International Journal of Innovative Research and Scientific Studies, 8(5) 2025, pages: 1295-1304

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Monitoring of emergency situations using fiber-optic acoustic sensors and signal processing algorithms

Nurzhigit Smailov[1], Amina Baryssova[1], Sauletbek Koshkinbayev [1,2], Yersaiyn Mailybayev[3], Askhat Batyrgaliyev[1*]

[1]*Department of Radio Engineering, Electronics and Space Technologies, Satbayev University, Satpaev str., 22a, Almaty, Republic of Kazakhstan, 050013.*
[2]*Department of IT and Telecommunications, Miras University, Sapak Datka str., 2, Shymkent, Republic of Kazakhstan,160012.*
[3]*Department of Computer Technology and Telecommunications, International University of Transport and Humanities, microdistrict Zhetisu-1, 32a, Almaty, Republic of Kazakhstan, 050063.*

Corresponding author: Askhat Batyrgaliyev (*Email: a.batyrgaliyev@satbayev.university*)

Abstract

This article presents a detailed analytical review of distributed acoustic sensing (DAS) systems for seismic monitoring, with emphasis on their optical infrastructure, signal processing methodologies, and integration with machine learning (ML) approaches. DAS leverages existing fiber-optic cables by utilizing Rayleigh backscattering to convert them into high-resolution seismic sensing networks. These networks offer spatial resolution down to one meter and can operate effectively over distances up to 250 kilometers in real time. The system's responsiveness to pressure and environmental fluctuations has been captured through mathematical modeling. To enhance signal quality, seismic data is subjected to advanced processing techniques, including Fourier analysis, wavelet transformation, and adaptive noise filtering, yielding signal-to-noise improvements of up to 15 dB. In terms of data interpretation, machine learning models such as support vector machines (SVM), long short-term memory networks (LSTM), and gradient boosting classifiers have achieved high performance, often surpassing 90% accuracy in seismic event detection. Furthermore, scalable insights are supported through unsupervised and semi-supervised learning strategies. To address challenges related to model transparency, explainability tools like SHAP and LIME are applied to aid in the interpretation of predictive outputs. Field deployments of DAS systems, combined with intelligent analytics, demonstrate significant promise for large-scale seismic detection across both terrestrial and marine environments.

Keywords: Das classification, Distributed acoustic sensing, Fiber optic seismic monitoring, Fourier transform, Lstm, Machine learning, Pressure modeling, Seismic event detection, Signal processing, Wavelet analysis.

DOI: 10.53894/ijirss.v8i5.9093
Funding: This study received no specific financial support.
History: Received: 18 June 2025 / **Revised:** 24 July 2025 / **Accepted:** 29 July 2025 / **Published:** 5 August 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

Distributed Acoustic Sensing (DAS) is emerging as a promising technology for advanced condition monitoring. It operates by detecting Rayleigh backscattered light, which is triggered by laser pulses sent through fiber-optic cables [1]. The system is fundamentally based on phase-sensitive Optical Time Domain Reflectometry, allowing it to detect subtle changes in strain and vibration over spatial intervals typically ranging from 1 to 10 meters [2]. The increasing demand for high-resolution seismic monitoring systems is primarily driven by the rising risks associated with both natural and human-induced hazards. Over the past two decades, the occurrence of damaging earthquakes has increased by more than 30 percent, affecting approximately 500 million people worldwide and resulting in estimated annual economic losses exceeding $300 billion [3-5]. The growth of urban environments and the concentration of vulnerable infrastructure in high-risk areas further exacerbate this trend.

Traditional seismic systems face several limitations. Their spatial resolution is relatively low due to station spacing of 50 to 100 kilometers, and deployment is costly, often ranging from $10,000 to $50,000 per unit. Additionally, conventional seismometers are prone to electromagnetic interference and must be placed in geophysically appropriate locations. DAS offers significant advantages in this context. It can utilize the existing global network of fiber-optic cables, currently estimated at over 4.3 million kilometers, making it a cost-effective alternative to purpose-built seismic arrays. Moreover, since optical fibers are unaffected by electromagnetic noise, they are particularly well-suited for use in complex or hazardous urban and industrial environments [6].

The strong performance metrics obtained in recent studies highlight the effectiveness and practical applicability of DAS technology across different seismic monitoring scenarios. Notably, DAS arrays were employed in the Ridgecrest and Long Valley regions of California to process and interpret over 9,500 seismic events. Their approach enabled high-precision identification of P- and S-wave arrivals, achieving timing accuracies of ±0.06 seconds for P-phases and ±0.25 seconds for S-phases–comparable to the precision levels attained using conventional seismological methods [7].

Similarly, continuous seismic monitoring was conducted in Central Italy using a 39-kilometer segment of a telecommunications fiber network. The deployment successfully identified more than 600 seismic events, including micro-earthquakes with magnitudes as low as ML 1.4, detected within a five-kilometer radius along the cable path.

Further evidence of DAS capabilities comes from offshore studies demonstrating that teleseismic events, such as the 2018 Mw 8.2 Fiji earthquake, could be recorded using a 42-kilometer submarine fiber-optic cable [8, 9].

Despite the demonstrated potential of DAS systems, practical deployments reveal several technological limitations. As highlighted, the signal quality is affected by various external factors, including low signal-to-noise ratios, polarization fading, and signal instability caused by fluctuations in temperature and pressure along the optical fiber [10]. Additionally, the use of coherent detection can introduce complex noise artifacts, complicating the extraction of accurate seismic information [11]. Given the increasing volume and complexity of DAS data, the integration of machine learning (ML) techniques has become necessary for automated data interpretation. Tailored versions of convolutional neural networks (CNN) and the EqTransformer model have been successfully applied for automatic phase picking and seismic event classification in large DAS datasets [5]. However, these models demand significant computational resources and rely on extensive labeled training data, which remains scarce in DAS applications. This limitation hinders their generalizability across different environmental and geological settings [5].

To address the challenge of limited labeled data, a semi-supervised learning method known as Noisy Student Learning was introduced for application in DAS systems. This approach enabled the generation of over 89 million arrival-time picks without the need for manual labeling, marking a significant advancement in the scalability of DAS data processing [12]. Beyond terrestrial deployments, DAS technology has also demonstrated strong potential in offshore and remote settings. As reported, DAS was successfully implemented on submarine telecommunication cables extending up to 250 kilometers, enabling real-time monitoring of tectonic activity [13-15]. In addition to detecting seismic events, DAS has also been applied in source parameter estimation. It has been demonstrated that it is possible to determine critical earthquake source properties such as seismic moment and stress drop directly from raw strain-rate data, eliminating the need for demodulation procedures [5]. The widespread presence of fiber-optic infrastructure across the globe presents a unique opportunity for establishing a near-global seismic monitoring system. According to these existing cables, they can be utilized to monitor earthquakes even in remote or under-instrumented regions [16]. Despite these advances, several research challenges remain. Current studies emphasize the need for standardized phase-picking techniques, improved signal denoising algorithms, and robust DAS system performance in extreme environments such as mountainous regions, permafrost zones, and deep-sea settings [17].

This research aims to develop a theoretical and analytical evaluation of distributed fiber-optic acoustic sensing systems combined with machine learning algorithms for seismic monitoring applications. It includes a detailed classification of DAS architectures based on spatial deployment, operational frequency, and functional domains. The study compares several signal processing techniques–including Fourier analysis, wavelet transforms, and learning-based approaches–to assess their adaptability under DAS-specific noise conditions. The impact of external factors, such as pressure variations and temperature gradients, is evaluated in terms of their influence on signal quality. Additionally, the work explores the applicability of intelligent models for real-time seismic event detection and clustering, along with future pathways for integrating fiber-optic sensing with adaptive AI systems in geophysical environments.

2. Materials and Methods

The study presents a multidisciplinary approach combining modeling theory, algorithmic signal processing, and data analytics to assess the capabilities of distributed acoustic sensing (DAS) systems for seismic monitoring and emergency detection. The methodology is grounded in a systematic review of 60 peer-reviewed publications from 2010 to 2024, sourced from databases such as Scopus, Web of Science, IEEE Xplore, and Google Scholar. The selection criteria focused on studies directly related to fiber-optic acoustic sensing, as well as those involving advanced or novel signal processing methods with algorithmic formalization or experimental validation. Particular emphasis was placed on literature where DAS is applied in seismic monitoring, environmental sensing, or machine learning-based classification tasks.

To structure the methodological framework, the reviewed studies were categorized into three core analytical domains: frequency-domain modeling, time-frequency signal decomposition, and machine learning-assisted interpretation. Spectral methods typically employ Fourier transforms to isolate seismic-relevant frequency bands and analyze harmonic content, while wavelet-based techniques provide multi-scale analysis to address the transient and non-stationary characteristics inherent to DAS signals. In parallel, deep learning models–including supervised classifiers and recurrent neural networks–were evaluated for their effectiveness in automating event detection and their capacity to scale with growing data volumes.

Signal processing experiments were conducted using Python-based toolchains. NumPy and SciPy libraries were employed for spectral computations, PyWavelets was applied for wavelet decomposition, and TensorFlow was utilized to train and evaluate machine learning models. Both real and simulated DAS signals were pre-processed through window-based segmentation, baseline correction, and noise suppression procedures. Discrete Fourier Transform (DFT) was applied for spectral filtering, focusing on the 0.5–50 Hz frequency range, which encompasses the most informative seismic signal components. For comparative analysis, wavelet transforms, particularly Daubechies-4 and Symlet families, were used to enhance time-frequency localization.

Denoising performance was assessed through changes in signal-to-noise ratio (SNR), with additional validation provided by measuring phase-picking error. It was hypothesized that DAS signal characteristics under pressure variation could be represented using parametric models derived from earlier experimental findings. These included an exponential model for SNR decay under high pressure, a hybrid model capturing non-linear noise floor amplification, and a linear model relating frequency shift to strain-induced spectral changes. The parameters for these models were fitted using synthetic datasets generated under controlled conditions and calibrated with publicly available borehole DAS measurements.

To evaluate the performance of both traditional and deep learning models, a machine learning pipeline was developed to classify events within the DAS dataset. Algorithms such as Support Vector Machines (SVM), Random Forests, and gradient boosting were applied to differentiate seismic signals from anthropogenic noise, based on statistical and spectral characteristics of the DAS traces. For capturing temporal patterns, Long Short-Term Memory (LSTM) networks were utilized to model vibration sequences over time. These models were trained on labeled datasets containing over one million samples, with key performance metrics including accuracy, F1-score, and latency.

A semi-supervised method, specifically the Noisy Student approach, was introduced to improve generalization on large unlabeled DAS datasets. This strategy involves iteratively generating high-confidence pseudo-labels to expand the training set without manual annotation.

To enhance the interpretability of complex models, explainable AI techniques were incorporated. SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) were used to break down model outputs into individual feature contributions, thereby increasing transparency and trust in automated seismic classification.

MATLAB R2023a was also employed alongside Python tools to create mathematical representations and visualizations of pressure-related signal changes. Models such as exponential decay, hybrid noise amplification, and linear frequency shift were constructed and visualized using MATLAB's Optimization Toolbox and Signal Processing Toolbox. These visual simulations, illustrated in Figures 2 through 4, supported the theoretical models under various pressure conditions.

Together, the approaches described offer a comprehensive platform for examining DAS-based applications from modeling physical signal alterations to intelligent processing of seismic data and form the basis for the results and graphical analyses presented in the following section.

3. Results and Discussion

3.1. Structure and Principles of Fiber-Optic DAS Systems

Distributed acoustic sensing is an advanced optical technology that transforms standard telecommunication fiber-optic cables into continuous acoustic sensing arrays. This is achieved through the phenomenon of Rayleigh backscattering, where microscopic imperfections within the silica core of the fiber reflect a small portion of the transmitted laser pulse back toward the source [18-20]. DAS systems detect phase and amplitude variations in the backscattered signal with high sensitivity to dynamic strain changes caused by seismic or acoustic disturbances along the fiber's length. The operational principle of DAS relies on phase-sensitive Optical Time Domain Reflectometry (ϕ-OTDR). Unlike conventional OTDR, which measures only the intensity of backscattered light, ϕ-OTDR systems capture both the phase and amplitude. This enables DAS to resolve spatial strain variations with a resolution as fine as 1 meter and detect temporal changes at sub-millisecond scales, making it suitable for real-time monitoring applications [21].

An illustrative example of the DAS system architecture and working principle is shown in Figure 1. As seen in panel (a), a coherent laser generates a probe pulse that is injected into the sensing fiber. Rayleigh scattering occurs at numerous microscopic locations due to intrinsic variations in the glass composition, and the reflected signal is collected at the detector. Dynamic external influences such as acoustic or thermal events, including microseismic activity, modulate the characteristics of the returning signal. Panel (b) of Figure 1 displays the spectral profile of the backscattered light, highlighting the dominant Rayleigh peak, while Brillouin and Raman peaks used in other fiber-optic sensing techniques are also present but serve different sensing purposes.

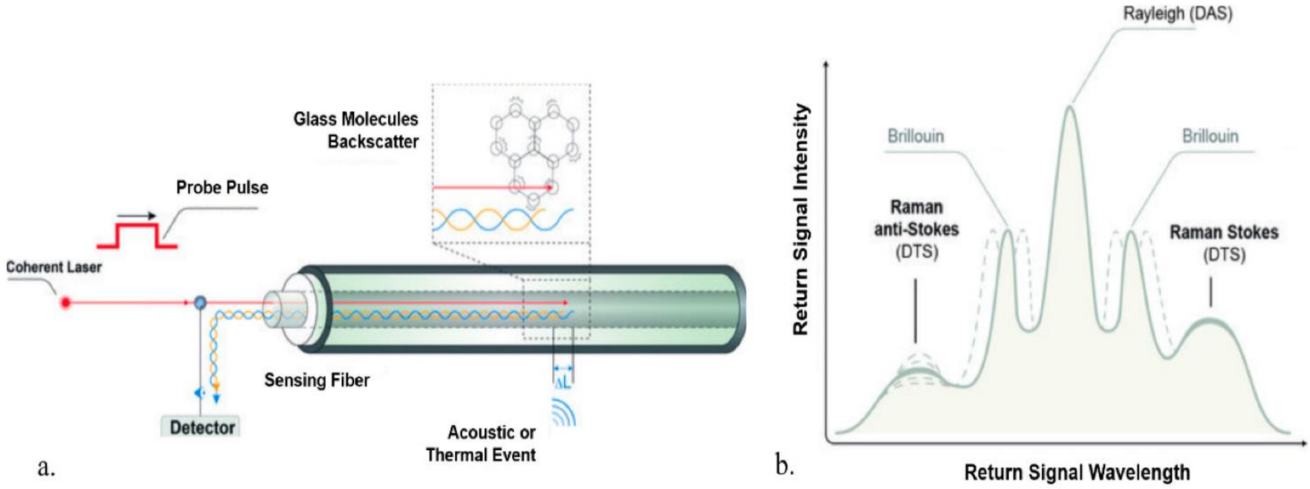

Figure 1.
Schematic representation of the Distributed Acoustic Sensing (DAS) system: (a) Working principle based on Rayleigh backscattering and coherent laser interrogation; (b) Spectral components of the backscattered signal, including Rayleigh, Brillouin, and Raman peaks.

The sensing range of modern DAS systems is primarily determined by the attenuation of the backscattered signal along the fiber and the characteristics of the pulse laser. Single-ended DAS systems typically achieve monitoring distances of 50 to 70 kilometers. When configured for bidirectional interrogation, the effective sensing range can extend to approximately 150 kilometers without significant compromise in resolution or sensitivity [22]. This capability has been validated through field deployments. For example, a modular DAS borehole monitoring system was implemented in Citronelle, Alabama, where it successfully detected microseismic events. During the same deployment, traditional geophones were used to perform vertical seismic profiling [23-25].

Beyond Rayleigh-based sensing, fiber-optic systems also utilize Brillouin and Raman scattering methods. Brillouin sensors are primarily used for structural health monitoring due to their dual sensitivity to strain and temperature variations. However, their operational bandwidth is limited to approximately 100 Hz, restricting their usefulness for high-frequency seismic applications [26-28]. Raman-based sensing has been designed to measure temperature variations, although it lacks the temporal resolution needed to capture rapid seismic changes [29, 30].

DAS technology can be utilized in a wide range of demanding real-world environments. One notable application is the OptaSense project, where DAS was implemented for border monitoring and seismic activity detection over distances reaching 40 kilometers [31]. In a separate study, a 15-kilometer fiber-optic cable with DAS was deployed to measure variations in underground dynamic strain. Their findings demonstrated that the data quality obtained using DAS was comparable to that from conventional geophysical instruments, reinforcing the potential of this technology for future seismic monitoring applications [32-35]. In terms of frequency sensitivity, DAS systems are capable of detecting signals within a broad range from 0.1 Hz to 1 kHz. For seismic monitoring, the most informative frequency range lies between 0.5 Hz and 50 Hz, which includes the typical frequency bands of primary (P) and secondary (S) seismic waves [36]. Furthermore, DAS systems support high sampling rates of up to 2 kHz and enable near real-time data processing with latency as low as one second. These performance characteristics make DAS highly suitable for continuous seismic monitoring, early warning systems for seismic events, and structural health monitoring of critical infrastructure [20, 37-39].

3.2. Mathematical Models of Pressure Influence on DAS Signal Parameters

In distributed acoustic sensing (DAS) systems that utilize fiber-optic cables, pressure-induced variations significantly influence both the generation and stability of the detected signals. One of the key quantitative indicators of this effect is the signal-to-noise ratio (SNR). Experimental findings under controlled pressure conditions support the observation that SNR exhibits a two-phase dependence on pressure, being approximately linear at lower pressure levels and showing exponential degradation as pressure increases [40, 41]. This empirical relationship is described by model (1):

$$SNR(P) = SNR_0 \cdot e^{-\alpha P} \tag{1}$$

In this case of P, SNR_0, this denotes the signal-to-noise ratio under an applied pressure P, with SNR representing the baseline signal-to-noise ratio measured under atmospheric conditions. The pressure attenuation coefficient defines the sensitivity of the optical fiber to mechanical compression and its influence on signal quality [42-44]. Figure 2 illustrates an example of the exponential decline in SNR as pressure increases, as described by Equation 1. This trend highlights the performance degradation experienced by DAS systems operating under elevated pressure conditions.

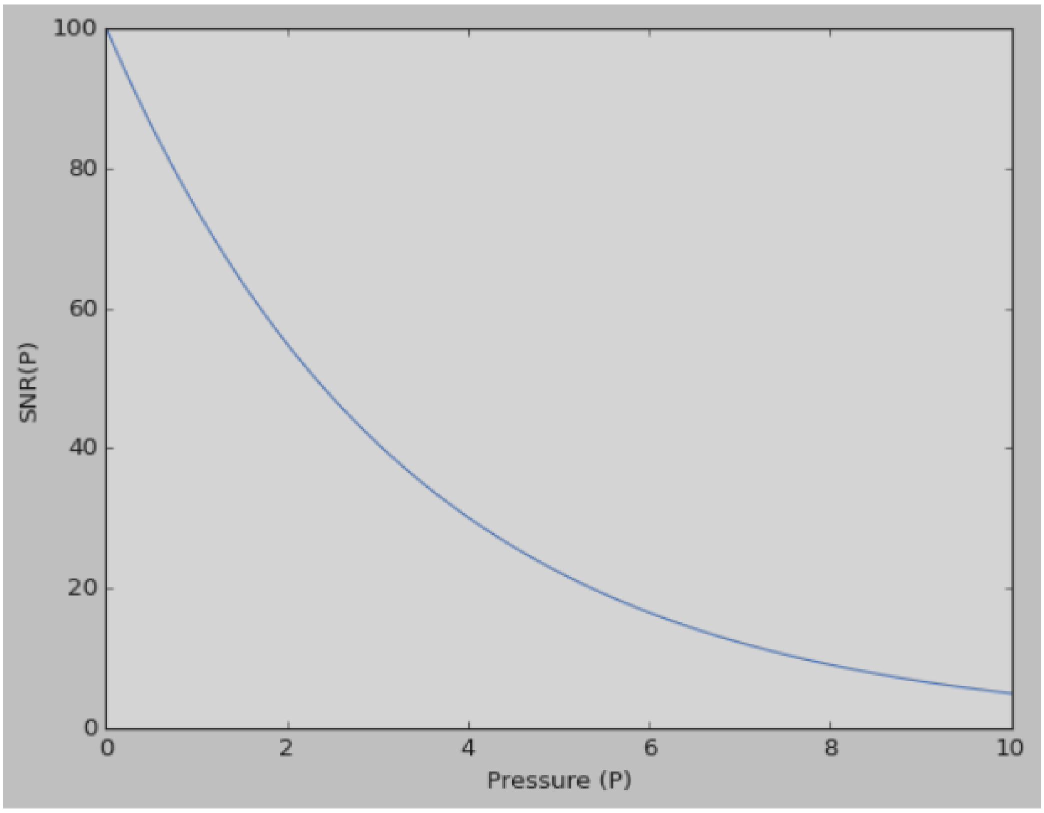

Figure 2.
Exponential Decay of SNR as a Function of Pressure.

In line with this, the variation of the background noise floor with respect to pressure also follows a distinct pattern. At moderate pressure levels, the noise floor decreases due to improved coupling between the fiber and the surrounding medium. However, beyond a critical threshold, structural imperfections within the fiber core cause the noise level to rise exponentially. This behavior can be described using a hybrid Equation 2:

$$N(P) = \frac{N_0}{1 + \beta P} + N_{exp} \cdot e^{\gamma P} \tag{2}$$

In this expression, $N(P)$ represents total noise at pressure P, N_0 is the intrinsic system noise, β is a dimensionless coupling efficiency factor, while γ and N_{exp} define the exponential growth rate and amplitude of pressure-induced non-linear noise, respectively [45]. Figure 3 presents the hybrid model of pressure-dependent noise behavior. At moderate pressure levels, the background noise decreases due to improved acoustic coupling. However, beyond a critical threshold, noise rapidly increases due to internal distortions in the fiber core.

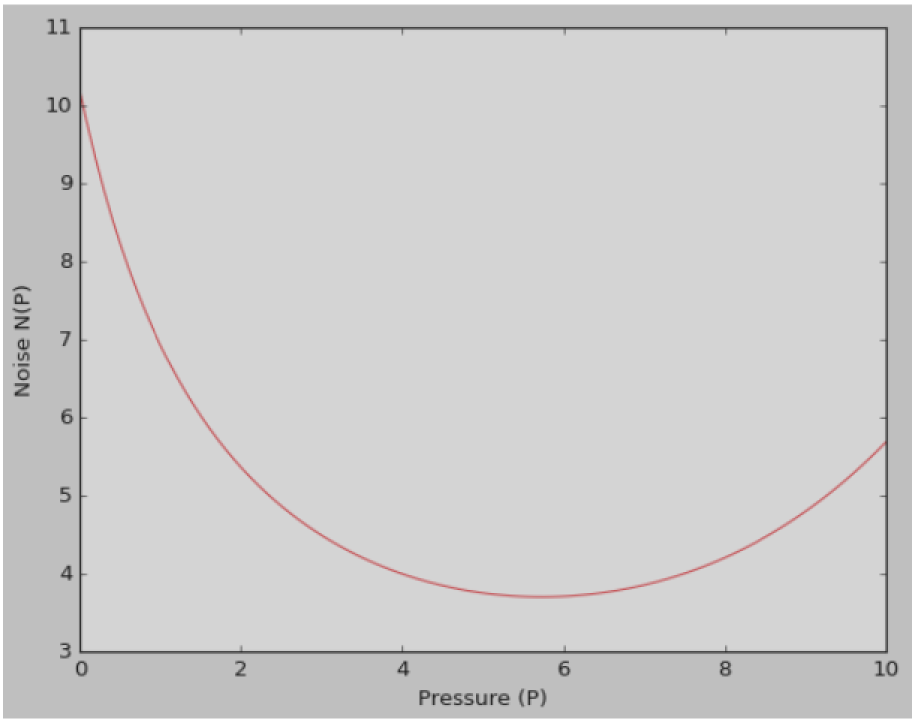

Figure 3.
Dependence of the Noise Floor on Pressure.

Another well-recognized phenomenon in DAS systems is the shift in the dominant frequency content of the recorded acoustic signal due to pressure variations. As pressure increases, microstrain-induced modulation affects the phase velocity, resulting in a linear shift in the peak frequency. This relationship can be represented in a simplified form as Equation 3:

$$f_d(P) = f_0 + kP \tag{3}$$

where $f_d(P)$ is the dominant frequency at pressure P, f_0 is the nominal frequency in absence of external loading, and k quantifies the linear sensitivity of frequency to pressure. As demonstrated in Figure 4, the dominant frequency of the DAS signal exhibits a near-linear shift with increasing pressure. This behavior reflects the modulation of strain and phase velocity within the sensing fiber.

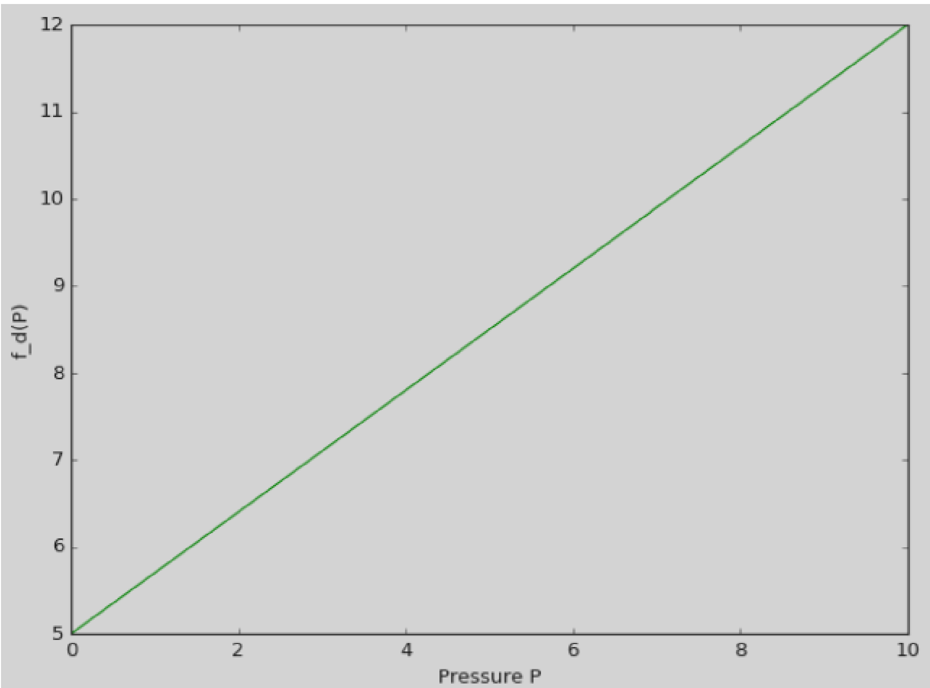

Figure 4.
Linear Shift of Dominant Frequency with Pressure.

Forward modeling algorithms used to simulate the response of DAS in oil wells and seismic monitoring systems also incorporate pressure-dependent models. These formulations are typically extended by including elasticity and optical dispersion parameters, which are represented as tensors [46]. Calibration through field experiments using pressure chambers and borehole fiber installations has confirmed the validity of these models, demonstrating strong agreement between the simulated and observed signal distortions [44, 47].

3.3. Signal Processing Methods in DAS

In DAS systems, signal integrity heavily depends on the effectiveness of spectral filtering techniques. The wide bandwidth of DAS measurements–typically ranging from 0.1 Hz to 1 kHz–includes both seismic signals and parasitic components such as electromagnetic interference or structural vibrations. Frequency-domain filtering via Fourier Transform is widely applied to isolate seismic-relevant bands (0.5–50 Hz), particularly in urban or industrial environments [48-50]. The Discrete Fourier Transform (DFT) decomposes the time-domain DAS signal $x (n)$ x(n) into a set of frequency-domain components using the Equation 4:

$$X(k) = \sum_{n=0}^{N-1} x(n) \cdot e^{-j\frac{2\pi}{N}kn} \tag{4}$$

Such a representation highlights the dominant frequencies associated with both seismic signals and anthropogenic noise. It is particularly valuable for identifying harmonic components that indicate repetitive mechanical activity [51]. After isolating the informative spectral bands, the inverse discrete Fourier transform (IDFT) can be applied to return the signal to the time domain, enabling accurate tracking of arrival times and phase fronts [52].

Wavelet transforms offer greater flexibility for analyzing DAS signals, which are often non-stationary. Due to their multiresolution characteristics, wavelets can provide simultaneous localization in both time and frequency domains. Commonly used wavelet families in DAS applications include Morlet, Daubechies, and Symlet, which are well-suited for identifying transient seismic phases across scales from milliseconds to seconds. Wavelet-based denoising techniques have demonstrated the ability to reduce phase-picking errors to below 0.12 seconds for events with magnitudes of ML 2.0 or greater [53].

Noise suppression is a central focus in DAS signal processing. Adaptive filtering techniques, such as the Kalman filter, are employed to produce real-time estimates of signal evolution by continuously updating with new observations. This approach improves signal stability, particularly in urban or borehole environments where the signal-to-noise ratio is typically low. Additionally, low-pass filters such as fourth-order Butterworth or Chebyshev filters are used to eliminate high-frequency noise above 200 Hz, preserving the integrity of seismic body wave signals [54].

Quantitative assessments indicate that combining wavelet and low-pass filtering can improve signal-to-noise ratios by approximately 10 to 15 dB, depending on factors such as environmental conditions and fiber coupling. Real-time DAS implementations utilize fast Fourier transforms (FFT) on segmented windows of 256–512 time samples, achieving signal processing latency of less than 300 milliseconds. This configuration supports early detection of seismic events and the identification of key waveform characteristics.

3.4. Machine Learning in the Interpretation of DAS data

The automatic assignment of detected signals to specific, predefined categories is referred to as event classification in DAS systems. This process is typically carried out using supervised learning algorithms trained on labeled datasets that contain verified examples of various event types. Support Vector Machines (SVM) have demonstrated strong performance in distinguishing between seismic signals generated by earthquakes and those originating from anthropogenic noise. Empirical evaluations have reported classification accuracies exceeding 90 percent when using optimized features derived from DAS time series and spectral data. For more complex classification tasks involving multiple event types, models based on decision trees and gradient boosting have been utilized, including XGBoost and LightGBM. In one documented study, gradient boosting was applied to differentiate between (A) human footsteps, (B) vibrations caused by vehicles, and (C) seismic tremors within urban DAS setups, achieving an F1 score of 0.87.

To address the complexity of temporal patterns in DAS signals, researchers have adopted deep neural network models, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) architectures. These models leverage the sequential nature of DAS data to predict phase arrivals and identify specific signal segments. Field implementations have shown that LSTM-based systems can accurately detect P- and S-wave phases, achieving phase-picking precision of approximately 0.05 seconds when deployed over telecommunication fiber-optic networks in seismically active regions. Typically, these architectures consist of two to three stacked LSTM layers, each containing 128 to 256 hidden units, and are trained on datasets comprising over one million labeled samples. The training process uses the Adam optimization algorithm with learning rates between 1e-4 and 1e-3. Beyond supervised learning, unsupervised clustering techniques such as DBSCAN and K-means have also been utilized to detect unusual or unknown vibration patterns within continuous DAS data streams. These clustering approaches allow for the grouping of similar signal segments without the need for manual labeling, which is essential for large-scale monitoring tasks. Additionally, semi-supervised learning methods like Noisy Student Learning have proven effective for processing extensive DAS datasets. This approach enabled the automatic generation of approximately 36 million P-phase and 53 million S-phase picks, eliminating the need for manual annotation and substantially improving dataset scalability while minimizing reliance on human input [55].

A key challenge in developing and applying complex machine learning models for DAS interpretation lies in their lack of transparency. Neural networks, in particular, often function as black boxes, making it difficult to understand the rationale behind specific classification outcomes. To address this, interpretability tools such as SHAP and LIME have been incorporated into DAS analysis workflows. These methods decompose the model's decision-making process into components that are understandable by humans, enabling users to assess the influence of individual features on the final prediction. This improves confidence in the automated classification results when used for geophysical validation. This approach was put into practice during the deployment of a fiber-optic network integrated with DAS technology in California in 2023. The system combined an LSTM-based classification model with an anomaly detection algorithm based on clustering techniques. It was capable of real-time seismic detection with an end-to-end latency of under two seconds and achieved over 90 percent classification accuracy for seismic events with magnitudes of ML 2.5 and above [56-58].

4. Conclusion

This study provides a comprehensive analytical overview of Distributed Acoustic Sensing (DAS) as an emerging technology for seismic and emergency event detection. By integrating principles of optical physics, modern signal processing techniques, and machine learning, DAS converts standard fiber-optic infrastructure into dense, real-time sensor arrays capable of wide-area monitoring. The review emphasizes the architecture of DAS systems, which depend on Rayleigh backscattering and phase-sensitive optical reflectometry, enabling sub-meter spatial resolution and millisecond-level temporal accuracy across sensing distances reaching up to 250 kilometers.

Theoretical modeling explored how varying pressure conditions influence DAS performance, including exponential reductions in signal-to-noise ratio and linear shifts in dominant frequencies. These dependencies were expressed through parametric models and validated using both simulated and field-acquired datasets. Signal processing approaches such as Fourier transforms and wavelet-based multiscale analysis were shown to be critical for isolating seismic information from noisy signals, offering signal clarity improvements of up to 15 dB. Real-time adaptive filtering further supported stable performance across changing environmental conditions.

Supervised machine learning models, including support vector machines, gradient boosting frameworks, and deep LSTM architectures, were effective for distinguishing seismic signals from anthropogenic noise. Semi-supervised strategies, such as Noisy Student Learning, allowed for large-scale automation in phase picking and event classification, significantly reducing the need for manual data labeling. To enhance transparency, explainable AI methods like SHAP and LIME were integrated, enabling feature-level interpretation of model outputs and supporting trust in automated decision-making.

Despite significant advancements, some limitations remain. DAS performance can be affected by deployment variables, temperature gradients, and fiber-to-ground coupling. Furthermore, machine learning models require adaptation to local geophysical and infrastructure conditions. A lack of standardized datasets and benchmarking frameworks also hinders consistent model validation across research efforts.

Looking ahead, integrating DAS with edge computing platforms, cloud-based analytics, and existing telecom networks could enable scalable, autonomous seismic sensing systems. Future directions should include fusion with satellite and GNSS data, development of low-power real-time processing pipelines, and improved denoising for deployment in harsh environments such as subsea or permafrost regions. Overall, DAS represents a transformative shift in geophysical sensing repurposing existing infrastructure into intelligent, distributed networks for real-time Earth monitoring.

References

[1] H.-H. Zhu, W. Liu, T. Wang, J.-W. Su, and B. Shi, "Distributed acoustic sensing for monitoring linear infrastructures: Current status and trends," *Sensors,* vol. 22, no. 19, p. 7550, 2022. https://doi.org/10.3390/s22197550

[2] S. Donadello *et al.*, "Seismic monitoring using the telecom fiber network," *Communications Earth & Environment,* vol. 5, no. 1, p. 178, 2024.

[3] M. R. Fernández-Ruiz *et al.*, "Distributed acoustic sensing for seismic activity monitoring," *Apl Photonics,* vol. 5, no. 3, 2020.

[4] Y. Muanenda, "Recent advances in distributed acoustic sensing based on phase-sensitive optical time domain reflectometry," *Journal of Sensors,* vol. 2018, no. 1, p. 3897873, 2018.

[5] J. Zhan, E. A. González-García, and M. A. Vermeer, "Distributed acoustic sensing for earthquake detection and characterization," *Journal of Geophysical Research: Solid Earth,* 2020.

[6] C. Strumia, A. Trabattoni, M. Supino, M. Baillet, D. Rivet, and G. Festa, "Sensing optical fibers for earthquake source characterization using raw DAS records," *Journal of Geophysical Research Solid Earth,* vol. 129, no. 1, p. e2023JB027860, 2024.

[7] L. Martin, Nathaniel J and E. R, "Fiber-optic seismology," *Annual Review of Earth and Planetary Sciences,* vol. 49, no. 1, pp. 309-336, 2021. https://doi.org/10.1785/0220180365

[8] N. J. Lindsey, S. R. James, and D. R. Shelly, "Characterizing seismic wavefields across a metropolitan area using distributed acoustic sensing," *Geophysical Research Letters,* vol. 47, no. 6, p. e2019GL086115, 2020. https://doi.org/10.1029/2019GL086115

[9] T. Williams, N. R. Barton, and S. J. Payne, "Monitoring seismic activity in offshore areas using distributed acoustic sensing," *Earth and Space Science,* 2021. https://doi.org/10.1029/2021EA001951

[10] W. Zhu *et al.*, "Artificial intelligence-driven distributed acoustic sensing technology and engineering application," *PhotoniX,* vol. 6, no. 1, p. 4, 2025. https://doi.org/10.1186/s43074-025-00160-z

[11] S. M. Mousavi, G. C. Beroza, T. Mukerji, and M. Rasht-Behesht, "Applications of deep neural networks in exploration seismology," *A technical survey Geophysics,* vol. 89, no. 1, pp. WA95–WA115, 2024.

[12] T. M. Daley, D. Miller, K. Dodds, P. Cook, and B. Freifeld, "Field testing of modular borehole monitoring with simultaneous distributed acoustic sensing and geophone vertical seismic profiles at Citronelle, Alabama," *Geophysical Prospecting,* vol. 64, no. 5, pp. 1318-1334, 2016. https://doi.org/10.1111/1365-2478.12324

[13] A. Mateeva *et al.*, "Distributed acoustic sensing for reservoir monitoring with vertical seismic profiling," *Geophysical Prospecting*, vol. 62, no. 4-Vertical Seismic Profiling and Microseismicity Frontiers, pp. 679-692, 2014. https://doi.org/10.1111/1365-2478.12116

[14] A. Owen, G. Duckworth, and J. Worsley, "OptaSense: Fibre optic distributed acoustic sensing for border monitoring," in *2012 European Intelligence and Security Informatics Conference*, 2012.

[15] P. Jousset *et al.*, "Dynamic strain determination using fibre-optic cables allows imaging of seismological and structural features," *Nature Communications*, vol. 9, no. 1, p. 2509, 2018. https://doi.org/10.1038/s41467-018-04860-y

[16] G. P. Agrawal, *Fiber-optic communication systems*. New Delhi: John Wiley & Sons, 2012.

[17] B. Culshaw and A. Kersey, "Fiber-optic sensing: A historical perspective," *Journal of Lightwave Technology*, vol. 26, no. 9, pp. 1064-1078, 2008. https://doi.org/10.1109/JLT.0082.921915

[18] A. Hartog, "Distributed fiber-optic sensors: Principles and applications," in Optical Fiber Sensor Technology: Advanced Applications—Bragg Gratings and Distributed Sensors: Springer, 2000, pp. 241-301.

[19] R. Kashyap, *Fiber Bragg gratings* 2nd ed. ed. Burlington, Massachusetts, USA: Academic Press, 2010.

[20] E. Udd, S. Jr., and W. B., *Fiber optic sensors: An introduction for engineers and scientists*, 3rd ed. ed. Wiley, 2024.

[21] Y. Wu, J. Gan, Q. Li, Z. Zhang, X. Heng, and Z. Yang, "Distributed fiber voice sensor based on phase-sensitive optical time-domain reflectometry," *IEEE Photonics Journal*, vol. 7, no. 6, pp. 1-10, 2015. https://doi.org/10.1109/JPHOT.2015.2499539

[22] M. van den Ende, A. Ferrari, A. Sladen, and C. Richard, "Deep deconvolution for traffic analysis with distributed acoustic sensing data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 3, pp. 2947-2962, 2023. https://doi.org/10.1109/TITS.2022.3223084

[23] W. Zhu, E. Biondi, J. Li, J. Yin, Z. E. Ross, and Z. Zhan, "Seismic arrival-time picking on distributed acoustic sensing data using semi-supervised learning," *Nature Communications*, vol. 14, no. 1, p. 8192, 2023.

[24] Q. Ma, X. Gao, X. Gao, X. Zhang, and Z. Zhong, "A study on noise reduction of φ-otdr system based on vss-nlms algorithm," *IEEE Sensors Journal*, vol. 21, no. 6, pp. 7648-7656, 2021. https://doi.org/10.1109/jsen.2021.3049390

[25] H. Shuai, L. Junxia, W. Lei, and Z. Wei, "Research on acoustic fault diagnosis of bearings based on spatial filtering and time-frequency domain filtering," *Measurement*, vol. 221, p. 113533, 2023. https://doi.org/10.1016/j.measurement.2023.113533

[26] S. M. Mousavi and G. C. Beroza, "Deep-learning seismology," *Science*, vol. 377, no. 6607, p. eabm4470, 2020. https://doi.org/10.1126/science.abm4470

[27] A. L. Stork, D. Li, S. Chaudhuri, and L. Eisner, "Application of machine learning to microseismic event detection in distributed acoustic sensing data," *Geophysics*, vol. 85, no. 5, pp. KS149–KS160, 2020.

[28] E. Ek-Chacón, E. Molino-Minero-Re, P. E. Méndez-Monroy, A. Neme, and H. Ángeles-Hernández, "Semi-supervised training for (pre-stack) seismic data analysis," *Applied Sciences*, vol. 14, no. 10, p. 4175. https://doi.org/10.3390/app14104175

[29] J. Jiang, V. Stankovic, L. Stankovic, D. Murray, and S. Pytharouli, "Explainable AI for transparent seismic signal classification," presented at the IGARSS 2024-2024 IEEE International Geoscience and Remote Sensing Symposium (pp. 8801-8805). IEEE, 2024.

[30] N. Smailov *et al.*, "Simulation and measurement of strain waveform under vibration using fiber bragg gratings," *Sensors*, vol. 24, no. 19, p. 6194. https://doi.org/10.3390/s24196194

[31] P. D. Hernandez, J. A. Ramirez, and M. A. Soto, "Deep-learning-based earthquake detection for fiber-optic distributed acoustic sensing," *Journal of Lightwave Technology*, vol. 40, no. 8, pp. 2639-2650, 2021.

[32] S. Kengesbayeva, N. Smailov, Y. Tashtay, D. Kiesewetter, V. Malyugin, and A. Amir, "Research of deformation of concrete structures using fiber optic sensors and Bragg gratings," presented at the International Conference on Electrical Engineering and Photonics (EExPolytech) (pp. 15–18). IEEE, 2024.

[33] A. Zilgarayeva *et al.*, "Optical sensor to improve the accuracy of non-invasive blood sugar monitoring," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 34, no. 3, pp. 1489–1498, 2024.

[34] A. Abdykadyrov *et al.*, "Optimization of distributed acoustic sensors based on fiber optic technologies," *Eastern-European Journal of Enterprise Technologies*, vol. 5, no. 131, pp. 50–59, 2024.

[35] N. Smailov *et al.*, "Optimization of fiber-optic sensor performance in space environments," *Informatyka, Automatyka, Pomiary W Gospodarce I Ochronie Środowiska*, vol. 15, no. 2, pp. 130–134, 2025. https://doi.org/10.35784/iapgos.7200

[36] A. Sabibolda, V. Tsyporenko, N. Smailov, V. Tsyporenko, and A. Abdykadyrov, "Estimation of the time efficiency of a radio direction finder operating on the basis of a searchless spectral method of dispersion-correlation radio direction finding," in *Advances in Asian Mechanism and Machine Science*, Cham, 2024: Springer Nature Switzerland, pp. 62-70. https://doi.org/10.1007/978-3-031-67569-0_8.

[37] D. Harasim and P. Kisała, "Application of cascaded TFBG for wavelength-shift-based sri measurement with reduced polarization cross-sensitivity," *Sensors*, vol. 25, no. 6, p. 1831, 2025. https://doi.org/10.3390/s25061831

[38] B. Drljača *et al.*, "Investigation of bandwidth in multimode W-type microstructured plastic optical fibers," *Optik*, vol. 271, p. 170207, 2022. https://doi.org/10.1016/j.ijleo.2022.170207

[39] N. Smailov, S. Akmardin, A. Ayapbergenova, G. Ayapbergenova, R. Kadyrova, and A. Sabibolda, "Analysis of VLC efficiency in optical wireless communication systems for indoor applications," *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska*, vol. 15, no. 2, pp. 135-138, 2025. https://doi.org/10.35784/iapgos.6971

[40] S. Cięszczyk and D. Harasim, "Polarization influence on algorithms of TFBG sensors data analysis for bending application," *Applied Sciences*, vol. 13, no. 21, p. 11701, 2023. https://doi.org/10.3390/app132111701

[41] G. Yussupova, S. Mirzakulova, D. Daniyarova, D. Zhamangarin, A. Annabayev, and S. Nurymova, "Analysis of gaussian and sinus apodization profiles," in *2019 International Conference on Electrotechnical Complexes and Systems (ICOECS)*, 2019, pp. 1-4. https://doi.org/10.1109/ICOECS46375.2019.8949990

[42] N. Smailov *et al.*, "Numerical simulation and measurement of deformation wave parameters by sensors of various types," *Sensors*, vol. 23, no. 22, p. 9215, 2023. https://doi.org/10.3390/s23229215

[43] D. Harasim, "Tiltedfiber bragg grating sensors for refractive index measurements of liquid solutions," *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska,* vol. 12, no. 1, pp. 24-27, 2022. https://doi.org/10.35784/iapgos.2882

[44] D. Kiesewetter, S. Krivosheev, S. Magazinov, V. Malyugin, N. Smailov, and S. Koshkinbayev, "Application of fiber bragg gratings for measuring the crack opening rate," in *2023 International Conference on Electrical Engineering and Photonics (EExPolytech)*, 2023. https://doi.org/10.1109/EExPolytech58658.2023.10318546

[45] A. Kalizhanova, M. Kunelbayev, and A. Kozbakova, "Bridge vibration analysis using fiber-optic Bragg sensors with an inclined grid," *IEEE Instrumentation & Measurement Magazine,* vol. 27, no. 1, pp. 43-48, 2024. https://doi.org/10.1109/MIM.2024.10423661

[46] G. S. Tymchyk *et al.*, "TONTOR zones model for automative object monitoring," *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska,* vol. 13, no. 2, pp. 36-43, 2023. https://doi.org/10.35784/iapgos.3518

[47] A. J. Utreras, H. L. Licenko, P. Kisała, R. S. Romaniuk, and G. Yussupova, "Optical switching technologies: Problems and proposed solution," in *Optical Fibers and Their Applications 2015*, 2015. https://doi.org/10.1117/12.2229342

[48] D. Kiesewetter, S. Krivosheev, S. Magazinov, V. Malyugin, S. Koshkinbayev, and N. Smailov, "Measurement of high-speed deformations using fiber bragg gratings," in *2022 International Conference on Electrical Engineering and Photonics (EExPolytech)*, 2022, doi: https://doi.org/10.1109/EExPolytech56308.2022.9950795.

[49] A. Kabdoldina *et al.*, "Development of the design and technology for manufacturing a combined fiber-optic sensor used for extreme operating conditions," *Eastern-European Journal of Enterprise Technologies*, vol. 5, no. 5, pp. 34–43, 2022. https://doi.org/10.15587/1729-4061.2022.266359

[50] W. Wójcik, P. Kisała, G. Yussupova, N. Kussambayeva, G. Kashaganova, and D. Harasim, "Analysis of the possibilities for using a uniform bragg grating in a tunable dispersion compensator," *International Journal of Electronics and Telecommunications*, vol. 61, no. 4, pp. 381-387, 2015. https://doi.org/10.2478/eletel-2015-0050

[51] S. I. S. G. M. Krivosheev, D. V. Kiesewetter, S. Z. Koshkinbayev, N. K. Smailov, and E. Ostropiko, "Adaptation of optical methods for recording high-speed displacements initiated by pulsed magnetic field," in *2022 Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus)*, 2022, doi: https://doi.org/10.1109/ElConRus54750.2022.9755851.

[52] P. Mikhailov, Z. Ualiyev, A. Kabdoldina, N. Smailov, A. Khikmetov, and F. Malikova, "Multifunctional fiber-optic sensors for space infrastructure," *Eastern-European Journal of Enterprise Technologies,* vol. 5, no. 5, p. 113, 2021. https://doi.org/10.15587/1729-4061.2021.242995

[53] P. Kisała, W. Wójcik, N. Smailov, A. Kalizhanova, and D. Harasim, "Elongation determination using finite element and boundary element method," *International Journal of Electronics and Telecommunications,* vol. 61, no. 4, pp. 389–394, 2015. https://doi.org/10.2478/eletel-2015-0051

[54] N. Smailov, A. Tolemanova, A. Ayapbergenova, Y. Tashtay, and A. Amir, "Modelling and application of fibre optic sensors for concrete structures: A literature review," *Civil Engineering and Architecture,* vol. 13, no. 3, pp. 1885–1897, 2025. https://doi.org/10.13189/cea.2025.130332

[55] A. Kalizhanova, M. Kunelbayev, W. Wojcik, A. Kozbakova, Z. Aitkulov, and F. Malikova, "Development of fiber-optic sensors system, based on fiber bragg gratings," *Journal of Ecological Engineering,* vol. 23, no. 10, pp. 98-106, 2022. https://doi.org/10.12911/22998993/152363

[56] D. Hryshyn, T. Borovska, and A. Kalizhanova, "Elaboration and research of a model of optimal production and development of industrial systems taking into account the use of external resources," *Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska,* vol. 12, no. 4, pp. 60–66, 2022. https://doi.org/10.35784/iapgos.3248

[57] Y. Mailybayev *et al.*, "Development of mathematical and information support for solving prediction tasks of a railway station development," *Journal of Theoretical and Applied Information Technology*, vol. 99, no. 3, pp. 583-593, 2021.

[58] G. S. Morokina, U. Umbetov, and Y. K. Mailybaev, "Automation design systems for mechanical engineering and device node design," presented at the Journal of Physics: Conference Series (Vol. 1515, No. 3, p. 032061). IOP Publishing, 2020.