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STRUCTURAL HEALTH MONITORING USING SMART MATERIALS AND SENSOR TECHNOLOGIES IN MECHANICAL ENGINEERING

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Abstract

Structural Health Monitoring (SHM) has emerged as a critical discipline in mechanical engineering for ensuring the safety, reliability, and optimal performance of structural systems throughout their service life. This study investigates the integration of smart materials and advanced sensor technologies as a transformative approach to real-time assessment and predictive maintenance of mechanical structures. Smart materials—such as piezoelectric ceramics, shape memory alloys, and fiber Bragg grating (FBG) sensors—enable the conversion of mechanical responses into measurable electrical signals, facilitating continuous and non- intrusive monitoring. The research analyses key sensing mechanisms, signal processing techniques, and data-driven diagnostic algorithms that enhance the detection of damage, stress variations, fatigue accumulation, and material degradation. Special emphasis is placed on the interoperability of wireless sensor networks and embedded systems, which significantly improve scalability and long-term deployment in harsh operational environments. Through a comprehensive review of recent advancements and experimental implementations, the study highlights how smart-material-based SHM systems contribute to improved failure prediction, reduced maintenance cost, and extended structural lifespan. The findings underscore the growing relevance of intelligent monitoring frameworks in aerospace, automotive, civil-mechanical hybrid structures, and high-performance machinery. This paper concludes that the synergy between smart materials and next-generation sensor technologies represents a pivotal advancement toward resilient, self-diagnosing mechanical systems aligned with Industry 4.0 and future autonomous engineering infrastructures.

Keywords: *Structural Health Monitoring (SHM); Smart Materials; Sensor Technologies; Predictive Maintenance; Mechanical Engineering Applications*

1. Introduction

Structural Health Monitoring (SHM) is a new important and fast developing field in mechanical engineering that has developed out of the necessity to provide the safety, reliability and viability of engineering structures that are used under an increasing number of demanding conditions. Mechanical systems that are exposed to complex loading, rough environmental conditions, and extended service life include the aerospace component, automotive structure, rotating machines, and industrial equipment as examples. SHM offers a framework approach to measuring the health of such structures through the combination of sensing technologies, data acquisition systems and analysis processes to identify damage, measure the structural performance, and help make informed maintenance and operational decisions. This has led to SHM being a critical component of contemporary engineering practice especially in high- value, safety-critical, and mission-critical applications.

Traditional methods of inspection and maintenance in mechanical engineering are largely founded on scheduled inspection, visual inspection, and non-destructive testing that is performed off-line. Although these methods have become common, they are mostly constrained when it comes to the detection of defects in the subsurface, early-stage damage or progressive degradation that could exist between inspection periods. Furthermore, periodic inspections may be time consuming, labour intensive and economically inefficient particularly where complex or inaccessible structures are concerned. These constraints have facilitated the shift to real-time and continuous monitoring approaches that could give early warning signs on structural degradation. The addition of sophisticated data analytics and artificial intelligence has also provided better SHM functionality through automated disappointments recognition, pattern identification, and decision-making, which has contributed to system independence and accuracy in diagnosing (Spencer Jr et al., 2025).

The wave-based techniques are one of the other techniques of SHM that have received a lot of attention because of their high sensitivity to minute defects and their capability to probe large structural regions with a small number of sensors. SHM methods based on guided ultrasonic waves are especially useful in crack, delamination, and corrosion detection in the complex- shaped mechanical components. These techniques are based on the interaction of propagating waves and structural discontinuities, and the fact that they make it possible to detect and localize damage by not having to cover the entire field with sensors. Combined with modern signal processing and machine learning technologies, guided ultrasonic wave-based methods have greater robustness and flexibility in practice with SHM (Yang et al., 2023). Nevertheless, the successful implementation of them requires sound sensing hardware and effective data management frameworks.

The speed at which sensor network technologies have been developed has been vital in increasing the scope of SHM to large-scale and distributed mechanical systems. The wireless sensor networks has become an appealing alternative compared to the traditional wired ones because of its better flexibility, lower installation complexity, and scalability. These benefits render wireless SHM systems especially appropriate in long-term observation of sophisticated mechanical assemblies and infrastructure systems, where a lot of cabling can be unrealistic or uneconomical. Moreover, wireless communications allow transmitting data remotely and in real time and contribute to proactive maintenance approaches (Yu et al., 2024). Irrespective of such advantages, wireless SHM systems still face a serious issue of energy that is largely required during the continuous and long-term monitoring.

Self-powered and energy-harvesting sensors have been proposed as a solution to the problem of power supply in order to make SHM deployment sustainable. The sensors also tap energy present in the surroundings like vibrations, thermal, or electromagnetic fields, thus, minimizing on the external systems and regular replacement of batteries. The approach to self-powered sensing technologies can make autonomous SHM systems much more practical, especially in inaccessible or hostile operating environments. They are highly appealing in the use of long- term structural monitoring systems because their adoption has helped to enhance better system reliability and low maintenance (Salehi et al., 2021).

Simultaneously with energy-harvesting solutions, the incorporation of embedded sensors into mechanical structures has enabled the creation of small, strong and very dependable SHM systems. The direct connection of the sensor to the host structure offered by embedded sensing enhances the accuracy of measurements and minimizes signal degradation due to external bonding. It is also compatible with real-time data capture and the smooth communication of sensing devices with data processing units, which results in improved system-level performance and longevity (Ferreira et al., 2022).

Smart materials have become an innovative element of the contemporary SHM systems since they allow structures to monitor the surrounding environment, react, and adapt to the changes. Piezoelectric ceramics and shape memory alloys are examples of materials with a built-in sensing and actuation capability, meaning that they can be used as structural components and at the same time as a sensor. Such multifunctional features make it possible to create self- sensing and self-diagnosing structures, which can track the presence of damage and performance without the use of external sensors. Large-scale studies have shown how smart and self-sensing materials can be useful in refining damage detection sensitivity and increasing the system intelligibility in a broad application in engineering practices (Vasconcelos et al., 2024). Techniques based on piezoelectric impedance have been widely studied in the context of multi-sensing applications since they are very sensitive to the localized structural changes and can be used in compact SHM applications (Parida and Moharana, 2023).

Besides smart materials, optical sensing technologies have also gained prominence in SHM because they have better accuracy of measurements and strong capabilities in extreme environment. FBG sensors are very common in strain monitoring, temperature monitoring, as well as damage monitoring due to their large resolution, insensitivity to electromagnetic effects, and the ability to be distributed to a wide area of interest. The mentioned properties render FBG sensors particularly useful when it comes to the monitoring of mechanical structures that experience either a severe environment or an electromagnetically noisy one. They have been proven to have a broad spectrum of SHM application and are considered a competitive substitute to the traditional sensing technologies due to their performance and versatility (Yassin et al., 2024). Comparative analyses have also brought out the merits of FBG sensors in the area of durability, multiplexing potential, and stability over the long term in comparison to other sensing methods (Alhussein et al., 2025).

More recently, the notion of digital twins has become a dominant paradigm of SHM as it allows blending physical structures with high-fidelity virtual models in real-time. SHM frameworks based on digital twins can be used to enable sustained synchronization between measured data and numerical simulations, which facilitates the advanced diagnostics, damage prognosis and predictive maintenance. Through the integration of sensing and computational models and analytics on data, digital twins can aid in making improved decisions and managing the lifecycle of mechanical systems. The given approach is very much in line with Industry 4.0 concepts and smart manufacturing programs, which emphasizes where intelligent and autonomous SHM systems are going (Wang et al., 2025).

This review paper aims to give an overview of the structural health monitoring in the field of mechanical engineering, and especially in the area of smart materials and sensor technologies. The paper presents the core concept of SHM systematically, surveys major smart materials and sensing technologies, describes the ways of data collection and smart algorithms of analysis, and points out to the new developments and research perspectives. This review is expected to introduce some valuable information to the research and practice community by integrating emerging trends and uncovering the existing challenges to help researchers and practitioners advance the design and implementation of next-generation SHM systems.

2. Fundamentals of Structural Health Monitoring

Structural Health Monitoring (SHM) is an organization method of assessing the health of the engineering construction by combining sensing technologies, data collection systems and analytical methods. The main idea of SHM is to detect the structural damage at a prior stage, evaluate it, and provide the knowledgeable decisions about the maintenance, repair and operational safety. SHM provides the ability to carry out continuous or near real-time analysis of the structural performance compared to the traditional forms of inspection that depend on periodic and in most cases, subjective assessments, thus making structure much safer, more reliable and in terms of life cycle management. The modern SHM systems are usually classified according to sensing methodologies, data transmission plans, and analytics designs that include local and global monitoring systems and passive and active sensing designs (Mardanshahi et al., 2025).

The use of a hierarchical system of levels of damage assessment is commonly used to describe the functional capabilities of SHM systems. The initial level is where damage detection is involved to establish whether there is damage or not. The second level is the damage localization which involves the spatial location of the damage in the structure. The third tier deals with the level of damage assessment, which is a measurement of the degree of deterioration. The last and most sophisticated level is the damage prognosis which is designed to forecast the future of the structure and to estimate the remaining useful life of the structure. The improvement of SHM levels needs complex sensing technologies, efficient modeling methods, and efficient data interpretation methods. Recent reports point to a substantial role of smart materials and intelligent sense systems in the development of increased sensitivity, flexibility, and diagnostic precision, which will lead to the implementation of superior SHM capabilities (Sundravel et al., 2025).

Although significant improvements have been made, a number of challenges still pose a challenge to the widespread application of SHM to mechanical structures. Mechanical systems have the disadvantage of working under variable loading conditions and harsh conditions, where temperature changes, humidity conditions and operating noise may affect sensor performance and data quality. Also, mechanical components are complicated by their complex geometry and dynamic behavior that makes characterization and interpretation of the damage complex. The problem of data uncertainty, sensor degradation and long-term system reliability is also a concern especially when it comes to large scale and long term monitoring. The growing bulk of information created by the systems of modern SHM also provides difficulties of storing, processing, and interpreting data in a meaningful way. To overcome these constraints, it is important to design smart sensors, adaptive algorithms, and smart strategy of managing assets (Preethichandra et al., 2023).

The basic architecture of a SHM comprises four main parts which include sensing, data acquisition, data processing and decision-making. The image shown in Figure 1 represents the schematic of the smart material based structural health monitoring system, including the interaction between sensors, data acquisition and decision-making modules.

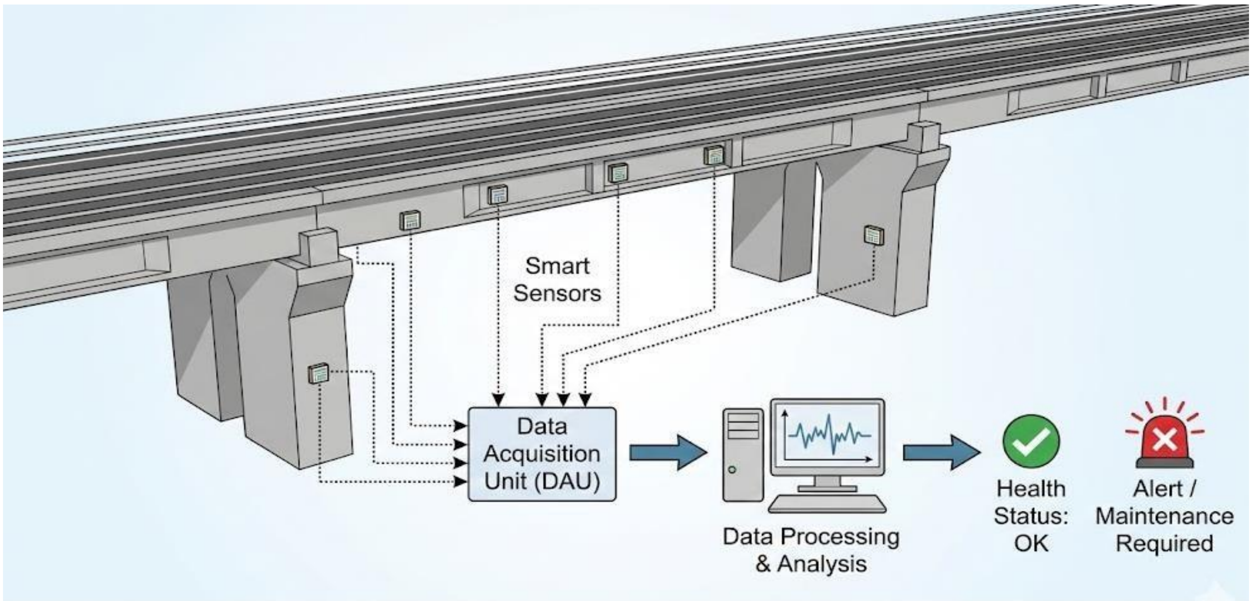

Figure 1. Schematic architecture of a smart material-based structural health monitoring (SHM) system showing sensing, data acquisition, processing, and decision- making

Structural health monitoring systems can be broadly classified based on their sensing and damage assessment approaches, as summarized in Table 1.

Table 1: Classification of Structural Health Monitoring (SHM) Systems

SHM Category	Monitoring Approach	Damage Detection Capability	Typical Applications	Key Advantages	Limitations
Passive SHM	Response monitoring only	Global damage detection	Bridges, machinery	Simple implementation	Low localization accuracy
Active SHM	Actuation + sensing	Local and global damage	Aerospace, composites	High sensitivity	Higher complexity
Hybrid SHM	Passive + active	Multi-level damage assessment	Complex structures	Balanced performance	Increased cost
Local SHM	Component- level sensing	Crack initiation	Joints, bearings	High precision	Limited coverage
Global SHM	Whole-structure response	Overall degradation	Large structures	Wide-area monitoring	Low damage resolution

The sensing layer consists of sensors, which can be piezoelectric, optical and smart material- based sensors, that detect structural response as associated with strain, vibration, temperature or wave propagation. Data acquisition layer takes care of signal conditioning, digitization and transmission, and usually includes wireless communication to make it more scalable and flexible to deployment. The data processing layer addresses feature extraction, signal analysis and pattern recognition and the decision-making layer combines the processed information with diagnostic or prognostic models to facilitate the maintenance planning. SHM technologies have also been enhanced through sensing technologies, which have significantly increased the strength and precision of the SHM architecture of a complex and large-scale structure (Kang et al., 2025).

Sensing systems based on optical fiber have gained a foothold in SHM practices of today because these are very sensitive, not affected by electromagnetic interference and can be utilized in distributed monitoring. These systems would make it possible to detect and predict the damage automatically when coupled with artificial intelligence to facilitate the creation of autonomous and resilient SHM solutions. Optical sensing technologies, smart materials, and intelligent algorithms convergence is one of the main developments in SHM system design to be applied in both mechanical and civil infrastructure (Golovastikov et al., 2025).

3. Smart Materials for Structural Health Monitoring

The use of smart materials is important in the development of structural health monitoring (SHM) which allows structures to have inherent sensing, actuation and adaptive capabilities. Smart materials can be integrated directly into mechanical structures unlike traditional externally mounted sensors, which allows tracking of structural response and environmental changes in general. The comparative illustration of key smart materials in structural health monitoring in the figure 2 indicates their sensing and actuation methods.

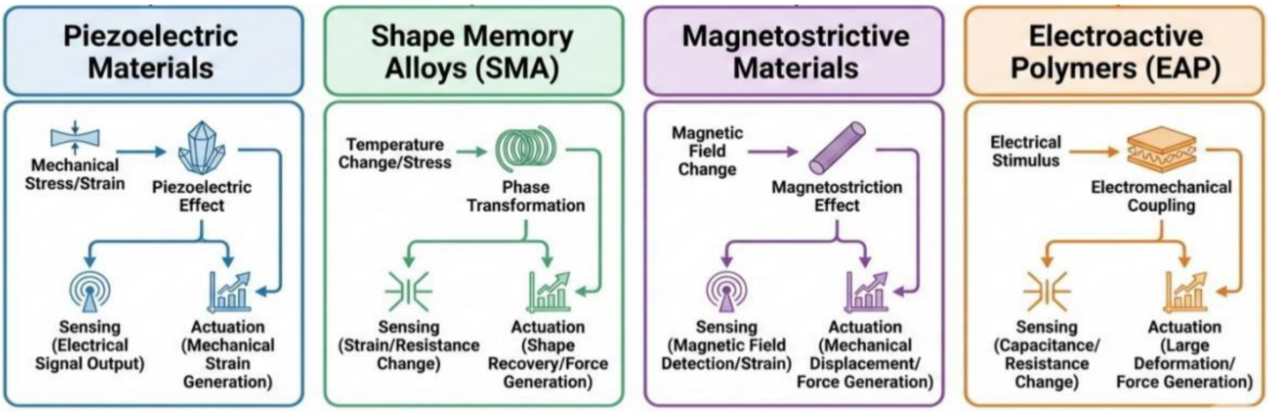

Figure 2. Sensing and actuation mechanisms of smart materials commonly used in structural health monitoring applications

A comparative overview of smart materials employed in SHM is provided in Table 2.

Table 2. Comparison of smart materials commonly used in structural health monitoring applications

Smart Material	Sensing Mechanism	Sensitivity	Durability	Typical SHM Applications
Piezoelectric materials	Electromechanical coupling	High	Moderate	Guided waves, impedance-based SHM
Shape memory alloys	Phase transformation	Moderate	High	Vibration control, self-healing
Magnetostrictive materials	Magneto-mechanical effect	High	High	Long-range guided-wave SHM
Electroactive polymers	Electric-field- induced strain	Moderate	Moderate	Flexible and soft structures

Their multifunctional performance contributes to the design of self-sensing and self-diagnosing systems, which is beneficial towards the enhancement of sensitivity in detecting damage, system reliability, and long-term monitoring efficiency. Of the smart materials used in SHM, piezoelectric materials, shape memory alloys (SMAs), magneto strictive materials and electroactive polymers have been popular because of their unique transduction mechanisms and engineering applications.

3.1 Piezoelectric Materials

Piezoelectric materials have the property of mechanically straining to give electrical signals and vice versa, which makes them to act as sensors and actuators at the same time. This is an electromechanical coupling that will render them greatly useful in both active and passive SHM. Piezoelectric transducers can be bonded or embedded within structures in order to excite mechanical waves, as well as to measure the response, which can be used to determine the presence of damage due to vibration-based, impedance-based, and guided wave methods. SHM that operates based on impedance is very sensitive to local changes in the stiffness, whilst guided wave techniques allow local measurements over extensive structural regions with a relatively small number of transducers. Although there are issues linked to brittle nature, thermodynamic sensitivity, and extended stability, a large amount of research has indicated the efficiency of piezoelectric materials and has outlined the methods of improving their strength and feasibility in engineering construction (Aabid et al., 2021).

3.2 Shape Memory Alloys (SMAs)

The shape memory alloys are described as having reversible phase changes between the martensite and the austenite phase when subjected to thermal or mechanical stress. This type of behavior enables SMAs to self-heal and reuse pre-defined shapes and create large actuation forces, hence their applications in adaptive and self-healing structural systems. SHM applications SMAs have sensing and actuation properties, useful in vibration control, damage detection and structural adaptation. The change of electrical resistance during deformation and phase transformation is the self-sensing of SMAs. Their modeling methods, the advantages of their performance, and the issues of the implementation of these systems in vibration control and SHM have been thoroughly reviewed (Tabrizikahou et al., 2022). Recent studies focus on the strength and flexibility of SMAs in structural engineering (Kangda et al., 2025), as well as on the fatigue behavior, energy efficiency and long-term reliability as major limitations that need to be further investigated (Hossain et al., 2025).

3.3 Magneto strictive and Electroactive Polymers

The magnetic fields respond to the magneto strictive materials and allow the efficient generation and reception of the ultrasonic guided waves. They are very much attached to the metallic structures and can be used long-range in SHM such as crack and corrosion detection due to their strong bondage with the metallic structure and resistance to the harsh environment conditions. The modeling and improved transducer designs have greatly enhanced the management and detection of waves in guided wave-based SHM systems (Sha and Lissenden, 2021; Li et al., 2023).

Electroactive polymers especially dielectric elastomers are intelligent types of flexible material that can be easily deformed significantly when an electrical field is applied. Their easy going and compliant properties are appropriate to use in strain and deformation measurements of soft and composite structures. The recent advancements of dielectric elastomer sensors and soft smart actuators have increased their opportunities of use in adaptive SHM system (Boe and Ehrlich, 2023; Enyan et al., 2025). Aerospace composite structures have also seen the heavy use of smart material-based sensing, in which embedded material monitoring is essential to ensure safety and performance (Rocha et al., 2021). Moreover, the use of guided wave methods provided by intelligent materials serves as a focus of long-range non-destructive testing and SHM, promising a wide future in terms of large-scale structural inspection (Cawley, 2024).

4. Sensor Technologies for Structural Health Monitoring

The fundamental element of structural health monitoring (SHM) systems is sensor technologies that allow measuring physical parameters, which indicate the state and quality of engineering structures. Sensors in mechanical engineering applications can be used to record strain, vibration, displacement, temperature and acoustic activity responses, which are used as damage initiation / progression indicators. The use of sophisticated sensors has made SHM systems to be highly accurate, reliable and scalable thus suitable to be used in large and complex structural applications.

Fiber optic sensors especially Fiber Bragg Grating sensors have received considerable attention because of their superior sensitivity, immunity to electromagnetic interference, and the ability to operate in a highly hostile environment among the other sensing methods. FBG sensors operate in such a way that certain wavelengths of light are reflected and changes in strain or temperature differences are detected and are used to accurately gauge and distribute measurements along the structural elements. They have a multiplexing property enabling several sensing locations to be integrated within one optical fiber and are thus very useful in the detection of large structures or structures that cannot be reached. It is also proven that FBG- based sensors are effective in identifying strain changes, temperature changes, and damage-related anomalies during SHM measurements (Yassin et al., 2024).

Another type of SHM sensing technology is embedded and MEMS-based sensors. Such sensors are normally embedded within structural elements with local and high-resolution measurements and external disturbances being reduced. Embedded sensors would increase the reliability of data as they are able to maintain direct contact with host structure and aid in real- time monitoring of certain parameters like acceleration, strain, pressure and vibration. They have been combined with data acquisition and processing units, which have enabled the creation of compact and smart SHM systems with the ability to work independently over a long period (Ferreira et al., 2022). Table 3 provides a comparison of the most popular SHM sensor technologies in terms of their key features.

Table 3. Comparison of sensor technologies used in structural health monitoring

Sensor Type	**Measured Parameters**	**Sensitivity**	**Environmental Robustness**	**Cost**	**Long-Term Suitability**
FBG sensors	Strain, temperature	Very high	Excellent	High	Excellent
MEMS sensors	Acceleration, vibration	High	Moderate	Low	Good
Acoustic emission sensors	Stress waves	Very high	Moderate	Medium	Moderate
Embedded sensors	Multi- parameter	High	High	Medium	Excellent

In addition to traditional sensing techniques, data-driven sensing systems have become useful instruments to assess the development of damages in complex structures. These models make use of sensor-based data along with statistical and machine learning methods, to discover patterns of damage and evaluate temporal degradation behavior. It can find its application especially when physical interpretation of sensor signals is difficult, allowing to predictively assess and understand better long-term structural decay (Soltangharaei, 2020).

Although major improvements have been made, issues like optimization of sensor location, environmental sensitivity, long term stability, and data management still pose a challenge to the performance of SHM systems. The literature review on massive SHM applications highlights the importance of standard sensing strategies, better sensor integration, and accurate data interpretation schemes to increase the applicability in the field (AlHamaydeh and Aswad, 2022).

5. Data Acquisition and Signal Processing Techniques

Structural health monitoring (SHM) systems are also made up of data acquisition and signal processing to convert raw sensor measurements into useful information that is associated with structural condition. The data acquisition phase is concerned with picking off signals of sensors which include strain gauges, acceleration sensors, piezoelectric sensors, and optical sensors in a way that ensures good quality of the signals. Signal conditioning, such as amplification, filtering and analog to digital conversion are applied in order to diminish the impact of noise, sensor drift and environmental noise. To have the necessary reliability of measurements and quality damage assessment, well-designed data acquisition systems are of great necessity (Farrar and Worden, 2021).

Signal processing methods are used to derive information about damage sensitivity in the data of structural response after acquisition. Parameters requiring assessment in time domain analysis includes peak values, root-mean-square response, and statistical moments to determine structural behavior change. The variations in natural frequencies and mode shapes and spectral characteristics related to stiffness degradation or mass variation are identified using frequency-domain analysis, which is typically based on fourier transforms. Under operating conditions however, structural responses are usually not stationary. To counter this, time frequency analysis algorithms, e.g. wavelet transforms, are extensively used since they offer both temporal and spectral information simultaneously, which are more sensitive to localized and transient damage (Taha et al., 2020). Table 4 provides a summary of signal processing techniques that are used in SHM.

Table 4. Signal processing techniques commonly used in structural health monitoring and their characteristics

Analysis Domain	Common Techniques	Damage Indicators	Strengths	Limitations
Time domain	RMS, peak value, kurtosis	Amplitude variations	Simple and fast	Low damage sensitivity
Frequency domain	FFT, PSD	Frequency shifts	Effective for global damage	Poor localization
Time– frequency domain	Wavelet transform, STFT	Localized features	High sensitivity	Computational cost

The process of feature extraction is a very important part of SHM in that the bulk of processed data can be reduced to small descriptors of the data that are sensitive to structural damage. Typical characteristics are statistical measures, spectral parameters, modal measures, and measures of energy. The ability to extract features efficiently enhances the detectability of damage, lowers computational requirements and is resistant to noise and environmental changes.

Features that are extracted are further utilized to compute damage indicators and metrics which are measures of deviations of a structural state. These measures assist in the damage detection, its localization, and the severity of the damage. With outlier analysis, data-driven approaches are also very useful in separating damage-induced changes to normal operation changes without necessarily involving complex physical models, which are applicable to complex structural systems (Worden et al., 2020). In general, emerging data acquisition and signal processing technologies continue to make modern SHM systems more reliable, sensitive, and practical.

6. Data-Driven and Intelligent SHM Approaches

The increased accessibility to high-fidelity sensing data has increased the pace of uptake of data-driven and intelligent methods in structural health monitoring (SHM). The purpose of these methods is to obtain the information about damages directly out of measured data, eliminating the need to rely on detailed physics-based models, and enhancing the monitoring to be able to handle complex structures invariability regarding the environment and operation. The use of machine learning techniques has become one of the pillars of modern SHM because of the ability to detect patterns of damage and assist with the automated decision-making process. Learning-based approaches can combine sensing, feature extraction, and classification in a single form of learning making damage detection and conditions assessment to be made efficient even in very high-dimensional and uncertain conditions. Machine learning paradigm has been demonstrated to provide scalability and flexibility in a broad variety of SHM applications (Bao and Li, 2021). Deep learning and artificial intelligence (AI) are additional solutions to SHM, as they allow the features to learn hierarchically, and the system to adapt itself. These methods decrease the reliance in manual feature engineering and promote smart and adaptive optimization of intelligent and adaptable structures. The use of AI in design and control of intelligent structures and metamaterials is also emphasized by recent studies as the way to enable adaptive and performance-oriented engineering solutions that can match the goal of intelligent monitoring and adaptive maintenance (Ogunniran et al., 2025). Pattern recognition and anomaly detection is an important tool in separating the damage induced variations and variations due to an environmental and operational influence. Mode shape curvatures, which are modal-based damage indicators, have been proved to be useful in the localization of damage in diverse environmental conditions to enhance the robustness and reliability of SHM systems (Shokrani et al., 2018).

7. Wireless Sensor Networks and Embedded Systems

The use of wireless sensor networks (WSNs) has been a central part of recent structural health monitoring (SHM) systems because it allows to achieve distributed, scalable, and flexible monitoring of large-scale and complex structures. A standard wireless SHM system is composed of spatially distributed sensor nodes that have sensing unit, embedded processors, wireless communication units and power supply. These nodes work in collaboration to receive, process and send structural response information to centralized or decentralized monitoring systems. The WSN-based SHM architectures have less installation complexity, better adaptability, and promote long-term monitoring of the structures that cannot be easily accessed, compared to traditional wired systems. Extensive surveys have shown that WSNs are highly beneficial in support of the practicality and scalability of SHM deployment in both civil and mechanical engineering uses (Noel et al., 2017).

Power supply has been among the most significant issues in wireless SHM system especially in using wireless SHM systems in long-term and continuous monitoring. To solve this problem, the wireless sensor nodes have been equipped more and more with energy harvesting and self- powered sensing technologies. Such solutions permit sensors to utilize sources of ambient energy like vibrations, thermal gradient or solar power to lower power consumption and limit maintenance costs. The use of self-powered sensors increases the sustainability and reliability of the system which is ideal when it is used in remote or environmentally hostile environments where periodic changes of batteries is not feasible. Recent works have mentioned the possibility of self-powered sensing solutions and made issues concerning energy efficiency, power storage, and energy management approaches (Javaid et al., 2023).

The development of embedded systems and communication technologies has also created an opportunity to implement edge computing in wireless SHM systems. Edge computing can also be used to process data and make decisions on sensor nodes or gateway devices, eliminating the need to reduce communication latency and bandwidth. This ability is especially high in real-time damage detection and prompt response application. The new wireless communication paradigms such as next-generation networks enable high data rates, low latency, and enhanced connectivity which is necessary to have reliable real-time SHM. The innovations also present new factors concerning the reliability of the systems and the security of the computer network because the wireless communication opens SHM systems to the risk of the loss of data, interference, and cyber-attacks. The literature on the future of wireless communication has highlighted the need to have effective security and network design to provide reliable and secure SHM operation (Akyildiz et al., 2020).

8. Applications in Mechanical Engineering

Structural health monitoring (SHM) has gained significant interest in the mechanical engineering fields to ensure safety, reliability, and life cycle engineering of the critical systems. Recent developments of sophisticated sensing systems, signal processing approaches and intelligent analysis methods have made it possible to monitor the beginning, development and degradation of damages in numerous mechanical systems. The developments have enhanced the capability of evaluating the structural integrity in complex loading and environmental conditions immensely.

SHM has been crucial in the aerospace engineering field in the tracking of lightweight composite structures which are extremely susceptible to impact, delamination and fatigue. The technique of guided Lamb waves has been widely used in damage detection of composite aircraft structures because of its ability to travel long distances and still be sensitive to structural discontinuities. These wave-based methods can detect the damage early, and incurring minimum extra sensor weight, which makes these methods highly applicable in aerospace scenarios where the weight and reliability factors are highly important (Su et al., 2006). Subsequent enhancements of ultrasonic guided-wave sensor systems have made it possible to have integrated SHM systems with the ability to detect and locate impacts to aid in real-time monitoring and enhanced structural integrity evaluation during service (Capineri & Bulletti, 2021).

The automotive industry is also using SHM technologies to perform the structural integrity and operation safety analysis under the condition of dynamic loading. One-class classification methods are data-based damage detectors that have demonstrated good capacity of detecting damage in automotive parts without a large pool of labelled damage data. They are specifically useful in tracking the suspension systems, chassis component, and load-bearing structures, where the patterns of damages can significantly change according to the operating conditions and the history of usage (Agarwal et al., 2021).

Another critical area of application of SHM is the rotating machinery and power systems which have the high economic and safety implications of unforeseen failures. The analysis of signal in time-frequency, specifically the wavelet-based signal analysis methods have gained popularity in fault detection of rotary machines, since they are efficient in capturing short-lived characteristics of faults in bearings, imbalance, and misalignment (Yan et al., 2014). Alongside the fault detection, the recent reports have also placed a central role in the remaining useful life (RUL) estimation as the main factor of predictive maintenance strategies, which would allow implementing proactive decision-making and optimizing maintenance schedules of rotating equipment (Kumar et al., 2024).

SHM has also been widely used in industrial and high-performance mechanical systems, where accuracy of sensing and premium materials are needed. Optical and laser-based sensing methods with high resolutions have been considered to measure the structural behavior in harsh environments, which would accurately measure the dynamic behavior in advanced engineering systems (Wang et al., 2023). Moreover, the invention of nanocarbon sensors has broadened SHM properties among smart and bio composite materials, and this method provides greater sensitivity and multifunctionality and compatibility with future mechanical structures (Das et al., 2024). Taken altogether, these applications prove the increasing significance of SHM in the process of making contemporary mechanical engineering systems safer, more reliable, and efficient.

9. Challenges, Limitations, and Future Research Directions

Although great progress has been achieved in structural health monitoring (SHM), there are several issues which remain and restrict its extensive and permanent use in realistic engineering systems. A factor that has remained most pervasive is the effect of variability on the environment and the operation of the sensors. Variations in temperature, humidity and loading conditions may greatly cause changes in structural responses and obscure features indicative of damage resulting in false alarms. Moreover, sensor aging and breakdown with time lower the reliability of data especially in SHM systems using wireless sensor networks that may be used to monitor long durations (Abdulkarem et al., 2020).

Data integrity problems and sensor faults also make

SHM implementation even more complicated. Large sensor networks are also susceptible to mass sensor failure, loss of communication and calibration drift that can severely affect the accuracy of the diagnostic unless detected and corrected appropriately. Even though there exist adaptive fault diagnosis methods to solve such issues, there is still an open research issue on designing fully fault- tolerant SHM systems that can be fully reliable in the real-life scenario (Al-Zuriqat et al., 2023). Also, modern SHM systems have increased the number of sensors, which has resulted in data overload, posing a problem in terms of effective data storage, processing and uncertainty management.

Further drawbacks of SHM systems include scalability and long-term deployment. A cyber-physical SHM system demands close coupling of sensing, computation and communication layers, thereby raising the complexity and computing requirements of the system. It is especially difficult to keep a high degree of reliability in performance during operational limitations that are imposed on large-scale infrastructure systems in the reality of continuous monitoring during long service periods (Doghri et al., 2022). In addition, the lack of standardized protocols and interoperability between sensors, data acquisition systems, and analytical platforms inhibit an unproblematic integration of the system and transfer of the technology to various uses (Gharehbaghi et al., 2022).

Another important issue in the implementation of SHM is economic feasibility. It is also hard to measure the benefits of SHM in relation to its installation, operation, and maintenance costs, especially in uncertainty. It has been demonstrated that the value of information based on SHM is highly dependent on the monitoring time, data quality, and decision context, and it would be useful to have optimal monitoring plans (Kamariotis et al., 2022). Value-based assessments are even more problematic by the presence of temporally dependent observations, because correlations in monitoring data will influence decision results and minimize informational benefits (Nielsen, 2022).

In the future, future studies in SHM are more oriented to the creation of self-diagnostic and autonomous monitoring systems that can adjust to the changing environment and conditions of operation. Automated feature learning, damage diagnostics, and decision making are some of the processes in which AI is likely to be at the center of it. It is emphasized by the recent research that AI-based SHM models are increasingly gaining prominence in enhancing infrastructure repair operations, as well as establishing superior safety management measures (Plevris and Papazafeiropoulos, 2024). Simultaneously, the concept of SHM being integrated with Industry 4.0 notions is increasingly taking momentum with the introduction of digital twin technologies that allow the synchronization of physical buildings with virtual ones in terms of advanced diagnostics, prognosis, and lifecycle management (Sun et al., 2024). Deep learning methods are also being sought to play a greater role in complex pattern recognition tasks in SHM, especially the large-scale infrastructure (such as bridges) where more advanced modeling techniques cannot be effectively used (Zhang et al., 2022). The efforts needed to achieve the robust, scalable, and digitally integrated SHM frameworks will be focused on overcoming the current issues in addition to adopting intelligent, adaptive, and digitally connected monitoring systems.

10. Conclusion

This review has provided a detailed literature review on the concept of structural health monitoring (SHM) in mechanical engineering with particular attention being given to the combination of smart materials, novel sensor systems, data collection systems and smart analysis tools. It was pointed out that smart materials like piezoelectric ceramics, shape memory alloys, magneto strictive materials and electroactive polymers make the process of sensing and actuation of materials multifunctional and much more sensitive in damage detection and system adaptability. Similarly, development of sensor technologies, such as fiber Bragg grating sensors, embedded sensors, MEMS sensors, and wireless sensor networks has increased the scalability and practicability of SHM systems to complex and large-scale mechanical structures. The review has also highlighted the importance of data acquisition, signal processing, and the use of data in converting the raw sensor data into accurate damage evidence and prognostics. The increasing usage of machine learning, artificial intelligence, and digital twin concepts evidences the obvious shift towards intelligent, autonomous, and predictive SHM frameworks in accordance with the concept of Industry 4.0. The widespread applicability and efficiency of SHM can be demonstrated by aerospace, automotive systems, rotating machinery, and high-performance mechanical structures as an example of applications. Although these breakthroughs have been made, environmental variability issues, sensor life, data uncertainty, system scalability, and economic viability continue to be major problems. The mentioned limitations will be removed via further investigation into the solid sensing strategies, fault tolerant design, standardized design, and adaptable intelligence. On the whole, the convergence of these three areas smart materials, next-generation sensors and intelligent analytics is a paradigm shift to resilient, self-diagnostic, and self-reliant mechanical systems, making SHM a fundamental technology of present and autonomous engineering systems.

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