This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3096930, IEEE Access

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.DOI

State-of-the-Art Review on the Acoustic Emission Source Localization Techniques

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ABSTRACT The acoustic emission technique has been applied successfully for the identification, characterization, and localization of deformations in civil engineering structures. Numerous localization techniques, such as Modal Acoustic Emission, Neural Networks, Beamforming, and Triangulation methods with or without prior knowledge of wave velocity, have been presented. Several authors have conducted in-depth research in the localization of AE sources. However, existing review papers do not focus on the performance evaluation of existing source localization techniques. This paper discusses these techniques based on the number of sensors used and the geometry of the structures of interest. Furthermore, it evaluates them on the basis of their performance. At the end of this paper, a comparative analysis of existing methods has been presented based on their basic principles, key strengths, and limitations. A deep learning circular sensor cluster-based solution has the potential to provide a low-cost reliable localization solution for acoustic emission sources.

INDEX TERMS Acoustic emission, beamforming, closed form, iterative methods, time reversal, source localization

I. INTRODUCTION

The localization of active damages using a set of sensors has become an interesting topic in recent years. It has been used extensively in many fields, such as structural health monitoring, deep mining, and intrusion detection. However, due to limitations associated with measurement errors and real-life implementation, it is hard to achieve the desired accuracy [116]. A variety of non-destructive testing (NDT) methods such as smart pigs, GPS mapping devices, guided wave ultrasonic, hydrostatic, and acoustic emissions (AE) have been used to monitor structures. Among these methods, AE is a passive method that can detect any deformation in various material structures. Acoustic emission is known as the class of processes where a rapid release of energy generates transient elastic waves from a localized source or sources within the material [79]. Various acoustic emission sources include the impact of a foreign object, crack or leak generation, delamination, structural element failure, corrosion, and fiber breakage in a composite material. AE sensors record data about the structure either periodically or continuously. These sensors cannot measure the damage but can measure the response of the structure against this damage. Thus, this data contains sensitive information. Feature extraction using advanced data analytics is a way to relate the observations with the damage characteristics. Feature extraction aims at the detection, localization, identification, and severity of the damages. Various sources of acoustic emission are shown in Fig. 1.

A significant amount of research has been published in the field of damage identification and localization using the acoustic emission technique. The majority of investigations on the analysis of AE signals are aimed at identifying the damage processes in diverse materials. Shigeishi et al. [114] evaluated the possibility of using acoustic emission technology to enable a long term condition monitoring of bridges at a low cost. Colombo et al. [17] further

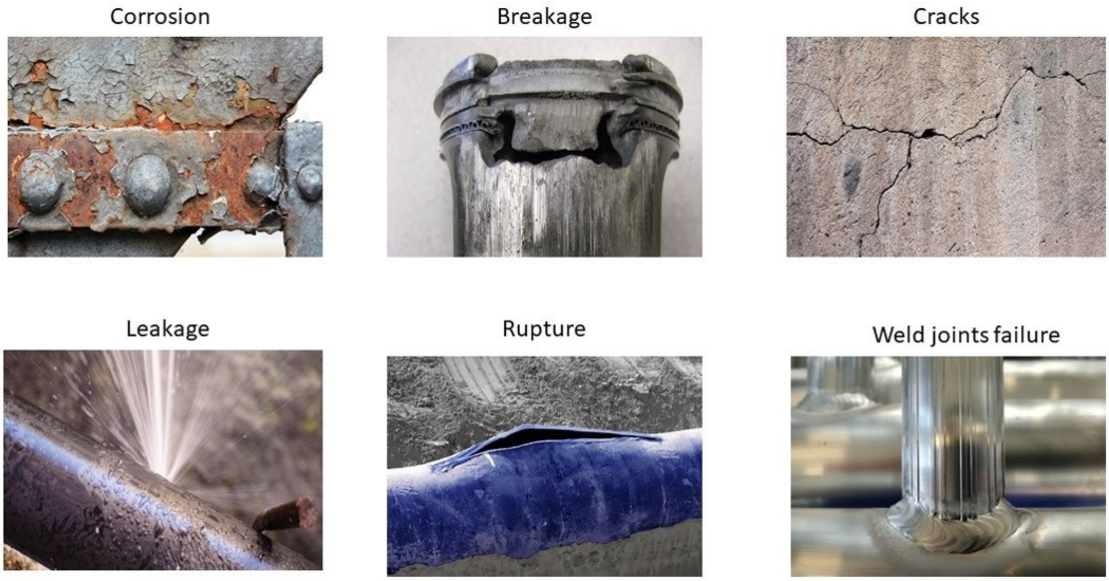


FIGURE 1. Various sources of acoustic emission in material structures.

introduced a new metric for the AE signal analysis called the "relaxation ratio" . The recorded AE energy was quantified, and the bending failure load of the RC beams showed a visible correlation. Clark et al. [16] claimed to have presented the first application of acoustic emission technique for monitoring the railway concrete sleepers. The ability to approximate the damage location corresponding to an energy event was also made feasible by channel-wise separation of AE data. Janeliukstis et al. [52] presented an innovative approach which significantly reduced the size of acquired AE data for characterizing cracking mechanism in railway prestressed concrete sleepers subjected to flexural loading.

The review by Ono [92] discussed several important fields of acoustic emission technology, such as the attenuation of AE signal, signal loss, and metal damping to provide a useful method for AE monitoring. He also discussed the source location, and bridge monitoring. Kundu [63] compared different techniques for localization of AE sources in a variety of structures, and discussed their merits, and demerits. Kannan et al. [5] discussed various AE parameters and some innovative methods for damage characterization using the acoustic emission technique. Finally, they mentioned a list of unpopular AE descriptors and explained the limited use of these descriptors in the FRPs. M. Saeedifar and D. Zarouchas [105] presented an extensive review on the damage characterization and the estimation of Remaining Useful Life (RUL) in laminated composites. They mainly focused on prognostic approaches for AE data such as regression models, artificial neural networks (ANN), and hidden Markov-based models. Verstrynge et al. [122] addressed specific challenges and their recent findings in the application of the acoustic emission technique for masonry structures in their comprehensive review. They discussed some site applications of identifying the crack location in historical masonry structures, buildings, and masonry arch bridges. Tziavos et al. [120] performed an experimental study of the application of AE on GCs under bending loads. Several AE parameters were investigated to find out the one which is most sensitive to failure, to be used as KPIs for damage assessment. Finally, b and Ib-values were also analyzed as a tool for crack detection for UHPC grouts. They concluded that RMS is one of the KPIs that can be used as a prognostic tool. McCann and Forde [80] discussed the major methods used within civil engineering, with their advantages and limitations. Fewer known methods were also discussed to familiarize the readers with the complete range of methods. Reza et al. [90] presented a comprehensive insight into the application of acoustic emission into brittle materials. They mainly addressed the properties related to crack growth behavior and localization. However, none of these research papers focused on the performance evaluation of contemporary techniques used for the localization of AE sources.

This paper aims to provide a review of the acoustic emission source localization techniques for a variety of structures such as steel structures, buildings, and seismology. The focus of research is to present a performance evaluation of the existing localization approaches such as analytical methods, time reversal methods, machine learning methods, and beamforming methods. Moreover, these techniques have been comparatively analyzed based on their basic principles, key strengths, and limitations.

This paper is organized as follows: Section II presents the

Nomenclature			
		CTFS	Cross-Time Frequency Spectrum
		MCMC	Markov Chain Monte Carlo
AE	Acoustic Emission	WORC	Wavelet-based Optimized Residual Complexity
NDT	Non-destructive Testing	MSC	Magnitude Square Coherence
FRP	Fiber Reinforced Plastic	DTW	Dynamic Timing Warping
RUL	Remaining Useful Life	CFRP	Carbon-Fiber Polymer Pressure
ANN	Artificial Neural Networks	TDM	Time Difference Mapping
MAE	modal acoustic emission	TSA	Thermo-elastic Stress Analysis
PLB	Pencil Lead Break	GP	Gaussian Process
HF	High Frequency	RBF	Radial Basis Function
LF	Low Frequency	RP	Refraction Path
CWT	Continuous Wavelet Transform	ASTM	American Society for Testing and Materials
RMSE	Root Mean Square Error	TOF	Time of Flight
MP	Matching Pursuit	ALM	A Localization Method
AIC	Akaike Information Criteria	MLM	Multi-step Localization Method
TDOA	Time Difference of Arrival	TLM	Traditional Localization Method
TDDT	Time Distance Domain Transformation	NBLM	Node Block Location Method
LLS	Linear Least Square	GA	Genetic Algorithm
CFC	carbon-fiber composite	FFNN	Feed-Forward Neural Networks
MFC	Macro-Fiber Composite	TDNN	Time Delay Neural Network
AMA	Adaptive Meshing Algorithm	MAR	Measured Amplitude Ratio
GMM	Gaussian Mixed Model	UWC	Unsupervised Waveform Clustering
PSO	Particle Swarm Optimization	SFLA	Shuffled Frog Leaping Algorithm
EKF	Extended Kalman Filter	TR	Time Reversal
SVD	Singular Value Decomposition	PCA	Principal Component Analysis
LMA	Levenberg-Marquardt Algorithm	VESPA	Velocity Spectral Analysis
FBBM	Fast Bartlett beamforming method	PDF	probability destiny function
HCBF	Hilbert curve-beamforming method	ICA	Independent Component Analysis
SDAE	Stacked denoising autoencoders	GRNN	Generalized Regression Neural Network
SART	Simultaneous Algebraic Reconstruction Technique	CLMAI	Collaborative Localization Method for analytical and iterative solutions
PCSWE	Preconditioned closed-form solution for weight estimation		

domain's background as preliminaries, mentioning various parameters of acoustic emission signal and the sensor placement in the localization process. Section III presents a detailed discussion of various source localization approaches used for AE source localization, along with their performance evaluation. Section IV includes a detailed discussion about the challenges in the application of localization using acoustic emission with recent developments. AE localization techniques have been analyzed based on their strengths, weaknesses, and limitations. Section V presents the conclusion and future research objectives.

II. PRELIMINARIES

AE is preferred for its real-time capability, high sensitivity, and its ability to be monitored globally [61]. AE sensors are used to collect transient waves and convert them into electrical signals for further processing. Distinguishing between burst and continuous signal types is one of the significant challenges in AE monitoring. AE is mainly concerned with the burst type signals because a burst is related to some abnormality in the structure. These burst signals can be described by their time domain, frequency domain, or joint time-frequency domain features. A burst signal, along with its time and frequency domain, is shown in Fig. 2.

Either the waveforms or the features which have been extracted from these waveforms are used for the analysis of the signal. Commonly used features are:

Threshold, which is the voltage for the AE signal. Values greater than a specific threshold are recorded as a hit. It is measured in decibels (dB).

Amplitude is considered as the height or voltage of the signal, and it is also recorded in dB.

The duration can be defined as the difference in time between the first and last crossing of the threshold level. Microseconds (μs) is the recording unit.

Rise time is the time interval between the first crossing of the threshold and the highest amplitude. It is recorded in microseconds (μs).

Counts refer to the number of times the signal crosses the threshold within one hit.

Energy is the area under the waveform within a specific duration. The reporting unit is attojoule (aJ) (1 aJ = 10-18 J).

A. LINEAR LOCALIZATION

This technique is suitable for rod-like structures where the length is far greater than the width, as shown in Fig. 3.

Let the time of arrival of the AE signal at AE sensor-1 and sensor-2 be represented by T_1 and T_2, and the wave velocity be represented by V. The difference of arrival times $\triangle T$ can be expressed mathematically as shown in Eq. (1).

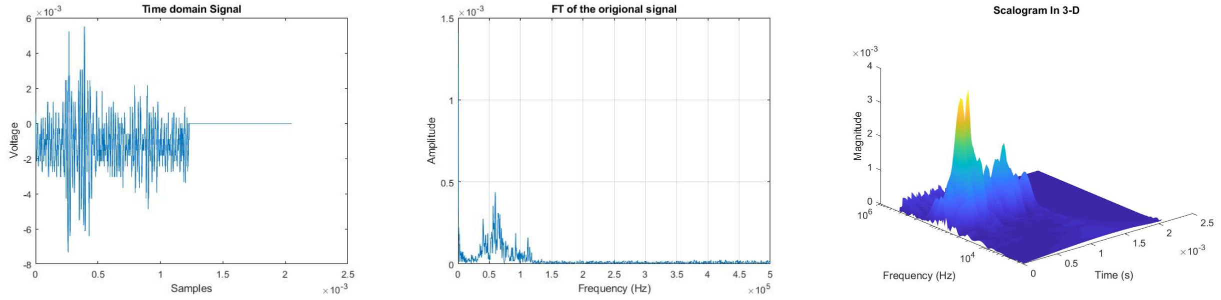
$$\triangle T = T_2 - T_1 \tag{1}$$

Then, the distance between AE sensor-2, which is closer, and the AE source d_2 can be calculated as shown in Eq. (2).

$$d_2 = 1/2(D - \triangle TV) \tag{2}$$

B. PLANAR LOCALIZATION

For plate-like structures, AE source localization can be considered as planar localization. Suppose $s(x_s, y_s)$ is an AE source in a uniform medium. AE sensors are placed on the plate to be monitored, and the coordinates of an arbitrary sensor i is (x_i, y_i) . The onset time of the AE signal is



(a) (b) (c)

FIGURE 2. The representation of an AE hit in (a) time domain, (b) frequency domain, and (c) time-frequency domain

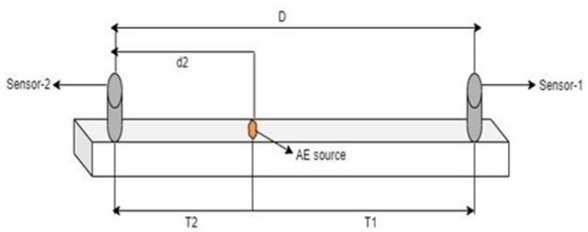


FIGURE 3. The diagram of the 1D linear.

denoted by T_0 , and it reaches to any sensor i at time T_i. The principle of planar location of an source is shown in Fig. 4.

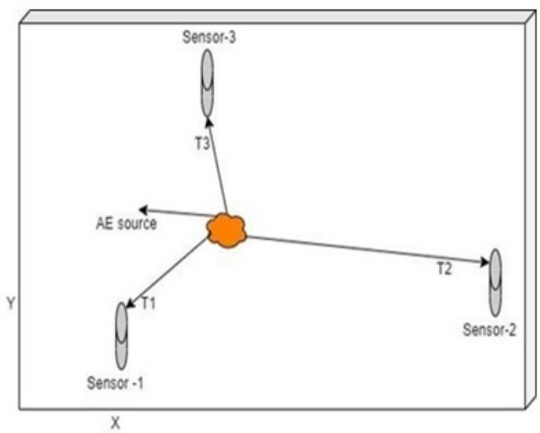


FIGURE 4. The diagram of the 2D planar location.

Then, the distance between AE sensor-2, which is closer, and the AE source d_2 can be calculated as shown in Eq. (3).

$$d_2 = 1/2(D - \triangle TV) \tag{3}$$

The distance between the AE source s and sensor i can be obtained by Eq. (4)

$$d_(x, y) = \sqrt{((x_s - x_i)^2 + (y_s - y_i)^2)} \tag{4}$$

As the exact time of arrival of AE signal T_0 is very difficult to measure accurately, the time difference of arrival (TDOA) of any two sensors i and j can be described as in Eq. (6):

$$\triangle T_(i - j) = d_(s - i)/V - d_(s - j)/V \tag{5}$$

According to the above relationships, it is possible to localize the AE sources using three acoustic emission sensors that are not placed linearly. Iterative algorithms are widely used in acoustic emission monitoring systems to calculate the numerical solution of a 2D planar location.

C. 3D LOCALIZATION

The 3D location principle of an AE source assumes an AE source $s(x_i, y_i, z_i)$ to be in some medium, as illustrated in Fig. 5. The AE sensors are mounted on the structure with the coordinates of an arbitrary sensor $i(x_i, y_i, z_i)$. The distance d between the AE source s and sensor i can be expressed by Eq. (5)

$$d_(s, i) = \sqrt{((x_s - x_i)^2 + (y_s - y_i)^2 + (z_s - z_i)^2)} \tag{6}$$

This equation provides the basis to obtain the solution of the analytic problems. The 3D localization technique has been shown diagrammatically in Fig. 5.

III. AE SOURCE LOCALIZATION TECHNIQUES

The damage diagnosis tools today aim at determining the best possible location of the damage in various structures [80]. To improve the accuracy and the error-tolerance in real-time implementation, various source localization techniques have been used. Each technique has its own advantages, disadvantages, and limitations. Each of these source localization techniques efficiently solve a specific class of the source localization problem. This study is an attempt to give a better understanding of the existing techniques. There is a dire need of a global method which can solve localization problems in isotropic as well as anisotropic structures with complex geometries. Some of the well-known techniques used for localization of acoustic emission sources are depicted in Fig. 6.

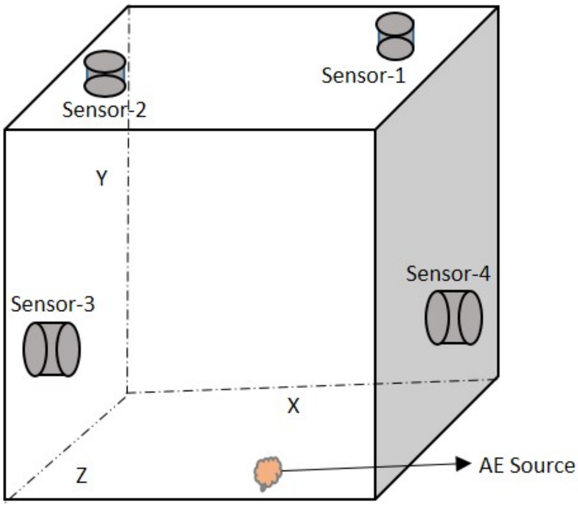


FIGURE 5. Localization of AE sources in 3-D structures.

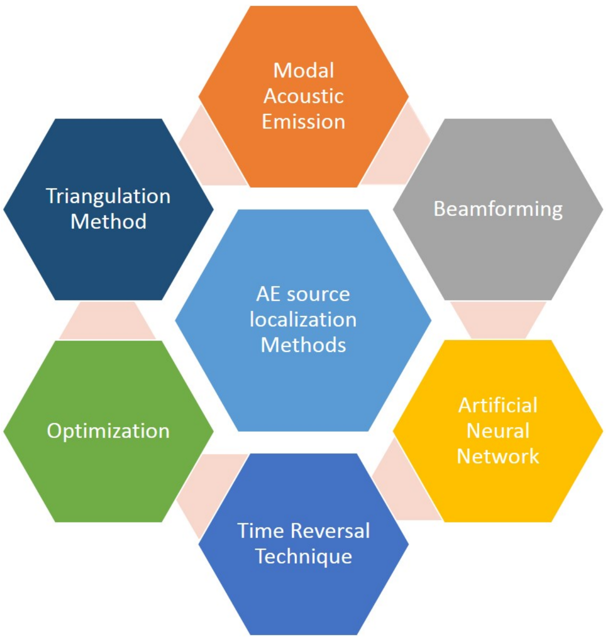


FIGURE 6. Source localization methods for acoustic emission.

A. MODAL ACOUSTIC EMISSION

Single sensor approaches rely on modal acoustic emission (MAE), which typically requires the identification of arrival times of extensional and flexural wave modes. Since group velocities for both the modes are different, it is possible to calculate the distance covered by propagating the wave modes if their respective velocities are known. The implementation of MAE has several associated issues. Some of the common issues are wave reflections and the separation of multiple AE events. Even within the same event, it is not straightforward to distinguish the two wave modes, especially in case of single transducers [34]. Furthermore, the calculations of arrival time for the direct paths from AE source to sensor, are the key reason behind the uncertainties in location estimation.

The method proposed by Ciampa and Meo [15] enabled the acoustic emission to be optimally focal in the time and frequency domain using a single passive sensor. Neither iterative algorithms, nor the advanced knowledge of the mechanical properties, or the anisotropic group velocity is essential for this method. Holford and Carter [47] analyzed Lamb waves' propagation to estimate the locations of sources of acoustic emission over long distances. A high pass frequency filter (>100kHz) and a lowpass frequency filter (<100kHz) were applied to the signal to separate the two modes present in the wave. The velocities of high frequency (HF) and low frequency (LF) components in steel were calculated as 5200 m/s and 3400 m/s, respectively. LabVIEW software was used to implement this approach. The extensional wave's attenuation was measured to judge its applicability in the long-range localization of the sources. Gorman [39] focused on the amplitudes of different modes of the waves to calculate the source's dimensions. Jingpin and Bin [56] developed a multimodal and dispersive algorithm which focused on the analysis of the AE signals using the Gabor wavelet transform to acquire a single-mode time at a specific frequency level. A three-step approach developed by Arvin Ebrahimkhanlou and Salamone [32] did not have any blind spot leverages. Estimating the distance between AE source and the sensor, yields the first step. They used continuous wavelet transform (CWT) and dispersion curves for this purpose. In the second step, an analytical model was developed that simulates the edge reflected waves using estimated distances. Finally, the location was estimated by using a correlation between the simulated and experimental waveforms. The performance of the algorithm was validated by the pencil lead break (PLB) test on an aluminum plate. They further investigated [33] the ambiguities in the AE source localization by proposing a probabilistic approach. The direct distance between the AE sources and the sensor was estimated, and the envelope of AE signals reflected from the edge was then reconstructed by using an analytical model. Finally, the location of the AE sources was estimated by using confidence contours. However, this approach ignored the impact of natural and geographical constraints on location accuracy.

Deep learning can learn the practical relationships between the inputs and the outputs. Some authors implemented it for the localization of AE sources. Ebrahimkhanlou et al. [31] proposed a pre-trained version of stacked autoencoders for the localization and classification of AE sources. Furthermore, the proposed approach was compared with the triangulation and machine learning approaches. Additionally, the generalization capability of the proposed approach was verified for the input patterns generated by complex morlet mother wavelets and 8th-order complex Gaussian. However, this approach was not successful in the case of raw signals as input patterns. Arvin Ebrahimkhanlou and

Salamone [34] used stacked autoencoders and convolutional neural networks for complex geometry metallic plates, like stiffeners connected with a rivet. Overall, both deep learning networks performed equally well in terms of consistency and flexibility. Comparatively better output was obtained by the stacked autoencoders (100 percent accuracy versus 95.2 percent). The convolutional neural network was more stable in allowing more information rich inputs in the frequency domain. The AE source zone was identified; however, finding the exact coordinates of the source could not be made possible.

MAE has also been implemented with more than one sensor. Castagnede et al. [9] proposed a method based on the speed of quasi-longitudinal bulk waves. It performed well for thick structures. However, the performance saw a gradual degradation for thin plates in cases of larger distance between the sensor and the point of impact. Sheer bulk and longitudinal waves' contributions were negligibly low in the obtained signals. Xin Qiu et al. [98] improved the location accuracy within asphalt mixtures by using a cross-correlation function. Mostafapour et al. [86] integrated wavelet packet decomposition with a cross-time frequency spectrum (CTFS). The comparison of the proposed method with traditional methods indicated that the average location errors estimated by the CTFS method are three times lower than those estimated by the correlation method. Yang Li et al. [73] used the cross-correlation and geometric positioning theory for localization of AE sources within plywood. However, it was found that if the signal is broken down, the length of the approximation signal is reduced, while the details are reduced by half. Yan and Tang [128] identified a Bayesian parameter to estimate the location and velocity at a given frequency. For the posteriors' estimation, a markov chain monte carlo (MCMC) algorithm was used for drawing the samples. Results obtained at multiple frequencies were then blended by a data fusion scheme to maximize the accuracy and minimize the uncertainty regarding the final location. Mostafapour and Davoodi [87] used a rectangular array of four sensors. The approach proposed by Perelli et al. [96] succeeded to overcome the issues related to the detection of arrival time using conventional threshold methods.

Wavelet packet decomposition at a frequency spectrum of 0 – 250 kHz was performed. A wavelet-based optimized residual complexity (WORC) function was used to determine the time delay of the captured signals. Dispersion curves were used for the calculation of frequency-varying velocity. The comparison of the proposed method with CTFS and cross-correlation techniques indicated that the proposed method could minimize the location error. Chen et al. [10] designed an identification technique to gauge the similarity in AE signals by integrating magnitude square coherence (MSC) with wavelet coherence and dynamic timing warping (DTW). The proposed method improved the accuracy with high quality signals using a more exact onset picking time compared to complicated optimization algorithms with low quality signals. Surgeon and Wevers [118] reduced the number of sensors required for modal acoustic emission localization. The estimation of linear source location could be possible in case of known arrival time difference between the two modes and the propagation velocity. Achdjian et al. [1] combined related features extracted from the average envelopes or the Schroder's integral with the early wave packet energies. This method did not require the sensors to be synchronized in time; however, the localization area was reduced comparatively. Some of the related papers about single sensor and modal acoustic emission are listed in Table 1.

Even though several contributions have been made to the algorithms for source localization using a single sensor, the requirements for the implementation of these algorithms are still challenging. It requires the collection of baselines in huge quantities, even for simple isotropic materials, and they are also computationally expensive [55].

B. TRIANGULATION METHOD

This procedure for AE source localization relies on the identification of precise arrival times and the knowledge of an appropriate propagation velocity. With these parameters, a triangulation method can be established where the source is identified as the intersection of three circles, whose centers are the sensors' location [103]. This approach is straight forward; however, several associated difficulties may arise because of reflections, and mode conversion and distortion of the waveform within anisotropic materials. The performance of the triangulation method degrades with unknown wave velocity. The triangulation method can be applied in two kinds of situations, either with or without known wave velocity.

1) SOURCE LOCALIZATION WITH KNOWN VELOCITY

Several works have been published about AE source localization in three-dimensional workspace, which considers a constant known propagation velocity V_p, which does not change even if the specimen incurs some damage. For three dimensional structures, Li and Dong [72] proposed a solution which can calculate V_p as well; however, this algorithm requires previous knowledge of the onset time of each signal. Rodriguez and Celestino [102] proposed the CLAPWaVe methodology which assumes a fixed value for V_p specified for a material. This assumption does not reflect a real-life situation and may yield unreasonable results. The analytical solution presented by Dong and Li [22] used six sensors. The relocation results were clear and realistic with actual coordinates in the monitoring network for internal and external events. Location error for the traditional time difference method was in the range of 0.01-0.03 m for internal events, while the location errors for external events were as large as 1080986 m. Zhou et al. [137] focused on propagating waves having refraction points. Snell's law was used to solve the refraction points integrated with TDOA equations. TDOA equations need to be converted to linear equations. The linear equations-based trial solution

TABLE 1. LIST OF PUBLISHED PAPERS USING SINGLE SENSOR AND MODAL ACOUSTIC EMISSION

Author	Methods/Models	Performance index (unit)	Value
Ebrahimkhanlou2017 [32]	MP model	Max offset (cm), Min offset (cm)	5.3 0.6
Jiao 2004 [55]	Gabor wavelet, & contour plot.	Location error (%)	<5
Ebrahimkhanlou2017 [33]	MP model	RMSE radial (cm) RMSE tangential (cm)	1 2.4
Ebrahimkhanlou2019 [31]	Stacked autoencoders	Zonal location Error % (inch) Zonal location Error % (inch)	44(1.7") 13(0.5")
Ebrahimkhanlou2018 [34]	Stacked autoencoders, convolutional neural networks	Auto-encoders zonal accuracy (%) CNN zonal accuracy (%)	100 95.2
Qiu 2020 [98]	Threshold rule optimized by Fruit Fly Optimization Algorithm (FOA)	RMSE (mm)	0.0459
Mostafapour 2014 [86]	Wavelet transform & CTFS	Max error (x) %, Max error (y) %	2.76 3.5
Li 2018 [73]	Wavelet analysis & cross correlation	Relative error (%)	<4
Yan 2015 [128]	CWT, MCMC algorithm	Max Error (%) Min Error (%)	5.3 1.1
Mostafapour 2017 [87]	Algorithm-Wavelet packet decomposition, WORC	Maximum source locating error (%)	3.5

is then updated iteratively to estimate the AE source's best possible location. However, there are certain limitations to the proposed algorithm. This method requires each layer to be of isotropic dispersive nature, the geometry of which should be known. Besides, the wave propagation velocity for each layer must be measured beforehand. Gollob et al. [38] improved the standard Dijkstra's algorithm by identifying the fastest path between different nodes. P waves generated from the same AE source are used to estimate the location. However, fastway needs many calculations as well as a matrix of the known wave velocity. The wave velocity is highly affected by any variation in factors such as air pressure, temperature, and geometry. Additionally, the premeasured velocity is not always the same for different paths.

Kalafat and Sause [57] used experimental training data acquired from carbon-fiber polymer pressure (CFRP) vessels. Comparison of the proposed method with established localization methods revealed that an improvement in accuracy is possible if an alternative strategy is applied to determine the signal's arrival time. Early identification of damage in reinforced fiber composite was demonstrated by Eaton et al. [30] using the time difference mapping (TDM) method. This approach produced relatively consistent results, and the root mean square (RMS) error was reduced by more than 30 mm in some cases. The results were validated by thermo-elastic stress analysis (TSA). Dehghan Niri et al. [91] presented two nonlinear Kalman filtering algorithms, extended Kalman filter (EKF) and unscented Kalman filter (UKF), for the estimation of location AE sources in anisotropic panels. These algorithms were applied to the cases such as known velocity profile and unknown velocity profile. The algorithms were compared with the traditional nonlinear least squares method.

Hensman et al. [46] used a gaussian process (GP) having radial basis function (RBF) kernels-based regression to investigate the relationship between the artificially created AE data and real damage location. Al-Jumaili et al. [3] presented a fully automated time difference $(\triangle T)$ mapping strategy based on the clustering algorithm for automatic identification and selection of events at each grid point, which are highly correlated. Simultaneously, for estimating the source location, a minimum difference of arrival approach was used. A skilled operator's prerequisite is eliminated in this approach, which saves time and is less error prone. Pearson et al. [95] integrated $(\triangle T)$ mapping with akaike information criteria to resolve the shortcomings of exact arrival time identification. The results indicated that the proposed approach could minimize the orientation that helps to determine the group velocities. Each node of the sensors array has a combination of $(\triangle T)$. A comparison of the estimated $(\triangle T)$ combinations and that of the map is made. This technique is known as "the best-matched point search method". For some instances, the location accuracy was high, but the reduced accuracy was observed on the plates' edge. Based on the current approaches Quy et al. [99] offered a novel approach for locating cracks in a fluid pipeline. The proposed method provided the frequency feature that allowed the elimination of unwanted emission sources for localizing AE sources, improving the location accuracy. The technique was designed to recognize Rayleigh waves in order to correlate wave velocity to flight time. This approach achieved a high level of localization accuracy.

To improve the location accuracy, Dong et al. [25] presented a multi-step localization method (MLM) which does not require the wave velocity to be known in advance for heterogeneous media. A 15% improvement in accuracy was observed with a premeasured velocity of 1350 m/s. However, the proposed method still has many drawbacks. Firstly, MLM requires an additional sensor relative to traditional localization methods. Secondly, the initial velocity for the proposed method should be calculated appropriately. Hu and Dong [48] proposed the A^* localization method (ALM) approach to solve the associated issues with fixed wave velocity dealing with irregular structures. The use of sensor grids avoids manual, repetitive training. ALM significantly improved the accuracy of localization. Without assuming the coordinate distribution, Zhou et al. [134] used a trivariate kernel density estimator, which could achieve good location accuracy and stability in the presence of TDOA outliers. However, in most scenarios, the TDOA measurements did not have the outliers and only contain random errors. In these scenarios, the proposed method did not achieve optimal accuracy. Moreover, due to the intensive computation of preliminary positioning, this method had poor real-time performance, especially in many sensors. Zhou et al. [138] developed a weighted linear least squares method which does not require the wave velocity to be measured in advance. Initially, the governing equations are linearized, and the mean reference equation is established. Then, the weight of these linear equations is used to estimate the residuals. Dong et al. [24] measured TDOA and localized the AE sources, employing a 3d analytical approach. The fundamental principle of this approach depends on solving several nonlinear governing equations. The proposed method could cover some of the drawbacks of the closed form solutions. Scholey et al. [108] were involved in generating time of arrival difference $(\triangle T)$ maps for some specific structures. The actual distance was used to calculate t and the fiber's orientation that helps to determine the group velocities in this method. Each node of the sensors array has a combination of t. A comparison of the estimated $(\triangle T)$ combinations and that of the map is made. This technique is known as the best-matched point search method". For some instances, the location accuracy was high, but the reduced accuracy was observed on the plates edge. Prasanna et al. [97] used a more generalized configuration by selecting the minimum energy path on a surface containing finite discontinuities. By applying both methods, AE sources can be localized in heterogeneous and irregular geometries with unknown properties of materials. However, due to a firm reliance on the grid's partition, the two approaches either have a high computational burden or unsatisfactory results. These conventional methods for localization where the velocity is known would lead to unavoidable errors.

Table 2 enlists the published papers about localization with known velocity. These location algorithms are based on known wave speed. These methods are applied only to multilayered structures of isotropic non-dispersive layers where the geometry and layer-to layer interfaces are known. The wave velocity should be measured in advance. Therefore, operational errors in velocities may occur, which can lead to errors in the final AE source locations. Moreover, the accuracy in localization also depends on sensor layout and structural geometry [137].

2) SOURCE LOCALIZATION WITH UNKNOWN VELOCITY

Meo et al. [83] calculated the wave speed and integrated it into a sequence of nonlinear equations to determine the source's location. For various loading levels, the cumulative error in the coordinates of the source was not more than 9 percent. The solution provided by Kundu et al. [64] did not require precise travel time. The proposed method performed equally well for both the isotropic and anisotropic plates. The simplex algorithm often faced a convergence to local minima, which has been fixed by finding the global minimum of the objective function. Kundu et al. [65] aimed towards the minimization of an objective function. The objective function components are the TDOA and the speed of the elastic waves in various directions, received at multiple sensors. The issues in the proposed strategy lie in the length of the terms for a large number of receiving sensors, which was addressed by Hajzargerbashi et al. [42], who modified the objective function. He implemented the technique using four sensors, whereas the earlier technique required three sensors. Koabaz et al. [58] used a different objective function to simplify the optimization procedure. The traditional threshold method was replaced with various peaks in the acquired time histories. Experiments were performed on a carbon-epoxy plate, having an acoustic source. Sen et al. [111] slightly modified the rhombus-based technique, taking three distinct wavefront shapes: a rhombus, an ellipse, and a parametric curve. They stopped believing that the wave propagates in a straight path. Sen and Kundu [112] proposed a strategy that was based on the elliptical wavefront. The location of the source is an iterative process where the objective function is reduced to a minimum. It does not presume the path of the wave propagation to be a straight line. The source location can be estimated with unknown material properties. They further investigated the issue of convergence to the exact coordinates by using a technique [113] based on the elliptical and parametric curves. The technique performed well for an unknown angle between axes of symmetry and the Cartesian reference coordinates. The orientation of the axes of symmetry was treated as an additional unknown in addition to the other various unknowns like the source coordinates and the curve parameters. This technique can be further expanded by considering the influence of the frequency contents in the acquired signals. Wang and Ge [123] addressed the issues regarding high background noise. They integrated digital filtering, an optimization method based on absolute value, a simplex algorithm, and the reliability analysis. Global convergence is not assured because of the presence of strong cohesion in determining high horizontal stresses for a limestone mine. The initial conditions are indispensable for minimizing extremely non-linear cost functions. A hybrid approach was introduced by Kundu et al. [67] for heterogeneous plates with unknown material properties. The initial step of the proposed method was to estimate the location with the assumption of straight-line wave

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3096930, IEEE Access

TABLE 2. PUBLISHED PAPERS ABOUT THE LOCALIZATION METHODS WITH KNOWN VELOCITY

Author	Methods/Models	Material	Wave velocity (m/s)	Performance index (unit)	Value
Zhou 2018 [137]	Refraction Path (RP) Method	Iron Marble Granite	6047 5007 4442	Absolute distance Error (mm) (11 layer)	1.05
Gollob 2017 [38]	Fastway velocity model	Steel reinforcing bar and EEP-concrete	4400	Average error median (mm)	17.4
Kalafat 2015 [57]	Advanced L-BFGS-B algorithm	CFRP	(x direction) 5636 (y direction) 4230	Mean location Error (cm)	1.31
Eaton 2012 [30]	Delta T mapping, TSA	Carbon fibre composite: MTM28-1/HS-135-34%RW	A0 (1500-1600) S0 (5300-7400)	Average Error (mm)	<8
Dehghan Niri 2014 [91]	EKF, UKF, Nonlinear least squares algorithm	CFRP	(1200-1600)	Average Error (cm)	0.6243
AlJumaili 2016 [3]	Automatic DTM algorithm	ASTM 516 gr 70 steel	4600	Av Error Isotropic (mm) Av Error Anisotropic (mm)	3.13 3.88
Pearson 2017 [95]	AIC-Delta-T algorithm	Complex geometry aluminum 2024-T3	5400	Average Errors (mm)	<4.2
Dong 2019 [27]	CLMAI	Kaiyang mine	4500	Absolute distance error (m)	39.82
Dong2017 [25]	MLM	Simplified building test model	1350	Location accuracy (%)	15
Hu2020 [48]	A Localization Method without premeasured velocity (ALM)	Granite block	5000	Average location error (cm) Max. location error (cm)	2.2 1.4
Zhou 2019 [48]	Trivariate kernel density estimator	granite specimen	5000	Max abs distance error (mm)	9.92
Zhou2018 [138]	Preconditioned closed-form solution based on weight estimation (PCSWE)	Granite	4600	Maximum distance Error (mm)	5.9

propagation. The step is based on minimizing the error function by considering wave energy propagation through a curved path. This approach decreased the probability of convergence into the local minima rather than the global minimum. To minimize the modeling and simulation issues associated with previous methods, Ciampa et al. [15] and Coverley and Staszewski [18] proposed an optimization approach based genetic algorithm for the analysis of the strain wave velocity. The finding was optimal, but even then, the real optimum results were not assured. Huang et al. [49] presented a localization algorithm based on Geiger optimization. The initial Geiger value was computed using the phase difference approach. The iterative version of the Geiger algorithm integrated with the least square method can get the optimal solution. The proposed method could reduce the average error by approximately 5 mm. Friswell et al. [109] proposed a search strategy based on the best-matched search method. Two tests were conducted on a heterogeneous carbon-fiber composite (CFC) plate and on a disc of oolitic limestone, where the source was located parallel to the disc's mid-plane. The result was excellent for the limestone location method, but some events could not estimate the location very well. Schumacher et al. [110] improved on the standard Geiger's method by combining the Markov Chain Monte Carlo (MCMC) and Bayesian analytical methods, where posterior probability density functions (PDFs) represented all the source location parameters. The impact of the uncertain parameters on accuracy is minimized by using either a Bayesian approach or the proposed approach. However, the latest probabilistic algorithm was unable to generate corresponding distributions.

To reduce the impact of wave velocity on location accuracy, Ciampa and Meo [14] proposed a method for isotropic and anisotropic plates. This method used six sensors to estimate the group velocity. Li et al. [69] established a cost function based on the quotient of the time-difference principle. The geometry of the AE source can be determined by scanning the initial value of the simplex method. Dong and Li [23] introduced a three-dimensional approach for locating the micro-seismic sources. This method utilizes the arrival times of longitudinal as well as transverse waves. The time of arrival of the flexural Lamb waves was identified by CWT. The linear search was conducted using an iterative approach called Local Newton, and the output was combined with the methods of polynomial backtracking. The source coordinates and the values of wave velocity were determined by solving a variety of nonlinear equations. The proposed technique reduced the number of sensors while still confidently and accurately predicting the acoustic source. The approach developed by Simone et al. [20] contains a set of non-linear equations. These equations are then linearized with the help of only four sensors. Ciampa and Meo [13] presented an unconstrained optimization strategy associated with the iterative method called local Newton. The coordinates of the source location and the wave speed were obtained by solving several nonlinear equations. This method surmounted the demerits associated with the triangulation method. Moreover, this proposed algorithm achieved convergence using several guess points. The algorithm is computationally efficient; however, the estimation goes wrong for distances longer than 650 mm. Li and Dong [71] compared the outputs of the nonlinear multi-robe location method. The findings of the proposed method were compared with the analytical method. It was demonstrated that the proposed method produces a single solution, and locating the source is comparatively easy. The analytical solution presented by Dong et al. [26] avoided the square root calculations for unknown wave velocity, which could calculate the source coordinates if the arrival time of P-waves and the sensors' coordinates were known. For the location determination of micro-seismic sources, log-logistic distribution was utilized. Zhang et al. [132] used a phased array method for the localization of radial and axial defects by considering the original propagation path of waves. The Time of Flight (TOF) difference for each sensor provided the basis for this method, which develops trajectory differences. However, the proposed algorithm is not applicable when system resolution is more than the difference in TOF. Comparatively better results were produced by Mahajan and Walworth [77]; however, these methods were intensely concerned with the number of AE sensors, and the adjustment of extra sensors in the network is hectic.

For highly dispersive mediums like composite materials, Duff et al. [68] estimated the source location by calculating time intervals. This method generated robust, flexible, and accurate results for a glass-fiber/epoxy plate. Das et al. [19] proposed a positioning method for uncertain wave velocity systems through independent spatial location modifications and the average wave velocity. This method requires the determination of sensor coordinates and arrival times with unknown wave velocity. Zhou et al. [135] presented a solution based on weighted linear least squares, which does not require to measure the wave velocity. The main equations are first linearized by establishing the mean reference equation. The estimated residuals are then used to set a weight for these equations. Finally, the location result considering the parameter constraint is obtained by introducing an orthogonal projection matrix. However, the basic assumption that the AE signal from the source to the sensor is a straight line, still exists. The velocity free system proposed by Zhou et al. [136] uses complete TDOA measurements. The nonlinear governing equations are first converted into a set of linear equations with complete TDOA measurements. Then, an orthogonal projection operator is introduced to reduce the ill-condition of this linear system. The proposed method has a significant deviation in the presence of outliers. Finally, an orthogonal matrix is introduced which can estimate the location keeping the parameter in mind. However, this approach assumes straight-line wave propagation which is not the case in real world signals.

Adaptive meshing algorithm (AMA) was presented by Boniface et al. [8], which has the capability to be quickly modified for modeling complex structures. However, compared to other algorithms, AMA performed poorly for errors that were less than 1 cm. A collaborative model, node block location method (NBLM), was proposed by Xiao et al. [126] for quasi- cylinders with complex holes. NBLM neglected the space and could represent the propagation of waves properly in the complex structures. NBLM outperformed the traditional methods, adaptive location method, and the time difference method. The key feature of the proposed strategy by Grabowski [41] was to compensate dispersion. Additionally, fewer input parameters were required. Phase shifting of the waveform was done by using a single sensor for more reliable output. The proposed solution is developed by integrating Time-distance domain transformation (TDDT) with a selection technique to calculate the best possible distance. The literature about localization methods with unknown wave velocity is listed in Table 3.

One of the limitations of the closed-form solutions is that they are highly dependent on the TDOA value. A high TDOA value in a noisy environment results in a huge localization error. Another limitation relates to the coefficient matrix of these linear equations. These matrices appear to be ill-conditioned because of the variation in their components by several orders of magnitude. In case the TDOA measurements contain outliers, the location result will have a great deviation. Therefore, a location method which can automatically identify and filter the outliers is important [102].

C. BEAMFORMING

Beamforming is a signal processing technique used in sensor arrays for directional signal transmission or reception [121]. Beamforming is used in acoustic source localization, for which several localization algorithms have been developed. For AE source localization, delay-and-sum algorithm is usually used. Delay-and-sum is a simple and effective algorithm utilized in beamforming techniques [129]. Considering the distance between AE source and array of sensors, the analysis schemes based on beamforming techniques can be divided into near-field and far-field methods. A common rule of thumb is that the near-field sources are located at a distance can be expressed by Eq. (7):

$$r \leq 2L^2/\lambda \qquad (7)$$

where r is the radial distance from an arbitrary array origin, L is the largest array dimension, and λ is the operating wavelength [78]. The acquired wave front from the sound source, in such conditions, is assumed to be spherical due to the transmission characteristics of waves. The far-field sources refer to those where the location r is larger than $2L^2/\lambda$, of which the wave front is usually assumed planar. The basic concept of beamforming can be illustrated as in Fig. (7).

The beamforming technique can measure the acquired signal from an array of sensors. The beamforming method has been applied successfully in several fields such as sonar, telecommunication, radar, source identification, and localization. AE beamforming approach was introduced by McLaskey et al. [82] for the localization of AE sources in civil engineering. They concluded that a more straightforward sensor arrangement, marginal channel attenuation, and localization of multiple sources make the beamforming method superior. The method proposed by Nakatani et al. [88] does not require accurate velocity. Two

TABLE 3. PUBLISHED PAPERS ABOUT ANALYTICAL LOCALIZATION METHODS WITH UNKNOWN VELOCITY

Author	Methods/Models	Performance index (unit)	Value
Meo2005 [83]	Orthotropic algorithm	Maximum location error (%)	9
Koabaz 2012 [58]	Simplex algorithm	Localization error (%)	<5
Sen 2018 [111]	Levenberg–Marquardt algorithm	Parametric location error (mm), Modified eclipse error (mm)	10.53 19.98
Sen 2020 [112]	Nelder-Mead algorithm	Error for n=5 (mm), Error for n=6 (mm)	25.11 19.8
Ciampa 2012 [15]	Line search method, polynomial backtracking technique	Quasi-isotropic CFRP MLE (mm) Sandwich plate MLE (mm)	3 2
Ciampa 2010 [14]	Unconstrained optimization and local Newton-Raphson iterative method	Max location error (mm), Wave velocity (m/s)	4 3
Das2019 [19]	Taylor's expansion and error optimization.	Av. error with slowness 1.1(cm) Av. error with slowness 3(cm)	2.63 3.89
Dong 2017 [26]	TDCAS-PDF	Arrival time error with 5%, Arrival time error with 10%, Arrival time error with 15%, Arrival time error with 20 %	Improved TD
Xiao2020 [126]	Node Block Location Method (NBLM)	Average error internal (mm) Average error external (mm)	7.7 11.3
Zhou 2020 [136]	Orthogonal projection operator to reduce the ill-condition.	Average absolute distance errors, standard deviation at different noise levels	Depends on noise scale
Boniface 2020 [8]	Adaptive Meshing Algorithm (AMA)	For errors <2 cm (%)	44
Grabowski2016 [41]	Time–Distance Domain Transformation (TDDT)	Localization error (m), Localization error (%)	0.7 14
Coverley 2003 [18]	Classical triangulation combined with Genetic Algorithms (GAs)	X-error (%), Y-error (%)	11.63 13.16
Zhou 2020 [135]	Novel weighted LLS method without wave velocity	absolute distance error (mm)	13.36
Zhou 2021 [133]	A new algebraic solution	average abs distance error (mm) minimum positioning accuracy (mm)	3.55 1.12

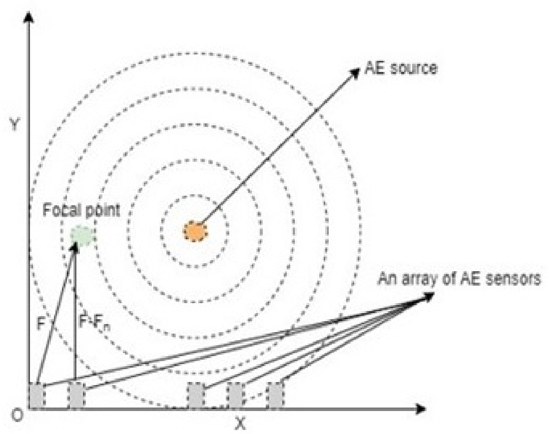


FIGURE 7. Concept of beamforming technique.

uniform sensor arrays were installed to estimate the location of various sources from two directions with an apparent divergence of the actual velocity from the localizing velocity. Yin et al. [131], Kundu et al. [66], and Kundu [62] arranged six sensors in two L shaped clusters. No knowledge of the direction dependent wave velocity was required for the implementation of this strategy in large complex structures. Tai et al. [119] proposed the fast Bartlett beamforming method for an L-shaped array which significantly enhanced the localization performance while maintaining the accuracy of broadband Bartlett beamforming. The proposed method was almost 224 times faster than traditional beamforming. Bartlett beamforming method (BBM), proposed by Huston [50], entirely ignored the damages that were perpendicular to the sensors array. Nakatani et al. [89] proposed two amendments in determining the accurate TDOA. The first one was to consider only the first dip and peak of the full-time histories. The second modification was related to sensor placement in the clusters. It was suggested to place the sensors as close as possible. These modifications significantly improved the localization accuracy. Mhamdi and Schumacher [85] proposed a circular phased array and compared it with the traditional time of arrival technique. Two circular arrays are capable to estimate the direction as well as the location of the source. A single phased array can only estimate the direction of the source. Phased array eliminates the need to select the wave phase. Sabzevari and Moavenian [104] presented a method based on attenuation analysis which requires fewer sensors. They used four sensors arranged in two clusters for the sources in anisotropic plates. This technique is capable to handle only a single source. The solution of eight unknowns is the main drawback of this approach. Aljets et al. [4] used a triangular array of three sensors for localization in composite plates. The time of flight (TOF) algorithm was combined with the modal source location algorithm to develop the proposed method. Wavelets transform (WT) was used at a specific frequency to determine the arrival time of the A_0 and its propagating angle. A numerical model can be formulated if the smallest and largest value for the wave velocity of S_0 wave mode is known. This technique is not suitable for complicated structures. Salamone et al. [107] arranged an array of macro-fiber composite (MFC) transducers as rosettes. This arrangement detects high-velocity wave modes in isotropic and anisotropic structures. This approach is favored since it does not require the wave's speed to be known in the material. Park et al. [94] proposed a technique for non-circular wavefronts for known material properties. The location can be estimated by using a geometric vector analysis or an optimization method. Two common shapes of wavefront typically found in highly anisotropic plates are rhombus and ellipse. However, since the waveforms acquired from the CFRP plate were comparatively more complicated than that of the isotropic steel plate, the overall accuracy is decreased if the A_0 mode is used in the location estimation.

For improving the accuracy in the beamforming methods, Liu et al. [74] used wavelet packet transform to decompose the generated AE signal due to damages in the welded joint. Validation results revealed the potential of the proposed technique to accurately estimate the location of the failure. He et al. [44] investigated the AE waves' dispersion behavior and its impact on the accuracy of the beamforming approach. Additionally, they proposed an approach to calculate group velocity by integrating plate wave theory with wavelet packet transformation. Rivey [101] observed the potential of beamforming methods to identify the origin location of stress waves by scattering, attenuation, and reflections. He et al. [43] introduced the Hilbert curve to minimize the cost and maximize the computational performance of AE beamforming. The efficiency could be improved approximately 154 times as compared to the traditional beamforming method. Wang et al. [125] proposed a joint localization method based on beamforming and TDOA. Both the simulation and experimental results demonstrate the improved accuracy of the proposed method. The amount of calculation is greatly reduced in comparison to the TDOA method and the beamforming method. xue et al. [127] looked at the positioning error of multi-sensor cluster systems with sensors organized in either an isosceles right-angled triangle or triangular pyramid form. The two-dimensional amendment algorithm outperformed with an average positioning error of 1.4 mm on the Plexiglas plate, which is 23.1 mm smaller than that of IRT (24.5 mm). While the average position error on concrete sheet is 46.6 mm, which is 18.1 mm smaller than that of IRT (64.7 mm). In case of anisotropic structures, the positioning accuracy of two-dimensional amendment algorithm in locating AE sources is 27.8 % higher than that of IRT. The arbitrarily triangle-shaped clusters approach was used by Fu et al. [36] to localize the AE sources in a cylindrical vessel. They compared the method with existing acoustic source localization techniques developed for flat plates and investigated its applicability potential for source localization in cylindrical structures. The findings provided a theoretical and experimental foundation for future research. The beamforming related papers are listed below in Table 4.

Although high localization precision is observed with great robustness in beamforming methods, its inherent limitations must be kept in mind during implementation. As beamforming compares the shape of signals, all the sensors in the array should have similar amplitude and phase responses. Moreover, to avoid spatial aliasing, the beamforming array is required to have a relatively small aperture. Similar ray paths from source to sensor experience the same propagation effects [121].

D. TIME REVERSAL AND ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) is an extremely effective procedure for the localization of AE sources. It is considered an alternative to classical triangulation methods. Contrary to the classical methods, the ANN-based location procedures have two important advantages: they are suitable for AE source location in highly anisotropic media, and elastic wave velocity is not a necessary input parameter of the algorithms [63]. The input parameters for the basic ANN-based algorithm use time differences, just like the common triangulation algorithm. However, determining the exact arrival time is a serious factor when using time differences. Therefore, in case of high noise background levels, these methods can give inaccurate results. Grabec et al. [40] proposed Neural Networks (NN) for the processing of AE data acquired from a small aluminum block. Baxter et al. [6] trained a structure by creating artificial acoustic emission sources. They used this knowledge to estimate the location of real AE sources by comparing with the recorded time of arrivals, which are called Delta-T. To resolve the issues related to nonlinear inversion, Spall et al. [117] used feed-forward neural networks (FFNN). They validated the approach on a steel beam. The velocity of AE signals in various propagation directions was contradictory even for isotropic materials. The training for a given NN configuration faced nonlinear parameter estimation, which requires picking NN weights from a collection of training data. Blahacek et al. [7] pointed out concerns about the calculation of correct arrival times. Standard parameters of the AE signals such as amplitude, duration, and rise time were used as input data set for the ANN based location algorithm. The algorithm successfully selected optimum parameter set scenarios. RMS was selected as the most sensitive parameter that can be modified to extract energy parameters. To resolve the drawbacks associated with ANN based approaches, Chlada et al. [12] proposed an approach, which does not need the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3096930, IEEE Access

TABLE 4. LIST OF BEAMFORMING RELATED PUBLISHED PAPERS

Author	Methods/Models	Performance index (unit)	Value
McLaskey 2010 [82]	VESPA (Velocity Spectral Analysis)	Confidence (%)	95
Yin 2018 [131]	Z-shaped array clusters	Error Min (cm) Error Max (cm)	0.76 1.59
Tai 2019 [119]	Fast Bartlett beamforming method (FBBM)	Average time (μs) Scanning accuracy (mm)	0.72 5
Nakatani 2014 [89]	Delay-and-sum algorithm, first dip and peak	Location Error	±10°
Mhamdi 2015 [85]	automatic onset time picking algorithm, Phased array approach	Max Error (mm)	9.6
Aljets 2012 [4]	Combination of TOF and modal source location algorithms	Location accuracy (%)	97.93
Park 2017 [94]	Levenberg-Marquardt Algorithm (LMA)	Error (Elliptic) mm, Error (rhombus) mm	18.8 2.68
He 2019 [44]	Nine-Four bisection' method, Hilbert curve-beamforming method (HCBF)	Min error in Steel (mm), Max error in Steel (mm), Min error in CRFP (mm), Min error in CRFP (mm).	2 15 5.4 20.2
Wang 2020 [125]	Joint beamforming and TDOA Localization Method	Average calculation time (s)	0.53
Xue 2021 [127]	Two-dimensional amendment algorithm	Average position error in Plexiglas plate (mm) Average position error in concrete (mm)	1.4 46.6
Fu 2021 [36]	The arbitrary triangular-shaped clusters	Min Error(cm) Max Error(cm)	0.42 3.72

material properties to be known. McCrory [81] concluded that much research is still required in AE source localization, after performing a comparison of various approaches such as delta-T, ANN, unsupervised waveform clustering (UWC), and modified measured amplitude ratio (MAR). Deng et al. [21] attempted to improve the location accuracy by integrating the potential of modified gaussian mixed model (GMM) and a time delay neural network (TDNN). Fu 2015 et al. [37] used backpropagation algorithm to adjust weights and biases. The minimum mean square error was found to be 0.93 if there were seven hidden neurons, and if the steady state arrived after 141 iterations. Minor errors were observed at the boundary points with a maximum error of 5.1 mm. For large monitoring areas, location accuracy is hard to maintain because of the attenuation of the stress wave attenuates propagating for the long distance. A chaotic neural network technique was introduced by Lu et al. [76] by proposing an improved version of particle swarm optimization (PSO), which did not require training samples or the adjustment of specific parameters. Cheng et al. [11] replaced the traditional gradient algorithm with shuffled frog leaping algorithm (SFLA). The latter proved to be more efficient as compared to the traditional gradient algorithm in the wavelet neural network parameter optimization. However, in case of insufficient training samples, the error rates were irregular. Liu et al. [75] improved the accuracy by proposing generalized regression neural network based on time difference mapping (GRNN-TDM). The time difference mapping data of all the sensors was used as input data for the training process, and the coordinates of the grid nodes were used as output data of the training. The performances of the traditional time difference mapping (T-TDM), improved time difference mapping (I-TDM), and GRNN- TDM methods were tested on different materials and structures. The accuracy of the localization results obtained from the proposed method was significantly improved. Yang and Xu [130] presented a pre-trained stacked denoising autoencoders (SDAE)-based framework to localize acoustic emission (AE) sources in common and complex metallic panels. Bayesian information criteria (BIC) approach was used to optimize the number of layers and hidden nodes of SDAE used for coordinate-based location. To improve the localization accuracy a ten-fold cross-validation method was utilized. The proposed method outperformed traditional machine learning approaches such as SVM and ANN with a zonal localization accuracy of 100%, and the root mean squared (RMS) localization errors of two metallic panels were 38 mm (1.5") and 48 mm (1.9"), respectively. Jang et al. [53] constructed a regression model for the estimation of impact location using the four multiplexed FBG sensor array. The constructed regression model was validated by non-baseline signals. Regression model accurately estimated the location of AE source with an average and maximum error of 4.77 cm and 9.00 cm, respectively for non-baseline cases. Ai et al. [2] presented an approach to localize SCC sources with fewest acoustic emission (AE) sensor. To enhance the traditional source localization, three machine learning approaches such as ANN, RF, SAE were used. Source localization is considered as a classification issue in this work.Stacked autoencoders performance was the best with an accuracy of 97.8%. The accuracy of random forest and ANN was 91.5% and 80.0% respectively.

TABLE 5. LOCALIZATION METHODS BASED ON ANN & TR

Author	Methods/Models	Performance index (unit)	Value
Chlada 2010 [12]	ANN, classical triangulation	Location error (mm)	9
Blahacek 2006 [7]	Backpropagation (BP) ANN	Max location error (mm)	70
Fu 2015 [37]	Backpropagation (BP) ANN	Max location error (mm)	10.6
Lu 2016 [76]	Improved PSO	Average error (m)	0.009
Cheng 2014 [11]	Wavelet Neural Network, Shuffled Frog Leaping Algorithm	Error rate (%)	<3
Liu 2020 [75]	GRNN-TDM algorithm	Absolute error (cm)	<2
Yang 2020 [130]	Stacked denoising autoencoders (SDAE)	RMSE (inches) RMSE (inches)	1.5 1.9
Ai 2021 [2]	ANN RF SAE	(Accuracy%)	80.0 91.5 97.8
Jang 2021 [53]	Regression	Average error (cm) Max error (cm)	4.77 9.00
Ing 2005 [51]	Time reversal technique	Contrast (8 sensors) Contrast (1 sensor)	≈4.9 ≈1.8
Ribay 2007 [100]	Time reversal technique	Correlation Coefficient (25C) Correlation Coefficient (26.5C)	0.96 0.72
Ernst 2014 [35]	Time reversal approach	Relative location error (%)	<5
Jiang 2015 [54]	SART algorithm, Adaptive medifilt2 and Medifilt2 iterative mean	Elapsed time (ET), Mean absolute error (MAE) Correlation coefficient (CC)	0.0553 0.1983 0.8281
Wang 2021 [124]	VTR	Location error in circumference direction	30°

TABLE 6. LOCALIZATION ALGORITHMS FOR MULTIPLE AE SOURCES

Author	Methods/Models	Performance index (unit)	Value
Choi 2017 [115]	Acoustic beating envelopes	-	-
Dubuc 2018 [29]	Sparse reconstruction approach with matching pursuit algorithm	-	-
He 2018 [45]	SVD BFM	Error (max) Error (min)	221 0
Sai 2016 [106]	Shannon wavelet transform, TR focusing model	All error (mm) Average Error (mm)	<11 7.3
Dris 2020 [28]	CWT, an EKF algorithm	Percentage error (%)	0.02–2.43
Kossel 2005 [60]	ICA	Average mean error (%) Maximum error (%)	<30 <50

Ing et al. [51] proposed an efficient concept called time reversal (TR) as a localization technique for acoustic emission sources in inhomogeneous objects irrespective of their shape. Ribay et al. [100] conducted numerical tests and observations to explain the mechanics of wave propagation. Owing to A_0 being dominant, a rise in temperature was expected to contribute to a stretching or compression of the impulse responses. Ernst and Dual [35] worked on the dispersive nature of flexural waves mode where the extraction of time-of-arrival (TOA) information is challenging. Li et al. [70] implemented it on steel plate. Apart from localizing, the orientation of the source was also identified through signal focusing. Park et al. [93] further extended it for complex isotropic or anisotropic structures. Additionally, the training process and the time-reversal based correlation calculations were convenient and straightforward. This approach was validated successfully on real wings of composite aircrafts. To locate and identify the damages in complex structures, Jiang et al. [54] integrated the concepts of tomography and simultaneous algebraic reconstruction technique (SART). Two artificially created damages verified the efficacy of this method on the Q235B steel plate. The proposed method produced a three-dimensional (3D) image that contained information about the location of the damage. Furthermore, an improvement in localization was observed after comparing the assessment indexes of Adaptive Medifilt2 and the Medifilt2 iterative mean, and the SART was conducted. Kocur [59] successfully suggested a deconvolution based approach that involves testing on small concrete and aluminum slabs effectively. They applied the convolution scheme to all the recorded waveforms. This approach suffers from practical drawbacks such as practical dispersion, stability, and high computational costs. Table 5 include the papers related to ANN and TR based localization methods. To find the leak source in cylindrical shell structures, Wang et al. [124] employed virtual time reversal (VTR) technique. The instantaneous abrupt characteristic of the signals were built by extracting WT coefficient of AE signal at specific frequency for further processing using VTR focusing image technique. They also provided an algorithm for determining the shortest path between the AE source and the sensor. The localization performance of the proposed method in circumferential direction was 30°.

One of the limitations of the ANN is that it needs large training sets. Producing large experimental training sets is very difficult and highly time-consuming. Alternatively, using a numerical model for the structure can generate training samples. Furthermore, if the ANN-based models are evaluated with a different dataset than the one that is generated, the performance may drop significantly [84].

E. MULTIPLE SOURCES LOCALIZATION

The triangulation approach requires the separation of multiple AE events to be separated and isolated in time. It means that individual events are localized individually. This scenario may work well where it is possible to isolate multiple events; however, in some scenarios it is not possible to distinguish the events in time. This kind of possibility may arise from corrosion and cracking. The main issue in the analysis of multiple events is the separation and identification of signal components, especially where the signal comes from a variety of unknown sources.

Kyoung-Sik Choi [115] proposed a reliable and cost-saving method to estimate the positions of multiple acoustic emission sources using acoustic beating envelopes. The longer wavelength of a beating signal compared to those of the original signals made it convenient to localize multiple acoustic emission sources. This method was based on the sparse reconstruction approach. Dubuc et al. [29] used sparse reconstruction approach for multiple acoustic emission sources within large diameter thin-walled pipelines. The technique is suitable for sources which are closely related in time. Both the matching pursuit algorithm and basis pursuit denoising approach were analyzed as potential numerical tools for the proposed method. He et al. [45] analyzed AE sources of varying frequencies and magnitudes using singular value decomposition (SVD) for preprocessing the signal, in order to solve the issues that result in a mislead estimation of the location. They implemented the proposed method for two sources in isotropic materials. However, in case of anisotropic materials it can be more challenging. Sai et al. [106] implemented the time reversal focusing imaging technique for installing a network of fiber Bragg grating sensors. Shannon wavelet transform was used to extract a narrow band signal at a specific frequency and to calculate the modulus value. However, this method requires fair characteristics of propagating waves. The sensors should be capable of covering the entire monitoring area, which may not be feasible in most of the engineering practices. A probabilistic approach was implemented by Dris et al. [28], where CWT was used to estimate the time of arrival. The lamb wave's group velocity at a specific frequency and the extended Kalman filter (EKF) were simultaneously used to estimate the AE sources' location. Even though this study produces significant results, it ignores the uncertainties associated with material properties. Kosel et al. [60] used independent component analysis (ICA) for the localization situations where the traditional TDOA based method failed. They first separated the signals of two synchronous AE sources and then used TDOA for individual sources. However, these methods lack strategy about the grouping of signals obtained in ICA. The literature about the localization of multiple acoustic emission sources is enlisted in Table 6.

The sparse reconstruction approach is suitable for structures with simple geometry and material properties. However, for geometrically complex structures, it is suitable to create a measurement-based dictionary [54].

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3096930, IEEE Access

TABLE 7. COMPARATIVE ANALYSIS OF AVAILABLE APPROACHES FOR AE SOURCE LOCALIZATION

Method	Basic Principle	Key strengths	Limitations
Modal Acoustic emission	Symmetrical (S0), the flexural (A0) minimum order antisymmetric (Sh) modes of the AE waves.	These methods require a reduced number of sensors. AE signal can be separated in different modes to reveal more hidden information.	Huge amount of baseline is required. These methods are computationally intensive and requires the knowledge of wave mechanics.
Beamforming	It is a signal processing technique which uses an array of sensors for directional signal transmission or reception.	Precise P-wave arrival time information is not required to implement beamforming. Sampling rates can be reduced by utilizing the band-limited nature of the AE signals. No need to timely synchronize spatially distance sensors is required.	These methods rely on the comparison of the shape of signals, which makes it crucial that all the sensors in the array have identical phase and amplitude. Relatively large aperture causes spatial aliasing.
Time Reversal approach	TRM compares the recording phase and the transmission phase to focus optimally on the wave back to the source.	TR method gives enhanced signal to noise ratio. It does not require the known wave velocity. It eliminates the problems with wave dispersion, attenuation, and reflections in a relatively simple way.	TR requires identical conditions for forward & backward propagation. Limitations present on the upper limit in the associated signal length and sampling rate. Boundary reflections affect accuracy.
ANN	ANN is composed of several artificial neurons which mimic the biological neurons in human brain.	They are suitable for highly anisotropic media. Wave velocity is not a necessary input parameter.	ANN is labor intensive. It requires plenty of training data. Repeated training is time consuming. Transferability of training data to any other object is not possible.
Triangulation Methods (Iterative methods)	Iterative methods begin with an approximate solution, and then the components of approximation are updated one or more times in a certified order before convergence is reached.	These methods generally tolerate a higher noise level and perform better in small scale laboratory environments.	Iterative methods require setting of certain parameters and an initial configuration. It is not recommended for real life situations. These methods are highly dependent on the TDOA value. They have high computational cost and face divergence and global convergence issues.
Triangulation Methods (Closed-form methods)	Closed-form methods are those methods in which the final expressions are expressed using a finite number of standard operations.	They are non-iterative in nature and are computationally more attractive. They do not face local minima and divergence problems.	The location error increases manyfold with an increase in noise level. These methods depend on the TDOA value. It is not recommended for real life situations.

IV. DISCUSSION

The AE localization algorithms are based on the distance traveled by the emitted waves. Their value can be achieved by multiplying arrival time to the propagation speed in the specific medium. The speed of the P-wave in a structure is closely related to the travel path. This paper includes a discussion of numerous localization techniques, improving the localization accuracy, where it is assumed that the P-wave travels in a straight line. This fact is valid for the monitoring environment in some isotropic propagation media having simple geometrical structures. For actual complex engineering structures, the trajectory of a real P-wave may not be simply straight. It is greatly affected by multiple propagation media and the geometry of the structure. It is assumed that if the P-wave travel paths are indicated by curves, multisegmented lines, and the combination of curves and multisegmented lines, the accuracy can be improved. This would be a slight variation of the measured travel path from the real one. Time reversal technique and the artificial neural network have been used in the literature for the AE localization problem. Various reliable and advanced strategies based on pattern recognition and neural networks have been developed for the analysis of AE and seismic data. These conventional methods work on a set of signal features extracted from the time or frequency domain. Time-frequency provides a broader range of time and frequency features simultaneously. The advantages of these techniques are that they do not require the knowledge of the wave velocity or the structural geometry and can estimate the intensity of the source and its location. However, the repeated training process of ANN is labor-intensive and computationally demanding. For covering a large structure, the training process may be conducted by manual impacts or by employing robotic devices. The beamforming technique has been discussed in the literature. An acoustic source could be localized in an anisotropic plate with the help of at least two arrays of sensors, each containing three sensors. This technique does not require the knowledge about direction-dependent velocity profile in the plate, nor does it require the solving of a system of nonlinear equations. For source localization in isotropic materials, a smaller number of sensors are required. The beamforming technique does not require the exact time of arrival of a specific wave mode, making it possible for it to handle noisy signals if the noise is Gaussian white noise. This approach has some limitations. One of the limitations is that the material properties must be known for the theoretical analysis beforehand. For an isotropic plate, it might not be a problem; however, getting all material properties accurately is very difficult for an anisotropic plate. Another restriction of this technique is that the mechanics' problem of wave propagation in a plate satisfying appropriate governing equations and boundary conditions must be solved first. Due to the nonlinear and non-convex nature of TDOA based localization problems, finding the AE sources' location is not a trivial task. Moreover, the non-linear hyperbolic equations become inconsistent if noises corrupt the TDOA measurements. Several methods based on TDOA positioning are available in the literature. These approaches can be divided into two categories. The first category includes iterative methods that require iteration to estimate an accurate location. The second category is of closed-form solutions that provide explicit solutions in AE source localization. Iterative approaches generally tolerate a higher noise level. However, they have certain limitations. These algorithms require certain parameters and an initial setup, which has a strong impact on the convergence of the algorithms. Convergence is not provided by the Newton–Raphson method at some points, which causes a deviation from the accurate solution with a high computational time. Closed-form methods are of non-iterative nature. They are generally more computationally attractive and do not have local minima and divergence problems, as compared to the iterative techniques. A brief comparison of these methods is presented in Table 7. The reliability in the AE source localization can be enhanced by combining these two kinds of methods. For example, the closed-form method's solution can be used as the initial guess of the iterative method, to avoid local convergence and achieve a higher level of noise tolerance before the thresholding effect occurs. The comparison is presented in Table 7. All the localization techniques possess some associated uncertainties in predicting the location of the damage because of errors in time of flight and the strain value. We propose a deep learning-based beamforming technique for the localizing of the acoustic emission sources on the surface of a cylindrical pipe, based on the assessment of different acoustic emission source localization techniques. It is important to concentrate on a decrease in the number of sensors used to incorporate sensor array-based monitoring methods. No prior information is required about acoustic emission velocity distribution in the structure. Compared to other traditional methods, the circular sensor cluster-based approach has a higher potential of in situ detection of acoustic emission sources in cylindrical pressure vessels and containers. Deep learning is a data-driven approach which does not require the manually designed and application specific features from data. Deep learning architecture is directly applied to data such as signals and images, because it automatically learns and extracts representative features from data. In this way, deep learning also achieves a better performance than the traditional feature-based algorithms.

V. CONCLUSIONS AND FUTURE DIRECTIONS

The following points are worth noting for the future research directions.

- Analytical techniques for AE source localization are challenging to apply in real-life structures that are complex. However, optimization techniques have been used to resolve source localization and characterization in complex structures.
- AE signals include noise. Sufficient expertise in signal processing is required to analyze the excellent quality of recorded AE signals for damage localization. However, in the absence of such expertise, the AE signals may wrongly be interpreted as original signals, resulting in incorrect localization results.
- Soft computing techniques like ANN have a tremendous potential for acoustic emission source localization. However, the considerable amount of training sets required for ANN makes it infeasible for large structures.

This study mostly contains the application of the source localization method to artificial sources. The localization is highly affected by the nature of the defect. The performance of the localization methods can be improved by investigating the effect of impact energy, impactor size, and material on the performance of network. The application of advanced deep learning algorithms such as deep belief networks and convolutional neural networks can bring a revolution in the field of acoustic emission source localization.

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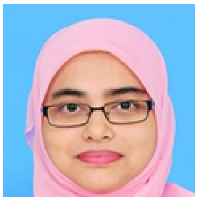

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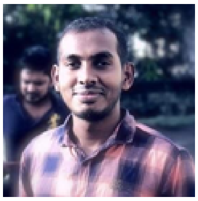

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