

Advancing Leak Detection in Supercritical CO₂ Pipelines: Addressing Traditional Leak Detection Challenges with Advanced Pressure Pulse Based Technology

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1 ABSTRACT

Supercritical CO₂ (sCO₂) pipelines, vital for carbon capture and storage (CCS) and gas transmission, operate at high pressures and ambient temperatures. sCO₂'s extreme compressibility, rapid phase transitions, and density sensitivity to minor temperature and pressure changes pose major leak detection challenges. Conventional methods—mass balance and computational pipeline monitoring (CPM)—struggle to separate small leaks from operational transients such as line packing, pump startups, or thermal expansions. This can result in frequent false positives, eroded operator trust, delayed responses, higher maintenance costs, and heightened risks, particularly in high-consequence areas.

An advanced negative pressure wave (NPW) system counters these limitations using ultra-high-frequency pressure sampling (1 kHz) and AI-driven signal processing. It captures leak-generated transient pressure signatures and employs machine learning to distinguish them from normal operational noise via comparison to comprehensive pattern databases, achieving high sensitivity with very low false-alarm rates.

This paper details a successful field deployment on a 12-mile, 8-inch sCO₂ pipeline segment. Using only two field processing units and pressure sensors, the system provides real-time monitoring, fast event detection, and accurate leak localization.

Commissioning featured controlled release tests down to 2% of flow rate. AI filtering reliably isolated leak signals amid sCO₂'s dynamic behavior. Outcomes from development testing, site acceptance testing, and a 3-month operational trial (including temperature fluctuations and routine activities) confirmed excellent false-positive rejection. The system markedly outperformed traditional methods in discriminating leaks from normal operational variations.

These results highlight the strengths of high-frequency NPW detection paired with AI analysis—including installation and testing strategies, quantitative metrics (detection speed, localization precision), and long-term performance. The technology promises enhanced safety, reliability, and scalability for sCO₂ pipelines supporting growing CCS networks.

Keywords: Supercritical CO₂, leak detection, negative pressure wave, machine learning, carbon capture storage, false positives, high-frequency sampling

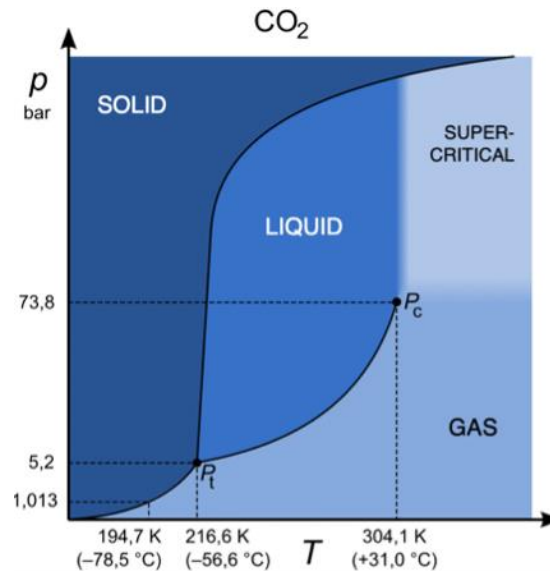
2 INTRODUCTION

2.1 BACKGROUND ON SUPERCRITICAL CO₂

Carbon dioxide (CO₂) in its supercritical state (sCO₂) is defined as CO₂ maintained above its critical point: a temperature of 88°F (31.1°C) and a pressure of 1,070 psi (7.39 MPa). At this point, the distinction between liquid and gas phases ceases to exist, resulting in a fluid that exhibits hybrid properties—gas-like viscosity and diffusivity combined with liquid-like density (typically 0.5–0.9 g/cm³). This state allows sCO₂ to expand and fill its container while maintaining high density, making it ideal for efficient transport in pipelines. However, sCO₂'s density is highly tunable and sensitive to small fluctuations in pressure and temperature, which can lead to compressible behavior more pronounced than in traditional liquids or gases.

In contrast to dense phase CO₂—a broader term encompassing high-pressure, single-phase CO₂ with liquid-like density but potentially below the critical temperature—supercritical CO₂ strictly requires conditions above both critical thresholds. Dense phase transport is common in pipelines to optimize mass flow, but sCO₂'s supercritical regime introduces additional complexities due to its proximity to the critical point, where properties like compressibility and speed of sound vary dramatically.

Figure 2-1 - Phase Diagram of Carbon Dioxide Illustrating Critical Point



The growing demand for sCO₂ pipelines stems from global efforts to mitigate climate change. The U.S. pipeline infrastructure for CO₂ is projected to expand up to 20 times by 2050, driven by carbon capture and storage (CCS) capacity growth of 16–80 times current levels. Innovative applications include using CO₂ as a carbon source for ethanol production and in enhanced oil recovery (EOR) followed by sequestration. These developments underscore the need for robust leak detection systems to ensure environmental safety, operational reliability, and regulatory compliance, particularly in regions like Texas where pipeline networks are extensive.

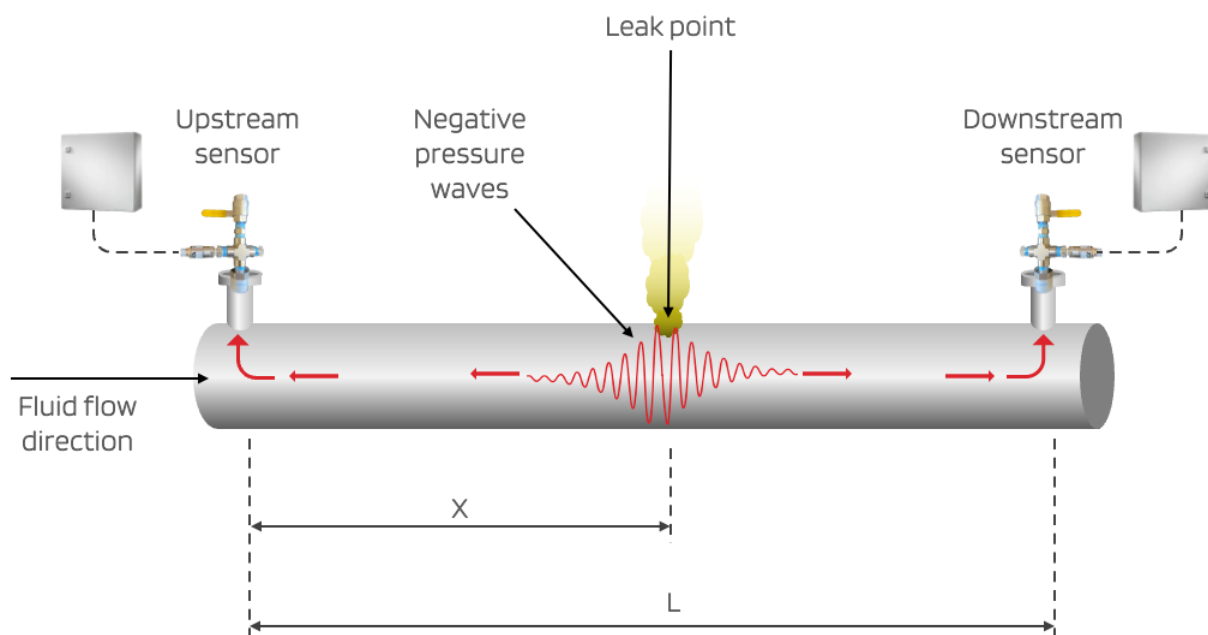
2.2 CHALLENGES IN LEAK DETECTION FOR sCO₂ PIPELINES

Supercritical CO₂ pipelines present several challenges even for more advanced model-based techniques such as real-time transient modeling (RTTM) leak detection, primarily due to the fluid's unique thermophysical properties and operational dynamics. The high compressibility, variable density, and sensitivity to impurities in CO₂-rich mixtures necessitate accurate equations of state (EOS) for modeling compressible flow, but commonly used models like Peng-Robinson^[1] exhibit non-negligible errors near the critical region, potentially leading to inaccuracies in pressure and flow predictions during transients such as pump startups or demand swings. These errors can propagate, causing false alarms when flow residuals are misinterpreted as leaks. Additionally, in multi-source CCUS networks, sudden composition changes from upstream events (e.g., plant trips) result in density variations that, if not updated in real-time due to slower composition measurement intervals compared to pressure and flow data, generate persistent positive or negative leak signals—up to 9% of flow rate in simulated cases—compromising system reliability. While high-pressure operations (>1,700 psig) mitigate some EOS inaccuracies, the need for rapid computation (simulator time orders of magnitude faster than data collection rates) and real-time boundary data from pipeline ends further complicates implementation, as does the potential for multi-phase flow during depressurization. Instantaneous

density measurements via Coriolis flowmeters can help mitigate potential errors, though density alone may not uniquely identify CO₂ composition [2].

Negative pressure wave (NPW) detection, which identifies leaks via pressure drops propagating as waves, is promising but challenged by sCO₂'s high compressibility, which dampens leak pulses. This necessitates highly sensitive thresholds, risking false positives from operational noise. Additionally, the speed of sound (SoS) in sCO₂ is highly variable—real world changes of ±5°F and ±100 psi seen during this case study can alter SoS by around ±79 ft/s, leading to leak location inaccuracies up to ±1,935 ft over a 12-mile segment with 24.5-second wave travel times.

Figure 2-2 - A schematic of the negative pressure wave method & equipment



This paper addresses these challenges through a case study of machine learning (ML) enhanced NPW system deployed on an operational sCO₂ pipeline. By integrating high-frequency pressure sampling with AI-driven analysis, the approach minimizes false alarms while achieving high detection sensitivity.

3 THEORETICAL BACKGROUND

3.1 NEGATIVE PRESSURE WAVE (NPW) PROPAGATION AND LEAK LOCALIZATION

NPW arises from a sudden pressure drop at the leak site, propagating at speed c . The leak location X from the upstream sensor is calculated as:

$$X = \frac{L + c\Delta t}{2}$$

assuming negligible fluid velocity v . More accurately, accounting for v :

$$X = \frac{(c - v)\Delta t}{(c - v) + (c + v)} \cdot L \approx \frac{(\Delta t \cdot c + L)}{2}$$

where L is segment length, Δt time difference between sensor arrivals.

3.1.1 Speed of Sound in sCO₂

The speed of sound c in a fluid is crucial for NPW propagation and leak localization. It is defined as:

$$c = \sqrt{\left(\frac{\partial P}{\partial \rho}\right)_s}$$

where the derivative is at constant entropy s . For sCO₂, c can be approximated using bulk modulus K and density ρ :

$$c = \sqrt{\frac{K}{\rho}}$$

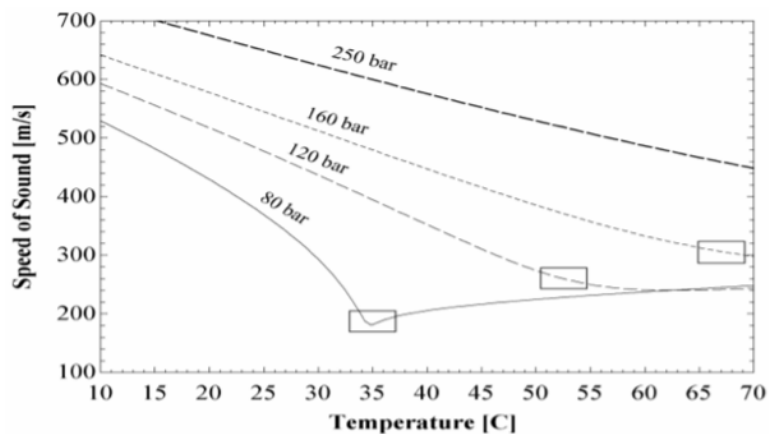
with $K = \rho \left(\frac{\partial P}{\partial \rho}\right)_s$. In pipelines, pipe wall elasticity modifies this to:

$$c = \sqrt{\frac{K}{\rho \left(1 + \frac{KD}{Ee}\right)}}$$

where D is pipe diameter, E Young's modulus, and e wall thickness.

In sCO₂, c varies significantly near the critical point.

Figure 3-1 – Speed of Sound in CO₂ Under Supercritical Conditions^[3]



4 METHODOLOGY

4.1 SYSTEM DESIGN AND NPW PRINCIPLES

The leak detection system employs an advanced NPW method, utilizing two FPUs positioned at the ends of the pipeline segment. Each FPU is equipped with high-sensitivity pressure sensors sampling at rates sufficient to capture transient pulses (typically 1 kHz). The core principle involves detecting the negative pressure wave generated by a leak, which propagates at the fluid's SoS.

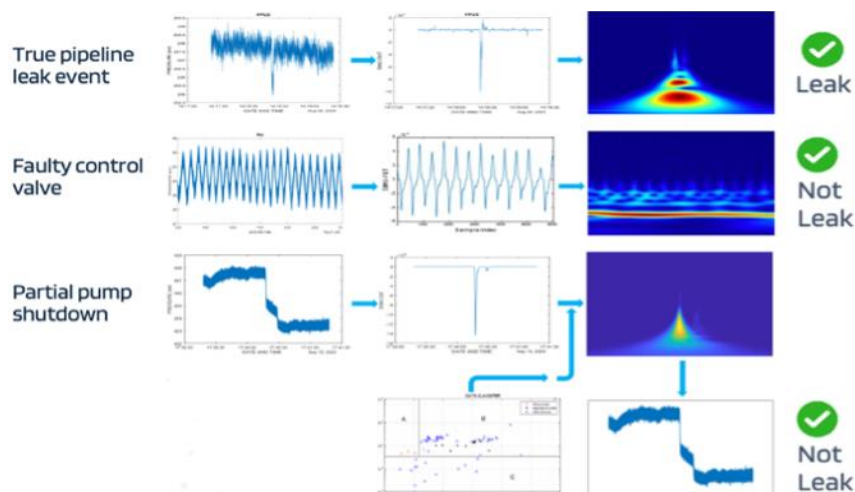
Traditional NPW systems use single thresholds set against background noise, but in sCO₂, high levels of pressure pulse attenuation require thresholds that are tighter to background hydraulic noise, potentially increasing false positive rates. To mitigate this, the system incorporates multi-stage filtering (Figure 4-1):

1. **Data Filtering and Thresholding:** Initial edge-based filtering removes noise, with potential leak events being captured and transmitted by each Field Processing Unit (FPU) to a common remote server for further analysis
2. **Initial Thresholding:** Initial thresholding is set off of short 1-3 second physical test releases of fluid from the pipeline at the required leak threshold size, and longer-term sampling of normal and abnormal (non-leak) operation.
3. **3D Frequency Conversion:** Potential leak events from each FPU are converted to 3D spectrograms (frequency-time-amplitude) for ML classification.
4. **Additional Filtering Methods:** For more dynamic pipeline systems that present pressure anomalies with similar filtered and frequency properties, additional filtering methods such as variable thresholding and 1D pressure shape analysis can be employed.

The 3D spectrogram ML model is trained on a dataset of over 42,000 images, including normal pipeline operations, pressure events, anomalies, and simulated leaks. This dataset encompasses diverse fluids—crude oil, natural gas, water, liquid gas products, and dense phase / supercritical CO₂—to generalize across behaviors.

Deployed filters, thresholds, and methods are adaptable based on pipeline-specific behavior, allowing customization for sCO₂'s dynamic properties.

Figure 4-1 – Example of Multi-Stage Filtering



4.2 ESTABLISHING INITIAL SPEED OF SOUND

The initial value for speed of sound under normal pipeline operating conditions is established by performing a controlled short pressure release at one of the pressure sensor manifolds and capturing that pulse at a second pressure sensor a known linear distance away. Using accurately time stamped data (common time from GPS satellite), the time of flight is established and speed of sound calculated.

5 CASE STUDY: DEPLOYMENT ON 12-MILE sCO₂ PIPELINE

5.1 PIPELINE DESCRIPTION

The case study pipeline is a 12-mile, 8-inch line transporting sCO₂ at approximately 2,000 psi from a compressor station to a client handoff point. The terrain includes urban and rural areas, with potential high-consequence zones. Two FPU's were installed, one at each end of the pipeline segment.

5.2 SYSTEM DEPLOYMENT AND TESTING PROTOCOL

The system was deployed on a 12-mile, 8-inch sCO₂ pipeline operating at ~2,000 psi between a compressor station and client handoff. Commissioning on September 16, 2025, took 30 minutes per site. Initial calibration involved short (~2 s) releases via 3/8-inch (5% flow) and 1/4-inch (2% flow) orifices at far-end and mid-point locations. Data was processed offline to select filtering algorithms, followed by an initial two weeks of monitoring for false positives.

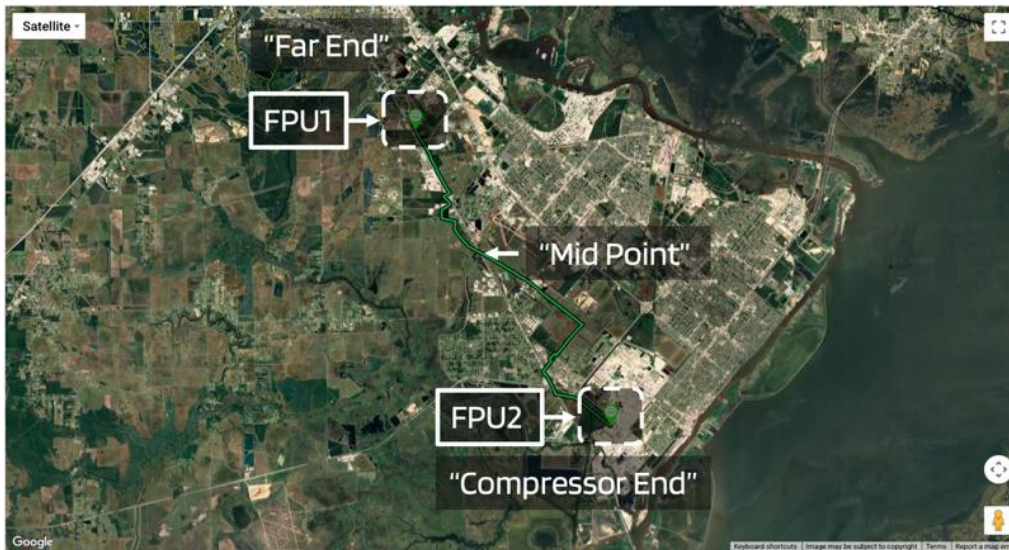
Subsequent tests (November 6, December 9, 15, 19, 2025) simulated leaks at compressor-end, mid-point, and far-end, addressing issues like release manifold icing during pressure release and noise due to an unexpected loss of compression.

The pressure release manifold used for testing, typical FPU installation and pressure sensor manifold is shown in Figure 5-1. The pipeline and installation locations are shown in Figure 5-2.

Figure 5-1 – Typical Equipment Installations



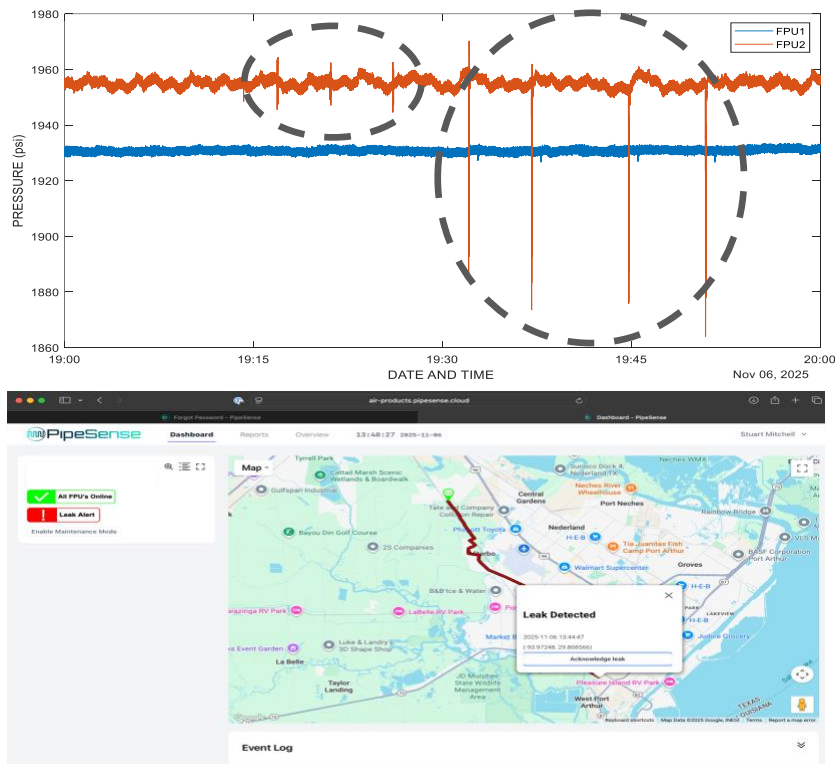
Figure 5-2 – Pipeline and Installation Locations



5.3 FIRST RELEASE TESTS (NOVEMBER 6, 2025)

Releases included 4×3/8-inch and 3×1/4-inch at compressor-end and far-end. All 3/8-inch leaks were detected and mapped within 3 minutes, with location accuracy <10 ft. No 1/4-inch detections occurred, revealing a large energy drop not attributable to orifice size variation alone. Investigations pointed to attenuation due to leak release manifold configuration / location versus actual through-wall leaks. See Figure 5-3.

Figure 5-3 – First Release Pulses and Mapping



5.4 RELEASE POINT ATTENUATION ANALYSIS

Re-testing separated the release point from the sensor manifold in order to measure the attenuation due to release point configuration / location, noting 94%–98% attenuation. A key discovery: the 1/4-inch releases were actually 1/8-inch due to incorrect orifice fitting selection, requiring additional retesting.

5.5 ACCEPTANCE TESTS (DECEMBER 9, 15, 19, 2025)

- **December 9:** 5 × 3/8-inch and 5 × 1/4-inch at compressor-end; 2 × 3/8-inch and 3 × 1/4-inch at mid-point. Far-end testing was compromised by icing. All 3/8-inch detected; 1 × 1/4-inch at compressor-end, 3 × 1/4-inch at mid-point. Detection <3 minutes; compressor-end accuracy <20 ft, mid-point average 191 ft.
- **December 15:** Far-end attempts faced noise from partial compressor loss. New more advanced bandpass edge filtering was developed, and re-testing planned.
- **December 19:** 5 × 3/8-inch and 4 × 1/4-inch at far-end. All 3/8-inch detected; 2 × 1/4-inch detected. Detection <3 minutes; accuracy <10 ft.

These tests equated to leak sizes of between 2% and 4.5% of flow in the 8-inch line. No additional refinement was pursued as the client required thresholds had been met.

Figure 5-4 – Leak Analysis Example and Mid-Point Mapping

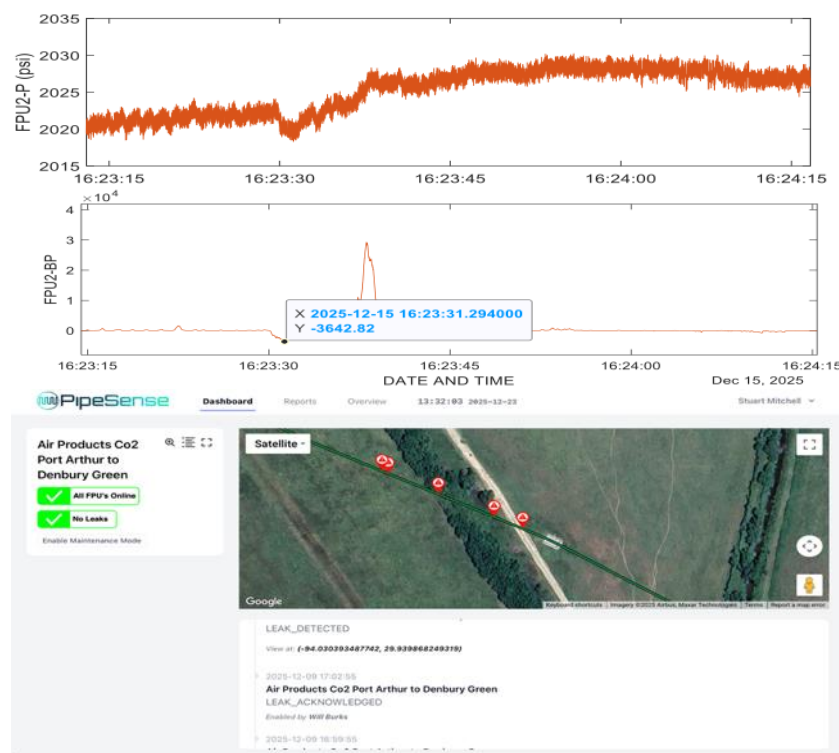


Table 5-1 - Testing Results Summary

Leak #	Date	Location	Size (inch)	Detected & Mapped	Time	Location Difference (ft)
1	12.09.25	Valero PA	1/4	No	-	-
2	12.09.25	Valero PA	1/4	No	-	-
3	12.09.25	Valero PA	1/4	Yes	< 3 minutes	<10
4	12.09.25	Valero PA	1/4	No	-	-
5	12.09.25	Valero PA	1/4	No	-	-
6	12.09.25	Valero PA	3/8	Yes	< 3 minutes	<10
7	12.09.25	Valero PA	3/8	Yes	< 3 minutes	<10
8	12.09.25	Valero PA	3/8	Yes	< 3 minutes	<10
9	12.09.25	Valero PA	3/8	Yes	< 3 minutes	<10
10	12.09.25	Valero PA	3/8	Yes	< 3 minutes	<10
11	12.09.25	MLV2	1/4	Yes	< 3 minutes	49
12	12.09.25	MLV2	1/4	Yes	< 3 minutes	100
13	12.09.25	MLV2	1/4	Yes	< 3 minutes	204
14	12.09.25	MLV2	3/8	Yes	< 3 minutes	299
15	12.09.25	MLV2	3/8	Yes	< 3 minutes	302
-	12.09.25	3514 Valve Site	Testing abandoned due to icing issues and use of incorrect release manifold			
16	12.19.25	3514 Valve Site	1/4	Yes	< 3 minutes	<10
17	12.19.25	3514 Valve Site	1/4	No	-	-
18	12.19.25	3514 Valve Site	1/4	Yes	< 3 minutes	<10
19	12.19.25	3514 Valve Site	1/4	No	-	-
20	12.19.25	3514 Valve Site	3/8	Yes	< 3 minutes	<10
21	12.19.25	3514 Valve Site	3/8	Yes	< 3 minutes	<10
22	12.19.25	3514 Valve Site	3/8	Yes	< 3 minutes	<10
23	12.19.25	3514 Valve Site	3/8	Yes	< 3 minutes	<10
24	12.19.25	3514 Valve Site	3/8	Yes	< 3 minutes	<10

6 REVIEW OF RESULTS

6.1 DETECTION PERFORMANCE

The system detected 3/8-inch (4.5% flow) reliably, and 1/4-inch (2% flow) leaks with further filtering refinement. Notifications were all within 2–3 minutes. Location precision was generally <20 ft, with mid-point location accuracy averaging 191ft. Zero false positives and zero downtime were observed over the 90-day formal monitoring period.

6.2 ATTENUATION AND ENERGY INSIGHTS

Attenuation studies showed 94%–98% signal loss when releases were not directly on the main line, emphasizing the need for realistic simulation. The orifice error highlighted the importance of verification in field testing. Through attenuation modeling, predicted decay matched observations.

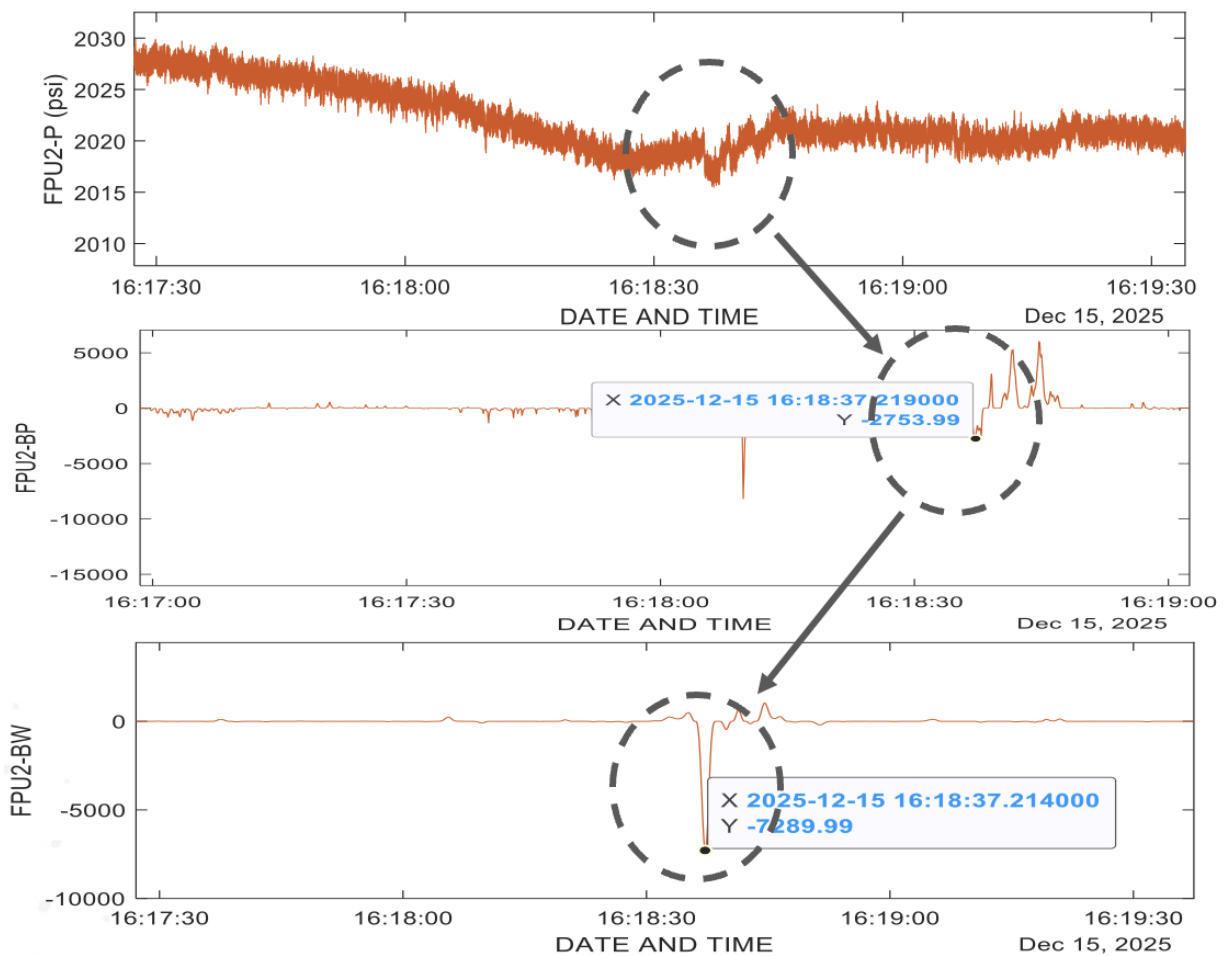
6.3 SPEED OF SOUND VARIABILITY

The average location error during final testing was on average 60.2ft. Using real-time speed of sound updates based on detecting and analysis outside propagated events is necessary for maintaining location accuracy in sCO₂. For instance, based on a 24.5-second mid-to-end travel time and speed of sound variation of 79 ft/s, location accuracy could vary by ±1,935 ft without correction.

6.4 NOISE HANDLING

Advanced filtering managed compressor noise effectively, allowing marginal thresholds without compromising reliability. Figure x shows filtering progression to maintain detection sensitivity through challenging compressor noise.

Figure 6-1 – Leak Analysis Example and Mid-Point Mapping



7 DISCUSSION

7.1 ADVANTAGES OVER TRADITIONAL METHODS

Unlike RTTM, which depends on accurate mass flow and EOS, the NPW-ML approach relies solely on pressure pulses, making it resilient to density-driven imbalances. The stage gate-based approach, with edge-based screening along with ML database's diversity allows for leak sensitivity without generating false positives, even in a hydraulically noisy environment.

7.2 SCALABILITY

The system's simplicity—two FPU's / pressure sensors, and flexibility in dashboard interface deployment—facilitates scaling to larger CCS networks, many of which will be required by the expected growth in CO₂ pipelines.

7.3 IMPLICATIONS FOR CCS EXPANSION

With U.S. CO₂ pipelines expected to grow 20x by 2050, this technology enhances safety, minimizing environmental risks from undetected leaks. It supports innovative uses like CO₂-to-ethanol processes and EOR-sequestration, aligning with net-zero goals.

8 CONCLUSION

This paper demonstrates the efficacy of an ML-enhanced NPW system for leak detection in sCO₂ pipelines. Through a real-world case study, we achieved sensitive, accurate detection with minimal false alarms, addressing key challenges like attenuation, SoS variability, and noise. Pressure pulse-based methods offer a superior, mass-flow-independent alternative, paving the way for reliable monitoring in expanding CCS infrastructure.

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