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Comprehensive review of distributed acoustic sensing technology: principles, configurations, applications and emerging trends

Arnaldo Leal-Junior^{1,2*}, Mariana Silveira¹, Stanislav Kepak³, Jan Nedoma³, Radek Martinek² and Carlos Marques^{4,5}

Abstract: In recent years, distributed acoustic sensing (DAS) has been a preferred choice in many practical applications due to its versatility and the possibility of using existing infrastructure. This paper presents a thorough review on DAS technology of all aspects of such sensing system. The review includes a market overview demonstrating the increasing trend in DAS market size (projected to USD 7.8 billion by 2030), focused on implementation in different fields. Then, the operation principles, fundamentals and theoretical background of the DAS systems are analyzed and compared in terms of different approaches. In addition, the myriads of DAS applications proposed in recent years are reviewed. Thereafter, current limitations and drawbacks of DAS are discussed and emerging technologies to address such drawbacks are analyzed in terms of benefits and future challenges for the next generation of DAS technology. This review paper's unique value is to comprehensively cover all aspects of DAS technology, from its theoretical basis and first laboratory demonstrations to practical implementation covering tens of kilometers. Such review can be used as a roadmap for DAS applications and to understand the application and implementation of ϕ -OTDR systems with critical perspective of the new possibilities of the next generation of DAS systems.

Keywords: optical fiber sensors; distributed acoustic sensing; phase-sensitive optical time domain reflectometry; rayleigh scattering

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1 Introduction

A smart environment is a physical space that leverages embedded sensors, actuators, and intelligent systems to enable contextually aware, adaptive, and automated services, improving efficiency, safety, and user comfort¹. General aspects also include characteristics of smart governance, economy, environment, living and transportation². At the core of such environments, sensors play a crucial role by continuously collecting data from the physical surroundings, which are then processed to inform real-time decision-making and control³. These sensors enable context recognition, user behavior modeling, and system optimization,

forming the foundational layer for smart homes, cities, industries, and healthcare systems⁴. As sensor technologies evolve, their integration with IoT and AI systems is making smart environments increasingly autonomous and responsive to dynamic conditions⁵.

As one important technology in sensing with a broad range of applications in smart environments, optical fiber sensing technology has evolved over several decades, with advances emerging over the years to address different application needs⁶. The motivation for the development of optical fiber sensors is related to advantages such as immunity to electromagnetic interference, compact size, mechanical flexibility for integration into various substrates, chemical

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resilience, galvanic isolation, and the capacity for multiplexed measurements⁷. Considering these advantages, a broad spectrum of sensing techniques have been introduced in recent years, including grating-based sensors⁸, sensors based on nonlinear effects⁹, intensity-modulated systems¹⁰, interferometric configurations¹¹, and reflectometry methods operating in both time and frequency domains^{12,13}. These technologies have been tailored to meet the demands of specific sectors such as healthcare^{14,15}, biomechanics¹⁶, structural integrity monitoring¹⁷, environmental sensing¹¹, systems monitoring¹⁸ and chemical detection¹⁹, among others.

The term optical fiber sensor encompasses a broad range of methods, which can be categorized according to different features. One common classification is based on whether the system supports spatially resolved measurements. From this perspective, sensors are typically divided into distributed and non-distributed systems with an additional classification of quasi-distributed system, which lies between distributed and non-distributed systems with discrete sensing regions along the optical fiber²⁰. Non-distributed systems rely on point-based measurements, interpreting changes over the entire fiber or within localized sensing regions²¹. In contrast, quasi-distributed systems incorporate multiple discrete sensing zones along the fiber, enabling limited spatial resolution²². Examples include fiber Bragg gratings (FBGs)²³ and multiplexed intensity-modulated sensors²⁴. However, these systems face challenges when applied to tasks such as three-dimensional shape reconstruction. Non-distributed sensors lack spatial resolution, and quasi-distributed systems do not lead to a continuous spatial measurement along the fiber cable, where dense FBG arrays can be used, but at the cost of fabrication complexity and additional changes in the optical fiber structure. Distributed optical fiber sensors offer continuous sensing along the fiber length, enabling high-resolution spatial measurements, often in sub-centimeter scales²⁵. Among these methods, Optical Frequency Domain Reflectometry (OFDR) and Optical Time Domain Reflectometry (OTDR) enable spatial tracking along the entire fiber. Unlike FBG-based approaches, which are constrained to specific sensing points, OFDR and OTDR enable continuous monitoring, enable accurate detection of parameters along the whole fiber²⁶.

Such advantages and wide spread of optical fiber sensors resulted in practical implementation and commercial solutions throughout the years. In general, the optical fiber sensors market is experiencing steady growth driven by increasing demand for high-performance sensing in critical sectors such as oil and gas, civil infrastructure, energy, transportation, and healthcare. The global market was valued at around USD 3.5 billion in 2023 and is projected to reach approximately USD 6.7 to 7.8 billion by 2030, growing at a compound annual growth rate (CAGR) of approximately 9% to 11%²⁷. The market is dominated by intrinsic optical fiber sensors (around 98% of the total market), which are the

optical sensors developed within the optical fiber cable. These sensors include FBG, distributed temperature sensing (DTS), distributed acoustic sensing (DAS), interferometric sensors, and other configurations²⁸. Among these, FBG holds the largest share (about 35%), followed by DTS and DAS, which are increasing due to their effectiveness in structural health monitoring and infrastructure surveillance (see Fig. 1). The distributed optical fiber sensor market represents one of the most technically significant and rapidly evolving segments within the optical sensing approaches due to their capability of continuous, real-time monitoring along the entire length of the fiber (which can achieve tens of kilometers). This capability makes them suitable in applications of long range detection, which include pipeline leak detection, structural health monitoring, perimeter security, and downhole oil and gas well surveillance²⁸.

In general terms, DAS is an optical fiber sensing technology that transforms standard optical fibers into dense arrays of virtual microphones capable of detecting and localizing acoustic or vibrational disturbances in real time, over tens of kilometers, commonly using Rayleigh backscattering analysis²⁹. DAS offers high spatial resolution without requiring active field instrumentation³⁰, which motivates growth in the global market, estimated at around \$600–700 million in 2023, and is projected to exceed \$1 billion by 2030, growing at a CAGR of 9%–12%³¹. This growth is related to the increasing demand for scalable, distributed monitoring solutions in practical field applications³². Despite challenges such as high interrogator costs and complex signal processing, DAS applications continue to increase through its compatibility with existing fiber networks and growing integration with AI-enabled analytics³³.

Considering the background on DAS developments and the emerging applications in this field, this paper presents a thorough review on the DAS technology in which all aspects of such a sensing system are discussed in detail. For this reason, the contribution of this review is a unified overview that covers the fundamental principles and theoretical background underlying traditional DAS systems, as well as typical configurations, commercial solutions, and the signal analysis workflow. Furthermore, the applications of such systems across different fields are discussed in detail and limitations of conventional DAS systems are depicted with new developments of key enabling technologies that can mitigate such limitations aiming at a new generation of DAS systems. The structure of the review is schematically represented in Fig. 2. In this case, after this introduction (Section 1), the theoretical background of DAS technologies is depicted in Section 2. Then, the commercial solutions and proposed configurations are presented in Section 3. Section 4 is focused on the many applications of DAS systems, covering different application scenarios in smart environments. Thereafter, in Section 5, the prospects of DAS technology are discussed considering the current drawbacks and

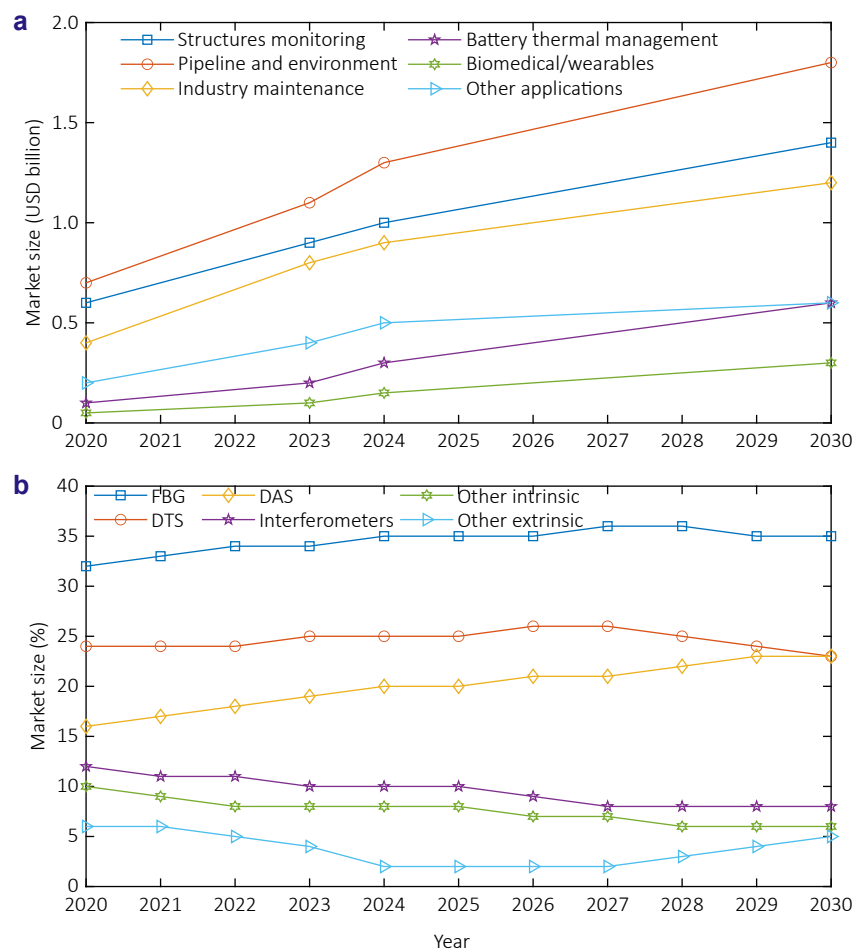


Fig. 1 | Market overview of optical fiber sensors. (a) Market size of different applications in optical fiber sensing. (b) Contribution of each optical sensing approach in the market size.

limitations of such systems, which set the scene for new developments in technologies that can overcome the limitations of traditional DAS systems. Finally, conclusions and future works prospects are drawn in Section 6.

2 Theoretical background on DAS technology

2.1 Rayleigh backscattering

Standard single mode optical fibers (SMF) are primarily composed of Silica and Germania molecules, being classified as vitreous structures. Differently from crystals, vitreous materials are amorphous, implying that two points spatially separated by a threshold distance (known as correlation length d) exhibit different local atomic arrangements, as illustrated in Fig. 3(a). In SMFs, the correlation length is on the order of a few nanometers, with a typical value around 5 nm³⁴. Inhomogeneities in the local molecular arrangement result in fluctuations in density and polariz-

ability of the material, giving rise to spatial variations in the fiber's permittivity³⁵. When an electromagnetic wave propagates through the core of the optical fiber, interactions between the silica molecules and the electric field induce radiating dipoles, resulting in light scattering in all directions. Since the correlation length is much smaller than the wavelength of light, this phenomenon is categorized as Rayleigh scattering³⁴.

In Rayleigh scattering, no energy is transferred to the glass (with partial losses when there are scattering outside the core), and the scattered light has the same wavelength as the incident light³⁶. Due to the isotropic nature of this phenomenon, a small portion of the radiation exits the optical fiber core, while the remaining portion is reflected back into the core, propagating in either the forward or backward directions. Losses in the transmitted optical power are mainly caused by scattered light that propagates backward, i.e. backscattering, and light absorption by silica³⁷. The intrinsic loss coefficient of the optical fiber due to Rayleigh scattering associate with a light beam with wavelength λ is expressed as,

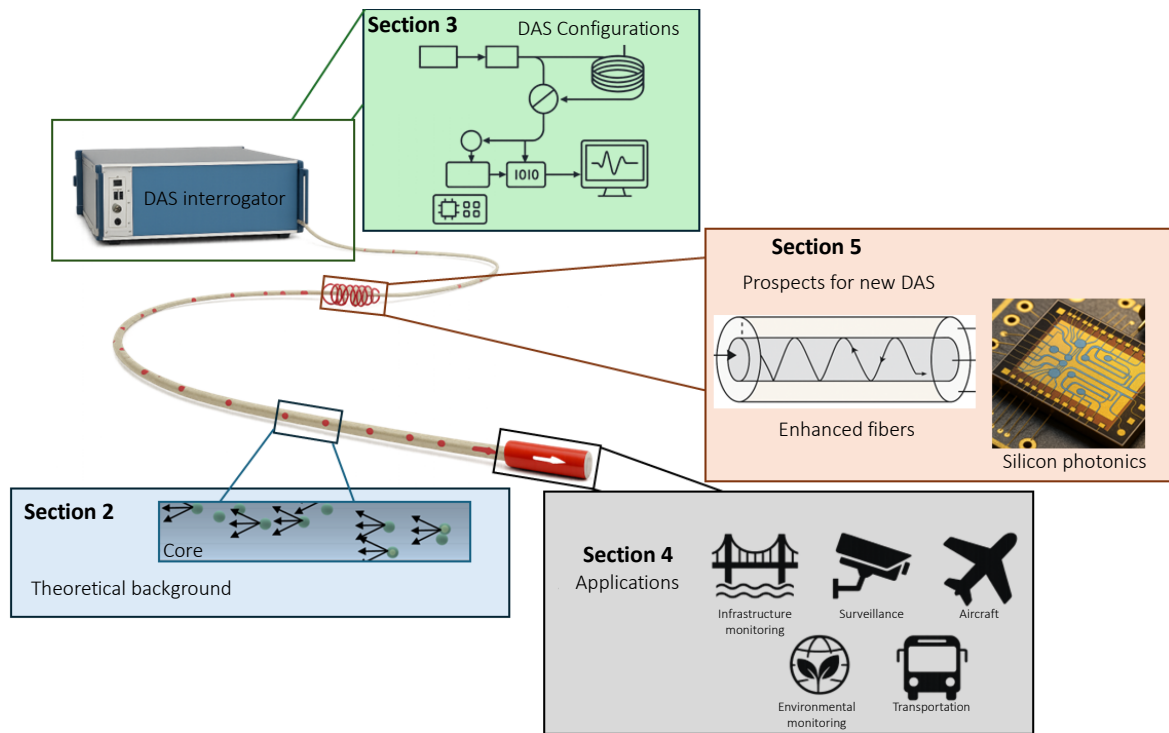


Fig. 2 | Schematic representation of the review structure.

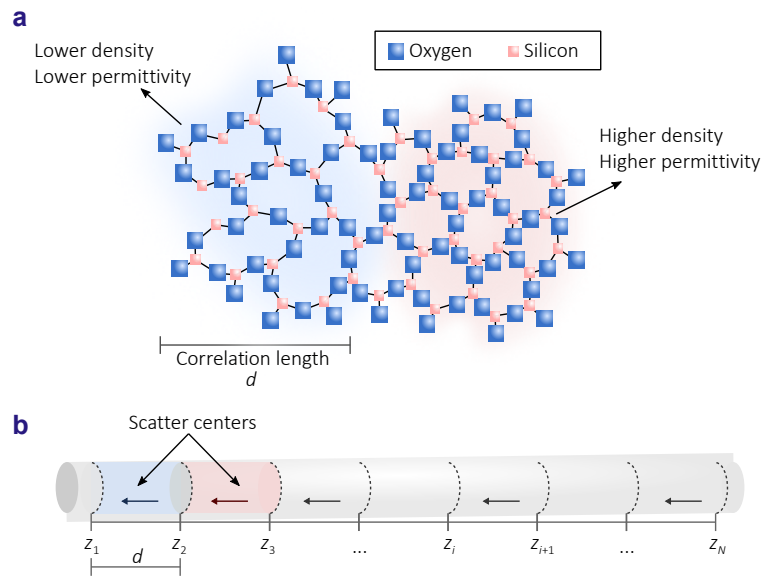


Fig. 3 | (a) Atomic arrangement of a vitreous structure. (b) Scatter centers of an optical fiber.

$$\alpha_r = \frac{A}{\lambda^4}, \quad (1)$$

where A typically ranges from 0.7 to 0.9 ($\text{dB} \cdot \text{km}^{-1} \cdot \mu\text{m}^{-1}$). The total attenuation coefficient α of a standard SMF operating with a 1550-nm-optical source is $0.2 \text{ dB} \cdot \text{km}^{-1}$. As the Rayleigh attenuation at this wavelength is about $0.12\text{--}0.16 \text{ dB} \cdot \text{km}^{-1}$, Rayleigh scattering configures the main cause of optical power losses in telecommunication

systems³⁶. Considering an incident power P_0 propagating along the space in the z -axis direction, the attenuation loss is

$$P(z) = P_0 \exp(-\alpha z). \quad (2)$$

Various models of Rayleigh backscattering in optical fibers have been thoroughly established in the literature, based on both conventional analytical theory^{38,39} and coupled-mode theory⁴⁰. In this work, a simplified approach

is adopted, relying on the coherent sum of the contributions from all fiber sections, with the aim of providing intuitive insight into the fundamental principle behind strain and temperature sensitivity. Rayleigh scattering can be modeled as the summation of multiple light rays scattered at different scatter centers spaced by the correlation length. Commonly, a one-dimensional model is utilized to describe this phenomenon in SMFs by representing the scattering coefficient as function of the propagation distance z . For an incident light pulse $a(t)\exp(j2\pi\nu_0 t)$ centered at the optical frequency ν_0 with an amplitude equal to $a(t)$, the backscattered light is⁴¹

$$h(t) = \sum_{i=0} a\left(t - \frac{2n_i z_i}{c}\right) r(z_i) \exp\left(-j\frac{4\pi n_i z_i \nu_0}{c}\right), \quad (3)$$

where n_i and z_i represent the refractive index of the optical fiber and the distance from the input-end of the i -th scatter center, respectively, and $r(z_i)$ is the scattering attenuation from the i -th scattering center. The speed of light in vacuum is represented by c . In the above formulation, the group refractive index and the phase refractive index are assumed to be identical for simplicity, which corresponds to neglecting the effects of dispersion. This assumption is adopted because the intended scope of the analysis is to highlight the apparent frequency variation, facilitating the understanding of strain and temperature sensitivity in cross-correlation-based OFDR and in ϕ -OTDR. In this context, it is worth noting that variations in the product $n_i z_i$ have a negligible effect on the amplitude term $a\left(t - \frac{2n_i z_i}{c}\right)$, while inducing a significant change in the term $\exp\left(-j\frac{4\pi n_i z_i \nu_0}{c}\right)$ due to

the order of magnitude of the central optical frequency ν_0 , owing to the order of magnitude of the central optical frequency ν_0 . For a standard SMF subjected to varying strain, changes in the product $n_i z_i$ cause a variation of the apparent frequency $\Delta\nu$ relative to the unstrained condition, which is given by:

$$\frac{\Delta\nu}{\nu_0} = -0.78\Delta\varepsilon. \quad (4)$$

In the case of temperature variations, the corresponding spectral shift is given by,

$$\frac{\Delta\nu}{\nu_0} = -6.67 \cdot 10^{-6} \Delta T. \quad (5)$$

Therefore, by monitoring the spectral shift between two undisturbed and disturbed conditions, it is possible to extract information about both temperature and strain along the optical fiber. This principle is particularly explored in the OTDR and OFDR techniques for distributed acoustic sensing.

2.2 Distributed optical fiber sensing technology

2.2.1 OFDR

The OFDR technique was first reported for use with SMF in 1981⁴². Since then, continuous advancements in OFDR methodology and optical component technology have enabled spatial resolutions on the order of micrometers⁴³. A typical OFDR system based on a Mach-Zehnder interferometer is illustrated in Fig. 4(a). In this scheme, a continuous-wave tunable narrow-linewidth laser is linearly modulated in wavelength, resulting in a frequency response that reflects

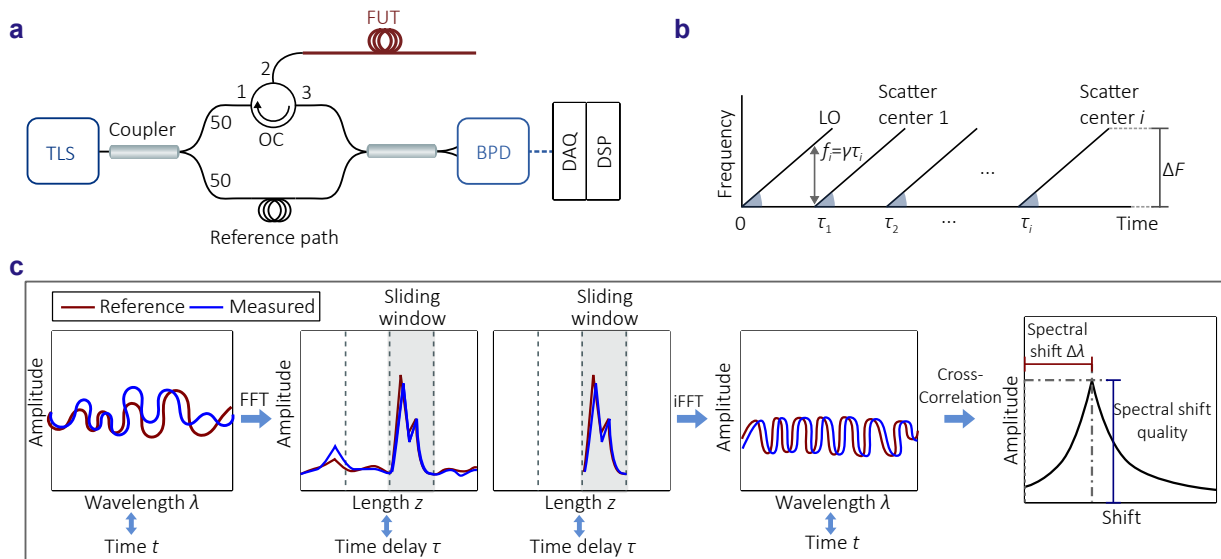


Fig. 4 | (a) A conventional OFDR setup based on a Mach-Zehnder interferometer. (b) Frequency backscattered from the i -th scatter center over time. (c) Cross-correlation method to obtain strain and temperature measurement.

the attenuation characteristics of the i -th fiber section.

In Fig. 4(b), the reference path is the local oscillator (LO), and the sensing path contains time-delayed information on the emitted probe light. The electromagnetic field of the LO light beam in function of time is⁴⁴,

$$E_i(t) = \sqrt{P_1} w\left(\frac{t}{T_s}\right) \exp[j(2\pi\nu_0 t + \pi\gamma t^2 + \phi(t))], \quad (6)$$

here, the optical P_1 is optical power on the LO, $w(t/T_s)$ is the time window function, T_s is the total sweeping time (i.e. the length of the time window), γ is the laser sweeping speed, and $\phi(t)$ is phase noise due to nonlinearities in wavelength sweeping and spontaneous radiation. The light beam coming from the i -th scattering center of the reference path can be described as,

$$E_i^r(t) = E_i w\left(\frac{t - \tau_i}{T_s}\right) \exp[j(2\pi\nu_0(t - \tau_i) + \pi\gamma(t - \tau_i)^2 + \phi(t - \tau_i))], \quad (7)$$

where E_i is the amplitude of the backscattered electromagnetic field at the i -th scatter center located at position z_i , and $\tau_i = 2z_i n_i/c$ is its corresponding round-trip time delay. Figure 4(c) depicts the frequency response at z_i as a delayed copy of the optical signal of the LO. The electric current produced at the photodetector is proportional to the sum of the interference signal of all i -th scattering centers.

$$I(t) \propto \sum \Re(E_i^*(t) \cdot E_i(t)). \quad (8)$$

As a result, the beating frequency at the photodetector is given by $f = (\nu_0 + \gamma t) - (\nu_0 + \gamma(t - \tau)) = \gamma\tau$. Neglecting the phase noise, the Fourier Transform of the electric current signal of the photodetector is given by⁴⁴,

$$I(f) = \sum_{i=1}^N A_i \exp[j(2\pi\nu_0 \tau_i - \pi\gamma \tau_i^2)] W(f - \gamma\tau_i), \quad (9)$$

where A_i is the amplitude of the scattering center with

beating frequency $f_i = \gamma\tau_i$ and phase $\phi_i = 2\pi\nu_0 \tau_i - \pi\gamma \tau_i^2$. The system's theoretical spatial resolution is,

$$\Delta z = \frac{c}{2n\Delta F}, \quad (10)$$

where c is the speed of light, n is the effective refractive index of the optical fiber core and ΔF is the wavelength sweeping range.

While the theoretical background of OFDR highlights its potential for high-resolution distributed sensing, practical implementations must account for some trade-offs involving range, resolution, and system complexity. For example, the broader the wavelength sweeping range, the higher the spatial resolution. However, this also increases the complexity of signal acquisition, requiring a larger DAQ buffer and/or faster sweeping speeds to meet a dynamical sensing requirement, which may demand higher sampling rates to accurately capture the full frequency content of the reflected signal. These constraints may impose practical limitations on system bandwidth and data processing stage.

In addition, the maximum measurable fiber length is constrained by the sampling rate of the data acquisition system and by the coherence length of the laser source. Extending the fiber length increases the optical path difference, leading to higher beat frequencies that must be sampled accurately to avoid aliasing. This requires higher sampling rates and larger data buffers, increasing the complexity and cost of the acquisition and processing hardware. Moreover, if the fiber length exceeds the coherence length of the laser, the interference signal may degrade, reducing the signal-to-noise ratio (SNR) and compromising the accuracy of the reflectivity measurements.

2.2.2 OTDR

The OTDR technique relies on detecting the round-trip delay τ of a backscattered light beam emitted by a pulsed source. Figure 5(a) illustrates a typical configuration, in which the distance z traveled by backscattered pulse is

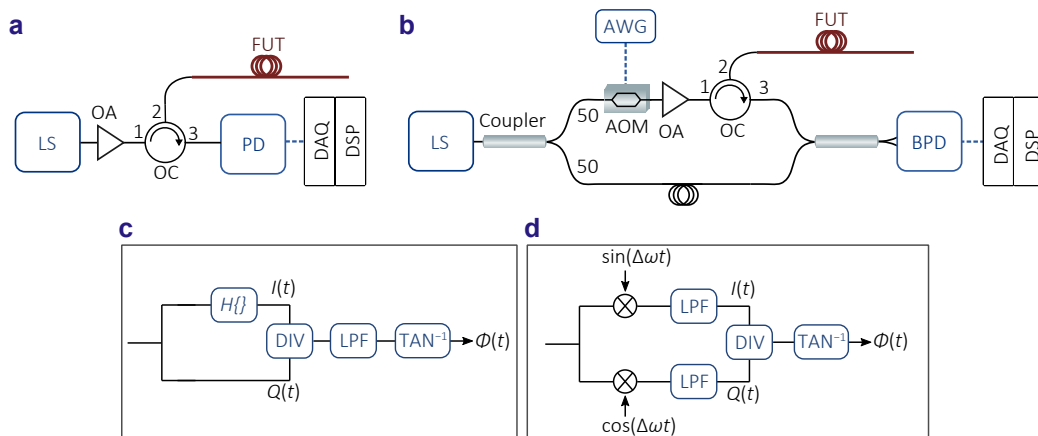


Fig. 5 | (a) Conventional OTDR configuration. (b) Typical setup of ϕ -OTDR. Demodulation and phase unwrapping stage based on (c) Hilbert Transform and (d) Q-I Phase Demodulation.

determined by the relation,

$$z = \frac{c\tau}{2n}. \quad (11)$$

The spatial resolution of a typical OTDR system is primarily determined by the width of the optical pulse. However, narrower pulses lead to a reduced pulse energy, lower SNR, higher noise levels, and reduced measurable fiber length. Moreover, short-duration pulses require a broader detection bandwidth, thereby increasing the complexity of both the hardware and the digital signal processing stages.

2.2.3 ϕ -OTDR

Phase-sensitive OTDR (ϕ -OTDR) is a variant of conventional OTDR that offers high sensitivity, wide dynamic detection bandwidth, and long sensing range, making it extensively employed in DAS applications⁴⁵. This technique is employed by incorporating a highly narrow-linewidth laser and an optical interferometer, as depicted in Fig. 5(b). In its most conventional configuration, the probe light from the laser source is modulated using an acousto-optic modulator (AOM) driven by an external electrical signal at frequency f_0 generated by an arbitrary waveform generator (AWG).

The electromagnetic field $E_p(t)$ after amplification of the probe light is given by,

$$E_p(t) = \sqrt{P_p} w \left(\frac{t}{T_p} \right) \exp(j2\pi t(\nu_0 + f_0) + \phi_L(t)), \quad (12)$$

here, P_p is the optical power, T_p is the pulse width, the term $(\nu_0 + f_0)$ represents the central laser frequency ν_0 shifted by the modulation frequency, and $\phi_L(t)$ represents the laser noise. The beating signal arriving at the photodetector is sum of all signals $E_i^r(t)$ backscattered at the i -th scatter center with the optical signal $E_i(t) = \sqrt{P_i} \exp(j2\pi\nu_0 t)$ from the local oscillator, where $\sqrt{P_i}$ is the power of the light entering the LO. Therefore, the electrical current produced by the photodetector is expressed as,

$$I(t) \propto \sum_{i=0}^N \Re(E_i^r(t) \cdot E_i^*(t)) = \sum_{i=0}^N A_i w \left(\frac{t - \tau_i}{T_p} \right) \cos[2\pi f_0(t - \tau_i) - 2\pi\nu_0\tau_i + \phi_L(t - \tau_i) - \phi_L(t)]. \quad (13)$$

here, A_i denotes the photocurrent amplitude corresponding to the Rayleigh backscattered signal from the i -th scattering point. External time-dependent perturbations, such as vibrations, modify the optical path length of the fiber, leading to time-dependent variations in the round-trip delay τ_i . These variations manifest as an apparent instantaneous frequency change in the detected signal, as described in Eq. (4), causing modulation of the optical phase. Therefore, vibration information is encoded in the phase term $\phi(t)$ of the electrical current $I(t)$, which is proportional to:

$$\phi \propto 2\pi\nu_0\tau_i + \phi_L(t - \tau_i) - \phi_L(t). \quad (14)$$

Finally, the demodulation stage can be utilized to retrieve

the phase $\phi(t)$ and extract the envelope $A_i(t)$.

Coherent OTDR (COTDR) is another variant of OTDR that relies on coherent detection to enhance sensitivity to Rayleigh backscattering along the fiber, detecting intensity variations⁴⁶. In contrast, ϕ -OTDR extends this approach by extracting the phase of the backscattered signal, enabling the detection of dynamic disturbances such as acoustic waves or mechanical vibrations^{47,48}. Both techniques share similar optical setups, including the narrow-linewidth laser, modulator, and coherent receiver, but ϕ -OTDR requires higher phase stability and often employs shorter probe pulses to improve temporal resolution. The core distinction lies in the signal processing: ϕ -OTDR requires phase demodulation to achieve high sensitivity to dynamic strain.

2.3 Signal processing approaches

2.3.1 OFDR

Strain sensing using OFDR can be performed either in the spatial domain (z -domain) or in the spectral domain (λ -domain), depending on the chosen signal processing approach and requirements on sensitivity. In the z -domain, external influences such as axial strain induce physical stretching or compression of the fiber, which leads to spatial shifts in the Rayleigh backscatter profile⁴⁹. Therefore, distributed strain may be estimated by performing two measurements, one under undisturbed conditions and the other under applied strain, and subsequently applying a cross-correlation analysis between the two traces in the z -domain. While this method provides intuitive spatial mapping, a more robust approach is to derive the phase shift directly from the wavelength domain⁵⁰.

Alternatively, in the wavelength-domain, both strain and temperature lead to measurable frequency shifts in the Rayleigh backscattered spectrum due to changes in the effective refractive index of the fiber segment. This is quantified through a spectral shift function, as detailed in Eq. (4). The most common algorithm is illustrated step-by-step in Fig. 4(c). First, two measurements are acquired under undisturbed and disturbed conditions. Then, the FFT is applied to both measured signals, converting them from the wavelength-domain to the space-domain (or, equivalently, the time-delay domain). In the next step, the measured backscattered spectra are divided into subsections using a sliding window approach. Then, an inverse Fast Fourier transform (iFFT) is applied to each window segment to retrieve the local Rayleigh backscatter signature in the wavelength domain. Finally, cross-correlation is performed between the corresponding signal segments to estimate the spectral shift, which is given by the lag at the peak of the cross-correlation function⁵¹. Strain can then be directly inferred from the spectral shift using Eq. (4).

Recent studies have demonstrated substantial progress in OFDR signal processing techniques. For example, the optimal length of the sliding window was analyzed in ref.⁵²,

considering the trade-off between spatial resolution and measurement accuracy. In ref.⁵³, a fast spectral shift demodulation algorithm based on Buneman frequency estimation (BFE) was proposed to improve the demodulation efficiency without penalizing performance metrics. Additionally⁵⁴, investigated real-time implementation strategies through hardware-accelerated FFT-based correlation.

2.3.2 ϕ -OTDR

Phase-sensitive OTDR is a powerful technique for distributed dynamic strain sensing. Because the phase information is contained within the acquired beating signal, specialized demodulation techniques are required to retrieve meaningful dynamic information from successive backscattered traces. Two commonly used techniques for phase retrieval in ϕ -OTDR systems based on heterodyne detection are the Hilbert transform and Q - I (quadrature) demodulation.

2.3.3 Hilbert transform

The Hilbert transform is widely used to obtain the analytic signal associated with the detected Rayleigh backscatter. By transforming a real-valued signal into its complex representation, the instantaneous phase can be extracted, enabling detection of dynamic perturbations. Given a real backscatter signal $s(t)$, the analytic signal $s_a(t)$ is constructed as⁵⁵:

$$s_a(t) = s(t) + jH\{s(t)\}, \quad (15)$$

where $H\{\cdot\}$ denotes the Hilbert transform operator. The instantaneous phase $\phi(t)$ is then:

$$\phi(t) = \arg(s_a(t)) = \tan^{-1} \left(\frac{H\{s(t)\}}{s(t)} \right). \quad (16)$$

Figure 5(c) illustrates the signal processing chain based on Hilbert-transform demodulation. At the digital signal processing stage, the Hilbert transform is applied to the acquired signal in order to generate its quadrature component. The original signal and its Hilbert transform are then combined to form an analytic signal, which is normalized by its magnitude. A low-pass filter (LPF) is subsequently applied to suppress high-frequency components and residual noise. Finally, the instantaneous phase is extracted by applying the arctangent operation, as described in Eqs. (15) and (16).

2.3.4 Q - I (quadrature) phase demodulation

Quadrature demodulation, also known as I - Q or in-phase/quadrature demodulation, uses two orthogonal reference signals (typically sine and cosine) to extract both amplitude and phase information from the backscattered signal. Coherent ϕ -OTDR setups employing heterodyne detection mix the backscattered signal with a local oscillator, and the resulting in-phase $I(t)$ and quadrature $Q(t)$ components are given by⁵⁵:

$$I(t) = A(t)\cos(\phi(t)), \quad Q(t) = A(t)\sin(\phi(t)). \quad (17)$$

Therefore, the instantaneous phase is reconstructed as,

$$\phi(t) = \tan^{-1} \left(\frac{Q(t)}{I(t)} \right). \quad (18)$$

Compared to the Hilbert transform method, this approach is simpler and have higher SNR and sensitivity; however, it is more affected by phase noise and polarization fading⁵⁶. In fading regions, the Rayleigh backscattered fields from multiple scattering centers interfere destructively, causing the detected signal amplitude at the photodetector to approach zero. Consequently, both the $I(t)$ and $Q(t)$ components become close to zero, and the arctangent phase retrieval becomes sensitive to noise, leading to large phase fluctuations or abrupt phase shifts.

The signal processing procedure based on I - Q demodulation is depicted in Fig. 5(d). The acquired signal is mixed with two local oscillator signals in quadrature, i.e., cosine and sine functions at angular frequency $\Delta\omega$, where $\Delta\omega$ is the heterodyne beating frequency f_0 , generating the in-phase (I) and quadrature (Q) components. Low-pass filters are then applied to the I and Q signals to remove high-frequency mixing products. The filtered I and Q components are subsequently combined using an arctangent operation to extract the phase information, as described in Eqs. (17) and (18).

2.3.5 Phase differentiation and unwrapping

After I - Q or Hilbert demodulation, the retrieved phase is inherently wrapped within the range of the arctangent operator, $(-\pi, \pi]$, which leads to artificial phase discontinuities when the true physical phase evolution exceeds this interval. Consequently, phase differentiation and/or phase unwrapping is required to reconstruct the continuous phase evolution. In DAS systems, phase recovery is typically performed through temporal and/or spatial differentiation followed by phase unwrapping. Temporal phase differentiation is commonly applied to suppress slow phase drifts and laser-induced refractive index fluctuations, which manifest as common-mode noise over time. In this approach, the phase of each sensing position is subtracted to a temporally averaged phase, reducing low-frequency phase noise. Spatial phase differentiation involves subtracting the phase of adjacent spatial positions along the fiber, which further mitigates laser phase noise. Phase unwrapping is performed by identifying apparent phase discontinuities close to $\pm 2\pi$ and compensating them accordingly. In addition, amplitude-based masking is often employed to exclude low-SNR or fading regions from the unwrapping process. Phase differentiation and phase unwrapping are described by the following equations⁵⁷,

$$\begin{cases} \text{Space: } \phi(z, t) = \phi'(z, t) - \phi'(z + \Delta z, t) \\ \text{Time: } \phi(z, t) = \phi'(z, t) - \frac{1}{N} \sum_{i=1}^N \phi'(z + t_i) \\ \text{Unwrapping: } \phi(z, t) = \phi'(z, t) \pm 2k\pi \end{cases} \quad (19)$$

2.4 Distributed measurement performance overview

2.4.1 Physical parameters measured by distributed acoustic sensors

DAS systems are capable of capturing mechanical vibrations and acoustic signals, being suitable to operate in multiple fields of application. For instance, DAS plays a crucial role in pipeline network health assessment by detecting anomalies such as leaks⁵⁸. In the context of power networks, DAS offers the capability to detect some anomalies, including conductor oscillations, sag, icing, and partial discharge^{59,60}. In aircraft and aerospace applications, it monitors aircraft noise and flutter in real time^{61,62}. Structural health monitoring in civil structures benefits from DAS's ability to identify stress, damage, and material fatigue in bridges, tunnels, and soil^{62–64}. In the oil and gas industries, DAS is widely used for leak monitoring, fracture diagnostics⁶⁵. Environmental sensing applications include seismic activity detection and the monitoring of marine life^{66,67}. For security and intrusion detection applications, DAS enables perimeter protection by identifying footsteps, digging, or vehicle movement near critical infrastructure⁶³. Road transportation monitoring benefits from traffic flow analysis and vehicle classification, while rail transportation monitoring includes the identification of rail integrity issues and train movement^{68–72}. Finally, in telecommunication applications, DAS enables the simultaneous operation of seismic measurement systems alongside existing telecom infrastructure, promoting cost-effective and dual-use deployment^{73,74}.

The performance of DAS systems in these multiple application fields can be assessed by comparing key metrics, such as accuracy and true/false alarm rates related to event detection, with those of conventional technologies employed in each respective field⁶³. When established reference systems

are available, such as seismographs for geoseismic sensing, they serve as a basis for evaluating the detection capabilities and overall effectiveness of DAS⁷⁵. Such comparative analysis is essential to determine whether the distributed sensing system meets the operational requirements and performance expectations for deployment in real-world monitoring scenarios.

In order to verify the signal output of a DAS application in laboratory conditions, Fig. 6 presents the phase output obtained from a commercial DAS system (QuantX, Luna Innovations, Virginia, USA⁷⁶) in response to an acoustic excitation consisting of a single 800-Hz tone, emitted near a 50-m FUT coil. Figure 6(a) shows the demodulated phase across 20 channels, each corresponding to a discrete 2-m segment of the sensing fiber. These channels are virtual sensing points defined by the processing window used during backscatter analysis and are spaced according to the system's sensor/channel spacing parameter⁷⁷. While often aligned with the gauge length (i.e. the effective spatial resolution, mainly determined by the width of the optical probe pulse), the channel spacing may differ depending on the signal processing strategy.

Figure 6(b) exhibits the FFT of the signals shown in Fig. 6(a) during the entire recording time. The red stripe at 800 Hz indicates the continuous tone applied during the experiment. This representation enables the identification of spectral components across time and space, and is especially useful in dynamic sensing scenarios. A more common visualization in DAS systems is the waterfall graph, which shows the frequency response of each channel's phase signal, computed via a short-time Fourier transform (STFT). Each vertical column corresponds to the spectrum of a given time window, forming a time-frequency map of the sensed vibration.

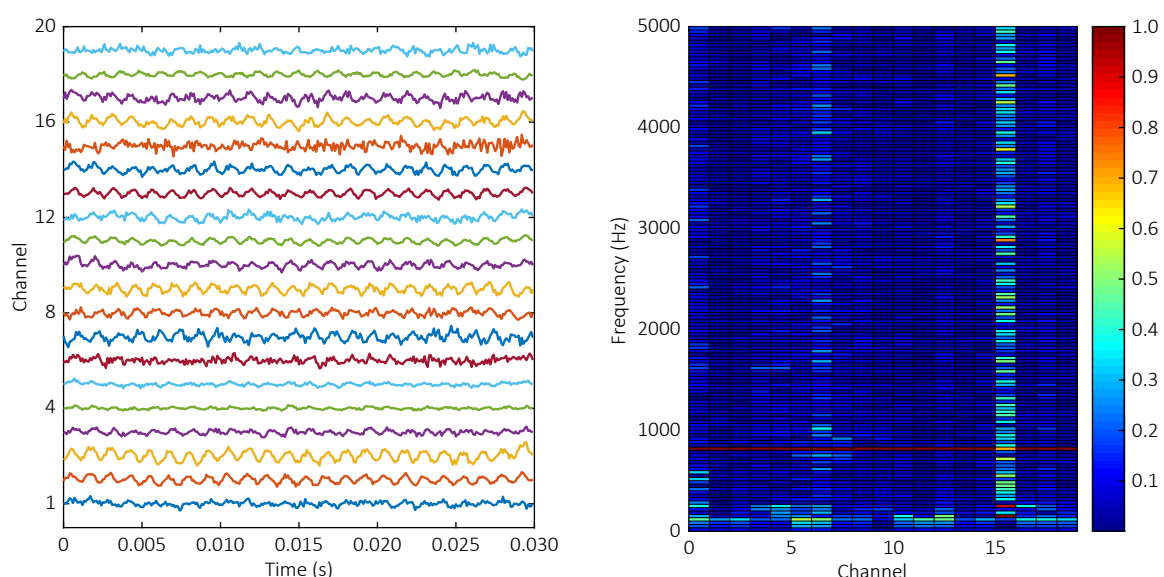


Fig. 6 | Examples of fiber-optic sensing deployments based on DAS across an integrated environment.

2.4.2 Performance indicators and shortcomings

Distributed sensing systems are characterized by a variety of performance indicators, and the selection of the most suitable system depends on the desired measurement objectives and the optimal trade-off among these metrics. Parameters commonly addressed in the literature include spatial resolution (i.e. gauge length), maximum length, number of channels, SNR, sensitivity, and dynamic bandwidth^{45,78,79}. As discussed in the previous sections, many of these parameters are inversely related, reinforcing the need for system designers and end-users to prioritize the parameters that best align with the sensing requirements of a given application.

In practice, ϕ -OTDR systems are subject to various constraints that can limit their performance. A well-known shortcoming of traditional distributed optical fiber systems is the cross-sensitivity between temperature and strain. As previously specified in Eqs. (4) and (5), distributed fiber-optic sensors suffer from strain-temperature cross-talk, since both measurands cause a frequency shift. A widely accepted solution to decouple these effects involves using a reference fiber segment that is mechanically isolated from strain. In a typical configuration, this strain-free reference fiber experiences only environmental temperature changes, while the adjacent sensing fiber is subject to both strain and temperature. By simultaneously acquiring the spectral shifts from both optical fibers and applying a linear system of equations, the independent contributions of strain and temperature can be obtained, relying only on a prior calibration to determine the fiber's sensitivity coefficients⁸⁰.

More recent approaches eliminate the need for a reference fiber by adopting dual-measurement analysis, in which the responses from distinct scattering mechanisms are combined, e.g. Rayleigh, Brillouin, and birefringence-induced effects. Due to their differing sensitivities to strain and temperature, these responses enable accurate decoupling of the two parameters^{81–83}. Another strategy involves deploying special fibers, such as doped optical fibers, which also exhibit different strain and temperature coefficients⁸⁴. Additionally, machine learning-based models have recently been explored to perform post-processing compensation by learning the joint influence of temperature and strain on the backscattered signal⁸⁵.

Standard distributed systems based on ϕ -OTDR are intrinsically affected by signal fading, which can significantly degrade the SNR of the distributed measurement. In many cases, the detected backscattered power decreases by a factor of 1000 in the fading areas, potentially leading to the alarm of false events⁸⁶. Polarization fading is a cause of this phenomenon and arises from mismatch between the polarization states of the Rayleigh backscattered signal and the local oscillator signal in the coherent detection scheme. These mismatches are caused by variations in the direction of the principal birefringence axis at each scatter center due to fluctuations in the fiber material density and ellipticity.

When combined at the coherent detection scheme, they lead to amplitude fluctuations and potential signal fading⁸⁷. A common solution consists of adopting the polarization diversity scheme, which captures and combines signals from multiple polarization states to improve detection performance⁸⁸. To mitigate discontinuities caused by the point-to-point aggregation method required by traditional multi-channel polarization diversity, digital filters can be incorporated into the digital signal processing stage to automatically identify and suppress fading areas. This strategy effectively reduces signal discontinuities and enhances the overall SNR⁸⁹.

A different strategy for mitigating the effects of signal fading involves applying an averaging filter to the attenuation signal in spatial and time domains to reduce rapid signal variations^{90,91}. However, this approach compromises temporal resolution and reduces the dynamic frequency range, which is especially undesired in applications requiring acoustic sensing⁹².

3 DAS technology and proposed configurations

3.1 Overview of system configuration

In ϕ -OTDR systems, frequency-division multiplexing (FDM) can be employed to enhance the frequency response of a DAS system. This technique improves channel utilization by assigning distinct frequency components to multiple parallel probe signals that propagate simultaneously along a single optical fiber⁸⁶. In many implementations, the frequency-tagged probe pulses are generated using AOMs driven by gated sinusoidal signals at different frequencies^{93,94}. In contrast, FDM schemes based on Mach-Zehnder modulators often experience signal energy loss and degraded SNR due to the generation of bilateral optical sidebands.

Additionally, FDM contributes to fading mitigation. Since the Rayleigh interference patterns associated with different frequency components are statistically independent, their combination reduces the probability of fading regions occurring simultaneously across all channels. Consequently, the aggregated response exhibits improved spatial uniformity and enhanced SNR along the entire sensing fiber. To further enhance the SNR and sensitivity, FDM schemes can be combined with additional multiplexing strategies, such as polarization diversity, dual-pulse configurations, or time-division multiplexing (TDM)^{95–97}. A drawback of FDM schemes stems from their limited scalability with respect to the number of carrier frequencies. In FDM-based systems, traces from probe pulses with different carrier frequencies can be distinguished using band-pass filtering. However, the number of available carrier frequencies is limited by the bandwidth of the optical modulator. Since the spectra of signals corresponding to different carrier frequencies

partially overlap, reliable separation becomes increasingly difficult as the frequency spacing is reduced. Consequently, a key drawback of this technique is the inefficient utilization of the transmission bandwidth, which limits the scalability of this approach.

Another technique for reducing fading effects is polarization-division multiplexing (PDM), which mitigates polarization fading by placing a polarization beam splitter (PBS) before the detection stage to separate the received light into two orthogonal polarization states⁸⁷. In such schemes, a polarization controller (PC) is typically inserted in the LO path to align the polarization states of the interferometer arms. Fading mitigation can be further enhanced by using two PBSs, one in the probe path and one in the LO path, which requires a polarization-diversity coherent receiver to independently separate and demodulate all in-phase and quadrature components⁹⁸. The PDM demodulation process involves phase retrieval from each polarization channel, which is achieved by reconstructing the complex optical field and computing the differential phase for each channel. The resulting phase signals can then be selected based on the highest SNR or combined using techniques such as maximum ratio combining (MRC) or weighted averaging to obtain a single robust phase trace^{88,99}.

FDM and PDM can be jointly utilized by incorporating an orthogonal frequency-division multiplexing (OFDM) scheme into a ϕ -OTDR to increase frequency response, improve SNR, enhance spectral efficiency and mitigate fading effects. In these schemes, multi-subcarrier OFDM waveforms are independently modulated and transmitted over orthogonal polarization states¹⁰⁰. The resulting quadrature components generate independently Rayleigh backscattering traces, which may be processed using a multiple-input multiple-output (MIMO) architecture in the fractional Fourier domain (FrFT) to suppress inter-carrier interference and polarization fading. Matched FrFT-based demodulation enables coherent signal recovery, while a sliding-window processing strategy is employed to reduce computational complexity.

Launching probe pulses with high optical power induce undesired nonlinear effects in the fiber. As an alternative, SNR can be increased by extending the pulse duration, albeit at the expense of spatial resolution. Pulse compression techniques have been proposed to increase the effective pulse energy, increasing the amplitude of the Rayleigh backscattered signal without degrading spatial resolution. Such approaches can be implemented using different methods, including linear frequency modulation (LFM) pulses and Golay codes^{96,100}. The performance of this technique degrades when lasers with significant phase noise or limited linewidth are employed. In contrast, ϕ -OTDR systems that do not rely on pulse compression are less affected, since differential phase extraction between adjacent sensing points effectively suppresses common-mode phase fluctuations¹⁰¹.

The dual-pulse configuration employs two probe pulses

launched with temporal delay, enabling differential phase measurement with improved SNR. By comparing the backscatter from closely spaced positions, this technique improves SNR, sensitivity and reduces susceptibility to phase noise and fading¹⁰². In PDM, a pair of optical pulses with a short temporal delay is generated independently for each polarization state, allowing polarization-diverse differential measurements. In FDM, a dual-pulse pair is generated for each frequency tone by modulating the corresponding AOM with two time-delayed envelopes⁹⁷. For demodulation, the differential phase is obtained by calculating the phase difference between the backscatter signals corresponding to the two pulses¹⁰³. In these systems, the spacing between the two probe pulses represents a critical design parameter that influences the trade-off between sensitivity and spatial resolution. Prior work has shown that increasing the temporal separation between dual pulses enhances measurement sensitivity by increasing the accumulated phase difference, which improves phase noise performance and weak signal detection in heterodyne schemes. However, analyses of dual-pulse parameters demonstrate that spatial resolution decreases linearly with pulse spacing^{104,105}.

In addition, space-division multiplexing (SDM) is a less complex alternative approach to mitigate signal fading. In ref.¹⁰⁶, a SDM scheme using a multi-core optical fiber (MCF) is proposed to suppress fading noise. The standard ϕ -OTDR configuration is preserved, while the single-mode sensing fiber is replaced with a seven-core MCF. Each core is accessed via a fan-in/fan-out structure and connected in an S-shaped series configuration to maintain signal continuity and enable signal reception. The MCF cores experience independent Rayleigh backscattering patterns due to their unique scattering point distributions, acting as parallel sensing channels for fading mitigation. Two optimization algorithms, namely the maximum amplitude selection (MAS) and the maximum spectrum similarity selection (MSSS), are employed to dynamically select or average signals from the cores with the strongest or most consistent responses, respectively.

In order to summarize the main differences in the DAS configurations, Fig. 7 shows the schematic representation of the aforementioned configurations aligned with the main components in conventional ϕ -OTDR systems. In addition, some fundamental trade-offs associated with each technique are outlined in Table 1.

3.2 Commercial solutions

Commercial solutions for optical acoustic sensing have been extensively developed in recent years. These systems typically consist of an optical fiber sensor connected to a single-ended interrogation unit capable of covering sensing areas ranging from tens to hundreds of kilometers^{76,107–111}. The selection of a commercial interrogator involves informed decisions based on multiple technical trade-offs, including

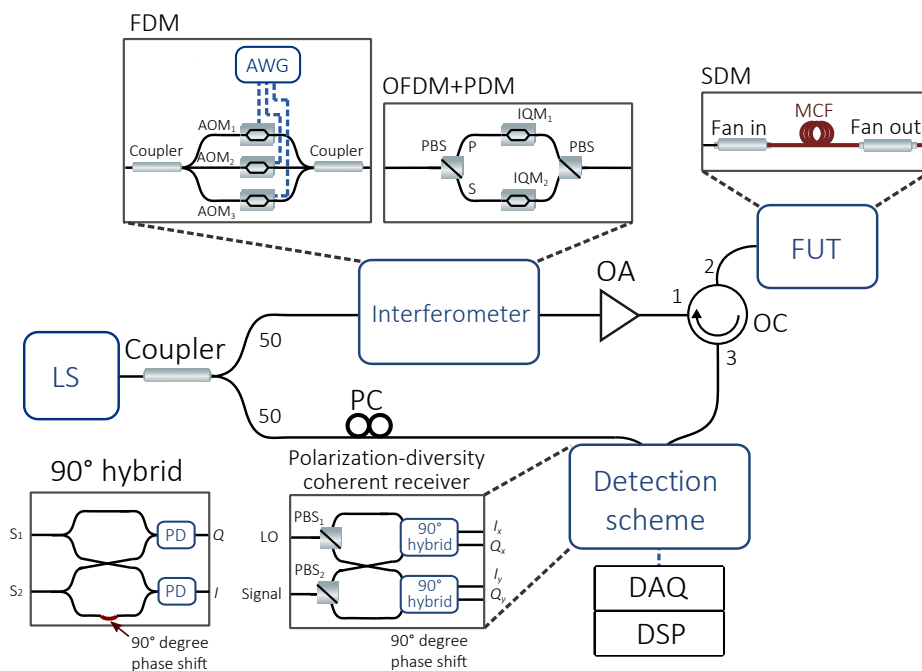


Fig. 7 | Some proposed ϕ -OTDR system configurations.

Table 1 | An overall comparison between different techniques applied to ϕ -OTDR.

Technique	Benefit	Shortcoming
FDM	Reduce fading, improve bandwidth	Inefficient transmission bandwidth
OFDM	Reduce fading, high bandwidth improvement	High hardware and DSP complexity, sensitivity to drift in optic-electrical components
PDM	Reduce fading, increase phase retrieval robustness, increase SNR stability	Increase system complexity
Dual pulse and, time-slot multiplexing	Reduce fading, improve SNR	Spatial resolution reduces for longer pulses
Pulse compression	Improve SNR	Degrade with laser noise
SDM	Reduce fading and noise	Reduce measurement range

measurement range, gauge length, dynamic bandwidth, strain sensitivity, and overall system cost. These decisions are typically guided by the requirements of the target application. Table 2 presents some commercial DAS systems, including some of their technical specifications.

A key feature of the commercial interrogation unit is its dynamic bandwidth. Some seismic and geological monitoring applications often involve the detection of acoustic waves with periods on the order of seconds, requiring the lower limit of the sensing bandwidth to reach frequencies as low as 0.01 Hz¹¹². In these scenarios, solutions such as those provided by MS-DAS¹¹⁰ (Ovlink, Wuhan, China), iDAS/iDAS-MG¹⁰⁷ (Silixa-Luna Innovations, Virginia, USA), and Treble¹¹³ (Terra15 Technology, Perth, Australia) are capable of achieving inferior bandwidth limits of, respectively, 0.01 Hz, 0.001 Hz and 0.01 Hz. On the other hand, applications that demand high interrogation rates, such as railway, pipeline and structural health monitoring, require

systems capable of capturing rapid acoustic events^{114,115}. These scenarios benefit from iDAS/iDAS-MG and MS-DAS, which offer interrogation frequencies beyond 50 kHz.

Another parameter that is highly emphasized in DAS development is the maximum measurement range. The OptaDAS and QuantX are promising solutions, offering coverage of up to 100 km and 150 km, respectively. These long-range systems are suitable for acoustic sensing applications in deep-sea marine environments, extensive railway networks and large perimeters¹¹⁶.

3.3 Recently proposed approaches and configurations of DAS systems

Advances in OTDR- and OFDR-based technologies have significantly enhanced the overall performance of DAS systems, leading to improvements in key metrics such as SNR, dynamic bandwidth, and measurement range. In the

case of ϕ -OTDR-based systems, dynamic bandwidths as high as 20 kHz over sensing lengths of 50 km and up to 50 MHz over 2.5 km have been reported in the literature over the past decade⁵⁶. In contrast, OFDR-based approaches are particularly well suited for applications requiring high spatial resolution, achieving centimeter-scale resolution over kilometer-long optical fibers¹¹⁷.

This section reviews recently reported DAS technologies and organizes them according to the primary performance limitations they address: the first part focuses on techniques aimed at increasing system bandwidth; the second part discusses methods designed to extend the sensing range and/or the dynamic strain range; while the final part covers cost-effective and reduced-complexity solutions. In addition, Table 3 provides a comparative summary of the configurations discussed in this section, highlighting their SNR, maximum sensing length, spatial resolution, and dynamic bandwidth.

The FDM technique can reduce fading effects by transmitting multiple frequency components simultaneously over the same optical channel. However, when Mach-Zehnder modulators are utilized, FDM degrades the SNR due to bilateral sideband and loss of energy. An alternative approach to mitigate signal fading is explored in ref.⁷⁸, where a phase-frequency modulation (PFM) via polyphase-coded was incorporated to a ϕ -OTDR setup, significantly improving the SNR due to pulse compression and efficient energy compensation. In this approach, the optical power remains concentrated within a single effective spectral band, mitigating interference between spectral sidebands. As a result, the system exhibits improved SNR, enhanced tolerance to

fading, and more efficient utilization of optical power, achieving an SNR of approximately 46.9 dB over a 21.6 km fiber, which represents an improvement of 7.81 dB compared with conventional FDM-based ϕ -OTDR systems.

Even though FDM improves the repetition rate in traditional ϕ -OTDR systems (where the repetition rate is constrained by the length of the fiber under test), FDM still suffers from inconsistent phase offsets, as it introduces phase offsets between different frequencies. To mitigate this issue and to increase the dynamic strain range, a multi-frequency time-slot multiplexing (MFTSM) scheme is proposed in ref.⁴⁵, with the objective of enhancing both bandwidth and dynamic strain range. This work integrates a series of modifications into the conventional ϕ -OTDR architecture, including quadrature modulation and an ultra-weak fiber Bragg grating (UWFBG) array as the sensing medium.

In this scheme, the majority of the optical power from a narrow-linewidth laser source is modulated by an IQ modulator to generate chirped single-sideband pulses at distinct frequency bands, while the remaining probe light is modulated by a Mach-Zehnder modulator to produce double-sideband pulses that enable phase compensation among frequencies. Experimental results obtained over a 765 m fiber demonstrate a threefold increase in response bandwidth, and a 4.66 dB improvement in dynamic strain range. In contrast to FDM-based schemes, this approach requires a UWFBG array, or another sensing medium with backscattering-enhanced points (BEPs), as well as increased computational complexity. Engineering applications that may benefit from MFTSM over FDM include scenarios requiring both high bandwidth and large strain sensing range, such as

Table 2 | Comparison between different commercial DAS interrogators.

Equipment	$L_{\max}$	Δz	Interrogation rate	Dynamic bandwidth
QuantX ⁷⁶	100 km	2 m	0.5–10 kHz	—
iDAS ¹⁰⁷	45 km	10 m	400 Hz–100 kHz	<0.001 Hz to 50 kHz
iDAS-MG ¹⁰⁸	30–50 km	3–30 m	400 Hz–100 kHz	<0.001 Hz to 50 kHz
DAS N5226A/R70 ¹⁰⁹	12–70 km	3.75–40 m	1–20 kHz	—
MS-DAS ¹¹⁰	20–50 km	1–10 m	0–50 kHz	0.01 Hz–25 kHz
OptoDAS ¹¹¹	> 150 km	> 2 m	—	—
Treble ¹¹³	20 km	>0.8 m	—	0.01 Hz–6.1 kHz

Table 3 | Comparison between different configurations in terms of the performance indicators.

Paper	Year	Method	SNR	$L_{\max}$	Δz	Dynamic bandwidth
ref. ⁷⁸	2025	PFM FDM ϕ -OTDR + PC modulation	46.9 (+7.81) dB	21.6 km	—	11 kHz
ref. ⁴⁵	2025	MFTSM ϕ -OTDR + UWFBG array	50 (+4.66) dB	765 m	5 m	20–118 kHz
ref. ¹¹⁸	2024	ϕ -OFDR + injection-locked LFS	27 dB	1 km	2 cm	Detected a 10-Hz vibration
ref. ¹¹⁷	2024	OFDR + polarization diversity scheme	—	1.5 km	10 cm	200 Hz
ref. ¹¹⁹	2024	OFDR + laser thermal modulation	8–9 dB	100.95 km	16.8 m	—
ref. ¹²⁰	2024	ϕ -OFDR + DFB + feedback algorithm + WFBG array	50 dB	—	4 cm	Detected a 200-Hz vibration
ref. ¹²¹	2025	FDM TGD-OFDR + FSL	55 dB	600 m	1.5 m	Detected a 496-kHz vibration

structural health monitoring and high-frequency mechanical diagnostics.

Proposals for bandwidth enhancement have also been reported for OFDR-based DAS systems. A common approach is the application of FDM to time-gated digital OFDR (TGD-OFDR) architectures. In TGD-OFDR, the sensing fiber is interrogated using temporally gated optical waveforms derived from a frequency-swept laser, and the backscattered signals are detected and processed digitally within predefined time windows corresponding to specific fiber segments. By combining TGD-OFDR with FDM, multiple frequency-shifted interrogation signals can be transmitted within a single sweep period, increasing the effective sampling rate and extending the measurable vibration bandwidth.

However, the effectiveness of FDM in this context is fundamentally constrained by the limited frequency-modulation range of the optical modulator. To address this limitation, ref.¹²¹ proposed a fiber frequency-shift loop (FSL) scheme that generates multiple detection pulses at distinct frequency ranges, which extends the detection bandwidth beyond that of conventional TGD-OFDR implementations based on AOM. As a result, the proposed configuration demonstrated a vibration detection bandwidth of 1.5 MHz over a 600 m fiber, with a spatial resolution of 1.5 m.

Beyond spectral efficiency, modifications in DAS systems also aim to improve the noise and coherence of the laser source. In ref.¹¹⁷, the performance of a ϕ -OFDR system is enhanced by generating a low-noise linear frequency sweeps (LFS) with different sweep ranges using an injection-locking technique. By suppressing dominant phase noise sources (such as laser frequency instability, polarization fading, and intensity noise) through injection locking, this approach achieves improved effective spatial resolution and measurement range due to the elimination of the auxiliary interferometer. In this work, two LFSs with sweep ranges of 12 GHz and 52 GHz were employed, yielding spatial resolutions of 2 cm and 5 mm, respectively, over a sensing distance of 1 km. In addition, weak reflector arrays (WRAs) are used to enhance the Rayleigh backscattered (RBS) signal by up to 27 dB, while the phase index method (PIM) further mitigates residual fading noise, improving the accuracy and robustness of phase demodulation. Although injection locking effectively improves laser coherence and sweep linearity, it introduces additional laser sources and stability constraints. The limited locking range restricts sweep bandwidth and speed, affecting significantly the dynamic bandwidth.

To surpass the laser coherence length limitation, a phase-noise-compensated OFDR (PNC-OFDR) system was introduced in ref.¹¹⁸, enabling long-range static and dynamic strain measurements over distances of up to 1.5 km by overcoming the coherence-limited range of conventional OFDR. In PNC-OFDR, a reference interferometer with a delay close to half the laser coherence time is employed to extract the

laser phase noise. For fiber locations whose round-trip delay exceeds the coherence-limited range of this reference, the phase-noise reference is digitally extended by generating additional reference signals corresponding to integer multiples of the original reference delay, which ensures phase-noise compensation over extended sensing distances. As a result, the PNC scheme improves the quality of Rayleigh spectrum correlation along the entire fiber under test (FUT), even at distances exceeding 100 times the laser coherence length¹¹⁶. In this work, the system achieves a maximum sensing length of 1.5 km for static measurements and up to 220 m for dynamic measurements with a bandwidth of 200 Hz.

Commonly, OFDR-based systems provide significantly higher spatial resolution than OTDR technology, owing to their frequency-swept interrogation and coherent spectral correlation, at the expense of having a reduced dynamic bandwidth and measurement range. This intrinsic trade-off makes OFDR particularly advantageous for distributed sensing applications where fine spatial resolution and accurate strain localization are prioritized over high-frequency/long-range dynamic response. Engineering applications that benefit from OFDR include structural health monitoring of civil infrastructure, such as bridges, and tunnels, where strain variations occur predominantly at frequencies of the order of tens or hundreds of Hz; and distributed strain mapping in composite materials and aerospace structures.

Among various OFDR technologies, cost-effective schemes exhibit limited performance compared with sophisticated ϕ -OFDR approaches. However, they typically offer reduced complexity and cost, and have more robustness, which continues to motivate their use in recent studies. Consequently, these solutions occupy a distinct niche among DAS technologies. In this context, a cost-effective solution is presented in ref.¹¹⁹, where a silicon photonic chip-based laser is employed for long-range distributed sensing, and internal thermal modulation is utilized to mitigate laser phase noise and the auxiliary interferometer. An arbitrary waveform generator is used to thermally induce a 10 GHz optical frequency sweep at a scanning frequency of 5 Hz over distances of up to 100.95 km.

By directly modulating the laser frequency through internal thermal tuning, the system benefits from improved optical power efficiency and enhanced SNR, since no optical power is lost in external components. This simplified architecture makes the approach particularly attractive for cost-sensitive long-range distributed sensing applications. However, thermal modulation is intrinsically slow due to the thermal response time, typically limiting the sweep repetition rate to the order of a few hertz. As a consequence, the dynamic bandwidth is substantially lower than that of OFDR systems employing external electro-optic or acousto-optic modulation, and orders of magnitude lower than ϕ -OTDR-based DAS. This restricts the applicability of thermally modulated OFDR to quasi-static or low-frequency

sensing scenarios (e.g. submarine geotechnical monitoring).

Aiming at cost efficiency with broader dynamic bandwidths, a high-spatial-resolution and high-speed vibration sensing system based on ϕ -OFDR is proposed using a standard telecom distributed feedback (DFB) laser, combined with a feedback iteration algorithm to suppress frequency sweep nonlinearity¹²⁰. Unlike conventional systems, the proposed architecture employs a single-branch sensing configuration incorporating a weak reflector array and a gold-plated fiber end to provide intrinsic reflection. Experimentally, the system achieves a spatial resolution of 4 cm, a repetition frequency of 4 kHz, and a SNR of 50 dB.

While numerous OFDR- and OTDR-based techniques have been proposed in the literature to enhance specific performance metrics, commercial DAS systems are designed to meet a broad and versatile operational field. As depicted in Table 2, commercial solutions typically specify sensing lengths up to tens of km, spatial resolutions on the order of tens of m, and dynamic bandwidths ranging from sub-millihertz to tens of kilohertz. These systems generally rely on ϕ -OTDR architectures, which inherently offer higher dynamic bandwidth compared with OFDR-based schemes¹⁰⁹. At the research level, several advanced modulation and multiplexing strategies have demonstrated dynamic bandwidths that exceed those of commercial implementations^{45,78}. In this context, silicon photonics-enabled implementations of FDM, pulse/phase diversity schemes, and coherent *I/Q* demodulation architectures represent promising pathways toward industrial adoption, as photonic integration can realize multi-carrier transmitters and coherent receiver front-ends (e.g., integrated *I/Q* modulators and optical hybrids) in compact and robust platforms¹²². Although research-oriented systems based on more complex modulation schemes and architectures (e.g., MFTSM) have demonstrated bandwidth and coherence enhancements, their increased system complexity, digital signal processing requirements, and reduced robustness may limit their attractiveness for compact, field-deployable commercial systems.

4 DAS applications

The variety of developments on the DAS technology, including the new configurations, signal processing methods and artificial intelligence integration lead to a myriad of practical applications proposed in the last few years¹²³. In this case, the distributed sensing and remote sensing capabilities resulted in applications of long range monitoring, which is crucial in geological applications, environmental sensing and transportation monitoring (both road and rail transportation). In addition, acoustic sensing capability leads to important applications in structural health monitoring in which such approach is used in civil engineering structures, aircraft monitoring and industrial applications, especially on oil and gas field⁴⁴. To that extent, the acoustic signals can be

used on leakage monitoring (in pipelines) as well as in the partial discharge analysis for power transmission lines. An illustrative example of these multi-domain applications is presented in Fig. 8, which depicts a representative environment integrating DAS deployment across terrestrial, marine, industrial, and urban infrastructures. Such applications are thoroughly analyzed and discussed in the following subsections.

4.1 Geophysics applications

DAS has rapidly emerged as a suitable technology in geophysical applications by enabling different optical fiber cables to function as dense arrays of sensors over tens to hundreds of kilometers⁷⁵. In this case, the sensing can be achieved using telecommunication, borehole, and purpose-deployed fibers, which provides unprecedented spatial coverage for earthquake monitoring, subsurface imaging, fault-zone studies, and hazard assessment in environments where conventional seismic instrumentation is sparse or difficult to deploy¹²⁴. However, some technical challenges need to be addressed for the direct and routine use of DAS in geophysics and seismic monitoring. An important technical challenge is that DAS fundamentally measures strain rate rather than ground displacement or velocity, requiring adjustment in the signal acquisition related to gauge length, directional sensitivity, and frequency-dependent effects to enable quantitative interpretation and comparison with conventional seismic sensors⁷⁵. In addition, the interpretation of sensors responses is further complicated by uncertain fiber-ground coupling and poorly constrained cable geometry, particularly when using preexisting telecommunication infrastructure, leading to spatially variable sensitivity and reduced reliability of absolute measurements¹²⁵. Another challenge is related to the single component measurement of DAS, which restricts full wavefield characterization and complicates source parameter estimation, fault mechanism studies, and ground-motion prediction, leading to the need to deploy dense multidirectional fiber coverage or hybrid networks.

Over the years, some researchers have successfully closed the gap between technical challenges and practical applications of DAS in geophysics with a progression of DAS from methodological validation to mature geophysical application. Over the years, some researchers have successfully closed the gap between technical challenges and practical applications of DAS in geophysics with a progression of DAS from methodological validation to mature geophysical application. Early demonstrations using existing telecommunication fibers established that DAS can record broadband seismic signals (0.1–100 Hz) with meter-scale spatial sampling over tens of kilometers, reproducing waveforms comparable to conventional seismometers and enabling dense wavefield imaging, earthquake detection, and fault-zone characterization¹²⁵. In an urban environment, seismic

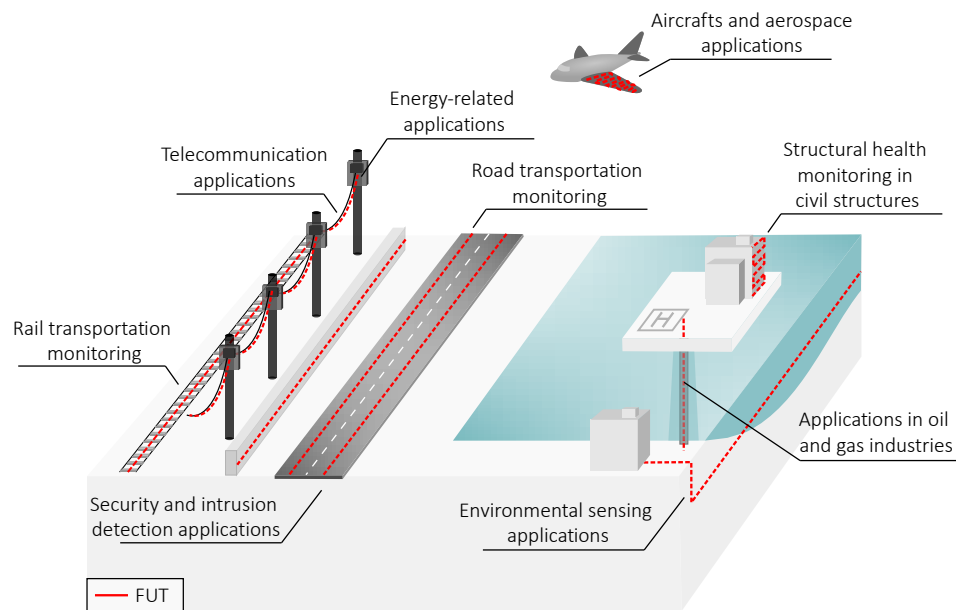


Fig. 8 | Examples of fiber-optic sensing deployments based on DAS across an integrated environment.

and general geophysics monitoring can be achieved using existing telecommunication infrastructures with optical fiber cables already deployed. Such preexisting infrastructure enables to monitor earthquakes, surface waves, and anthropogenic noise at city scale¹²⁶. In another crucial analysis in geophysics, volcanological applications were proposed in ref.¹²⁷, which deployed a dense network at Long Valley Caldera, demonstrating that the use of thousands of virtual channels can dramatically improve tomographic resolution in the upper crust, resolving velocity structure, anomalies related to different wave velocities (V_p/V_s), and fluid-dominated unrest processes that were previously ambiguous. Alternatively, the high range of temperature stability of optical fibers enable the use of DAS in cryospheric studies to investigate glaciers, ice sheets, snow, and avalanches, demonstrating detection of icequakes, basal slip, crevassing, and ice–water interactions across frequency bands from millihertz to hundreds of Hertz¹²⁸. Similarly, DAS is also an important technology for offshore monitoring by using different submarine cables for geophysics monitoring in different regions, where the dark fibers in telecommunication cables already deployed can be used as distributed sensing elements¹²⁹. It is also important to mention that some industrial processes have a direct impact on geophysics. One of these processes is hydraulic fracturing, a common process in the oil and gas industry to extract oil and natural gas from low-permeability rock formations by injecting water, sand, and chemical additives at high pressure to create fissures. In ref.¹³⁰, the authors demonstrated that both high-frequency DAS (kHz sampling) and low-frequency DAS (below 0.05 Hz) can constrain fracture geometry, stress shadowing, and quasi-static deformation at interwell scales, demonstrat-

ing DAS as an important technology for real time evaluation of the process and its impact on the environment.

The advances in DAS technologies enable the mitigation of some of the application-specific technical issues and resulted in the aforementioned applications. Considering the advances in DAS, the improvements in interrogator design with higher dynamic range, lower phase noise, better laser stability, and flexible gauge-length configurations that are directly addressing long-standing limitations in low-frequency drift, phase wrapping during large events, and amplitude fidelity, which are critical for earthquake hazards, volcanology, and deformation studies¹²⁷. Moreover, the emergence of multi-frequency and multi-physics distributed sensing (e.g., combined DAS, distributed strain sensing, and distributed temperature sensing) allows separation of mechanical strain from thermal effects, improving interpretation of slow deformation, fluid migration, and hydrothermal processes. As the signal interpretation is a crucial issue in geophysics applications, the advances in machine learning and automated phase-picking algorithms tailored to DAS (e.g., dense-array PhaseNet variants) are enabling reliable event detection, picking, and association across thousands of channels, making large-scale tomography and real-time monitoring feasible¹²⁵. The main consequence of such advance is the correlation with the wavefield modeling and strain-to-motion conversions, which improves the quantitative use of DAS data for imaging, source characterization, and comparison with conventional seismometer. Finally, the continuous progress in edge computing, compression, and cloud-based processing enable efficient data management and mitigation of latency constraints that can lead to near-real-time applications such as earthquake early warning and

offshore monitoring.

Table 4 summarizes the characteristic performance of DAS across the discussed geophysical and seismic application domains. In particular, the comparison emphasizes the trade-off between DAS's broadband sensitivity and its strain-based, single-component measurement, as well as the distinct roles of high-frequency DAS for dynamic processes (e.g., seismic wavefields, hydraulic fracturing diagnostics) and low-frequency DAS for quasi-static deformation and stress evolution.

4.2 Structural health monitoring in civil structures

The versatility and precision of DAS make it a cornerstone in modern Structural Health Monitoring (SHM), enhancing the safety and longevity of (civil) structures and enabling real-time monitoring of structural integrity across various civil engineering applications¹³¹. In civil engineering, DAS is particularly impactful in structural and crack monitoring, where it detects minute deformations and stress concentrations that precede structural failures. In geotechnical engineering, it provides insights into soil movements and slope stability, crucial for landslide detection and prevention⁶². Additionally, DAS is instrumental in tunneling construction and integrity monitoring, ensuring the safety and durability of underground structures. Its application extends to bridges, where it can monitor load distribution and detect early signs of damage, and buried infrastructure⁶³. DAS is increasingly used as structural sensing technology, since it provides continuous, large-scale, and infrastructure-wide monitoring that is difficult to achieve with point sensors or visual systems. Compared to FBGs, Microelectromechanical Systems (MEMS) sensors, and accelerometers, DAS offers greater spatial resolution, measurement length and sensor density with comparable accuracy and measurement resolution¹³¹. Unlike vision-based systems, DAS operates without line-of-sight, preserves privacy, and can sense both surface and subsurface processes. In general, DAS enhances scalability and resilience while for large scale measurement enabling a persistent, meter-scale monitoring over kilometer-scale

assets with minimal additional hardware.

For a clearer description of DAS systems compared with other technologies for SHM, DAS systems typically provide spatial resolutions on the order of 0.5 to 10 m and sensing ranges exceeding 10 to 50 km. In contrast, FBG-based systems have their resolution related to the gratings positioning along the fiber and it is limited to discrete sensing points with typical multiplexing of 10–100 sensors per fiber, which can be insufficient for long range applications. Furthermore, the typical spatial resolution of DAS can provide up to 10^3 to 10^4 measurement points per kilometer, which is also not achievable with discrete sensors such as accelerometers and general MEMS-based sensing approaches. In terms of strain resolution, DAS and FBGs can reach sub-microstrain resolution ($< 1 \mu\epsilon$) under controlled conditions with typical monitoring in the order of $10 \mu\epsilon$. However, sampling rates above 1 kHz and well-calibrated dynamic responses with high signal-to-noise ratios can be achieved with MEMS sensors and accelerometers, whereas DAS systems are typically constrained to lower effective bandwidths (often below 1 kHz depending on gauge length and interrogator settings) and exhibit reduced dynamic range due to phase wrapping and noise accumulation, which is an active challenge in DAS research. In a quantitative comparison with vision-based systems, the DAS can outperform such systems in terms of strain resolution, since vision-based systems can achieve sub-millimeter displacement accuracy under ideal conditions. Moreover, vision-based systems have critical limitations by line-of-sight and coverage, which typically is around hundreds of meters per camera setup instead of a continuous measurement in kilometer range of DAS systems. These quantitative differences indicate that DAS prioritizes spatial coverage and sensing continuity being the most suitable approach for long range sensing applications.

Despite the advantages of DAS systems in SHM applications, there are still technical challenges to overcome in such application scenario. One technical challenge is dependence of measurement quality on fiber installation and coupling, where differences in bonding methods, cable packaging, and

Table 4 | Overview of DAS applications in geophysics.

Reference	Spatial resolution	Sampling rate	Detection range	Frequency range	Measurement capabilities
General DAS seismology	1–10 m	100–10,000 Hz	Local–telesismic	0.01–100+ Hz	Axial strain/strain rate; dense wavefield sampling; earthquake detection; ambient noise imaging
Urban monitoring	1–10 m	200–2000 Hz	10–100 km	0.1–50 Hz	Earthquake detection; surface-wave imaging; anthropogenic vibration monitoring
Volcanology	1–5 m	500–2000 Hz	Local–regional (≤ 100 km)	0.1–40 Hz	P/S picking; seismic tomography; V_p/V_s imaging; fluid–magma discrimination
Cryosphere	1–10 m	200–5000 Hz	m–tens of km	0.01–200 Hz	Icequakes; basal slip; crevassing; firn/ice structure; avalanches
Hydraulic fracturing	1–5 m	5000–10,000 Hz	≤ 1 –2 km	1–500 Hz	Perforation detection; fluid allocation; high-frequency fracture diagnostics

host material properties lead to spatially variable sensitivity and uncertainty in strain amplitudes. Moreover, there is the sensitivity to temperature variations and interrogator drift, which lead to the necessity of temperature-compensation methods, which is especially undesirable for low-frequency and long-term monitoring. However, at higher frequencies and high strain levels, dynamic range limitations and phase wrapping require phase unwrapping and filtering strategies, increasing processing complexity and reducing robustness under extreme loading conditions. Such technical challenges have been addressed throughout the years with the development of different SHM applications with in-field implementations as discussed below.

Damage identification and seismic monitoring based on ambient vibration data represent some of the most effective applications of DAS within SHM. The combination of DAS with advanced data-driven techniques been used as effective damage detection and classification systems. For example, Brusamarello et al.⁶⁴ demonstrated that DAS measurements, combined with machine learning algorithms, can successfully detect and distinguish multiple damage types in multi-layer structures by exploiting changes in wave propagation, natural frequencies, and vibration modes, achieving an F1-score of 93%. At a larger spatial scale, seismic monitoring using DAS deployed in existing urban telecommunication infrastructure has been shown to provide stable, continuous measurements of near-surface properties. Fang et al.⁶⁶ used a two-dimensional DAS array on the Stanford University campus to identify anthropogenic and quarry-blast sources and to track statistically significant surface-wave velocity changes associated with construction activities, demonstrating the potential of DAS for long-term, real-time SHM in urban environments.

Beyond seismic response monitoring, DAS has also been successfully applied to a wide range of civil infrastructure systems due to its versatility and scalability. Rodet et al.¹³² demonstrated that dark-fibers (in existing infrastructures) DAS deployed across a metropolitan area can extract modal parameters of bridges, including natural frequencies, damping ratios, and mode shapes, with strong agreement to conventional velocimeters, while enabling continuous monitoring of day–night variability driven by traffic and temperature. The applicability of DAS to emerging construction technologies was further illustrated by Zhao et al.¹³³ with the monitoring of the dynamic response of a large 3D-printed bridge and successfully detected various operational and environmental events using relatively simple signal processing techniques. In addition, advances in DAS hardware and interrogation schemes have enabled high-frequency, distributed strain sensing with kHz sampling rates and meter-scale resolution, as shown by Hoult et al.¹³⁴, where DAS achieved strain measurement accuracy comparable to OFDR systems over significantly longer sensing lengths. Finally, comparative studies on wind turbine towers^{114,135} demonstrated that DAS can reliably capture dynamic strain

profiles, modal characteristics, and displacement with performance comparable to industry-accepted OFDR systems, while offering advantages in sensing range and robustness under high strain-rate conditions. Thus, the previously reported works demonstrated the feasibility of DAS as a powerful and flexible SHM technology capable of supporting damage detection, seismic monitoring, and dynamic response characterization across a large range of structural applications. Table 5 summarizes the sensors applications in SHM in terms of measurement range, spatial resolution and sampling frequency.

4.3 Rail transportation monitoring

While SHM provides valuable insights into the integrity and performance of civil structures, its applications extend beyond static infrastructure. Transportation systems, including roads, railways, and bridges, form a critical part of our built environment and require continuous dynamic monitoring to ensure safety and efficiency of the mentioned systems. As we transition from general structural SHM to more specific applications in traffic and railway monitoring, it's important to note that these systems often fall under the broader umbrella of condition monitoring. The following section will delve into the unique challenges and technologies associated with monitoring these dynamic transportation networks and infrastructure.

DAS revolutionizes railway monitoring by transforming existing fiber optic infrastructure into dense sensor arrays capable of real-time detection of train movements, track integrity assessments, and anomaly identification across extensive rail networks using machine learning techniques. This innovative approach not only enables continuous surveillance of vibration patterns, speed variations, and wheel-rail interactions but also provides crucial insights into the structural health of the tracks themselves, offering a comprehensive solution for monitoring both rolling stock and fixed railway assets with unprecedented detail and efficiency while often leveraging already installed communication cables.

In the last few years, there is a chronological progression in the use of DAS for railway monitoring, beginning with early demonstrations of continuous train detection and speed estimation using existing fiber infrastructure. One of the earliest large-scale studies, Kowarik et al.⁷¹, demonstrated infrastructure-free monitoring along a 35 km high-speed rail line in Germany using dark-fibers in cable tunnels, achieving reliable train speed estimation through both conventional signal processing and deep neural networks. This work established the feasibility of long-distance, real-time railway monitoring with DAS. Then, Wiesmeyr et al.¹³⁶ investigated real-time train tracking over approximately 20 km of rail, comparing tunnel-installed fibers with open-track installations directly attached to the rail. Their results showed that tunnel deployments provide

Table 5 | Overview of DAS applications in structural health monitoring.

Reference	Spatial resolution	Sampling rate	Detection range	Frequency range	Measurement capabilities
ref. ¹³¹	Not specified	1–10 Hz	100 m–1 km	Not specified	Minute deformation and crack detection in SHM
ref. ⁶³	Not specified	1–10 Hz	100 m–1 km	Not specified	Tunnel and buried infrastructure monitoring
ref. ⁶⁴	Centimeter-scale (layer-specific)	Not specified	1 m (lab model)	10–1000 Hz	SVM classification of 3 damage types with 93% F1-score
ref. ⁶⁶	Around 1 m	Multiple daily samples	13.3 km	0.1–10 Hz (ambient + blasts)	Detection of quarry blasts and excavation-related changes
ref. ¹³²	Meter-scale	1 Hz	24 km	0.1–10 Hz (bridge modal frequencies)	Modal parameter extraction (frequencies, damping, mode shapes)
ref. ¹³³	5–10 m	10–100 Hz	10–50 m	1–100 Hz (human/wind vibrations)	Detected wind, walking, climbing, knocking on 3D-printed bridge
ref. ¹³⁴	800–1000 mm	4000 Hz	1–2 m	Up to several kHz	Accurate dynamic strain sensing
ref. ¹¹⁴	Tens of meters	kHz-level	30–100 m	1–100 Hz (natural frequency analysis)	Dynamic strain in wind turbines (5% error)

signals with significantly lower noise and higher robustness, with train tracking accuracies exceeding 98%, indicating the importance of coupling conditions and the mitigation of such technical issue.

The DAS-based railway monitoring was expanded to a wider range of operational environments and signal processing strategies. Munoz et al.⁷⁰ exploited a 30-year-old, 24 km optical cable installed along railway tracks and also confirmed that tunnel sections provided optimal mechanical coupling, leading to highly repeatable train-induced signals with correlations above 0.8 across repeated passages. In parallel, Zhang et al.¹³⁷ introduced a beamforming-based methodology using vespagrams to detect trains and estimate their speeds from a 2 km trackside telecom fiber, demonstrating good agreement with official train schedules. The combination of temporal filtering, spatial averaging, and learning-based models^{71,136} demonstrated a methodological evolution toward hybrid frameworks that combine physics-based processing with data-driven techniques to improve robustness and accuracy.

Recent studies have shifted the focus from train detection toward railway condition monitoring and defect identification, marking a further maturation of DAS applications. Fan et al.⁷² demonstrated high-precision detection and localization of rail defects using bidirectional elastic wave propagation and dual-frequency joint processing, achieving 100% recognition with sub-meter accuracy. Deep learning approaches were subsequently introduced by Wang et al.^{89,138} that converted DAS data into spatiotemporal images and achieved defect classification accuracies above 97% using semi-supervised learning. These advances were complemented by studies targeting a broader range of defects, including rolling contact fatigue and unsupported sleepers¹³⁹, rail breaks¹⁴⁰, and loose fasteners^{141,142}, consistently reporting high detection performance and low latency. These works indicate a clear chronological progres-

sion from early train tracking to comprehensive, data-driven railway health monitoring, establishing DAS as a scalable and versatile technology for real-time railway operation and safety assessment, as summarized in Table 6.

4.4 Road transportation monitoring

DAS offers a new method for monitoring road transportation using existing or minimally invasive fiber infrastructures for continuous distributed sensing measurement along roads. This approach allows for continuous measurement of vehicle traffic, road vibrations, and surface conditions along road networks. DAS systems can enable scale traffic monitoring and smart transportation applications, ranging from ranging from vehicle detection and speed estimation to advanced classification and occupancy analysis. However, the challenges of this application scenario are related to the fiber installation conditions, fiber-ground coupling, and environmental noise, which can introduce variability and reduce accuracy in real-world scenarios^{143,144}. Additionally, spatial heterogeneity along the sensing path and the increasing complexity of data-driven applications require robust calibration, generalization, and data management strategies. These considerations provide possibilities of new developments in DAS systems that can be an important technology for the evolution from basic traffic monitoring toward advanced, scalable, and intelligent transportation sensing systems.

One of the first developments on DAS-based road traffic monitoring primarily focused on demonstrating the feasibility of vehicle detection and speed estimation using optical fibers deployed near roadways. Liu et al.¹⁴⁵ presented one of the first integrated systems using a short (320 m) sensing fiber installed along a campus road, demonstrating that DAS is suitable for detecting passing vehicles, estimate their speeds with errors below 5%, and distinguish between basic

Table 6 | Summary of DAS applications in rail transportation monitoring.

Reference	Year	Spatial resolution	Sampling rate	Detection range	Frequency range	Measurement capabilities
ref. ¹³⁶	2020	1 cm–m scale	Real-time (not specified)	20 km	10–1000 Hz	>98% train tracking accuracy; false alarms in open track
ref. ⁷¹	2020	<10 m	Continuous (Not specified)	35 km	1–100 Hz	±0.8 km/h speed error (ANN); ±4.8 km/h (conventional)
ref. ¹³⁷	2022	Meter-level	Daily data over 6 days	2 km	Hz–kHz	Train speed via vespagrams; schedule alignment
ref. ⁷²	2022	Sub-meter	Not specified	250 m	Multi-kHz	100% defect recognition; sub-meter accuracy
ref. ¹³⁸	2022	Not specified	17 s windows	3 km	Hz–kHz	97.91% defect classification; UDA, FixMatch DL
ref. ⁷⁰	2023	Meter-level	250 Hz	24 km	Hz–kHz	Train detection in tunnels >0.8 correlation
ref. ¹³⁹	2024	Sub-meter resolution	109.4 ms recognition time	8.5 km	Not specified	94% defect recognition; 109.4 ms detection time
ref. ¹⁴⁰	2024	cm–m scale detection	Not specified	28 km	Hz–kHz	Rail break detection; 99.17% accuracy, F1 = 90.32%

vehicle classes. This concept was subsequently extended to highway-scale monitoring by Narisetty et al.¹⁴⁴, who exploited 44.5 km of existing optical fiber along an expressway to estimate average traffic speeds with accuracies exceeding 90% when compared against loop detectors. In addition, to address one important challenge in DAS systems, An et al.¹⁴⁶ evaluated three fiber installation methods for DAS with varying degrees of mechanical coupling: uncoupled fiber on the road surface, fiber housed in plastic channels beneath the road, and cement-bonded fixed fiber optic cable on the road shoulder. Among the tested configurations, the shoulder-installed cement-bonded fiber performed best, delivering the highest SNR and vibration signal energy. The subsurface-installed fiber ranked second, exhibiting 40 dB lower SNR and an order of magnitude lower passage energy. The loose surface fiber proved least effective due to overall very low SNR and vulnerability to physical damage.

After these initial demonstrations, later studies emphasized long-distance monitoring and operational scalability using existing or minimally invasive fiber installations. Corera et al.⁶⁸ described a 40 km traffic monitoring system based on a buried optical fiber installed along a road shoulder, achieving a high vehicle detection and classification rate of 97.7%. Similarly, Min et al.¹⁴³ investigated traffic monitoring over two long fiber sections (18.1 km and 24.8 km), demonstrating that DAS can reliably distinguish traffic-related signals from background activity over extended distances, with performance that remains robust under controlled conditions and reasonably effective in real-world environments.

Recent research has shifted toward traffic characterization using advanced learning-based frameworks, including vehicle type and occupancy estimation. Chiang et al.¹⁴⁷ demonstrated that DAS measurements along a 4.8 km urban road segment can be used not only to detect vehicles but also to infer vehicle size and passenger occupancy, achieving high classification accuracy and underscoring the value of spatially distributed sensing. However, to achieve better performance in such detailed characterization of the traffic, additional research on cable deployment was proposed. In this context, Thomas et al.¹⁴⁸ compared cables placed in tele-

com trenches alongside the road, directly within the base course layer of the road structure, and in the sub-base course layer. Moreover, some cables were installed directly within these layers while others were installed inside protective cable ducts. Direct cable installation within the road structure (base course layer) yielded the highest SNR, provided an uniform acoustic coupling with the environment, and a more stable signal intensity along the cable. In contrast, ducted cable degraded the SNR, although the long-term durability of ducted cables was greater, which can be used as a selection guideline depending on the accuracy and time between maintenance required for a road monitoring application. Then, Wang et al.⁶⁹ further advanced large-scale DAS traffic monitoring by applying deep learning-based object detection to DAS data collected over 10–30 km of highway, achieving over 92% accuracy in classifying passenger and commercial vehicles. These recent studies build directly on earlier large-scale demonstrations^{68,143}, illustrating a clear progression from basic vehicle detection and speed estimation toward comprehensive, data-rich traffic monitoring systems enabled by DAS, as summarized in Table 7.

4.5 Applications in oil and gas industries

DAS has become an important technology in the oil and gas industry. It uses optical fiber cables to detect sound waves, providing valuable information about various processes in oil and gas operations. DAS has many uses, from monitoring wells and pipelines to studying reservoirs and improving hydraulic fracturing. As companies look for ways to work more efficiently and safely, DAS offers real-time data that helps them make better decisions¹⁴⁹. DAS is used for monitoring various aspects of wells, including vertical seismic profiling (VSP), flow monitoring, sand detection, valve monitoring, and can provide the well integrity assessment. By detecting leaks and monitoring well integrity, DAS can help to prevent accidents and extensive environmental damages⁶⁵.

The applications of DAS in the oil and gas industries are mainly based on pipeline monitoring and interaction between the fluid and the pipeline, which established a physical feasibility of distributed vibration-based sensing.

Table 7 | Overview of DAS applications in road transportation.

Reference	Year	Spatial resolution	Detection range	Measurement capabilities
ref. ¹⁴⁵	2020	m-level	320 m	Speed error <5%; >70% class accuracy (cars/SUVs/trucks)
ref. ¹⁴⁴	2020	Not specified	44.5 km	>90% speed accuracy
ref. ¹⁴⁶	2023	m-level	Up to 500 m	Best SNR with cemented shoulder fiber; 40 dB SNR gain vs buried
ref. ⁶⁸	2023	10 m gauge	40 km	97.7% vehicle classification using SVM & pulse compression
ref. ¹⁴⁸	2024	Not specified	km scale	Direct base-layer cable best; ducted durable but lower SNR
ref. ¹⁴³	2024	m-level	18.1 km & 24.8 km	80% real-world traffic detection accuracy, F1 up to 0.76
ref. ¹⁴⁷	2024	20 cm	4.8 km	98% occupancy (5-class); 94% size class accuracy
ref. ⁶⁹	2025	10 m gauge	10–30 km	92% vehicle classification accuracy F1 = 0.911

Muggleton et al.¹⁵⁰ systematically investigated leak detection sensitivity using multiple fiber types and burial configurations, showing that DAS can detect small leaks but with performance strongly dependent on fiber protection, coupling, and gauge length, and generally exhibiting higher noise levels than geophones at higher frequencies. Considering the concept of vibration-based monitoring, Li et al.¹⁵¹ demonstrated a non-intrusive DAS system for distributed flow-rate estimation by relating flow-induced vibrations to fluid velocity through theoretical modeling and laboratory validation, confirming the potential of DAS for quantitative pipeline monitoring while also highlighting reduced accuracy at low flow rates due to weak signal strength and environmental noise.

Subsequent research expanded DAS applications to oil well structural monitoring and subsurface imaging, using permanent or semi-permanent fiber deployments with strong coupling. Young et al.¹⁵² demonstrated high-resolution VSP imaging using DAS fibers cemented behind casing, producing high-quality 3-D reverse-time migration images of gas hydrate-bearing sands and near-well faulting, and highlighting the value of DAS for reservoir-scale imaging and characterization. Furthermore, Li et al.¹⁵³ reviewed DAS-based cement–casing integrity monitoring, showing that fibers deployed behind casing, on production tubing, or temporarily via dip-in surveys can provide continuous diagnostics of wellbore conditions, with machine learning methods³³ emerging as particularly effective for extracting diagnostic features. The results indicated the connection between imaging and integrity monitoring by demonstrating well-coupled DAS installations for both structural diagnostics and geophysical interpretation over the full life cycle of an oil well.

As another implementation possibility of DAS in oil and gas applications, high-sensitive detection of localized anomalies, including sand production and pipeline leaks are proposed with the integration coupled sensing cable designs and learning-based interpretation. Shetty et al.¹⁵⁴ demonstrated that DAS can identify sand ingress and migration patterns by capturing characteristic frequency signatures of sand slurry flow, with DAS-derived slip velocities showing good agreement with analytical models. Chen et al.¹⁵⁵ inves-

tigated DAS-based detection of pinhole leaks in buried gas pipelines, showing high sensitivity to small leak diameters and low pressures, and subsequent work by Zhang et al.¹⁵⁶ refined installation strategies by recommending fiber placement both above and below pipelines to maximize angular coverage. Deep learning approaches further advanced real-time leak identification, with Zhan et al.⁴⁷ achieving over 99% accuracy using a dedicated DAS pipeline leakage recognition network, and Fu et al.¹⁵⁷ enhancing sensitivity through a microporous, elastically coupled sensing cable that significantly improved localization accuracy. Table 8 summarizes the discussed results for highly sensitive, real-time DAS-based monitoring solutions for oil and gas infrastructure.

A comparison between vibration-based flow monitoring and leak detection approaches using DAS indicates that signal quality and signal-to-noise ratio are key limiting factors. Flow-rate estimation methods demonstrate reduced accuracy at low flow velocities due to weak vibration signatures, whereas leak detection methods benefit from distinct acoustic emissions but remain sensitive to environmental noise and background interference. Similarly, VSP and structural monitoring applications achieve high-resolution imaging and reliable diagnostics under well-coupled conditions, but their performance degrades significantly when fiber coupling is inconsistent or installation conditions are suboptimal. These results indicate a dependence on installation configuration and sensing cable design. In this case, standard fiber deployments enable detection of small leaks and enhanced coupling strategies such as microporous or elastically coupled cables significantly improve sensitivity and localization accuracy. Reported detection capabilities range from identifying pinhole leaks at low pressures to achieving classification accuracies exceeding 99% with learning-based approaches. From a practical perspective, installation quality and fiber–structure coupling remain critical determinants of measurement reliability, particularly in buried or cemented configurations. Furthermore, DAS measurements are inherently sensitive to environmental and operational noise for long-term stability, requiring advanced filtering or machine learning techniques for robust interpretation.

Table 8 | Summary and comparison of DAS applications in oil and gas industries.

Reference	Spatial resolution	Sampling rate	Detection range	Frequency range	Measurement capabilities
ref. ¹⁵²	< 1 m	ms range	hundreds of m	10–1000 Hz	3-D RTM imaging; hydrate-bearing sands and faults
ref. ¹⁵³	1 m	Hz–kHz	hundreds of m	10–1000 Hz	Integrity monitoring; ML-based feature extraction
ref. ¹⁵⁴	Sub-meter	Up to 1 kHz	5 m	200–800 Hz	Sand detection via FFT + FBE, velocity estimation
ref. ¹⁵¹	10 cm	High-rate (not specified)	20 m	Not specified	0–3.6 m/s flow; error 25% at low flow
ref. ¹⁵⁵	10–30 cm	< 1 kHz	10–30 m	60–120 Hz	2 mm leaks at 0.1 MPa
ref. ¹⁵⁰	20 cm to 5 m	kHz	Up to 5 m from leak source	10–2000 Hz	Bare fibers had highest response; 2 dB above noise
ref. ⁴⁷	10 m gauge	0.6 s	176 m	10–1000 Hz	99.04% accuracy, F1 = 99.03% in 0.6 s samples
ref. ¹⁵⁷	0.11 m	ms range	several m	Hz–kHz	0.11 m location accuracy using enhanced strain transfer

4.6 Aircrafts and aerospace applications

DAS represents a progressive fiber optic technology that is increasingly finding applications within the aerospace industry, offering unprecedented capabilities for aircraft detection, noise analysis, structural health monitoring, and aerospace security applications¹²³. Using optical fibers as continuous sensors, DAS enables the detection of acoustic signals and vibrations across large structures or wide areas with cutting-edge signal processing, often in real time¹⁵⁸. As the demand for safer, more efficient and intelligent aerospace systems grows, the ongoing development of DAS is poised to significantly influence the future of aircraft monitoring and aerospace operations.

First reports on aircrafts applications with DAS were based aircraft monitoring on the ground within airport environments, focusing on safety-critical operational awareness. Merlo et al.¹⁵⁹ presented one of the first comprehensive airport ground monitoring systems based on DAS, demonstrating that buried optical fibers installed along runways, taxiways, and internal roadways could supplement conventional radar systems. By exploiting DAS’s immunity to electromagnetic interference and its ability to provide continuous spatial coverage, the article showed that aircraft movements on the ground could be reliably detected and classified with recognition accuracies approaching 98%. This work positioned DAS as a robust, infrastructure-integrated sensing layer for airport operations and laid the groundwork for later applications that extend beyond ground motion to airborne and structural phenomena.

Subsequent research expanded DAS applications into aircraft structural monitoring and near-field acoustic sensing. Bakhoum et al.⁶¹ introduced the first documented use of DAS for real-time aircraft flutter monitoring, demonstrating that a minimal fiber deployment embedded within wings and stabilizers could accurately detect critical flutter modes in a scaled Boeing 747 model, with results validated against conventional accelerometers and strain gauges. This study highlighted the potential of DAS to dramatically simplify onboard sensing architectures while maintaining high spatial and temporal resolution. Complementing this structural focus, Fang et al.¹⁶⁰ demonstrated DAS-based drone

detection and localization using enhanced fiber-optic acoustic sensors arranged in a compact array, achieving high signal-to-noise ratios and precise direction-of-arrival estimates comparable to traditional microphones, which indicate a transition from fixed ground infrastructure to both onboard and localized sensing systems for monitoring aircraft dynamics and low-altitude aerial vehicles.

As another breakthrough of DAS in such application, there is the possibility of large-area airborne acoustic monitoring and extreme aerospace events. Gurevich et al.⁶² showed that shallow-buried telecommunication fibers can detect aircraft noise propagating through the ground–air interface over kilometer-scale distances, successfully identifying propeller-driven aircraft while highlighting gauge-length limitations for higher-frequency jet noise. Extending DAS to even more extreme regimes, Carr et al.¹⁶¹ demonstrated the first successful DAS recordings of a hypersonic space capsule atmospheric entry, capturing both air-coupled and ground-converted signals associated with the sonic boom of the OSIRIS-REx return capsule. Therefore, the DAS implementation in aerospace monitoring has a clear progression from airport ground monitoring¹⁵⁹, to onboard structural sensing⁶¹, including distributed airborne and atmospheric detection^{62,161}. The summary of DAS applications in aerospace fields is presented in Table 9.

4.7 Environmental sensing applications

In the last few years, DAS is rapidly emerging as a powerful tool for environmental sensing across diverse marine and terrestrial applications. As one of the core advantages of such sensing system is the possibility of using existing fiber optic infrastructure. In this context, DAS enables dense real-time acoustic monitoring on large spatial scales with minimal additional hardware. In marine environments, DAS has proven effective in offering valuable insights for marine biology, oceanography, and passive acoustic monitoring in remote regions. On land, DAS has shown capabilities in detecting landslides, tracking groundwater fluctuations, and providing seismic imaging with sub-meter spatial resolution. The applications discussed in this section demonstrate the suitability of DAS technology for continuous, distributed

Table 9 | Overview of DAS implementations in aircraft and aerospace applications.

Reference	Spatial resolution	Sampling rate	Detection range	Frequency range	Measurement capabilities
ref. ⁶¹	10 cm	100 kHz sampling	248 cm	Modes at 5.1 Hz, 7.8 Hz	Real-time flutter detection; 5.1 & 7.8 Hz modes
ref. ⁶²	1 m channel spacing; 10 m gauge length	1 ms sampling (1 kHz)	2.5 km	70–120 Hz	Aircraft detection via shallow-buried telecom cable
ref. ¹⁶⁰	4 m resolution	20 kHz	60 m	150–500 Hz	Drone localization; 1.47° DOA RMSE
ref. ¹⁵⁹	Meters	50 μ s repetition rate (20 pulses avg.)	Not specified	Not specified	Aircraft detection; 97.8% accuracy using RVM
ref. ¹⁶¹	1.23–2 m spacing; 5–10 m gauge	500 Hz	12 km total	> 100 Hz	Captured sonic boom & ground signals during reentry

environmental monitoring with applications in ecology, geotechnics, and climate resilience.

DAS has become an increasingly important tool for geotechnical monitoring and natural hazard detection, offering continuous, high-resolution observations of ground motion and subsurface changes that are difficult to achieve with conventional sensors. Ghazali et al.⁴⁸ demonstrated that DAS can support environmental sensing and early warning systems by detecting landslides, monitoring groundwater dynamics, and tracking seasonal velocity variations linked to rainfall and river level changes, with observed seismic velocity variations of 2%–3% in the Sacramento Valley. These studies illustrate that DAS provides actionable geotechnical information, supporting safer infrastructure development and climate resilience. The success of these terrestrial applications motivated extensions of DAS into offshore and subseafloor environments, where similar challenges of scale, accessibility, and continuous monitoring exist.

In offshore geotechnical and subseafloor characterization, DAS has been shown to deliver high-resolution imaging and material property estimation over kilometer-scale distances. Trafford et al.¹⁶² applied DAS to offshore shear-wave profiling using seabed-deployed fibers, successfully resolving shear-wave velocity structures relevant for offshore wind farm foundations and showing strong agreement with cone penetration tests and conventional seismic data. Complementing this approach, Otchere et al.¹⁶³ demonstrated that deep-sea telecommunication cables can be repurposed as dense seismic arrays capable of imaging shallow sedimentary reflectors down to depths of 2.6 km using ambient noise and local earthquakes. These studies establish a clear link between onshore geotechnical monitoring and offshore subsurface imaging, highlighting DAS as a cost-effective alternative for environments where traditional surveys are logistically challenging or environmentally constrained.

Beyond solid-earth applications, recent work has expanded DAS into underwater acoustic sensing and marine ecosystem monitoring, further broadening its environmental relevance. Douglass et al.¹⁶⁴ showed that submerged DAS cables can detect near-surface hydroacoustic signals with broadband sensitivity, validating DAS as a feasible option for large-scale ocean acoustic monitoring despite lower signal-to-noise ratios compared to hydrophones. At smaller scales and higher frequencies, Arbel et al.¹⁶⁵ demonstrated a

novel distributed fiber-optic array capable of detecting ultrasonic signals with centimeter-scale spatial resolution, opening pathways for underwater structural monitoring and navigation. At the opposite end of the frequency and spatial spectrum, Bouffaut et al.⁶⁷ used a 120 km submarine telecom cable to passively monitor baleen whale vocalizations in the Arctic, revealing spatial and temporal patterns in marine mammal activity without invasive instrumentation. These previously published works connect geotechnical, geophysical, and ecological applications, underscoring DAS as a versatile and scalable environmental sensing technology, as summarized in Table 10.

4.8 Telecommunication applications

In urban areas, the integration of DAS into existing telecommunication infrastructure is an opportunity to explore dual-functional optical fiber networks. Single mode optical fiber cables can be exploit for acoustic sensing applications, such as the monitoring of geological activity and structural disturbances, and simultaneously achieve data transmission rates on the order of hundreds of Gb/s per channel over distances beyond 300 km¹⁶⁶. The coexistence of DAS with existing urban infrastructure dismisses the installation of additional physical sensing cables, preventing high installation costs and facilitating scalable solutions for new applications in smart cities. In addition, it enables the use of underutilized "dark" fibers, enhancing the network usage efficiency¹⁶⁷.

A field trial that demonstrates the feasibility of co-propagating DAS, coherent 400 GbE transmission, and analog radio-over-fiber (ARoF) signals on the same fiber infrastructure was reported in ref.⁷³. The study shows that constant-amplitude DAS can coexist with dense wavelength division multiplexing (DWDM) data traffic without degrading the quality of transmission (QoT) of the 400 GbE signal, provided careful power management is applied. In contrast, high-power pulse-based DAS signals can introduce burst errors due to cross-phase modulation, even when pre-FEC bit error rates remain low. Using reconfigurable optical add-drop multiplexers (ROADMs), the authors dynamically multiplex DAS and data signals, monitor real-time traffic in Manhattan, New York City, USA, and enable DAS-informed preemptive switching of 400 GbE traffic to backup routes

Table 10 | Summary of DAS implementations in environmental sensing applications.

Reference	Spatial resolution	Sampling rate	Detection range	Frequency range	Measurement capabilities
ref. ⁴⁸	Sub-meter	Real-time (not specified)	Not specified	Not specified	Landslide detection, groundwater variation (2%–3% velocity change)
ref. ¹⁶²	Meter-scale	High rate (not specified)	Kilometer-scale	1–10 Hz	Matched CPT data; improves offshore wind geotechnics
ref. ¹⁶³	1 m	Passive event-triggered (multi-day)	2.6 km	Not specified	2.6 km subseafloor imaging from ambient data
ref. ¹⁶⁴	Meters	up to 700 Hz	Not specified	Up to 700 Hz	Hydroacoustic detection; responsive to cable burial
ref. ¹⁶⁵	5 cm	300 kHz	5 m	300 kHz	Ultrasound localization with telecom fiber (5 cm)
ref. ⁶⁷	High resolution (not specified)	Continuous (Not specified)	120 km	20 Hz	69,671 fin whale and 1,291 blue whale calls recorded

during simulated link failures. The findings confirm that with appropriate optical channel spacing and signal design, optical fiber networks can support simultaneous communication and sensing, enabling new applications in smart cities, infrastructure monitoring, and network resilience without dedicating separate fibers for sensing functions.

A two-mode optical fiber was employed in a hybrid dual-functional acoustic sensing system and telecommunication network in a via mode-division multiplexing (MDM)⁷⁴. The system uses a photonic lantern to excite two orthogonal linearly polarized modes: LP_{01} for communication and LP_{11} for acoustic sensing, enabling both functionalities on the same wavelength without using WDM. A ϕ -OTDR configuration is used to realize a DAS, detecting Rayleigh backscattering to localize and identify mechanical vibrations at designated positions along the fiber. Parallel experiments with on-off keying (OOK) and OFDM modulation schemes show that the system maintains a SNR above 2 dB, even in the presence of active communication channels. The OFDM setup achieves a gross data rate of 4.2 Gbps with a BER of 3.2×10^{-3} , demonstrating efficient spectral utilization and robust performance through adaptive bit and power loading. Despite minor performance degradation due to intermodal crosstalk and shared spectrum, the system confirms that DAS and data communication can effectively coexist in a shared link.

In ref.¹⁶⁸, a scheme for simultaneously performing optical data transmission and distributed acoustic sensing using the same fiber and wavelength channel, referred to as Integrated Sensing and Communication in Optical Fiber (ISAC-OF). The authors utilize a periodic LFM optical carrier that serves dual roles: as the light probe for ϕ -OTDR sensing and as the optical carrier for transmitting a 56 Gbit/s PAM4 signal. Experimental results over a 24.5-km standard single-mode fiber show that ISAC-OF enables precise vibration sensing with a 4-m spatial resolution, $4.32\text{-n}\epsilon/\sqrt{\text{Hz}}$ strain resolution, and frequency response exceeding 21 kHz. Specifically, ISAC-OF increases the optimal launching power by 7 dB and achieves a 1.3 dB BER improvement at the 7% FEC threshold due to effective suppression of stimulated Brillouin scattering (SBS) and enhanced self-phase modulation (SPM) effects. The system design achieves high

spectral efficiency by avoiding additional channels for sensing, reduces demodulation complexity by sharing optoelectronic components with standard PAM4 transmission, and shows robustness across a range of bit rates and LFM bandwidths.

In addition, DAS has emerged as a promising tool for telecommunications network monitoring. By analyzing the backscattered acoustic signal along telecommunication networks, DAS systems can detect subtle structural changes, network health and traffic loss¹⁶⁹. Furthermore, the integration of machine learning algorithms with distributed sensing technologies, such as OTDR and ϕ -OTDR, has enabled real-time classification and localization of fiber faults, even in passive optical networks (PONs) with a diagnostic accuracy greater than 95.9%^{170,171}. These methods are critical for improving the maintenance of telecommunication optical fiber networks, encouraging predictive strategies and reducing maintenance time and costs.

In ref.¹⁷², distributed fiber optic sensing was combined with deep learning to enable real-time intrusion detection and impulsive acoustic event classification over existing optical fiber networks. The proposed system is based on ϕ -OTDR and supports two primary applications: perimeter security via buried fibers and gunshot/event detection via aerial fibers. The authors introduce a multi-task learning approach for fine-grained intrusion classification, comparing distributed label encoding (DLE) and one-hot encoding (OLE), with DLE showing superior generalization under diverse weather conditions and reduced training data. For impulsive acoustic event classification, the study evaluates multiple signal representations (e.g., waveform, Mel spectrogram, MFCC) and machine learning models (ConvNets, Vision Transformers, Random Forests), revealing that ConvNet with Mel spectrograms performs best under high-SNR conditions, while raw waveform inputs perform better in low-data, low-SNR settings. Table 11 shows the overview of the discussed implementations of DAS in telecommunication networks.

4.9 Security and intrusion detection applications

In the context of security and intrusion detection, DAS

systems enable real-time detection and localization of unauthorized activities such as perimeter breaches, tampering with critical infrastructure, or unauthorized access to protected zones. Scientific articles increasingly explore the effectiveness, accuracy, and practical challenges of deploying DAS in various security scenarios, highlighting its potential to enhance surveillance and protection of sensitive sites.

Meng et al.¹⁷³ presented a railway perimeter intrusion detection system using a 20 km standard single-mode fiber integrated into existing railway communication cables, showing that DAS combined with machine learning can reliably distinguish multiple intrusion types, including digging, fence crossing, walking, and vehicle activity, with an overall accuracy of 98.5%. This work demonstrated DAS as a feasible security solution for extensive railway corridors exposed to diverse environmental noise conditions. Considering a similar concept, He et al.¹⁷⁴ deployed a buried DAS fiber beneath a fence and introduced a dual-stage recognition framework that balanced accuracy and computational efficiency, achieving 97.6% average recognition accuracy during a month-long field test.

Subsequent research expanded DAS intrusion monitoring to more complex threat scenarios and multimodal sensing configurations. Han et al.¹⁷² introduced a versatile DAS-based system capable of detecting both perimeter intrusions and impulsive acoustic events such as gunshots, using buried, fence-mounted, and aerial fiber deployments. Their results showed that DAS can accurately classify high-risk acoustic events with an F1-score of 98.2%, while maintaining low false alarm rates under challenging field conditions. These findings complement earlier perimeter-focused studies^{173,174} by demonstrating that DAS systems can simultaneously address security threats ranging from slow-moving intrusions to rapid, high-energy acoustic events, thereby broadening the operational scope of fiber-optic security

monitoring. Pierau et al.¹⁷⁵ demonstrated real-time intrusion detection in commercial fence-mounted and buried-fiber installations spanning up to 40 km, showing that automated frequency selection and hyperspectral representations significantly improve detection accuracy while maintaining sub-five-second response times. In parallel, Xu et al.¹⁷⁶ proposed a lightweight DAS intrusion detection framework using Gram Angle Field transformation and knowledge distillation, achieving 98% accuracy with substantially reduced model complexity and faster response times. These advances build directly on earlier machine learning-based approaches^{172–174}, illustrating a clear progression from high-accuracy classification toward efficient, real-time, and scalable DAS intrusion detection systems suitable for deployment in different infrastructure, as summarized in Table 12.

5 Prospects for new generation of DAS

Despite the advances described throughout this document, DAS technology still faces several critical limitations that restrict its wider adoption and performance in real-world applications¹⁷⁷. One of the greatest challenges is related to the high sensitivity to noise and environmental variability, which leads to low SNR, especially in uncontrolled field applications¹⁷⁸. This feature leads to the necessity of additional preprocessing and denoising algorithms as discussed in Section 3.3. In addition, all DAS applications are related to big data handling, which can exceed terabytes per day in large-scale deployments, since there are important issues on data storage, transmission, and real-time processing infrastructure¹⁷⁹. Recently, many machine learning approaches were proposed for DAS systems (see Section 3.3), but even with these approaches, there is the limited availability of labeled data, particularly for rare or context-specific events, which harms the training of reliable machine learning and

Table 11 | Overview of DAS implementation in telecommunications-related applications.

Reference	Spatial resolution	Sampling rate	Detection range	Frequency range	Measurement capabilities
ref. ⁷³	> 1 m	400 Gb/s data rate	10–50 km	1–10 kHz	Coexistence of 400 GbE, ARoF & DAS in ROADM/DWDM
ref. ⁷⁴	1–2 m	4.2 Gb/s data rate	> 1 km	1 Hz – 10 kHz	Sensing & communication via MDM; 4.2 Gbps, BER = 3.2×10 ^{−3}
ref. ¹⁶⁸	4 m	> 21 kHz	24.5 km	Up to > 21 kHz	PAM4 + ϕ -OTDR sensing; 1.3 dB BER improvement
ref. ¹⁶⁹	> 1 m	> 1 Hz response	Up to 30 km	10 Hz – 1 kHz	> 95.9% fault detection accuracy in PONs
ref. ¹⁴¹	> 1 m	kHz	Higher than 100 m	100 Hz – 5 kHz	Multi-task intrusion & gunshot detection using deep learning

Table 12 | Overview of DAS applications in intrusion detection and perimeter security.

Reference	Spatial resolution	Detection range	Frequency range	Measurement capabilities
ref. ¹⁷³	10.2 m	20 km	500 Hz	Integrated in railway cable (accuracy 98.5%)
ref. ¹⁷⁴	Not specified	3.2 km	Not specified	Under metal fence (accuracy 97.6%)
ref. ¹⁷²	1 m (coils)	30 m	2 kHz (intrusions), 20 kHz (gunshots)	Buried, fence-attached, aerial coils
ref. ¹⁷⁵	0.5 m	10 km (fence), 40 km (buried)	5 kHz (fence), 2 kHz (buried)	Fence (accuracy 81.8%) and buried (accuracy 60.4%)
ref. ¹¹⁴	10 m	Not specified	20 kHz	Simulated roadside (accuracy 98%)

deep learning model¹⁸⁰. Such limitation also inhibits the event generalization and transferability, since applications in larger areas generally cannot be applied in different geographic or operational context due to variations in cable coupling, terrain, or ambient conditions¹⁷⁷. To that extent, the new generation of DAS heavily rely on advanced AI models able of overcoming these limitations, where advanced paradigms such as transfer learning, domain adaptation, or few-shot learning can be applied and will be discussed in this section.

As another important limitation of current DAS systems, the optical fiber properties can lead to major limitations in the hardware technology. In this case, single-mode telecom fibers produce weak Rayleigh backscattering, resulting in low signal-to-noise ratios, particularly over long distances¹⁸¹. In addition, with uncontrolled scattering, there is interference fading that leads to sensitivity fluctuations and blind spots along the fiber¹⁸². Optical attenuation further reduces the backscattered signal, requiring amplification that introduces noise and complexity. In terms of field applications, conventional fiber cable designs are often rigid to provide an optimized for telecommunications, which leads to poor acoustic coupling that further reduces the sensitivity¹⁸³. Furthermore, since DAS already have multiple cross-sensitivities due to environmental noise, the fiber cable design provides additional challenges related to the distortion of acoustic signals due to environmental conditions. Thus, there is a continuous development of enhanced backscattering fibers to mitigate these limitations on current DAS technology, where such fibers can be tailored for improved DAS performance¹⁸¹.

As a critical limitation in many real-world applications, traditional DAS systems are based on discrete optical components such as modulators, coherent receivers, lasers, amplifiers, and circulators¹⁸⁴. This results in bulky, complex systems with high cost and difficult scaling in terms of size of acquisition unit. Such limitation critically harms the applications in which the low cost is a major requirement. In this case, applications such as healthcare for remote patient monitoring of patients is not covered by current DAS technology (and the majority of distributed sensing), since the cost-effectiveness is mandatory for a widely employment¹⁸⁵. In addition to the cost, wearable applications are not used with traditional DAS systems, since the bulkiness of the devices make them unfeasible for wearable monitoring¹⁸⁶.

Another important technical challenge is the persistent gap between qualitative detection and quantitative accuracy, i.e., DAS has been proved as a suitable method for identifying the presence, location, and relative evolution of events, but extracting absolute physical quantities (e.g., strain amplitude, displacement, velocity) remains a difficult task for current signal processing methods due to uncertainties in gauge length, coupling conditions, and directional sensitivity¹²⁵. Such limitation is also related to the calibration challenges for real-world deployments of DAS cables, since

the coupling of the fiber and the measured structure (or ground) varies spatially and temporally, influenced by installation method, soil properties, temperature, and aging infrastructure. These variations complicate amplitude calibration, long-term repeatability, and transferability of models across sites, often requiring site-specific tuning or adaptive normalization¹⁷⁷. Such drawback not only hinder the accurate quantitative methods, but also adds challenges to long-term stability of the measurement system, since aging fibers, microbending, moisture ingress, connector degradation, and repeated mechanical or thermal loading can gradually alter sensitivity and noise characteristics, affecting monitoring consistency over months to years and complicating trend analysis.

Finally, the lack of standardization in DAS data formats, processing workflows, and performance metrics presents a major barrier to broader adoption of such system. Such lack of standardization also comes from the DAS interrogator itself, since major differences in interrogator hardware, proprietary preprocessing, gauge length definitions, and reporting practices make it difficult to compare results across studies or vendors and to establish accepted benchmarks for accuracy, resolution, and reliability. Addressing these issues not only require effort from the researchers, but also from the industry to achieve coordinated efforts toward standardized data representations, hardware, calibration protocols, and application-specific performance metrics, which are essential for large-scale operational deployment of DAS technologies.

Considering the developments of traditional DAS systems, the aforementioned drawbacks are important barriers in wider spread of such technologies in the daily living. To that extent, new technologies and approaches are incorporated into DAS (and general distributed sensing technologies) to overcome these limitations. Such technologies are related to advances in signal processing, in optical fiber fabrications and interrogation unit size and cost reduction as well as new distributed sensing approaches focused on low cost detection. [Figure 9](#) presents a schematic representation of the limitations of current DAS technologies and some of the key technologies for mitigating such limitations for a new generation of DAS systems.

5.1 Recent advances in signal processing and artificial intelligence in DAS systems

Artificial Intelligence, so-called AI, is one area of computer science that focuses on the creation of intelligent machines that normally requires human intelligence^{187,188}. It includes adaptations, learning processes, planning and even problem solving. AI algorithms are designed to make artificial machines capture, store and analyze massive amounts of data. This actionable intelligence allows for a more real-time decision-making process based on a situation that is as human as possible¹⁸⁷. Machine Learning (ML) is a core part

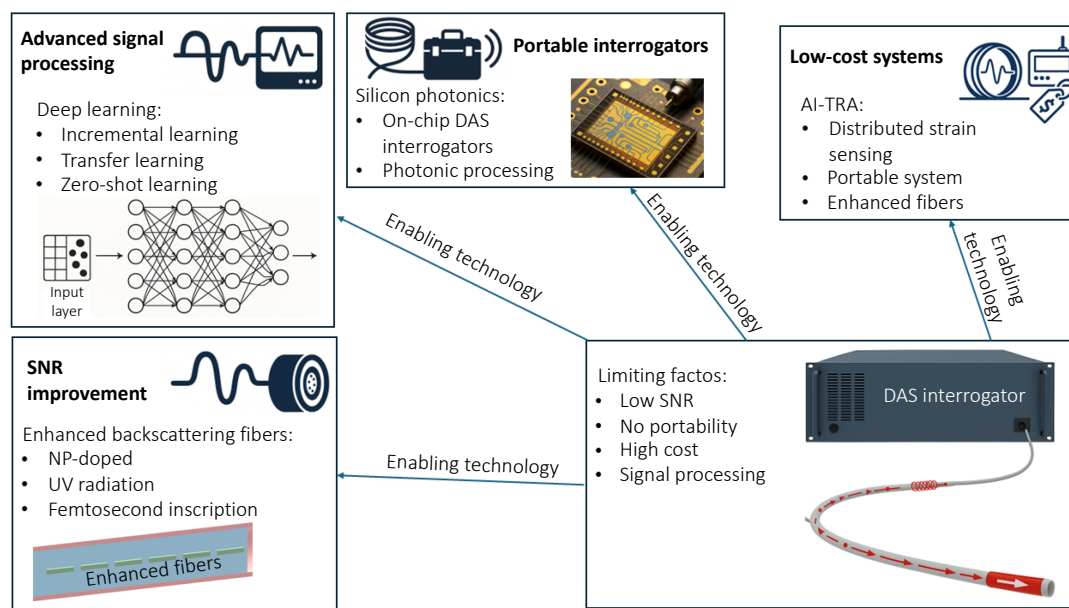


Fig. 9 | Schematic representation of the limitations and prospects in DAS technology.

of AI that deals with the simulation of intelligent behavior in computers.

Deep learning has emerged as a new tool in the advancement of DAS technology, pushing the boundaries of DAS achievements in terms of automation, adaptability, and intelligence. Deep learning not only overcomes these limitations but opens new research directions that aim to enhance system accuracy, generalization, and operational efficiency¹⁸⁹. However, even current deep learning methods struggle with the development of DAS system, where advanced approaches such as contrastive learning and pseudo-labeling for unlabeled data as well as few-shot and zero-shot learning to classify novel or underrepresented events¹⁷⁷.

The specificity of DAS applications leads to the necessity of specifically tailored deep learning architectures for DAS systems. In this context, more expressive models such as Transformers are used to obtain long-range temporal dependencies and spatial correlations in data¹⁹⁰. In contrast, there is also the development of optimized models for smaller computational efforts (especially for edge computing, further defined in ref.¹⁹¹) are explored to ensure a real-time analysis of crucial parameters in certain applications¹³⁶. This includes the use of 1D-CNNs with minimal parameters, model quantization, and neural architecture search (NAS) to design efficient yet accurate pipelines¹⁸⁹. Aiming at mitigating the influence of big data and unlabeled data in traditional DAS systems, incremental learning methods have been proposed to update models with new information without losing previously acquired knowledge, which is critical for systems deployed in dynamic or long-term monitoring scenarios¹⁹².

In general, the analysis of DAS signals follows a structured pipeline as presented in Fig. 10. In this case, the AI algorithm can be implemented at each step of the pipeline to enhance system capability, scalability, and automation¹⁹³. As schematically depicted in Fig. 10, the process begins with signal acquisition, where optical backscatter data is collected via an acquisition unit, which can be translated into high-frequency, multichannel time-series data. In this stage, the AI is not directly used, but adaptive acquisition techniques using reinforcement learning are a future research direction. Then, the signal preprocessing is performed using traditional methods such as baseline removal, noise reduction, and data segmentation¹⁹⁰, where AI algorithms can be used through deep denoising models and transformer-based architectures that effectively remove environmental and system noise without degrading critical features¹⁸⁹. In the feature extraction stage, traditional approaches utilize statistical or time-frequency domain methods (e.g., STFT, wavelet transform). On the other hand, deep learning models automatically learn features directly from raw or minimally processed signals¹⁷⁸, which plays a crucial role for handling complex event morphologies in long fiber spans¹⁷⁷. For the next step, event detection identifies spatiotemporal regions of interest, followed by a classification and interpretation stage. In these steps, AI models present a high contribution on the feature extraction and their classification using approaches such as YOLO, Faster R-CNN, ResNet-18, CNN-BiLSTM, and even custom architectures like the Time Forest Neural Network (TFNN)¹⁷⁸. Such classifications are used on the Decision-making to trigger appropriate responses, where AI models incorporating uncertainty estimation or reinforcement learning can prioritize alerts or

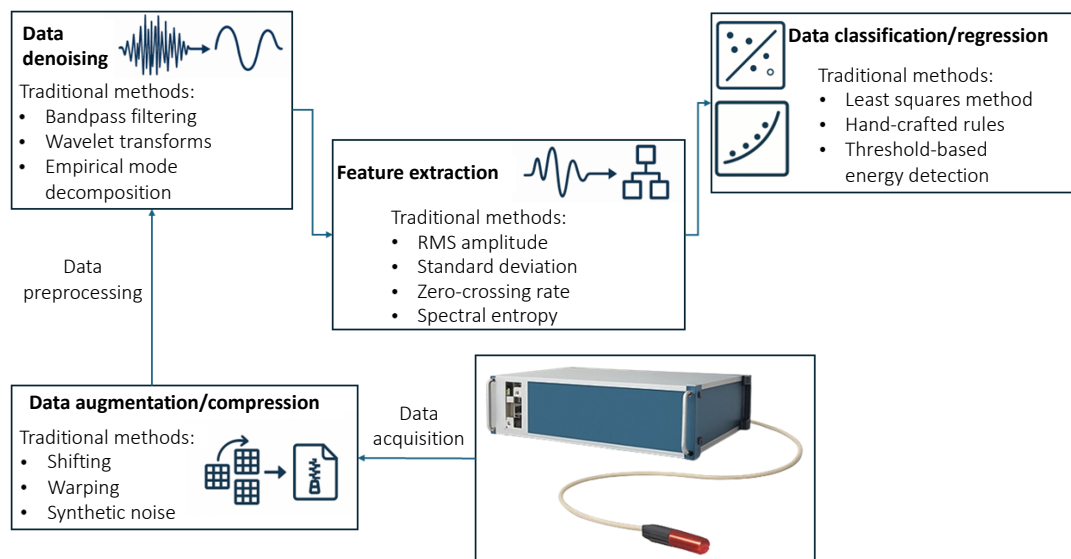


Fig. 10 | Schematic representation of the flowchart for signal analysis in DAS.

suggest human review only when necessary¹⁹⁴. Finally, the continuous learning loop allows DAS systems to improve over time via transfer learning, semi-supervised learning, and federated learning techniques, enabling robust performance across various operation, installation and noise conditions¹⁹⁵. Thus, the flowchart of DAS signal processing is presented in Fig. 10. It is important to mention that different AI algorithms can be implemented for each process represented in the flowchart with higher performance than the classical methods depicted in Fig. 10. However, the gap between the classical methods and the AI algorithms (mainly the deep learning) is larger on the feature extraction and data classification or regression, where the new deep learning methods provide additional detection possibilities that were not possible without such methods. Thus, the AI algorithms for each step of the flowchart will be discussed with further discussion of deep learning algorithms for feature extraction and data classification.

Considering the main developments of AI approaches in DAS signal processing, the data augmentation and compression can be used to provide balanced datasets and handle with big data, particularly given the constraints of limited labeled data, class imbalance, and high data volume¹⁷⁷. DAS typically produces enormous amounts of high-frequency, multi-channel time-series data, making storage, transmission, and real-time analysis increasingly challenging¹⁹⁵. To address these issues, AI-based data augmentation techniques are employed to enrich training datasets and improve model generalization¹⁸⁰. Traditional augmentation methods include time-domain manipulations such as shifting, warping, and adding synthetic noise¹⁹⁶. However, recent approaches using Generative Adversarial Networks (GANs) such as CycleGAN and DCGAN, which can learn the statistical characteristics of minority class events (e.g., digging,

walking) and generate realistic synthetic samples, where the synthetic data can be used for model training without the issues of large noisy and unlabeled datasets acquired in some applications¹⁹⁷. In addition, for highly imbalanced datasets, hybrid strategies such as kS-DCGAN, which combines k-SMOTE oversampling with GAN-based generation, have been shown to improve classification robustness and accuracy, as discussed in ref.¹⁷⁷. In contrast, data compression is also vital to manage the scale of DAS outputs, since the amount of data puts a burden in storage, processing and label of the data¹⁹⁸. The SEER (Spectral Extraction, Encoding, and Reconstruction) framework offers an AI-driven, lossy compression method that selectively encodes only the most relevant spectral components for classification, reducing data volume by a factor of 20 while preserving inference accuracy¹⁷⁹. Alternatively, autoencoders are employed to compress signal data into latent representations that can either be reconstructed or used directly for downstream tasks like anomaly detection and classification¹⁸⁹. This dual use of autoencoders supports both storage efficiency and feature learning. Moreover, lightweight architectures such as the 1D-CNN proposed by Pamukti et al.¹⁹⁰ are specifically designed to work efficiently with compressed and augmented data, enabling edge deployment in real-time DAS monitoring scenarios. Therefore, such data handling approaches can optimize the training process and enhance model resilience without harming the computational feasibility (through the reduction of computational cost), which is especially important in field applications.

As another important step in signal processing, denoising is critical in the analysis of DAS signals, since these systems often operate in environments with significant noise contamination due to environmental interference, system limitations, and installation artifacts. Effective denoising

enhances the SNR, improves the clarity of event features, and directly impacts the accuracy of downstream AI models for classification, detection and/or regression¹⁹⁹. Conventional denoising methods include bandpass and high-pass filtering, wavelet transforms, and empirical mode decomposition (EMD), which are useful for removing specific frequency components or decomposing signals into intrinsic modes²⁰⁰. However, these techniques often struggle with non-stationary noise or overlapping frequency bands between noise and signals of interest. To overcome these limitations, recent works propose AI-based denoising techniques, especially using deep learning²⁰¹. For example, DnCNN (Denoising Convolutional Neural Network) and autoencoders have been employed to learn noise distributions directly from DAS data, outperforming classical filters by preserving subtle event features while suppressing noise¹⁸⁹. In another developments MSI-Net²⁰² and Transformer-based denoisers, specifically seismic data denoising Transformer (SDT)²⁰³, use spatial and temporal attention mechanisms to isolate relevant signal regions and remove structured and unstructured noise. These models presented high generalization and robustness under low SNR condition in practical applications²⁰⁴. A different denoising approach is based on image denoising in which the DAS signal matrices are treated as grayscale images, allowing the application of computer vision methods such as non-local means (NLM), adaptive bilateral filtering, and edge-preserving convolutional operations¹⁷⁷. Furthermore, unsupervised or self-supervised denoising techniques (e.g., DAS-N2N) have been explored to handle unlabeled DAS datasets by learning to reconstruct clean signals without ground-truth supervision²⁰¹. These denoising frameworks not only enhance the visibility of events but also serve as effective pre-processing stages for convolutional neural networks (CNNs), ResNets, and hybrid models in real-time DAS classification systems.

After the AI approaches for data handling and denoising, the feature extraction is one of the steps with the highest integration with deep learning/ML models. It transforms raw, high-dimensional, and often noisy data into representations that are more meaningful and discriminative for classification, detection, or regression tasks²⁰⁵. In traditional approaches, feature extraction relies on manually engineered descriptors derived from time-domain, frequency-domain, and time-frequency domain analysis, where features such as RMS amplitude, standard deviation, zero-crossing rate, and spectral entropy are commonly used to characterize DAS signals¹⁹⁰. Moreover, STFT, Mel-frequency cepstral coefficients (MFCCs), and wavelet transforms are frequently applied to convert time-series data into 2D time-frequency representations, which can be used as images for input into CNNs²⁰⁶. These transformations help to reveal patterns associated with specific events that might be hidden in the raw signal domain. To that extent, deep learning methods are also widely used to perform automatic feature

extraction, eliminating the need for manual design and tuning. CNNs, in particular, learn hierarchical spatial features from DAS signal matrices, detecting local textures, gradients, and high-level semantic patterns directly from raw or minimally processed data²⁰⁷. In addition, there are hybrid architectures such as CNN-BiLSTM, CNN layers first extract spatial features, which are then passed to BiLSTM layers that capture temporal dependencies, resulting in more comprehensive spatiotemporal representations of vibration events²⁰⁸. Some studies convert DAS time-series into grayscale or color images using methods like Gramian Angular Fields (GAF), Markov Transition Fields (MTF), or recurrence plots (RP)—a process that allows the use of image-based models like ResNet and YOLO for both classification and localization^{209,210}. Furthermore, attention-based models such as Transformers or hybrid CNN-Transformer architectures are being explored for their ability to selectively focus on salient spatial-temporal features, which is particularly useful in long or noisy DAS recordings²¹¹.

A natural step after the feature extraction is the events recognition and/or their localization along the optical fiber²¹². Traditional approaches for feature extraction in DAS systems rely on hand-crafted rules or threshold-based energy detection methods to recognize and localize events, but these are often unreliable in noisy environments or with overlapping signals²¹³. In contrast, AI-based methods, especially deep learning, have proven highly effective in both recognizing event types and pinpointing their locations across spatially distributed sensing channels²¹⁴. As an application example, CNN-based models are widely used to classify DAS signal segments into distinct event categories such as walking, running, jumping, knocking, and digging as shown in ref.²¹³. These models operate on either raw 1D signals, spectrograms, or grayscale representations of DAS time-distance matrices. Hybrid architectures such as CNN-BiLSTM further improve accuracy by incorporating both spatial and temporal context, achieving classification accuracies exceeding 98% in some test cases¹³⁶. Event localization, or the task of determining where along the fiber the event occurred, is often handled as a parallel or upstream task in the AI pipeline. Some approaches treat the DAS time-distance matrix as an image and apply object detection models such as YOLO, Faster R-CNN, or single-shot detectors to simultaneously classify and localize events²¹⁵. These models return bounding boxes or coordinates in the time-space domain, effectively identifying both the type and position of events in real time. AI-enhanced localization is also augmented by attention mechanisms or Transformer-based models that can track spatial shifts in signal intensity over time—useful for moving sources such as vehicles. The AI algorithm enables multi-event recognition and localization under noisy or low-SNR conditions, a major advancement over traditional methods, since such methods generally have classification issues when signals overlap or are masked²¹⁶.

As a common analysis of sensors responses, the regression models are used to obtain a continuous measurement of the desired parameter along the optical fiber in different distributed sensing approaches²¹⁷. Such approach is used where estimating a physical quantity, rather than classifying discrete event types, is required. Although many developments in DAS applications are focused on event detection and classification, regression models are critical for tasks such as shape sensing, displacement tracking, strain estimation, and environmental quantification¹⁷⁸. To that extent, an application of regression regression model in DAS is presented in ref.²¹⁸, where a CNN-based deep regression model is used for high-resolution sensing. In addition, the regression models can be boosted by the CNN, where the neural network can learn the pattern of small changes in spectral features that are typically considered noise in classical analysis. These features contributed to robust continuous shape estimation highlighting the ability of deep regression to extract physically meaningful relationships from complex, high-dimensional input data²¹⁹. Regression models for these applications typically employ CNNs, fully connected deep networks, or recurrent models (e.g., LSTM) depending on whether the input is spatially structured, time-dependent, or both. In summary, AI enhances each step of the DAS signal analysis pipeline, which enhances the traditional signal analysis approaches into a dynamic, adaptive, and highly intelligent system capable of real-time event recognition, anomaly detection, and decision support in critical applications, where the summary of the AI-based models and approaches for each step on DAS analysis flowchart is presented in Table 13. It is important to clarify that the selection of the best AI model for each specific application case needs to consider different parameters and overview of each specific case (including the type of data, the input values, the real-time requirements, the specifications of the task, among other parameters) that make it difficult to generalize and define a best model for all cases. Table 13 presents the discussed AI-driven processing steps by

summarizing the preferred model architectures, input-output relationships, and associated performance metrics, providing a structured reference for DAS signal analysis. This can be used as a first approach for model selection for an application scenario by means of investigating the necessary input for the model, the output that the model offers and key metrics that can be used for the choice of a preferred model.

For a given DAS processing task, the selection of AI models is primarily governed by tradeoffs between accuracy, computational cost, and data requirements, which can have some differences depending on the application scenario. In feature extraction and classification, CNN-based models offer higher computational efficiency and strong performance for localized spatial patterns, making them suitable for real-time and edge deployments (compared with other preferred AI models in Table 13). In contrast, Transformer-based models provide improved capability in capturing long-range spatial-temporal dependencies, particularly in long DAS recordings, but at the cost of higher computational complexity, larger training datasets, and increased inference latency. In time-series modeling, recurrent architectures such as LSTM and BiLSTM exhibit different performance characteristics for all processing steps. Standard LSTM models process signals in a single temporal direction and are generally more computationally efficient, while BiLSTM models exploit both past and future temporal context, leading to improved classification accuracy (typically below 10% improvement, which is significant depending on the application) at the expense of increased computational cost and memory usage. This makes BiLSTM more suitable for offline or batch processing, whereas LSTM is preferred in low-latency and/or real-time applications.

Similarly, in event classification and localization tasks, object detection models such as YOLO provide fast, real-time inference with slightly reduced accuracy compared to two-stage detectors like Faster R-CNN, which achieve higher detection precision but with significantly higher

Table 13 | Comparison between different signal in terms of performance indicators.

Processing Step	Preferred AI models	Input data	Output	Key metrics
Data Augmentation	CycleGAN, DCGAN, ks-DCGAN, Time-domain transforms	Raw signals, synthetic signals	Augmented balanced dataset	Improved minority class representation (10% accuracy boost)
Data Compression	SEER, Autoencoders, 1D-CNN	Raw signals, latent vectors	Compressed signal representations	20x data reduction (retained inference accuracy)
Denoising	DnCNN, Autoencoders, MSI-Net, SDT (Transformer), DAS-N2N	Raw signal matrices, spectrograms	Denoised signal with enhanced SNR	Robust under low SNR (better than traditional filters)
Feature Extraction	CNN, BiLSTM, ResNet, GAF, RP, Transformers	Time-series, spectrograms, GAF images	Feature vectors, image embeddings	Improved classification accuracy with auto features
Classification	CNN, BiLSTM, YOLO, Faster R-CNN, Transformer	1D/2D DAS matrices, spectrograms	Event class and spatial location	Real-time detection and localization (Accuracy >98%)
Regression	CNN, LSTM, Deep FC Networks	Spectral features, signal matrices	Continuous estimates (e.g., strain, displacement)	High spatial resolution, robust continuous sensing

computational overhead. Thus, such two-stage models are preferred only if there is an offline application in which the accuracy is the most important parameter. These comparisons indicate that no single model is universally optimal and model selection should be guided by the specific application constraints, including required accuracy, available computational resources, data volume, and real-time processing requirements.

After the discussion of AI models at every step of the DAS signal analysis, special focus is given to deep learning methods for classification and data extraction. Deep learning models are aligned with the future developments of DAS systems and can be used to address open technical challenges in DAS signal interpretation that current models are not able to achieve, which mainly includes a unified multi-task systems capable of performing denoising, event detection, localization, and classification in a single end-to-end model. Considering the semi-supervised learning (SSL) approaches, these models are trained on a small labeled dataset supplemented with a much larger dataset of unlabeled data, specifically FixMatch or pseudo-labeling methods are able to generate artificial labels or consistency regularization, effectively improving model robustness without manual labeling¹⁸⁹. Such approaches are applied in DAS for different field testing, where only a few ground-truth events are known. Similarly, few-shot and zero-shot learning aim to obtain classification (or regression) in scenarios where there are very limited or no training data²²⁰. In this case, the few-shot classifiers include prototypical networks or Siamese networks, which are suitable for classifying new DAS signals using only a few labeled instances¹⁸⁰. As an emerging area in deep learning, the zero-shot learning can be regarded as an improvement of the few-shot learning in which a preliminary classification is performed without retraining the model even in case of unexpected events¹⁷⁷. An example of technical route for zero-shot learning implementation is the one presented in ref.²²⁰ in which there is a conversion of DAS raw data into spatio-temporal images followed by the mapping of event types into a semantic space defined by physically meaningful vibration attributes. Semantic similarity between known and unknown events is used to construct mixed classes from known events that share transferable characteristics with the unknown class. Dedicated feature extraction networks are then trained for each mixed class using a reinforcement-guided strategy to isolate common and generalizable features, whereas a standard feature extractor preserves discriminative information for known classes. Features extracted from the mixed classes are synthesized in the feature domain to generate representative features for the unknown event class without using any real samples. These synthesized features are combined with known-class features to train a unified classifier that treats unknown events as standard classes. During inference, the system enables direct identification of previously unseen events, demonstrating a practical and structured approach

to zero-shot event recognition in DAS systems.

Transfer learning is one of the most widely adopted paradigms in DAS AI pipelines. Models pretrained on large, generic signal or image datasets (e.g., ImageNet for CNNs or speech datasets for time-series models) are fine-tuned using DAS-specific data²¹³. In ref.¹⁹², a ResNet-18 model is used for DAS signal classification by adapting them to grayscale representations of DAS matrices. Such approach significantly reduces training time and data requirements while maintaining high accuracy, which leads to a lower computational effort for real-time applications. As an example of transfer learning implementation, Li et al.²²¹ present a fast and computationally efficient method for event recognition in ϕ -OTDR systems. The authors propose a hybrid framework that leverages transfer learning using a pre-trained AlexNet to extract discriminative features from DAS data transformed into RGB images and then employs a support vector machine (SVM) for classification. The method eliminates the need for large datasets, deep network training, or GPU hardware —achieving high accuracy (94.67%) with only 13 seconds of training on a CPU-only system. Even when reducing the training data to as few as 1146 samples, the model maintains a validation accuracy above 90%. The approach demonstrates the effectiveness of using pretrained CNNs for feature extraction in DAS, supported by global and local interpretation techniques (e.g., integrated gradients), validating that extracted features are meaningful for classification.

In another SSL implementation, Shi et al.²²⁰ propose a novel event recognition model for ϕ -OTDR systems that combines the strengths of deep residual learning and attention mechanisms. In this case, there is a design of neural network architecture based on ResNet18, enhanced with an attention module, to automatically learn and emphasize discriminative features from DAS time-distance signal matrices. The attention mechanism guides the model to focus on important spatial regions, improving recognition accuracy for vibration events such as digging, walking, running, and background noise. Experimental results demonstrate that the proposed ResNet-Attention model achieves higher accuracy and faster convergence than traditional CNNs and vanilla ResNet, with a test accuracy of 96.52%, which confirms the effectiveness of integrating attention mechanisms into deep convolutional structures for DAS signal processing.

As another critical application for future developments in signal processing of DAS systems, the incremental learning adapt to changing background noise profiles, new event types, or sensor drift without forgetting previously learned patterns. This method includes approaches such as elastic weight consolidation (EWC) or replay-based methods to retain performance on old tasks while learning new ones, which is an important step towards a new generation of DAS technology with adaptive AI²²². They enable more flexible, efficient, and intelligent DAS systems capable of maintaining

high performance over time and across different deployments with minimal human intervention. Their growing adoption signals a shift from static, supervised pipelines toward self-improving, context-aware sensing platforms suitable for large-scale, real-time monitoring applications.

5.2 Enhanced backscattering optical fibers

As discussed and schematically represented in Fig. 9, an important limitation of the current DAS systems is the waveguide itself, since standard optical fibers are designed for telecommunication applications in which the backscattering is generally kept at minimum. This feature is a shortcoming in DAS systems, since they rely on the backscattered signal¹⁸¹. Thus, a reduced backscattering generally results in small SNR, poor spatial resolution and sensitivity as well as the need of highly sensitive detection mechanisms that generally leads to bulk and high cost systems. To address this issue, enhanced backscattering fibers are proposed following different fabrication methods, which include increasing the scattering through UV radiation and gratings inscription^{223,224}. Another method is proposed in ref.²²⁵, where an enhanced backscattering fiber can be achieved without structural modifications in the standard optical fiber by means of developing of optical fibers doped with nanoparticles (NP)^{226,227}. The NP-doped optical fibers enhance the Rayleigh scattering, which leads to higher backscattering levels that generally result in higher SNR, spatial resolution and measurement sensitivity²²⁸.

Such fibers were employed in OFDR systems throughout the years in which a higher resolution and detection sensitivity was demonstrated in not only in biological detection²²⁹, but also in shape reconstruction²³⁰. The fibers also enable novel multiplexing approaches in which the scattering-level multiplexing (SLMux) systems (proposed in ref.²³¹) resulted in the development of shape reconstruction systems with multiple fibers combined with delay lines²³². Furthermore, the integration of NP-doped optical fibers with deep learning techniques can enhance the detection performance, making it possible to provide a 3D shape reconstruction with a single optical fiber cable distributed along the sensing structure²¹⁷.

As another approach for enhanced backscattering fibers, the enhanced backreflection fibers (EBRFs) are specially engineered optical fibers designed to improve the signal-to-noise ratio in distributed optical fiber sensing systems, particularly for long-range applications like DAS²³³. Unlike enhanced backscattering fibers, which increase Rayleigh scattering at the cost of higher loss, EBRFs introduce low-loss reflectors—either continuously (as weak gratings) or discretely (as reflector arrays)—to provide strong, directional backreflection with minimal added attenuation. Similarly, the femtosecond laser inscription have enabled the creation of ultra-low-loss enhanced backreflection (ULEB) fibers, which achieve over 20 dB signal enhancement and

allow sensing distances exceeding 200 km from a single end¹⁸¹. These fibers offer broadband reflectivity, resistance to interference fading, and compatibility with high-speed interrogation, making them the leading choice for next-generation long-distance fiber optic sensing.

As an example of EBRF in DAS systems, Westbrook et al.²³⁴ introduced a purpose-engineered EBRF for DAS. Similarly, the proposed fiber integrates a precisely spaced array of ultra-weak reflectors, fabricated using a femtosecond laser micromachining process. Each reflector exhibits an average reflectivity below -60 dB and is spaced periodically to form a deterministic backscattering pattern. The fabrication process ensures minimal insertion loss—less than 0.001 dB per reflector—resulting in a total attenuation of approximately 0.2 dB/km, which is comparable to that of standard telecom fiber. The enhanced backscattering structure yields a total backscattered intensity increase exceeding 30 dB, dramatically improving the signal-to-noise ratio in DAS systems. This improvement enables high-fidelity acoustic signal detection in single-shot mode without the need for averaging, with demonstrated phase noise levels below 0.1 rad over distances greater than 100 km. Unlike traditional DAS implementations that suffer from coherent fading and inconsistent sensitivity due to the stochastic nature of Rayleigh scatter, the engineered fiber delivers spatially uniform and temporally stable backscattering. This uniformity eliminates interference-induced noise and supports scalable, long-range acoustic monitoring applications. The experimental validation of this enhanced fiber in a DAS configuration confirms its ability to accurately detect and resolve low-amplitude acoustic events under conditions where standard Rayleigh-based systems would fail. These results suggest strong potential for deployment in infrastructure monitoring, security surveillance, and geophysical sensing, where sensitivity, spatial coverage, and reliability are critical.

In an improvement compared with previous works, Masoudi et al.²³⁵ demonstrated a 152 km-range single-ended DAS through a so-called micromachined enhanced-backscattering fiber (μ -ENHF), which uses femtosecond laser-inscribed point reflectors at regular intervals to significantly boost the Rayleigh backscattered signal while maintaining low attenuation (0.01 dB per 100 reflectors). Unlike traditional EBFs that suffer from high loss due to continuous gratings, μ -ENHF provides discrete, low-loss reflectors with adjustable reflectivity, enabling high signal fidelity and low noise. Combined with inline optical amplification via distributed Raman and remotely pumped erbium-doped fiber amplifiers, the system achieves 5 m spatial resolution, a minimum detectable strain of 40 ne at 1 Hz, and a sensing bandwidth of 0.1–100 Hz—making it a robust solution for long-range DAS applications. Table 14 presents a comparative overview between the different Enhanced Backscattering Optical Fibers with a summary of key advantages and drawbacks of each discussed fiber.

Table 14 | Comparison between different methods for enhanced backscattering optical fiber fabrication.

Fiber type	Optical attenuation	Backscattering gain	Fabrication complexity	Key characteristics
Nanoparticles Doped Fibers	Can be 100 higher than conventional SMF	Higher than 40 dB	Low (same process used for SMF fabrication)	The attenuation and backscattering can be tailored by the nanoparticles
UV radiation	Not reported	20 dB	High (need additional lasers and pulling systems)	Method needs UV radiation in different regions of the fiber
Weak gratings	Less than 0.001 dB increase per reflector	30 dB	High (femtosecond laser setups)	Method results in fibers for long range monitoring, but need costly components and higher complexity
Weak reflectors	0.001 dB increase per reflector	Around 30 dB	High (femtosecond laser setups)	Method results in the smallest optical attenuation combined with a high backscattering gain, but also needs costly components and long fabrication times

The compatibility of enhanced backscattering fibers with ϕ -OTDR interrogators is primarily based on the interaction between the fiber scattering profile and the probe pulse parameters. In conventional DAS systems using standard SMF, probe pulse widths typically range from 10 to 100 ns, corresponding to spatial resolutions of approximately 1–10 m. Regarding the pulse duration, the use of short pulses is necessary for achieving high resolution in weak backscattering systems. Thus, using enhanced back-scattering fibers can result in higher resolution with longer probe pulses. However, in weak grating-based fibers such as EBRF or μ -ENHF, the reflector spacing imposes a constraint on the pulse width, which must be shorter than or comparable to the reflector spacing to avoid overlap of backreflected signals. However, it still can be used with commercial ϕ -OTDR interrogators, since they provide a typical wide range of pulse width. The enhanced and deterministic backscattering provided by these fibers also affects coherence requirements. Conventional Rayleigh-based DAS typically requires narrow-linewidth lasers to ensure phase stability over the pulse duration and round-trip time. In weak grating-based fibers, the increased backscattered intensity improves the signal-to-noise ratio and relaxes the minimum optical power requirements and can lead to longer sensing distances. The deterministic nature of the reflectors can tolerate slightly larger linewidths (on the order of a few kHz) without significant degradation, provided that the coherence length remains longer than the pulse length (e.g., higher than 10 to 20 m).

For nanoparticle-doped fibers, the distributed increase in Rayleigh scattering enhances backscatter levels without introducing discrete reflections, enabling direct compatibility with standard ϕ -OTDR configurations. Nevertheless, the higher scattering coefficient may increase attenuation, which can reduce the effective sensing range unless compensated by amplification. In terms of source requirements, NP-doped fibers do not fundamentally relax linewidth constraints, as phase-sensitive detection still requires coherence lengths exceeding the gauge length. Thus, narrow linewidths (e.g., below 1–5 kHz) remain necessary for stable operation.

5.3 Silicon photonics as a new tool for DAS interrogation systems

The use of discrete optical components and bulk devices leads to complex devices, which hinder the portability of DAS systems. To that extent, silicon photonics is rapidly evolving from a niche research field into a mainstream technology, driven by its success in optical transceivers for data centers and its potential in diverse applications such as LIDAR²³⁶, biosensing²³⁷, quantum computing²³⁸, and photonic processing²³⁹. It enables integration of multiple photonic components on a single chip²⁴⁰. As the technology matures with improved process design kits, design tools, and manufacturing processes, the silicon photonics approach can be transitioned into large scale and programmable systems for developments in sensing technologies²⁴¹. Silicon photonics has important advantage in implementation due to its compatibility with complementary metal-oxide-Semiconductor (CMOS) fabrication technology, compact size, and scalability²⁴⁰.

An implementation of silicon photonics in devices for signal acquisition in DAS systems is proposed in ref.²⁴². In this case, the authors proposed a silicon-based on-chip electro-optical modulator (EOM) with ultra-high extinction ratio (ER) of up to 68 dB, designed to replace bulky and power-hungry AOMs in DAS systems. The EOM is composed of four coupled microrings on a silicon-on-insulator platform and has compact size of $260 \times 185 \mu\text{m}^2$, low power consumption (3.6 mW), and modulation speed with 6.5 ns rise time, which is useful for DAS applications. The proposed chip is integrated into a ϕ -OTDR system, where the DAS system with on-chip EOM achieves a strain sensitivity of $4 \text{ p}\epsilon/\sqrt{\text{Hz}}$ and spatial crosstalk noise as low as $-68.1 \text{ dB rad}^2/\text{Hz}$, which is a performance comparable with commercial AOMs. Experimental results confirm that increased ER significantly reduces crosstalk and marginally improves the noise floor.

In another application of silicon photonics in DAS, Jin et al.¹²² present the first demonstration of a fully integrated silicon photonic interrogator for DAS, fabricated on a silicon on insulator (SOI) platform. The chip integrates a Mach-Zehnder modulator (MZM) transmitter and a

dual-quadrature, dual-polarization coherent receiver, enabling different configurations for DAS systems such as time-gated digital optical frequency domain reflectometry. Experimental validation shows the integrated interrogator achieves strain resolutions of $59 \text{ p}\epsilon/\sqrt{\text{Hz}}$ over 12.1 km (1.14 m spatial resolution) and $81 \text{ p}\epsilon/\sqrt{\text{Hz}}$ over 49.0 km (3.78 m spatial resolution), which is also comparable with discrete DAS systems. Thus, the continuous advances in silicon photonics can provide a scalable, energy-efficient solution for next-generation compact DAS systems.

5.4 AI-enabled low cost distributed strain sensing approaches

Although distributed optical fiber sensing offers numerous advantages, there are limitations that restrict its adoption in specific applications. A major concern is the relatively high cost associated with these technologies, which can pose challenges for projects that demand cost-efficient solutions²⁴³. This elevated cost is largely attributed to the required signal acquisition hardware, which often involves a large number of discrete optical components and costly elements such as modulated laser sources and, in some instances, microwave photonic modules, as well as low-noise detectors²⁴⁴. Furthermore, the overall portability of such systems is compromised due to the bulkiness of the components used in traditional distributed optical fiber sensor configurations⁶.

The Transmission-Reflection Analysis (TRA) technique presents a cost-effective alternative to conventional distributed optical fiber sensors, particularly those based on OFDR and ϕ -OTDR, for sensing mechanical disturbances along optical fiber cables²⁴⁵. This method relies on measuring both forward-transmitted and backward-scattered optical signals using a continuous-wave light source without modulation²⁴⁶. As a result, low-cost components such as light-emitting diodes can be employed, leading not only to lower overall cost, but also to an enhanced device portability²⁴⁶. Signal acquisition in TRA is simplified through the exclusive use of photodetectors, which further reduces complexity and cost. However, the spatial resolution of TRA is limited to approximately one meter when applied to conventional silica fibers, due to their inherently low Rayleigh scattering levels²²³. Furthermore, initial TRA implementations were restricted to identifying single mechanical event at any given time²⁴⁷. The technique typically interprets disturbances by correlating changes in transmitted power with their corresponding backscattered signals, where each transmission-reflection pairing indicates the location of a perturbation. Consequently, TRA is primarily challenged by two issues: i) limited spatial resolution due to the weak backscattering signal in standard fibers, and ii) inability to detect multiple simultaneous mechanical events due to the limitations of its signal analysis.

To overcome the inherent limitations of TRA, it is possi-

ble to use the EBFs discussed in Section 5.2, which enable substantial improvements in spatial resolution that can be reduced to the centimeter scale²⁴⁸. This approach represents a step forward in the design of cost-efficient distributed sensing systems. In comparative evaluations, NP-doped fibers demonstrated spatial resolutions nearly a thousand times smaller than those of conventional single-mode fibers. In this case, resolution capabilities improved from approximately 1 meter in standard fiber to about 1 centimeter when using fibers co-doped with magnesium and erbium²⁴⁹.

It is noteworthy that NP-doped optical fibers can be engineered with different material compositions to customize their characteristics for specific sensing needs²²⁵. In ref.²⁴⁹, an experimental investigation explored the differences between NP-doped fibers using the TRA method under sequential mechanical perturbations, such as localized macro-bending. In this context, the fibers were evaluated and compared in terms of key performance metrics such as spatial resolution, signal-to-noise ratio, measurement precision, and optical attenuation. The findings demonstrated that both the material composition and the size of the embedded nanoparticles significantly impacted sensor behavior. In particular, particles with diameters near 100 nm were associated with higher optical losses, yet they also enhanced backscattered signal strength, which result in a tradeoff in the EBF selection, where the best spatial resolution is generally for the fibers with highest attenuation, leading to smaller sensing lengths.

A second major limitation of the TRA technique is due to its signal processing, which typically employs linear regression to interpret both transmitted and backscattered optical signals. This method cannot handle when multiple mechanical events occur concurrently along the fiber, due to the complex overlapping of signals. To overcome this issue, employing nonlinear models that map both the intensity and position of disturbances to the observed optical signals can enhance the system's ability to resolve multiple events simultaneously²¹⁴. In this case, neural network-based methods show the possibility in improving sensing capabilities through nonlinear data interpretation. In ref.²¹⁴, a feed-forward neural network (FFNN) was implemented to tackle the signal processing challenges of the TRA method. This model, featuring two hidden layers with 600 and 300 neurons respectively, was trained to classify disturbance locations across six distinct fiber segments. Its primary aim was to localize simultaneous disturbances, even when amplitudes varied. The system demonstrated strong performance, accurately identifying up to three simultaneous perturbations along a single NP-doped fiber, with a classification accuracy of 99.43%²¹⁴.

The discussed approaches can be regarded as a significant improvement in the development of cost-efficient distributed optical fiber sensing systems, as it addresses one of the primary drawbacks of the TRA method, i.e., its limitation to detecting a single disturbance at a time. Enabling the identification of multiple concurrent events broadens the

scope of practical applications, especially in fields like healthcare, where continuous monitoring of multiple parameters is essential and the conventional distributed sensing is not widely employed in such application field. As a result, TRA-based sensors have been implemented in various scenarios, including distributed strain monitoring using optical fibers embedded in flexible textile substrates²⁵⁰ and in rigid flooring systems¹⁸⁵. Furthermore, the deployment of multiple fibers allows for multiparameter detection and can facilitate shape reconstruction across different spatial planes²⁵¹.

5.5 Overview of new developments of DAS

Despite the significant advances in DAS (and general distributed optical fiber sensing) technologies in the last decades, there are still limitations and challenges to overcome. To that extent, some key technologies were discussed in this section as possible candidates to mitigate the limitations of traditional DAS method. In an effort to develop a new generation of DAS, the deep learning methods, focused on incremental learning, transfer learning and methods such as zero- or few-shot learning can mitigate current limitations on noisy data, cross-sensitivities issues and data classification or regression in different application scenarios. Then, considering the low backscattering of conventional optical fibers, the EBFs were presented and explored as a feasible method to improve the SNR, spatial resolution and sensitivity in distributed optical fiber sensor systems, which can reduce the burden on signal processing and data extraction in DAS systems. Regarding the bulkiness of the interrogation system, the silicon photonics emerged as an enabling technology for the integration of discrete components in a single chip, providing a possible portable solution. In concurrent developments, the proposal of different techniques for distributed optical fiber sensing is performed to fill specific gaps in current OFDR and ϕ -OTDR systems, approaches such as TRA can enable healthcare and wearable applications due to its inherent low cost and portability, where such applications (especially the wearable ones) are not covered by conventional distributed sensing technologies.

It is important to mention that the enabling technologies discussed in this section also suffer from their own limitations and challenges. For deep learning methods, a major bottleneck remains the lack of standardized datasets and benchmarks, prompting calls for open, labeled DAS repositories that support reproducible research and model comparison. Furthermore, models trained in one location typically have issues in generalizing to new settings due to variations in terrain, cable installation, or background noise. Their high computational demands also make them unsuitable for real-time edge deployment without significant model optimization. In addition, most deep learning architectures function as black boxes, offering limited interpretability, which is a critical issue when it is essential to

understand the decisions. They can also be sensitive to noise, sensor drift, and environmental changes, resulting in reduced robustness over time.

In the case of the EBFs the improvement of sensor performance contrasts with current drawbacks of such approach, which is related to increased optical attenuation resulting from the fiber modification method to enhance Rayleigh scattering. This limits the feasible length of EBF and restricts their use in long-range applications unless paired with standard low-loss fibers. Additionally, the fabrication processes are complex and costly, harming large-scale production and deployment. The uniformity of backscatter along the fiber is difficult to control in some cases, leading to inconsistent sensitivity, and the presence of strong or densely spaced reflectors can introduce coherent noise and phase instability. Moreover, mechanical integrity may also be compromised depending on the inscription method.

The integrated photonic interrogator also presents important drawbacks related to the current state of silicon photonics. It still requires external components such as laser source, amplifier, and circulator, which limits the benefits of full integration. The performance of the integrated system, while promising, shows slightly higher noise and reduced sensitivity compared to commercial systems, particularly for longer sensing distances. Losses due to electrical and optical interfaces, especially between on-chip and off-chip components, contribute to these performance gaps. Moreover, thermal management is still a concern, since maintaining stable operation and minimizing phase drift in the integrated modulator and receiver requires careful temperature control, which is not yet fully embedded on-chip. Another issue is polarization handling, which could affect system stability in real-world environments where fiber birefringence changes over time, leading to the necessity of dynamic polarization control. Thus, the integrated photonic interrogator offers a promising path toward compact, energy-efficient, and scalable DAS systems, but continuous development is needed to achieve fully integrated solutions with performance and reliability that match or exceed traditional discrete systems.

Finally, considering the cost-effective approaches to distributed optical fiber sensors, limitations arise from the performance of such systems compared to conventional OFDR and ϕ -OTDR systems. The major limitation of such a method is the limited detection range of such approaches, which hinders the application in monitoring of long lengths and wide areas. In addition, the sensor resolution of current cost-effective distributed sensor system cannot match the ones from ϕ -OTDR systems, where the strain sensing resolution is still not able to match the small strains obtained from acoustic pressure. Thus, the cost-effective methods for distributed sensing still need major improvements in terms of sensitivity to be able of matching the performance required for acoustic detection.

Considering the advantages and drawbacks of the

enabling technologies, Table 15 presents an overview of such technologies in terms of which shortcoming of traditional DAS they can overcome as well as their benefits in distributed sensing technologies, impact on DAS technology and challenges to be addressed. It is expected that the current challenges of the technologies presented in Table 15 can be addressed in the following years with continuous advances in fabrication, materials sciences and data-driven methods. Then, all enabling technologies can be combined for the development of new generation distributed sensing.

6 Conclusions

This paper presented a comprehensive review of DAS sensing technologies and their many advantages, shortcomings, and real-world applicability. The review includes a market overview that demonstrated the increasing trend on DAS market size, focused on implementations in different fields or focusing on implementation in different fields. Then, the operation principles, fundamentals and theoretical background of the DAS systems are analyzed and compared in terms of different approaches and configurations. In addition, commercial equipment and recent advances in DAS configurations are discussed and compared with additional analysis on AI algorithms for data analysis in DAS applications. Therefore, this review paper is the first to comprehensively cover all aspects of DAS technology, from its theoretical basis and first laboratory demonstrations to practical implementation covering tens of kilometers. Such review can be used as a roadmap for DAS applications and to understand the application and implementation of ϕ -OTDR systems. Moreover, DAS technology and emerging trends also open new pathways for the new developments of differ-

ent DAS approaches that can expand the capabilities of current DAS approaches.

Despite the high potential and the prospects for DAS applications, there are still pressing research gaps that motivate future works and new developments in the field. One important important concern with such highly sensitive technology is on potential misuse of the system, where surveillance without consent and potential militarization raise ethical and privacy concerns in application, since it can lead to potential eavesdropping in public and even in private spaces. Furthermore, the lack of standardized training data for DAS AI models also is an important concern in the majority of applications in which the generalization, big data handling and multiple classification of different events need specific efforts in advances AI models. Such concerns and shortcomings lead to the necessity of different future works and call for action in the scientific community for further improvement of such sensor system. In order to further advance in the signal processing of DAS it is important to define across the scientific community specific guidelines for signal acquisition and labeling with public database storage (also aligned with open research guidelines) to allow different research groups in computer science and AI algorithms to develop even better algorithms that can be used in different application through transfer learning approaches. Moreover, future developments include different application scenarios in which the discussed prospects of new technologies can be employed not only to enable new applications that DAS systems are not conventionally applied (e.g. wearable systems and general healthcare applications), but also to enhance the performance of conventional applications in DAS systems. The suggestions for future developments are summarized in Table 16 as a function of development

Table 15 | Summary of the benefits and challenges of some emerging approaches in DAS technology.

Category	Technology/Approach	Key metrics	Benefits	Challenges
Deep Learning in DAS	Transformers, 1D-CNN, ResNet, Few-shot learning, Transfer learning	Up to 96.52% ResNet+Attention; >94.67% (AlexNet+SVM); 13 sec CPU-only training	Improved automation, few-shot/zero-shot classification, efficient models for edge deployment	Limited labeled data, high computational demand, adaptation to new events
Enhanced Backscattering Fibers	UV-grating fibers, NP-doped fibers	Resolution improved from 1 m to 1 cm; SNR increase from enhanced Rayleigh scattering	Improved sensitivity, spatial resolution; multiplexing and 3D shape sensing	Higher attenuation in NP-doped fibers, trade-off between resolution and loss
Enhanced Backreflection Fibers	Micromachined reflectors, Femtosecond laser inscription	30 dB backscatter gain; <0.001 dB reflector loss; <0.1 rad phase noise at >100 km; 5 m resolution at 152 km	Long-range DAS with uniform backscatter; supports real-time, low-noise detection	Fabrication complexity, managing insertion losses, integration into existing networks
Silicon Photonics for DAS	On-chip EOM, Fully integrated photonic interrogator	68 dB extinction ratio (EOM); $4 \text{ p}\epsilon/\sqrt{\text{Hz}}$ sensitivity; 59–81 $\text{p}\epsilon/\sqrt{\text{Hz}}$ resolution (12–49 km)	Miniaturization, lower power, scalable photonic integration for portable DAS	Thermal stability, integration with existing fiber systems, signal integrity over long range
Low-Cost AI-Enabled DAS	TRA, FFNN	Spatial resolution 1 cm (NP-doped); 99.43% accuracy	Cost reduction, multiple event detection, compatibility with flexible substrates	Low spatial resolution in standard fiber, initial TRA limited to single-event detection

Table 16 | Future prospects and applications scenarios suggestions.

Scenario	Key enablers	Application	Details
Portable DAS	Enhanced backreflection fibers deep learning in DAS low-cost methodology silicon photonics	Wearable systems Healthcare security	- Portable systems embedded in textiles - use of low-cost technology for closer use with civilians - Widespread of portable technology for perimeter security
High-end infrastructure	Enhanced backreflection fibers new methods for enhanced spatial resolution deep Learning in DAS	Energy industry Geology	- New distributed sensing combining different domains - standardized datasets for new AI algorithms
Hybrid opto-electronic systems	Silicon photonics low-cost methodology	Aerospace Telecommunications Environmental sensing	- Implementation in fields conventionally instrumented with electronic sensors for combined analysis using DAS as complementary technology - use of silicon photonics for integrated devices - hybrid sensor system can combine the biosensing platform with physical detection

scenarios, which include portable DAS, high-end infrastructure, and hybrid sensor systems.

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Author contributions

All authors commented on the manuscript. Arnaldo Leal-Junior proposed the original idea, performed the literature review and supervised the project. Mariana Silveira and Stanislav Kepak performed the literature review. Jan Nedoma, Radek Martinek, and Carlos Marques supervised the project and revised the paper.

Competing interests

The authors declare no competing financial interests.



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