



Study on the fluidization behavior of Geldart B iron ore powders based on deep learning-assisted bubble detection algorithm

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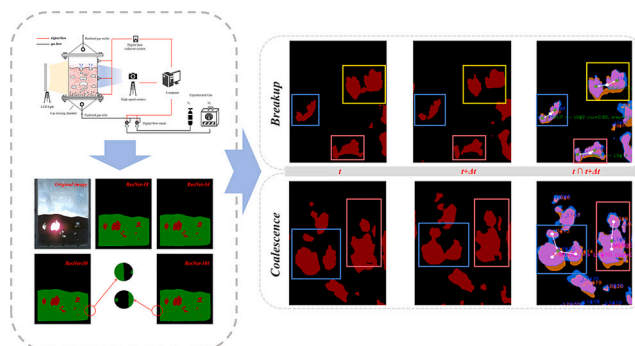
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HIGHLIGHTS

- A deep learning-assisted bubble detection algorithm is developed for bubbling beds.
- Bubble morphology, breakup, coalescence, and rising dynamics are accurately quantified.
- Effects of particle size, fluidization number, and H₂ fraction are systematically revealed.
- H₂ shows a nonlinear suppression on bubble size, velocity, and dynamic event frequency.
- Bubble dynamics transition from breakup-dominated to breakup-coalescence balanced regimes.

GRAPHICAL ABSTRACT



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ABSTRACT

Hydrogen-based fluidized bed direct reduction is a key technology for low-carbon ironmaking, and the distinct properties of iron ore powders and hydrogen require renewed investigation of their fluidization behavior. In this study, a deep learning-assisted bubble detection algorithm was developed to automatically identify, track, and quantify bubble morphology and dynamic events from experimental images. This algorithm was combined with a deep learning-based image segmentation method with a compact backbone network and quasi-two-dimensional bubbling fluidized bed experiments to systematically examine the fluidization behavior of Geldart B-type iron ore powders under varying particle sizes, fluidization numbers (fn), and hydrogen volume fractions. The results show that using ResNet18 as the backbone network achieves an optimal balance between segmentation accuracy and computational efficiency. As fn and particle size increase, the bubble size, rising velocity, and bed fluctuation amplitude all increase significantly, while bubble shapes become more regular. Bubble dynamics analysis further reveals that bubble breakup occurs more frequently in small-particle systems, whereas coalescence dominates in large-particle systems. Spatially, bubble breakup prevails near the bottom of the bed, while bubble coalescence is predominant near the top. Finally, the introduction of hydrogen exerts a clear suppressing effect on bubble morphology, rising velocity, and the frequency of breakup and coalescence events. This suppressing effect, however, is nonlinear and tends to saturate as the hydrogen volume fraction increases beyond a certain level.

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Novelty and significance statement: This study proposes a deep learning-assisted bubble detection algorithm for quantifying bubble dynamics in bubbling fluidized beds under H_2 and N_2 atmospheres. By integrating a light-weight ResNet18 segmentation network with a customized bubble-tracking algorithm, the method reliably identifies bubble morphology, breakup, coalescence, and rising dynamics under complex imaging conditions. The results systematically evaluate the combined effects of particle size, fluidization number, and H_2 volume fraction on the bubble hydrodynamics of Geldart B-type iron ore powders. Key findings include: as the fluidization number increases, bubble dynamics transition from a breakup-dominated regime to a balanced breakup-coalescence state; bubble events exhibit clear spatial differentiation within the bed; and H_2 exerts a nonlinear suppressing effect on bubble size, rising velocity, and the frequency of breakup and coalescence events, with this suppression saturating as the H_2 volume fraction increases beyond a certain level. These insights provide essential mechanistic guidance for improving H_2 -solid contact efficiency, enhancing reactor stability, and supporting the scale-up of H_2 -based fluidized bed direct reduction technology.

1. Introduction

Under the “Dual Carbon” goals and the European Union’s Carbon Border Adjustment Mechanism (CBAM), the metallurgical industry — one of the largest sources of carbon emissions — urgently needs to transition toward green and low-carbon development [1–4]. Among emerging decarbonization technologies, hydrogen metallurgy, which replaces carbon with hydrogen as the reducing agent for iron ore, has been recognized as a promising pathway to achieve carbon neutrality in metallurgical processes. In particular, the hydrogen-based direct reduction (HDR) process, characterized by its simplified flow, low energy consumption, and minimal emissions, is regarded as a key direction for the future development of the steel industry [5–7]. Based on different process principles, HDR can be categorized into two main technological routes: gas-based shaft furnace reduction and fluidized bed reduction. Among them, hydrogen-based fluidized bed metallurgy has attracted growing attention due to its excellent heat and mass transfer performance and its ability to directly process fine iron ore particles (<5 mm). Consequently, it is considered a potential core technology for achieving the continuous reduction of fine iron ore particles [8–13].

For gas-solid fluidization systems, the physical properties of both the gas and solid phases play a decisive role in determining the fluidization behavior. In the case of hydrogen-based fluidized reduction of iron ore powder, the particles possess a relatively high density ($\approx 4000 \text{ kg/m}^3$) and can be classified as Geldart B-type particles according to Geldart’s classification. Meanwhile, hydrogen gas has a much lower density and significantly different viscosity compared with air [14]. As a result, the fluidization behavior of the hydrogen-iron-ore system is expected to differ markedly from conventional systems, necessitating a re-evaluation and systematic study of its fluidization characteristics.

From the perspective of fluidization regime evolution, as the superficial gas velocity increases, the particle bed undergoes a progressive transition — from a fixed bed to a particulate fluidization regime, followed by bubbling, slugging, turbulent, and fast fluidization, and eventually reaching the pneumatic conveying regime [15]. Among these, the bubbling fluidized bed represents the most fundamental and extensively studied flow regime. The generation, coalescence, breakup, and motion of bubbles govern the internal flow structure and energy transfer within the bed. Bubble evolution not only dictates particle transport and mixing but also controls the transition toward more complex regimes such as slugging and fast fluidization. Therefore, investigating the bubble dynamics within bubbling beds provides essential insights into the fundamental mechanisms of gas-solid interactions and lays the groundwork for understanding and predicting complex hydrodynamic behaviors under higher fluidization states.

In the study of bubble dynamics, the combination of high-speed imaging and digital image analysis (DIA) has become one of the most common and effective approaches [16–19]. However, due to early technical limitations, previous research largely relied on traditional image segmentation methods, such as threshold-based or clustering-based techniques. These conventional methods often exhibit poor

robustness when processing complex fluidization images and are highly sensitive to varying operating conditions [20,21]. For example, Yuan et al. employed a MATLAB-based thresholding approach to investigate the fluidization behavior of Geldart B-type quartz sand in a two-dimensional bubbling bed [22,23]; Zhu et al. applied a similar method to analyze Geldart B-type glass beads under pressurized bubbling conditions [24]; while Xu et al. studied the fluidization characteristics of Geldart A-type pulverized coal [25]. In addition to thresholding, clustering-based segmentation algorithms have also been applied, primarily for identifying clusters in fast fluidization regimes [26].

In recent years, with the rapid development of artificial intelligence and computational hardware, deep learning-based image segmentation techniques have gradually replaced traditional methods and demonstrated superior performance in terms of accuracy, efficiency, and generalization ability [27–29]. Once trained, these models can adapt to diverse experimental conditions and maintain high robustness, while their performance can be further improved as the training dataset expands — a key advantage for long-term, large-scale image analysis in fluidization research. Jiang et al. applied a U-Net deep learning network to study bubble behavior in an air-glass-bead bubbling bed [30]; Fu et al. employed the DeepLabV3+ framework to analyze single-bubble dynamics within a fluidized bed, achieving highly accurate segmentation results [31]; and Peng systematically compared the U-Net and DeepLabV3 architectures, revealing that while DeepLabV3 provided higher segmentation accuracy, U-Net achieved faster inference speeds with comparable precision [32].

Overall, extensive previous studies based on traditional image segmentation methods have struggled to achieve precise segmentation across large datasets. Moreover, most existing works have focused on model particle systems (e.g., FCC catalysts, glass beads, and quartz sand), whereas research on high-density iron ore powders remains limited, and studies under hydrogen-rich fluidization atmospheres are even scarcer. To address these gaps, the present study employs a deep learning-based image segmentation model to accurately distinguish the solid and bubble phases in fluidized bed images. An automated algorithm was further developed to identify bubble coalescence and breakup behaviors in bubbling beds, enabling detailed analysis of bubble dynamics under varying particle sizes and fluidization numbers. Additionally, this work investigates the influence of hydrogen volume fraction in the fluidizing gas on the fluidization behavior of iron ore powders, thereby providing experimental evidence and theoretical insights for future research on hydrogen-based fluidized bed reduction processes.

2. Experimental details

The experimental system used in this study is shown in Fig. 1. Fig. 1 (a) illustrates the quasi-two-dimensional micro fluidized bed employed for fluidization experiments, which was made of transparent acrylic. The internal dimensions of the bed were 100 mm in length, 5 mm in thickness, and 200 mm in height. The upper and lower gas mixing chambers

were constructed from aluminum alloy and fastened to the bed body with screws. Silicone gaskets were installed between the chambers and the bed to ensure airtight sealing of the entire system. Two layers of 1200-mesh stainless-steel screens, each with a thickness of 0.1 mm, were placed between the lower gas mixing chamber and the bed as the gas distributor.

Fig. 1(b) shows the optical image acquisition system. A LED back-light source and a high-speed camera were positioned on opposite sides of the fluidized bed at the same horizontal level to enhance the contrast between the bubble phase and the solid phase. The relative ground positions and tripod heights of the light source and the camera were marked to ensure identical optical alignment in all experiments. The high-speed camera (Phantom, USA) was operated at a frame rate of 200 fps, and the captured images had a resolution of 800×786 pixels. Each recording lasted for 1 min, and to minimize experimental randomness, each operating condition was recorded three times.

In addition, Fig. 1(b) also illustrates the directions of gas flow and digital flow in the system. Pressure transducers were mounted above the gas distributor and near the fluidized gas outlet to monitor pressure fluctuations in the bed during fluidization. The gas flow was regulated by two mass flow controllers (Huacheng Electronics Co., Ltd., China) with measuring ranges of 50 L min^{-1} and 2 L min^{-1} , respectively. Both the pressure transducers and the mass flow controllers were connected to a computer for real-time control and data acquisition through dedicated software. The fluidized gases used in the experiments were hydrogen (H_2) and nitrogen (N_2). Nitrogen (99% purity) was supplied by Haipu Gas Co., Ltd., while H_2 was generated by a hydrogen generator capable of providing a stable flow rate of up to 3 L min^{-1} .

The particles used in the experiments were Middle Eastern iron ore powders with different size ranges, obtained by sieving through meshes with aperture sizes of 0.1–0.2 mm and 0.2–0.3 mm, respectively. According to the Geldart classification, both types of particles belong to Group B. The particle size distributions, measured using a laser particle size analyzer (Malvern Panalytical, Mastersizer 2000), are shown in Fig. 2. The true and bulk densities of the materials are listed in Table 1.

Typically, the minimum fluidization velocity of the powders was determined using the pressure-drop method. Fig. 3 shows the measured bed pressure drop as the superficial velocity was gradually decreased during fluidization. Based on the pressure-drop data, under a nitrogen

atmosphere, the minimum fluidization velocity of the iron ore powder was determined to be 0.0775 m/s for particles with a size of 0.1–0.2 mm and 0.174 m/s for particles with a size of 0.2–0.3 mm. Under a gas atmosphere consisting of 50% H_2 and 50% N_2 , the minimum fluidization velocity of the 0.1–0.2 mm iron ore powder was measured to be 0.0838 m/s .

In the experiments, N_2 was first used to investigate the effects of increasing superficial gas velocity and varying particle size on the fluidization behavior of the iron ore powder. Subsequently, H_2 was gradually introduced into the fluidizing gas atmosphere in increments of 10 vol% up to 50 vol% in order to further examine the influence of H_2 concentration on the fluidization behavior, using iron ore particles with a mean diameter of $100 \mu\text{m}$ and maintaining a fluidization number (fn) of 1.5. The main symbols used in this study are summarized in Table 2.

3. Image data processing

3.1. Deep learning-based image segmentation

Previous studies have demonstrated that deep learning-based image segmentation methods offer significant advantages in both accuracy and efficiency for gas-solid two phase flow identification. Therefore, in this study, the dataset was further expanded with additional operating conditions and the model was retrained based on the DeepLabV3+ framework previously established by our research group [33]. Detail information about the model architecture and training strategy can be found in our earlier work and is not repeat here. The training was performed on two NVIDIA GeForce RTX 4090 GPUs, each equipped with 24 GB of memory.

The accuracy, training time, and storage requirements of models with different backbone networks during retraining are summarized in the Tables 3 and 4. Overall, although the performances of the models showed slight variations when applied to entirely unseen images, all of them were capable of effectively segmenting the bubble and solid phases under complex conditions.

According to Table 3 and 4, ResNet34 achieves the highest mean IoU (0.949) with comparable pixel accuracy, while ResNet18 attains the lowest validation loss (0.03057) and demonstrates the best computational efficiency—featuring the fewest parameters, smallest memory

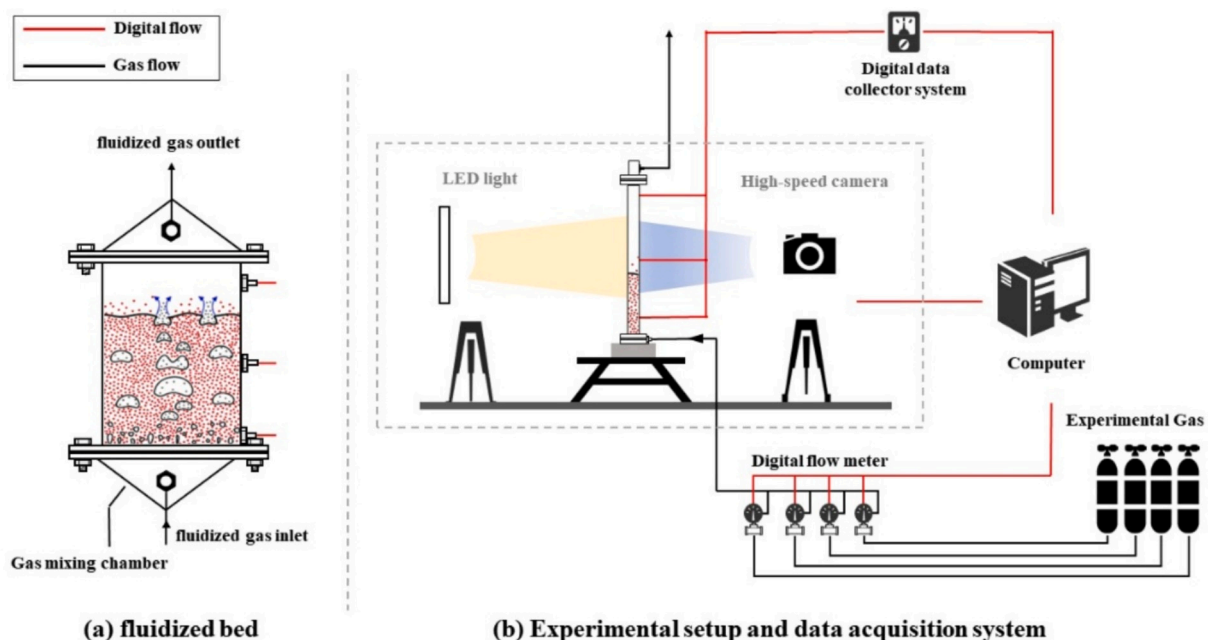


Fig. 1. Mini-quasi-two-dimensional fluidized bed setup.

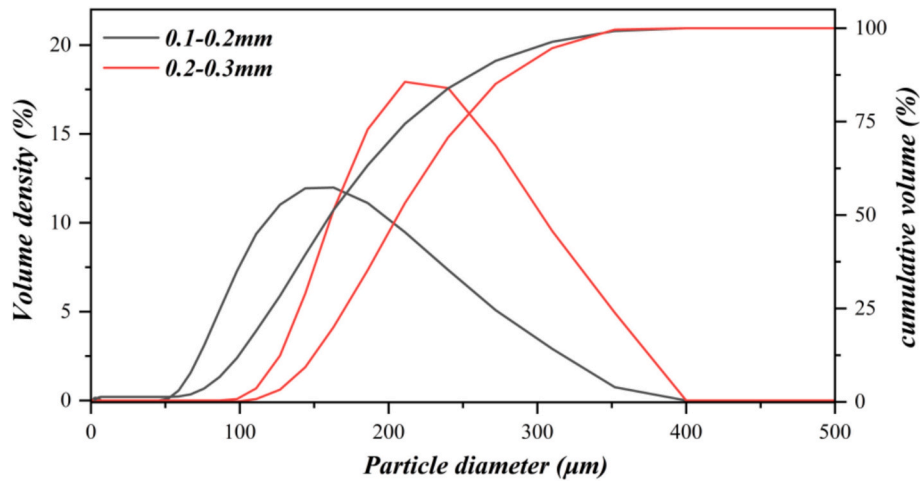


Fig. 2. Particle size distributions of Middle Eastern iron ore powders.

Table 1
Physical properties of the particles.

Particle size	Ture density (kg/m ³)	Bulk density (kg/m ³)	D50 (μm)
0.1–0.2 mm	5050.32	2930.44	124
0.2–0.3 mm		2704.86	253

footprint, and shortest training time per epoch. As the depth of the ResNet backbone increases, the number of parameters and computational cost rise sharply, whereas the validation accuracy shows no significant improvement and even declines slightly, which may be attributed to overfitting during training. Considering the trade-off between segmentation accuracy, computational efficiency, and storage requirements, ResNet18 was ultimately selected as the backbone network for subsequent analyses. By contrast, ResNet50 and ResNet101 exhibited slightly lower segmentation performance and occasional misclassification at the reactor boundaries-where the nuts were incorrectly identified as part of the solid phase-as illustrated in Fig. 4. The figure also shows that the segmentation results of ResNet18 and ResNet34 are nearly identical, further confirming the reliability and adequacy of the chosen network for gas–solid flow image segmentation.

3.2. Image analysis method

3.2.1. Morphological and dynamic analysis of bubbles

It is generally recognized that the bubble size is closely related to the

Table 2

List of main symbols used in this study.

Symbol	Description	Unit
fn	Fluidization number	–
d_b	Equivalent bubble diameter	mm
u_b	Bubble velocity	m/s
ΦH_2	Hydrogen volume fraction	%
AR	Bubble aspect ratio	–
H	Bed height	mm

Table 3

Segmentation performance comparison of backbone networks.

Backbone	Validation Loss	Pixel Accuracy	Mean IoU
ResNet18	0.03057	0.989	0.948
ResNet34	0.03248	0.989	0.949
ResNet50	0.03340	0.988	0.946
ResNet101	0.03164	0.989	0.945

Table 4

Computational efficiency of backbone networks.

Backbone	Total Parameters (M)	GPU Memory (MiB)	Model Size (MB)	Time per Epoch (s)
ResNet18	16.6	8161	127 MB	10.17 s
ResNet34	26.71	15,069	213 MB	12.53 s
ResNet50	40.35	18,094	323 MB	18.62 s
ResNet101	59.34	20,845	475 MB	23.72 s

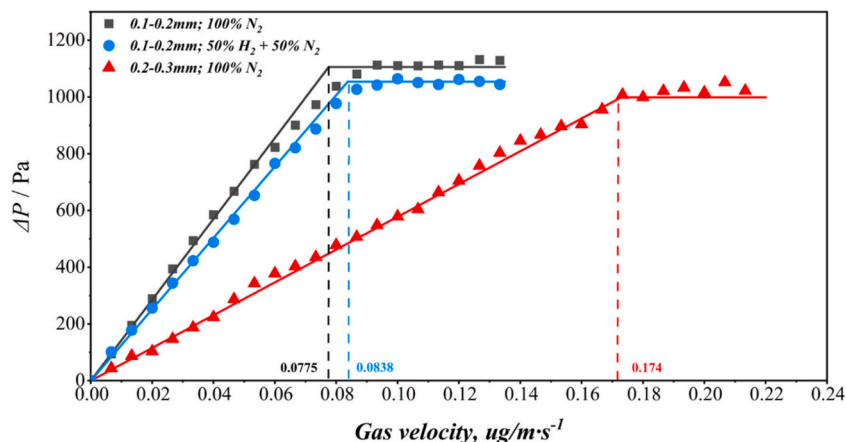


Fig. 3. Pressure drop of the iron ore powder during fluidization.

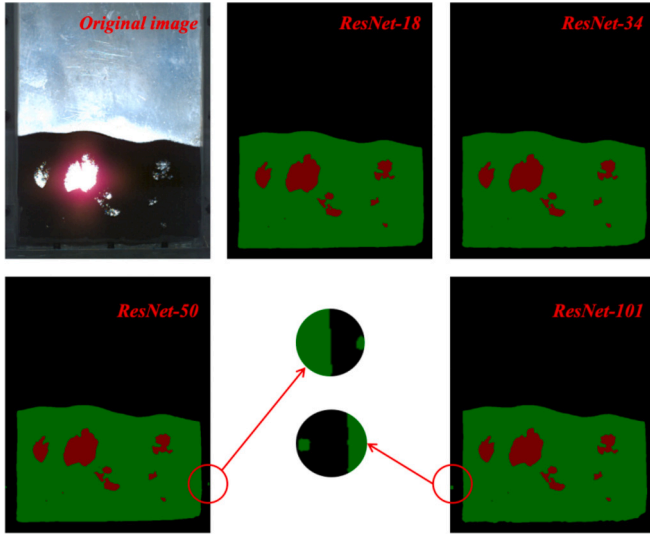


Fig. 4. Comparison of segmentation results obtained using different backbone networks.

bed height at which the bubble is located. To describe this relationship, a series of correlations have been proposed by researchers based on experimental observations and theoretical analysis. Typical examples include the correlations developed by Darton [34], Shen [35] and Lim [36], as expressed below:

$$d_b(h) = 0.54 \frac{(u_g - u_{mf})^{2/5} (h + 4\sqrt{A_{orf}})^{4/5}}{g^{1/5}} \quad (1)$$

$$d_b(h) = \left(\frac{8(u_g - u_{mf})(2^{3/4} - 1)h}{\pi\sqrt{g}\lambda} \frac{8(u_g - u_{mf})A_{orf}}{\pi\sqrt{g}\lambda} \right)^{2/3} \quad (2)$$

$$d_b(h) = 0.89 \frac{\left[(u_g - u_{mf}) \left(h + \frac{3A_{orf}}{l_{orf}} \right) \right]^{2/3}}{g^{1/3}} \quad (3)$$

In these correlations, $d_b(h)$ denotes the equivalent bubble diameter varying with bed height; u_g represents the superficial gas velocity; u_{mf} is the minimum fluidization velocity; A_{orf} and l_{orf} are the area and perimeter of the distributor orifice, respectively; λ is an empirical constant (typically taken as 2) [36]; and g is the gravitational acceleration. According to these empirical correlations, a higher superficial gas velocity leads to a more pronounced increase in the equivalent bubble diameter with rising bed height. In subsequent analyses, the above correlations will be compared with the experimental results to further examine the effects of different experimental factors on bubble morphology. In addition, the probability density distributions of the bubble equivalent diameter and aspect ratio (defined as the ratio of vertical length to horizontal length) were also analyzed as supplementary parameters.

It is widely accepted that, under identical operating conditions, the bubble rise velocity is primarily governed by the bubble size [35]. Larger bubbles experience greater buoyant forces and therefore rise faster. The corresponding correlation can be expressed as follows:

$$u_{rising} = k\sqrt{gd_b} \quad (4)$$

where k is an empirical parameter and d_b is the equivalent bubble diameter.

The bubble velocity was determined from the displacement of the centroid of corresponding bubbles between two consecutive frames in both the vertical and horizontal directions. The centroid was calculated as the area-weighted mean position of the segmented bubble region. It

should be noted that, owing to the symmetry of the fluidized bed in the horizontal direction, the horizontal velocity was taken as the absolute value during statistical analysis. As illustrated in Fig. 5, where the white dots denote the bubble centroids, the vertical and horizontal velocities of a bubble between two consecutive frames were calculated as follows:

$$v_y = \frac{dy}{\Delta t}, \quad v_x = \left| \frac{dx}{\Delta t} \right| \quad (5)$$

3.2.2. Bubble coalescence and breakup identification algorithm

Bubble coalescence and breakup are important hydrodynamic characteristics in bubbling fluidized beds, which have a significant impact on heat and mass transfer within the bed. To identify bubble coalescence and breakup events between consecutive time frames, an overlap-based algorithm was developed using the positional information of bubbles at successive time steps.

First, an overlap matrix $\mathbf{M}$ is calculated between two consecutive image frames. If the numbers of bubbles in the two frames are n_t and $n_{t+\Delta t}$, respectively, then the matrix $\mathbf{M}$ has a shape of $n_t \times n_{t+\Delta t}$. Each element M_{ij} in the matrix represents the overlapping area between the i -th bubble at time t and the j -th bubble at time $t + \Delta t$; a zero value indicates no overlap. It is computed as: $M_{ij} = |A_i^t \cap A_j^{t+1}|$, where A_i^t and A_j^{t+1} are the areas of the corresponding bubbles at times t and $t + \Delta t$, respectively. In the overlap matrix, each row corresponds to a bubble at time t , and each column corresponds to a bubble at time $t + \Delta t$. For breakup detection, each row of the overlap matrix is analyzed. If a row contains more than one nonzero element, it indicates that a single bubble at time t corresponds to multiple bubbles at time $t + \Delta t$. To eliminate spurious matches, a local overlap threshold τ_{local} is applied—only overlaps exceeding this threshold are considered valid. Then, the total area of all validly overlapping bubbles at time $t + \Delta t$ is compared with the area of the corresponding bubble at time t . If the areas are approximately equal, the event is identified as a bubble breakup. Since bubble areas are not strictly conserved due to flow disturbances, an area consistency threshold τ_{area} is introduced to allow reasonable deviation. For coalescence detection, the columns of the overlap matrix are analyzed in the same manner. If a column contains

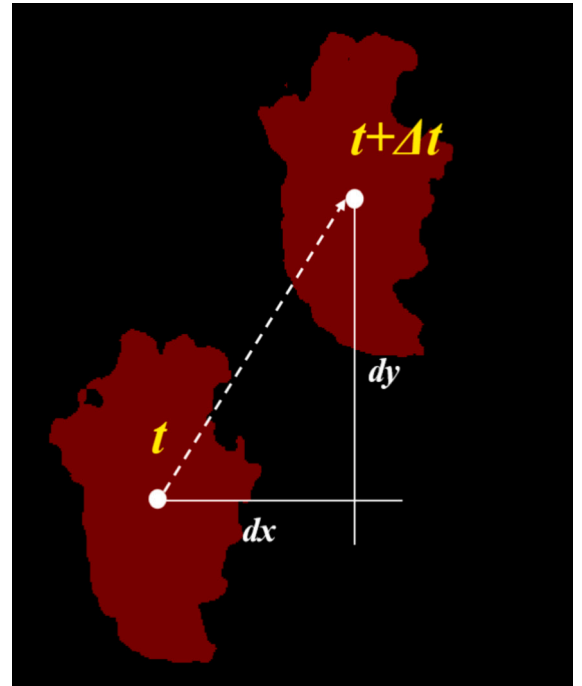


Fig. 5. Schematic diagram of bubble velocity calculation.

more than one nonzero element and satisfies the same threshold conditions, it is determined that several bubbles at time t have merged into one bubble at time $t + \Delta t$. By iterating this process over all frames, all bubble breakup and coalescence events within a given time series can be identified and statistically analyzed.

Fig. 6 illustrates typical examples of bubble coalescence and breakup. The white centroids and orange regions denote bubbles at time t , while the green centroids and blue regions correspond to bubbles at time $t + \Delta t$. The centroids were calculated using the same method as that employed for the bubble velocity calculation in Section 3.2.1. The purple regions indicate the overlap between the two frames, clearly revealing the evolution of bubble behavior.

3.2.3. Bed-scale hydrodynamic characterization

Bed fluctuation can intuitively reflect the intensity of bubbling behavior in fluidized beds. Benefiting from the accurate segmentation of the solid phase achieved by the deep learning-based image segmentation method used in this study, a quantitative analysis of the overall fluctuation of the solid bed was further conducted. Using custom code, each image frame was scanned column by column to extract the highest pixel coordinate corresponding to the solid phase in each column. The average of these coordinates was then calculated to obtain the mean pixel height of the bed for that frame. Subsequently, the pixel height was converted into the actual physical height according to the image-to-scale ratio, yielding the temporal evolution of the mean bed height.

Moreover, due to the intense and complex gas–solid interactions within the fluidized bed, it is necessary to perform a Fast Fourier Transform (FFT)-based frequency-domain analysis of the bed height time series to characterize the statistical features and periodicity of bed fluctuations. In general, the low-frequency region of the fluctuation spectrum corresponds to long-period oscillations, representing the global motion of the bed and large bubble clusters, whereas the high-frequency region corresponds to short-period oscillations associated with bubble breakup, coalescence, and local particle disturbances. The mathematical expression of the FFT is given as follows:

$$\hat{H}(k) = \sum_{t=0}^{N-1} H(t) e^{-j2\pi k t / N} \quad (6)$$

where $\hat{H}(k)$ represents the frequency-domain signal obtained by applying the discrete Fourier transform (DFT) to the time-domain bed height fluctuation signal $H(k)$. N is the total number of sampled data

points, k is the discrete frequency index, t is the time index, and j is the imaginary unit.

The gas–solid contact intensity is an important parameter in fluidized-bed reactors, as it determines the efficiency of heat and mass transfer as well as chemical reactions within the bed. Based on the two-dimensional image recognition method developed in this study, the gas–solid contact intensity was defined as the absolute length of the gas–solid interface within a specified region. Specifically, the contact intensity L was quantified by calculating the total contour length of the gas–solid interface identified in the segmented image, as given by:

$$L = P_{\text{contour}} \quad (7)$$

where P_{contour} represents the perimeter of the gas–solid interface within the analyzed region. Considering that both the bubble number and bubble shape have a pronounced effect on the gas–solid contact intensity, and that the bubble shape has already been characterized by the aspect ratio, an additional analysis of bubble number distributions in different regions was conducted to reveal the potential influence of bubble number on gas–solid contact intensity.

4. Results and discussion

4.1. Bubble morphology and distribution

The relationship between the equivalent bubble diameter and the bed height under different operating conditions is illustrated in Fig. 7 (the experimental values represent region-averaged results, while the corresponding scatter data are provided in Fig. S1 in the Supplementary Material). As observed from Fig. 7(a)–(d), the bubble size at the same bed height increases significantly with the rise of the fn , and the maximum height that bubbles can reach within the bed also increases accordingly. Overall, in the lower and middle regions of the bed, all three correlations can satisfactorily describe the variation in bubble size with bed height under different fn . However, noticeable deviations appear at the top of the bed, where the predicted results diverge from the experimental data. This discrepancy is likely due to strong interfacial disturbances occurring as bubbles approach the bed surface, causing severe deformation of bubble shapes that exceed the applicability range of the empirical formulas. Furthermore, the higher the fn , the more intense the interfacial disturbance becomes. Consequently, the deviation between the correlations and the experimental results near the bed

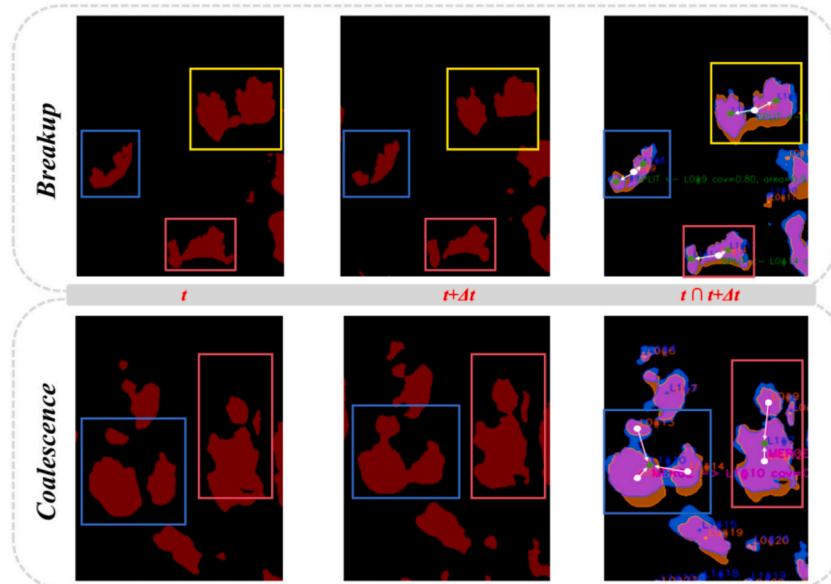


Fig. 6. Bubble breakup and coalescence in the fluidized bed.

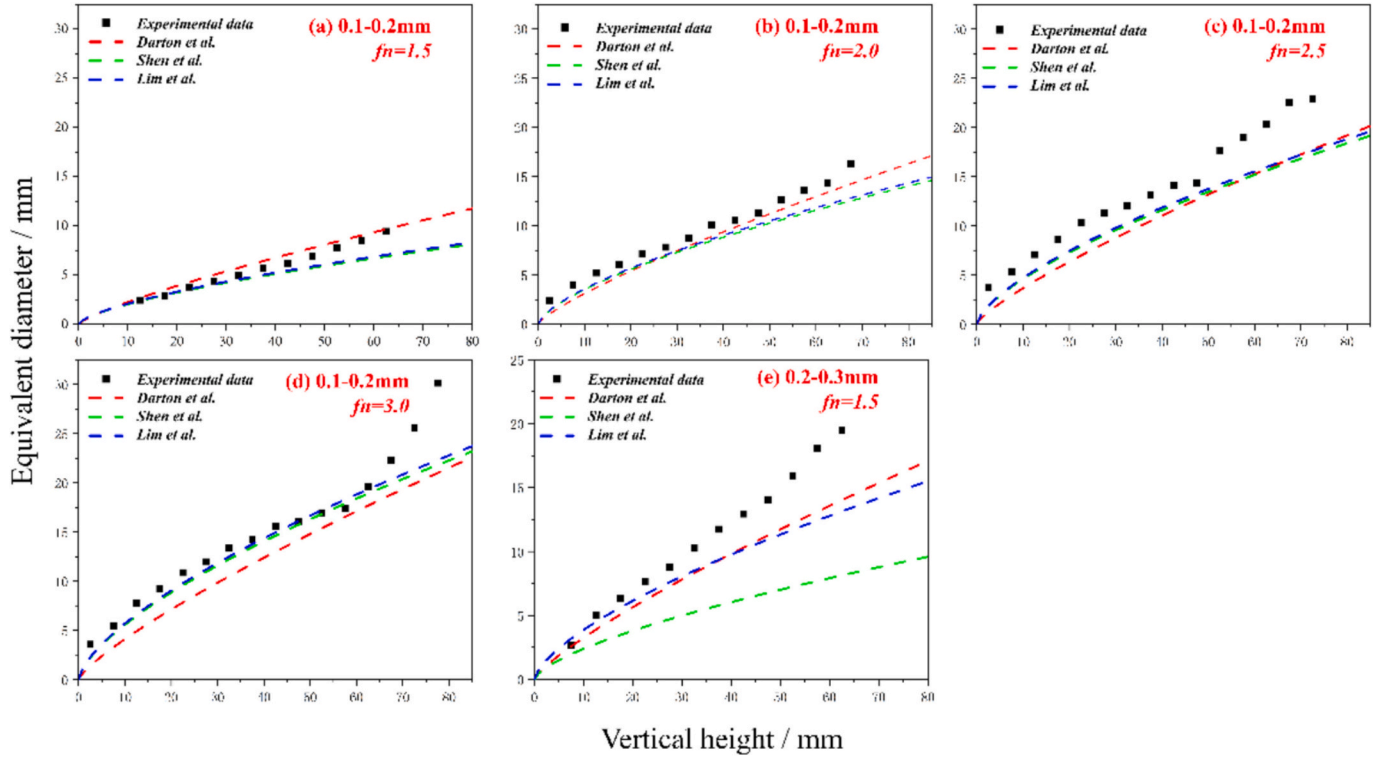


Fig. 7. Relationship between equivalent bubble diameter (d_b) and bed height (H).

surface increases with increasing fn .

By comparing Fig. 7(a) and (e), it can be observed that for larger particle sizes, the predictions of bubble size from the Darton and Lim correlations are nearly identical and both are significantly higher than those from the Shen correlation. Overall, none of the three empirical correlations can accurately capture the variation trend of bubble size with bed height; all tend to underestimate the bubble size within the bed, and the prediction deviation becomes more pronounced with increasing bed height. As the particle size increases, the equivalent bubble diameter at the same bed height increases markedly. Moreover, when the particle size is small, bubbles are hardly observed near the bottom of the bed, whereas in systems with larger particles, distinct small-scale bubbles appear in the lower region. Owing to the higher superficial gas velocity associated with larger particles, the bubbles can

rise to significantly greater heights. In summary, the particle size not only affects the initial formation position of bubbles but also has a pronounced influence on their growth behavior within the bed.

Fig. 8 illustrates the variation of the equivalent bubble diameter with bed height when different volume fractions of H_2 were introduced into the fluidizing gas (detailed scatter distributions shown in Fig. S2). Since the umf under the 50% N_2 + 50% H_2 atmosphere is slightly higher than that under pure N_2 , the Darton, Shen, and Lim correlations corresponding to both gas atmospheres are included in the figure, with arrows indicating the effect of increasing H_2 volume fraction. As shown in the figure, within approximately 20 mm above the gas distributor at the bottom of the bed, the addition of H_2 led to a slight reduction in the size of incipient bubbles, although the overall change remained limited. In contrast, in the middle and upper regions of the bed, the bubble size at

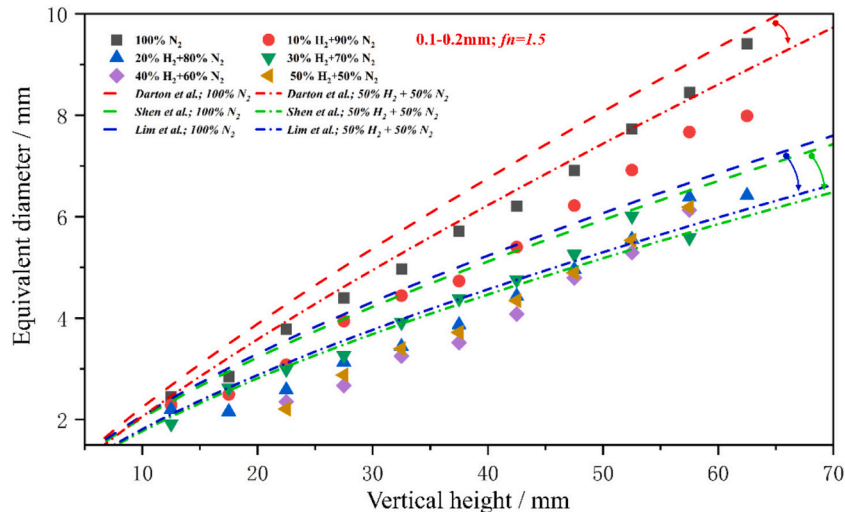


Fig. 8. Equivalent bubble diameter (d_b) versus bed height (H) at different H_2 .

the same height was noticeably smaller than that observed under pure H₂ conditions, indicating that H₂ suppresses bubble growth within the bed. However, with further increases in the H₂ volume fraction, the reduction in bubble size tended to level off. This observation suggests that the influence of H₂ on fluidization behavior is nonlinear. In addition, with increasing H₂ volume fraction, the predictive performance of the Shen and Lim correlation for bubble size gradually improves.

This nonlinear behavior is worthy of further analysis. In general, when the superficial gas velocity exceeds the minimum fluidization velocity u_{mf} , the excess gas forms bubbles. Bubble formation typically originates from gas cavities generated immediately above the gas distributor, which subsequently develop and grow within the emulsion phase of the bed, eventually rising and erupting at the bed surface [37,38]. For porous gas distributors, the characteristic size of the gas cavities can usually be described by a semi-empirical correlation [39]:

$$\frac{L_j}{d_{or}} = 15 \left\{ \left(\frac{\rho}{\rho_p - \rho} \right) \frac{U_{or}^2}{g d_{or}} \right\}^{0.187} \quad (8)$$

Where L_j is the characteristic length of the gas cavity, d_{or} is the equivalent diameter of the distributor orifice, ρ is the gas density, ρ_p is the particle density, U_{or} is the gas jet velocity at the distributor orifice, and g is the gravitational acceleration.

From this correlation, it can be seen that the size of gas cavities is closely related to the gas density ρ , the particle-gas density difference ($\rho_p - \rho$), and the gas jet velocity at the distributor U_{or} . With increasing H₂ volume fraction, the density of the gas mixture decreases markedly, weakening the balance between gas inertia and effective buoyancy and leading to a reduction in the size of incipient gas cavities formed above the distributor. Although the gas viscosity does not appear explicitly in the above correlation, it inevitably affects the physical properties of the emulsion phase and thus plays an important role in governing subsequent bubble growth within the bed. It should be noted that the viscosity of gas mixtures cannot, in general, be obtained by simple volume-fraction weighting, but is instead commonly calculated using empirical methods such as the Wilke correlation (Eqs. (9) and (10)). As a result, the gas viscosity itself exhibits a distinctly nonlinear dependence on the H₂ volume fraction, as shown in Fig. 9. This nonlinear variation in viscosity further affects the momentum transfer between the gas and particles, thereby indirectly influencing bubble formation and growth.

$$\mu_{mix} = \sum_{i=1}^n \frac{x_i \mu_i}{\sum_{j=1}^n x_j \Phi_{ij}} \quad (9)$$

$$\Phi_{ij} = \frac{\left[1 + \left(\frac{\mu_i}{\mu_j} \right)^{1/2} \left(\frac{M_j}{M_i} \right)^{1/4} \right]^2}{\sqrt{8 \left(1 + \frac{M_i}{M_j} \right)}} \quad (10)$$

where μ_{mix} denotes the gas mixture viscosity, x_i is the mole fraction of species i , μ_i and M_i are the viscosity and molar mass of species i , respectively, Φ_{ij} represents the Wilke interaction parameter, and n is the total number of gas species.

Therefore, the nonlinear behavior observed experimentally can be tentatively interpreted within the framework of classical gas-solid fluidization theory. At low H₂ volume fractions, the combined effects of reduced incipient cavity size and the nonlinear variation in gas viscosity exert a stronger suppressing influence on bubble formation and growth, resulting in a pronounced decrease in bubble size with increasing H₂ content. As the H₂ volume fraction increases further, the variations in gas density and viscosity become less pronounced, and part of the gas may preferentially flow through the interstitial spaces between particles in the form of the emulsion phase, thereby providing support to the particle framework and reducing the amount of excess gas available for bubble growth. As this effect gradually approaches saturation, the modulation of fluidization characteristics weakens, leading to a leveling-off of the decreasing trend in bubble size.

The probability density distributions of the equivalent bubble diameter and aspect ratio under different operating conditions are presented in Fig. 10. As shown in Fig. 10(a-1) and (a-2), the distribution range of equivalent bubble diameter gradually broadens with increasing fn , and a more pronounced long-tail effect is observed. This indicates the emergence of a more evident multiscale bubble structure, which is consistent with physical expectations. Although the peak position of the aspect-ratio distribution slightly decreases, the overall variation is minor, with the main peak remaining around 1.2. Therefore, the increase in fn significantly enlarges the bubble size in the bed but has a limited influence on bubble shape. Fig. 10(b-1) and (b-2) show that during the fluidization of small particles, the bubble-size distribution is relatively concentrated, with the probability density peaking around 4 mm. In contrast, the bubble-size distribution becomes much broader for larger particles, suggesting that fluidization with larger particle sizes produces a higher proportion of large bubbles and a more pronounced multiscale bubble structure. Regarding the aspect-ratio distribution, the bubbles in the large-particle system exhibit aspect ratios closer to unity, implying more regular bubble shapes within the bed. Fig. 10(c-1) and (c-

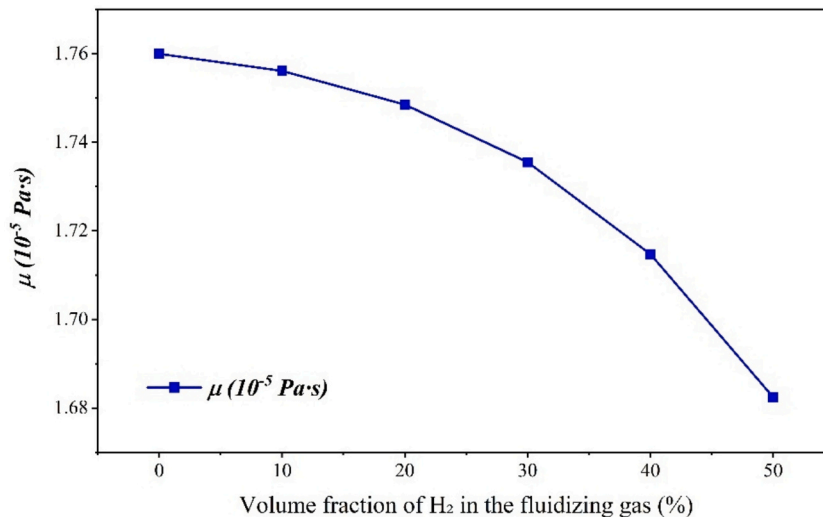


Fig. 9. Gas mixture viscosity (μ) as a function of H₂ volume fraction (Wilke correlation).

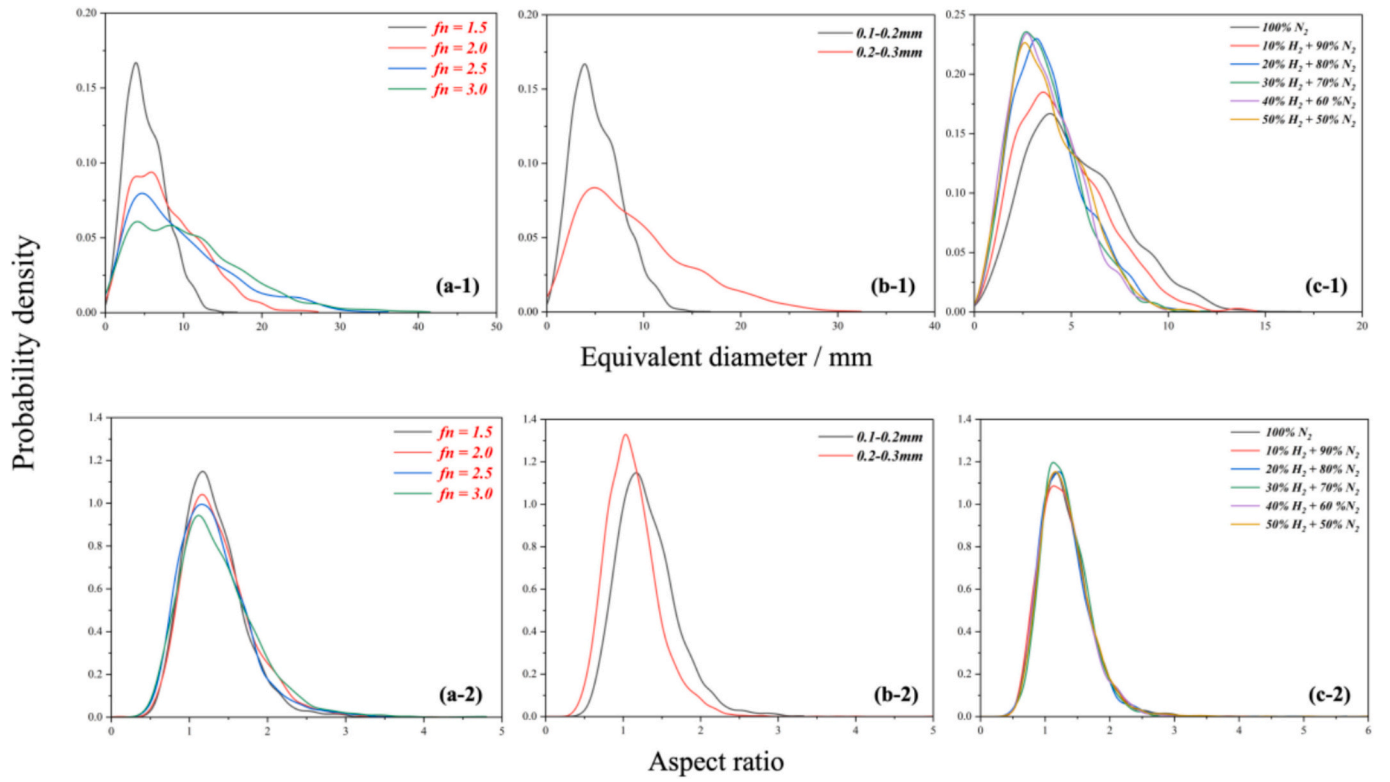


Fig. 10. Probability density distributions of equivalent bubble diameter (d_b) and aspect ratio (AR).

2) demonstrate that, compared with pure N_2 fluidization, introducing H_2 into the fluidizing gas results in a narrower distribution of equivalent

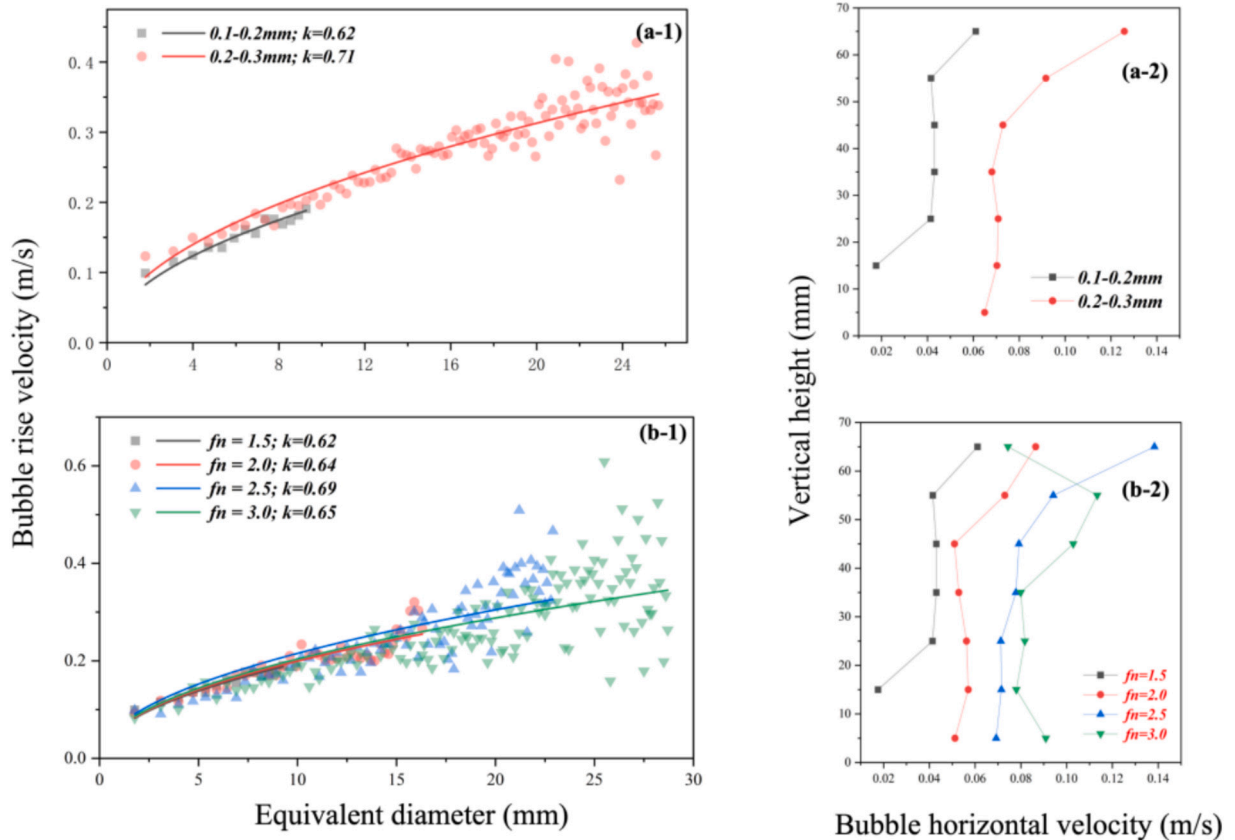


Fig. 11. Relationship between bubble velocity (u_b) and equivalent bubble diameter (d_b).

bubble diameter. Furthermore, as the H_2 volume fraction increases, the overall bubble size decreases. This reduction is more pronounced at low H_2 concentrations but tends to level off when the H_2 fraction exceeds 20%. On the other hand, the aspect-ratio distributions remain nearly unchanged, indicating that the introduction of H_2 has little effect on bubble shape. Hence, adding a moderate amount of H_2 can suppress the overall bubble size within the bed to some extent, while its influence on bubble morphology is limited.

4.2. Bubble velocity

The relationship between bubble velocity and equivalent bubble diameter under different fn and particle sizes is illustrated in Fig. 11. As shown in Fig. 11(a-1), in systems with larger particles, bubbles of the same size exhibit significantly higher vertical rise velocities. Moreover, according to the experimental data points, bubbles in the large-particle system exhibit more pronounced fluctuations in their upward motion as they approach the bed surface, which can be attributed to the bursting of large-scale bubbles at the bed surface. From the distribution of horizontal bubble velocity shown in Fig. 10(a-2), it can also be observed that at the same bed height, bubbles in the large-particle bed display more vigorous horizontal motion, and this effect becomes increasingly evident with height.

As indicated in Fig. 11(b-1), when the fn increases from 1.5 to 2.5, the rise velocity of bubbles with the same equivalent diameter gradually increases, suggesting that the fn exerts a strong enhancing effect on bubble rise velocity. It is worth noting, however, that a considerable proportion of bubbles exhibit markedly reduced rise velocities as they approach the bed surface under all operating conditions. This behavior becomes more pronounced for larger bubbles, particularly at $fn = 3$, leading to a slight decrease in the fitted coefficient k . This phenomenon can be attributed, on the one hand, to disturbances induced by bubble breakup at the bed surface and, on the other hand, by analogy with the deceleration of bubbles approaching a free surface in liquid systems, to the gradual weakening of emulsion-phase continuity and particle support as bubbles approach the top of the bed. Within the bed, bubbles exist as low-solid-fraction regions of excess gas embedded in a continuous emulsion phase, and their upward motion relies on the pressure reaction provided by the surrounding emulsion as well as the momentum feedback associated with the wake structure. As bubbles approach the bed surface, part of the gas escapes directly into the air, and the overlying emulsion layer becomes thinner and less continuous, making it difficult to sustain the internal pressure balance and wake structure, thereby weakening the dynamic support for coherent bubble rise. Fig. 11(b-2) shows that the horizontal bubble velocity within the bed increases with fn . At $fn = 3$, a pronounced anomaly in horizontal

motion is observed near the top of the bed, which is likewise attributed to the combined effects of disturbances induced by bubble escape and interfacial inhibition experienced by bubbles in the vicinity of the bed surface.

Fig. 12 shows the relationship between bubble velocity and the H_2 volume fraction in the fluidizing gas. It can be clearly observed that as the H_2 content increases, the rise velocity of bubbles with the same equivalent diameter gradually decreases. From the distribution of horizontal bubble velocity, it is found that the addition of H_2 has little effect on the horizontal motion of bubbles in the upper region of the bed. It is worth noting that as the H_2 content increases, the number of observable bubbles near the bottom of the bed decreases significantly, leading to statistical deviations in that region. Therefore, the irregular distribution of data points in the lower region does not hold practical significance.

4.3. Bubble coalescence and breakup

The overall statistics of bubble behavior in the bed under different particle sizes and fn are presented in Fig. 13. It can be seen that bubbles in the small-particle system tend to undergo more frequent bubble break-up, whereas those in the large-particle system are more likely to coalesce. Moreover, as the fn increases, both bubble break-up and coalescence events become more frequent, and the overall tendency approaches a dynamic balance.

To further analyze the spatial distribution of bubble coalescence and break-up within the bed, the bed was divided into uniformly spaced regions along the vertical height, as illustrated in Fig. 14. Fig. 14(a)–(d) show the distributions of bubble coalescence and break-up at different bed heights under various fn . It can be clearly observed that both coalescence and break-up events exhibit an arch-shaped distribution pattern, with higher frequencies in the middle region and lower frequencies near the bottom and top of the bed. In addition, regardless of whether the fluidization velocity is low or high, bubble break-up dominates in the lower part of the bed, whereas bubble coalescence prevails in the upper part. The region with the most frequent bubble interactions is mainly located in the middle of the bed. As the fn increases from 1.5 to 3, this high-frequency region gradually shifts downward toward the lower part of the bed. Furthermore, by comparing Fig. 14(a) and (e), it can be seen that in the large-particle system, bubble coalescence is more pronounced than break-up across all height regions, and the most active region remains located in the middle of the bed. These results indicate that increasing both particle size and fluidization intensity promotes a transition in bubble behavior from break-up-dominated to coalescence-dominated.

Figs. 15 and 16 respectively present the overall and vertically resolved distributions of bubble coalescence and break-up behaviors

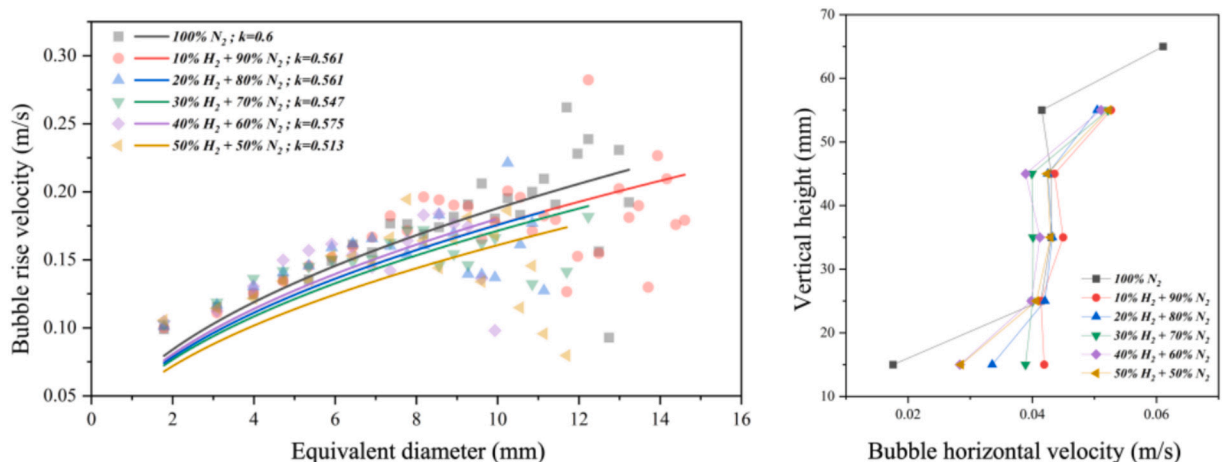
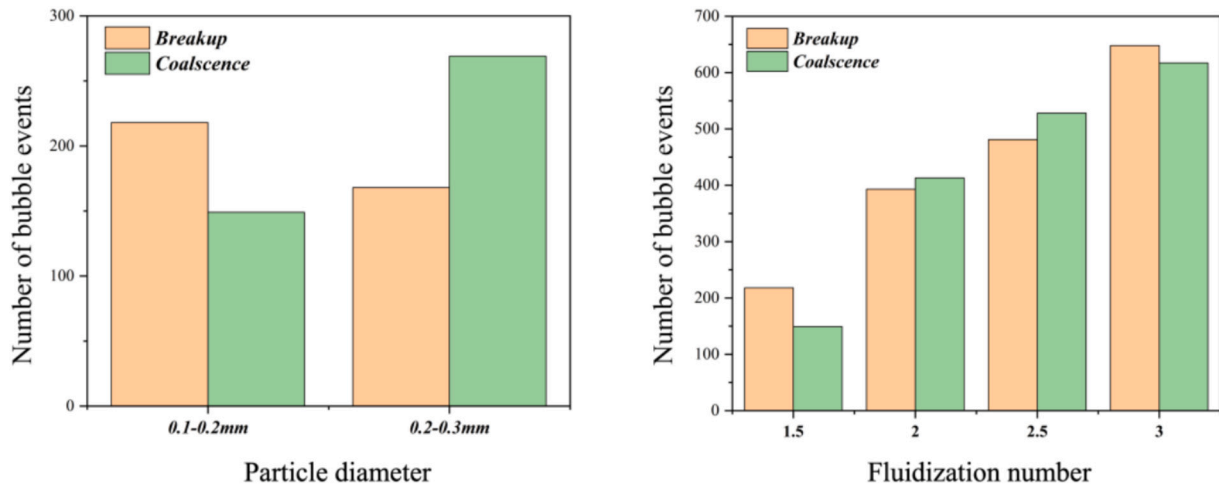
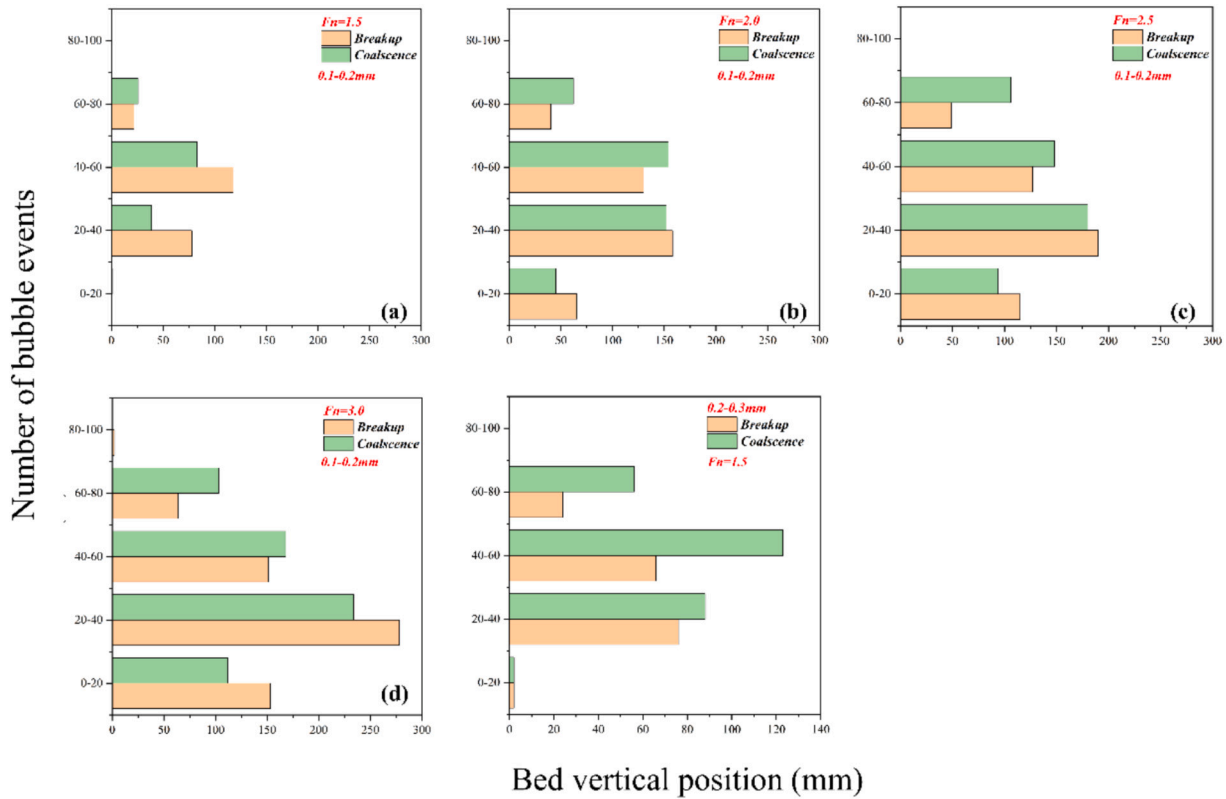


Fig. 12. Bubble velocity (u_b) versus H_2 volume fraction (ϕ_{H_2}) in the fluidizing gas.

Fig. 13. Bubble behavior under different particle sizes (d_p) and fn .Fig. 14. Vertical distribution of bubble behavior along the bed height (H).

under different H_2 volume fractions in the fluidizing gas. As shown in Fig. 15, the number of bubbles undergoing coalescence or break-up within the bed decreases markedly with increasing H_2 content. This indicates that a higher H_2 fraction in the fluidizing gas helps to attenuate bed disturbances and results in a gentler fluidization process. However, it is worth noting that this mitigating effect becomes progressively weaker as the H_2 fraction further increases, and when the H_2 concentration reaches 50%, both bubble coalescence and break-up show a slight enhancement. In addition, under all H_2 concentrations, bubble break-up events are clearly dominant over coalescence events in the fluidized bed. As illustrated in Fig. 16, with increasing H_2 content in the fluidizing gas, both bubble coalescence and break-up become less frequent at the same bed height. The distributions of these two behaviors

exhibit similar arch-shaped patterns, with the most intense bubble interactions occurring in the 40–60 mm region of the bed. Therefore, introducing H_2 into the fluidizing gas can suppress bubble coalescence and break-up within the bed to some extent; however, it does not alter the break-up-dominated behavior observed in the small-particle bed under a fn of 1.5.

4.4. Bed fluctuation

Fig. 17 shows the bed fluctuation states and average bed heights under different particle sizes and fn . It can be clearly observed that with increasing particle size, both the average bed height and the fluctuation intensity increase. In addition, the effect of the fn on bed behavior is also

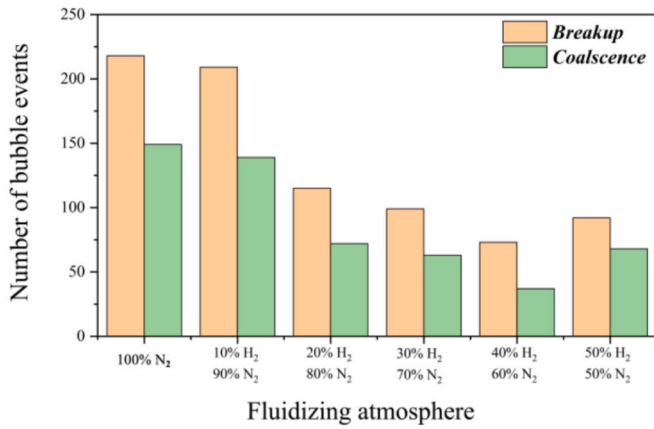


Fig. 15. Bubble behavior under different H₂ volume fractions (ϕ_{H_2}).

significant. As the fn increases from 1.5 to 3, the average bed height exhibits an approximately linear increase, with the bed height rising by about 4–5 mm for every 0.5 increment in the fn . Meanwhile, the amplitude of bed fluctuations also increases markedly.

To further reveal the detailed characteristics of bed fluctuations, Fig. 18 presents the fluctuation spectra of the bed under different fn and particle sizes. As shown in Fig. 18(a)–(d), the dominant frequencies for all four fn are concentrated within the range of 0–10 Hz, while their intensities gradually increase with the fn . This indicates that similar fluctuation modes exist in the bed, but their amplitudes become stronger as the fluidization intensity increases. When the fn reaches 3, a distinct and sharp peak appears around 4–5 Hz, implying the emergence of a dominant low-frequency oscillation mode that leads to more periodic and organized bed motion. Meanwhile, it is also observed that the high-frequency components above 20 Hz become more pronounced with increasing fn , reflecting the strengthening of small-scale, rapid

disturbances. Overall, increasing the fn not only amplifies the overall fluctuation intensity but also enhances the high-frequency small-scale dynamics within the bed. By comparing Fig. 18(a) and (e), it can be seen that the fluctuation frequencies in both particle systems are mainly concentrated in the 2–7 Hz range, indicating that similar fluctuation modes exist for both particle sizes. However, as the particle size increases, the amplitude of bed fluctuations becomes larger, and the frequency spectrum exhibits a more pronounced long-tail effect, suggesting the presence of stronger small-scale, high-frequency fluctuations in the large-particle bed.

Similarly, the bed fluctuation behaviors and their corresponding frequency spectra under different H₂ volume fractions were analyzed, as shown in Figs. 19 and 20, respectively. According to Fig. 19, the introduction of H₂ into the fluidizing gas leads to a noticeable decrease in bed height and a significant reduction in fluctuation amplitude, indicating that H₂ effectively suppresses the bed fluctuations. This suppression can be attributed to several coupled mechanisms. On the one hand, bed fluctuations are closely related to bubble size, and as discussed in Section 4.1, increasing the H₂ content leads to a reduction in the characteristic size of gas cavities formed above the distributor. In addition, as shown in Section 4.3, a higher H₂ volume fraction reduces bubble breakup and coalescence within the bed, which favors the maintenance of a more stable bed structure. Moreover, bed stability may also be influenced by the jet strength above the distributor, which can be characterized by the jet momentum flux:

$$J_{or} = \rho_g U_{or}^2 \quad (11)$$

where ρ_g is the gas density and U_{or} is the gas jet velocity at the orifice. As the H₂ volume fraction increases, the density of the gas mixture decreases markedly. As a result, even when the orifice gas velocity remains unchanged, the jet momentum flux J_{or} is significantly reduced, thereby weakening the disturbance and lifting effect of the gas jet on the emulsion phase, suppressing the formation and development of gas cavities above the distributor, and ultimately affecting the overall

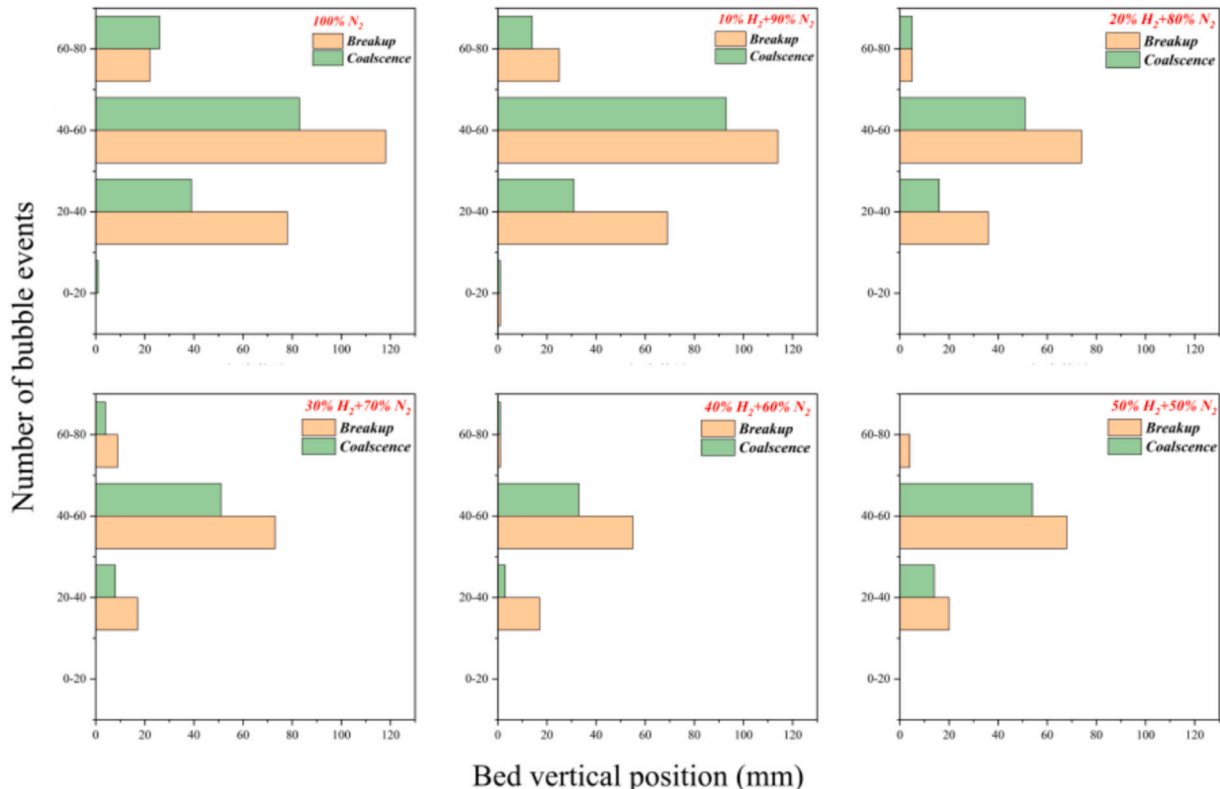


Fig. 16. Vertical distribution of bubble behavior along the bed height (H).

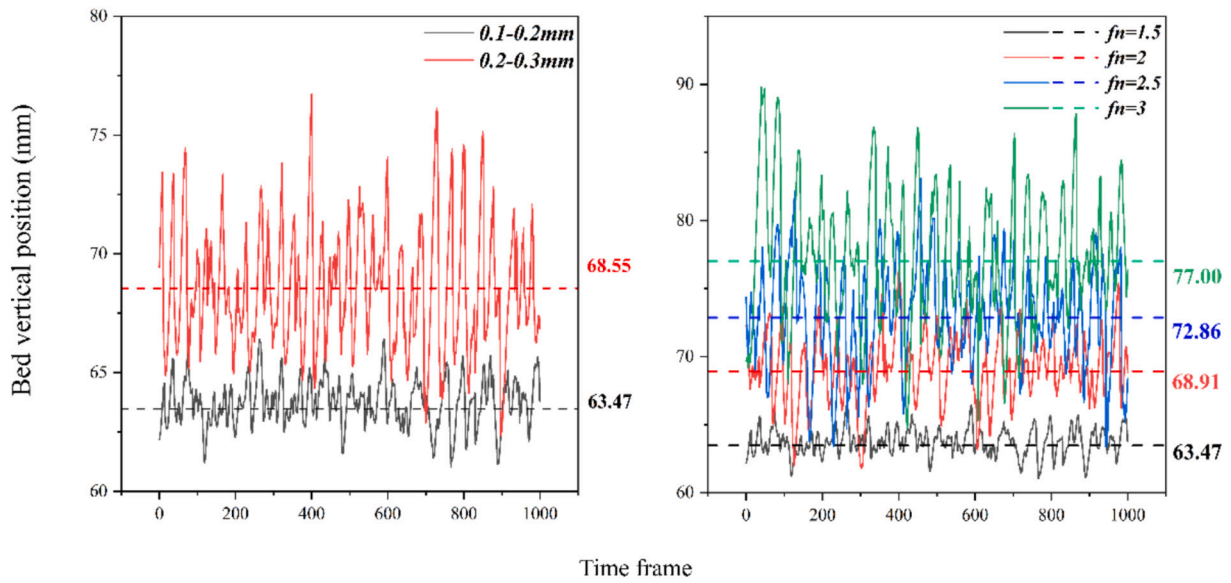


Fig. 17. Bed fluctuations and average heights.

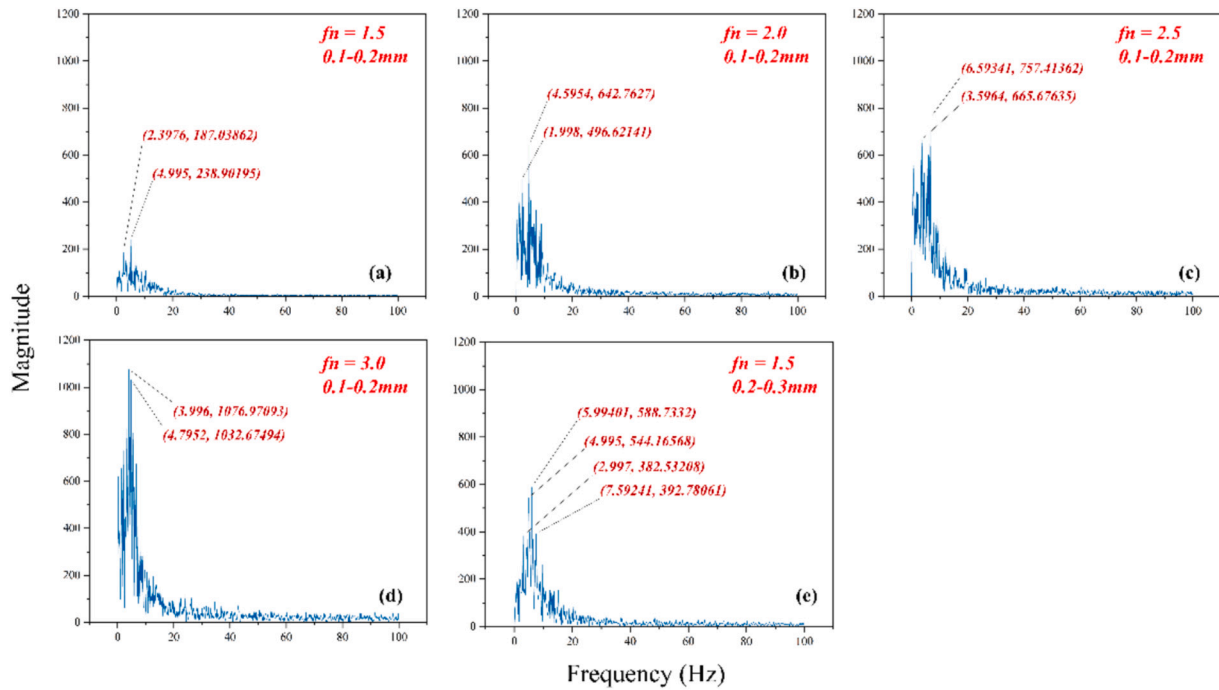


Fig. 18. Frequency spectra of bed fluctuations.

fluidization behavior of the bed. Similar to the variation in bubble size, the suppressing effect of H_2 on bed fluctuations exhibits a nonlinear trend with increasing H_2 concentration. Overall, H_2 exerts the most pronounced influence on bed fluctuation characteristics at low volume fractions, while its effect gradually saturates at higher concentrations.

Further analysis of Fig. 20 reveals that regardless of whether H_2 is present in the fluidizing gas, the dominant fluctuation frequencies remain concentrated within 4–6 Hz, while the peak amplitude decreases gradually with increasing H_2 concentration. This suggests that the addition of H_2 does not alter the dominant oscillation mode of the bed but reduces its intensity. It is also noteworthy that as the H_2 fraction increases, a distinct peak appears around 1 Hz, indicating the emergence of a slower, large-scale bed oscillation and a tendency toward lower dominant frequencies. Meanwhile, the spectral energy above 20 Hz

diminishes significantly, reflecting a reduction in small-scale, high-frequency disturbances within the bed. In summary, the introduction of H_2 weakens both low- and high-frequency fluctuations while maintaining the original dominant oscillation mode, resulting in a gentler and more stable fluidization behavior.

4.5. Gas-solid contact intensity

The distributions of gas-solid contact intensity and bubble number along the bed height under different operating conditions are presented in Fig. 21. As shown in Fig. 21(a-1), the overall gas-solid contact intensity gradually increases with increasing fn , and the region of maximum contact intensity tends to shift toward the lower part of the bed. In contrast, Fig. 21(a-2) shows that the total number of bubbles in

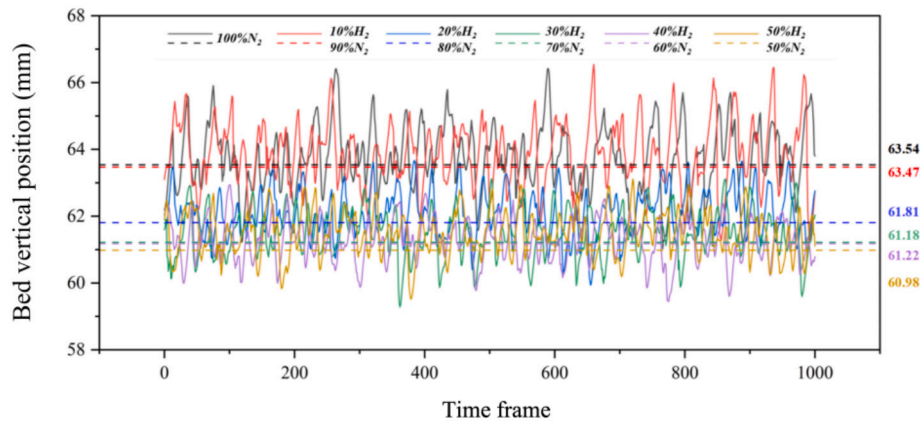


Fig. 19. Bed fluctuations under different H_2 volume fractions (Φ_{H_2}).

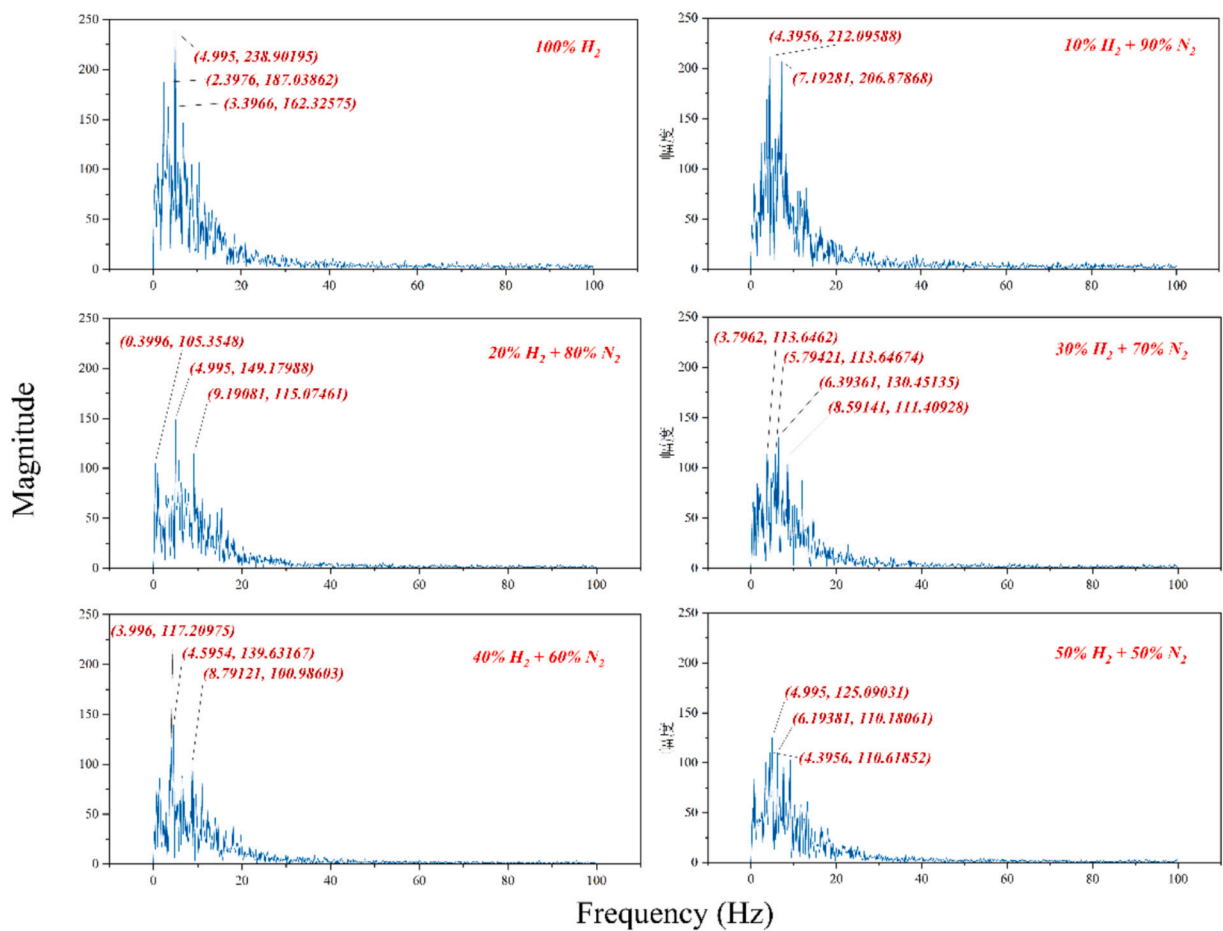


Fig. 20. Frequency spectra of bed fluctuations under different H_2 volume fractions (Φ_{H_2}).

different regions decreases with increasing ϕ_n . Overall, under high fluidization conditions, the bed contains fewer bubbles but exhibits stronger gas–solid contact intensity, indicating more sufficient interaction between individual bubbles and the solid phase. According to Fig. 21(b-1) and (b-2), both the peak of gas–solid contact intensity and the maximum bubble number in the large-particle bed are located closer to the bottom of the bed, and their distributions are similar. This suggests that the stronger gas–solid contact intensity in the large-particle system is primarily attributed to the formation of more bubbles near the distributor region.

As shown in Fig. 21(c-1) and (c-2), both the gas–solid contact

intensity and the number of bubbles exhibit a gradual decreasing trend with increasing H_2 volume fraction, indicating that the introduction of H_2 weakens gas–solid interactions and attenuates bubble formation. This behavior can be attributed to the significant modification of the thermophysical properties of the gas mixture caused by H_2 addition, which reduces the size and momentum of the gas cavities formed above the distributor plate. As a result, the number of bubbles decreases, and according to Eq. (7), the gas–solid contact intensity decreases accordingly. Meanwhile, consistent with the observations discussed above, it can be observed that H_2 exerts a stronger influence on gas–solid contact intensity at low volume fractions, whereas the sensitivity of the

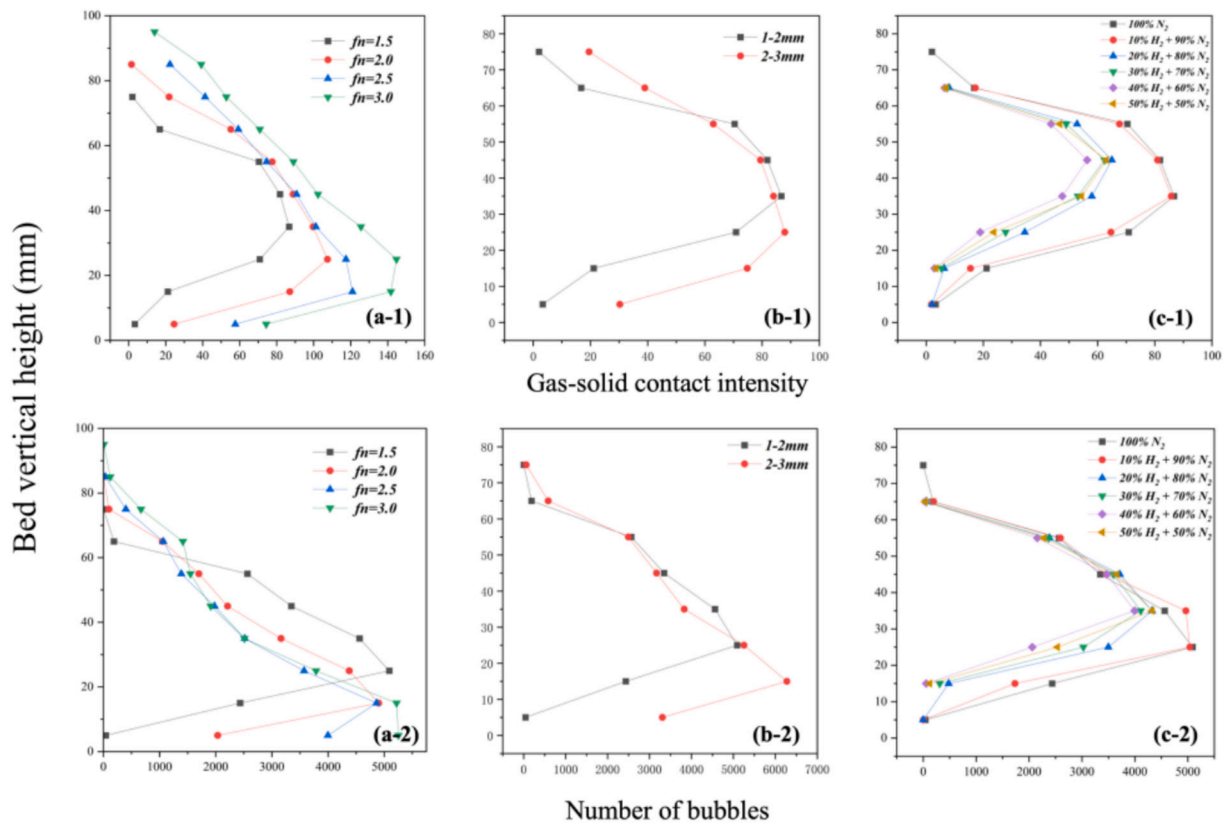


Fig. 21. Distributions of gas-solid contact intensity and bubble number along the bed height (H).

gas-solid contact intensity to further H_2 addition gradually decreases at higher volume fractions. This nonlinear influence mechanism is similar to that described in Section 4.1 and is mainly attributed to variations in the thermophysical properties of the gas mixture (such as viscosity, as shown in Fig. 9) as well as the complex gas-solid interactions within the emulsion phase.

5. Conclusion

To better elucidate the gas-solid flow mechanisms in the context of hydrogen-based fluidized-bed metallurgy, this study employed a custom deep learning-assisted bubble detection algorithm in combination with a deep learning-based image segmentation method and a quasi-two-dimensional micro fluidized bed experimental setup. A systematic investigation was conducted on Geldart B-type iron ore powders to examine bubble morphology, bubble rise velocity, bubble coalescence and breakup behavior, bed fluctuation characteristics, and overall gas-solid contact intensity under different particle sizes, f_n , and H_2 volume fractions. These parameters serve to characterize the intrinsic fluidization behavior of high-density particles such as iron ore powders and provide important reference information for high-temperature reactive fluidized-bed systems. The main conclusions are summarized as follows:

1. When the dataset was expanded to 1000 images, using ResNet18 as the backbone network achieved a balance between segmentation accuracy and computational cost. Under the same training hardware, compared with the previous ResNet50-based model, the training time per epoch was reduced by approximately 8 s, GPU memory usage decreased by about 10 GB, and the model size was reduced by around 200 MB, demonstrating higher training efficiency and resource utilization.
2. With increasing f_n and particle size, the bubble size within the bed increased significantly and bubble velocities increased markedly, accompanied by an increase in overall bed fluctuation amplitude and average bed height. Bubble breakup dominated in the small-particle system, whereas bubble coalescence was more pronounced in the large-particle system. As f_n increased, bubble breakup and coalescence gradually approached a dynamic equilibrium. At higher f_n , the contact efficiency between bubbles and particles was enhanced, while for larger particle sizes, the increased number of bubbles also contributed to a significant enhancement in gas-solid contact intensity.
3. The introduction of H_2 into the fluidizing gas exerted a pronounced attenuating effect on the overall fluidization behavior. This was manifested by weakened bed fluctuations, reduced bubble size, and gradually decreased bubble velocities. Meanwhile, bubble coalescence and breakup activities, as well as gas-solid contact intensity, also decreased. This behavior may be associated with the reduction in gas mixture density caused by H_2 addition, which weakens the morphology and motion of bubbles generated near the distributor plate.
4. H_2 exhibits a more pronounced influence on fluidization behavior at low volume fractions, whereas at higher volume fractions the sensitivity of gas-solid contact intensity to further increases in H_2 content gradually decreases. This behavior may be related to the nonlinear variation of gas mixture properties, such as viscosity, with increasing H_2 volume fraction, as well as more complex gas-solid flow mechanisms. Therefore, when configuring fluidizing gases for hydrogen-based metallurgical processes, in addition to reduction reactions, the influence of the unique physical properties of H_2 on fluidization behavior should not be overlooked and warrants further investigation through refined experiments and numerical simulations.

CRediT authorship contribution statement

Wang Chuanhao: Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Wang Linwei:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition. **Liu Yuchen:** Software, Methodology, Data curation. **Zhang Jiehan:** Validation, Methodology, Investigation, Conceptualization. **Li Shiyuan:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.powtec.2026.122354>.

Data availability

Data will be made available on request.

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