Engineering and Technology Journal e-ISSN: 2456-3358

Volume 11 Issue 06 June-2026, Page No.- 10607- 10625

DOI: 10.47191/etj/v11i06.37, I.F. – 8.595

Passive Acoustic Monitoring of Leaks in Underwater Wells and Pipelines

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ABSTRACT: Subsea wells and pipelines are critical components of offshore energy systems, water management networks, and industrial fluid transport infrastructure. Undetected leaks carry severe consequences, including environmental contamination, significant financial loss, and safety hazards for personnel and communities. Traditional inspection approaches, including diver-based surveys and active sonar scanning, are expensive, intermittent, and often impractical in deepwater environments. Passive Acoustic Monitoring (PAM) offers a compelling non-intrusive alternative: rather than emitting signals and analysing echoes, PAM simply listens, capturing the acoustic fingerprints naturally produced by escaping fluid, bubble formation, turbulence, and structural vibration (Zimmer, 2011; Van Parijs et al., 2009).

Modern PAM systems deploy hydrophones and distributed acoustic sensing (DAS) networks to capture signals across wide frequency ranges (Ferguson et al., 2010; He and Liu, 2021). These raw signals are processed through signal processing pipelines, pattern recognition algorithms, and machine learning tools to separate meaningful leak signatures from background noise whether from ship traffic, marine life, or ocean currents (Siddique et al., 2023; Gemeinhardt and Sharma, 2023). Time-frequency analysis, spectral density estimation, and automated feature extraction have all improved how reliably these systems identify and classify leak events (Ghazali et al., 2012; Ahadi and Bakhtiar, 2010).

When PAM is integrated with autonomous underwater vehicles or fixed seabed sensor arrays, it becomes capable of covering large, complex pipeline networks in real time (Premus et al., 2022; Eleftherakis and Vicen-Bueno, 2020). Challenges remain: false positives are still a persistent problem, sensor placement requires careful planning, and consistent performance in noisy or variable environments is not always straightforward (Van Walree, 2013; Stojanovic and Preisig, 2009). Active research continues on multi-modal sensing, adaptive signal processing, and AI-driven localization to push detection sensitivity and spatial accuracy further. Taken together, PAM holds genuine promise for transforming subsea asset monitoring, enabling early leak identification, reducing environmental damage, and improving operational efficiency across both mature offshore markets and rapidly expanding developing economies.

KEYWORDS: Passive acoustic monitoring, underwater leak detection, hydrophones, distributed acoustic sensing, pipeline integrity, subsea infrastructure, anomaly detection, signal processing, autonomous monitoring, predictive maintenance.

1. INTRODUCTION

Subsea wells and pipelines are, in many ways, the hidden infrastructure that makes offshore energy systems work. They transport oil, natural gas, and industrial fluids from production sites to processing facilities and distribution networks, often spanning hundreds or thousands of kilometres under high pressures, in corrosive seawater, and through constantly changing ocean conditions (Kishawy and Gabbar, 2010; Bai and Bai, 2014). Maintaining the reliability and integrity of these systems is not merely a technical priority, it is a safety and environmental imperative. A breach anywhere along that chain can cascade into production delays, environmental disasters, and long-term damage to marine ecosystems.

The consequences of undetected leaks are multi-layered. Escaping hydrocarbons or chemicals harms marine habitats, degrades water quality, and damages aquatic biodiversity. From a safety standpoint, undiscovered leaks pose risks to offshore workers, vessels, and nearby equipment (Du et al., 2023; Etiope et al., 2002). Economically, operators face resource loss, emergency response costs, regulatory fines, and lasting reputational damage. All of this makes a strong case for monitoring systems that can detect problems early and respond quickly (Wegner et al., 2023; Bai and Bai, 2014).

Traditional leak detection tools have real limitations. Visual inspections by divers or ROVs are constrained by underwater visibility and are impractical for deepwater or extended pipeline networks. Chemical sensors can be slow and tend to miss intermittent or low-level leaks. Active sonar systems are energy-intensive, susceptible to external noise, and cannot run continuously (Malcher and White, 2023; Mahmutoglu and Turk, 2018). On their own, these approaches are insufficient for the round-the-clock, comprehensive monitoring that modern subsea infrastructure demands.

Passive Acoustic Monitoring steps into this gap. PAM relies on the sounds that leaks naturally produce — fluid escaping under pressure, bubbles forming and collapsing, and structural vibrations in pipe walls and well casings (Sharma, 2013; Giro et al., 2022). By recording and analyzing these signals with hydrophones or distributed acoustic sensing networks, PAM can continuously monitor for leaks, localize them with reasonable precision, and do so without requiring physical intervention (Ross et al., 2023; Gibb et al., 2019).

This paper examines how PAM is being applied to offshore wells and pipeline systems. It covers the core technical principles, sensor architectures, signal processing, and AI methods driving detection accuracy, and a realistic assessment of where PAM stands today and what limitations remain. Two additional sections address future directions and real-world field applications, offering a forward-looking perspective on where the technology is heading and how it has already been deployed in operational contexts (Wegner et al., 2021a; Wegner et al., 2023).

2.0 METHODOLOGY

This review drew on a structured literature search across four major academic databases: Scopus, Web of Science, IEEE Xplore, and ScienceDirect, covering publications from 2000 to 2025. Search terms included combinations of phrases such as "passive acoustic monitoring," "underwater pipeline leak detection," "hydrocarbon leak monitoring," "subsea acoustic sensors," and "leakage detection systems," with Boolean operators and synonyms used to ensure comprehensive coverage.

After initial retrieval, duplicates were removed, and the remaining studies were screened by title and abstract against predefined inclusion and exclusion criteria. Studies were included if they applied passive acoustic monitoring to leak detection in underwater pipelines or wells, reported experimental, field-based, or simulation results, and were published in English in peer-reviewed journals or conference proceedings. Work focused on active acoustic methods, non-pipeline leak contexts, or editorial pieces was excluded. Full-text review then confirmed eligibility, with emphasis on studies addressing sensor configurations, acoustic signal analysis, detection performance, or deployment strategies.

Data were extracted using a standardized form capturing sensor types, deployment configurations, frequency ranges, signal processing algorithms, detection thresholds, operational environments, and reported outcomes. Quality assessment evaluated methodological rigor, experimental design, and practical applicability. Extracted findings were synthesized qualitatively to identify patterns across sensor technologies, signal processing approaches, and deployment strategies, providing a comparative picture of current capabilities and where gaps remain.

The review followed PRISMA guidelines throughout, with flow documentation tracking the number of studies identified, screened, excluded, and retained at each stage to ensure transparency and reproducibility.

2.1 Underwater Leak Phenomenology

To use PAM effectively, it helps to understand how underwater leaks actually behave, what causes them, how they manifest physically, and what kinds of sounds they produce. Subsea pipelines and wells operate under demanding conditions: high pressures, fluctuating fluid compositions, and a dynamic ocean environment all contribute to the complexity of leak detection and characterization (Du et al., 2023; Sharma, 2013).

Leaks can originate in several ways. Pinhole leaks form from localized corrosion, minor coating damage, or material imperfections (Cosham and Hopkins, 2002; Amirat et al., 2006). Despite their small size, these quietly accumulate significant fluid loss over time and still generate detectable acoustic signals. Pressurized fluid squeezing through a tiny orifice produces characteristic high-frequency turbulent noise. More serious are propagating cracks, which tend to develop in high-stress areas such as weld seams, pipeline bends, and around high-pressure valves. Left unchecked, crack propagation can lead to rupture, a sudden, uncontrolled release of fluid or gas that produces intense acoustic energy (Zhu and Leis, 2012; Etiope et al., 2002).

From a PAM perspective, the physical behaviour of escaping fluids determines what sounds are produced. When pressurized fluid forces its way through a defect, it expands rapidly into the surrounding water, creating turbulent jet noise whose intensity reflects the fluid velocity, pressure differential, and opening size (Malcher and White, 2023; Giro et al., 2022). Smaller pinholes produce predominantly high-frequency signals; larger breaches generate broadband noise with substantial low-frequency content (Bie et al., 2016).

Gas leaks introduce additional acoustic complexity through bubble dynamics. Escaping gas forms microbubbles that oscillate and collapse, producing brief but distinctive acoustic pulses across a wide frequency range (Peng et al., 2021; Mahmutoglu and Turk, 2018). Bubble collapse events in particular can generate high-amplitude spikes that stand out clearly against background noise. Flow-induced vibrations and structural resonance further shape the acoustic signature. Fluid interacting with the pipeline wall sets off mechanical vibrations that propagate through the structure and can either amplify or modulate the leak signal (Shi et al., 2022).

Gas and liquid leaks have different frequency-domain characteristics. Gas leaks tend to produce higher-frequency components driven by rapid bubble formation and burst; liquid leaks generate lower-frequency broadband noise tied to turbulent jets and wall vibrations. This spectral difference gives PAM systems a way to not only detect leaks but to infer what type of leak is occurring and where (Garbatov et al., 2022; Du et al., 2023).

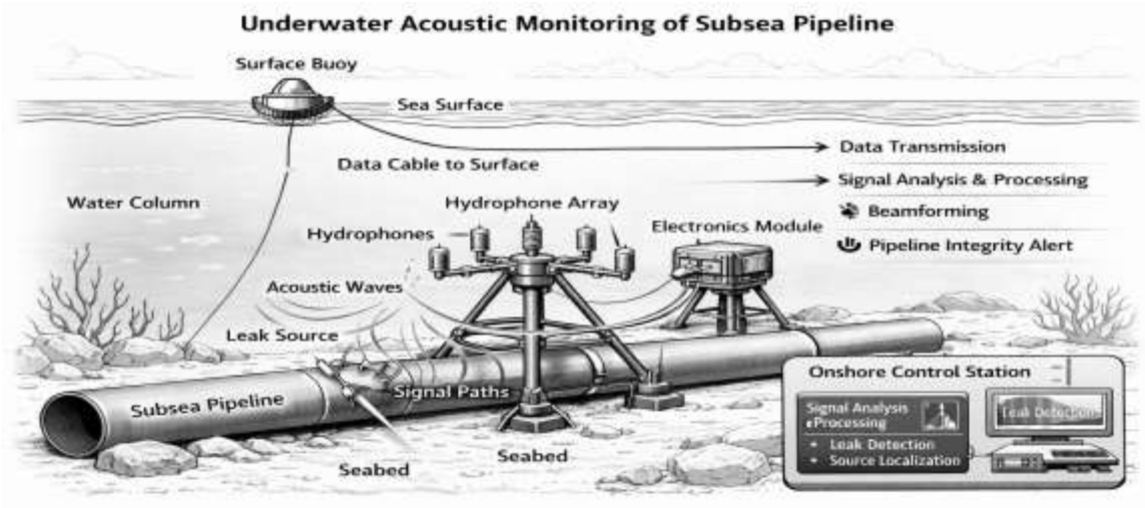

Figure 1: Illustration of acoustic emissions produced by an underwater pipeline leak — including turbulent jet noise, bubble oscillation, and structural vibration signatures captured by a subsea hydrophone array (Malcher and White, 2023; Giro et al., 2022)

The acoustic properties of escaping fluid are additionally influenced by the acoustic impedance mismatch between the transported medium and the surrounding seawater. When high-pressure gas or liquid pushes through a hole in a subsea pipeline wall, it enters a medium with very different acoustic properties. This causes some of the acoustic energy to bounce back into the pipe structure and some to move into the water column. The pressure difference, the shape of the breach, and the densities of the fluids all affect the ratio of transmitted to reflected energy. When gas leaks, the difference in impedance between the escaping gas and seawater is very high. This means that even small volumetric flow rates can make acoustic signatures that hydrophones placed meters or tens of meters away from the source can pick up (Giro et al., 2022; Bie et al., 2016). For liquid leaks that carry oil or produced water, the impedance contrast is lower, but turbulent jet formation makes up for it by creating wideband pressure fluctuations that spread quickly through the surrounding ocean.

The depth of the water makes it even harder to understand how leak acoustics work and spread. At shallow depths, hydrostatic pressure is not very high. This means that the gas that escapes expands quickly when it is released, and the bubbles are bigger, which lowers the dominant frequencies in the oscillation spectrum. In deeper water, high hydrostatic pressure stops bubbles from growing, which makes them smaller and higher-frequency oscillating bubbles with collapse signatures that are more compact and have more high-frequency content (Peng et al., 2021; Mahmutoglu and Turk, 2018). Because of this depth dependence, PAM systems that were made and set up for monitoring pipelines in shallow water may need to have their frequency bands and detection thresholds adjusted when they are used in deepwater fields. Well annulus leaks at subsea wellheads are a different kind of problem. The annular shape acts like a resonant cavity, amplifying some frequencies and reducing others. This creates a unique spectral signature that is very different from open-pipe leaks and needs special signal processing.

The Reynolds number of the flow that is escaping controls the change from laminar to turbulent leak regimes, which in turn controls the sound output. When the flow is slow and there are only a few small defects, it stays laminar and quiet. But when the flow speed increases past the turbulent transition threshold, the sound output rises sharply and spreads out over a wider range of frequencies. For PAM detection, this means that the severity of a leak and how easily it can be heard are not always the same: a big, slow leak through a corroded area under low differential pressure may be quieter than a small, high-pressure pinhole. To set the right detection thresholds and correctly understand when there isn't a strong signal, you need to know how flow regime, pressure differential, and acoustic output are related (Malcher and White, 2023; Du et al., 2023; Giro et al., 2022).

2.2 Fundamentals of Passive Acoustic Monitoring

At its core, Passive Acoustic Monitoring is straightforward: rather than generating signals and analyzing what bounces back, PAM simply listens. It captures the sounds that are already present, produced by fluid flow, structural vibrations, gas release, or any other acoustic activity in the monitored environment. This makes it inherently non-intrusive and well-suited to continuous operation, since no active energy is being put into the system (Zimmer, 2011; Sugai et al., 2019).

PAM works underwater by deploying hydrophones or other sensitive acoustic transducers that convert pressure variations in the water into electrical signals. Those signals are then amplified, filtered, and analyzed, examining frequency content, amplitude patterns, and temporal characteristics to distinguish normal operating sounds from anything suggesting a leak or structural problem (Van Parijs et al., 2009; Ross et al., 2023).

The distinction between passive and active acoustic approaches matters in practice. Active systems like sonar or ultrasonic testing equipment emit controlled sound pulses and measure what reflects back. They can provide high-resolution spatial data but also introduce acoustic energy into the environment, potentially disturbing marine life or altering local fluid dynamics. PAM avoids this entirely, imposing no additional acoustic burden and running for extended periods without disrupting what is being monitored (Gibb et al., 2019; Tramontana et al., 2011).

This passive approach carries several practical advantages. PAM systems can operate for long periods with minimal maintenance, building datasets that support trend analysis, early warning systems, and predictive maintenance scheduling. Continuous monitoring catches transient events, small pressure variations, and brief leak signatures that periodic inspections would miss. PAM's low-intrusion profile is especially valuable in sensitive marine environments where invasive methods would be problematic. And because hydrophone arrays are scalable, PAM can be extended to cover complex multi-segment pipeline networks without proportionally increasing complexity (Sugai et al., 2019; Van Parijs et al., 2009).

PAM does have limitations. Background noise from ship traffic, marine life, weather, and ocean turbulence can mask or distort the signals of interest. Environmental factors, including temperature gradients, salinity, pressure, and seabed composition, all affect how sound travels through water, introducing variability that complicates source localization and signal classification. PAM also provides limited information about the physical dimensions of a detected anomaly, often requiring complementary techniques for quantification (Gibb et al., 2019; Ross et al., 2023). Sensor placement is critical; poorly positioned hydrophones create blind spots or yield ambiguous localization results, and extracting useful information from raw acoustic data requires both specialized expertise and robust computational tools.

2.3 Acoustic Sensor Technologies

The effectiveness of any PAM system depends heavily on the quality and configuration of its sensors. In subsea and pipeline monitoring, two technologies dominate: hydrophone systems and distributed acoustic sensing (DAS). Each has distinct strengths, and how they are deployed shapes what a monitoring system can realistically detect.

Hydrophones remain the workhorse of underwater acoustic monitoring. They convert pressure changes in the surrounding fluid into electrical signals, capturing everything from low-frequency structural vibrations to the high-pitched sounds associated with small leaks (Ferguson et al., 2010; Foote, 2008). Hydrophones come in broadband and narrowband varieties. Broadband units capture a wide range of frequencies, making them versatile for different leak signatures; narrowband units are tuned to specific frequency ranges, improving signal-to-noise ratios when the target signature is well understood. Key performance parameters include sensitivity, dynamic range, and noise floor (Campopiano et al., 2009; Cranch et al., 2003). Fiber-optic interferometric hydrophones have emerged as a particularly powerful development, offering large-scale remote interrogation of sensor arrays across extensive subsea infrastructure (Cranch et al., 2003; Plotnikov et al., 2019). Both directional and omnidirectional configurations are used: directional units for source localization, omnidirectional designs for broader environmental awareness (Murad et al., 2015).

Distributed Acoustic Sensing represents a major leap in monitoring scale. Rather than discrete sensor nodes, DAS uses optical fiber cables as continuous sensing elements detecting acoustic disturbances along their entire length by analyzing backscattered laser light (He and Liu, 2021; Zhan, 2020). This turns existing fiber-optic infrastructure into a densely sampled sensing array, which is particularly attractive in subsea environments where fiber cables are already installed for telecommunications or control systems. DAS delivers high spatial resolution, the ability to pinpoint acoustic events to specific locations along the fiber, and can do so in real time (Daley et al., 2013; Molenaar and Cox, 2013). Research has demonstrated DAS performance across a range of geotechnical and seismic applications, confirming its sensitivity and reliability in complex environmental conditions (Rossi et al., 2022; Farghal et al., 2022).

Table 1: Comparison of primary PAM sensor technologies for subsea leak detection

Technology	Operating principle	Spatial coverage	Key strength	Key limitation
Hydrophone (broadband)	Pressure-to-electrical conversion	Point / array	Wide frequency capture; versatile	Discrete nodes; placement critical

Hydrophone (fiber-optic)	Interferometric sensing	Large-scale arrays	Remote interrogation; low noise floor	Complex infrastructure; higher cost
Distributed Acoustic Sensing (DAS)	Backscattered laser light analysis	Continuous along fiber (km-scale)	Full-length coverage; uses existing cables	Sensitive to cable noise; high data volume
AUV-mounted hydrophone	Mobile pressure sensing	Adaptive / targeted	On-demand survey; reaches complex geometries	Mission duration limited by power

Table 1: Comparison of primary PAM sensor technologies for subsea leak detection — operating principles, spatial coverage, and performance trade-offs (Ferguson et al., 2010; He and Liu, 2021; Cranch et al., 2003; Premus et al., 2022).

Deployment configuration is as important as sensor selection. Fixed seabed arrays provide ongoing surveillance of offshore structures or subsea pipelines. Pipeline-mounted acoustic nodes are attached directly to the infrastructure, offering highly localized structural monitoring and early leak detection. At production wells, systems integrate hydrophones or DAS interfaces with existing wellhead control equipment, enabling anomaly detection right at the source. Mobile platforms, including autonomous underwater vehicles and ocean gliders, provide flexible, on-demand monitoring that complements static arrays (Premus et al., 2022; Gillespie et al., 2022). Seismic acquisition systems using autonomous marine vehicles towing 3D sensor arrays have demonstrated that large-scale spatial coverage is achievable without permanent infrastructure (Pai et al., 2017).

2.4 Signal Propagation and Environmental Effects

Even with excellent sensors in place, the acoustic signals a PAM system captures reflect more than just what is happening at the leak site. Sound in underwater environments is shaped by the medium it travels through, and the ocean is far from a uniform, predictable medium. Temperature, salinity, pressure, water depth, seabed composition, and ambient noise all leave their mark on how signals behave between source and sensor (Hovem, 2007; Stojanovic and Preisig, 2009).

Shallow water, typically less than 200 meters, creates a particularly complex acoustic environment. Sound reflects repeatedly between the seafloor and the surface, producing a mix of constructive and destructive interference patterns. The resulting multipath propagation distorts signals and reduces signal-to-noise ratios. Shallow environments also tend to have higher acoustic attenuation from surface turbulence and bottom absorption that further limits detection range (Preisig, 2007; Llor and Malumbres, 2012).

Deep water behaves differently. Sound can be channeled horizontally through structures like the SOFAR channel, where refraction effects guided by vertical gradients in temperature, salinity, and pressure enable efficient acoustic energy propagation over long distances. While surface turbulence is less of a factor at depth, other features, such as seamounts, thermoclines, and irregular seafloor topography, can still cause scattering and signal loss (Van Walree, 2013; Wegner et al., 2021a). Sensor placement needs to account for these depth-dependent propagation characteristics to maximize signal reception.

The water column itself introduces variability through vertical gradients in temperature, salinity, and pressure, all of which affect the speed of sound. These gradients cause acoustic refraction: sound waves bend upward or downward as they pass through layers with different sound speeds. Thermoclines, with their sharp temperature boundaries within the water column, can create acoustic shadow zones where signals are substantially weakened or lost entirely. For accurate leak localization, these gradients need to be carefully modelled (Hovem, 2007; Stojanovic and Preisig, 2009).

The seabed also plays an active role. When sound reaches the ocean floor, some energy reflects, some is absorbed, and some scatters, depending on sediment type, roughness, and composition. In areas with rocky outcrops or irregular topography, secondary arrivals from scattered reflections can be mistaken for leak events if propagation models are not site-specific (Preisig, 2007; Van Walree, 2013). Background noise is ever-present: marine animals contribute wideband acoustic energy across leak-relevant frequencies, vessel traffic introduces low-frequency propulsion noise, and wind, rain, and wave action create surface turbulence and bubble-related noise that varies seasonally and diurnally (Larsen and Radford, 2018; Llor and Malumbres, 2012). Distinguishing a genuine leak signal from this dynamic acoustic backdrop requires adaptive filtering, statistical noise modelling, and careful analysis (Long et al., 2003).

Seasonal and temporal fluctuations in ocean thermal structure directly impact PAM system performance, which are frequently underestimated during deployment planning. In temperate and high-latitude areas, the surface heating in the summer makes a strong thermocline that keeps sound waves from reaching sensors that are deeper in the water column. Winter cooling breaks down this stratification, making the sound speed profile more even and allowing it to travel over longer vertical distances. This means that the effective detection range for a fixed sensor array that is monitoring a subsea pipeline can change a lot from season to season. Alarm thresholds or sensitivity settings that work well in one season may not work as well in another (Hovem, 2007; Stojanovic and Preisig, 2009). Because of this, routine environmental surveys and oceanographic models are not just something to think about when deploying PAM, but something that needs to be done all the time to keep PAM working well all year.

There is a big difference between near-field propagation near a leak source and far-field behavior. This difference is important for designing PAM systems for specific pipeline uses. In the near field, within a few pipe diameters of the defect, the direct source characteristics, turbulent jet noise, bubble formation, and structural vibration dominate the acoustic signals. There is not much change in the environment. When signals reach the far field, reflections from the pipe wall, the seabed, and the water surface start to mix with the direct signal. This makes time-of-arrival estimates harder to make and makes the signal less coherent. Near-field models are good for pipeline-mounted acoustic nodes that are close to possible leak sites. Far-field propagation models, such as multipath and environmental gradients, must be used for reliable source localization for remote hydrophone arrays or DAS-based systems that cover long pipeline segments (Van Walree, 2013; Preisig, 2007).

Biological noise from marine life is a source of acoustic interference that changes a lot depending on the area, depth, and time of year. It is also often not given enough weight in the design of PAM systems. In tropical and subtropical shallow waters, snapping shrimp colonies make a lot of crackling noise that can directly overlap with high-frequency leak signatures. Sounds made by whales, fish singing together during spawning, and urchins grazing all add energy across frequencies that are important for leak detection. In areas with a lot of marine life or vocal species that come together at certain times of the year, biological noise floors can rise by 10 to 20 decibels above non-biological ambient levels. This makes it much harder to detect passive signals (Larsen and Radford, 2018; Van Walree, 2013). Plans for deploying PAM in areas with a lot of biodiversity should include baseline acoustic surveys to describe the biological noise environment throughout the year. Detection algorithms should also be tested against noise datasets that include real biological interference instead of just abiotic noise models.

2.5 Signal Processing and Feature Extraction

Raw acoustic data from hydrophones is rarely clean or straightforward; it is typically high-dimensional, noisy, and filled with signals from sources other than the leak of interest. Signal processing transforms this raw input into something meaningful: isolating the characteristics of leak events, improving detection reliability, and preparing data for classification or predictive analysis (Ghazali, 2012; Cawley et al., 2003).

Time-domain analysis is often the starting point. By examining how signal amplitude, envelope shape, and waveform morphology evolve, analysts can spot abrupt transients or repeating patterns that suggest micro-leaks or turbulent flow. Techniques like peak detection, autocorrelation, and moving-average smoothing help identify recurring events or unusual oscillations. Time-domain features are particularly informative for impulsive events — rapid crack propagation, sudden gas release — where the timing and shape of the signal carry diagnostic value (Ghazali et al., 2012; Ahadi and Bakhtiar, 2010).

Frequency-domain analysis, carried out through the Fast Fourier Transform, reveals which frequencies dominate the acoustic signal. This makes it possible to identify frequency components, harmonics, and periodicities associated with turbulent flow or vibrations linked to leaks. Bandpass, low-pass, and high-pass filters are routinely applied to isolate relevant frequency bands and suppress unwanted noise (Siddique et al., 2023; Rashid et al., 2013).

For non-stationary signals, those whose spectral content shifts over time, time-frequency representations like the Short-Time Fourier Transform and wavelet transforms are particularly useful. Wavelet analysis is well-suited to leak detection because it can resolve both transient events and longer-duration signals at multiple scales simultaneously (Siddique et al., 2023; Ting et al., 2019). When leak severity changes or flow conditions vary, the acoustic signature shifts, and wavelets can track those changes in ways that purely time-domain or frequency-domain methods cannot (Ghazali, 2012; Ghazali et al., 2012).

Feature extraction takes processed signals and converts them into numerical descriptors that a classification model can work with. Commonly extracted features include statistical measures (mean, variance, kurtosis), spectral peaks, energy ratios across frequency bands, and wavelet coefficients. More advanced representations might incorporate entropy-based metrics, cepstral coefficients, or higher-order moments to capture subtle signal dynamics. These features form the input layer for machine learning models used in automated leak classification, severity assessment, and predictive maintenance (Rashid et al., 2013; Ahadi and Bakhtiar, 2010).

Noise suppression is built into every stage of the processing pipeline. Wiener filtering, spectral subtraction, and adaptive filtering reduce background interference while preserving the integrity of leak-related signals. At the array level, beamforming and correlation-based denoising leverage the spatial distribution of multiple sensors to improve signal quality further, allowing the system to focus on specific directions and filter out off-axis interference (Long et al., 2003; Cawley et al., 2003).

Cross-correlation and matched filtering are two of the most effective methods for detecting weak leak signals in subsea environments with high noise levels. Cross-correlation between hydrophone signals from widely spaced locations exploits the coherence of the leak source across the array. The leak signal, which arrives at each sensor at slightly different times, creates a peak in the cross-correlation function that can be distinguished from incoherent background noise. Generalized cross-correlation with phase transform (GCC-PHAT) weighting is very useful because it lowers the weight of frequency components that are mostly noise and raises the weight of those that have a lot of inter-sensor coherence. Matched filtering uses a similar method by convolving the received signal with a template of the expected leak signature to make detection more sensitive for a known signal shape (Siddique et al., 2023; Ghazali et al., 2012). Both methods work well with a wide range of sensors in an array, and they work even better when the number of sensors decreases. This makes them great for scalable PAM deployments where the number of active nodes may change.

Feature selection and validation are ongoing challenges that distinguish PAM systems that excel in laboratory settings from those that maintain reliability in operational deployment. In controlled environments, numerous extracted features such as spectral centroids, wavelet energy distributions, kurtosis, and cepstral coefficients may seem informative due to an artificially advantageous signal-to-noise ratio. In actual ocean settings, numerous features deteriorate swiftly due to tidal noise, shipping interference, and sensor drift, resulting in a diminished subset that maintains discriminative capability across varied conditions. For rigorous feature validation, you need to test against noise datasets that were collected in real-world field environments. You also need to make sure that the biological and anthropogenic noise profiles are realistic and change with the seasons (Rashid et al., 2013; Ahadi and Bakhtiar, 2010). Principal component analysis and other methods for reducing dimensionality can help by finding which features contain unique information and which are redundant or driven by noise. This makes the model less complicated and makes it easier to apply to new deployment sites.

Adaptive noise cancellation is especially important in places where tidal currents and flow-induced structural vibrations make low-frequency noise that changes all the time with the speed and direction of the current. Standard static filters set to a certain noise floor quickly stop working when the tides change, letting noise leak into the detection band. Adaptive algorithms, like least mean squares and recursive least squares filters, change their coefficients all the time based on a reference noise input. This input usually comes from a dedicated noise-sensing channel that is set up to pick up ambient flow noise without letting signal contamination through. This cancellation method, based on a reference signal, gets rid of noise that is correlated with the main detection channel while keeping the leak signal that is not correlated (Long et al., 2003; Cawley et al., 2003). In DAS-based systems, parts of the fiber that are far away from any possible leak source can be used as distributed noise reference channels. This lets noise cancellation happen across the whole length of the monitored pipeline.

Table 2: Signal processing and feature extraction methods used in PAM-based leak detection systems.

Method	Domain	Primary use in PAM	Key strength	Key limitation
Time-domain analysis	Temporal	Detecting impulsive transients and waveform morphology changes	Simple; effective for sudden crack or burst events	Miss gradual or frequency-modulated leak signatures
Fast Fourier Transform (FFT)	Frequency	Identifying dominant frequency components and harmonic content	Computationally efficient; establishes spectral baseline	Assumes stationarity; loses temporal resolution
Short-Time Fourier Transform (STFT)	Time-frequency	Tracking non-stationary signals as leak severity evolves	Reveals time-varying spectral content	Fixed window size limits joint time-frequency resolution

Wavelet transform	Time-frequency	Multi-scale leak signature analysis; transient detection	Resolves both transient and sustained signals simultaneously	Wavelet basis selection requires domain expertise
GCC-PHAT cross-correlation	Spatial/temporal	Inter-sensor delay estimation for TDOA localization	Robust against noise; handles multipath environments	Requires at least two coherently sampled sensors
Matched filtering	Temporal/spectral	Detecting known leak signature shapes in noisy streams	Maximizes SNR for signals matching the template	Requires prior knowledge of the expected leak signature
Adaptive noise cancellation	Temporal	Suppressing tidal, current, and flow-induced noise	Continuously updates to changing noise conditions	Needs a dedicated noise reference channel
Feature extraction (kurtosis, MFCC, entropy)	Statistical	Generating input descriptors for ML classification models	Captures signal dynamics beyond spectral peaks	Feature relevance degrades in novel noise environments

Table 2: Summary of signal processing and feature extraction methods applied in PAM-based subsea leak detection, classified by domain, primary use, and performance trade-offs (Ghazali et al., 2012; Siddique et al., 2023; Rashid et al., 2013; Long et al., 2003).

2.6 AI and Machine Learning for Leak Detection

The integration of artificial intelligence and machine learning into PAM systems has meaningfully changed what is possible in subsea leak detection. Traditional approaches, such as manual inspection, pressure drop analysis, and localized sensor triggering, are slow, labour-intensive, and prone to missing gradual or intermittent leaks. AI-driven systems working with acoustic, pressure, and flow data can detect anomalies in real time, predict developing issues before they become serious, and do so with far greater precision (Banjara et al., 2020; Ullah et al., 2023).

Machine learning models for leak detection fall broadly into supervised and unsupervised categories. Supervised methods support vector machines, random forests, and gradient boosting classifiers that learn from labelled historical data, building models that distinguish normal pipeline operation from leak-induced anomalies. These models can achieve high accuracy when sufficient labelled data are available, and operating conditions are well-characterized (Ahn et al., 2019; Gemeinhardt and Sharma, 2023). Unsupervised approaches, such as clustering algorithms and autoencoders, take a different tack: they learn what normal looks like and flag deviations, without needing pre-labelled leak examples. These are particularly valuable in environments where labelled data are scarce or where leaks manifest in diverse and unpredictable ways (Vanijjirattikhan et al., 2022; Rahim et al., 2020).

Deep learning has pushed detection capability further. Convolutional neural networks applied to spectrogram images of acoustic data are particularly effective at capturing spatial patterns in time-frequency representations. Recurrent architectures like Long Short-Term Memory networks handle temporal dependencies in continuous audio streams, modelling how acoustic signatures evolve (Banjara et al., 2020; Ullah et al., 2023). Together, these architectures can detect subtle leak signatures that simpler feature-based methods miss while distinguishing leak sounds from other sources of noise like pump vibrations, subsea currents, or flow turbulence (Ahn et al., 2019; Gemeinhardt and Sharma, 2023).

Real-time anomaly detection and risk scoring tie all of this together at the operational level. Statistical process control, moving-average filters, and deep autoencoders can flag departures from known baseline behaviour as they happen, catching abrupt pressure shifts, high-frequency acoustic bursts, or persistent low-amplitude signals that may indicate a developing micro-leak. Early warning systems built on these methods enable prompt intervention, limiting both fluid loss and environmental exposure before a situation escalates (Vanijjirattikhan et al., 2022; Rahim et al., 2020).

Digital twins, virtual replicas of actual pipeline systems built from real-time sensor data, operational history, and simulation models, represent one of the most powerful applications of AI in pipeline management (Grieves and Vickers, 2016; Hartmann et al., 2018). A well-maintained digital twin lets operators run scenario analyses, test proposed interventions, and assess system resilience without touching the physical pipeline. Combined with AI-driven analytics, digital twins can continuously update structural performance forecasts, corrosion progression estimates, and defect evaluations as new inspection data arrives.

Robustness and explainability remain active challenges. Models can be thrown off by sensor drift, environmental noise variations, or adversarial inputs, generating false positives or missing real events. Equally important is that explainability operators need to understand why the system raised an alarm before committing to expensive shutdowns or interventions. Methods like SHAP (Shapley Additive explanations) and attention mechanisms in neural networks are being incorporated into detection systems to make their reasoning more transparent, building operator confidence and supporting regulatory documentation requirements (Banjara et al., 2020; Ullah et al., 2023).

2.7 Leak Localization and Characterization

Detecting that a leak exists is only part of what is needed. Knowing where it is, how large it is, and at what rate fluid is escaping are equally important for deciding how to respond. PAM systems address these questions through a combination of spatial signal analysis, acoustic modelling, and uncertainty quantification.

Time-Difference-of-Arrival (TDOA) is the most widely used approach for passive acoustic localization. Multiple sensors are placed at known positions across the monitored area, and differences in when a leak signal arrives at each sensor are used to triangulate the source location geometrically. High-frequency leak signals enable fine temporal resolution, and cross-correlation algorithms help align signals and reduce the effect of noise on arrival time estimates (Sundar et al., 2018; Hassan et al., 2021). Advanced TDOA implementations perform well even in noisy conditions, shallow coastal waters, or areas with heavy ship traffic by incorporating compensations for multipath propagation (Dang et al., 2022; Heydari and Mahabadi, 2023).

Beamforming extends TDOA concepts by exploiting the spatial coherence of signals across sensor arrays. By applying weights to signals from different array elements and combining them directionally, beamforming can suppress off-axis interference and focus sensitivity toward a particular region of interest (Bai et al., 2018; Grosse, 2009). Adaptive beamforming methods, such as Minimum Variance Distortion less Response, dynamically optimize these weights to track moving sources or handle changing acoustic conditions. These techniques become especially powerful when applied to distributed sensor arrays, allowing simultaneous monitoring of multiple pipeline segments (Sundar et al., 2018; Hassan et al., 2021).

Beyond localization, PAM data can inform estimates of leak size and flow rate. The amplitude, frequency content, and temporal pattern of acoustic signals carry information about the pressure differential, orifice geometry, and fluid dynamics at the leak site. High-pressure leaks produce intense, wideband turbulence noise; smaller defects yield lower-amplitude, higher-frequency signals (Malcher and White, 2023; Giro et al., 2022). Empirical and computational models convert these acoustic characteristics into volumetric flow estimates, enabling severity assessments that support maintenance prioritization.

Uncertainty is an unavoidable aspect of subsea localization. Multipath reflections produce ambiguous arrival times; environmental variability introduces errors into sound speed assumptions and propagation models. Clock drift, background noise, and slight misalignments in sensor positioning all add to this uncertainty. Quantitative methods, including Bayesian inference, Monte Carlo simulation, and covariance analysis, provide confidence intervals around leak location and flow rate estimates, giving operators a realistic sense of how much to trust the system's outputs (Hassan et al., 2021; Dang et al., 2022).

When choosing between single-array and multi-array localization architectures, you have to make some big trade-offs in terms of coverage, redundancy, and accuracy. A single hydrophone array placed at one point along a pipeline can find leak sources within its aperture with good angular resolution. However, it doesn't cover areas outside of its effective range and only gives a single, unverified position estimate. Multi-array deployments, with sensors spaced out along the pipeline, provide overlapping coverage that lets you cross-validate position estimates. For example, if two independently positioned arrays detect a leak at the same relative bearing, you can be much surer of the leak's location than if only one array detects it. The intersection geometry of two or more beams can also narrow down the source location to a much smaller uncertainty volume (Hassan et al., 2021; Sundar et al., 2018). Single-array solutions are often not enough for complicated pipeline geometries that include risers, jumpers, manifolds, and flexible flowlines. This is because the structural complexity creates multiple acoustic reflection paths that mess up simple TDOA estimates. Multi-array systems, when used with structural acoustic models of the pipeline's shape, are better at separating these reflections and correctly linking acoustic arrivals to their sources.

Depth uncertainty in DAS-based localization leads to localization errors in ways that are different from how traditional hydrophone array systems work and need to be dealt with in a specific way. DAS interrogators can find the position of an acoustic event along a fibre with great accuracy, usually within a meter or two for modern systems. However, they don't do as well at finding the position of an event in a direction that is not along the fibre. In a pipeline-following DAS deployment where the fibre runs parallel to the pipe, this means that the resolution along the pipe is great, but it's not clear if an event comes from the pipe itself, from the seabed below it, or from a nearby structure above it. Combining DAS with cross-pipeline hydrophone pairs or with acoustic triangulation from offset sensors clears up this confusion and gives a better idea of where the source is in three dimensions (He and Liu, 2021; Dang et al., 2022). Also, the local sound speed profile, which changes with temperature and salinity at depth, can cause errors in the assumed acoustic propagation time used for TDOA calculations. Even a one percent error in sound speed can move a localized position by several meters at typical detection ranges. Sound speed profiling should be seen as a normal operational input rather than a one-time deployment parameter.

2.8 System Integration and Operational Deployment

PAM technology only delivers its full value when properly integrated into the broader operational ecosystem, not just sensors in the water, but the architecture that turns acoustic data into actionable intelligence. Effective deployment requires coordinating hardware, software, communications, and operational protocols into a coherent system (Wegner et al., 2021a; Bai and Bai, 2014).

A key design decision is where data processing takes place. Edge computing places processing capability close to the sensors themselves on embedded computers at hydrophone nodes or subsea hubs, enabling low-latency detection, real-time event classification, and immediate alerting without depending on high-bandwidth connections to remote servers (Shi et al., 2016; Wang et al., 2020). Cloud-based processing, by contrast, offers essentially unlimited computational resources for running complex machine learning models, storing long-term data, and conducting historical trend analysis. In practice, the most capable systems combine both initial detection and anomaly flagging at the edge, with deeper analysis and model training in the cloud.

Real-time alerting and decision support are central to operational value. Once an anomaly is detected, the system needs to assess its significance and communicate clearly with operators. Automated alerts can be routed through SCADA interfaces, mobile applications, or integrated operations centres, ensuring relevant personnel are notified quickly (Boyer, 2004; Mahmoud and Hamdan, 2018). Decision support tools layer in risk scoring, confidence metrics, and visual dashboards, helping operators understand not just that an alarm has been triggered, but how serious it is, where the issue is located, and what the recommended response might be.

Integration with SCADA and subsea control systems closes the loop between monitoring and action. When acoustic data are correlated with pressure, flow, and temperature readings, multi-parameter anomaly validation becomes possible, reducing false positives and providing a richer picture of what is happening in the pipeline. Where PAM is integrated directly with subsea control systems, it can enable automated or semi-automated responses closing valves, triggering shutdown procedures, or activating backup systems in response to confirmed leak events (Boyer, 2004; Liu et al., 2011). Achieving this level of integration requires alignment with established communication protocols, data standards, and cybersecurity practices.

Autonomous and semi-autonomous monitoring modes further expand what these systems can do. Cooperative monitoring architectures in which multiple distributed sensors share data in real time add redundancy and improve confidence in detection outputs. Mobile monitoring using autonomous underwater vehicles and wave glider platforms has demonstrated the feasibility of real-time passive acoustic monitoring across large maritime areas without permanent infrastructure (Premus et al., 2022; Bayat et al., 2017). Sensor systems deployed specifically to increase the security of underwater communication cables have also shown that non-intrusive acoustic monitoring can be extended to critical subsea infrastructure beyond pipelines (Eleftherakis and Vicen-Bueno, 2020).

2.9 Environmental and Regulatory Considerations

Deploying acoustic monitoring systems in marine environments is not just a technical challenge; it comes with environmental obligations and regulatory requirements that shape how and where these systems can operate. Responsible deployment means aligning with marine protection standards, demonstrating that the technology meets regulatory expectations, and maintaining rigorous data governance throughout (ISO 31000, 2018; Muhlbauer, 2004).

Regulatory frameworks from bodies like the International Maritime Organization, the EU Water Framework Directive, and various national authorities set limits on activities that could affect marine ecosystems, including noise emissions. PAM systems, while generally low-impact compared to active technologies, still need to demonstrate that hydrophones, DAS cables, and mobile platforms like AUVs operate within accepted noise thresholds. This often means conducting environmental impact assessments before deployment and implementing mitigation measures if needed (ISO 55001, 2014; Dann and Huyse, 2018).

One of the genuine environmental strengths of PAM is how much less disruptive it is compared to traditional inspection approaches. Hydrophones and DAS systems are largely passive; they sit and listen without physically interacting with the environment. And because PAM enables early detection of leaks and structural anomalies, it helps prevent the far worse environmental outcomes that result from undetected failures, oil spills, gas releases, and chemical contamination. High-resolution environmental data gathered during monitoring operations can also provide useful ecological information, contributing to a broader understanding of the acoustic and biological character of monitored areas (Zimmer, 2011; Van Parijs et al., 2009).

Data governance underpins the environmental and regulatory value of these systems. Acoustic monitoring platforms generate substantial volumes of time-series data, leak events, environmental acoustic profiles, and system health metrics. Governance frameworks need to ensure that this data is stored accurately, transferred securely, and accessible for audit and reporting purposes. Regular reporting to regulatory authorities covering inspection logs, anomaly events, and any mitigation actions taken is typically required. Secure data handling also enables post-event forensic analysis, which can be critical for incident investigation and for demonstrating ongoing environmental compliance (ISO 31000, 2018; Wegner et al., 2021a).

Regional regulatory frameworks impose specific requirements on subsea monitoring that go well beyond the generic ISO standards applicable to all asset management operations. The OSPAR Convention for the Protection of the Marine Environment of the North-East Atlantic sets rules for offshore operators in the North Sea about monitoring the environment, dumping waste, and stopping pollution from subsea installations. Operators using PAM systems in OSPAR-regulated waters must show that the monitoring activities themselves do not harm protected marine species and that the acoustic data collected during operations can be used for environmental reporting. The Bureau of Safety and Environmental Enforcement (BSEE) set certain standards for inspecting and monitoring deepwater wells and pipelines in the Gulf of Mexico in the United States. Continuous acoustic monitoring is becoming more widely accepted as a way to show that structural integrity surveillance is being done (ISO 31000, 2018; Dann and Huyse, 2018). The Norwegian Petroleum Directorate also requires risk-based inspection programs for subsea infrastructure on the Norwegian Continental Shelf. Operators who want to extend their inspection intervals must show that they can detect problems.

The International Maritime Organization's rules about underwater radiated noise are becoming more and more important for PAM deployment on mobile platforms like AUVs, wave gliders, and survey vessels. PAM receivers are passive and don't add to underwater noise. However, the ships and vehicles used to set up, maintain, and recover PAM equipment must follow IMO rules for reducing noise from propulsion and machinery when they are working in sensitive marine areas. For operators using AUV-mounted hydrophone systems to do long surveys in places that are ecologically sensitive or home to protected cetacean species, it is becoming standard for regulators to expect environmental impact assessments and operational noise budgets before deployment (Zimmer, 2011; Van Parijs et al., 2009). These requirements make PAM deployments more complicated, but they work well with the technology's low-disturbance profile. Operators who work with regulators on acoustic environmental management are finding that PAM deployments are seen as responsible stewardship.

Data retention and audit requirements that are unique to subsea monitoring operations add a governance aspect that operators should plan for ahead of time, not as an afterthought. Most places have rules that say you have to keep inspection records, anomaly event logs, and related response documentation for a certain amount of time, usually between five and twenty-five years, depending on the jurisdiction and the importance of the asset. This means that PAM systems that constantly make high-frequency time-series data need a lot of long-term storage space. Selective retention strategies, keeping raw data for specific alert windows and archiving compressed summaries for routine monitoring periods, can help manage storage volumes while making sure that the full acoustic record of any important event is kept for regulatory audits and incident investigations (Muhlbauer, 2004; Wegner et al., 2021a). Regulators are increasingly requiring chain-of-custody documentation for acoustic datasets, such as calibration records, sensor health logs, and processing software versions. This is to make sure that post-event forensic analyses are defensible and that monitoring data can be used as evidence in enforcement or litigation situations.

2.10 Economic and Risk Management Implications

Beyond the technical and environmental case for PAM, there is a compelling economic argument for its adoption. Offshore and subsea operations involve expensive assets, significant operational risk, and substantial costs when something goes wrong. PAM addresses several of these cost drivers directly, reducing the need for frequent physical inspections, enabling earlier leak detection, and providing data that supports smarter risk management (Wegner et al., 2023; Thodi et al., 2009).

Conventional inspection campaigns, particularly those relying on ROVs, are resource-intensive. Mobilizing a vessel with ROV capability, deploying and operating the equipment, and navigating complex subsea terrain to inspect pipeline sections can cost anywhere from tens of thousands to several million dollars per campaign. And these inspections are, by nature, periodic; they provide a snapshot in time rather than continuous coverage. PAM changes this equation. Hydrophone arrays and DAS systems can monitor continuously, flagging anomalies as they develop. Over the life of a pipeline, the reduction in expensive mobilization events, combined with more reliable detection, can translate into substantial cost savings (Bai and Bai, 2014; Muhlbauer, 2004).

PAM also enables a risk-based approach to inspection planning. Rather than scheduling inspections at fixed intervals regardless of actual condition, continuous acoustic surveillance produces data on flow dynamics, structural stress indicators, and leak probability data that can direct inspection resources toward the highest-risk segments (Dann and Huyse, 2018; Thodi et al., 2009). Integration with digital twin models and predictive analytics further refines this: operators can model likely failure scenarios and schedule maintenance proactively, avoiding unplanned shutdowns and extending asset service life (Grieves and Vickers, 2016; Hartmann et al., 2018).

Early leak detection is where PAM's economic and environmental benefits converge most clearly. Small defects, pinholes, and developing cracks often progress slowly before becoming critical. Detecting them early, while fluid loss is still minimal and intervention is straightforward, prevents the far more expensive scenario of a major spill requiring emergency response, remediation, and regulatory penalties. The cost of avoiding a single significant spill event can easily exceed the total cost of deploying and maintaining a PAM system over many years (Wegner et al., 2023; Chang et al., 2014).

Insurance and liability risk management also benefit from PAM adoption. Regulators and insurers increasingly respond favourably to operators who can demonstrate proactive, continuous monitoring and documented detection capability. PAM-equipped pipelines represent lower undiscovered-leak risk, which reduces the frequency and severity of insurance claims related to environmental damage, third-party liability, and operational disruption. High-resolution acoustic data can support faster and more defensible incident investigations. Demonstrating compliance with tightening regulatory standards through documented PAM deployment can reduce both legal exposure and insurance premiums over time (Wegner et al., 2021b; Thodi et al., 2009).

2.11 Problems and Things That Are Not Working Right Now

This review shows that PAM technology has come a long way, but practitioners who are planning operational deployments need to be honest about the challenges that still exist. A lot of the limitations aren't just engineering problems that need to be fixed soon; they are basic physical and operational limits that need careful system design and realistic expectations.

One of the most common problems in operations is still the false positive rates. PAM systems that work all the time in complicated acoustic environments will always pick up noise events like biological sounds, vessel transients, equipment vibrations, and flow-induced structural noise. These events have spectral and temporal properties that are similar to real leak signatures. Even well-designed AI-driven detection systems that have been trained on high-quality labelled data can still cause false alarms at rates that can be very hard to deal with if not handled properly. Every false positive that requires a response costs money, whether it's sending out inspection teams, shutting down pipeline sections, or sending ROVs to look into the situation. High rates of false positives make operators less trusting of the system and put pressure on them to raise detection thresholds, which could mean missing real low-level leaks (Banjara et al., 2020; Gemeinhardt and Sharma, 2023). To lower the number of false positives without losing sensitivity, you need to use multi-modal validation, fine-tune algorithms for each site, and set up human review workflows that include PAM alerts in a larger picture of operational situational awareness instead of just triggering automatic responses.

It is still very hard to optimize sensor placement, especially for complex three-dimensional pipeline geometries that include risers, manifolds, and clustered wellheads. Acoustic shadow zones are areas where structural elements, seabed topography, or acoustic refraction block or greatly reduce signal propagation. This means that no sensor layout can provide perfectly even coverage across a complex subsea field. Before deployment, site-specific acoustic propagation modeling is needed to find and reduce shadow zones. This adds time and money to the commissioning process and needs oceanographic data that may not always be available at the right resolution (Hovem, 2007; Van Walree, 2013). For operators who have to manage large pipeline networks that run through a wide range of underwater terrain, figuring out the best places to put sensors all over the network is a difficult logistical and technical problem that doesn't have a single solution.

Workforce capability and institutional readiness are less talked about, but they are important factors that limit the use of PAM. To run a continuous acoustic monitoring system well, you need people who know a lot about underwater acoustics, signal processing, machine learning, and subsea operations. This is a set of skills that is not yet common in the offshore industry. Many operators are still learning how to interpret AI-generated alerts, keep sensors calibrated, fix data quality problems, and use acoustic findings to make maintenance decisions (Wegner et al., 2023; Wegner et al., 2021a). Companies that buy PAM hardware but don't also train their employees to use and understand it often find that the technology doesn't work as well as it could. This shows how important it is to train workers as part of any PAM deployment program.

Table 3: Key operational challenges in PAM deployment and associated mitigation strategies

Challenge	Root cause	Operational impact	Mitigation approach
High false positive rates	Biological, vessel, and flow noise mimicking leak signatures	Unnecessary inspection mobilisation; raised detection thresholds; eroded operator trust	Multi-modal validation; site-specific algorithm tuning; human review workflows
Acoustic shadow zones	Signal attenuation from structural elements, seabed topography, and refraction	Coverage blind spots; undetected leaks in shadowed segments	Pre-deployment acoustic propagation modelling; multi-array overlapping coverage
Sensor placement complexity	Complex 3D pipeline geometries including risers, manifolds, and jumpers	Suboptimal detection range and localization accuracy	Site-specific modelling; iterative array geometry refinement from field calibration
Seasonal environmental variability	Thermal stratification, thermoclines, and variable sound speed profiles	Seasonal drift in detection range and signal-to-noise ratios	Routine oceanographic surveys; adaptive threshold adjustment; temperature-compensated models
DAS depth ambiguity	Fiber aligned parallel to pipe with no cross-pipe discrimination	Uncertainty in 3D source location; misattribution of off-pipe events	Combination with cross-pipeline hydrophone pairs or offset sensor triangulation
Workforce capability gap	Shortage of PAM-trained personnel with acoustics, signal processing, and AI skills	System underperformance; slow alert response; poor data quality management	Structured operator training; explainable AI dashboards; decision-support tools
Data storage and governance	High-volume continuous time-series from long-duration deployments	Long-term storage costs; regulatory audit complexity	Selective retention strategies; compressed archiving; chain-of-custody documentation
Regulatory compliance uncertainty	Evolving and jurisdiction-specific acoustic monitoring standards	Deployment delays; risk of non-compliance	Early regulator engagement; alignment with OSPAR, BSEE, and ISO 31000 frameworks

Table 3: Summary of key operational challenges in PAM deployment, their root causes, impacts, and recommended mitigation strategies (Banjara et al., 2020; Hovem, 2007; Van Walree, 2013; Wegner et al., 2023; ISO 31000, 2018).

3.0 NEW TECHNOLOGIES AND FUTURE DIRECTIONS

Passive Acoustic Monitoring is a field that is always changing, and the next generation of systems is expected to be much better than the ones we have now. There are new developments in sensor technology, signal processing, artificial intelligence, and autonomous platforms that are all coming together. Each one is pushing the limits of what PAM can find, where it can work, and how reliably it can do so.

On the sensing side, fiber-optic cables are making distributed acoustic sensing much better. New fiber designs and deployment configurations are making DAS systems more useful in difficult subsea environments (He and Liu, 2021; Zhan, 2020). Improvements in interrogator sensitivity and spatial resolution are also making DAS systems more accurate and useful over longer distances. Thin cable fiber-optic hydrophone arrays are a promising new way to do large-scale passive surveillance. They combine the coverage benefits of DAS with the acoustic sensitivity of traditional hydrophones (Plotnikov et al., 2019; Cranch et al., 2003). Fiber Bragg grating-based hydrophones have more benefits when used in multiplexed, distributed setups that make it easier and cheaper to set up large arrays (Campopiano et al., 2009).

Artificial intelligence is likely to become more and more important. Deep learning architectures are getting better at dealing with the noise and variability that are common in real subsea acoustic environments. This lowers the number of false positives and makes it easier to find things at low signal-to-noise ratios (Gemeinhardt and Sharma, 2023; Ullah et al., 2023). Transfer learning approaches, which involve fine-tuning models trained in one environment for use in another, will lessen the amount of data needed to set up AI-driven PAM in new places. Tools that help people understand AI alerts are also getting better. For example, SHAP and attention-based visualization are making it easier for operators to understand and trust AI-generated alerts, which is becoming more and more important for operational use (Banjara et al., 2020; Ahn et al., 2019).

The combination of PAM and digital twin technology may be the most important long-term change. Digital twins of subsea pipeline networks can run predictive failure models, simulate maintenance scenarios, and make inspection recommendations based on risk (Grieves and Vickers, 2016; Hartmann et al., 2018). These models are always getting new data on pressure, temperature, and flow. As these models get better, they will change how pipelines are managed from periodic reactive inspections to continuous, condition-based stewardship that uses real-time information about the asset's acoustic state.

Autonomous and cooperative monitoring platforms are another area to explore. Wave glider-based towed hydrophone systems and AUV-mounted sensor arrays have already shown that it is possible to do long-term passive acoustic monitoring over large areas of the ocean (Premus et al., 2022; Gillespie et al., 2022). Future systems are expected to use swarm-based methods, which means that fleets of smaller, cheaper autonomous platforms will work together to take acoustic measurements over large areas. This will increase the area covered while lowering the cost per kilometer monitored. Improvements in energy harvesting, such as from ocean currents and thermal gradients, will make missions last longer and make it easier to replace batteries in remote locations (Bayat et al., 2017; Nsalo Kong et al., 2021).

Multi-modal sensing, which combines passive acoustics with other types of sensing like optical sensing, chemical detection, and pressure monitoring, will make detection even more reliable. Cross-validating acoustic signatures against independent sensor streams helps multi-modal systems find leaks with high confidence, which is what is needed to support automated operational responses. These advancements establish PAM not only as a leak detection instrument but also as a fundamental component of intelligent, adaptive subsea infrastructure management (Wegner et al., 2023; Eleftherakis and Vicen-Bueno, 2020).

3.1 Field Applications and Case Studies of Operations

The technical capabilities of PAM systems are well-documented in the literature; however, their practical application in offshore oil and gas operations, subsea communication cable monitoring, and marine environmental surveillance offers the most compelling evidence of operational efficacy. Field applications have shown that PAM has a lot of potential, but it also has a lot of problems when used in the real world, which is much more complicated than a lab or simulation setting.

PAM has been used in the offshore oil and gas industry to keep an eye on subsea wellheads, flowlines, and riser systems for signs of leaks or structural damage. Continuous acoustic monitoring of high-pressure subsea infrastructure, where the cost of an undetected leak amounts to millions of dollars and considerable environmental consequences, has demonstrated significant utility (Du et al., 2023; Etiope et al., 2002). Field studies have shown that PAM systems can reliably tell the difference between leak-induced acoustic signatures and background ocean noise in deepwater environments, as long as sensor arrays are set up correctly and signal processing pipelines are tuned to the specific acoustic conditions of the site (Malcher and White, 2023; Mahmutoglu and Turk, 2018).

In subsurface monitoring applications, such as hydraulic fracture stimulation diagnostics, distributed acoustic sensing using fiber-optic cables has been field-tested. It has been shown that it can detect and locate acoustic events in real time along kilometers of fiber in operational well environments (Daley et al., 2013; Molenaar and Cox, 2013). These field tests have shown that DAS is a reliable technology for continuous subsea monitoring. The results show that the spatial resolution is high enough to pinpoint acoustic events to specific parts of the monitored infrastructure.

Monitoring underwater communication cables is another well-known use case. Passive acoustic and vibration sensing systems have been installed on cable infrastructure to identify external disturbances such as vessel anchoring, fishing activities, and seabed movement that may jeopardize cable integrity

(Eleftherakis and Vicen-Bueno, 2020; Zhan, 2020). These deployments have shown that DAS-based sensing systems can keep an eye on threats to important subsea infrastructure from hundreds of kilometers away, all the time.

Monitoring programs for marine mammals and the environment have collected a lot of field data on how well PAM systems work in real ocean environments. Long-term deployments of stationary and mobile PAM systems have yielded validated datasets regarding ambient noise levels, signal propagation characteristics, and detection ranges under diverse oceanic conditions (Zimmer, 2011; Van Parijs et al., 2009). The target signals are different from those used in industrial leak detection, but the basic acoustic principles are the same. The performance data from ecological PAM deployments gives us direct evidence of system reliability, false alarm rates, and how changes in the environment affect detection performance (Gibb et al., 2019; Ross et al., 2023).

Real-time acoustic beamforming for marine sensing has been tested in the field, and new low-cost architectures have shown that high-quality spatial acoustic monitoring is possible at operational scales without the high costs and difficulties of traditional military-grade array systems (Nsalo Kong et al., 2021). Wave glider-based PAM systems towing hydrophone arrays have been autonomously operated for extended durations at sea, substantiating the concept of continuous, mobile passive acoustic surveillance without reliance on crewed vessels or permanent infrastructure (Premus et al., 2022).

These field applications set a clear standard: PAM is not just a lab idea; it has been shown to work in a variety of subsea and maritime situations. The primary takeaway from field deployments is unchanging: PAM systems work best when their design takes into account the specific acoustic environment of the deployment site, when sensor placement and array geometry are optimized through prior modeling, and when signal processing pipelines are tested against ground truth data from known leak or disturbance events (Malcher and White, 2023; Du et al., 2023; Wegner et al., 2023).

CONCLUSION

Passive Acoustic Monitoring offers real, practical value for leak detection across subsea pipelines, wells, and associated offshore equipment. Its core strength lies in continuity rather than providing periodic snapshots. PAM monitors in real time, using the acoustic signals that fluid movement, gas release, and structural vibration naturally produce. This allows operators to act on emerging problems before they become serious, reducing downtime, limiting environmental exposure, and protecting the integrity of offshore assets. It is also scalable, making it applicable across both simple single-pipeline installations and complex, multi-segment subsea networks (Zimmer, 2011; Bai and Bai, 2014).

The environmental and asset integrity benefits deserve specific mention. Detecting leaks early and accurately means less fluid reaches the environment, less regulatory risk accumulates, and marine ecosystems are better protected. Continuous monitoring of pipeline conditions supports proactive maintenance strategies that extend asset life and reduce the chance of catastrophic failure, contributing directly to both operational and sustainability goals (Wegner et al., 2023; Du et al., 2023).

PAM's compatibility with autonomous and semi-autonomous operation is equally significant. When properly integrated with edge computing, SCADA systems, and advanced signal processing, these systems can function with minimal human intervention, maintaining situational awareness around the clock in environments where deploying personnel is expensive or dangerous. This autonomy enhances overall operational safety and allows intervention timing to be optimized based on actual conditions rather than scheduled cycles (Premus et al., 2022; Boyer, 2004).

Looking ahead, the convergence of advanced DAS sensing, AI-driven analytics, digital twin technology, and autonomous platform deployment will produce PAM systems that are substantially more capable, more reliable, and more cost-effective than what exists today. Self-learning systems capable of detecting, classifying, and responding to subsea anomalies with little human oversight, integrated seamlessly with broader infrastructure management platforms, represent the next frontier of offshore asset monitoring. Passive Acoustic Monitoring is the enabling technology that makes this future conceivable, and investment in it now is investment in the resilience and sustainability of the subsea infrastructure that the global energy and water systems depend on (Grieves and Vickers, 2016; Wegner et al., 2023; He and Liu, 2021).

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