

Reconstruction-Free EIT for Injection-Pattern Classification and Superficial Gas Velocity Regression as Proxies for Local Gas Holdup in Bubble Columns

Published as part of *Industrial & Engineering Chemistry Research* special issue “Smart Reactors - Towards Adaptive, Resilient, and Autonomous Process Systems”.

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Cite This: *Ind. Eng. Chem. Res.* 2026, 65, 19801–19817



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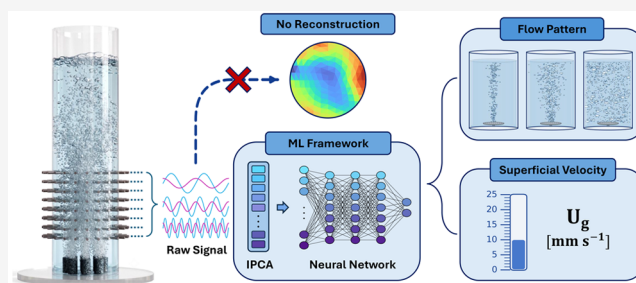


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ABSTRACT: Electrical impedance tomography (EIT) as a noninvasive tomographic technique is increasingly applied to multiphase reactor monitoring; however, conventional image reconstruction is ill-posed and regularization-dependent and may be redundant in applications where the primary objective is operating-state identification rather than explicit spatial conductivity field reconstruction. Here, we present a reconstruction-free, measurement-domain framework for bubble-column monitoring that maps raw complex boundary impedance data directly to two reactor-relevant inference tasks: (i) gas injection pattern classification and (ii) superficial gas velocities regression. Together, these two quantities — the spatial injection distribution and the total volumetric flow — constitute the primary process-state information from which gas holdup can subsequently be inferred and are therefore reported as proxies for local gas holdup monitoring. Experiments were conducted in an acrylic bubble column (600 mm height, 104 mm inner diameter) equipped with a 256-electrode array distributed over eight axial rings and operated at four excitation frequencies (1 kHz–1 MHz). Experiments covered gas flow rates between 1.0 and 6.5 L min^{−1} ($U_g = 1.96 \rightarrow 12.75$ mm s^{−1}), within which near-perfect gas injection pattern classification was achieved with accuracies of 93–100% for excitation frequencies between 1 and 100 kHz using the full 256-electrode configuration. For quantitative superficial gas velocity estimation, increasing calibration density along U_g reduced the mean absolute error from 0.388 to 0.105 L min^{−1} ($MAE[U_g] = 0.76 \rightarrow 0.205$ mm s^{−1}, i.e. 7.0% $\rightarrow$ 1.9% of the operating range) for localized injection and from 0.298 to 0.157 L min^{−1} ($MAE[U_g] = 0.585 \rightarrow 0.307$ mm s^{−1}, i.e. 5.4% $\rightarrow$ 2.8% of the operating range) for distributed injection conditions. These results demonstrate that direct inference from raw EIT boundary measurements enables accurate, real-time monitoring of bubble-column operation without tomographic reconstruction and provide quantitative guidance on excitation frequency selection, axial sensing placement, and calibration resolution.



INTRODUCTION

Multiphase reactors are central to a wide range of chemical, biochemical, and energy conversion processes, where reaction performance and product quality are intimately coupled to the underlying flow dynamics. Owing to their intrinsically complex hydrodynamics and interphase interactions, reactor behavior is highly sensitive to even minor variations in flow distribution,^{1–3} fouling,^{4–6} or equipment degradation.⁷ Consequently, effective process monitoring is essential to ensure stable, efficient, and safe operation. Such deviations can result in reduced conversion efficiency,⁸ off-specification products,^{9,10} or unsafe operating conditions. The implementation of robust monitoring strategies enables the early detection of abnormal behavior and facilitates a transition from purely schedule-based to condition-based maintenance. Consequently, reactor

reliability, operational availability, and energy efficiency are enhanced, while unplanned shutdowns and overall lifecycle costs in continuous processing facilities are significantly reduced.

Over the past decades, numerous measurement techniques have been developed to address this problem. Early approaches were primarily based on differential pressure measurements

Received: March 11, 2026

Revised: August 4, 2026

Accepted: August 5, 2026

Published: September 10, 2026



and local probes, such as conductivity or optical fiber sensors, to infer gas fraction. Notably, Neal and Bankoff developed one of the earliest high-resolution resistivity probes for measuring local void fraction and bubble characteristics in gas–liquid pipe flow,¹¹ establishing an important milestone in quantitative two-phase flow diagnostics. In a related context, Mena et al. employed a monofiber optical probe to quantify local void fraction and bubble velocity in three-phase flows, demonstrating good agreement with independently obtained global gas holdup and superficial gas velocity measurements.¹²

Collectively, these studies illustrate the capability of probe-based techniques to capture detailed local hydrodynamic features and to advance the characterization of bubble dynamics in multiphase reactors.^{13,14} However, despite their strong local diagnostic capabilities, such methods remain inherently intrusive and fundamentally restricted to pointwise measurements. Consequently, they are unable to directly provide cross-sectional or fully three-dimensional phase distribution information in complex multiphase flow systems.

Beyond intrusive probe-based diagnostics, a broad spectrum of nonintrusive measurement techniques has been developed to provide global or spatially resolved information in such systems. These methods aim to overcome the inherent pointwise limitation of local probes, yet they introduce distinct practical, interpretative, and operational constraints.¹⁵

At the most fundamental level, global measurement approaches—such as time-averaged pressure drop analysis and dynamic gas disengagement—offer robust and comparatively simple means of estimating gas and solid holdup while enabling basic flow-regime identification.^{16–19} However, by their very nature, these techniques yield integral or averaged quantities. Their interpretation further relies on simplifying assumptions (e.g., homogeneous dispersion or negligible wall friction), which may not hold under heterogeneous or strongly coalescing flow conditions.

Extending beyond purely integral measures, tracer-based residence time distribution (RTD) methods provide insight into liquid holdup and mixing behavior.^{20,21} Although diagnostically valuable, RTD analysis requires careful tracer selection and model-based deconvolution, and remains sensitive to concentration measurement biases under nonideal flow conditions.

To obtain direct internal phase distribution information, radiation-based attenuation techniques—including X-ray,²² γ -ray,²³ and neutron methods,²⁴ as well as their tomographic reconstructions—have been developed. These approaches enable cross-sectional measurements with true internal access and high quantitative accuracy. Nevertheless, their practical implementation is constrained by high capital and operational costs, safety considerations related to ionizing radiation, and frequently limited temporal resolution due to mechanical scanning or signal averaging requirements.

Optical diagnostics, such as high-speed imaging, particle image velocimetry (PIV), and laser Doppler or phase Doppler anemometry (LDA/PDA), provide excellent spatio-temporal resolution of bubble morphology, velocity fields, and liquid turbulence structures.^{25–27} Their applicability, however, is largely restricted to transparent systems with sufficient optical access and moderate gas fractions, as signal quality deteriorates in dense or highly opaque multiphase flows.

Finally, advanced modalities—including nuclear magnetic resonance (NMR) imaging,²⁸ radioactive particle tracking,²⁹ and ultrasonic tomography³⁰ offer detailed two- or three-

dimensional phase and velocity field information. Despite their diagnostic sophistication, these techniques remain technically complex and costly, and are therefore predominantly confined to laboratory-scale investigations or quasi-steady conditions rather than routine industrial process monitoring.

Collectively, these developments demonstrate significant progress toward spatially resolved multiphase flow diagnostics. Yet, a persistent gap remains between high-fidelity laboratory techniques and robust, economically viable solutions suitable for continuous industrial condition monitoring.

In response to this persistent gap, electrical imaging methods—most prominently Electrical Impedance Tomography (EIT) and Electrical Resistance Tomography (ERT)—have attracted increasing attention for application in multiphase reactors and bubble columns.^{31–34} These techniques offer a practical compromise between spatial information content and industrial deployability. Unlike many optical or radiation-based approaches, EIT/ERT systems are comparatively low-cost, mechanically simple, and straightforward to maintain, as they typically employ electrode arrays mounted on the vessel wall. At the same time, they remain nonintrusive and provide high temporal resolution, enabling the tracking of dynamic flow-regime transitions and transient hydrodynamic phenomena. Their operational robustness and real-time capability therefore position EIT/ERT as particularly promising candidates for continuous monitoring under industrially relevant conditions.

Despite their practical advantages and high temporal resolution, the quantitative application of electrical imaging techniques remains constrained by fundamental methodological challenges. In particular, the reconstruction of conductivity or impedance fields from boundary voltage measurements constitutes an inherently ill-posed inverse problem.³⁵ Ensuring numerical stability therefore requires regularization, which typically reduces effective spatial resolution and introduces smoothing artifacts when compared with high-end tomographic techniques.^{36–38}

Moreover, the reconstructed impedance values do not directly correspond to actionable process variables.^{39,40} Their interpretation depends on mixture of constitutive relationships, electrode polarization and contact effects,⁴¹ as well as flow-dependent phase distributions.⁴² Consequently, reliable extraction of process parameters such as local phase fractions or interfacial characteristics generally requires calibration procedures or complementary measurements. However, such calibrations are often system-specific and cannot be readily transferred or generalized across different reactor geometries, or operating conditions.

To mitigate the ill-posed nature and low spatial resolution of classical EIT reconstructions in multiphase flows, recent work has increasingly turned to data-driven approaches that learn the inverse mapping from boundary voltages to conductivity fields or directly to gas holdup distributions. Early investigations in air–water bubble columns primarily demonstrated EIT hardware feasibility and conventional reconstruction performance.^{43,44} More recent studies, particularly in industrial two-phase flow contexts, have employed machine-learning models such as radial-basis-function neural networks (RBFNNs),⁴⁵ in some cases hybridized with swarm-intelligence optimizers (e.g., ABC-RBFNN)⁴⁶ to enhance localization accuracy and robustness relative to classical iterative reconstructions.

In parallel, deep convolutional architectures—including 1D convolutional neural networks (CNNs),⁴⁷ multibranch CNNs,⁴⁸ and encoder-decoder frameworks such as U-Net, V-Net,^{49–51} and generative adversarial networks (GANs)^{52,53}—have been adapted for EIT/ERT. In simulated and laboratory-scale multiphase systems, these models frequently yield sharper reconstructed interfaces and reduced visual artifacts compared with traditional regularized solutions.

Nevertheless, several fundamental limitations persist. First, most data-driven models rely on large, geometry-specific training data sets—often dominated by synthetic simulations—so their generalization across varying column diameters, electrode configurations, fluid properties, and flow regimes remains uncertain. Second, these methods do not circumvent the intrinsic information limits imposed by low-frequency boundary measurements; apparent improvements in spatial resolution are therefore constrained by the underlying physics. Third, in many implementations, neural networks are trained to reproduce conductivity images rather than directly infer physically meaningful process variables. As a result, the subsequent mapping from predicted conductivity to quantities such as local gas holdup, interfacial area, or flow-regime descriptors remains weakly constrained and rarely accompanied by rigorous uncertainty quantification.

In contrast to reconstruction-centered strategies, in this work we adopt a fundamentally different approach. Rather than solving the ill-posed inverse problem to obtain conductivity images, we directly exploit the information contained in the raw boundary impedance measurements for flow-state inference.

For this purpose, a bubble column equipped with a high-density electrode array (256 electrodes arranged in eight axial rings of 32 electrodes each) was constructed to generate a rich measurement space. Multiple gas spargers were installed at the column base and individually regulated via valves connected to a mass flow controller, enabling controlled variation of inlet gas distribution. By systematically activating different sparger combinations and varying gas flow rates (corresponding to different superficial gas velocities), a wide range of hydrodynamic states and bubble patterns were produced. For each operating condition, complex impedance data were recorded at excitation frequencies of 1 kHz, 10 kHz, 100 kHz, and 1 MHz, thereby capturing frequency-dependent electrical response characteristics.

Instead of reconstructing conductivity fields, machine-learning models were trained directly on these high-dimensional raw measurement outputs to perform bubble pattern recognition and flow-state classification. Operating entirely in measurement space eliminates the need for regularized image reconstruction, thereby avoiding smoothing artifacts and reducing computational overhead associated with classical inverse reconstruction algorithms. Moreover, direct inference from raw data enables substantially faster evaluation, facilitating real-time applicability.

Moreover, the systematic variation of injection patterns through sparger configurations and superficial gas velocities provides a diverse data set that reflects representative bulk hydrodynamic behavior within the reactor. This comprehensive experimental design enhances model robustness and supports generalizable flow-state inference without relying on intermediate tomographic images.

The remainder of this work is organized as follows: (i) the theoretical foundations of EIT are outlined, with emphasis on

the rationale for direct inference from boundary measurements; (ii) the experimental bubble-column system and measurement protocol are described, including the multi-frequency EIT configuration and the operating-state matrix used for data generation; (iii) the data-analysis methodology is presented, detailing the modeling framework for classification and regression tasks; and (iv) the **Results and Discussion** section evaluates injection pattern identification and superficial gas velocity prediction, with particular focus on the effects of excitation frequency, electrode-ring selection, and calibration density on measurement-domain inference performance.

■ THEORY OF EIT

Electrical Impedance Tomography (EIT) is a boundary measurement technique used to infer the internal distribution of electrical admittivity within a conductive domain. For time-harmonic excitation at angular frequency ω , and at the spatial scales typical of conductive liquid reactors, the quasistatic approximation of Maxwell's equations is applicable. The electrical properties of the medium are described by the complex admittivity

$$\gamma(\mathbf{x}, \omega) = \sigma(\mathbf{x}, \omega) + j\omega\epsilon(\mathbf{x}, \omega) \quad (1)$$

where σ and ϵ denote conductivity and permittivity, respectively. The complex electric potential $u(\mathbf{x}, \omega)$ inside the domain Ω satisfies

$$\nabla \cdot (\gamma(\mathbf{x}, \omega) \nabla u(\mathbf{x}, \omega)) = 0 \text{ in } \Omega \quad (2)$$

Complete Electrode Model

In practical systems with finite-sized electrodes, the forward problem is most accurately described by the Complete Electrode Model (CEM).⁵⁴ The governing equation above remains valid in Ω , while the boundary conditions are replaced by

$$u + z_l \gamma \frac{\partial u}{\partial n} = U_l \text{ on electrode } E_l \quad (3)$$

$$\int_{E_l} \gamma \frac{\partial u}{\partial n} ds = I_l \quad (4)$$

where U_l and I_l denote the electrode voltage and injected current, respectively, and z_l represents the effective contact impedance of electrode E_l . On the remaining boundary,

$$\gamma \frac{\partial u}{\partial n} = 0 \quad (5)$$

The CEM accounts for electrode geometry and contact effects and constitutes the standard forward model used in numerical implementations of EIT, typically discretized using finite element methods.

Inverse Problem and Linearization

Reconstruction of the internal admittivity distribution from boundary voltage measurements constitutes a nonlinear inverse problem. Denoting the forward operator by $\mathcal{F}(\gamma)$, the measured electrode voltages satisfy

$$\mathbf{V} = \mathcal{F}(\gamma)$$

To facilitate computation, the inverse problem is commonly approached by linearizing $\mathcal{F}$ around a reference background γ_0 , yielding the first-order approximation

$$\delta \mathbf{V} \approx \mathbf{J} \delta \gamma \quad (6)$$

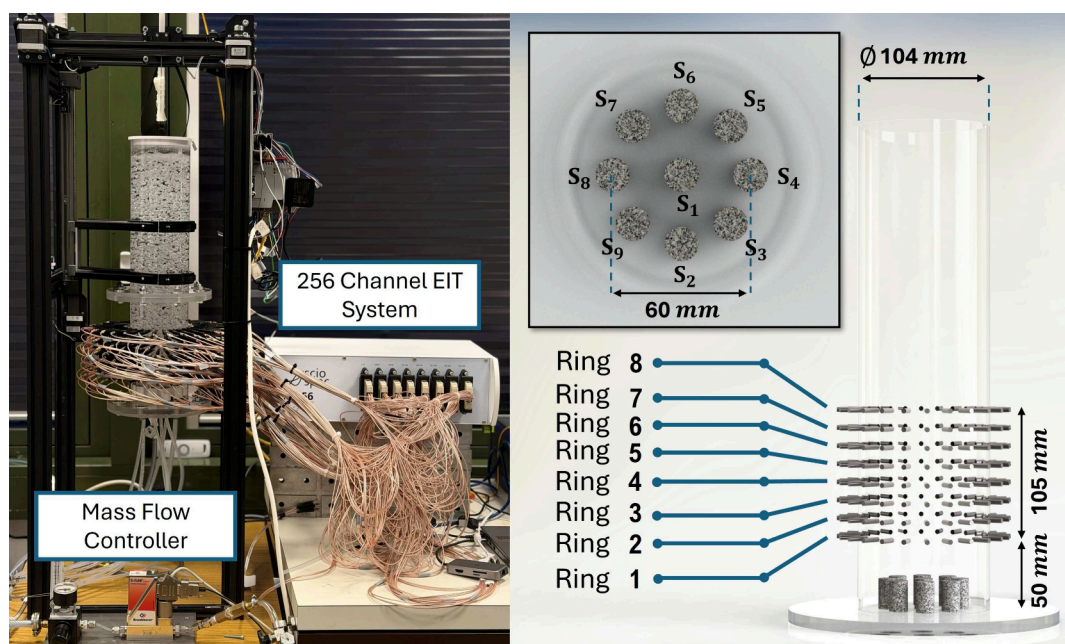


Figure 1. Schematics of the experimental setup. The column (600 × 104 mm I.D.) maintains a 550 mm static water level, which expands during gas induction. Gas is injected via nine base spargers: one central sparger, and eight spargers distributed radially and equidistantly (at 45° intervals) with their centers located 30 mm from the column center. The EIT system comprises 256 electrodes across eight axial rings (32 electrodes/ring, 15 mm vertical spacing), spanning 105 mm and starting 50 mm above the column floor.

where $\mathbf{J}$ is the Jacobian (sensitivity) matrix relating perturbations in admittivity to variations in the measured boundary voltages. However, $\mathbf{J}$ is typically highly ill-conditioned. Small measurement noise can therefore produce disproportionately large errors in the reconstructed solution. Moreover, because the measurements are restricted to the boundary, the spatial resolution of the recovered admittivity field is fundamentally limited. Consequently, stable inversion requires the incorporation of additional constraints.

To stabilize the solution, reconstruction is commonly formulated as a regularized optimization problem,

$$\hat{\delta\gamma} = \arg \min_{\delta\gamma} \{ \|\delta\mathbf{V} - \mathbf{J}\delta\gamma\|_2^2 + \lambda \mathcal{R}(\delta\gamma) \} \quad (7)$$

where $\mathcal{R}(\cdot)$ encodes prior assumptions on the solution, such as smoothness (e.g., Tikhonov regularization⁵⁵), edge preservation (e.g., total variation⁵⁶), or sparsity-promoting penalties.⁵⁷

While such regularized approaches yield visually interpretable conductivity maps, they inevitably introduce smoothing effects and reconstruction artifacts. Furthermore, iterative solution of the associated optimization problem can become computationally demanding, particularly in high-frame-rate monitoring scenarios.

Measurement Protocol

Experimentally, boundary data were obtained by injecting alternating currents through surface-mounted electrodes and measuring the resulting voltages. In this study, measurements were performed using the adjacent (Brown–Seagar) excitation protocol.⁵⁸ For each drive pattern $(l, l + 1)$, differential voltages were recorded between neighboring electrode pairs $(m, m + 1)$ that exclude the active drive electrodes. The drive pair was shifted sequentially around the boundary to obtain a complete measurement frame. A schematic representation of the excitation and measurement configuration is shown in Figure 2.

Direct Inference from Boundary Data

Although the classical EIT framework provides a mathematically well-defined route to reconstruct conductivity distributions, the primary objective in many process-monitoring applications is not image formation itself, but rather the identification of reactor operating states, such as flow regimes or gas distribution patterns.

Accordingly, the present work bypasses explicit image reconstruction and instead learns a direct mapping

$$f: \mathbf{x} \mapsto \mathbf{y}, \quad (8)$$

where $\mathbf{x}$ denotes the raw boundary impedance measurements and $\mathbf{y}$ represents reactor-relevant quantities, formulated either as discrete classification labels or continuous regression targets. Operating directly in measurement space offers two principal advantages: it avoids reconstruction artifacts and regularization bias associated with solving for γ , and it substantially reduces computational latency, thereby enabling real-time inference even for high-dimensional data acquired at elevated sampling rates. The specific model architectures and training procedures are described in the following sections.

EXPERIMENTAL SETUP AND DATA ACQUISITION

Bubble Column Reactor

Experiments were performed in a cylindrical bubble column manufactured from transparent acrylic glass to enable visual observation of the flow. The column had a total height of 600 mm and an inner diameter of 104 mm. Pressurized nitrogen gas was introduced through multiple cylindrical porous spargers mounted flush with the bottom plate. Each sparger measured 15 mm in diameter and 25 mm in height and was arranged according to the symmetric configuration shown in Figure 1, within a circular footprint of 60 mm. Independent valves were assigned to each sparger, allowing selective activation and controlled variation of inlet gas distribution. This modular configuration enabled systematic adjustment of

injection patterns, thereby generating a broad range of hydrodynamic states within the column.

EIT System

The column was equipped with a high-density electrical measurement array consisting of 256 stainless-steel electrodes (2 mm diameter) distributed across eight axial rings, each comprising 32 uniformly spaced electrodes. The lowest ring was positioned 50 mm above the sparger plane, and the axial spacing between consecutive rings was 15 mm. All electrodes were interfaced with a commercial 256-channel electrical impedance tomography system (Sciospec GmbH, Germany). Complex impedance measurements were acquired sequentially at excitation frequencies of 1 kHz, 10 kHz, 100 kHz, and 1 MHz. While the frame acquisition time decreases from 1 kHz to 10 kHz, the Sciospec system reaches an absolute hardware sampling limit of 143.4 μ s at 100 kHz. Because of this hard limit, the temporal window plateaus. Consequently, the 100 kHz and 1 MHz measurements share an effectively equivalent temporal observation window of ~ 0.19 s per frame. This ensures that the temporal averaging of the highly fluctuating bubble dynamics remains consistent across these two highest frequencies. Additionally, the system's high-frequency measurement capabilities are bounded by electrical instrumentation limits; manufacturer resistor phantom validation tests confirm that baseline signal precision begins to decay at 100 kHz, with minimum accuracy dropping to 91.0% and minimum reciprocity to 88.1%, and further unquantified degradation is expected at 1 MHz as it operates outside the manufacturer's standard validated frequency range.

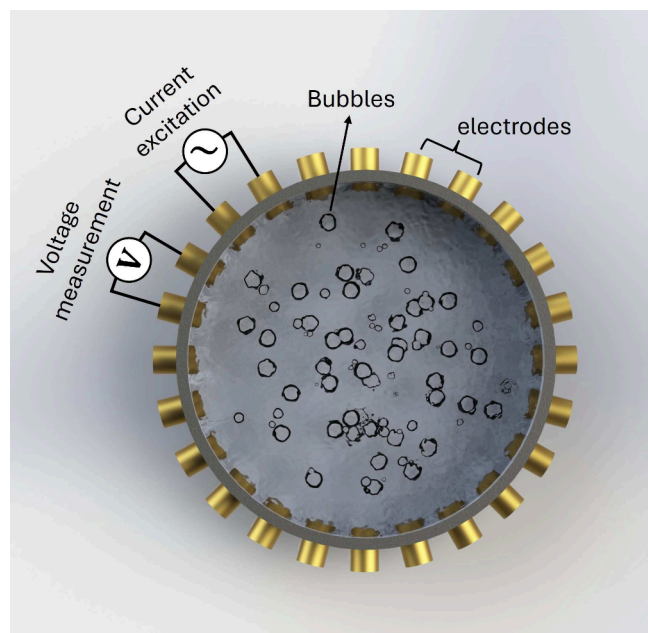


Figure 2. Schematic of the EIT measurement principle.

Gas Supply and Flow Control

Nitrogen was used as the dispersed gas phase. The inlet flow rate was regulated using a mass flow controller (EL-Flow, Bronkhorst, Netherlands) operated via the FlowSuite software interface to ensure precise and reproducible gas delivery. Nitrogen was selected instead of compressed air to reduce dissolution of atmospheric CO_2 into the liquid phase, which would otherwise modify the baseline electrical conductivity during operation. By combining independently controlled sparger activation with systematic variation of gas flow rates, a comprehensive set of operating conditions was established, covering a wide range of bubble distribution patterns and hydrodynamic regimes within the column.

To express the imposed gas throughput in a geometry-independent form, the volumetric gas flow rate Q_g supplied by the mass flow controller was converted to the superficial gas velocity U_g , defined as

$$U_g = \frac{Q_g}{A_c} = \frac{4Q_g}{\pi D_c^2}$$

where A_c is the column cross-sectional area and $D_c = 104$ mm is the inner column diameter. Accordingly, the investigated superficial gas velocity range of 1.96–12.75 mm s^{-1} corresponds to a superficial-gas-velocity range of 1.96–12.75 mm s^{-1} .

Liquid Phase Preparation

The column was filled with 3.5 L of deionized water. To establish a stable and reproducible baseline conductivity of approximately 500 $\mu\text{S/cm}$, 4 mL of 5 M HCl were added to the liquid phase. The liquid temperature was monitored throughout the measurements and remained stable around 21 $^\circ\text{C}$. The electrolyte concentration was selected to ensure sufficient electrical contrast between the continuous liquid phase and the dispersed gas phase while maintaining stable measurement conditions throughout the experiments.

Measurement Configuration

The measurements were designed as a structured sweep over sparger activation index and gas-flow conditions. Sparger configurations—including single-, multi-, and all-sparger activation cases—were selected according to the geometric layout shown in Figure 1 and are summarized in Table 1. For each configuration, the total gas flow

Table 1. Measurement Protocol: Operating Conditions and Acquisition Settings

Category	Specification
Sparger configurations	$S_1, S_2, S_3, S_4, S_5, S_6$ $S_{12}, S_{23}, S_{24}, S_{25}, S_{26}$ $S_{123}, S_{234}, S_{235}$ S_{345}, S_{236} S_{all}
Flow-rate sweep	$Q \in [1.0, 6.5] \text{ L min}^{-1}$ with $\Delta Q = 0.5 \text{ L min}^{-1}$ ($U_g \in [1.96, 12.75] \text{ mm s}^{-1}$ with $\Delta U_g = 0.98 \text{ mm s}^{-1}$)
Excitation frequencies	$f \in \{1 \text{ kHz}, 10 \text{ kHz}, 100 \text{ kHz}, 1 \text{ MHz}\}$
Frames per operating point	100 EIT frames per (configuration, Q) at each frequency
Total operating points	204 (configuration, Q) combinations
Total frames	20,400 frames per frequency; 81,600 frames total

rate Q was systematically varied across the prescribed range using a mass flow controller, leading to changes in superficial gas velocities in the bubble column. At every operating point, EIT data were recorded at four excitation frequencies, with 100 consecutive frames acquired per frequency unless stated otherwise. The resulting number of operating points and total frames are summarized in Table 1. After each adjustment of the gas flow rate, a waiting period of 60 s was allowed to ensure that a quasi-steady-state flow condition was reached.

This protocol yields a data set that spans both injection-pattern variations and superficial gas velocity changes, thereby enabling simultaneous evaluation of classification tasks (sparger index identification) and regression tasks (superficial gas velocity estimation) directly from the multifrequency boundary measurements. The ground truth for each operating point is defined by the commanded sparger activation state (providing the classification label) and the set-point flow rate read from the Bronkhorst EL-Flow mass flow controller and then converted to superficial gas velocity (providing the regression label). No additional sensor was employed to independently verify local gas holdup; the controller set-point constitutes the reference value against which all predictive accuracy metrics are reported. This approach is analogous to using a calibrated source instrument as a primary reference, which is standard practice in sensor-based flow characterization.

Simulation Hardware

All data preprocessing, statistical evaluation, and model training were conducted on a dedicated high-performance computing system. Large-scale data handling and EIT signal processing were performed on a 32-core AMD EPYC 9354P processor with 768 GB DDR5 memory, ensuring efficient management of high-resolution calibration data sets and minimizing I/O overhead. Training and hyperparameter optimization of the proposed EIT Transformer models (detailed in following sections) were carried out on an NVIDIA RTX 6000 Ada GPU (48 GB VRAM), enabling accelerated deep learning computations for both classification and regression tasks.

MACHINE LEARNING FRAMEWORK

The transition from raw electrical impedance measurements to a robust classification of hydrodynamic regimes is achieved through multistage processing designed to handle the dimensionality and inherent redundancy of EIT data. It is well established that EIT measurements contain substantial redundancy; the removal of such redundant components has been shown to reduce imaging artifacts and improve reconstruction stability in simulated bubbly flows.⁵⁹ Similarly for flow imaging through Electrical Capacitance Tomography (ECT) the elimination of redundant measurement information has been reported to enhance reconstruction fidelity.⁶⁰ In this work, the flow characterization problem is formulated as a supervised learning task where the objective is to map complex-valued boundary voltage vectors—representative of the time dependent phase distribution—onto (i) discrete flow regimes and (ii) continuous superficial gas velocities. The proposed methodology follows a three-tier architecture, consisting of data preprocessing, latent feature encoding, and task-specific decoding as illustrated in Figure 4. This structure is specifically engineered to address the nonlocal and globally coupled nature of EIT measurements, with detailed design considerations provided below.

Data Preprocessing via Incremental Principal Component Analysis (IPCA)

Incremental Principal Component Analysis (IPCA) is employed to extract the dominant spatial-spectral modes embedded in the impedance measurements.⁶¹ Unlike conventional PCA, IPCA enables efficient processing of large-scale making it particularly suitable for large-scale 3D EIT measurements. The dimensionality reduction step mitigates measurement redundancy, enhances signal-to-noise characteristics, and preserves the principal variance associated with hydrodynamic structures. While the proposed Transformer architecture could in principle accept raw boundary measurements directly, the 65,536-dimensional input would increase the embedding layer alone by a factor of ~ 330 , placing excessive demands on training data and computational resources. IPCA therefore serves a dual purpose: it reduces input dimensionality from 65,536 to 200 components while discarding noise-dominated directions that would otherwise inflate model complexity.

Transformer-Based Encoding

The reduced feature representations are provided as input to a Transformer-based deep learning model.⁶² Transformer architectures have recently demonstrated promising performance in three-dimensional EIT reconstruction tasks.⁶³ Moreover, the combination of Principal Component Analysis (PCA) and deep learning has been successfully applied to EIT-based fault detection, where dimensionality reduction enhances robustness and computational efficiency prior to

supervised learning.⁶⁴ It is important to note, however, that in these prior studies feature extraction is performed on reconstructed conductivity fields rather than directly in the raw measurement domain.⁶⁴

This distinction is fundamental. In the imaging domain, reconstructed conductivity distributions exhibit spatial continuity and localization, such that hydrodynamic structures manifest as coherent spatial patterns. Under these conditions, neighboring pixels or voxels tend to be physically and statistically correlated, making locality-preserving inductive biases—such as those embedded in convolutional neural networks—well aligned with the data structure. In contrast, the present work operates directly on boundary voltage or impedance measurements. Due to the intrinsic soft-field nature of EIT, localized conductivity perturbations within the domain induce spatially diffuse and globally coupled responses at the boundary.^{65,66} Consequently, spatial proximity in the physical domain does not translate into locality in the measurement space. The measurement topology is therefore fundamentally nonlocal, and this characteristic is preserved—even after dimensionality reduction via IPCA—since the compressed features represent global variance modes rather than spatially contiguous structures. This nonlocal data structure imposes specific architectural requirements. Models that rely on predefined local neighborhood assumptions may be suboptimal when physically local phenomena manifest as distributed signatures across the entire observation vector. A self-attention-based architecture is therefore particularly well motivated. Unlike convolutional approaches, the Transformer does not impose spatial adjacency constraints. Instead, it learns pairwise dependencies across the full feature sequence, enabling the recovery of latent global interaction patterns that arise from the soft-field physics of EIT.⁶² Accordingly, the use of a Transformer is not merely a performance-driven choice but a physics-consistent modeling decision: it aligns the inductive bias of the network with the globally coupled structure of raw EIT measurements, making it especially suitable for raw-measurement-based flow characterization.

Task-Specific Decoding

The final layer is configured according to the learning objective: a softmax-based classification head for flow regime identification and a regression head for continuous superficial gas velocity prediction. This modular design allows the architecture to be flexibly adapted to distinct but related flow characterization tasks.

The proposed framework integrates physics-aware dimensionality reduction with a globally attentive sequence modeling strategy to address the nonlocal structure of raw EIT measurements. By combining redundancy mitigation through IPCA, dependency learning via self-attention, and modular task-specific output layers, the methodology establishes a coherent end-to-end pipeline for robust hydrodynamic regime classification and quantitative flow estimation.

LIMITATIONS OF FLOW CLASSIFICATION IN THE IMAGE RECONSTRUCTION DOMAIN

The reconstruction of conductivity fields σ from EIT boundary measurements U constitutes a nonlinear, ill-posed inverse problem that typically requires regularization, as expressed in Eq. 7. In turbulent bubbly flows, however, the presence of numerous dynamically evolving phase interfaces challenges the simplifying assumptions often used to tune the regularization

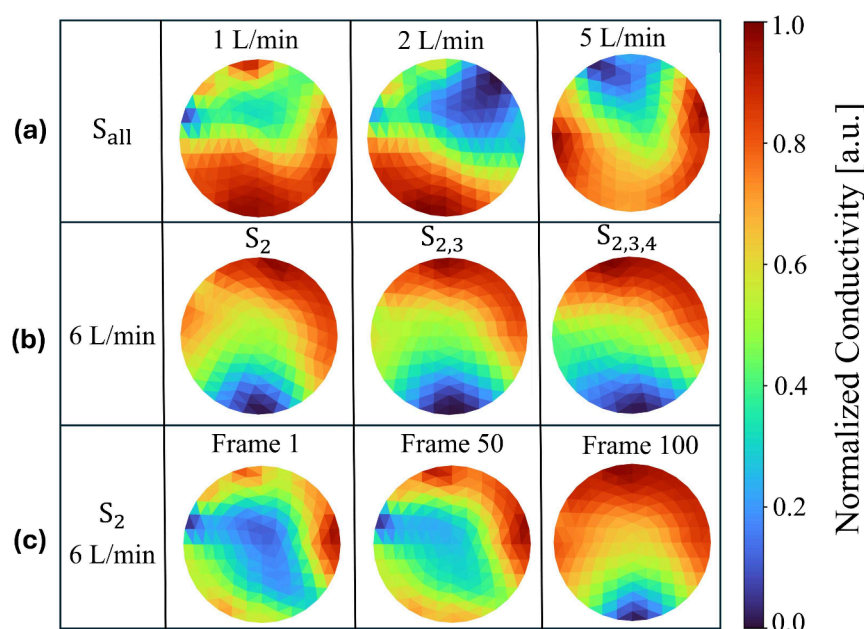


Figure 3. EIT image reconstructions using EIDORS⁶⁷ for electrode ring 1 under different operating conditions. (a) Effect of superficial gas velocity with all spargers activated (S_{all}) at 1, 2, and 5 L min⁻¹ (corresponding to $U_g = 1.96, 3.92,$ and 9.81 mm s⁻¹). (b) Effect of sparger configuration (S_2 , $S_{2,3}$, and $S_{2,3,4}$) at a constant gas flow rate of 6 L min⁻¹ ($U_g = 11.77$ mm s⁻¹). (c) Temporal variability under constant operating conditions at sparger S_2 at 6 L min⁻¹ ($U_g = 11.77$ mm s⁻¹), shown for frames 1, 50, and 100.

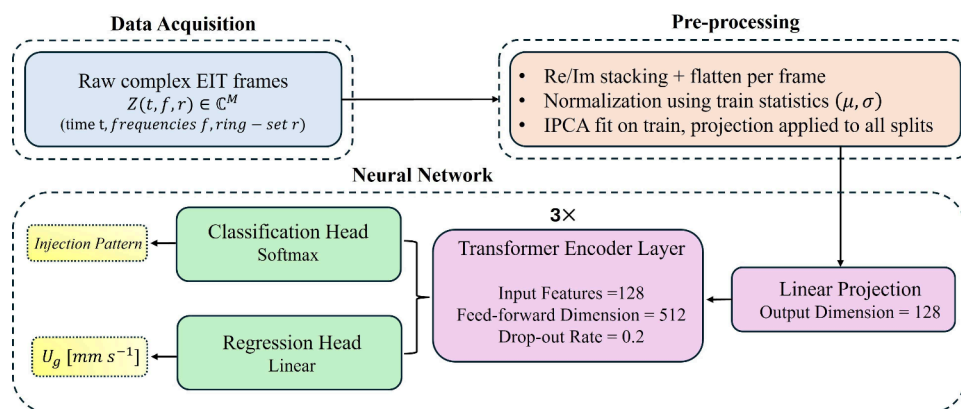


Figure 4. Overview of the end-to-end multitask EIT framework. The pipeline integrates raw impedance preprocessing and IPCA-based dimensionality reduction followed by a Transformer-based encoder. Task-specific decoding is facilitated by discrete regression and classification heads. Both the encoder and its corresponding task-specific head are trained independently for each objective, utilizing Huber and Cross-Entropy losses for superficial gas velocity and injection pattern tasks, respectively.

parameter λ , such as isolated or quasi-static inclusions. As a result, interpreting reconstructed conductivity fields in terms of reactor operating conditions can be difficult. Figure 3 illustrates representative reconstructions obtained from electrode ring 1 under different operating conditions. In Figure 3(a), the gas flow rate is varied (1, 2, and 5 L min⁻¹ corresponding to $U_g = 1.96, 3.92,$ and 9.81 mm s⁻¹) while all spargers are activated (S_{all}). Although the reconstructed conductivity maps visibly respond to changes in operating conditions, the relationship between the observed morphological features and the actual superficial gas velocity remains difficult to interpret quantitatively. Figure 3(b) shows reconstructions for different sparger configurations (S_2 , $S_{2,3}$, and $S_{2,3,4}$) at a constant flow rate of 6 L min⁻¹ ($U_g = 11.77$ mm s⁻¹). While changes in injection pattern clearly influence the reconstructed structures, the resulting spatial features remain complex and difficult to interpret directly in terms of gas distribution within the reactor. Finally,

Figure 3(c) highlights the temporal variability of reconstructed images under identical operating conditions at sparger S_2 at 6 L min⁻¹ ($U_g = 11.77$ mm s⁻¹) using three representative frames. Despite unchanged operating parameters, the reconstructed spatial patterns vary noticeably over time.

This variability arises because reconstructed conductivity maps reflect not only the underlying hydrodynamic state but also the instantaneous phase distribution and the influence of regularization in solving the inverse problem. Consequently, the morphological structures observed in reconstructed images represent a complex superposition of hydrodynamic fluctuations and reconstruction-related artifacts, which complicates their direct quantitative interpretation.

These observations highlight a fundamental limitation when using reconstructed images for flow characterization. Because the conductivity maps are the regularized outcome of an ill-posed inversion, any flow characterization derived from them

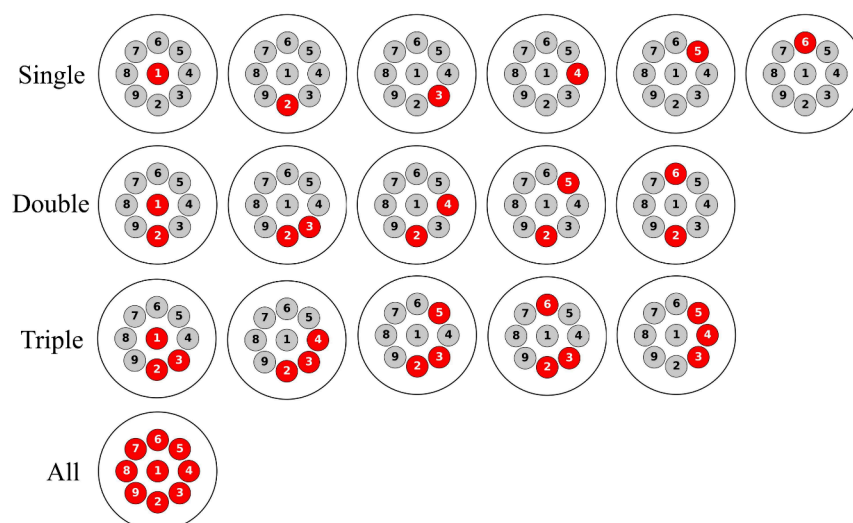


Figure 5. Schematics of the sparger configurations (injection patterns).

inevitably reflects the assumptions embedded in the reconstruction procedure. In turbulent bubbly flows, where the instantaneous phase distribution is inherently stochastic and ground-truth spatial fields are inaccessible, this dependence further complicates the interpretation of localized image structures. These limitations motivate a measurement-domain approach in which boundary impedance data are analyzed directly using data-driven models to infer reactor operating states without reconstructing conductivity distributions.

RESULTS AND DISCUSSION

Gas–liquid flow in bubble columns exhibits inherently nonlinear behavior, such that variations in gas flow, and viscosity can reorganize bubble break up and coalescence, gas holdup distributions, and mixing patterns, thereby altering the boundary impedance signatures measured by EIT.^{68–70} As a result, identical superficial gas velocities may produce different impedance responses under distinct injection patterns, and conversely similar impedance patterns may correspond to different U_g values. To evaluate virtual sensing under these state-dependent conditions, each EIT frame is labeled by its operating state, defined by the active sparger configuration and the superficial gas velocity $U_g \in [1.96, 12.75] \text{ mm s}^{-1}$, and two predictive tasks are considered: multiclass classification of the injection pattern and continuous regression of U_g . We first assess the identifiability of injection patterns and analyze the influence of measurement design, including electrode-ring selection and excitation frequency, on classification stability. Subsequently, superficial gas velocity estimation is evaluated using two calibration granularities—a fine-scale data set with a resolution of 0.33 mm s^{-1} and a coarse-scale data set with a resolution of 0.98 mm s^{-1} —thereby separating sensor-configuration effects governing state recognition from calibration-density effects that limit quantitative superficial gas velocity prediction. The layout of the sparger configurations (for injection patterns) used for data acquisition is shown in Figure 5.

Data Set Partitioning and Prevention of Temporal Data Leakage

Each operating point comprises 100 consecutive EIT frames acquired at a fixed sparger configuration and superficial gas velocity. Because consecutive frames from the same operating

point are temporally correlated, a naive random assignment of frames to training and test sets would place adjacent, nearly identical frames in both partitions, artificially inflating the apparent generalization performance (data leakage). To eliminate this artifact, a strictly chronological, per-operating-point split is applied: for each (sparger, superficial gas velocity) combination, the 100 frames are ordered chronologically by acquisition time and divided per operating point as follows—frames 1–70 (70%) are assigned to training, frames 71–85 (15%) to validation, and frames 86–100 (15%) to the held-out test set. This strategy ensures that no training-set frame temporally overlaps with or precedes any test-set frame within the same operating condition, and that the test set always reflects the later dynamics of each experimental run. IPCA is fitted exclusively on training-set frames; the learned projection is then applied to validation and test sets without refitting. To further test generalization we performed systematic exclusion studies—designated as generalization A (GenA) and generalization B (GenB)—to test predictive performance on unseen data. In study GenA, data corresponding to distinct superficial gas velocities (2.94 , 6.87 , and 10.79 mm s^{-1}) were held out from both the training and validation phases. In study GenB, specific sparger configurations (S_3 , S_{26} , S_{235}) were similarly excluded. The course of this section will mainly focus on the chronological split with partial comparison to the generalization studies. Conclusive data on the generalization and the arising limitations can be found in the [Supporting Information](#).

Injection Pattern (Sparger Configuration) Prediction

The prediction framework must account for the coupled influence of reactor operating conditions and measurement design. Changes in gas distribution and superficial gas velocity directly modify bubble dispersion and hydrodynamic behavior within the column, thereby altering the impedance signatures observed at the boundary. At the same time, the reliability of state inference depends strongly on the sensing configuration, particularly the selected electrode-ring combinations and excitation frequencies.

Full Electrodes Scheme. As an initial step, the model was trained using measurements from all eight electrode rings, and the injection pattern classification performance was evaluated across different superficial gas velocities and excitation

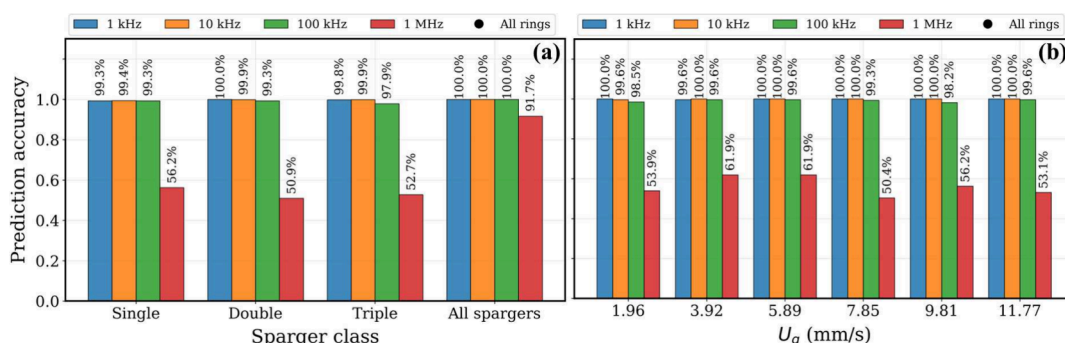


Figure 6. (a) Overall classification accuracy for different sparger configuration (single, double, triple, all) aggregated across superficial gas velocities. (b) Superficial-gas-velocity-resolved classification accuracy averaged over all sparger configurations. Colored bars correspond to individual excitation frequencies (1 kHz, 10 kHz, 100 kHz, 1 MHz), and black markers denote results obtained using all electrode rings.

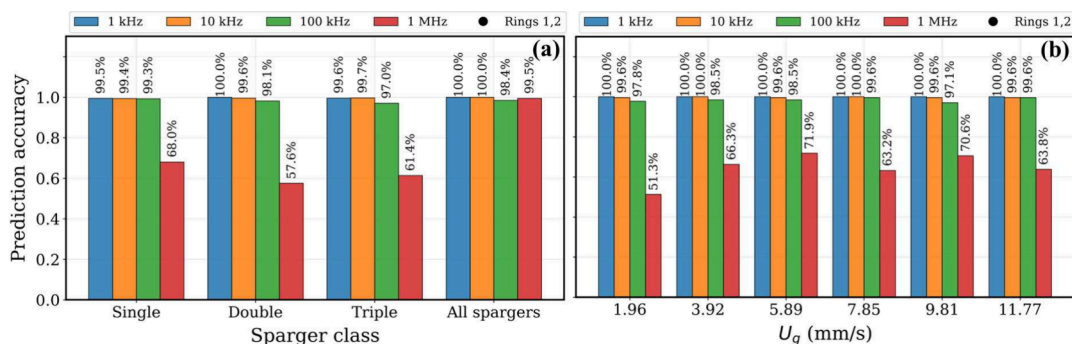


Figure 7. (a) Overall classification accuracy for different sparger configuration (single, double, triple, all) aggregated across superficial gas velocities for rings 1–2. (b) Superficial-gas-velocity-resolved classification accuracy averaged over all sparger configurations for rings 1–2. Colored bars correspond to individual excitation frequencies (1 kHz, 10 kHz, 100 kHz, 1 MHz).

frequencies. Figure 6(a) presents the results for the various injection patterns. For clarity, the individual sparger configurations listed in Table 1 were grouped into four categories: *Single* (average over all single-sparger cases), *Double* (average over all two-sparger combinations), *Triple* (average over all three active spargers), and *All spargers* (simultaneous activation of all spargers). Figure 6(b) shows the classification accuracy as a function of superficial gas velocity, averaged over all sparger configurations.

The results reveal stable and near-perfect classification performance for excitation frequencies up to 100 kHz. In contrast, the 1 MHz measurements exhibit a marked reduction in accuracy. This behavior likely arises from the interaction between hydrodynamic averaging and frequency-dependent measurement fidelity.

In the present bubble-column system, EIT signals reflect the temporally integrated response of dynamically fluctuating bubble plumes. Lower excitation frequencies yield longer integration windows, which smooth hydrodynamic fluctuations and enhance classification robustness. However, hardware sampling limits at 100 kHz cause this effective observation window to plateau, meaning 100 kHz and 1 MHz measurements share an identical temporal acquisition time. Because there is no reduction in temporal averaging between these two frequencies, the severe predictive deterioration observed at 1 MHz cannot be attributed to the acquisition window. Instead, this degradation is driven entirely by the measurement system's limited frequency response and elevated noise levels. Operating beyond the manufacturer's validated frequency range introduces uncompensated front-end nonidealities—such as parasitic capacitances, phase distortions, and common-

mode effects^{71–73}—which severely degrade the hardware's frequency response and lower the signal-to-noise ratio. Therefore, the reduced accuracy at 1 MHz is an artifact of frequency response limitations and hardware noise, rather than a temporal or hydrodynamic phenomenon.

Partial Electrodes Scheme. To investigate how the axial placement of the sensing region influences injection pattern classification, the full eight-ring measurement configuration was reduced to two localized subsets: rings 1–2, positioned closest to the sparger plane, and rings 7–8, located furthest downstream. This comparison isolates two distinct sources of predictive information along the column height. The lower rings predominantly capture the near-field gas distribution immediately after injection, where plume localization is strongest. In contrast, the upper rings sample the flow after significant rise, dispersion, and interplume interaction have occurred. For each ring subset, the machine-learning models were trained and evaluated independently using only the corresponding measurements. This separation ensures that no cross-ring information leakage occurs and that the reported performance reflects the predictive capability of the selected axial sensing region alone.

For rings 1–2, injection pattern classification remains nearly identical to the full eight-ring case at excitation frequencies up to 100 kHz (see Figure 7). Across all investigated superficial gas velocities, accuracy ranges between 97.4–100.0% at 1 kHz, 96.7–100.0% at 10 kHz, and remains highly stable at 100 kHz (96.3–99.6%). Similarly, grouped sparger categories remain robust, achieving accuracies between 99.5–100.0%, 99.4–100.0%, and 97.0–99.3%, respectively. This indicates that the most discriminative information is generated in the immediate

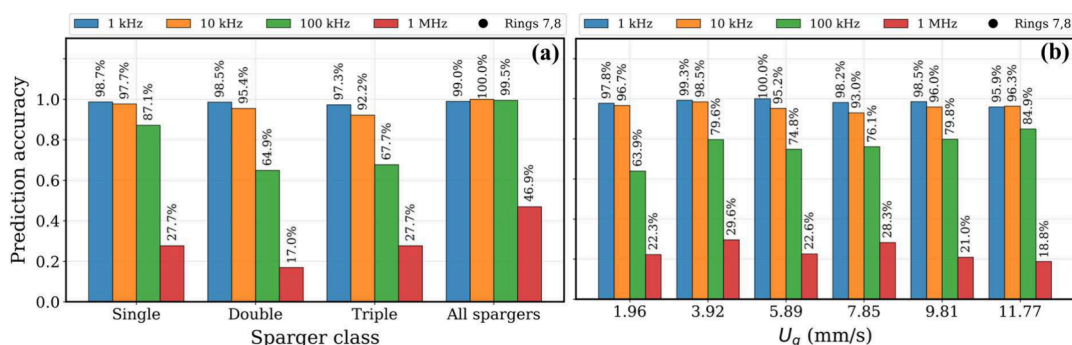


Figure 8. (a) Overall classification accuracy for different injection patterns (single, double, triple, all) aggregated across superficial gas velocities for rings 7–8. (b) Superficial-gas-velocity-resolved classification accuracy averaged over all injection patterns for rings 7–8. Colored bars correspond to individual excitation frequencies (1 kHz, 10 kHz, 100 kHz, 1 MHz).

Table 2. Model Performance for the in-Distribution Consecutive Split and the GenA Generalization Condition^b

Model	Consecutive split			GenA		
	Acc	MAE	MAE%	Acc	MAE	MAE%
Logistic Regression	99.69	1.258	11.7	95.80	40.854 ^a	378.6
Linear SVM	99.66	1.875	17.4	96.58	41.427 ^a	383.9
Random Forest	99.48	0.724	6.7	93.39	1.060	9.8
XGBoost	99.45	0.790	7.3	94.66	0.932	8.6
MLP	99.72	1.280	11.9	95.63	66.034 ^a	611.9
Transformer(proposed)	99.69	0.532	4.9	97.36	0.769	7.1

^aMAE exceeds the full operating range (10.79 mm s⁻¹); model extrapolates outside the training manifold. ^bHeld-out superficial gas velocities 2.94, 6.87, 10.79 mm s⁻¹; IPCA fitted on training-partition frames only). Acc = sparger classification accuracy [%]; MAE in mm s⁻¹; MAE% = MAE as a percentage of the 10.79 mm s⁻¹ operating range.

vicinity of the gas-injection zone, where individual sparger activations imprint a strongly localized and reproducible structure on the boundary impedance field. Performance degradation becomes evident only at higher frequencies: at 1 MHz, accuracy declines significantly to 51.3–73.4% across superficial gas velocities and 57.6–99.5% across sparger groups.

The results for rings 7–8 provide complementary insight. Despite being located furthest from the injection plane, these rings still achieve high accuracy at low frequencies, reaching 95.2–100.0% at 1 kHz and 92.6–98.5% at 10 kHz across superficial gas velocities (see Figure 8). Thus, even after significant rise and dispersion, the model remains capable of inferring the original injection pattern from downstream measurements. This implies that injection pattern leaves a persistent global signature on the flow, reflected not only in localized plume structures but also in downstream plume interaction, gas-holdup asymmetry, circulation patterns, and bubble-size statistics. However, at 100 kHz the degradation is substantially stronger for rings 7–8, with accuracy decreasing to 64.9–99.5% across superficial gas velocities, although the *All spargers* case remains highly identifiable (99.5%). At 1 MHz, predictive performance collapses entirely, with accuracy dropping to 17.0–46.9% across sparger configurations and 13.7–42.6% across superficial gas velocities. The findings indicate that highly symmetric, high-gas-fraction states remain detectable far from the sparger, whereas finer distinctions among single-, double-, and triple-sparger patterns are progressively obscured by axial transport and dispersion.

Compared with the full eight-ring configuration, the reduced subsets show that lower rings capture the most direct information on the injection pattern, whereas upper rings retain a measurable downstream signature of the upstream

operating state. Combining all rings therefore provides the most robust performance, especially at 100 kHz and 1 MHz, although the strong low-frequency results for rings 7–8 indicate that full volumetric coverage is not essential when axial placement and excitation frequency are chosen appropriately.

Generalization on Unseen Superficial Gas Velocities.

To evaluate model generalization to unseen superficial gas velocities (GenA), the IPCA transform was fitted exclusively on the training split. This approach simulates a strictly static predeployment calibration where the model encounters completely novel hydrodynamic conditions online. As indicated in Table 2, classification accuracy remains highly robust under this paradigm, achieving 97.36% under strict predeployment calibration.

Superficial Gas Velocity Prediction

Following the evaluation of injection-pattern classification, the second prediction task addresses the continuous estimation of the superficial gas velocity U_g from the EIT measurements. Whereas pattern classification targets discrete operating states, superficial gas velocity regression evaluates whether the impedance measurements also resolve gradual quantitative variations in gas throughput. To train such a model, measurements must be acquired at discrete operating points spanning the investigated U_g range. The spacing between these operating points defines the calibration density along the superficial gas velocity axis and determines how finely the relationship between impedance measurements and U_g is sampled. Two calibration strategies were therefore considered. In the **coarse-scale** regime, all sparger configurations listed in Table 1 were included, and the superficial gas velocity was sampled at intervals of 0.98 mm s⁻¹ across the full operating

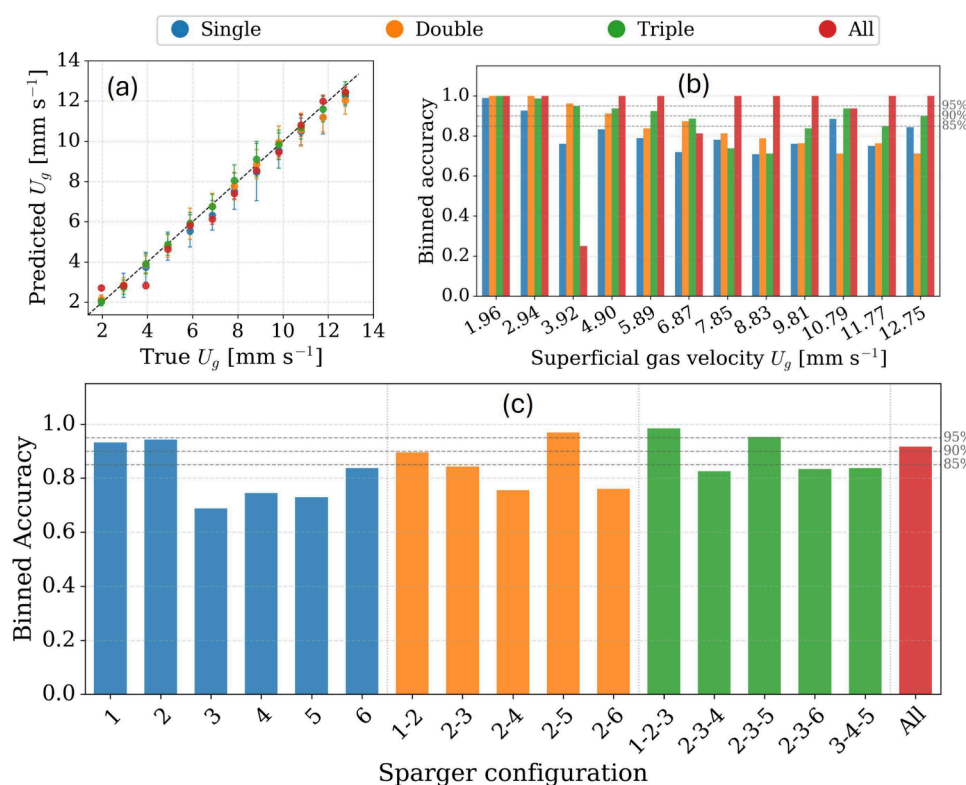


Figure 9. Coarse-scale regression results for superficial gas velocity estimation. (a) Parity plot of predicted versus true superficial gas velocity U_g for different injection patterns. (b) Binned accuracy as a function of U_g grouped by sparger configuration. (c) Binned accuracy distribution across all sparger configurations, averaged over the full range of superficial gas velocities.

range. In this setting, the regression model must capture variations in both injection pattern and superficial gas velocity.

In the **fine-scale** regime, the analysis was restricted to two representative configurations, S_3 and S_{all} , while the calibration spacing along the superficial gas velocity axis was refined to 0.33 mm s⁻¹. This increased calibration density allows the model to learn a more detailed mapping between impedance features and U_g under otherwise fixed hydrodynamic conditions. Together, these two regimes isolate two limiting factors in superficial gas velocity prediction: variability in reactor hydrodynamics and the calibration density along the U_g axis.

Moreover, while conventional regression metrics such as the mean absolute error (MAE) quantify continuous prediction deviations, the operational objective is often the correct identification of the discrete hydrodynamic state. Therefore, the reliability of the regression outputs was additionally evaluated using a *binned accuracy* metric.

Binned accuracy is defined as the proportion of continuous predictions, $\hat{U}_{g,i}$ that fall within the discrete operating class of the true superficial gas velocity, $U_{g,i}$. Because the experimental superficial gas velocities are spaced on a regular 0.98 mm s⁻¹ grid, class membership can be expressed using an absolute error tolerance ϵ :

$$\text{Binned Accuracy} = \frac{1}{N} \sum_{i=1}^N \mathbb{I}(|U_{g,i} - \hat{U}_{g,i}| \leq \epsilon) \quad (9)$$

where N is the number of samples, $U_{g,i}$ the true superficial gas velocity, and $\hat{U}_{g,i}$ the predicted value. The indicator function $\mathbb{I}(\cdot)$ equals 1 when the prediction lies within the correct bin and 0 otherwise. This formulation explicitly links the

continuous regression error to the discrete condition monitoring requirements, providing the mathematical basis for the tolerance-accuracy curves and confusion matrices presented in the results.

Coarse-Scale Prediction

The coarse-scale regression results (shown in Figure 9) demonstrate that the model recovers the superficial gas velocity U_g with high accuracy across different sets of injection patterns shown in Figure 5. As illustrated by the parity plot in Figure 9 (a), the predicted values closely follow the identity line $y = x$ across the entire operating range of 1.96 to 12.75 mm s⁻¹, indicating that the impedance features retain a monotonic dependence on gas throughput.

A more detailed assessment is provided by the grouped prediction accuracies as a function of superficial gas velocity (Figure 9(b)). Across most operating points, the binned accuracy remains at or above 80%, with several cases approaching or exceeding 95%. These results indicate that even at the coarse calibration spacing of 0.98 mm s⁻¹, the relationship between impedance features and U_g is sufficiently resolved to enable reliable quantitative prediction.

The results further show that the regression performance is not uniform across injection patterns. The *All Spargers* case generally yields the highest binned accuracy, particularly at intermediate superficial gas velocities, whereas the *Double* and *Triple* configurations exhibit slightly larger deviations at lower and midrange U_g . This behavior is physically plausible, as simultaneous activation of all spargers produces a more spatially distributed and symmetric gas-holdup field, which may result in a more stable and globally representative impedance signature. In contrast, partially activated sparger

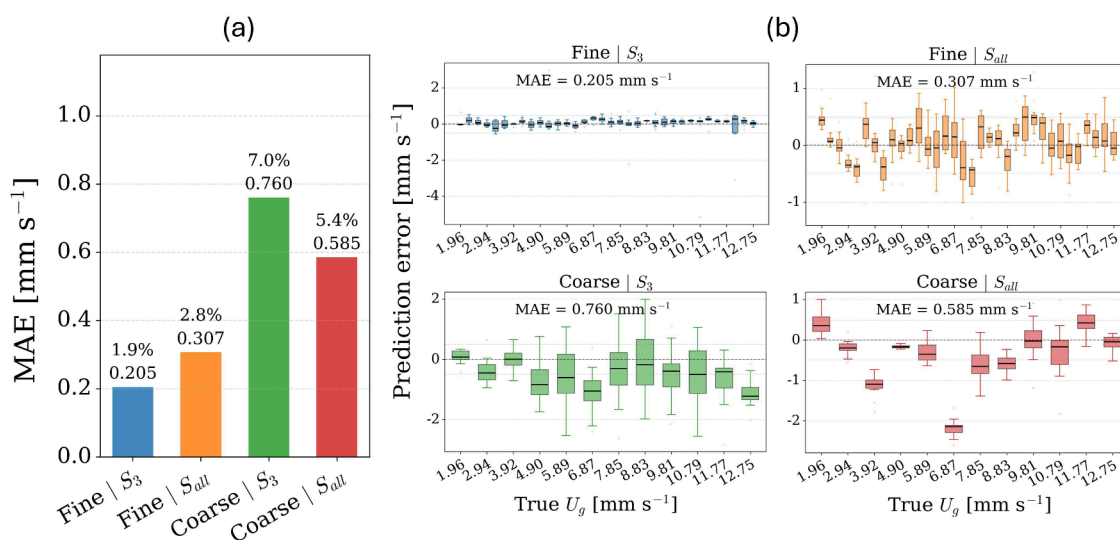


Figure 10. Superficial gas velocity estimation performance binned to the accuracy of 0.98 mm s^{-1} for the four model variants (fine/coarse calibration and sparger configurations S_3 and S_{all}). (a) Overall mean absolute error (MAE). (b) Prediction error ($\hat{U}_g - U_g$) versus true superficial gas velocity, for each operating point.

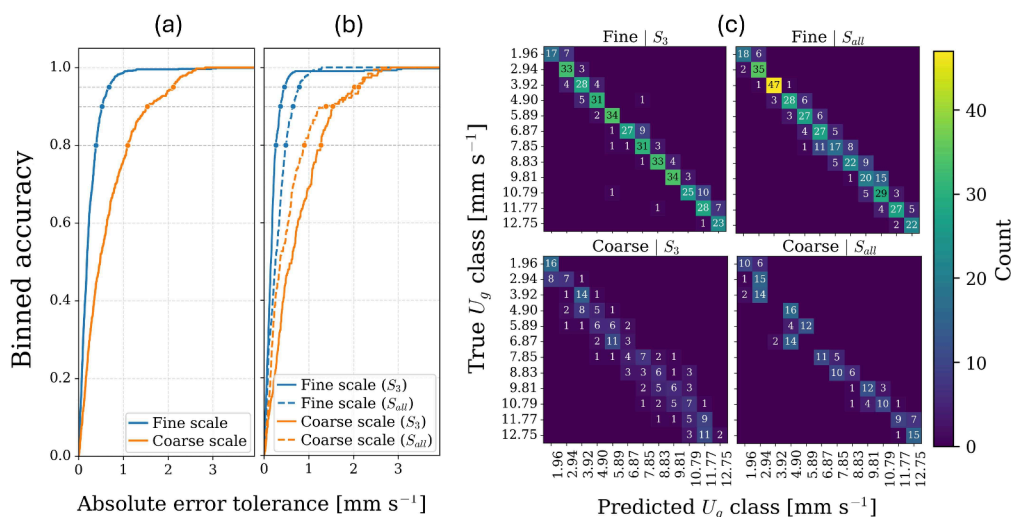


Figure 11. Comparison of superficial gas velocity estimation performance on the common 0.98 mm s^{-1} grid. (a) Cumulative tolerance-accuracy curves for the global fine- and coarse-scale models. (b) Tolerance-accuracy curves for the four individual resolution–sparger configurations. (c) Count-based confusion matrices after rounding predictions to the nearest 0.98 mm s^{-1} operating class.

configurations generate more heterogeneous plume interactions, likely introducing increased variability into the regression task.

Another notable trend is the gradual improvement in binned accuracy with increasing superficial gas velocity. At low U_g , bubble plumes are comparatively weak and the associated conductivity perturbations are likely small, which may render the regression task more sensitive to local hydrodynamic fluctuations and measurement noise. As the superficial gas velocity increases, the gas-induced modulation of the impedance field is expected to become stronger and more reproducible, potentially enhancing the separability of neighboring operating points and thereby improving regression fidelity.

Fine-Scale Prediction

To assess the impact of calibration density on superficial gas velocity prediction, the fine-scale models were trained with a refined superficial gas velocity resolution of 0.33 mm s^{-1} ,

compared to 0.98 mm s^{-1} in the coarse-scale case. For direct comparison, all models were evaluated on the common 0.98 mm s^{-1} operating grid spanning 1.0 to 12.75 mm s^{-1} (Figure 10). Performance was quantified using the mean absolute error (MAE) and the distribution of prediction residuals ($\hat{U}_g - U_g$).

As shown in Figure 10(a), increasing the calibration density markedly improves accuracy. The fine-scale S_3 model achieves the lowest MAE of 0.205 mm s^{-1} , followed by fine-scale S_{all} with 0.307 mm s^{-1} . In contrast, the corresponding coarse-scale models yield substantially larger errors (0.76 mm s^{-1} for coarse S_3 and 0.585 mm s^{-1} for coarse S_{all}). These results demonstrate that denser sampling along the U_g axis significantly enhances quantitative superficial gas velocity estimation, with the strongest gain observed for the single-sparger configuration.

The residual distributions in Figure 10(b) further support this trend. Fine-scale models exhibit narrow, nearly unbiased residuals across the entire operating range, indicating stable and consistent inference. In contrast, the coarse-scale models

display broader residual spreads, particularly for S_3 , reflecting reduced precision when interpolation across sparsely sampled calibration points is required. Although coarse S_{all} performs better than coarse S_3 , consistent with the more spatially uniform gas-holdup field generated by full sparger activation, both coarse-scale models remain clearly inferior to their fine-scale counterparts.

The practical implications are illustrated in Figure 11, which evaluates the regression output by projecting the continuous estimates onto the discrete superficial gas velocity scale and computing the proportion of predictions that fall within a specified tolerance of the ground-truth value. In this representation, the horizontal axis denotes the allowable deviation from the true superficial gas velocity, while the vertical axis indicates the resulting binned accuracy. As the tolerance increases, a larger fraction of predictions falls within the permitted range, leading to higher reported binned accuracy.

The curves reveal that the fine-scale model achieves a high acceptance rate already at small tolerances, indicating that its predictions cluster closely around the true superficial gas velocity values and therefore exhibit higher precision. The coarse-scale model, in contrast, requires larger tolerances to reach comparable binned accuracy, reflecting a broader spread of predictions. Consequently, the curves visualize the inherent tradeoff between precision and binned accuracy: strict tolerances emphasize how tightly predictions concentrate around the ground truth, whereas relaxed tolerances reflect the probability that a prediction falls within an acceptable operating range.

This behavior is consistent with the corresponding confusion matrices, where the fine-scale model exhibits a pronounced main diagonal and only limited off-diagonal spreading. Importantly, when deviations occur, they are predominantly confined to adjacent 0.98 mm s^{-1} classes, indicating that the estimator generally preserves the correct operating region even if the exact class assignment is not achieved.

Beyond the comparison of the two model variants, the results also highlight a fundamental implication for the sensing concept. The attainable resolution of the estimator is largely governed by the scale at which labeled training data are available rather than by an intrinsic physical indistinguishability of neighboring operating points—at least within the range explored in the experiments. In other words, the effective measurement accuracy of the sensor can be directly shaped by the granularity of the calibration data, as reflected by the steeper and more favorable tolerance-accuracy curve obtained with finer-scale training.

Overall, the results demonstrate that increasing calibration resolution substantially improves both the quantitative accuracy and the operational robustness of EIT-based superficial gas velocity estimation.

From a process-monitoring perspective, these results demonstrate that fine-scale calibration enhances not only regression metrics but also the practical reliability of the inferred superficial gas velocity estimate. Denser sampling of U_g establishes a more precise and stable relationship between EIT measurements and reactor operating state, thereby reducing both average prediction error and residual uncertainty. This is particularly relevant for condition monitoring, where estimator usefulness depends not only on low mean error but also on

maintaining narrow and unbiased residual distributions across the operating range.

Generalization Studies. The results of the GenA generalization study demonstrate that the superficial gas velocity regression models remain stable when evaluated on unseen superficial gas velocities with a slight degradation in accuracy. Restricting the IPCA fit strictly to the calibrated superficial gas velocities results in a Mean Absolute Error (MAE) of 0.77 mm s^{-1} (7.1% off the operating range). These outcomes indicate that while flawless interpolation between operating points cannot be assumed, the model successfully captures and tracks the underlying superficial gas velocity regimes.

Conversely, the GenB study highlights the operational boundaries of the superficial gas velocity estimator. When the model is evaluated on entirely unseen flow injection patterns, the MAE increases significantly, yielding an MAE of 2.06 mm s^{-1} (19% of the operating range) under the strict predeployment IPCA calibration. This reveals that while the architecture can interpolate missing superficial gas velocities under known spatial distributions, it struggles to accurately quantify gas throughput when confronted with uncalibrated sparger configurations. Comprehensive performance metrics for the generalization scenarios are detailed in the Supporting Information.

Benchmarking against Different Architectures

To justify the selection of the proposed transformer architecture, its predictive performance was benchmarked against a collection of standard machine-learning baselines: Logistic Regression, Random Forest, XGBoost, a linear Support Vector Machine (SVM), and a Multilayer Perceptron (MLP). Given the high dimensionality of the raw EIT measurements, IPCA was applied as a preprocessing step for all baseline models to reduce feature width and ensure computational feasibility during training. The architectures were evaluated using the consecutive data split and the two previously introduced generalization studies. The results, summarized in Table 2, reveal distinct performance disparities among the evaluated models across both discrete state recognition and continuous quantitative estimation. Further data can be found in the Supporting Information.

Injection Pattern Classification. In-distribution classification accuracy is near-perfect (>99.4%) across all evaluated models, indicating that when calibration density is sufficiently high, standard machine learning architectures can reliably map boundary impedance measurements to their respective sparger configurations. However, generalization gaps emerge when evaluating unseen superficial gas velocities (GenA), yet all models maintain a relatively high accuracy (>93%). The proposed Transformer architecture demonstrates the highest robustness, achieving 97.36%, marginally ahead of linear baselines such as Linear SVM (96.58%) and Logistic Regression (95.80%). While the benchmark models also demonstrate the ability to extract spatial signatures of the injection patterns, this strong accuracy retention confirms that the proposed Transformer exhibits the highest robustness among the tested architectures, remaining stable even as bubble dispersion and gas holdup shift due to uncalibrated gas throughput.

Superficial Gas Velocity Regression. The most pronounced differences between the architectures manifest in the continuous regression task. While linear models (Logistic

Regression, Linear SVM) and the standard Multilayer Perceptron (MLP) perform adequately on in-distribution data, they fail significantly when forced to predict unseen superficial gas velocities. Their Mean Absolute Error (MAE) values degrade severely exceeding the full operating range of the experiment. This sharp performance drop highlights the inherently nonlinear nature of the impedance-to-superficial-gas-velocity mapping; simpler functional approximations were not able to accurately capture the complex hydrodynamic variations occurring between the calibrated measurement points.

Tree-based models (Random Forest, XGBoost) handle this nonlinear interpolation considerably better, maintaining unseen MAE values around 0.932 mm s^{-1} . However, the proposed Transformer outperforms all baseline architectures in both regimes. It achieves the lowest in-distribution MAE (0.532 mm s^{-1}) and degrades the least on unseen data, yielding an MAE of 0.769 mm s^{-1} .

The transformer-based model maintained a higher classification accuracy on unseen data, demonstrating greater empirical robustness to the hydrodynamic variations associated with unobserved superficial gas velocities.

CONCLUSION

In this work, we demonstrated a reconstruction-free EIT framework for direct inference of reactor operating states in a bubble column from raw multifrequency boundary impedance data, thereby avoiding the ill-posed image reconstruction step and its associated smoothing artifacts. Using a 256-electrode, eight-ring measurement system in combination with IPCA-based feature compression and a Transformer model, the proposed approach enabled highly accurate prediction of injection patterns and reliable estimation of superficial gas velocities across 204 operating points and 81,600 total frames. Injection pattern classification remained near-perfect at excitation frequencies up to 100 kHz, reaching 97.4–100.0% accuracy at 1 kHz and 96.7–100.0% at 10 kHz for rings closest to the gas-injection region. Downstream electrode planes also retained substantial predictive content, whereas deterioration at 1 MHz indicated that high-frequency operation is more sensitive to hydrodynamic variability and measurement-chain nonlinearities. Notably, the classification proved robust under unseen superficial gas velocities maintaining an accuracy of 97.36%.

For quantitative superficial gas velocity estimation, the results showed that continuous prediction directly in the measurement space is highly feasible and improves markedly with denser calibration sampling. Fine-scale calibration reduced the mean absolute error (MAE) from 0.76 to 0.205 mm s^{-1} for S_3 and from 0.585 to 0.307 mm s^{-1} for S_{all} relative to coarse-scale calibration. These results indicate that performance could improve with a higher calibration density; however, this effect remains entangled with the narrower range of flow regimes and the greater volume of training data per sparger configuration present in the fine-scale setup. Given the near-perfect classification of known flow states, it is reasonable to hypothesize that similar results could be achieved in more diverse settings by conditioning the regression task on the predicted flow-state classification, a subject that remains for future research. Crucially, evaluating the predictions via a binned accuracy metric confirmed the estimator's practical reliability for discrete condition monitoring, as it preserved the correct operational region even when exact continuous

regression deviated slightly. Furthermore, benchmarking justified the selection of the Transformer architecture; while standard linear models and MLPs failed severely when interpolating unseen superficial gas velocities, the Transformer demonstrated superior nonlinear interpolation capabilities, retaining a low MAE of 0.769 mm s^{-1} on uncalibrated gas throughputs.

However, the generalization studies also define the clear operational boundaries of the proposed framework. While the model successfully interpolates missing superficial gas velocities under known spatial distributions (GenA), it struggles to quantify gas throughput accurately when confronted with entirely unseen injection patterns (GenB), where the MAE increased significantly to 2.06 mm s^{-1} . This reveals that while performance scales with calibration density along the superficial gas velocity axis, the architecture inherently relies on encountering a representative variety of spatial gas distributions during training.

Taken together, these findings establish raw-measurement-based EIT, coupled with data-driven inference, as a credible virtual sensing strategy for bubble-column monitoring without reliance on tomographic reconstruction. The successful discrimination of distinct injection patterns demonstrates that the method captures physically meaningful bulk flow structures rather than merely abstract measurement features, and robust prediction remains achievable even with reduced sensing configurations. In summary, reconstruction-free EIT combined with data-driven modeling offers a promising pathway toward simplified, industrially deployable reactor-monitoring systems capable of providing real-time insight into multiphase flow behavior.

ASSOCIATED CONTENT

Data Availability Statement

The data underlying this study are openly available in Zenodo at [10.5281/zenodo.21773393](https://doi.org/10.5281/zenodo.21773393), and the associated code is available at [10.5281/zenodo.21167281](https://doi.org/10.5281/zenodo.21167281).

Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.iecr.6c01116>.

Extended Benchmark Results, including full-electrode and electrode-subset ablation performance tables, cross-validation metrics for consecutive splits, and generalization analyses for coarse and fine-scale data sets (PDF)

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Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the collaborative research program SMART Reactors, funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation; SFB 1615- 503850735), for making this work possible.

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