particles in a small pseudo-2D gas-fluidized bed. The simulation results will be directly compared with experimental measurements conducted in a lab set-up using the extended PIV (Dijkhuizen et al., 2007) and IB techniques. Detailed comparisons are reported for pressure drop over the bed, bed expansion, time-averaged solids flux field, as well as the granular temperature. This paper is organized as follows: the issue on the definition or interpretation of the granular temperature is first addressed; subsequently, the immersed boundary method and the two experimental measuring techniques are introduced, followed by the description of the modelled/experimental set-up; later, detailed comparisons between experimental data and simulation results are presented; finally, conclusions are given in the end of this paper.

2. Definition of the granular temperature

The concept of granular temperature arises from an analogy between the random motion of individual particles in granular systems (like fluidized beds) and the thermal motion of molecules in kinetic theory. The granular temperature concept is playing an important role in characterizing the unsteady component of the particle velocity (Cody et al., 1996). Various granular temperatures may be defined depending on whether one includes the random kinetic energy associated with rotational and vibrational modes (Potapov and Campbell, 1996), as well as the basic translational motions. However, in many cases, experimental measurements are not able to distinguish the contributions due to those different velocity components. Besides, with a time-averaged measurement in time-variant systems, an apparent granular temperature might be defined based on the fluctuations in the bulk motion as a function of time (Jung et al., 2005). In addition, one can even define a granular temperature based on the fluctuation velocities due to the interaction between the solids and gas phase (Campbell, 2006). In the opinion of the authors, all those definitions of granular temperature are reasonable, depending simply on what is the investigating target by defining a granular temperature. For instance in the kinetic theory of granular flows, it is interesting to understand the relative (translational) motion between particles. This paper reports a granular temperature characterizing such particle fluctuation (translational) velocities, the definition of which is given as follows.

We denote the particle random translational velocity as $v$ in fluidized beds. This velocity is decomposed into the sum of two components, namely the averaged velocity $\langle v \rangle$ and the fluctuation velocity $v - \langle v \rangle$. The granular temperature $\Theta$ is defined as the average of the squared fluctuation velocity, i.e., $\Theta \equiv \langle (v - \langle v \rangle)^2 \rangle$. In kinetic theory, the granular temperature is obtained by applying ensemble averaging, which is defined instantaneously at each point in time. This ensemble average however is a mathematical idealization and does not exist in experimental measurements. Further, for the experimental measurements in fluidized beds, Jung et al. (2005) identified two different “types” of granular temperatures in terms of the type of realistic averaging. The first was termed particle granular temperature, which is defined by local spatial averaging $\langle (v_v \cdot v_v) \rangle$ and corresponds to the instantaneous variance in the velocity distribution. Such a granular temperature is due to the random oscillations of particles in small regions for a small time period, and varies with time and position. The second was further employed by Müller et al. (2008), where it was given as the time-averaged $\langle \langle (v_v \cdot v_v) \rangle \rangle$ variance of the mean velocity and was termed bubble granular temperature. Conversely, this bubble granular temperature does not represent relative motion between particles but rather fluctuations that occur at longer time and length scales. In bubbling fluidized beds, the bubble granular temperature due to the motion of the bubbles is usually higher than the particle granular temperature due to the particle oscillations. According to this classification, most of the reported experimental techniques such as the magnetic resonance (MR) and positron emission particle tracking (PEPT) measure the bubble granular temperature or a combined bubble with particle granular temperature.

In this work, we report the particle granular temperature based on the spatial averaging of squared fluctuation (translational) velocity of particles, i.e., the first “type” granular temperature of Jung et al. (2005). Experimental measurements are conducted using the extended PIV technique, which will be detailed in Section 4.1. Calculations from numerical simulations will be given in Section 6.3. Importantly, the optimal choice of the size of the unit volume, which is taken to apply the spatial averages of $\langle v_v \rangle$ and $\langle v_v \cdot v_v \rangle$, respectively, is subtle. Note that these two averaging can take place with two nonequal volume sizes. Consequently, this volume size affects the obtained granular temperature in the following way: if a too small volume size is used, larger statistical errors occur in the measurements; if a large volume size is applied, the obtained granular temperature involves the local heterogeneity (within the volumes) that is influenced by the flow behavior at a macro scale. Thus, an ideal volume size should be chosen large enough to avoid the statistical errors, but small enough to capture the spatial variations in the locally relative motion of particles. A careful analysis on this issue will be given in Section 6.3.
3. Immerged boundary method

Direct numerical simulations in this work refer to the most detailed model in the multiscale modelling scheme introduced by van der Hoef et al. (2004) for an industrial scale fluidized bed. In this DNS model, the gas phase is solved on a grid smaller than the size of the particles, and the solid phase is described by individual particles with their interaction with the gas phase modeled by employing boundary conditions at the surface of the particle. An immersed boundary method (IBM) is adopted to perform direct numerical simulations of a gas-fluidized bed in this work. This method has been successfully applied in our previous work to study the interaction forces in dense gas–solid flows. Implementation details of this method can be found in Kriebitzsch (2011), and therefore only a brief introduction is given here.

A schematic explanation of the IBM methodology is presented in Fig. 1. The gas phase is governed by the NS equations, which are solved on a fixed and structured Eulerian grid with its grid size $h$ (much) smaller than the particle diameter $d_p$. These equations are solved using state-of-the-art CFD methods, where second-order schemes are used for space and time discretization of the momentum equations, in which the convective, viscous, and pressure terms are treated in an explicit, semi-implicit and implicit manner, respectively. For the solids phase, each particle is represented by a set of marker points that are distributed in terms of a spherical diameter $d_m$. A hard-sphere model is used for the particle–particle and particle–wall interactions, where the collisions are considered binary, instantaneous and non-ideal. The motion of particles follows Newton’s second law, from which the translational and rotational velocities are updated every CFD time step.

Additionally, a force term $f_{IB}$ is added to the NS equations to describe the gas–solid coupling:

$$\rho_g \frac{\partial \mathbf{u}}{\partial t} + \rho_g (\nabla \cdot \mathbf{u}) = -\nabla P + \rho_g \nabla^2 \mathbf{u} + f_{IB},$$

with gas density $\rho_g$ velocity $\mathbf{u}$, modified pressure ($P = p - \rho_g g \cdot \mathbf{x}$) and dynamic viscosity $\mu_{sc}$. This force term is computed at each marker point $m$ such that the local gas phase velocity $\mathbf{U}_m$ is equal to the surface velocity $\mathbf{V}_m$ at this particular location $X_m$. Thereby, the no-slip boundary condition is enforced at the surface of the particle. The sum of this force term originating from the marker points of one particle equals the total force that the particle exerts on the gas. A regularized delta function $D(x - X)$ suggested by Deen et al. (2004) is employed for the communication between marker points and adjacent Eulerian grid points, which takes places with a support of $3h$ as indicated by the shaded square in Fig. 1. To be more specific, the velocity at a marker point is interpolated from the surrounding grid points and reversely the force term is distributed back to these grid points indicated as $\mathbf{x}_{ijk}$:

$$\mathbf{U}_m = \sum_{ij,k} D\left(\frac{X_{ijk} - X_m}{h}\right) \cdot \mathbf{u}_{ijk},$$

$$f_{IB} = \frac{\rho_g}{\Delta t} (\mathbf{V}_m - \mathbf{U}_m),$$

$$f_{IB} = \sum_{m} D\left(\frac{X_{ijk} - X_m}{h}\right) \cdot \mathbf{F}_{m} \cdot \Delta V_m / h^2,$$

where $\Delta V_m$ is the volume assigned to each marker point, the sum of which forms a spherical shell with a width of $h$. Besides, an iterative procedure is applied for the above forcing calculation in order to obtain a more accurate enforcement of the no-slip condition.

Traditionally in IBM, the marker points are uniformly distributed over the particle surface, which means $d_m = d_p$. However, as a consequence of the use of a regularized delta function, the sharp interface of the particle is smeared into a thin spherical shell, and the boundary where the no-slip condition is truly fulfilled departs slightly away from the real particle surface. Consequently, the accuracy of such IBM simulations is poor, especially at relatively low resolutions. In this study an optimal $d_m$ was evaluated for marker points distribution according to the methodology detailed in Tang et al. (2014). The principle of this methodology is that, by locating the marker points slightly inwards the interior of the particle as shown in Fig. 1, the no-slip boundary condition is supposed to be satisfied as close as possible to the particle surface, and consequently the accuracy is improved for predictions of the gas–solid interactions as well as the flow field. This optimal $d_m$ was further found to be dependent on the solids volume fraction, the grid resolution and the Reynolds number.

4. Experimental techniques

4.1. Extended Particle Image Velocimetry

In this work, the PIV technique extended by Dijkstra et al. (2007) is used to simultaneously measure the instantaneous particle velocity and granular temperature fields in a pseudo-2D fluidized bed. A high speed CCD camera is used to record the front view of the bed, which is illuminated using a pair of LED lamps. Two subsequent images of particles, recorded with a short time delay $\Delta t$, are divided into small interrogation areas. Cross-correlation analysis is applied to determine the volume-averaged displacement, $\mathbf{S}(\mathbf{x}, t)$, of the particle images between the interrogation areas in the first and second images. Note that outliers are
removed with a standard median filter. Subsequently, the velocity within the interrogation area is found by dividing this displacement with image magnification \( M \) and the time delay:

\[
\mathbf{v}(x, t) = \frac{\mathbf{s}(x, t)}{M \Delta t}
\]

(5)

The spatial cross-covariance of two images results in the displacement correlation peak, which can be represented as follows:

\[
R_0(x, z) = N_l \cdot \mathbf{f}_I(x, z) - F_0 \cdot \mathbf{f}_I(x, z) \psi(x, z),
\]

(6)
in which \( N_l \) is the number of pixel images in the interrogation area; \( F_0(x, z) \) indicates the loss of correlation arising from in-plane movement of the particles out of the interrogation area; \( F_0 \) represents the loss of correlation arising from particles leaving the interrogation area perpendicular to the plane; \( F_I(x, z) \) describes the shape of the peak resulting from the particle image properties and \( \psi(x, z) \) represents the shape of the peak attributed to the particle size function within the interrogation area perpendicular to the plane; \( F_0 \) is the particle size function by auto-correlation analysis. In this pseudo-2D function, the particle size function \( \psi(x, z) \) is assumed to be Gaussian and can therefore be described as:

\[
\psi(x, z) = \exp(-x^2/2\sigma_{z}^2) \cdot \exp(-z^2/2\sigma_{x}^2)
\]

(7)

Note that \((x_0, z_0)\) represents the center of the correlation peak (average displacement), whereas the width in the \( x_– \) and \( z_– \) directions can be expressed as the standard deviation \( \sigma_{x} \) and \( \sigma_{z} \), respectively. The width of the peak in the cross-correlation has two contributions. One is due to the fact that the particles have a finite size and are non-uniformly lighted, which can be presented by the peak width of the particle size function \( F_I(x, z) \). The other contribution is from \( \psi(x, z) \) due to the shape of the particle velocity distribution, which is a function of the granular temperature. To obtain the correlation of the velocity distribution, the particle size function \( F_I(x, z) \) has to be eliminated, which can be done by calculating the auto-correlation of both individual images and take the average:

\[
F_I(x, z) = \exp(-(x-x_0)^2/(2\sigma_{x}^2)) \cdot \exp(-(z-z_0)^2/(2\sigma_{z}^2))
\]

(8)

where \( \sigma_{x} \) represents the standard deviation in the particle size function by auto-correlation analysis. In this pseudo-2D fluidized bed with nearly elastic particle collisions, the velocity profile is also assumed to be Gaussian and can therefore be described as:

\[
\rho(x, z) = \exp(-(x-x_0)^2/(2\sigma_{x}^2)) \cdot \exp(-(z-z_0)^2/(2\sigma_{z}^2))
\]

(9)

where \( \sigma_{x} \) represents the standard deviation in the displacement. The convolution of Gaussian functions by combining Eqs. (7)-(9) yields the following relations:

\[
\sigma_{x}^2 = \sigma_{c}^2 - \sigma_{x}^2
\]

(10)

\[
\sigma_{z}^2 = \sigma_{c}^2 - \sigma_{z}^2
\]

(11)

The definition of the granular temperature, written in terms of displacement, can be given by Eqs. (12) and (13). For a Gaussian velocity profile the variance of the displacement can be easily related to the standard deviation \( \sigma \):

\[
\Theta_x = \langle (v_x - \langle v_x \rangle)^2 \rangle = \frac{1}{(M \Delta t^2)} \langle (x-x_0)^2 \rangle = \frac{1}{(M \Delta t^2)} \sigma_{x}^2
\]

(12)

\[
\Theta_z = \langle (v_z - \langle v_z \rangle)^2 \rangle = \frac{1}{(M \Delta t^2)} \langle (z-z_0)^2 \rangle = \frac{1}{(M \Delta t^2)} \sigma_{z}^2
\]

(13)

The overall granular temperature – based on 2D experimental measurements – can now be calculated as:

\[
\Theta = (\Theta_x + \Theta_z)/2
\]

(14)

4.2. Digital Image Analysis

The DIA algorithm is used to compute the instantaneous profile of the solids volume fractions from the images of particles. The digital image consists of pixels with different intensities, distinguishing the particles from the gas phase. After a series of preprocessing steps, namely, background subtraction, elimination of overexposed and underexposed pixels, the image is corrected for inhomogeneity and then normalized between 0 and 1. Here 1 is representative for the brightest particles and 0 for the background or the gas. The normalized intensity values are then averaged over the interrogation areas of the same size as used for PIV to obtain the apparent solids volume fraction, referred as 2D fraction \( \phi_{2D} \). However, the obtained \( \phi_{2D} \) introduces an error, since the pixel intensity of the acquired images does not contain any depth information of the solids hold-up. Thus, these results of \( \phi_{2D} \) are subsequently translated/calibrated to the true volume fraction, referred as 3D fractions \( \phi_{3D} \), using the correlation proposed by de Jong et al. (2012):

\[
\phi_{3D}(x, t) = \begin{cases} 
A \phi_{2D}(x, t) & \text{if } \phi_{2D}(x, t) < 0.6 \\
0.6 & \text{if } \phi_{2D}(x, t) \geq 0.6
\end{cases}
\]

(15)

where, the parameter \( A \) is determined by the bed depth \( D \) and the particle diameter, as \( A = 1.028d_p/D \). While the remaining fitting parameter \( B \) is determined such that the deviation between the computed bed mass averaged in time and the experimental bed mass is minimal (usually less than 0.05%). The computed bed mass is obtained by multiplying the tested \( \phi_{3D}(x, t) \) averaged in space with the solids density and the bed volume.

4.3. Combined PIV and DIA

The instantaneous particle velocity vectors obtained from PIV do not account for the number of particles that possess those velocities. When time-averaged velocity profiles are computed using PIV data only, the dynamics of the particles can be misinterpreted, especially because of particle raining through the bubbles, where a small number of particles possess a relatively high velocity, while the particle volumetric flux is small. To correct for this, the instantaneous particle velocity is multiplied with the instantaneous solids volume fraction, followed by averaging over time to obtain the time-averaged volumetric particle flux:

\[
\langle \Phi(x, t) \rangle = \frac{1}{N_t} \sum_{t=1}^{N_t} \langle \mathbf{v}(x, t) \phi_{3D}(x, t) \rangle,
\]

(16)

which provides a better representation of the solids motion.

5. Experimental/simulation set-ups

Simulations and experiments are performed for a pseudo-2D fluidized bed, which is sketched in Fig. 2. The sizes of the bed are given in Table 1, together with the properties of the glass particles used in our study. The spherical particles possess a diameter of 2.5 mm and a density of 2526 kg/m³, which are the Geldart D type particles. The depth of the bed is assumed to be sufficiently small to display pseudo-2D behavior and is large enough to avoid extreme particle-wall interaction. For the experiments, the air flow rate was controlled by a digital mass flow controller and supplied at the bottom of the bed through a porous plate gas distributor. To prevent electrostatic build-up, the air was first humidified to 60—70% relative humidity. The pressure drop over the bed was recorded by a high frequency differential pressure sensor, which was connected to the inside bed through a fine mesh net at the location indicated in Fig. 2. Fig. 3 shows the determination of the minimum fluidization
velocity ($u_{infl} \approx 1.33 \text{ m/s}$) from the pressure drop data, which were measured as gradually increasing the superficial gas velocity $u_g$ (converted from the flow rate) during the experiments. One can observe that the pressure drop in static bed increases nonlinearly with the superficial gas velocity. This is attributed to the relatively large size of particles utilized in this work, for which Ergun equation expresses the pressure drop along the length of a packed bed. Two sets of experiments were conducted at $u_g$ of 2.4 m/s and 2.6 m/s, which correspond to 1.8$u_{infl}$ and 1.95$u_{infl}$, respectively. Digital images of particles were recorded by a LaVision ImagerPro HS CCD camera with the exposure time set to 1 ms and zero delay time. The acquired images correspond to a magnification of $M=4800 \text{ px/m}$ and an average displacement of about 6 px. The frequency with which the PIV image pairs were recorded was 100 Hz. The PIV calculations of the velocity field were conducted with the commercial software package DaVis (LaVision). A multi-pass correlation algorithm was performed using interrogation areas of $64 \times 64$ pixels during the first pass and $32 \times 32$ pixels with an overlap of 50% during the second pass. Accordingly, the interrogation of $32 \times 32$ pixels was used for DIA and the granular temperature measurements as well.

Table 1 also gives the parameters used for our IBM simulations. Note that the height of the entire column (i.e., size of the freeboard) was reduced, in comparison with the height of the experimental set-up, to drop the computational load. However, exactly the same number of particles were used in the experiments and simulations. For the simulation no-slip boundaries were applied at the walls confining the bed in the lateral directions. Restitution coefficients and friction coefficients corresponding to glass beads were used in the hard-sphere model for particle–particle (p–p) and particle–wall (p–w) collisions. Initially the particle bed was assumed to be at rest. The inflow velocity was specified at the bottom, while a constant pressure outflow boundary condition was used at the top. In principle, it would be perfect if the influence of the outflow boundary condition on the simulation results were examined. However, as the current simulations are very expensive, it is almost impossible for us to perform such tests. Nevertheless, we set the computational freeboard as 2.5 times the bed width, which is much higher than the averaged particle bed height we observed from experiments (also shown later in the results section). Therefore, it is reasonable to assume that the computational domain is sufficient to diminish the influence (if any) of the outflow boundary condition. Simulations were performed at a grid resolution of $d_p/h = 5$, along with the optimal diameter $d_m$ of 1.65 mm and 1.6 mm at $u_g = 2.4 \text{ m/s}$ and $u_g = 2.6 \text{ m/s}$, respectively. Utilization of such a low resolution (less grids) can drastically reduce the computational cost, which however in conventional IB methods will result in poor predictive accuracy of the simulations. Conversely, the use of an optimal $d_m$ can bring the results from IBM simulations at low resolutions as close to the converged results that can be obtained at a sufficiently high resolution (also high computational cost). The values of $d_m$ in this study for simulations at $d_p/h = 5$ are estimated on the basis of our early work (Tang et al., 2014, 2015).

6. Results

In this section, we will present the results from both IBM simulations and the experimental measurements. Although two gas velocities have been considered in our study, we focus on reporting the results for $u_g=2.6 \text{ m/s}$, corresponding to 1.95$u_{infl}$. Similar observations, which will be discussed in the following sections, have also been found for the other case ($u_g=2.4 \text{ m/s}$).
and the top plane is about to commence. Accordingly in the particle velocity profile reaches the top of the particle bed, where the eruption of this bubble over the Fig. 4(b), where the vectors represent the particle velocities averaged computed as the difference: 

\[ \text{particle and one otherwise. Subsequently the bed pressure drop is computed by} \]

\[ \text{the gas motion is very difficult to obtain experimentally.} \]

\[ \text{channeling of the gas through the roof of the bubble. Such an instantaneous velocity profile has also been obtained from our experiments using the PIV/DIA measurement, as shown in Fig. 5.} \]

The instantaneous gas velocity profile in the central plane of the bed is given in Fig. 4(c), where the vector indicates the direction and the color represents the magnitude of the velocity. Note that only the gas velocities located in grid cells with an interval of \(2d_p\) are visualized here. Clearly, the channelling of the gas flow through the bubble and recirculation of the gas around the bubble are visible in the vector plot. Consequently, the high-velocity gas flows in the central part of the bed. Conversely, such detailed quantification of the gas motion is very difficult to obtain experimentally.

6.1. Pressure fluctuation

The pressure drop predicted from the IBM simulation is computed by first averaging the pressure at the bottom plane \(z_1 = 0.5h\) and the top plane \(z_2 = H - 0.5h\) over the horizontal grid cells, viz:

\[ \langle P(z, t) \rangle = \frac{\sum_{i=1}^{n_x} \sum_{j=1}^{n_y} \sigma_i \sigma_j P_i(z, t)}{\sum_{i=1}^{n_x} \sum_{j=1}^{n_y} \sigma_i \sigma_j}, \]

where \(\sigma_i\) equals zero if the grid cell center is located inside a solid particle and one otherwise. Subsequently the bed pressure drop is computed as the difference:

\[ \Delta P(t) = \langle P(z_1, t) \rangle - \langle P(z_2, t) \rangle. \]

\[ \text{1 Each simulation took approximately 1000 h of computation time for 1 s of real time, computed with a partially parallel code on 8 Intel Xeon E5-2670 processors in HPC cluster at Eindhoven University of Technology.} \]

\[ \text{The simulation results for the pressure drop calculated via Eqs. (17) and (18) are plotted over time in Fig. 6. Whereas Fig. 6(b) plots the difference between the pressure at the central point of the bottom plane from the simulation and the atmosphere pressure. It is seen that different values of time-averaged pressure drop are obtained from these two calculations, namely, average measurement and point measurement. This point measurement from simulations is obtained in the same way as our experimental measurement using a differential pressure sensor. A part of the experimental data is plotted in Fig. 6(c), which gives the same value of time-averaged pressure drop as obtained by point measurement from the simulation results shown in Fig. 6(b). Note that the time-averaged value in Fig. 6(c) is obtained over a longer time (about 5 min) than shown in this figure.} \]

\[ \text{The complex pressure fluctuation phenomenon in gas-fluidized beds, as evident from these figures, has been studied by many researchers and reviewed by Bi (2007). Pressure fluctuations are composed of many contributions, including local bubble-induced fluctuations, global bed oscillations, and propagating pressure waves.} \]
originating in other locations (e.g., bed surface and distributor). Different approaches of the pressure measurement can lead to quantitative deviation in the results as demonstrated by Fig. 6(a) and (b).

Since the main path of bubbles is along the central axis of the bed, the point measurement is strongly influenced by the local bed dynamics as a consequence of bubble passage. In contrast, by taking spatial averaging of the pressures, the variation of the pressure drop reflects the global bed oscillations or periodic bubble formation. Besides, the fluctuations of pressure drop in Fig. 6(c) measured from experiments turn out to be more complex in comparison with those of simulation data in Fig. 6(d). This can be caused by the pressure waves originating from the central plane of the experimental set-up. For instance, the porous plate at the bottom of the bed can not possibly provide a perfectly uniform gas distribution as specified in simulations. Consequently, it occurs the fluctuations in the preferred direction of bubble passage in the bed. Moreover, in the experiments, the air was humidified by flowing through a vessel of water. This procedure is not fully stable and might introduce propagating pressure waves from the bottom of the bed. Nevertheless, the time-averaged pressure drop ($\Delta P = 5.4 \text{ mbar}$) predicted by the IBM simulation is consistent with the experimental result. Besides, the in-bed pressure measurements are commonly used to characterize the dynamics of gas-fluidized beds for different fluidization regimes. According to Johnson et al. (2000) and van Ommen et al. (2011), our simulation results of pressure fluctuations shown in Fig. 6(a) and (b) indicate a single bubble regime. Whereas, the pressure fluctuations measured experimentally shown in Fig. 6(c) correspond to a single bubble (8–10.6 s) combined with exploding bubble (10.6–13 s) regime. Fig. 7 shows some snapshots obtained from our simulations and experiment for fluidization at $u_g = 1.95u_{mf}$. A very similar flow behavior can be observed from this comparison, which corresponds to the single bubble regime. In this regime, big bubbles (larger than half of the width bed dimension) are formed, with their center, on a time average basis, coincides with the center-line of the bed. After the eruption of a bubble, the bed collapses to a state free of bubbles, lasting for a short time, during which the velocity is not higher than minimum fluidization velocity. The large single bubbles lift a major part of the bed mass above the location of the pressure measurement, resulting in periodic pressure fluctuations. In this sense, the single bubble regime resembles a slugging regime. In contrast, large exploding bubbles possess a similar size to those of the single bubble regime, since the maximum bubble size is limited by the bed height. After the eruption of the exploding bubbles, the bed collapses like in the single bubble regime. However, some particles form clusters in the freeboard, which influence on the formation of coming bubbles, and consequently the pressure fluctuations of the exploding bubbles have an amplitude greater than that of the single bubbles. The exploding bubble regime is also governed by the dynamics of large bubbles, but the signal is more complex than that of the single bubble regime and no clear periodicity can be observed.

6.2. Time-averaged results

The filtered time-averaged solids volumetric flux, computed using PIV/DIA based on the experimental images, is shown in Fig. 8 (a), whereas the results obtained from the IBM simulation are shown in Fig. 8(b). To calculate the time-averaged solids velocities from simulation results, the computational domain (except the depth direction) is divided into small volumes of the same dimensions as for the interrogation areas in the PIV/DIA measurements. For each time step, simulation results in the velocities and locations of all the particles. A mean particle velocity is calculated in each individual small volume by averaging over all the particles inside that volume. Subsequently, a time-averaging is taken for the mean velocities in small volumes. In Fig. 8, the solids circulation patterns can readily be observed from both results, clearly revealing the existence of two symmetric vortices with their centers located at a bed height of 0.045 m (about $18d_p$). In these circulation patterns, particles move upwards in the center of the bed and flow downwards close to the side walls. At such an intermediate fluidization velocity ($1.95u_{mf}$), the down-flow regions extend completely down to the distributor. Using the PIV images, we observe that bubbles, after formation at the distributor, move very rapidly towards the center of the bed and then rise vertically until they erupt at the surface of the particle bed. Thus, the pronounced upward motion of the particles in the central region is induced by the bubble motion. In other words, the particles are carried or driven by the rapidly rising bubbles. These results correspond well to observations reported in many other studies (Bokkers et al., 2004; de Jong et al., 2012; Dang et al., 2013; Patil et al., 2015).

Qualitatively, the solids circulation patterns predicted by the IBM simulation are in agreement with the trend as found experimentally using PIV/DIA measurements. However, one can notice that the degree of symmetry in the circulation pattern in Fig. 8(b) is less pronounced compared to that in Fig. 8(a). The fact that the IBM results lack complete symmetry can be attributed to the relatively short simulation time, of about 7 s, in comparison to a total time of 40 s for PIV/DIA imaging. Another noticeable difference between
these two figures is the bed expansion. Namely, the time-averaged bed expansion obtained from PIV/DIA is slightly larger than that predicted by the IBM simulation. Some possible reasons for this discrepancy are as follows. First, as discussed above, large exploding bubbles occur in the experiment due to the propagating pressure waves originating from the bottom of the bed, which consequently cause the increase of the bed expansion. Secondly, the DIA algorithm utilizes a correlation to convert the solids volume fractions from 2D to 3D. This correlation was however derived by using DEM simulation results, the accuracy of which is a priori dependent on the incorporated closures. Therefore, the use of such a correlation might lead to some departure of the 3D results from the true experiment. Furthermore, the collision coefficients used in the IBM simulation are chosen on reported values in the early work by Hoomans (2000). As is known, the energy dissipation due to the p–p and p–w interactions has a strong influence on the bed behavior. Consequently, some difference of the predicted solids pattern might result from a slight mismatch of these parameters between simulations and experiments. In addition, we apply an optimal diameter \( d_m \) in the simulation to achieve a better prediction of the gas–solid interaction force. However, the \( d_m \) was found dependent on the grid resolution, the solids volume fraction as well as the mean flow
Thus, applying a constant from the comparison in Fig. 8, the bed expansion might be slightly underestimated by the use of meters (solid interaction hence the seems a simplification). The slight difference of the time-averaged bed expansion is attributed to several reasons in regard to experimental measuring techniques as well as input parameters for the simulations.

6.3. Granular temperature

As a very important parameter to characterize the flow behavior in dense gas-fluidized beds, the granular temperature is measured from the experiments and simulations conducted in this study. Note that the granular temperatures, measured experimentally and numerically in this work, both correspond to the particle granular temperature reported by Jung et al. (2005). Whereas, the bubble granular temperature is out of the interest here since it does not represent relative motion between particles. The experimental measurement using the extended PIV technique has been introduced in Section 4.1. Whereas from the IBM simulations, which provide in detail the information of individual particles, the granular temperature is calculated as:

\[ \Theta_{3D} = (\Theta_x + \Theta_y + \Theta_z)/3, \quad \Theta_{2D} = (\Theta_x + \Theta_z)/2; \]  

\[ \Theta_k = \frac{1}{n_p} \sum_{i=1}^{n_p} [v_k(i,t) - \langle v_k(t) \rangle]^2 \quad k = x, y, z; \]  

\[ \langle v_k(t) \rangle = \frac{1}{n_p} \sum_{i=1}^{n_p} v_k(i,t). \]  

with \( n_p \) the number of particles in unit volume applied for spatial averaging. As addressed in Section 2, the issue on the volume size will be first analyzed on the basis of the simulation results in the following discussion.

If the size of the unit volume equals the size of the particle bed, which means \( n_p \) equals the total number \( N_p \) of particles, the obtained granular temperature characterizes the relative particle motion at a macro scale, which is dominated by the motion of big bubbles in such

![Fig. 9. Lateral profiles of the axial solids flux from the simulation and the experiment at different bed heights (see legends).](image)

![Fig. 10. Square root of the granular temperature (\( n_p = N_p \) in Eqs. (20) and (21)) as a function of time obtained from the simulation of fluidization at the superficial gas velocity of 1.95\( \sqrt{\text{m/s}} \).](image)
a bubbling fluidized bed. Fig. 10 gives the square root of this granular temperature, in other words, the root mean square deviation of the particle velocity, calculated with $n_p = N_p$ in both Eqs. (20) and (21). A distinct difference in the magnitudes of the granular temperature between 2D and 3D is observed in Fig. 10(a) near the peak areas. This can be explained by the highly anisotropic behavior of the granular temperature revealed in Fig. 10(b). In other words, the granular temperature in the vertical ($z$) direction (the direction of the flow), is much more pronounced than in lateral ($x, y$) directions. The ratios of $\Theta_z/\Theta_x$ and $\Theta_z/\Theta_y$ in Fig. 10(b) are on average $\sim 5.8$ and $\sim 13$, respectively. The finding of anisotropy is in agreement with the reported observations for the time-averaged granular temperature (Holland et al., 2008; Müller et al., 2008). Besides, another interesting observation can be made by comparing Fig. 10 with Fig. 6(a). The peaks in the plot of pressure drop over time imply the lowest particle bed with the smallest porosity, whereas the valleys indicate the highest bed expansion. Accordingly in Fig. 10, starting from the static particle bed, the granular temperature continuously increases with the upward motion of the particles carried by the bubble. This increase progresses till the highest bed expansion is attained, when the bubble reaches the surface of the particle bed. Subsequently, the eruption of the bubble induces the second increase of the granular temperature up to the maximum, although the bed expansion starts to decrease due to the downward motion of those particles at the top of the bubble. This second increase stops once the bubble eruption is completed. Afterwards, the granular temperature decreases to the minimum with the mean downwards motion of all the particles. This observation implies that the highest values of the granular

![Fig. 11. $\sqrt{\Theta}$ as a function of time from the simulation of fluidization at the superficial gas velocity of 1.95$m_{mf}$, calculated by two different approaches i and ii with different window sizes from $2d_p$ to $10d_p$. (a) case i, $10d_p$, (b) case ii, $10d_p$, (c) case i, $4d_p$, (d) case ii, $4d_p$, (e) case i, $2d_p$, and (f) case ii, $2d_p.\]
temperature appear when the maximum bubble velocity prevails. This can be attributed to the dominated influence by the motion of big bubbles on the motion of particles, thus on the macroscopic granular temperature in such a bubbling fluidized bed.

Conventionally in many applications, the granular temperature characterizes the relative motion of the particles at a small scale. Thus, one would consider the so-called locally spatial averaging with a unit volume of small size, which is assumed to consist of a relatively homogeneous system. In this sense, we subdivide the computational domain into small boxes with a dimension of \( l \times D \times l \). For each of these boxes (or windows), the calculation is conducted using the velocities of the particles present in the box. Fig. 11 shows the results obtained by applying different window sizes \( l \) of 10\( d_p \), 4\( d_p \), 2\( d_p \), using two approaches: (case i) the local granular temperatures are obtained by evaluating both Eqs. (20) and (21) within the small boxes \((l \times D \times l)\); a mean value is subsequently obtained by averaging the local granular temperatures over the boxes which contain particles. (case ii) Eq. (21) is calculated within individual small boxes \((l \times D \times l)\) to obtain the local averaged particle velocity \( \langle \nu^2 \rangle(t) \), with \( b \) the box/window index; the granular temperature is obtained by averaging over the entire bed, i.e., \( n_D = N_p \) in Eq. (20), with \( \langle \nu^2 \rangle(t) \) used for those particles that locate in the same box \( b \). Note that when the box size \( l \) is increased as the dimension of the particle bed, both case i and case ii result in the same granular temperature as obtained in Fig. 10.

By inspecting Fig. 11, a distinct difference is observed between the results obtained from these two approaches. The granular temperatures obtained in case i are on average \( \sim 10\% \) larger than in case ii. Conversely, the curves in case ii, especially with a larger \( l \), resemble more the variation of the granular temperature shown in Fig. 10(a). On the other hand, inspection of Fig. 11 with respect to the box/window size reveals that by reducing the box size \( l \) from 10\( d_p \) to 2\( d_p \), the magnitude of \( \Theta \) decreases with 25%. The differences in the obtained granular temperatures correspond to that to what extent the macroscopic relative motion of the particles are involved in individual small windows/boxes. When the window size is reduced to 2\( d_p \), the granular temperature obtained in case ii is very close to the conventional granular temperature based on ensemble averaging in the kinetic theory of granular flows. In addition, it is also seen that the difference between \( \Theta_{3D} \) and \( \Theta_{2D} \) is reduced. This can be explained by Fig. 12, which shows the three components, \( \Theta_x, \Theta_y \), and \( \Theta_z \), calculated using the two approaches with \( l = 2d_p \). When comparing to Fig. 10(b), the anisotropy of the granular temperature remains in Fig. 12, but the differences between the components of \( \Theta \) are significantly reduced. In this figure, the granular temperature in the vertical direction exceeds the granular temperature in either of the horizontal directions by a factor of \( \sim 2 \), where it is \( \sim 15 \) and \( \sim 13 \) for \( x \)- and \( y \)-directions shown in Fig. 10(b). These numbers might also explain the disagreement with respect to the reported ratios by Holland et al. (2008) and Müller et al. (2008). In addition, as shown in Fig. 12 with the use of a small window size, the difference of the obtained granular temperature between two horizontal \((x \text{- and } y \text{-})\) directions is negligible. This implies an effective way to obtain \( \Theta_{3D} \) from 2D information such as in experimental measurements, i.e., \( \Theta_{3D} = (2\Theta_x + \Theta_y)/3 \). Last but not the least, the granular temperatures obtained in Fig. 11 with small window sizes, regardless of the two approaches, no longer reveal the turning point shown in Fig. 10, which reflects the eruption of the bubble.

The above analysis indicates the subtlety in the measurement or interpretation of the granular temperature, especially in case direct comparison between experiments and simulation results (obtained...
from e.g. DEM and TFM) is undertaken. In our experimental work, the granular temperature measured by the extended PIV technique can be easily understood to be similar to the calculation used in case i. In Fig. 13, we compare results from the experiment, the IBM simulation and the IBM-PIV. For the IBM-PIV calculation, we first create rendered images using different snapshots from the IBM simulation, where the locations of individual particles are provided. In these images, the normalized intensity is between 0 and 1, with 0 representing the gas phase, 1 representing the particles that locate near the front wall of the bed, and values in between representing the rest of particles in terms of their location in bed depth. Subsequently, the granular temperature on the basis of these images is calculated using the extended PIV technique, with applying the same interrogation areas as for the experimental images. From Fig. 13, a very good agreement can be observed on the magnitude as well as the variation of the granular temperature. Furthermore, we also find the same characteristic frequency ( \( f = 2 \pm 0.3 \, \text{s}^{-1} \) ) of the fluctuations of granular temperature, as shown in the frequency spectra plotted in Fig. 14. Hereby, it is indicated the first successful application of this technique for experimentally measuring the granular temperature in a fully developed gas-fluidized bed, extending the findings of Dijkhuizen et al. (2007). However, such experimental measurements are not yet able to capture the detailed variations of the granular temperature, such as shown in Fig. 10 from a direct numerical simulation.

7. Conclusions

The methodology developed in our earlier work allows for better predictions of the gas–solid interaction force using an immersed boundary method with a relatively coarse grid. This enables the direct numerical simulation of a small but real gas-fluidized bed. In this work, we performed IBM simulations of a pseudo-2D gas-fluidized bed with 5000 spherical particles. The simulation results are directly compared with experimental data using the extended PIV and DIA techniques. A reasonably good agreement with respect to the time-averaged solids motion is obtained between simulations and experiments, where typical circulation patterns are obtained with the solids moving upwards in the middle of the bed and downwards near the walls. A slight difference is observed in the time-averaged bed expansion, which can be attributed to various reasons including the relatively short computing time, simulation input data such as the particle properties and the used constant \( d_m \), some practical experimental conditions, as well as the 2D to 3D volume correlation used in the DIA algorithm.

Besides, as IBM simulations provide the information (velocities, positions) of individual particles, it allowed us to investigate the granular temperature in detail. The observed anisotropy of the granular temperature is consistent with the conclusions reported in literature. However, the ratio of the components of \( \Theta \) should be examined as well with respect to the interpretation or definition of the granular temperature, in case experimental and simulation data are compared. Furthermore, it turns out that the granular temperature at the macro scale reveals more details of the gas–solid flow, such as the upward and downward motions of the particles as well as the eruption of the bubbles. Conversely, such details are not observed from the conventional measurements of the granular temperature as in experimental studies and large-scale models (like TFM), which measure the granular temperature at micro scales. In TFM, the unresolved particle interactions are described by the KTGF closures, which calculate the granular temperature related to the relative motion of particles at a small length scale. In turn, one could also use the computed larger-scale velocity field from TFM to calculate the granular temperature at macro scales, which is related to the variance of the velocities in the resolved solids phase. Furthermore, distinct differences are observed between the magnitudes of those obtained granular temperatures with respect to different volume/window/box sizes for the spatial average. Therefore, we suggest that care should be taken in studies of granular temperature, especially for direct comparison between experiments and simulations while using different types of models. Subsequently, using the rendered images generated from the IBM simulation results, we demonstrate the successful application of the extended PIV technique for measuring the granular temperature in the bubbling fluidization regime. Quantitative agreements have been obtained between our experiments and IBM simulations, with respect to the granular temperature and its spectral characteristics as well.

Finally, we conclude that a successful comparison has been made in this study between IBM simulations and experiments conducted for a pseudo-2D gas-fluidized bed. Direct numerical simulations of fluidized beds, in all aspects, provide more detailed and valuable quantitative information for understanding the bed behavior.

Nomenclature

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( D )</td>
<td>bed depth, (m)</td>
</tr>
<tr>
<td>( d_m )</td>
<td>diameter for markers distribution, (m)</td>
</tr>
<tr>
<td>( d_p )</td>
<td>particle diameter, (m)</td>
</tr>
<tr>
<td>( f, F )</td>
<td>force, (N)</td>
</tr>
<tr>
<td>( F_I )</td>
<td>In-plane particle loss correction factor, (–)</td>
</tr>
<tr>
<td>( F_O )</td>
<td>Out-of-plane particle loss correction factor, (–)</td>
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<td>( F_T )</td>
<td>Shape of the correction peak due to the particle size, (–)</td>
</tr>
<tr>
<td>( h )</td>
<td>grid size, (m)</td>
</tr>
<tr>
<td>( H )</td>
<td>height, (m)</td>
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<td>( l )</td>
<td>window size, (m)</td>
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<td>( M )</td>
<td>image magnification, (px/m)</td>
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<td>( N, n )</td>
<td>counting numbers, (–)</td>
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<tr>
<td>( N_I )</td>
<td>number of particles in the interrogation area, (–)</td>
</tr>
<tr>
<td>( P )</td>
<td>pressure, (N/m³)</td>
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<tr>
<td>( R_D )</td>
<td>Displacement correlation peak, (–)</td>
</tr>
<tr>
<td>( \bar{s} )</td>
<td>averaged displacement, (px)</td>
</tr>
<tr>
<td>( t )</td>
<td>time, (s)</td>
</tr>
<tr>
<td>( u, U, \bar{u} )</td>
<td>gas velocity, (m/s)</td>
</tr>
</tbody>
</table>
minimal fluidization velocity, (m/s)

\( u_{\text{mf}} \)

\( v, V, \dot{v} \)

particle velocity, (m/s)

\( x, x \)

\( x \)

position or coordinates, (m)

\( y, y \)

x-position in digital image, (px)

\( x \)

\( y \)

y-position in digital image, (m)

\( x_0 \)

\( z \)

exact x-location of the cross-correlation peak, (px)

\( z_0 \)

\( 
\begin{align*}
\mu & \quad \text{dynamic viscosity, (Pa·s)} \\
\phi_{\text{2D}} & \quad \text{solids volume fraction, (—)} \\
\phi_{\text{3D}} & \quad \text{calibrated (true) solids volume fraction in DIA measurement, (—)} \\
\rho & \quad \text{density, (kg/m}^3\text{)} \\
\rho(x, z) & \quad \text{shape of the correlation peak due to the velocity distribution, (—)} \\
\sigma & \quad \text{standard deviation, (px)} \\
\Theta & \quad \text{granular temperature, (m}^2/\text{s}^2\text{)} \\
Y & \quad \text{complex Fourier coefficient, (—)} \\
\end{align*}
\)

\( a \)

auto-correlation

\( b \)

box/window index

\( c \)

cross-correlation

\( g \)

gas

\( i, j, k \)

indices

\( m \)

marker points

\( p \)

particles

\( x, y, z \)

in x, y, z direction

\( t \)

time

2D, 3D

two, three dimensions

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References


