Innovative Source Localization in Composite Pressure Vessels Using a Lightweight Neural Network Based on Acoustic Emission Features

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ABSTRACT

This work presents a data-driven framework for acoustic emission source localization in composite overwrapped pressure vessels (COPVs), which combines traditional signal processing and machine learning techniques. A reference localization is first obtained using a classical time-of-arrival approach implemented in commercial acoustic emission software, which serves as a baseline under simplified wave propagation assumptions.

To overcome the limitations associated with anisotropic materials and complex geometries, a feature-based strategy is introduced. The acoustic emission signals were processed to extract physically meaningful descriptors, which were then used to train a set of conventional machine learning models. These models achieve high localization accuracy, reaching values close to 95%, while maintaining a low computational cost and suitability for embedded implementations.

Finally, a Bidirectional Long Short-Term Memory (BiLSTM) network is proposed to exploit the spatial relationships between sensors by modeling feature sequences. This approach further improves localization performance, achieving the highest accuracy among all evaluated methods. The results highlight the value of feature-based learning for acoustic emission source localization and demonstrate that sequence modeling provides an additional benefit for complex composite structures.

Keywords: Acoustic Emission, Acoustic Source Localization, Composite Pressure Vessels, Machine Learning, BiLSTM, Structural Health Monitoring.

INTRODUCTION

Hydrogen storage systems are gaining increasing relevance in transportation and energy applications due to their potential to support low-emission mobility and more sustainable energy infrastructures. In this context, Type IV composite overwrapped pressure vessels (COPVs), featuring high strength to weight ratio, have become a key solution for onboard hydrogen storage. However, despite their advantages, these structures are exposed to demanding operating conditions and complex damage mechanisms that may compromise their structural integrity.

Ensuring the safe operation of composite vessels requires monitoring strategies capable of detecting damage at an early stage. Among the available non-destructive techniques, Acoustic Emission (AE) is particularly attractive because it enables real-time, in-situ detection of active damage processes such as matrix cracking, delamination, or fiber fracture. AE captures the transient elastic waves released and propagated during these mechanisms and provides direct information about the evolution of structural degradation while the vessel is still in service.

In Type IV COPVs, source localization is linked with several challenges, such as wave propagation anisotropy (direction dependent wave speed), vessel's curvature, and high signal attenuation in layered media. Consequently, classical formulations based on constant velocity assumptions often lack the necessary robustness for these complex geometries. This work addresses this gap by comparing a standard industrial workflow against two data-driven strategies: classic feature-based machine learning and Bidirectional Long Short-Term Memory (BiLSTM) sequence modeling. This study aims to identify a high-resolution ML-based localization framework that overcomes acoustic emission source localization challenges for future structural health monitoring (SHM) applications.

STATE OF THE ART

AE is a well-established technique for SHM, particularly suitable for detecting active damage mechanisms at an early stage. As discussed by Ospitia et al. [1], AE has been widely applied for the monitoring of structural materials because it captures real-time signals from processes such as matrix cracking, delamination, or fiber fracture. This makes AE especially attractive for composite structures, where internal damage may evolve before any visible external evidence appears.

A key objective in AE-based monitoring is not only to detect the existence of damage, but also to determine its location. However, source localization becomes challenging when the structure deviates from the simplified assumptions behind classical methods. As reviewed by Ge [2], [3], Kundu [4], Hassan et al. [5], Ma et al. [6], and Jierula et al. [7], AE source localization has been extensively studied from both theoretical and practical perspectives, including iterative and non-iterative algorithms, anisotropic media, and different structural dimensions. These reviews show that localization accuracy strongly depends on assumptions about wave speed, geometry, and signal quality.

In plate-like and relatively simple structures, localization is often based on differences in arrival times. Kundu et al. [8] proposed an optimization-based strategy for isotropic and anisotropic plates, where the source position is obtained by minimizing the error associated with difference in time of arrival. However, this approach still requires prior knowledge of direction-dependent wave velocity, which is difficult to define accurately in composite materials. To reduce this dependency, Kundu et al. [9] introduced a localization approach based on L-shaped sensor clusters, while Park et al. [10] later extended this idea by considering non-circular wave fronts in anisotropic plates. In a different direction, Sen and Kundu [11] proposed an energy-based method that avoids explicit time-of-arrival calculations, and this idea was later studied experimentally in composite laminates by Chenning Ma et al. [12] and in plate structures with discrete sensor arrays by Chenning Ma et al. [13]. These contributions are relevant because they show how researchers have tried to overcome the limitations of classical triangulation in anisotropic media, although often at the cost of higher sensors number or more demanding formulations.

The problem becomes even more challenging in filament-wound composite pressure vessels. In these structures, anisotropy combines with curvature, layered architecture and signal attenuation, which strongly affect wave propagation. As described in the original paper, these factors make traditional localization based on constant velocity assumptions particularly unreliable for cylindrical composite vessels, especially near junctions and structural interfaces.

For this reason, machine learning approaches have progressively gained relevance in AE interpretation and localization. Ciaburro and Iannace [14] reviewed machine-learning-based methods for acoustic emission testing and showing that these methods can learn directly from measured data, without relying on explicit wave propagation models. In impact and damage localization problems, Haywood et al. [15] used an artificial neural network for composite panels and showed that high localization accuracy could be achieved even with a reduced number of sensors. Similarly, Sharif-Khodaei et al. [16] employed neural networks trained on simulated impact data to locate impacts in composite stiffened panels, demonstrating that data-driven approaches can remain effective even in structurally complex configurations.

More directly related to AE source localization, Kim and Lee [17] applied least-squares support vector machines using delta time-of-arrival features and obtained accurate source prediction in both isotropic and anisotropic plates. Fu et al. [18] developed an artificial neural network for source localization using fiber optic AE sensors with good accuracy in both aluminum and CFRP plates. Particularly relevant for the present work, Kalafat and Sause [19] proposed an ANN-based (Artificial Neural Networks) AE localization method for a type III carbon-fiber pressure vessel and showed that the neural-network approach clearly outperformed a conventional delta-time method. In addition, Kundu et al. [20] presented a more general machine learning framework for AE-based damage localization and characterization, stressing the value of learning directly from data rather than assuming a fixed signal-to-damage relationship.

Recent work has continued to confirm the potential of data-driven AE localization. Barbosh et al. [21] proposed a wavelet-assisted deep learning approach based on a 2D convolutional neural network for damage localization, while Zhao et al. [22] used deep transfer learning with AE-derived images to localize damage in composite laminates. Won et al. [23] also developed an AI-based localization methodology for carbon-fiber reinforced composites, showing that deep architectures can effectively address anisotropic propagation effects when properly trained. These studies support the idea that learning-based methods can provide a practical alternative when classical localization models become inaccurate due to material complexity or uncertain propagation behavior.

The present work addresses AE source localization in a Type IV composite pressure vessel. To do so, it compares a classical commercial baseline against feature-based machine learning models and a Bidirectional LSTM architecture.

EXPERIMENTAL SETUP

COPV Specimen

To evaluate the proposed localization framework, experiments were conducted on a 40.6 L Type IV Composite Overwrapped Pressure Vessel (COPV) manufactured by FABER Industrie, Italy. The vessel consists of a plastic liner reinforced by a filament-wound composite overwrap made primarily of TORAY T700S carbon fiber. This vessel was chosen as a representative hydrogen-storage component, combining realistic geometry and material complexity, which both make AE-based localization particularly challenging.

Structure and sensor layout

To generate the dataset for the localization study, the vessel surface was divided into 40 predefined source regions, arranged as a grid over the cylindrical section with four circumferential sectors (A to D) and ten axial positions (0 to 9). This discretization turns localization into a classification problem, where each AE event is assigned to one of the predefined zones.

Four acoustic emission sensors were installed on the vessel and connected to a Vallen® AE acquisition system. The setup included two VS75-SIC sensors (75 kHz), and two VS150 sensors (150 kHz) with integrated 34 dB preamplifiers. The AE sensors were acoustically coupled to the surface of the vessels with grease. To ensure the permanent proper pressure over the attached sensors, they were fixed with an elastic rubber.

The experimental configuration is illustrated in Figure 1, which shows both the sensor layout and the division of the vessel into discrete localization zones. Sensor positions were chosen to cover both the cylindrical section and the vessel ends, while maintaining complementary propagation paths. The sensors are located 50 mm far from the dome-to-cylindrical transition region.

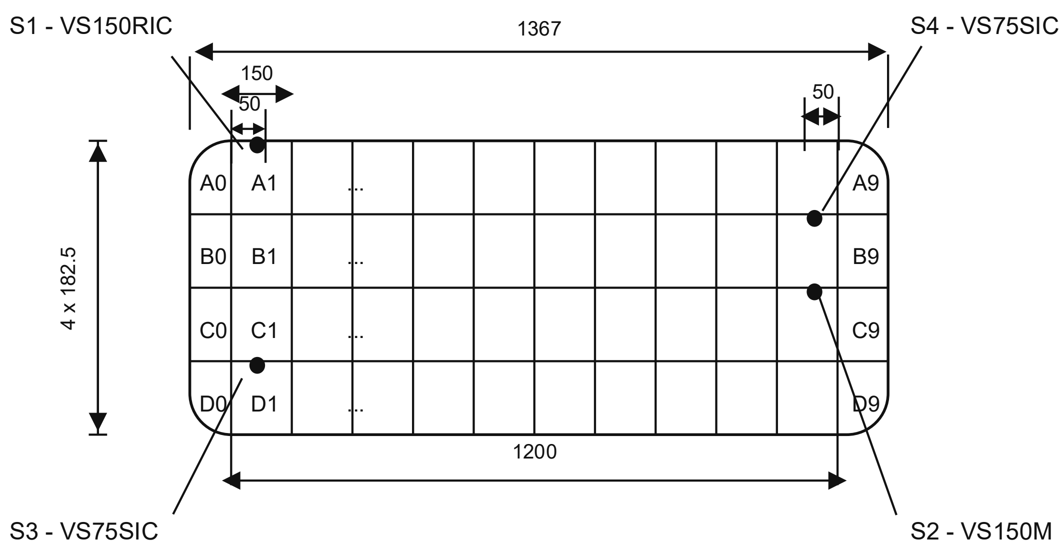

Figure 1: COPV experimental setup showing sensor placement and the 40-zone discretization for source localization.

AE generation and data acquisition

The experimental campaign aimed to produce a controlled and repeatable AE dataset. AE sources were generated using the Hsu-Nielsen procedure, A.K.A Pencil Lead Break- PLB. The PLB is a standard procedure which involves breaking a 0.5 mm 2H pencil lead against the vessel surface. The wave generated following the pencil break will propagate over the vessel's surface and can be sensed by the AE transducers.

For each of the 40 labelled regions, 110 signals were generated at random positions within the corresponding area. In this way, the dataset reflects real spatial variability within each zone while keeping a known label for every event. To reduce the influence of boundary constraints and unwanted dissipation effects, the vessel was suspended from an aluminum frame using cables during testing.

The four sensors were connected to a Vallen AMSY-5 acquisition system, and all recorded signals were exported for post-processing. The acquisition parameters were fixed to ensure consistency across the full dataset: a sampling rate of 2 MHz, a waveform length of 4096 samples, a pre-trigger length of 500 samples, and an amplitude threshold of 30.6 dB. These settings provided sufficient temporal resolution to analyze inter-sensor arrival behavior while preserving the waveform descriptors required for later feature extraction. The photo of the experimental setup and detail description of the built dataset is published in an open database [24].

Event definition and preprocessing

Following a PLB, all recorded AE hits are treated as an individual event. The first arriving hit within an event is considered as the leading hit, while the remaining detections were the associated hits from the same wavefront. The absolute time of flight to each sensor is unknown, therefore, the relative time of arrival of the hits, with respect to the first arriving hit shall be used in the analysis. This transformation sets the earliest response to zero and preserves only the inter-sensor propagation information, which is the relevant quantity for localization.

A dedicated cleaning stage was then applied to improve dataset reliability. The extracted event features were visually inspected to identify anomalous measurements and spurious detections caused by transient noise, coupling irregularities or other acquisition disturbances. Events considered inconsistent were removed from the dataset before model training. In addition, when reduced sensor configurations were analyzed, relative times were recalculated after sensor removal, so that the remaining sensors did not carry over timing references from the removed channel. This avoided the called ghost-sensor effect and ensured that each reduced configuration remained physically self-consistent.

Feature extraction for data-driven localization

After cleaning, each event was represented by features extracted from the signals recorded at all sensors. The main descriptors retained for the subsequent analysis were arrival time, amplitude, duration, energy, RMS, and rise time. To improve numerical consistency and reduce redundancy, the features were normalized, filtered by correlation analysis, and then reduced using Principal Component Analysis (PCA) separately for each sensor, preserving at least 95% of the variance. The resulting compact representation served as input for both the conventional machine learning models and the BiLSTM architecture.

METHODOLOGY

Overview of three localization strategies

Three localization strategies were evaluated on the instrumented composite pressure vessel against the ground truth. The first strategy was a conventional localization routine from commercial AE software, serving as a physics-based baseline. The second relied on conventional ML classifiers trained on extracted AE features. The third used a BiLSTM architecture fed with the same feature representation, but organized as ordered sensor sequences to capture spatial dependencies across the array.

Classical localization using Vallen software

As a baseline, AE sources were localized using the algorithm built into the Vallen AE system. In this approach, hits detected across channels within a 2 ms window are grouped into a single event, and the source position is estimated through a two-dimensional cylindrical localization routine based on differences in time of arrival between sensors (Geiger's method). The method assumes a constant average propagation velocity over the structure, which must be specified in advance. In the original work, this velocity was estimated experimentally using the pulse-through function of the AMSY-5 system in a pitch-and-catch configuration between sensor pairs. The resulting surface-wave velocities varied depending on the propagation path, confirming the non-uniform propagation conditions in the vessel. A parametric sweep from 3900 to 6900 m/s was performed to identify the optimal velocity for the localization routine. The resulting localization performance is discussed in the Results section.

This baseline is retained in the present paper because it provides a direct reference against a standard industrial workflow. At the same time, it also exposes the limitations of classical time-of-arrival localization in anisotropic curved composite structures, where constant propagation speed and idealized wave paths are only rough approximations.

Feature-based machine learning models

The second strategy uses the pre-processed feature set, composed of arrival time, amplitude, duration, energy, RMS, and rise time, to train a benchmark of conventional classifiers. After normalization and PCA-based reduction preserving 95% of the variance, a broad family of models was evaluated, including SVMs, k-nearest neighbors, and ensemble methods. This stage assesses whether accurate localization can already be achieved from engineered features alone, providing a lower-complexity alternative to recurrent architectures.

BiLSTM-based localization using feature sequences

The third strategy builds on the same reduced feature representation but introduces sequence modeling to exploit the ordered structure of sensor responses. In this approach, PCA is applied independently to the features of each sensor, and the resulting descriptors are organized into sequences, where each event is represented by four steps, one per sensor. This formulation allows the model to interpret the AE response as a spatial sequence rather than as an unordered feature vector.

This representation is then used to train a BiLSTM network. The architecture consists of three stacked BiLSTM layers, where the first two return full sequences to preserve intermediate spatial relationships, and the final layer outputs a compact representation of the event. Batch normalization is applied after each recurrent block to improve training stability. The recurrent module is followed by a fully connected layer with 256 neurons and ReLU activation, and a final SoftMax layer that assigns each event to one of the 40 localization zones.

The internal structure of the model is illustrated in Figure 2. As shown, the BiLSTM processes the input as an ordered spatial sequence, enabling bidirectional learning of propagation patterns across the sensor array before mapping these dependencies to the final classification. Training is performed using the Adam optimizer with an initial learning rate of 0.0005, reduced by a factor of 0.5 every five epochs. The maximum number of epochs was set to 200, with a mini-batch size of 256, gradient clipping, and L2 regularization. The dataset is split into 60% training, 20% validation, and 20% testing.

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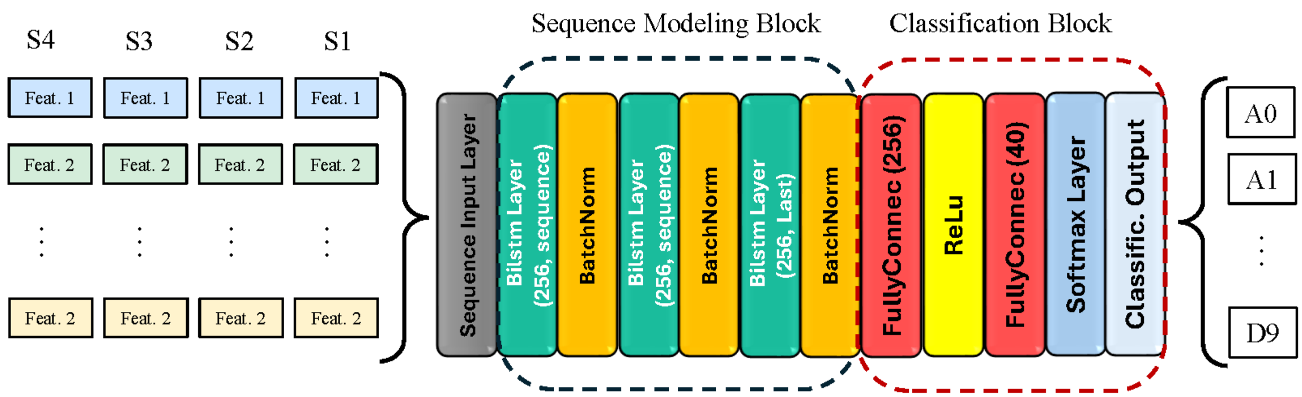

Figure 2: BiLSTM network architecture for spatial sequence modeling of AE features.

This architecture is well suited to the problem, as it treats the sensor array as a structured spatial sequence rather than an unordered input. The resulting localization performance is presented in the Results section.

RESULTS AND DISCUSSION

For all three strategies, localization performance was evaluated in terms of overall accuracy and per-zone accuracy derived from confusion matrices over the 40-zone classification problem. However, the confusion matrix itself is presented and discussed only for the proposed BiLSTM model, as it represents the primary contribution of this work. For the other methods, only the key accuracy metrics are reported.

Classical localization using Vallen software

A parametric velocity sweep identified 4300 m/s as the optimal value for the cylindrical routine, yielding a maximum localization accuracy of 37.63%. This low performance confirms that purely time-of-arrival-based strategies under constant velocity assumptions are insufficient for high-resolution monitoring in filament-wound structures. In these materials, fiber-induced anisotropy and vessel geometry significantly distort wave propagation.

Per-zone accuracy analysis showed that the method performed better in the central cylindrical zones of the vessel, where the geometry is more regular and propagation paths are less affected by boundary effects. In contrast, the regions near the vessel ends exhibited substantial misclassification, with many events misassigned to neighboring or opposite zones. This behavior is consistent with the intrinsic difficulty of applying constant-velocity localization to a filament-wound composite vessel, where anisotropy, curvature, and attenuation distort the assumptions behind the classical algorithm. The Vallen result thus serves as a practical industrial reference point, rather than a competitive solution for high-resolution localization in this geometry, particularly given the anisotropic wave propagation behavior inherent to filament-wound composite materials.

Performance of conventional machine learning models

The second strategy evaluated conventional machine learning methods trained on the extracted AE features. The results show that the selected feature set is highly informative, enabling strong performance even without recurrent sequence modeling. Figure 3 compares the test accuracy obtained by the different conventional machine learning models considered in this study.

Several models achieved high classification performance, with top accuracies reaching around 95%. As shown in Figure 3, the best results were obtained by Support Vector Machine (SVM) models, with Cubic, Linear, and Quadratic SVMs appearing among the strongest performers. Ensemble methods, such as Bagged Trees, and shallow neural approaches also produced highly competitive results. This pattern suggests that the localization problem becomes well-separable once raw sensor information is transformed into a suitable structured feature representation.

These results suggest that preprocessing and feature extraction, including event cleaning, relative timing normalization, and PCA-based reduction, are central to the localization pipeline. The high performance of several conventional classifiers also indicates that accurate localization can be achieved with models far simpler than recurrent deep learning architectures.

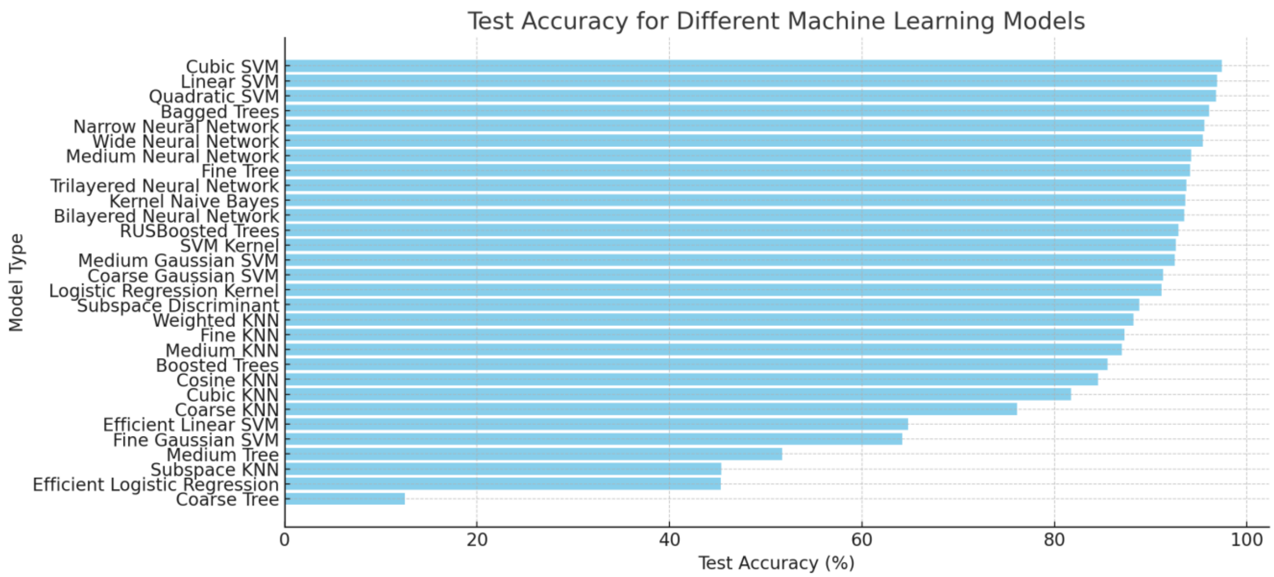

Figure 3: Test accuracy comparison of conventional machine learning models trained on extracted acoustic emission features.

BiLSTM localization results

The BiLSTM architecture was evaluated by organizing the compact feature representations into ordered sensor sequences. Under this configuration, the model achieved a localization accuracy of 97.17%, which represents a substantial improvement over the Vallen baseline and surpasses the performance of conventional machine learning models. These results indicate that source localization benefits significantly from the explicit modeling of spatial relationships between sensor responses. By processing each event as an ordered sequence, the BiLSTM captures propagation patterns that conventional classifiers only model indirectly. This approach proves especially advantageous in curved anisotropic vessels, where the source position is encoded in the combined response across the sensor array. As shown in the confusion matrix in Figure 4, the predictions are dominated by the main diagonal, confirming stable classification across all 40 zones with minimal misclassification between neighboring regions. Consequently, the BiLSTM architecture provides the highest overall performance, offering a critical improvement in robustness by incorporating sequence based dependencies.

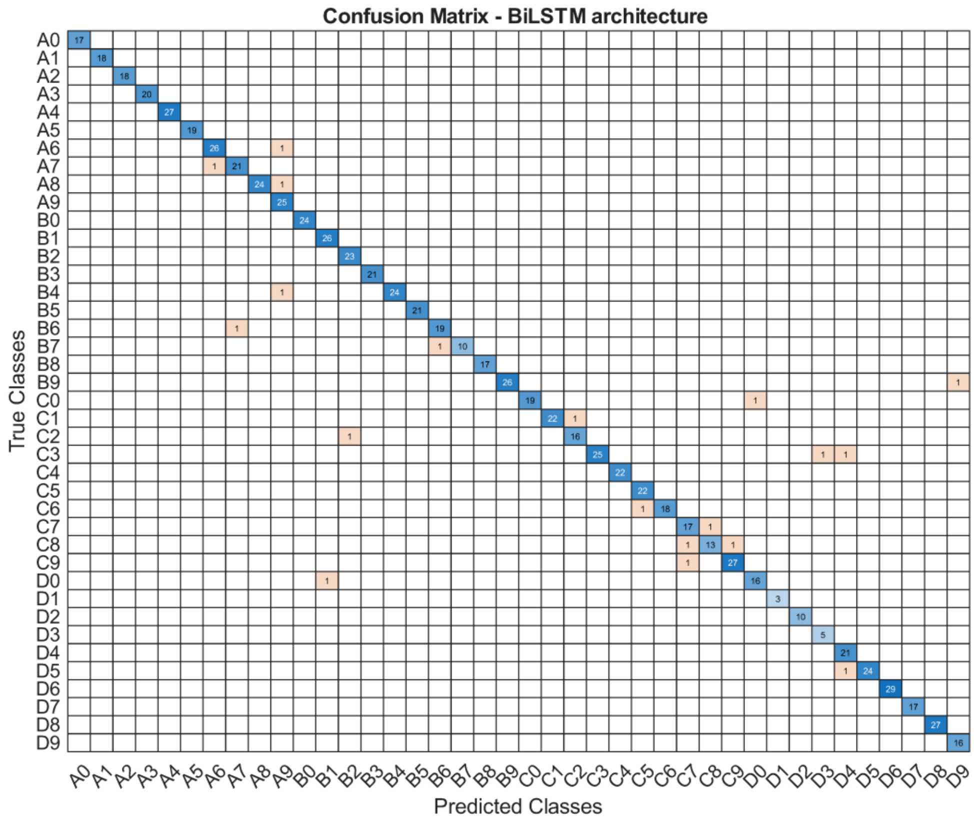

Figure 4: Confusion matrix of the BiLSTM model for AE source localization across the 40 predefined vessel regions.

Comparative discussion

The results reveal a clear ranking across the three strategies. The traditional 2D planar localization in Vallen Systeme GmbH (37.63%) highlights the limitations of standard industrial workflows when dealing with complex geometries and materials. In contrast, conventional ML models (95%) demonstrate that a well-designed feature space can overcome most physics-based limitations. Finally, the BiLSTM model (97.17%) provides the most robust result by incorporating sequence-aware modeling. This comparison is summarized in Figure 5.

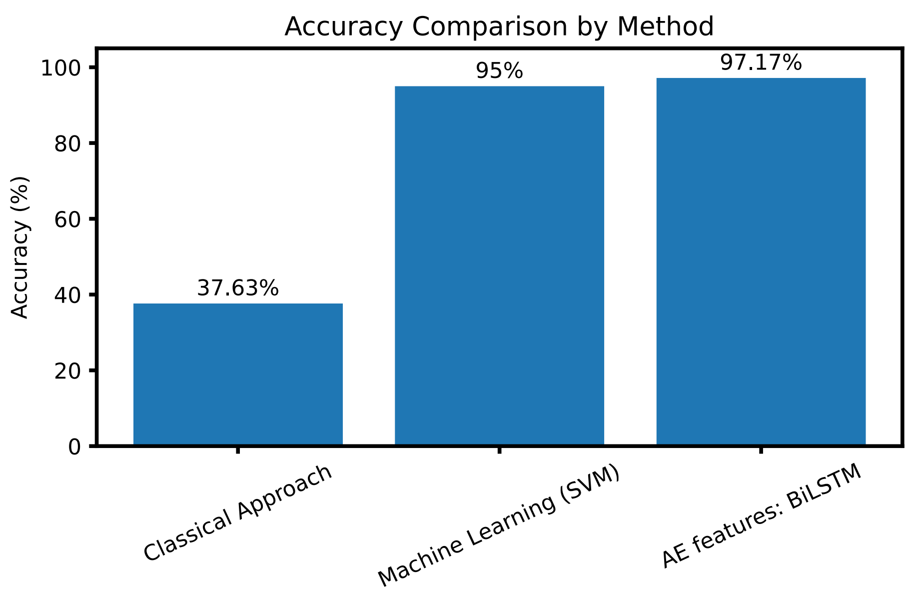

Figure 5: Localization accuracy comparison between classical time-of-arrival, feature-based machine learning (SVM), and BiLSTM approaches.

This hierarchy reflects the broader evolution of AE event localization: from simplified propagation-based models to feature-based classification, and finally to sequence-aware modeling. From an application perspective, the results suggest a trade-off: while the BiLSTM architecture offers the highest accuracy, SVM-based models remain attractive for practical implementations where lower computational complexity is preferred. Overall, the study confirms that AE source localization in Type IV COPVs is most effectively addressed through data-driven frameworks that exploit the structured variation of features across the sensor array.

CONCLUSIONS

This study validates the transition from physics-based to data-driven AE source localization for Type IV COPVs. While classical time of arrival methods were limited to 37.63% accuracy due to geometric and material complexity, feature-based ML models reached approximately 95%. The highest accuracy (97.17%) was achieved by BiLSTM architecture, which exploits the ordered structure of sensor responses to overcome anisotropic propagation effects. These results demonstrate that sequence-aware modeling provides a robust and scalable framework for SHM of complex composite pressure vessels.

ACKNOWLEDGEMENTS

This work has been supported by the project *"ICARUS - Inspección y Control Automatizado con Redes neuronales y UAVs en Sistemas Fotovoltaicos"* (ref. SI4/PJI/2024-00233), funded by the Comunidad de Madrid through the direct grant agreement for the promotion of research and technology transfer at the Universidad Autónoma de Madrid.
The author also acknowledges support from the Fulbright Visiting Scholar Program, funded by the U.S. Department of State and administered by the Institute of International Education (IIE). This work has been partially developed during the research stay at Florida Polytechnic University within the framework of the Fulbright grant.
The authors gratefully acknowledge FABER Industrie S.p.A. (Italy) and TÜV Austria Holding AG for providing the Type IV COPV used in this experimental study.

REFERENCES

[1] N. Ospitia, E. Korda, K.-A. Kalteremidou, G. Lefever, E. Tsangouri, and D. G. Aggelis, "Recent developments in acoustic emission for better performance of structural materials," *Dev. Built Environ.*, vol. 13, p. 100106, 2023.
[2] M. Ge, "Analysis of source location algorithms Part I: Overview and non-iterative methods," *J. Acoust. Emiss.*, vol. 21, no. 1, pp. 14–28, 2003.
[3] M. Ge, "Analysis of source location algorithms: Part II. Iterative methods," *J. Acoust. Emiss.*, vol. 21, no. 1, pp. 29–51, 2003.
[4] T. Kundu, "Acoustic source localization," *Ultrasonics*, vol. 54, no. 1, pp. 25–38, 2014.
[5] F. Hassan et al., "State-of-the-art review on the acoustic emission source localization techniques," *IEEE Access*, vol. 9, pp. 101246–101266, 2021.
[6] C. Ma, Z. Zhou, J. Liu, Z. Cui, and T. Kundu, "Acoustic source localization using L-shaped sensor clusters: A review," *Ultrasonics*, vol. 132, p. 107020, 2023.
[7] A. Jierula, C. Wu, A. Kali, and Z. Fu, "A review of acoustic emission source localization techniques in different dimensions," *Appl. Sci.*, vol. 14, no. 19, p. 8684, 2024.
[8] T. Kundu, S. Das, and K. V. Jata, "Point of impact prediction in isotropic and anisotropic plates from the acoustic emission data," *J. Acoust. Soc. Am.*, vol. 122, no. 4, pp. 2057–2066, 2007.
[9] T. Kundu, H. Nakatani, and N. Takeda, "Acoustic source localization in anisotropic plates," *Ultrasonics*, vol. 52, no. 6, pp. 740–746, 2012, doi: 10.1016/j.ultras.2012.01.017.
[10] W. H. Park, P. Packo, and T. Kundu, "Acoustic source localization in an anisotropic plate without knowing its material properties – a new approach," *Ultrasonics*, vol. 79, pp. 9–17, 2017.
[11] N. Sen and T. Kundu, "A new signal energy-based approach to acoustic source localization in orthotropic plates: A numerical study," *Mech. Syst. Signal Process.*, vol. 171, p. 108843, 2022.
[12] C. Ma, Z. Zhou, J. Liu, Z. Cui, and T. Kundu, "A signal energy-based approach for acoustic source localization in composite laminates," *Mech. Syst. Signal Process.*, vol. 221, p. 111709, 2024.
[13] C. Ma, Z. Cui, J. Liu, and T. Kundu, "A signal energy approach of acoustic source localization in plate structures using a discrete sensor array," *Ultrasonics*, vol. 148, p. 107555, 2025.
[14] G. Ciaburro and G. Iannace, "Machine-learning-based methods for acoustic emission testing: A review," *Appl. Sci.*, vol. 12, no. 20, p. 10476, 2022.
[15] J. Haywood, P. T. Coverley, W. J. Staszewski, and K. Worden, "An automatic impact monitor for a composite panel employing smart sensor technology," *Smart Mater. Struct.*, vol. 14, no. 1, pp. 265–271, 2005.

[16] Z. Sharif-Khodaei, M. Ghajari, and M. H. Aliabadi, "Determination of impact location on composite stiffened panels," *Smart Mater. Struct.*, vol. 21, no. 10, p. 105026, 2012.
[17] K.-R. Kim and Y.-S. Lee, "Acoustic emission source localization in plate-like structures using least-squares support vector machines with delta t feature," *J. Mech. Sci. Technol.*, vol. 28, no. 8, pp. 3013–3020, 2014.
[18] T. Fu, Z. Zhang, Y. Liu, and J. Leng, "Development of an artificial neural network for source localization using a fiber optic acoustic emission sensor array," *Struct. Health Monit.*, vol. 14, no. 2, pp. 168–177, 2015.
[19] S. Kalafat and M. G. Sause, "Acoustic emission source localization by artificial neural networks," *Struct. Health Monit.*, vol. 14, no. 6, pp. 633–647, 2015.
[20] A. Kundu, S. Sikdar, M. Eaton, and R. Navaratne, "A generic framework for application of machine learning in acoustic emission-based damage identification," in *Proc. 13th Int. Conf. Damage Assessment of Structures (DAMAS 2019)*, Porto, Portugal, Jul. 2019, pp. 244–262.
[21] M. Barbosh, K. Dunphy, and A. Sadhu, "Acoustic emission-based damage localization using wavelet-assisted deep learning," *J. Infrastruct. Preserv. Resil.*, vol. 3, no. 1, p. 6, 2022.
[22] J. Zhao, W. Xie, D. Yu, Q. Yang, S. Meng, and Q. Lyu, "Deep transfer learning approach for localization of damage area in composite laminates using acoustic emission signal," *Polymers*, vol. 15, no. 6, p. 1520, 2023.
[23] J. Won, H. Oh, and J. Sakong, "Research on the acoustic emission source localization methodology in composite materials based on artificial intelligence," arXiv:2407.05405, Jul. 2024, doi: 10.48550/arXiv.2407.05405.
[24] D. Blaha, D. Bogomolov, S. Zolfagharysaravi, N. Testoni, and A. Marzani, “AE data (Hsu-Nielsen tests) from overwrapped composite pressure vessel type-IV,” Mendeley Data, V1, 2025, doi: 10.17632/ndwr9vb53p.1731.