Title: AI-Driven Real-Time Detection and Monitoring of Static and Dynamic Instabilities of Developing Two-Phase Flows in Vertical Pipes

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Understanding and controlling two-phase flow development in vertical pipes is crucial for optimizing the performance of gas-lift systems. Flow instabilities are not just operational challenges—they directly impact production efficiency, pressure stability, and overall system reliability. Poorly managed flow development can lead to oscillatory behavior, severe fluctuations in liquid delivery, and even chaotic, uncontrolled flow regimes, ultimately reducing the effectiveness of gas-lift operations and increasing operational costs. This presentation introduces an AI-driven, scale-independent diagnostic framework designed for real-time detection and monitoring of both static instabilities—axial flow pattern transitions—and dynamic instabilities, including density wave oscillations and phase interaction-induced fluctuations in the developing regions of gas-lift systems. The framework offers a rapid, high-fidelity assessment of instability onset and spatiotemporal evolution, leveraging only short-duration instantaneous void fraction (i.e., gas holdup) signals to extract flow characteristics with exceptional precision. At the core of this approach lies a synergistic integration of advanced signal processing and deep learning techniques. Void fraction signals are first transformed into high-resolution time-frequency scalograms via continuous wavelet transform (CWT), capturing the intricate spectral signatures of static and dynamic instabilities. These scalograms are then processed through a custom-engineered convolutional neural network (CNN), enabling precise detection and classification of flow instabilities while tracking their evolution across spatial and temporal domains. Under low injected gas flow rates (i.e., slug flow conditions), the framework distinguishes fully unstable, quasi-unstable, quasi-stable, and near-stable states in the flow through tracking the emergence, attenuation, dissipation, and/or persistence of dynamic instability mechanisms. Conversely, at high injected gas flow rates, the framework identifies axial flow pattern transitions—characterized by the spatial propagation of static instabilities—classifying them into semi-annular, churn, churn-slug, and unstable slug flow regimes, which serve as critical indicators for optimizing gas-lift performance. Experimental validation was conducted using a laboratory-scale gas-lift system at the Multiphase Flow and Energy Lab, University of Guelph, employing both air-water and CO_2-water flows. The system comprises a 2.54-inch ID riser pipe (70D in length), designed to ensure the flow remains within the developing region. Void fraction signals were recorded at multiple spatial locations along the pipe riser using high-frequency capacitance sensors, while high-speed imaging technique provided complementary visual insights into the underlying instability dynamics. With a classification accuracy of 96% for dynamic instability monitoring and 99% for static instability detection, the framework presents a great tool for gas-lift monitoring. It offers robust, scalable solutions for real-time instability detection, improved flow stability control, and optimized production efficiency, providing opportunities for more reliable and efficient gas-lift operations. By bridging the gap between physics-driven diagnostics and data-driven intelligence, this approach establishes a path toward next-generation gas-lift automation and performance enhancement. While the framework is specifically designed for the developing region of gas-lift flows, it lays a strong foundation for extending AI-driven instability diagnostics to real-world gas-lift operations in long wellbores, where persistent instability mechanisms necessitate advanced real-time monitoring and control.