



A Comprehensive Analysis of the Literature Concerning the Detection of Mechanical Faults in Industrial Machines Through the Use of Overlapping Acoustic Anomalies

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Abstract: Anomaly detection without the requirement for specific sensors for each industrial unit is one of the most important methods for preventive factory maintenance. Due to the frequent corruption and interference caused by routine production sounds in factory-collected sound data, the implementation of sound-data-based anomaly detection is an overly complex procedure. Acoustic techniques have long been used to identify system anomalies. Unfortunately, there is little information available about the use of the acoustic technique for industrial machine failure detection. This article offers a thorough analysis of current structural advancements and applications of acoustic methods for mechanical failure diagnosis.

Keywords: acoustic recognition; mechanical failure; industrial machines; systematic review

Introduction

All obtained signals and pictures are inevitably contaminated by noise during collection, compression, and transmission, causing distortion and information loss. The presence of noise degrades the effectiveness of any signal processing operations. Signal denoising is thus essential in modern signal processing systems, such as those involved in image processing, voice recognition or biomedical signal processing for medical diagnostics.

Noise in telecommunications causes signal jitter and information loss as well as a reduction in the bandwidth of communication channels.

Noise pollution and its detrimental effects on public health are common in metropolitan settings. In many industrial applications and in construction engineering, noise is also hazardous. Industrial noise is the acoustic noise that is produced in workplaces and businesses as a consequence of the manufacturing process, while machinery, equipment, and tools are in use. Industrial noise has the effect of shortening the lifespan of industrial equipment and/or increasing the risk of industrial accidents.

Structural vibration, which theoretically is comparable to noise, may result in a variety of noise-related issues, including structural fatigue failure discomfort for users or onlookers disruption of sensitive equipment, etc. Analysis of vibration data is a vital first step in the actual technical implementation of unit condition monitoring and fault detection in order to identify the most representative issue features and improve the diagnostic and analytical precision. Therefore, accurate noise analysis of the collected vibration signals is essential for determining the unit's malfunction.

Not every instance of mechanical failure on every single machine in large-scale enterprises, where several industrial machines are involved, could be immediately recognized by widely utilized sensors. The high level of noise in the location where the machines are used is one of the factors contributing to this handicap. The typically utilized sensors, such as ultrasonic and infrared sensors, will incur a significant level of distortion and have trouble detecting disturbances or failures in a particularly loud environment, whether brought on by light or sound pollution.

To find industrial machine failures, many research have been done. Such failures may be found, for instance, using deep-learning-based anomaly detection, a recent detection technique in another field of signal processing. The acoustic approach is another technique



that is often used to find mechanical damage in machinery. Because measurements can be made without coming into close touch with the monitored equipment, this approach offers a better degree of security than other methods. There is a long history of using acoustic techniques to identify systemic anomalies. Changes in the acoustic signal's properties, such as frequencies and amplitude, may often be used to identify abnormal circumstances at a measurement equipment or location.

The acoustic approach has an advantage over other methods in that the acoustic signal's characteristics may be retrieved and utilized for more thorough failure detection. Additionally, acoustic techniques are used to track changes in the behavior of living things. A lot of pertinent techniques and tools have developed over the last several years in response to the research community's rising interest in the detection of failures by acoustic methods in general and, in particular, failures in high-noise situations. This solution has been made possible by a number of secondary investigations, but there are currently relatively few systematic studies in this field of study.

The systematic literature review (SLR) that was utilized to assess and synthesize the pertinent works on failure detection by acoustic techniques, as well as the technology that has been and will be employed for failure detection by acoustic methods, is the primary contribution of this study. The fundamental methodologies and algorithms for acoustic-based failure detection are also investigated in this study, as well as many ways that show the possibility of using these techniques. Several taxonomies are discussed in this paper as well. This research used a systematic, objective selection and assessment procedure as a form of transparency and to assure the inclusion of all relevant studies. It also employed an evidence-based, systematic review technique to cover the most current literature.

The major goals of this investigation are:

- categorizing methods and procedures for acoustic mechanical failure analysis;

- Examining the study that has already been done in this field;
- Being aware of the key problems that need to be solved;
- Determining prospective study areas for the future.

Related Work

The study on the early detection of mechanical breakdowns using acoustic techniques is briefly discussed in this section. A comparison of reviews and surveys about it is shown in Table 1. Internal combustion engines (ICM) are monitored using the vibro-acoustic approach, according to Delvecchio et al.'s review. In a review, Leaman et al. discussed the use of acoustic emission technologies to identify planetary gearbox (PG) faults. A review on the use of acoustic emissions technology to identify offshore and onshore pipeline breaches was written by Lukonge and Cao. A study of condition monitoring methods and defect and failure detection on a gearbox based on the acoustic emission (AE) approach was presented by Raghav and Sharma.

Reviews were done and reported in accordance with the Preferred Report Items for Systematic Reviews and Meta-Analysis Statements (PRISMA) and the criteria for systematic literature reviews, as well as the systematic mapping research procedure. This thorough and unbiased selection of all peer-reviewed articles pertinent to the published study material is made possible by the well-designed research methodology that served as the foundation for this systematic review.

In order to expose the actual status of the current research in the application of failure detection technology, this methodology is used to gather pertinent articles from reliable scientific sources, which are then sorted and mapped into numerous categories. Practitioners and scholars may use this research map to identify cutting-edge areas and research issues for the future.

Determining use cases or applications of acoustic methods to detect failures is crucial, but



it's also necessary to grasp the drawbacks and difficulties of using such techniques. We also look at the most recent developments in the technological techniques, processes, and ideas that are put into practice when using these methods.

Research Methodology

The objective of employing an SLR is to identify, assess, and look at prior and connected works that are pertinent to the topic of current piece. SLR writing may be produced by reviewing papers using a logical and objective research methodology. According to Kitchenham, the research approach must be able to guarantee that the assessment process is completed as fast as feasible. However, completing the gaps in each region is the main objective of doing an SLR. Additionally, since this systematic review is unique, it needs previous research of a comparable sort to act as a model.

Research Design

The findings of the preliminary research based on the research question and keywords associated with the research question are identified and explained in this paragraph as the current research needs.

Literature Review Questions

The techniques for finding and illuminating failure detection methods employing acoustic approaches have taken a long time to develop. Over time, a number of approaches, procedures, and techniques have been created to characterize the components of acoustical failure detection. As a consequence, this research will answer the following queries:

- What kinds of industrial machine failures can acoustic technologies identify?
- What are the current approaches and potential technologies for the acoustic detection of mechanical failures?
- What difficulties does acoustical failure detection face?

- What are the acoustic techniques for mechanical failure detection's future research trends and directions?

Research Process

This literature review technique focuses on obtaining reputable primary research papers rather than materials taken from scholarly journals. Additionally, the proceedings of scientific conferences are recognized important research resource. The following sources were utilized to continue the extraction of SLR review articles.

Search Terms

The search for and collection of publications relevant to this research required using a number of internet database sources. These sources were chosen based on the reputation they have so far built. The publications utilized as references in this investigation. The most significant publications and conferences related to the detection of acoustical failures may be found in this database, together with their complete texts and highest impact articles.

After entering keywords into this database, the relevant studies were reviewed for compliance. This study employed search engines for investigation.

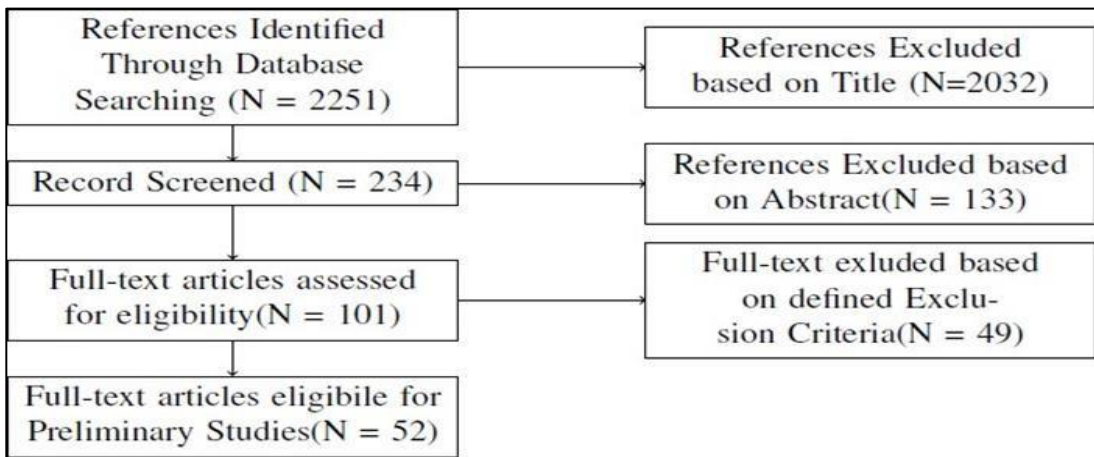
- “Acoustic Mechanical Failure Detection Industrial Machine” OR “Acoustic Mechanical Fault Detection Industrial Machine”
- “Acoustic Mechanical Failure”
- “Acoustic Detection”
- “Acoustic”
- “Mechanic Failure”
- Detection
- Failure
- Machine

Review Conduction

This section describes systematic literature review approaches. This review article's rules and processes affect SLR search.

Paper Selection

After gathering preliminary research, the papers should be assessed for relevancy. A second



examination determined the original research's significance. After screening, a systematic assessment of the selected publications ensured consistency of inclusion and exclusion criteria. Figure 1 shows how this systematic review selected research.

Figure 1. Procedure of research selection for the present schematic review

The procedures listed below were used to find relevant research studies:

- Locate the database and use the defined keywords to find earlier works that are connected to the research.
- Discard documents that do not fit the specified search criteria.
- Discard articles with ambiguous connections between the title and abstract.

- Read the papers in their entirety before evaluating them.
- Consider the bibliography.
- Complete the first research.

Inclusion and Exclusion Criteria

Non-auditory mechanical failure detection research was omitted from this paper. Our study focused on relevant SLR research. The study also lacked comparative studies.

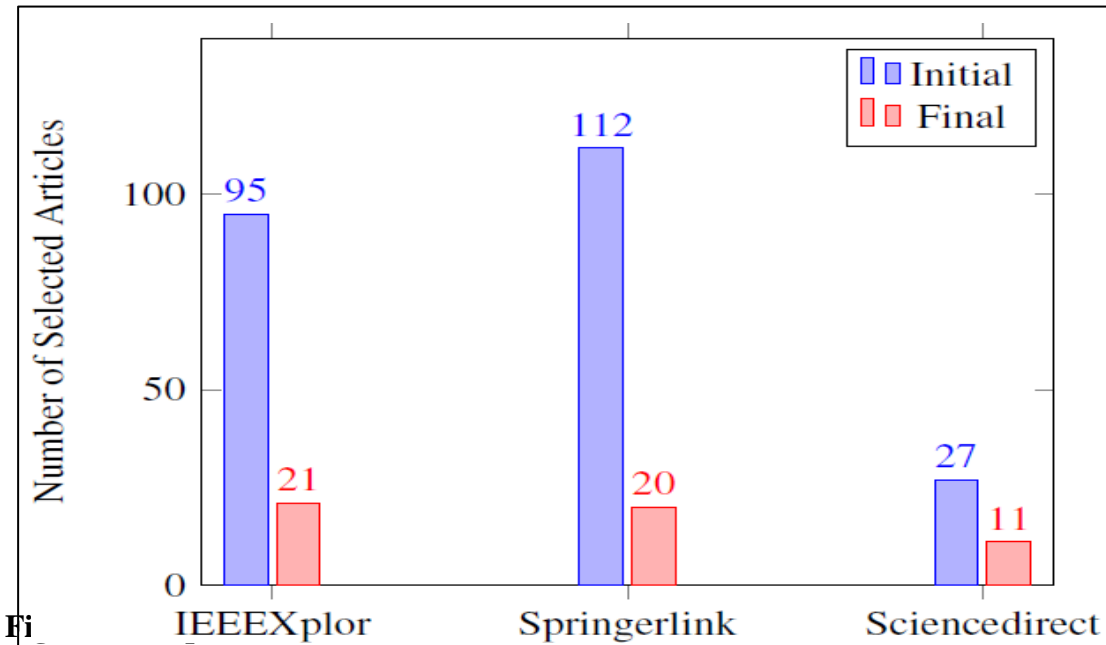


Table 1. Inclusion and exclusion criteria

Inclusion Criteria	
1	Peer-reviewed original articles
2	Articles proposing an acoustical method for mechanical failure detection
3	Articles that utilize acoustical method for failure detection
4	Recency of articles in case of multiple repeated studies
Exclusion Criteria	
1	Articles that are not written in English
2	Studies with unvalidated techniques and algorithms
3	Articles that utilize acoustical approach for other purposes
4	Articles that do not utilize acoustical methods
5	Articles that do not clearly mention acoustic/sound/noise approaches in the title
6	Articles providing unclear results or findings
7	Duplicated studies

Data Extraction

During the data extraction procedure, pertinent data was taken from the articles and entered into a database. The elements in this database are presented in Table 2.

Table 2. Data extraction.

Data Item	Description
Title	Article title
Year	Year of publication
Author(s)	The article author(s)
Publication type	Journal, proceeding, etc.
Publication medium	The medium via which the article is published
Country	Researchers' affiliation country
Contribution	The major contribution of the article
Summary	Summary of the article from our perspective

Demographic Data and Overview

The systematic review's results are here. Figure 1 shows a search method that found 2251 scientific publications. The title and keyword screening eliminated 2032 items, leaving 233 for further screening. The search methodology was included in the relevant papers since the abstract was related to the strategy, even though the publication did not commit to using acoustic methods to discover problems. After reading the abstracts and introductions and conclusions, we screened the articles using Table 3's criteria. It selected 101 articles. After examining all selected articles, 49 were removed because they did not focus on industrial equipment problem detection. 52 research articles were selected after screening.

Articles span 2006–2021. Figure 3 shows that 11 of the papers were published in 2021. 37 of 52 articles were published between 2017 and 2021. This shows that acoustical techniques for failure detection are still quite new and that interest in this issue is growing rapidly as the number of publications grows.

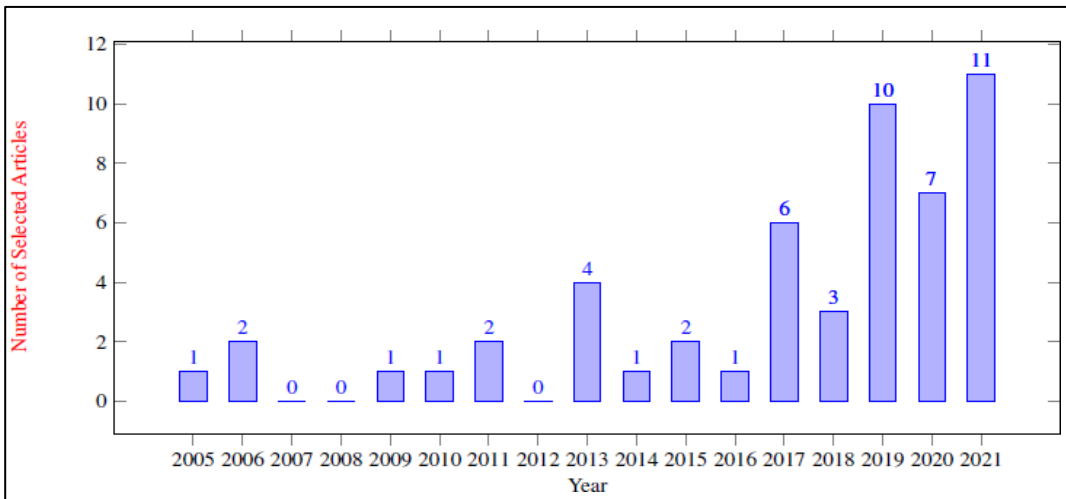


Figure 3. Year of publication

Using the authors' institutions' countries, the geographic distribution of researchers

interested in acoustic failure detection investigations was also determined. If the letter's author is unknown, the first author identifies the item's country of origin. Figure 4 shows the writers' locations. China supplied 11 of the 52 pieces, followed by South Korea and the UK with five apiece. Three countries—Malaysia, Poland, and the US—contributed four pieces each. Brazil and India donated three articles, while 13 countries gave one.

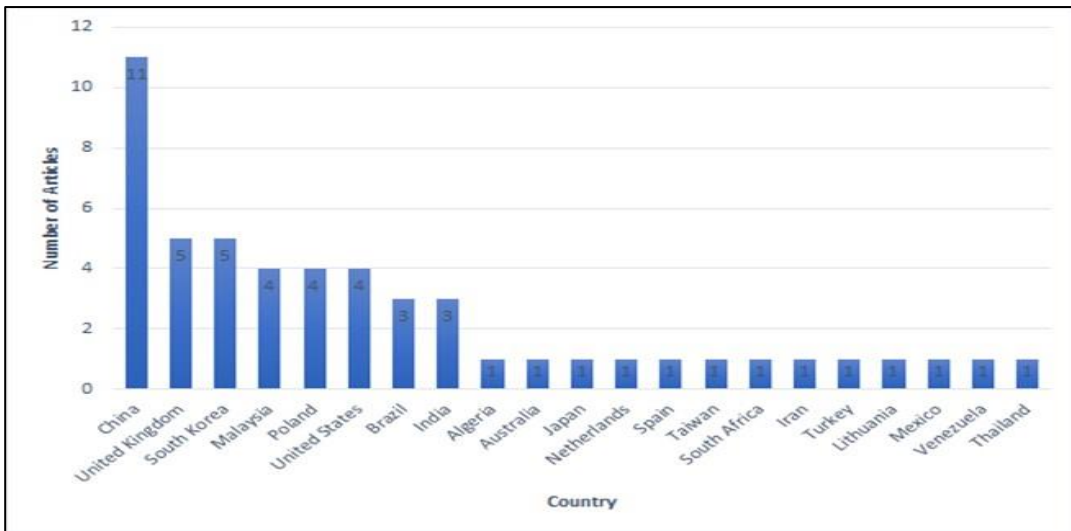


Figure 4. Article distribution by country of origin

The kind of publication chosen will determine whether or not the work will be presented at conferences and published in journals. The several publishing categories that were used for the collected works are shown in Figure 5. 38 of the publications that were considered for this study were previously published in peer-reviewed scientific journals, making up 73% of the total. The selected articles came from scientific conferences a total of 14 times, which accounts for 27% of the total. Journals and conferences.

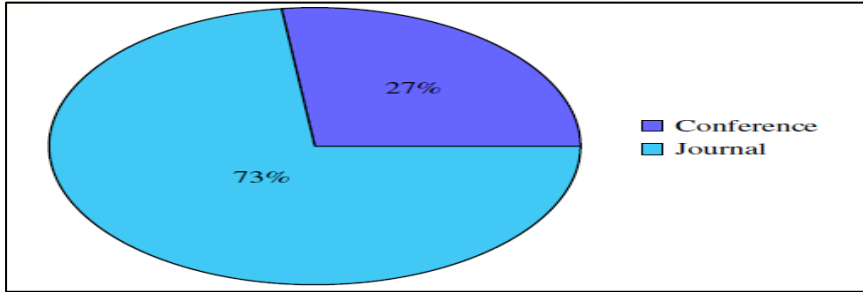


Figure 5. Categories of publication

Results and Discussion

Answering Research Questions

This portion presents the outcomes of part 3.1.1's research questions. These enquiries assessed research progress in using acoustic methods to detect industrial equipment problems. Answers are derived from the scientific studies' results.

Acoustic methods detect which industrial machine failures?

Acoustic damage types to industrial machines. The acoustic technique may detect faults, wear, fractures, leaks, and other mechanical issues. Grinding burn is caused by high grinding temperatures. Gao et al. employed wavelet coherence analysis and acoustic emission data to detect grinding burns. Acoustic methods may also detect mechanical damage on milling machines, according to Sun et al.'s research. Depending on the items, the acoustic technique may detect corrosion, fractures, leakage, wear, rubbing, pitting, and more.

Mechanical failure impairs or terminates device functioning. Cracks, distortion, wear, age, bending, and other reasons may cause its failure. A spike in engine temperature or an unusual sound indicate mechanical failure.

What Acoustic Mechanical Failure Detection Methods Are Available and Coming?

A distinctive audio signal may occur while the engine is operating. This damage signal

frequently has a distinct frequency and loudness. Tagawa et al. state that plant acoustic data are easier to collect due to the low cost of installing microphones in existing facilities.

Acoustic Emission-Based

A mechanical action releases a small amount of elastic energy into a structure, causing acoustic emission (AE). The acoustic emission signal is just the combination of the deterministic and failure signals. Deterministic signals indicate engine health. During engine operation, the failure signal indicates a problem. Assuming the deterministic and failure signals are unrelated, Liu et al. express the acoustic emission signal as Equation (1), where $y(n)$, $d(n)$, and (n) are the corresponding signals. $y(n) = d(n) + (n)(1)$ for $n = 1, 2, \dots, M + N$.

Microphone-Based

The acoustic emission procedure is one of various ways to extract the acoustic signal from the component to be investigated. Acoustic signal recovery involves microphone pickup. The microphone may be a single device, a stethoscope, or a smartphone. A microphone should be used to sample the unit's sound when it's working properly. The microphone can pick up signals using a mobile phone's sampling frequency of 44.1 kHz and sounds between 10 Hz and 10 kHz, which people can hear. Using a microphone is easier than other methods for data collection and installation. However, the microphone's careless positioning will affect measurements.

Ultrasonic-Based

Ultrasonic waves may also discover defects. Jo et al. investigated 300 kHz ultrasonic turbine blade failure detection. Acoustic diagnostics may detect partially missing and deformed blades during turbine operation.

What Are the Challenges Faced by Acoustical Failure Detection?

Industrial equipment breakdowns may be difficult to detect without halting operations.

Sensor, measurement, and computer technology have overcome these problems.

Industrial machines and components may fail. Gears, actuators, distributors, and bearings may fail. Acoustic technology may analyze faults efficiently and effectively without shutting down industrial operations. This technique is useful for early failure detection and problem resolution. The acoustic technique also has drawbacks.

- The spectrum of impulse signals will affect all measured frequencies, making failure analysis difficult.
- Brittle components are liable to fail. Since fault sizes change frequently, measuring flaws or leaks will provide different results.
- Multiple machine breakdowns may occur concurrently. Flaws, cracks, leaks, wear, and other factors may cause failure. Failures affect measurement signals and failure analysis methods.
- Active machines may fail. Interference signals from nearby failed equipment may harm microphone-based sensors.

What Are the Future Research Trends and Directions in Mechanical Failure Detection Using the Acoustic Method?

Based on more than 100 publications, several study paths and possible research subjects have been identified. First, acoustic emission methods dominate failure detection research. This shows that new detection methods may yet be developed. As hardware and software technology advances, more new ways will be possible.

Second, acoustic methods for mechanical breakdown detection are understudied. Laboratory studies dominate. This suggests more inquiry into unsettled circumstances. Acoustic data collection results rely on real-world noise levels.

Third, smartphone hardware specs have gotten more complicated as technology has improved. Portable failure detection systems may use this study, albeit there has been little.



Forensic investigations often use cell phone audio signal data. Thus, cellphones replacing sensors will remain a matter of discussion.

Fourth, acoustic mechanical defect detection utilizing artificial intelligence is becoming increasingly prevalent. However, more AI algorithms for failure detection may be implemented and created. According to our investigations, different analytical methodologies are required for different equipment failure locations and types.

Fifth, industrial equipment mechanical failure and workplace safety research are inextricably linked. The control system must warn when industrial equipment fails audibly. Thus, real-time and central failure detection, severity, and attitude decision-making study is needed.

Finally, past research mostly identified machine-specific faults. Identifying cumulative machine breakdowns requires investigation. Many machines in a room cause this. Thus, creating a failure detection system for multi-device situations would be exciting.

Threats to Validity

Bias in publication or selection, data extraction errors, and underestimate may undermine systematic mapping studies.

Academics are biased toward publishing positive results. Positive results are publicized and quoted more. Reviewers struggle with publication prejudice. Searching multiple reliable scientific databases for as many relevant papers has solved this issue. Thus, many articles with disappointing results were published while others with positive results were ignored. However, restricting article searches may overlook important material like industry authority reports. However, filtering articles from specific databases may increase the probability of finding high-quality scientific publications.

Selection bias—the tendency to omit relevant papers from the research due to inadequate search methods—affects reviewers more. This study's search approach found all relevant



documents. Care was made to include and exclude articles that accurately reflected all relevant publications for the research project. Since this research focused on peer-reviewed studies, company websites, discussion forums, and other comparable sources were off limits. Reviewers' failure to accurately and rapidly extract data from selected articles may lead to data extraction errors and calculations. We used bibtex and JabRef to organize and handle all the study publications. Researchgate.net creates bibtex publishing data. Data is

captured and structured in Microsoft Excel and statistically analyzed.

Conclusions

Industrial equipment failure detection systems benefit from acoustic approaches. Acoustic failure detection methods are popular due to their low cost and ease of usage.

Assessing current solutions' originality requires comprehensive evaluation and analysis of existing methodology, supporting technology, and applications. This SLR analyzes the latest acoustic industrial engine failure detection research. Methodical and objective screening selected 53 publications that passed rigorous inclusion and candidate research quality standards. This research shows that scientists prefer sonic emission for a broader variety of failure detection methods. Wear, cracks, and seeded failures remain the key research areas. However, academics favor SVM, k-Nearest Neighbors, artificial neural networks, and others. Fragility and failure still plague this research.

This thorough review identified many future research issues, including a much-needed emphasis on failure detection using mobile phones to evaluate data and recognize failures.

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