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Enhancements and Future Horizons in Electromechanical Impedance-Based Damage Detection: A Comprehensive Systematic Review

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Abstract

The Electromechanical Impedance (EMI) method presents an attractive option for engineering system monitoring due to its non-destructive nature, cost-effectiveness, and high sensitivity to even minor damages. Establishing a robust conditional maintenance program in Structural Health Monitoring (SHM) systems necessitates accurate information regarding damage presence, beginning with early detection. Consequently, recent years have witnessed the development of various approaches aimed at enhancing damage detection processes within the EMI-SHM domain. This paper offers a meticulous, systematic review of the latest technological advancements to augment damage detection capabilities within the EMI-SHM framework. A meticulous analysis of the selected journal articles focuses on the methods developed and the research emphases. Moreover, attention is directed towards contextualizing issues pertinent to industrial application, encompassing considerations such as temperature variation and compensation techniques, sensor reliability, and the inherent nature of the work. A thorough statistical examination of the findings is undertaken, affording invaluable insights into the contemporary landscape of EMI-SHM research. Additionally, a detailed analysis of temperature compensation techniques and sensor reliability methodologies is executed, identifying crucial gaps for implementation in industrial settings. The insights leveraged not only shed light on the current state of investigation but also furnish invaluable guidance for future endeavors in EMI-based damage detection technologies suitable for industrial-scale deployment.

Keywords: Electromechanical Impedance, Damage detection, Damage prediction, Structural Health Monitoring

1. Introduction

The Electromechanical Impedance (EMI) method has garnered prominence as a proficient approach for structural system monitoring. This is attributed to its cost-effectiveness, nondestructive attributes, and remarkable sensitivity in discerning even small changes in structural conditions [1 - 4]. Moreover, its inherent characteristics render the technique amenable to integration within a comprehensive autonomous monitoring framework [5].

The EMI technique relies on the electromechanical coupling between the host structure and the piezoelectric patch attached to it embedded within it. Excitation of the piezoelectric patch by a sinusoidal voltage signal allows a signature of the structure status attributable to both the converse and direct piezoelectric effects. These acquired signatures are intrinsically linked to the structure's health, such that any changes in them reveal changes in the structural conditions, enabling the detection of damages [4], [6 - 8].

In recent years, a concerted endeavor among researchers has been directed toward enhancing the efficacy and reliability of EMI-based damage detection methodologies in the realm of Structural Health Monitoring (SHM). These endeavors have led to the development of numerous innovative techniques, algorithms, and instrumentation approaches to enhance the sensitivity, accuracy, and robustness of EMI-SHM-based systems. Consequently, a comprehensive appraisal of these recent advancements is imperative to elucidate the state-of-the-art in this domain, identify emerging trends, and highlight avenues for future research.

This contribution undertakes a systematic review focusing on methodologies developed within the past five years to enhance damage detection. Through a meticulous synthesis and analysis of extant literature, this review offers a comprehensive and statistical examination of the evolved technologies, assessing the methods used, research emphases, and implementation challenges pertinent to using the EMI technique in real-world scenarios. Moreover, this review delineates prospective avenues for EMI-SHM-based damage detection.

2. Materials and Methods

The systematic study used the Knowledge Development Process - Constructivist (ProKnow-C) methodology described in Ensslin et al. [9]. Fig. 1 illustrates the steps used herein.

Since this work aimed to investigate the latest techniques for enhancing damage detection using the electromechanical impedance method, the search strings used were *electromechanical impedance*, *damage detection*, and *damage identification*. The AND operator linked the first two, and the OR operator linked the last two. The period investigated was the most recent five years.

The search was conducted from January 19 to January 29, 2024, using three databases: IEEE Xplore, Scopus, and

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Springer. The results were narrowed to include only journal articles and peer-reviewed material in English.

After filtering the results, the first step was to analyze the alignment of the title, keywords, and abstract with the actual research. This step (Fig. 1) resulted in the selection of 4 journal articles from IEEE Xplore, 52 from Scopus, and nine from Springer databases. In this stage, 57 items were selected after identifying and removing eight duplicates.

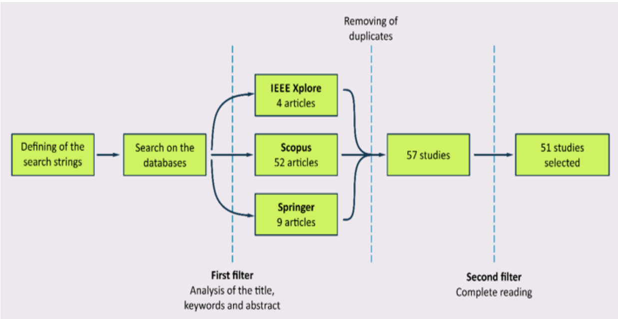

Fig. 1. Flowchart illustrates the steps to select the journal articles for the systematic analysis.

The papers were then thoroughly reviewed to determine their effective alignment with the research topic. The selection criteria were focused on approaches aimed at enhancing damage detection in EMI-SHM systems, with consideration given to all aspects related to damage detection tasks. At this stage, 51 papers were identified as fully aligned with the scope of the research. The selected documents were then moved to the second stage for systematic analysis.

The following aspects were evaluated in each paper: (1) the method used for damage detection; (2) the focus of the study on the overall system for structural health monitoring; (3) the type of method used, whether it depends on a previous structural model to achieve results or not; (4) the material investigated in the study; (5) how the damage was created in the monitored specimen; (6) the temperature range considered in the study; (7) the intrinsic nature of the research, delineating between theoretical, experimental, or industrial-scale endeavors, and; (8) the incorporation or absence of a structural model about the monitored specimen.

From the gathered information regarding the defined points, statistical analysis was performed using the Python packages Numpy 1.24.4 version [10] and Pandas 1.5.3 version [11], which were used to process the imported raw data, and Matplotlib 3.7.2 version [12] and Squarify 0.4.3 version [13], used to plot the results.

The points investigated herein provide a detailed overview of the latest developments in damage detection techniques using the electromechanical impedance method in Structural Health Monitoring (SHM). This information helps to understand the current research directions and identify areas that require further study, guiding future research. The following section describes the analysis's results and their corresponding discussions.

3. Results and Discussions

The analysis of the approaches developed for damage detection revealed an organization into three general groups: (1) data-driven methods, which do not rely on the development of a structural model; (2) Machine Learning (ML)-based techniques, which require training an ML model for damage detection; and (3) model-based methods, which require a previous structural model to detect damages in the monitored structure.

The proportion of each group (Fig. 2) shows that data-driven methods were the most used approach, representing 62.7 % of the total number of papers investigated. This was followed by ML-based techniques (31.4 %) and model-based approaches, which accounted for 5.9 %.

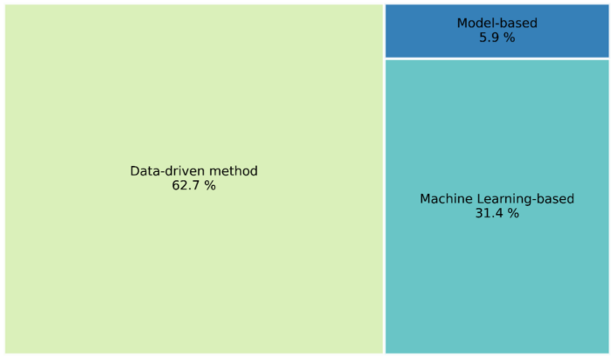

Fig. 2. Proportions of general approaches used to improve damage detection in the EMI-SHM.

The results indicate a trend toward developing approaches that do not rely on structural model-based methods, which can be time-consuming and costly for complex structures. Additionally, ML-based approaches require specific training for each condition. Conversely, data-driven methodologies offer pronounced advantages due to their adaptability and capacity for seamless extension to diverse scenarios. Furthermore, their capacity to furnish real-time resolutions renders them the preferred choice [14].

Investigating the number of papers by year (Fig. 3) shows an increasing trend in research on techniques to improve damage detection using information from the electromechanical impedance method, instilling a sense of optimism about the future of the field. However, there has been a lack of studies regarding model-based techniques in the last three years, possibly due to their need for a previous structural model, which would be a disadvantage in real-life situations. According to the results, only ML-based techniques and data-driven methods have been applied recently, with an increasing trend for each class of techniques.

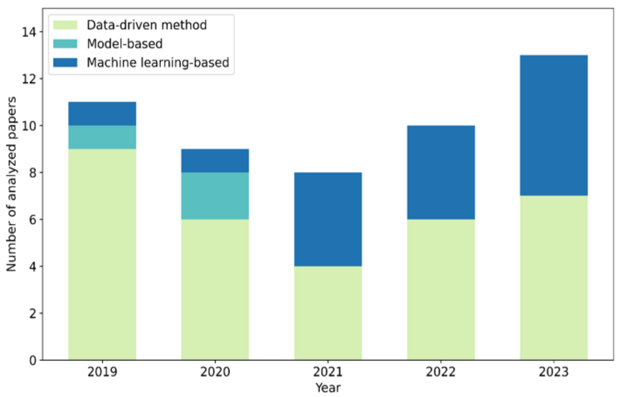

Fig. 3. Trend analysis of approaches employed to enhance damage detection in the EMI-SHM over the recent years.

The examination of techniques used to enhance damage detection in EMI-SHM identified five classes: (1) Improvement of instrumentation and hardware; (2) Machine learning techniques; (3) Numerical or analytical methods; (4)

Optimization techniques; and (5) Statistical techniques. Tab. 1 shows the list of studies that used each of these techniques.

Tab. 1 shows that statistical and ML techniques are widely used. Fig. 4 reveals that statistical techniques are the most commonly used, accounting for 37.3 % of the analyzed papers. They are followed by ML techniques (31.4 %), numerical and analytical methods, and improvements in instrumentation and hardware, each accounting for 13.7 %.

Table 1. List of studies for each class of methods used to improve damage detection in the EMI-SHM.

Method class	References
Improvement of instrumentation and hardware	[1], [15-20]
ML techniques	[21-36]
Numerical or analytical methods	[37-43]
Optimization techniques	[44-45]
Statistical techniques	[46-64]

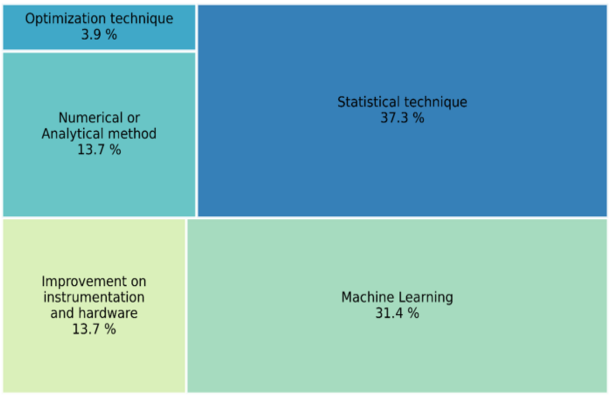

Fig. 4. Classes of methods employed to enhance damage detection in the context of EMI-SHM.

Statistical techniques and other data-driven methods often do not require prior data on the monitored structure. This flexibility offers a key advantage in industrial-scale applications, making them well-suited for these conditions, where system information is limited or unavailable. Needing or previous information on the monitoring structure is critical for large-scale monitoring systems, where structural conditions and behaviors cannot be fully anticipated in advance.

Another aspect investigated was the research's focus on the overall EMI-SHM system. This system includes the data collection system, the electromechanical impedance (EMI) theoretical model implemented in the software to acquire the signatures, and techniques for processing the collected data, which aim to detect damage [14], [65-67]. Sometimes, indexes are used to reveal the occurrence of damage. Also, there are techniques to compensate for temperature effects that occur in real-life situations.

From this basis, the works studied were classified into five classes based on their emphasis on the overall EMI-SHM system: (1) development of damage indicators, (2) improvement of the EMI model, (3) instrumentation and hardware focus, (4) signal processing for damage detection, and (5) development of temperature compensation approaches. Tab. 2 shows the list of the studies with their respective class.

Table 2. List of studies regarding the research emphasis on the improvement of damage detection in the context of the EMI-SHM.

Method class	References
Damage indicator	[41], [43], [49], [52], [53], [57], [60]
Electromechanical impedance (EMI) model	[38], [39], [40], [42].
Instrumentation and hardware	[1], [15-20].
Signal processing for damage detection	[21-24], [27-34], [36], [44-48], [50-51], [54-56], [59], [61]
Temperature compensation	[25-26], [35], [37], [58], [62-64]

The analysis of the classes (Fig. 5) reveals a significant emphasis on signal processing techniques to enhance damage detection, which accounted for 49.0 % of the total number of papers evaluated. This was followed by a focus on temperature compensation techniques, explored in 15.7 % of the total, and the development of damage indicators, instrumentation, and hardware, each accounting for 13.7 %.

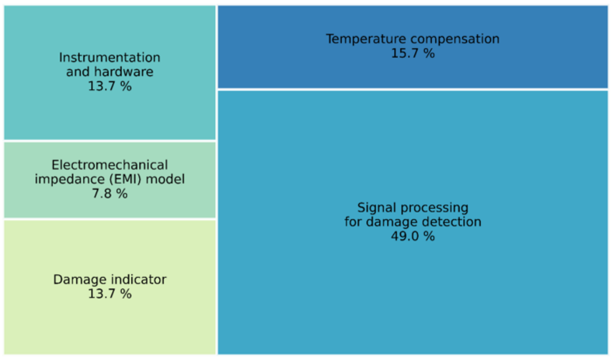

Fig. 5. Distribution of the research focuses to improve damage detection in the EMI-SHM.

Looking deeper into the relationship between the developed methods and the research focus (Fig. 6), it is possible to delineate the application of each method in each part of the EMI-SHM system.

Fig. 6 shows that ML methods were the most used for signal processing (25.5 %), followed by statistical techniques (19.6 %). Optimization techniques were used in only 3.9 % of the papers analyzed.

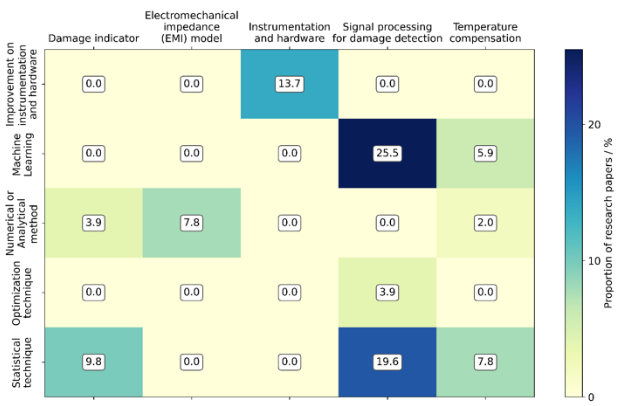

Fig. 6. Heatmap relating the classes of methods (y-axis) and the focusing of the researches (x-axis) applied to improve the damage detection in the context of the EMI-SHM.

Within the domain of machine learning (ML) techniques applied to damage detection, Convolutional Neural Networks (CNN) have emerged as a predominant choice, featured in 62.5 % of the selected works employing ML methodologies. Noteworthy mentions of CNN employment include studies by Rezende et al. [22], Alazzawi and Wang [23-24], Ai et al. [27], Le et al. [28], Nguyen et al. [30], Ai and Cheng [31], Ai and Zhang [32], Ai et al. [33], Du et al. [34-35], and Rezende et al. [36].

Beyond CNN, diverse ML approaches have been explored within the selected literature. Alazzawi and Wang investigated the utilization of a Deep Residual Network (DRN) [23] and a two-layer-based CNN algorithm [24]. At the same time, Du et al. delved into the realm of few-shot learning [34] and developed a multi-task CNN approach for damage detection [35]. Freitas et al. [25] contributed to the discourse by applying an adaptive neuro-fuzzy inference system, and Meher et al. [29] explored the efficacy of a feed-forward backpropagation neural network. Additionally, Perera et al. [21] introduced k-means (KM) clustering as a methodological tool, and Silva et al. [26] provided insights into Transfer Learning Analysis (TCA) as a viable option for damage detection tasks.

The primary advantage of CNN-based frameworks is their ability to discern subtle alterations in EMI spectra without requiring a pre-processing step. Utilization of CNNs for damage detection has yielded encouraging outcomes. Du et al. [35] demonstrated a high generalization ability using a CNN-based framework, with an average accuracy of 93.21 %. Alazzawi and Wang [24] put forth a CCN-structured framework for the detection of various types of damage, attaining a test accuracy of 100 %.

Despite the advantages of the CNN in damage detection tasks, DRN-based workflows have emerged to overcome some limitations of the CNN methods. The DRN method offers a more expeditious training process, facilitates easier gradient transmission, and enables constructing a deeper neural network with reduced gradient vanishing [23]. The deployment of this approach has yielded remarkable outcomes, attaining a test accuracy of 100 % [23]. This performance not only surpasses the capabilities of the CNN but also exceeds those of the Deep Auto-Encoder (DAE) and the Long-Short Term Memory (LSTM) methods.

Nevertheless, the necessity for a substantial quantity of training data regarding the system under observation can present obstacles to implementing these methods in real-scale conditions. This is because the information required for these methods is often not readily available in practical situations.

Alternative methods, such as few-shot learning, which require fewer input data than CNN methods, can be investigated in greater depth to address this issue. Its application has demonstrated high recognition ability, with an average accuracy of 97.63 % [34]. Moreover, utilizing transfer learning methodologies can circumvent this limitation and represent a subject worthy of further detailed investigation.

Statistical techniques, the most used of all the methods surveyed, were used most often to process signals in the damage detection process (19.6 %), develop damage indicators (9.8 %), and then in the research about temperature compensation techniques (7.8 %).

Numerical or analytical methods were mainly used to improve the theoretical model of electromechanical coupling, accounting for 7.8 % of the total. The other applications were poorly explored. Numerical or analytical methods applied to developing damage indicators accounted for 3.9 %, and only 2.0 % were used to research temperature compensation approaches.

The nature of these methods means that they are used more in formulating mathematical models. Despite their other applications, this can explain their higher use in improving the electromechanical coupling model.

Temperature is an essential issue in EMI-SHM systems because it affects the impedance or admittance measurements. In this sense, the development of temperature compensation techniques is critical to achieving reliable results and reducing false positive alarms [68-76].

Regarding the improvement of temperature compensation techniques, Fig. 6 shows that the most used techniques were the statistical methods (7.8 %), followed by the ML techniques with 5.9 %. Only 2.0 % was attributed to the numerical or analytical methods.

When evaluating the temperature range considered in each study (Fig. 7), it was found that most studies did not consider temperature variation, accounting for 52.9 % of the total analyzed. 21.6 % of the studies provided no information on temperature, and only 25.5 % considered temperature variations, which simulated more realistic conditions.

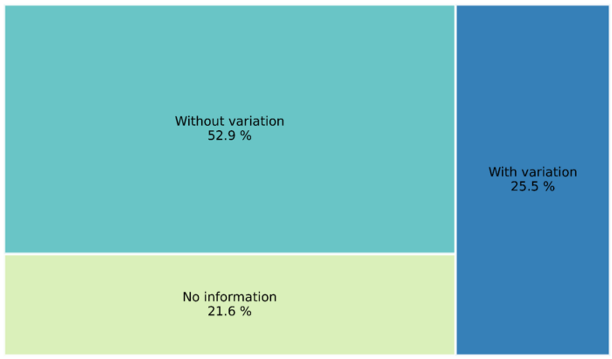

Fig. 7. Emphasis on temperature range considerations in the reviewed studies.

According to the results, there is a lack of investigations considering temperature variations. Developing techniques that include temperature compensation steps and damage detection is crucial to achieving a more robust system and bringing it closer to industrial applications. It can also provide more insight into the effects of temperature on measurements.

Another aspect examined was the type of material used in the studies. Fig. 8 shows the number of times each material was used in all the papers. Aluminum was the most used material in the experiments, appearing 23 times, followed by steel (20 times) and composites (9 times). Concrete was used eight times, and Acrylonitrile Butadiene Styrene (ABS), a thermoplastic polymer, appeared in only one work.

Regarding the composites, only the use of Carbon Fiber Reinforced Polymer (CFRP) and Glass Fiber Reinforced Polymer (GRFP) was noted. The former was used by Castro et al. [47], Castro et al. [48], Perera et al. [21], Zhu et al. [38], and Soman et al. [41], and the latter by Soman et al. [41], Singh et al. [53], Malinowski et al. [55], Singh et al. [59] and Kim and Na [19].

An evaluation of the damage types used in the research papers (Fig. 9) shows that the simulation of damage by mass addition was the most frequently used, occurring 12 times. Drilling was used 11 times, and cracking was used ten times. The other types accounted for only a fraction of the total.

The type of damage investigated often reflects the nature of the research, with specific damages such as mass addition and drilling being most common in laboratory-scale studies.

A high prevalence of these damage types suggests that a significant proportion of research has been conducted under laboratory conditions.

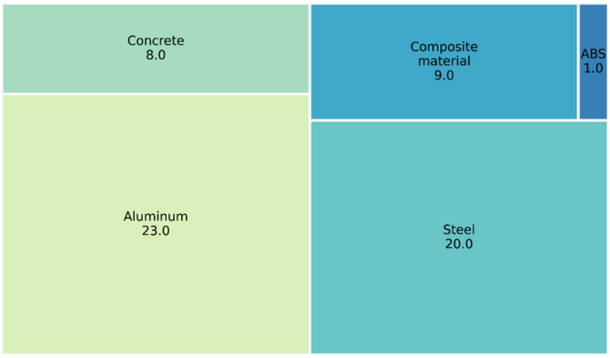

Fig. 8. Distribution of material utilization in the reviewed papers, indicating the absolute frequency of each material's application.

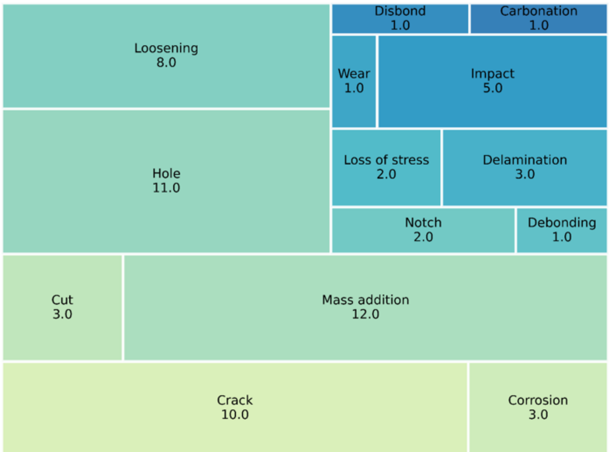

Fig. 9. Distribution of the damage types investigated in the reviewed studies, highlighting the absolute frequency of each one.

A thorough examination of the studies confirmed that all were conducted in laboratory settings without accounting for industrial-scale conditions. This highlights the need for further research utilizing EMI-SHM systems under such conditions to reflect practical applications better.

In addition to the types of structural failures, some researchers have investigated how to improve sensor failure detection and differentiate them from structural damage, as seen in Huynh et al. [40], Jiang et al. [54], and Le et al. [28]. In these works, the sensor failures most investigated were pseudo-soldering, wear, breakage, and debonding. Additionally, these aspects related to the shear-lag phenomenon were explored by Huynh et al. [40].

Detecting sensor damage is essential in real-world EMI-SHM applications, as sensors are exposed to environmental conditions that can cause sensor failure. In this sense, it is necessary to distinguish these from structural damage to avoid false alarms and implement a reliable maintenance program. Given the importance of this aspect on EMI-SHM practical applications, recent findings on this realm are discussed in the next section.

An essential inquiry pertinent to industrial applications employing EMI-SHM pertains to establishing a robust framework capable of furnishing dependable data to inform decision-making processes. In this context, an assessment was conducted to ascertain whether the studies were conducted under industrial conditions. The analysis revealed that all investigations were predominantly experimental. This observation underscores a distinct need for research endeavors focusing on damage detection within industrial environments, which aligns with the findings from Na and Baek [77].

The investigation under actual conditions, wherein structures are inherently exposed to diverse environmental factors, including but not limited to ultraviolet (UV) radiation and thermal cycling induced by heating and cooling processes, can provide information to evolve the EMI-SHM systems to an industrial-scale application.

The evaluation of the works' nature revealed that 27.5 % of the total presented a structural model of the monitored structure. The majority of these models (21.6 %) were generated using the Finite Element Method (FEM), as seen in Adhikari and Bhalla [15], Antunes et al. [37], Fan et al. [44], Fan and Li [51], Hamzeloo et al. [39], Zhang et al. [45], Ai et al. [57], Baral et al. [62], Djemana et al. [58], Le et al. [28], and Wang et al. [61]. Other models were obtained using numerical or analytical methods, as described by Kim and Wang [16] and Huynh et al. [40].

In the realm of structural modeling methodologies, some research [78], [79], [80], [81], [82], [83], [84] has incorporated the Spectral Element Method (SEM) instead of the FEM. SEM has demonstrated superior performance, particularly in scenarios involving electromechanical coupling, owing to its necessity for accurately accommodating exceedingly short wavelengths within the model to replicate the complexities of electromechanical interactions. Therefore, SEM could be considered for structural modeling in EMI-SHM.

Practical Aspects of EMI-SHM Implementation

This section addresses critical challenges in damage detection for real-scale monitoring, focusing on two main aspects: (1) the impact of temperature variations on impedance measurements and recent methods to mitigate these effects, and (2) approaches developed to distinguish between structural damage and sensor failures.

The influence of each variable on the EMI-SHM system is examined in the context of industrial applications. This highlights critical issues in real-world monitoring and proposes research directions to enhance the functionality and reliability of EMI-SHM systems.

On temperature-induced effects and compensation techniques

Impedance measurements are highly temperature-dependent, necessitating proper correction to prevent false structural damage diagnoses, as temperature impacts peak frequency and magnitude [34], [64]. Studies indicate that temperature variations cause a primarily linear frequency shift and vertical shifts in peak magnitude, particularly in resonant peaks, which may exhibit quadratic or cubic behavior. These shifts are also frequency-dependent, becoming more pronounced at higher frequencies [37], [62], [85], [86], [87], [88].

This pattern has been employed in formulating compensation techniques based on the adjustment of shifts by a reference thermal state. Approaches structured on the concept of Effective Frequency Shift (EFS) [63], [64], [87], [89] identify the necessary frequency shift to achieve the maximum cross-correlation coefficient (CC) between the actual and reference impedance data. Building on the analysis of the similarity between impedance signatures, other classes of CC-based frameworks were also proposed [58], [90].

The shifts have also been corrected by shifting the impedance curve in the opposite direction of the temperature-induced shifts [91] or directly correcting the horizontal and vertical shifts independently in sequential steps [92].

Through a detailed analysis of the temperature-induced changes in the impedance signatures, Baral et al. [62] developed compensation equations for horizontal and vertical shifts derived from linear regression analysis. Furthermore, Antunes et al. [37] investigated the linear relationship between the variables and employed a linear interpolation approach to execute the temperature compensation.

Additionally, models based on polynomial interpolation [85], [93] have been proposed, with the relationship between temperature and EMI signals serving as the foundation for these models.

Temperature compensation models that directly adjust signals to mitigate temperature-induced changes typically rely on a reference state for effective performance [34], [37], [91], [94]. Recent advancements have introduced alternative solutions to address the limitations of these approaches.

Statistical methods have played a significant role in these developments, including (1) the Akaike Information Criterion (AIC), which, through feature extraction, has proven effective in identifying and isolating temperature-induced variations in signals [46]; (2) a combined framework employing Dickey-Fuller and Johansen tests, which distinguishes structural damage from temperature effects in time series data [50]; (3) the development of a Hurst exponent-based damage index, robust against horizontal and vertical shifts in impedance signals [60]; and (4) the use of fiber Bragg grating (FBG) sensors and Linear Mixed Models (LMM) for direct temperature compensation without the need for external reference patterns [94].

Machine learning (ML) techniques have further expanded the range of methodologies. Du et al. [35] proposed a CNN framework incorporating a temperature compensation subnetwork based on a modified 1-D U-Net architecture, demonstrating high recognition accuracy and strong generalization capabilities. In the context of domain transfer, Silva et al. [26] applied a TCA-based workflow that initializes with a baseline condition (source domain) and transfers knowledge to an unknown condition (target domain).

Additionally, a database of temperature and frequency was used as input for an Adaptive Neuro-Fuzzy Inference System (ANFIS) to develop fuzzy rule-based systems (FRBS). The framework proposed by Freitas et al. [25] generated output impedance signatures corresponding to baseline states, with predicted signatures closely aligning with actual measurements.

Despite advances in compensation techniques, some researchers are exploring ML-based frameworks as an alternative to bypass this process. A pivotal criticism of traditional compensation methods is their failure to account for changes in the shape of the EMI curve [34].

In this context, Du et al. [34] proposed a few-shot learning approach based on a modified prototype network enhanced specifically to process EMI data. Similarly, Rezende et al. [22], [36] introduced a workflow centered on a CNN model capable of bypassing temperature compensation. Leveraging deep learning models' ability to capture subtle signal variations, the proposed frameworks eliminate the need to process temperature effects.

Based on the studies analyzed, recent research in EMI-SHM systems highlights three main approaches for addressing temperature effects: signal-shift-based, statistical-based, and ML-based methods. Signal-shift-based approaches rely on prior databases of impedance signatures and corresponding temperature data, while ML-based models for temperature compensation often require large datasets to achieve reliable results. This challenges practical applications, where such data may be difficult or impractical. In ML frameworks, transfer learning has emerged as a potential solution, reducing the need for extensive data.

Statistical-based methods have proven effective in distinguishing between temperature-induced variations and structural changes in EMI data, making them attractive for real-world applications. However, most approaches have not accounted for multiple damages, highlighting the need for further research to evaluate their performance under such conditions.

Recent advances in sensor reliability

Differentiating sensor failure from structural damage represents a critical challenge within real-scale EMI-SHM systems. Misinterpreting these two phenomena can result in false positives, necessitating comprehensive research to elucidate their behavior under sensor failure conditions.

In pursuit of elucidating the behavior of EMI-SHM systems under sensor failure conditions, Huynh et al. [40], in investigations on the shear-lag effect, sensor breakage, and debonding, concluded that the defect on sensors affects the signatures in different manners. Specifically, it was found that sensor defects affect both resonant and non-resonant frequency bands, whereas structural damages primarily influence resonant frequency bands.

Moreover, sensor debonding causes decreased resonance magnitudes and steeper slopes in the susceptance signatures, whereas sensor breakage induces upward shifts in the resistance patterns and decreased slopes in the susceptance [40]. These findings elucidate that the imaginary admittance and impedance slope are practical diagnostic markers for identifying sensor faults.

In addition to these diagnostic markers, alterations in the magnitude of the resonant conductance peak [95], shifts in the peak frequency of real admittance [95], [96], and variations in the magnitude of the resonant real impedance peak [97] have been identified as reliable indicators for the detection of sensor failures.

Consequently, meticulous analysis of the real and imaginary components of the impedance (or admittance) signatures can yield crucial insights into identifying and differentiating sensor failures from structural damages.

Identifying key features plays a pivotal role in sensor fault detection and can be achieved through integrated frameworks that leverage a combination of techniques and methodologies. In this context, the synergistic application of Principal Component Analysis (PCA) to extract primary features, coupled with a k-Nearest Neighbor (k-NN)-based classifier – a supervised learning technique – has demonstrated formidable efficacy, achieving a recognition accuracy of 100 % in identifying several types of mechanical failures in PZT patches [98].

A similar approach by Jiang et al. [99] employed PCA to extract principal components (PCs) representing critical characteristics of the admittance spectrum. These were then used in a KM algorithm, an unsupervised ML technique, to cluster different sensor faults. An Artificial Neural Network (ANN) model trained by these features could discern the degrees of sensor damage with an accuracy of 100 %. Furthermore, the combination of PCA with the Library for Support Vector Machines (LibSVM) achieved a fault recognition accuracy of 97.5% [54].

These studies underscore the efficacy of integrating fundamental feature extraction techniques with ML classifiers for the reliable detection and differentiation of multiple types of sensor faults. However, as observed, these approaches require a pre-processing step before the classification task.

Techniques capable of automatically selecting key features can eliminate this pre-processing step. In this regard, CNN-based models have demonstrated the ability to distinguish between different types of sensor damage, even in the presence of noise, relying solely on raw data inputs [100].

Current state-of-the-art research on sensor fault detection has predominantly focused on mechanical defects, overlooking critical electrical faults such as weld breakage and electrical cable rupture. However, including electrical defects is essential for comprehensively analyzing real-world EMI-SHM systems. These defects can be incorporated into the pre-processing step by monitoring the electrical current passing through the PZT patches. Significant reductions in current to zero, or current saturation, may serve as critical indicators of underlying electrical issues, providing valuable diagnostic insights that complement mechanical fault detection.

Moreover, the analyzed studies show a significant gap in sensor damage detection research, which largely neglects the impact of temperature variations. As this parameter affects the impedance (or admittance) measurements, developing strategies to identify sensor faults under temperature variations is critical for implementing real-scale EMI-SHM systems.

Addressing challenges in industrial-scale EMI-SHM systems

The analysis conducted in this study revealed several key insights: (1) EMI-SHM research has predominantly focused on laboratory-scale conditions, often neglecting the complexities of industrial-scale environments, and (2) current damage detection studies have not integrated sensor failure detection with temperature compensation strategies.

The primary execution of research in laboratory-scale conditions can be due to confidentiality agreements in collaborations with industry partners. In such cases, the outcomes may be protected as patents.

In this context, Gallo et al. [101] proposed a system that captures the resistive component of the electrical impedance from PZT patches to enable real-time monitoring of aircraft components. The system compares real-time data with baseline measurements and issues alerts upon detecting damage, accounting for the compensation for environmental effects.

Focusing on monitoring industrial tanks in the oil industry, Gallo et al. [102] developed an EMI-based system comprising subroutines for data acquisition, data processing, interpretation, and visualization of the results, and a wireless communication system. The industrial solution can detect damages in fuel tanks and monitor reinforcement beams and the tank's roof support system.

The lack of investigation under real-world conditions underscores the urgent need for research to develop EMI-SHM systems suitable for industrial applications. Establishing strategies for sensor failure detection and temperature compensation is essential for advancing operational, real-world-adapted EMI-SHM systems.

However, developing such systems presents significant challenges. The framework must incorporate techniques and methods that are interoperable, ensuring that information generated by one method is seamlessly usable in subsequent stages. The system must effectively manage temperature variations, detect sensor failures, and provide reliable data for downstream processes such as damage localization. Addressing these challenges requires a workflow that ensures both accuracy and trustworthiness in damage diagnosis. Additionally, the necessary infrastructure may demand substantial investment, emphasizing the need for close collaboration between industry and research institutions.

To address these challenges in industrial-scale EMI-SHM systems, a comprehensive workflow could include the following sequential steps: pre-processing and removal of anomalous signatures for each PZT patch, temperature compensation, sensor failure detection, structural damage detection, and then damage localization. Future research should focus on developing reliable techniques capable of processing information at each step, ensuring robustness and accuracy throughout the system.

4. Concluding Remarks

The presented work provides an overview of the current research status on enhancing damage detection through systematic analysis. By examining the selected works, it was possible to investigate various facets of the research stage, including the methods used for damage detection, the focus of the research studies, temperature variations, materials used, types of damages considered, and the general nature of the research, whether experimental or industrial-scale. Following a rigorous analysis of these dimensions, the ensuing conclusions have been delineated:

- The majority of methods used to improve damage detection were data-driven, accounting for 62.7 % of the total analyzed. This makes them the most investigated approach for addressing damage detection issues. Additionally, there has been a recent trend in using data-driven and ML techniques to improve damage detection. Data-driven techniques are an exciting option for industrial applications as they only require input data to provide results without requiring previous or specific model training for each structure. Therefore, future research focusing on industrial-scale applications could consider these techniques due to their flexibility.
- Statistical and ML techniques were the most used in damage detection. Statistical methods were used for signal processing to detect damages, formulate damage indicators, and develop temperature compensation strategies. The latter was applied as a signal processing approach to detect damages, as some ML techniques can select the best features to analyze automatically, do not require a pre-processing step, and compensate for the temperature effect by learning the relations between the impedance signatures and the temperature levels at each structural condition.
- The necessity for a substantial quantity of data in ML-based methodologies may prove to be a limitation in industrial-scale implementation, given the typical constraints on the availability of information in such settings. To address this challenge, future research should prioritize investigations into few-shot learning and transfer

learning approaches, which may offer enhanced suitability for industrial-scale deployment.

- Regarding the temperature range used in the studies, only 25.5 % have considered variations in the temperature conditions. This shows a lack of investigations considering temperature variations, making the research more closely related to real-life conditions. It is, therefore, incumbent upon future investigations to diligently incorporate considerations of temperature variations, particularly when developing industrial-scale monitoring systems.
- Incorporating considerations regarding temperature, a mere 15.7 % were dedicated to advancing temperature compensation methodologies. The lack of research inquiries into this realm is notably conspicuous, given the profound impact of temperature fluctuations on impedance measurements. This gap becomes particularly pronounced when contemplating deploying industrial-scale electromechanical impedance systems.
- All of the studies investigated exclusively comprised experimental inquiries and did not encompass investigations at an industrial scale. Consequently, a conspicuous deficit in industrial-scale research is apparent. Therefore, future research targeting industrial applications will contribute to developing accurate, efficient, and trustworthy EMI-SHM systems.
- Research on sensor failure detection has not encompassed temperature variation, leading to a gap in investigations addressing sensor reliability alongside temperature compensation. Future studies on distinguishing sensor failures from structural damage must integrate temperature compensation techniques. Developing such frameworks is crucial for establishing reliable EMI-SHM systems suitable for industrial-scale applications.

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