Abnormal Vibration Triangulation Modelling Methods in Internal Combustion Engines

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***Abstract*— This paper presents a comprehensive review of vibration analysis techniques for fault detection in internal combustion engines (ICEs). The use of vibro-acoustic signals has been pivotal in diagnosing complex issues related to ICE sub-components such as the pistons, bearings, and turbochargers. Traditional signal analysis methods, including Fourier transforms, wavelet analysis, and empirical mode decomposition (EMD), have been evaluated alongside advanced computational techniques like support vector machines (SVM) and artificial neural networks (ANN). The findings suggest that combining multiple domains of signal analysis (time, frequency, and angular domains) offers a robust mechanism for detecting and diagnosing faults. Furthermore, the potential integration of these techniques with real-time monitoring systems is discussed.**

Keywords—component, formatting, style, styling, insert (**key words**)

I. Introduction

Internal combustion (IC) engines are crucial in various applications, from automotive systems to industrial machinery. Their reliability and efficiency depend on mechanical integrity, with vibration serving as a key indicator of potential faults. Abnormal vibrations, caused by factors like misalignment, imbalance, or component wear, can lead to mechanical failures and costly downtime if unaddressed.

Advancements in sensor technology and data processing have underscored the importance of precise vibration monitoring, particularly using accelerometers, which offer high sensitivity and real-time data. Triangulating abnormal vibration sources with multiple accelerometers enhances fault diagnosis accuracy in IC engines [1]. Vibration analysis interprets signals generated during engine operation, revealing misalignments, imbalances, and defects, allowing engineers to detect wear early and prevent breakdowns [2], [3].

This paper reviews state-of-the-art methods for abnormal vibration triangulation in IC engines, focusing on the use of multiple accelerometers for precise localization. It explores recent advances, such as novel signal interpretation algorithms, machine learning for pattern recognition, and the integration of these techniques into modern diagnostics. Aimed at researchers and practitioners, this review provides insights into both theoretical and practical aspects of vibration analysis, promoting further innovation in this essential area of mechanical engineering.

A. Challenges in Localizing Abnormal Vibrations

Localizing abnormal vibrations in internal combustion engines (ICEs) presents several challenges due to the complexity of both mechanical and acoustic behaviors. ICEs generate vibrations from multiple sources, including mechanical impacts like piston slap, valve clearances, and gear vibrations, along with combustion noise and aerodynamic noise from components such as fans and ducts. These overlapping vibro-acoustic signals make it difficult to isolate and accurately identify the origin of abnormal vibrations [4]. Additionally, these signals are often non-stationary and transient, meaning they change with engine speed and time, complicating analysis. Traditional signal processing methods that work for stationary signals may not suffice, necessitating the use of more advanced techniques like Short-Time Fourier Transform (STFT) and wavelet transforms [5]–[7]. Another significant challenge is the presence of background noise from both the engine and the environment, which can mask the signals of interest and make it harder to detect and locate abnormal vibrations [8]–[10]. Moreover, vibrations in ICEs can propagate through multiple paths—airborne or structure-borne—further complicating the task of localization [11], [12]. In addition, the overlap of vibration signals from closely operating engine components such as pistons, valves, and injectors can make it difficult to differentiate between normal and faulty conditions. To address these challenges, techniques like cyclostationarity, spectral kurtosis, and wavelet transforms have proven effective in detecting and localizing faults in such complex environments.

B. Research Design

This research adopts a Systematic Literature Review (SLR). This research employs a Systematic Literature Review (SLR) to comprehensively gather, evaluate, and synthesize studies on abnormal vibration triangulation and vibration analysis in internal combustion (IC) engines. The SLR method provides an exhaustive overview of the research landscape, identifying key trends and knowledge gaps, thereby enhancing the reliability and validity of conclusions. The process includes formulating research questions, developing a structured search strategy, and rigorously screening and selecting relevant, high-quality studies. The selected studies are then thematically and comparatively analyzed to gain insights into vibration analysis and abnormal vibration localization in IC engines.

II. Literature Review

A. Fundamentals of Vibration Analysis in IC Engines and its impact

Vibrations in internal combustion (IC) engines stem from multiple sources, including mechanical imbalances, combustion factors, and structural resonances, each impacting the engine's overall vibration profile. Mechanical imbalances, such as uneven mass distribution in rotating components like the crankshaft and flywheel, generate centrifugal forces causing vibrations that affect performance and lead to long-term wear [13]–[15]. Combustion-related vibrations result from pressure fluctuations due to uneven fuel-air mixtures or ignition issues, with phenomena like knocking producing sharp pressure spikes and high-frequency vibrations [16]–[18]. Structural resonances occur when engine components resonate at their natural frequencies, amplifying vibrations and risking fatigue or failure[19], [20].

Other specific events, like piston slap and valve train dynamics, add to the vibrational behavior. Piston slap arises when pistons contact cylinder walls, indicating potential wear, while valve train dynamics from camshafts and gears introduce periodic vibrations, affecting both performance and noise levels [21], [22]. Similarly, the dynamics of the valve train, which includes the operation of camshafts, valves, and timing gears, can introduce periodic vibrations, especially if components are worn or improperly adjusted. These vibrations not only affect engine performance but also contribute to the overall noise levels, which can be a significant concern in both automotive and industrial applications [23], [24].

Abnormal vibrations significantly impact engine efficiency, safety, and longevity. Excessive vibrations disrupt smooth operation, increase fuel consumption, and reduce power output. For instance, an imbalanced crankshaft can misalign the power transmission system, lowering engine efficiency [1], [25]. For example, excessive vibrations caused by an imbalanced crankshaft can lead to misalignment in the power transmission system, ultimately reducing the overall efficiency of the engine [26], [27]. Continuous vibrations accelerate wear, particularly on bearings, seals, and fasteners, leading to fatigue failure and potentially costly repairs [28]–[30]. High vibration levels also pose safety risks, as loose fasteners can lead to component detachment or, in resonance cases, structural failure, which is especially hazardous in high-speed applications [31]–[33].

Vibrations correlate with noise, both as a byproduct and diagnostic tool, signaling issues like misfiring or misalignment. Early intervention can prevent serious damage, making regular vibration monitoring essential for maintenance [34], [35]. Persistent abnormal vibrations shorten engine lifespan due to cumulative component damage, underscoring the importance of design, maintenance, and monitoring to enhance durability and performance [36], [37].

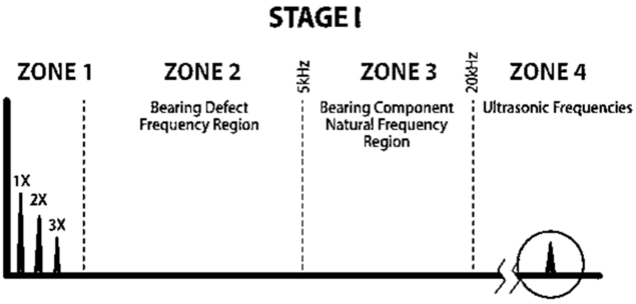

Fig. 1. Stage I of bearing defect progression across frequency zones

The understanding of the sources and impacts of vibrations in IC engines is crucial for the development of effective diagnostic and maintenance strategies. The next section will explore the principles of triangulation techniques used for the precise localization of these vibration sources within the engine.

The four stages of bearing failure of an IC engine are illustrated in the fig. 1 – fig. 4. Stage I (fig. 1) represents the initial phase where defects are microscopic, undetectable by noise or temperature but identifiable through high-frequency methods like Shock Pulse Method (SPM), primarily in the ultrasonic range (~20 kHz). In Stage II (fig. 2), the defect grows, causing increased high-frequency energy due to excitation of the bearing's natural frequency, generally above 5 kHz. Envelope analysis can detect these vibrations, though it requires advanced computation. Stage III (fig. 3) is characterized by prominent low-frequency patterns, such as Ball Pass Frequency of the Outer race (BPFO), Ball Pass Frequency of the Inner race (BPFI), and Ball Spin Frequency (BSF), along with sidebands indicative of severe damage. This stage is ideal for predictive maintenance, as the bearing is damaged but not yet critically. Finally, Stage IV (fig. 4) marks advanced deterioration, with distinct bearing defect frequencies replaced by random vibrations and looseness in the system. At this point, continued operation risks catastrophic failure, making immediate bearing replacement critical.

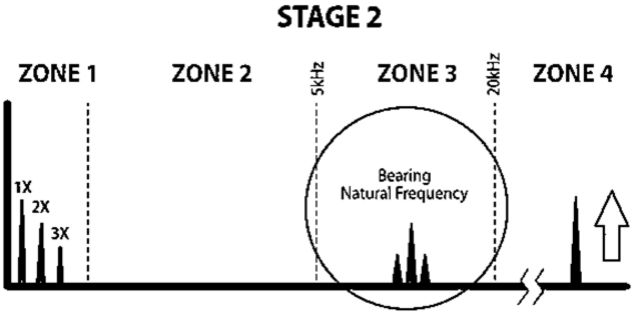

Fig. 2. Stage II of bearing defect progression across frequency zones

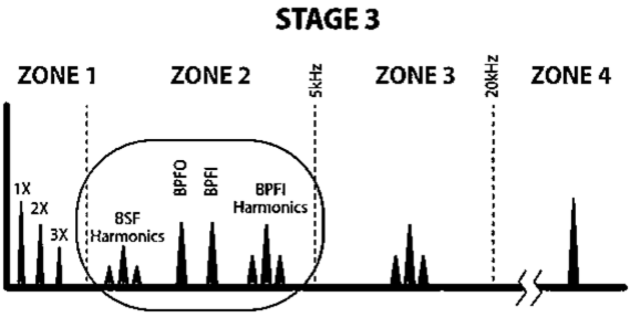

Fig. 3. Stage III of bearing defect progression across frequency zones

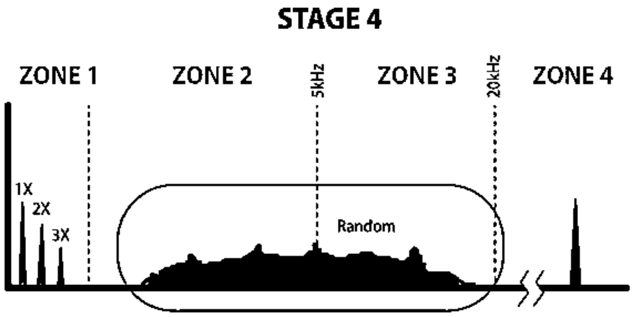

Fig. 4. Stage IV of bearing defect progression across frequency zones

B. Principles of Triangulation for Vibration Source Localization

Localizing vibration sources in internal combustion (IC) engines is essential for effective condition monitoring and fault diagnosis, enabling early detection of issues to prevent severe damage and extend engine life. Triangulation techniques are particularly effective, as they accurately determine vibration source locations by analyzing data from multiple sensors positioned around the engine. Fig. 5 illustrates a triangulation-based localization method where sensor nodes estimate location by measuring distances from three anchor nodes.

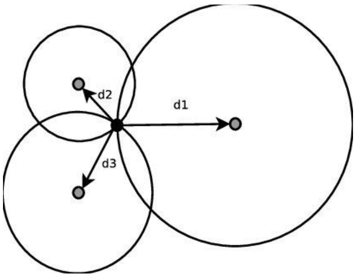

Fig. 5. Triangulation-based Localization [38]

C. Overview of Triangulation Techniques

Triangulation techniques are based on the geometric principles of determining a point's location by measuring angles or distances from known points. In the context of vibration analysis, triangulation involves using data from multiple sensors to infer the location of a vibration source within the engine.

- Time Difference of Arrival (TDOA): One of the most widely applied triangulation methods in vibration analysis is the Time Difference of Arrival (TDOA). TDOA calculates the difference in arrival times of a vibration wave at different sensors to estimate the location of the vibration source. This method assumes that the vibration propagates at a constant speed through the engine's structure. TDOA is particularly useful in environments where vibrations travel through uniform materials, as it can accurately locate sources even in complex mechanical systems [39]–[41]. However, the accuracy of TDOA can be affected by factors such as reflections, refractions, and varying material properties within the engine, which can distort the signal's path.

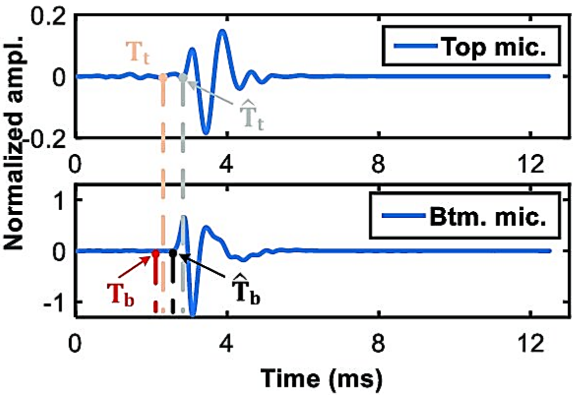

Fig. 6. Analysis of the TDoA of noise detection from top and bottom microphones for identify the location of the fingure on a mobile phone display [42].

- Amplitude-Based Triangulation: Another approach is amplitude-based triangulation, which uses the relative amplitudes of vibration signals received by different sensors to estimate the source's location. The underlying principle is that the amplitude of a vibration signal decreases as the distance from the source increases. By comparing the amplitudes recorded by multiple sensors, it is possible to infer the position of the vibration source. This method is advantageous in environments where the medium's properties might cause variations in signal propagation speed, as it relies on amplitude rather than time-based measurements [43]–[47]. However, amplitude-based methods are sensitive to environmental noise and signal attenuation, which can lead to inaccuracies if not properly accounted for.
- Phase Difference Methods: Phase difference methods involve measuring the phase shifts of a vibration signal as it propagates through the engine structure. The phase difference between signals received by different sensors is used to determine the relative positions of the sensors with respect to the vibration source. These methods are particularly effective in detecting high-frequency vibrations, where phase shifts are more pronounced and can be measured with higher accuracy [48]–[50]. However, phase difference methods require precise sensor calibration and are highly sensitive to changes in environmental conditions, such as temperature fluctuations, which can affect the speed of sound and, consequently, the accuracy of the localization.

III. Signal Processing Techniques in Vibration Triangulation

Signal processing is a critical component in the analysis of vibration data for the purpose of triangulation and source localization in internal combustion (IC) engines. The complex nature of engine vibrations, which often consist of overlapping signals from multiple sources, necessitates the use of advanced processing techniques to accurately isolate and identify the origin of specific vibrations. This section explores the various signal processing methods employed to enhance the quality of vibration data and improve the accuracy of triangulation in IC engines. Fig. 7 present the general stages of signal processing of vibration data used in vibration detection systems.

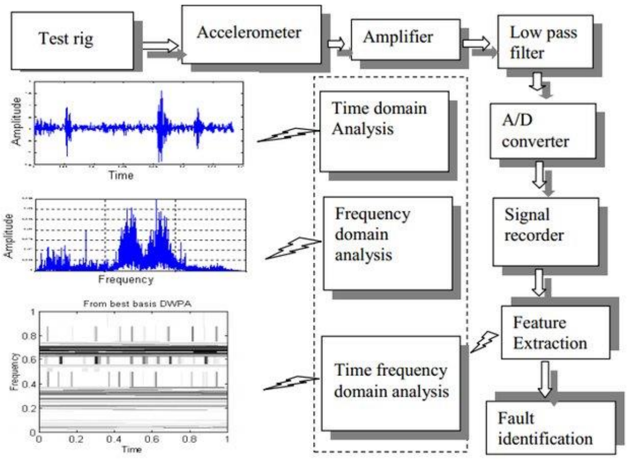

Fig. 7. General stages of signal processing of vibration data [51].

A. Noise Reduction

Noise reduction is a crucial step in processing vibration signals, especially for IC engines, where noise can stem from environmental factors, mechanical interference, and electrical disturbances. Effective noise reduction techniques are vital to ensure that vibration signals accurately represent the engine's mechanical condition, free from distortion by extraneous elements.

Several filtering techniques are commonly used for noise reduction in vibration analysis. The Butterworth filter, known for its flat frequency response in the passband, is widely used to remove high-frequency noise while preserving the essential components of the vibration signal [52], [53]. Similarly, the Kalman filter is employed to minimize the impact of random noise on the signal by providing an optimal estimate of the underlying signal based on a series of measurements over time [54], [55]. This filter is particularly effective in dynamic environments where the noise characteristics may change over time, such as in varying engine operational conditions.

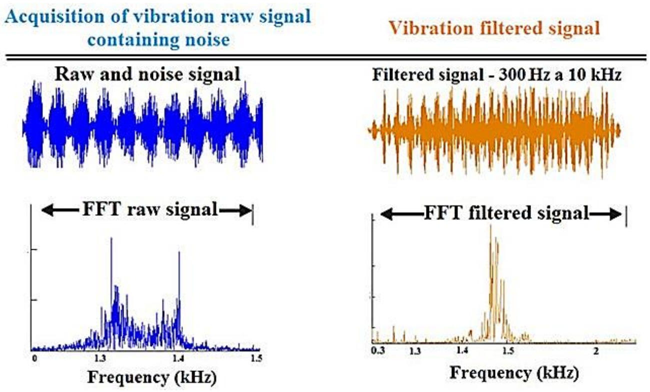

Fig. 8. Comparision between raw signal and filtered signal of vibration data [56].

Fig. 8 illustrates the process of acquiring and filtering vibration signals. The left side shows the raw, noisy vibration signal and its frequency spectrum obtained via FFT, revealing multiple frequency components. The right side displays the filtered signal within the 300 Hz to 10 kHz range, with its FFT spectrum showing clearer frequency peaks. This process underscores the importance of filtering for accurate vibration analysis.

Another advanced technique for noise reduction is the Wavelet Transform. Unlike traditional filtering methods that operate in the frequency domain, the wavelet transform analyzes the signal in both time and frequency domains, allowing for the identification and removal of noise components that are localized in both time and frequency [57]. This makes the wavelet transform particularly effective in handling non-stationary signals, which are common in IC engines where the vibration characteristics can change rapidly due to varying loads and speeds.

B. *Feature Extraction*

Feature extraction involves identifying and quantifying key characteristics of vibration signals relevant to fault detection and localization. Effective feature extraction enhances the accuracy of vibration analysis, aiding in the identification of specific engine faults.

In the time domain, common features extracted from vibration signals include Root Mean Square (RMS), peak amplitude, and crest factor. These features provide insight into the overall energy and intensity of the vibrations, which can be indicative of the presence and severity of faults [58], [59]. For example, an increase in RMS value may indicate an imbalance in the rotating components of the engine, while a high peak amplitude might suggest a sudden impact or mechanical failure.

In the frequency domain, Fast Fourier Transform (FFT) is one of the most commonly used tools for converting time-domain signals into the frequency domain. FFT allows for the identification of dominant frequencies within a vibration signal, which correspond to various mechanical issues within the engine [60]–[62]. For example, specific frequency peaks may indicate the presence of misalignment, imbalance, or bearing defects. The FFT is particularly useful for identifying periodic vibrations that result from rotating components within the engine.

Additionally, the Short-Time Fourier Transform (STFT) and Wavelet Transform provide time-frequency representations of the signal, enabling the analysis of how the vibration frequencies evolve over time. This is particularly useful for detecting transient faults that may not be evident in a purely frequency-domain analysis [61]. These advanced techniques are essential for capturing the dynamic behavior of engine vibrations under varying operating conditions.

C. *Advanced Signal Processing*

Advanced signal processing techniques, including machine learning and AI, are increasingly used in vibration analysis to improve fault detection and localization. Machine learning models like Support Vector Machines (SVM) and Neural Networks classify vibration patterns and predict faults based on historical data, learning from large datasets to identify subtle patterns undetectable by traditional methods [63]. Principal Component Analysis (PCA) reduces vibration data complexity by transforming features into principal components that capture key variations, preserving essential information for fault detection [64].

AI-driven techniques, especially Deep Learning models such as Convolutional Neural Networks (CNNs), have demonstrated promise in automatically extracting and analyzing vibration features, allowing for accurate fault diagnosis suited to real-time monitoring and predictive maintenance in IC engines [65].

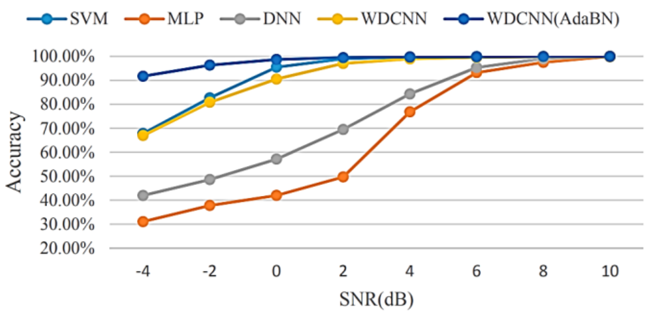

Fig. 9. Comparison of classification accuracy under different noisy environment [66].

Fig. 9 compares classification accuracy of various fault diagnosis models under different noise levels (SNR from -4 dB to 10 dB), illustrating that traditional methods like FFT-based SVM and Multi-Layer Perceptron (MLP) suffer accuracy drops with increasing noise, while the Wide First-layer Kernel Deep Convolutional Neural Network (WDCNN) maintains higher accuracy due to its wide kernels, which effectively suppress high-frequency noise. AdaBN, a domain adaptation method, further enhances WDCNN's robustness, showing high accuracy across noise levels and emphasizing the value of domain adaptation for noisy conditions [66].

D. *Challenges and Limitations in Current Research*

Despite advancements in vibration source localization for IC engines, technical and practical challenges limit the consistency and reliability of triangulation techniques in real-world applications, impacting their broader adoption in fault diagnosis systems.

One major technical challenge is sensor limitations. Accelerometers often struggle in harsh engine environments of extreme temperatures, pressure, and mechanical stress, as many lack durability for long-term performance. Their sensitivity and frequency range can also restrict detection of subtle anomalies, causing high-frequency fault-indicative vibrations to go undetected [67], [68]. Environmental noise, originating from combustion, mechanical interactions, and auxiliary systems, complicates data collection, making it difficult to separate fault signals from operational noise, even with advanced signal processing methods [69]. Signal attenuation, especially in engines with complex geometries or distant sensors, reduces vibration signal amplitude as it travels through components, complicating fault detection in remote areas [70].

Practical challenges also hinder real-world implementation. High-precision sensors capable of withstanding engine conditions are costly, and multiple sensors are required for accurate localization, raising costs further [71].

Deployment is complex, needing precise sensor placement, calibration, and ongoing maintenance, with phase difference techniques highly sensitive to placement accuracy. Scalability remains a concern in larger engines, like marine or industrial applications, where more sensors are needed, increasing installation and maintenance costs and logistical complexity. Additionally, the durability of sensors is a constraint; they degrade over time under mechanical stress, heat, and corrosive environments, requiring frequent recalibration or replacement, which is costly and logistically challenging, especially where minimizing downtime is crucial.

IV. Discussion

A. *Synthesis of Key Findings*

The review of triangulation techniques for vibration source localization in IC engines highlights advancements and challenges. Key findings emphasize the importance of sensor placement; positioning sensors near critical areas like the crankshaft or exhaust manifold enhances fault detection for issues such as misalignments or misfires. Strategic configurations, especially in complex engine geometries like multi-cylinder or turbocharged engines, also help reduce signal attenuation and reflection. Additionally, signal processing techniques, including Fast Fourier Transform (FFT), Wavelet Transform, and Kalman filtering, effectively enhance signal quality, isolating fault-related vibrations from noise and enabling time- and frequency-domain analysis for detecting transient and high-frequency faults. The integration of machine learning techniques, like Support Vector Machines (SVM) and deep learning, automates feature extraction and improves fault classification accuracy.

B. *Implications for Industry*

Improved triangulation methods in IC engines offer significant benefits for the automotive and manufacturing industries by enabling earlier fault detection, reducing downtime, maintenance costs, and preventing catastrophic failures. More accurate fault localization allows for targeted maintenance, extending engine life and avoiding unnecessary repairs. Integrating these methods into real-time monitoring systems supports predictive maintenance, essential for high-performance engines in sectors like aerospace, marine, and heavy machinery. Additionally, scalable solutions for large industrial engines, as noted in recent studies, benefit industries such as marine transport and power generation, where reliable, effective condition monitoring minimizes downtime and yields economic advantages.

C. *Gaps in Current Research*

Despite the significant advancements, several research gaps have been identified that need further exploration. One notable gap is the integration of new sensor technologies. While current sensors exhibit limitations in high-temperature and high-vibration environments, advances in MEMS (Micro-Electro-Mechanical Systems) and fiber-optic sensors offer promising avenues for more resilient and precise vibration monitoring in IC engines. Research into these emerging sensor technologies is still in its early stages and has yet to be widely adopted in vibration triangulation studies.

Another gap lies in the need for standardized methodologies. Although various triangulation techniques have been developed, there is little consensus on best practices for different engine types or operational environments. The effectiveness of techniques like TDOA, amplitude-based triangulation, and phase difference methods varies significantly based on the engine's configuration, size, and operating conditions. A standardized framework for sensor placement, calibration, and signal processing across different applications would help streamline the adoption of these techniques in industry.

D. *Future Research Directions*

Future research should focus on creating adaptive sensor systems that adjust to changing engine conditions, with self-calibrating sensors to reduce issues like sensor drift and positioning errors. Exploring hybrid triangulation methods, such as combining TDOA and phase difference techniques, could also enhance accuracy in complex settings. Additionally, AI-driven predictive maintenance systems that merge real-time vibration monitoring with historical data could improve fault prediction. Machine learning models that learn from ongoing engine data would boost diagnostic robustness and accuracy, particularly with large datasets and intricate engine setups.

E. *Limitations of the Review*

This review covers a wide range of recent research on triangulation techniques for vibration source localization in IC engines but has several limitations. It primarily focuses on vibration analysis, excluding in-depth discussion of other diagnostic methods like thermal or acoustic monitoring, which may limit the broader applicability of some findings. Additionally, as the field of vibration analysis evolves quickly with advancements in sensor technology, signal processing, and machine learning, the review may not fully reflect the latest innovations, which could soon impact current conclusions.

V. Conclusion

This review offers a comprehensive analysis of triangulation techniques for localizing vibration sources in internal combustion (IC) engines. Key findings emphasize the critical role of optimal sensor placement and advanced signal processing techniques—such as Fast Fourier Transform (FFT), Wavelet Transform, and machine learning algorithms—in enhancing diagnostic accuracy and reliability. Various methods, including Time Difference of Arrival (TDOA), amplitude-based triangulation, and phase difference approaches, were compared, showcasing their differing effectiveness depending on engine configurations and conditions.

The review also highlighted challenges such as sensor limitations, signal attenuation, environmental noise, and practical constraints like cost and scalability. Although there have been notable advancements, technical and practical challenges remain, requiring further research to fully realize the potential of vibration triangulation for IC engine diagnostics.

A. *Recommendations*

Based on this review's findings, the following recommendations are proposed for industry professionals and researchers:

1. **Prioritize Sensor Placement:** Effective sensor placement is crucial for accurate vibration source localization. Industry professionals should focus on deploying sensors strategically near high-impact areas, such as the crankshaft and cylinder head, where vibrations commonly originate. Researchers should investigate innovative placement strategies suited to specific engine geometries and configurations.

2. **Leverage Advanced Signal Processing:** FFT, Wavelet Transform, and machine learning-based feature extraction techniques should be incorporated into vibration diagnostics. These methods are effective in isolating fault signals from noise and detecting early-stage issues that might otherwise be missed.

3. **Adopt Hybrid Techniques:** Combining TDOA, amplitude-based, and phase difference methods can enhance diagnostic robustness and accuracy across various operating conditions, overcoming limitations inherent to individual techniques.

4. **Invest in Sensor Technology Development:** Industry leaders should support next-generation sensors, such as MEMS and fiber-optic types, which are durable in harsh engine environments while maintaining high sensitivity and precision. Such sensors are essential for enhancing durability and diagnostic accuracy.

5. **Implement Predictive Maintenance Systems:** Integrating real-time vibration monitoring with machine learning in predictive maintenance systems can reduce downtime, cut maintenance costs, and prevent severe failures through early fault detection.

The need for continued research in vibration triangulation for IC engines is paramount. As engine designs become increasingly complex, precise and reliable diagnostics will be vital. Technological advancements in sensors, signal processing, and artificial intelligence show promise in overcoming current challenges. Addressing these will help improve IC engine efficiency, reliability, and lifespan, fostering innovation in diagnostics and maintenance.

In conclusion, while significant progress has been made in vibration-based diagnostics for IC engines, much work remains. Interdisciplinary collaboration among mechanical engineers, data scientists, and sensor technologists will be essential to advance this research and support its successful application across industries.

REFERENCES

[1] H. Mahdisoozani et al., 'Performance Enhancement of Internal Combustion Engines through Vibration Control: State of the Art and Challenges', *Applied Sciences*, vol. 9, no. 3, p. 406, Jan. 2019 [Online]. Available: 10.3390/app9030406.

[2] F. Xu et al., 'An abnormal vibration diagnosis and control method for internal combustion power plant', *J. Phys.: Conf. Ser.*, vol. 2184, no. 1, p. 012012, Mar. 2022 [Online]. Available: 10.1088/1742-6596/2184/1/012012.

[3] H. T. Toivonen and F. Östman, 'Model-based torsional vibration control of internal combustion engines', *IET Control Theory & Applications*, vol. 2, no. 11, pp. 1024–1032, Nov. 2008 [Online]. Available: 10.1049/iet-cta:20070479.

[4] J. Antoni, 'Cyclostationarity by examples', *Mechanical Systems and Signal Processing*, vol. 23, no. 4, pp. 987–1036, May 2009 [Online]. Available: 10.1016/j.ymssp.2008.10.010.

[5] M. Wang, 'Modified short-time Fourier transform'.

[6] F. Al-Badour et al., 'Vibration analysis of rotating machinery using time–frequency analysis and wavelet techniques', *Mechanical Systems and Signal Processing*, vol. 25, no. 6, pp. 2083–2101, Aug. 2011 [Online]. Available: 10.1016/j.ymssp.2011.01.017.

[7] L. Li et al., 'Adaptive short-time Fourier transform and synchrosqueezing transform for non-stationary signal separation', *Signal Processing*, vol. 166, p. 107231, Jan. 2020 [Online]. Available: 10.1016/j.sigpro.2019.07.024.

[8] H. Wu et al., 'Vibration Detection in Distributed Acoustic Sensor With Threshold-Based Technique: A Statistical View and Analysis', *J. Lightwave Technol.*, vol. 39, no. 12, pp. 4082–4093, Jun. 2021 [Online]. Available: 10.1109/JLT.2020.3036450.

[9] B. J. Malone et al., 'Background noise exerts diverse effects on the cortical encoding of foreground sounds', *Journal of Neurophysiology*, vol. 118, no. 2, pp. 1034–1054, Aug. 2017 [Online]. Available: 10.1152/jn.00152.2017.

[10] G. Wang et al., 'Noise analysis of the fiber-based vibration detection system', *Opt. Express*, vol. 29, no. 4, p. 5588, Feb. 2021 [Online]. Available: 10.1364/OE.416615.

[11] V. Fridman, 'Vibrations of an Internal Combustion Engine', in *Theory of Elastic Oscillations*, Singapore: Springer Singapore, 2018, pp. 239–247[Online]. Availablehttp://link.springer.com/10.1007/978-981-10-4786-2_12[Accessed: 8September2024].

[12] A. Ordubadi et al., 'Vibration and noise prediction of internal combustion engine based on cascade modeling of components', *The Journal of the Acoustical Society of America*, vol. 65, no. S1, pp. S64–S64, Jun. 1979 [Online]. Available: 10.1121/1.2017367.

[13] E. El-Kharashi et al., 'The impact of the unbalance in both the voltage and the frequency on the performance of single and cascaded induction motors', *Energy*, vol. 181, pp. 561–575, Aug. 2019 [Online]. Available: 10.1016/j.energy.2019.05.169.

[14] X. Wang et al., 'Reliability and maintenance for performance-balanced systems operating in a shock environment', *Reliability Engineering & System Safety*, vol. 195, p. 106705, Mar. 2020 [Online]. Available: 10.1016/j.ress.2019.106705.

[15] G. Kokieva et al., 'Influence of imbalance of balancing of crankshafts during engine repair', *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 1001, no. 1, p. 012085, Dec. 2020 [Online]. Available: 10.1088/1757-899X/1001/1/012085.

[16] J. Jarosuski and S. Wojcicki, 'The mechanism of interaction between a combustion region and acoustic resonatort'.

[17] A. Can Altunlu et al., 'Sensitivity of Combustion Driven Structural Dynamics and Damage to Thermo-Acoustic Instability: Combustion-Acoustics-Vibration', *Journal of Engineering for Gas Turbines and Power*, vol. 136, no. 5, p. 051501, May 2014 [Online]. Available: 10.1115/1.4025817.

[18] A. Taghizadeh-Alisaraei et al., 'Characterization of engine's combustion-vibration using diesel and biodiesel fuel blends by time-frequency methods: A case study', *Renewable Energy*, vol. 95, pp. 422–432, Sep. 2016 [Online]. Available: 10.1016/j.renene.2016.04.054.

[19] R. Hickling et al., 'Cavity resonances in engine combustion chambers and some applications', *The Journal of the Acoustical Society of America*, vol. 73, no. 4, pp. 1170–1178, Apr. 1983 [Online]. Available: 10.1121/1.389261.

[20] N. S. Ahirrao et al., 'Dynamics and Vibration Measurements in Engines', *Procedia Manufacturing*, vol. 20, pp. 434–439, 2018 [Online]. Available: 10.1016/j.promfg.2018.02.063.

[21] N. Dolatabadi et al., 'On the identification of piston slap events in internal combustion engines using tribodynamic analysis', *Mechanical Systems and Signal Processing*, vol. 58–59, pp. 308–324, Jun. 2015 [Online]. Available: 10.1016/j.ymssp.2014.11.012.

[22] E. E. Ungar and D. Ross, 'Vibrations and noise due to piston-slap in reciprocating machinery', *Journal of Sound and Vibration*, vol. 2, no. 2, pp. 132–146, Apr. 1965 [Online]. Available: 10.1016/0022-460X(65)90091-X.

[23] K. Ohta et al., 'Analysis of Piston Slap Induced Noise and Vibration of Internal Combustion Engine (Effect of Piston Profile and Pin Offset): (Effect of Piston Profile and Pin Offset)', *JEE*, vol. 6, no. 3, pp. 712–722, 2011 [Online]. Available: 10.1299/jee.6.712.

[24] Z. Geng and J. Chen, 'Investigation into piston-slap-induced vibration for engine condition simulation and monitoring', *Journal of Sound and Vibration*, vol. 282, no. 3–5, pp. 735–751, Apr. 2005 [Online]. Available: 10.1016/j.jsv.2004.03.057.

[25] N. A. Patil and L. P. Raut, 'Vibration Analysis Of Ci Engine Using Fft Analyzer'.

[26] A. Moosavian et al., 'The effect of piston scratching fault on the vibration behavior of an IC engine', *Applied Acoustics*, vol. 126, pp. 91–100, Nov. 2017 [Online]. Available: 10.1016/j.apacoust.2017.05.017.

[27] J. Antoni et al., 'Effective Vibration Analysis Of Ic Engines Using Cyclostationarity. Part I-A Methodology For Condition Monitoring', *Journal of Sound and Vibration*, vol. 257, no. 5, pp. 815–837, Nov. 2002 [Online]. Available: 10.1006/jsvi.2002.5062.

[28] S. Madhavan et al., 'Vibration based damage detection of rotor blades in a gas turbine engine', *Engineering Failure Analysis*, vol. 46, pp. 26–39, Nov. 2014 [Online]. Available: 10.1016/j.engfailanal.2014.07.021.

[29] D. Kim et al., 'Vibration Analysis of Bracket for Vehicle Components', in *ASME-JSME 2018 Joint International Conference on Information Storage and Processing Systems and Micromechatronics for Information and Precision Equipment*, San Francisco, California, USA, 2018, p.V001T09A001[Online].Availablehttps://asmedigitalcollection.asme.org/ISPS/proceedings/ISPS-MIPE2018/51937/San%20Francisco,%20California,%20USA/276954[Accessed: 9September2024].

[30] S. M. Ramteke et al., 'Diagnosis of Liner Scuffing Fault of a Diesel Engine via Vibration and Acoustic Emission Analysis', *J. Vib. Eng. Technol.*, vol. 8, no. 6, pp. 815–833, Dec. 2020 [Online]. Available: 10.1007/s42417-019-00180-7.

[31] D. Du et al., 'Intense vibration mechanism analysis and vibration control technology for the combustion chamber of a liquid rocket engine', *Journal of Sound and Vibration*, vol. 437, pp. 53–67, Dec. 2018 [Online]. Available: 10.1016/j.jsv.2018.08.023.

[32] N. S. Ahirrao et al., 'Dynamics and Vibration Measurements in Engines', *Procedia Manufacturing*, vol. 20, pp. 434–439, 2018 [Online]. Available: 10.1016/j.promfg.2018.02.063.

[33] S. Madhavan et al., 'Vibration based damage detection of rotor blades in a gas turbine engine', *Engineering Failure Analysis*, vol. 46, pp. 26–39, Nov. 2014 [Online]. Available: 10.1016/j.engfailanal.2014.07.021.

[34] B. Yang et al., 'VIBEX: an expert system for vibration fault diagnosis of rotating machinery using decision tree and decision table', *Expert Systems with Applications*, vol. 28, no. 4, pp. 735–742, May 2005 [Online]. Available: 10.1016/j.eswa.2004.12.030.

[35] K. Wegener et al., 'Noise and vibrations in machine tools', *CIRP Annals*, vol. 70, no. 2, pp. 611–633, 2021 [Online]. Available: 10.1016/j.cirp.2021.05.010.

[36] K. Prażnowski et al., 'The Use of Multicriteria Inference Method to Identify and Classify Selected Combustion Engine Malfunctions Based on Vehicle Structure Vibrations', *Sensors*, vol. 21, no. 7, p. 2470, Apr. 2021 [Online]. Available: 10.3390/s21072470.

[37] H. Mahdisoozani et al., 'Performance Enhancement of Internal Combustion Engines through Vibration Control: State of the Art and Challenges', *Applied Sciences*, vol. 9, no. 3, p. 406, Jan. 2019 [Online]. Available: 10.3390/app9030406.

[38] K. Liu et al., 'Towards Resilient Geographic Routing in Wireless Sensor Networks', 2005.

[39] J. Yang et al., 'Polynomial Fitting and Interpolation Method in TDOA Estimation of Sensors Network', *IEEE Sensors J.*, vol. 23, no. 4, pp. 3837–3847, Feb. 2023 [Online]. Available: 10.1109/JSEN.2022.3232625.

[40] M. L. Fowler and X. Hu, 'Signal models for TDOA/FDOA estimation', *IEEE Trans. Aerosp. Electron. Syst.*, vol. 44, no. 4, pp. 1543–1550, Oct. 2008 [Online]. Available: 10.1109/TAES.2008.4667729.

[41] Y. Liu et al., 'An Improved Algebraic Solution for TDOA Localization With Sensor Position Errors', *IEEE Commun. Lett.*, vol. 19, no. 12, pp. 2218–2221, Dec. 2015 [Online]. Available: 10.1109/LCOMM.2015.2486769.

[42] Z. Xiao et al., 'Keystroke Recognition With the Tapping Sound Recorded by Mobile Phone Microphones', *IEEE Trans. on Mobile Comput.*, vol. 22, no. 6, pp. 3407–3424, Jun. 2023 [Online]. Available: 10.1109/TMC.2021.3137229.

[43] B.-W. Jang and C.-G. Kim, 'Acoustic emission source localization in composite stiffened plate using triangulation method with signal magnitudes and arrival times', *Advanced Composite Materials*, vol. 30, no. 2, pp. 149–163, Mar. 2021 [Online]. Available: 10.1080/09243046.2020.1786903.

[44] B.-W. Jang and C.-G. Kim, 'Impact localization of composite stiffened panel with triangulation method using normalized magnitudes of fiber optic sensor signals', *Composite Structures*, vol. 211, pp. 522–529, Mar. 2019 [Online]. Available: 10.1016/j.compstruct.2019.01.028.

[45] J. Wang et al., 'Noncontact Distance and Amplitude-Independent Vibration Measurement Based on an Extended DACM Algorithm', *IEEE Trans. Instrum. Meas.*, vol. 63, no. 1, pp. 145–153, Jan. 2014 [Online]. Available: 10.1109/TIM.2013.2277530.

[46] S. V. Dvoynishnikov et al., 'Phase triangulation method with spatial modulation frequency optimization', *Measurement*, vol. 145, pp. 63–70, Oct. 2019 [Online]. Available: 10.1016/j.measurement.2019.05.054.

[47] E. Aparicio-Esteve et al., 'Experimental Evaluation of a Machine Learning-Based RSS Localization Method Using Gaussian Processes and a Quadrant Photodiode', *J. Lightwave Technol.*, pp. 1–8, 2022 [Online]. Available: 10.1109/JLT.2022.3198009.

[48] G. W. Wei et al., 'A Novel Approach for The Analysis Of High-Frequency Vibrations', *Journal of Sound and Vibration*, vol. 257, no. 2, pp. 207–246, Oct. 2002 [Online]. Available: 10.1006/jsvi.2002.5055.

[49] I. Santamaría et al., 'A Comparative Study of High-Accuracy Frequency Estimation Methods', *Mechanical Systems and Signal Processing*, vol. 14, no. 5, pp. 819–834, Sep. 2000 [Online]. Available: 10.1006/mssp.2000.1321.

[50] D. Chen et al., 'Phase-detection distributed fiber-optic vibration sensor without fading-noise based on time-gated digital OFDR', *Opt. Express*, vol. 25, no. 7, p. 8315, Apr. 2017 [Online]. Available: 10.1364/OE.25.008315.

[51] S. Riaz et al., 'Vibration Feature Extraction and Analysis for Fault Diagnosis of Rotating Machinery-A Literature Survey', vol. 5, no. 1, 2017.

[52] D. G. E. Robertson and J. J. Dowling, 'Design and responses of Butterworth and critically damped digital filters', *Journal of Electromyography and Kinesiology*, vol. 13, no. 6, pp. 569–573, Dec. 2003 [Online]. Available: 10.1016/S1050-6411(03)00080-4.

[53] R. G. T. Mello et al., 'Digital Butterworth filter for subtracting noise from low magnitude surface electromyogram', *Computer Methods and Programs in Biomedicine*, vol. 87, no. 1, pp. 28–35, Jul. 2007 [Online]. Available: 10.1016/j.cmpb.2007.04.004.

[54] D. Wang et al., 'Adaptive Unscented Kalman Filter for Target Tacking with Time-Varying Noise Covariance Based on Multi-Sensor Information Fusion', *Sensors*, vol. 21, no. 17, p. 5808, Aug. 2021 [Online]. Available: 10.3390/s21175808.

[55] W. Bai et al., 'On extended state based Kalman filter design for a class of nonlinear time-varying uncertain systems', *Sci. China Inf. Sci.*, vol. 61, no. 4, p. 042201, Apr. 2018 [Online]. Available: 10.1007/s11432-017-9242-8.

[56] P. O. C. Junior et al., 'Feature extraction using frequency spectrum and time domain analysis of vibration signals to monitoring advanced ceramic in grinding process', *IET Science, Measurement & Technology*, vol. 13, no. 1, pp. 1–8, Jan. 2019 [Online]. Available: 10.1049/iet-smt.2018.5178.

[57] M. Lang et al., 'Noise reduction using an undecimated discrete wavelet transform', *IEEE Signal Processing Letters*, vol. 3, no. 1.

[58] B. R. Nayana and P. Geethanjali, 'Analysis of Statistical Time-Domain Features Effectiveness in Identification of Bearing Faults From Vibration Signal', *IEEE Sensors J.*, vol. 17, no. 17, pp. 5618–5625, Sep. 2017 [Online]. Available: 10.1109/JSEN.2017.2727638.

[59] Y. Yang et al., 'Vibration signal analysis using parameterized time–frequency method for features extraction of varying-speed rotary machinery', *Journal of Sound and Vibration*, vol. 335, pp. 350–366, Jan. 2015 [Online]. Available: 10.1016/j.jsv.2014.09.025.

[60] P. Charles et al., 'Detecting the crankshaft torsional vibration of diesel engines for combustion related diagnosis', *Journal of Sound and Vibration*, vol. 321, no. 3–5, pp. 1171–1185, Apr. 2009 [Online]. Available: 10.1016/j.jsv.2008.10.024.

[61] R. De Jesus Romero-Troncoso, 'Multirate Signal Processing to Improve FFT-Based Analysis for Detecting Faults in Induction Motors', *IEEE Trans. Ind. Inf.*, vol. 13, no. 3, pp. 1291–1300, Jun. 2017 [Online]. Available: 10.1109/TII.2016.2603968.

[62] K. Jafarian et al., 'Misfire and valve clearance faults detection in the combustion engines based on a multi-sensor vibration signal monitoring', *Measurement*, vol. 128, pp. 527–536, Nov. 2018 [Online]. Available: 10.1016/j.measurement.2018.04.062.

[63] B. Samanta et al., 'Artificial neural networks and support vector machines with genetic algorithm for bearing fault detection', *Engineering Applications of Artificial Intelligence*, vol. 16, no. 7–8, pp. 657–665, Oct. 2003 [Online]. Available: 10.1016/j.engappai.2003.09.006.

[64] I. M. Johnstone and A. Y. Lu, 'On Consistency and Sparsity for Principal Components Analysis in High Dimensions', *Journal of the American Statistical Association*, vol. 104, no. 486, pp. 682–693, Jun. 2009 [Online]. Available: 10.1198/jasa.2009.0121.

[65] R. Hickling et al., 'Cavity resonances in engine combustion chambers and some applications', *The Journal of the Acoustical Society of America*, vol. 73, no. 4, pp. 1170–1178, Apr. 1983 [Online]. Available: 10.1121/1.389261.

[66] W. Zhang et al., 'A New Deep Learning Model for Fault Diagnosis with Good Anti-Noise and Domain Adaptation Ability on Raw Vibration Signals', *Sensors*, vol. 17, no. 2, p. 425, Feb. 2017 [Online]. Available: 10.3390/s17020425.

[67] W. R. Fahrner et al., 'Sensors and smart electronics in harsh environment applications', *Microsystem Technologies*, vol. 7, no. 4, pp. 138–144, Nov. 2001 [Online]. Available: 10.1007/s005420100089.

[68] D. G. Senesky et al., 'Harsh Environment Silicon Carbide Sensors for Health and Performance Monitoring of Aerospace Systems: A Review', *IEEE Sensors J.*, vol. 9, no. 11, pp. 1472–1478, Nov. 2009 [Online]. Available: 10.1109/JSEN.2009.2026996.

[69] C. Qin et al., 'DTCNNMI: A deep twin convolutional neural networks with multi-domain inputs for strongly noisy diesel engine misfire detection', *Measurement*, vol. 180, p. 109548, Aug. 2021 [Online]. Available: 10.1016/j.measurement.2021.109548.

[70] P. Nivesrangsan et al., 'AE mapping of engines for spatially located time series', *Mechanical Systems and Signal Processing*, vol. 19, no. 5, pp. 1034–1054, Sep. 2005 [Online]. Available: 10.1016/j.ymssp.2004.10.008.

[71] M. Z. A. Bhuiyan et al., 'Quality-Guaranteed Event-Sensitive Data Collection and Monitoring in Vibration Sensor Networks', *IEEE Trans. Ind. Inf.*, vol. 13, no. 2, pp. 572–583, Apr. 2017 [Online]. Available: 10.1109/TII.2017.2665463.