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A Structural Health Monitoring Framework For Intelligent and Sustainable Infrastructure: A Conceptual Perspective

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ABSTRACT: This paper presents a vision for next-generation Artificial Intelligence (AI) based structural health monitoring (SHM) systems through the lens of DREAM-SHM: a framework comprising Dynamic, Real-time, Evaluative, Adaptive (AI-based), Modular, Self-diagnostic, Holistic, and Multi-sensory principles. The aim is to enable smart infrastructure that can sense, and evolve corresponding to structural behaviour, material degradation, environmental effects, and changing operational or economic constraints. The paper reviews current SHM technologies, highlighting the strengths and limitations of contact-based sensors, such as accelerometers, strain gauges, fibre optic sensors, and non-contact approaches including vision-based systems, infrared thermography, radar, and ultrasonic techniques. Emphasis is placed on their integration with wireless sensor networks, Internet of Things (IoT) platforms, and Artificial Intelligence (AI) for advanced data fusion, anomaly detection, and predictive analytics. The computational aspects underpinning SHM systems, such as cloud-edge processing, machine learning, and multi-modal sensor data integration, are described to enable timely and informed decision-making. In addition, the paper situates DREAM-SHM within the context of sustainability, demonstrating how adaptive and intelligent SHM systems support the goals of circular economy and net-zero carbon by prolonging asset life, reducing maintenance burdens, and improving environmental responsiveness. This work outlines a pathway toward structurally intelligent and resource-efficient infrastructure.

KEYWORDS: Structural Health Monitoring (SHM), Intelligent infrastructure, Sustainable infrastructure, Multi-modal sensing, Contact-based sensing, Non-contact sensing, Internet of Things (IoT).

1 INTRODUCTION

The infrastructure of the future should be smart, adaptive, and capable of responding to both operational and environmental challenges in real-time. As urbanisation continues to accelerate and infrastructure ages, ensuring safety, efficiency, and longevity of our built environment has never been more crucial. Traditional methods of structural inspection and maintenance, though important, are often time-consuming, costly, and prone to human error. The Structural Health Monitoring (SHM) paradigm offers an innovative solution to these challenges, enabling continuous, non-destructive assessment of structural integrity and performance [1-3]. SHM aims to detect and diagnose faults early, ensuring that any issues are addressed before they escalate into catastrophic failures. It involves assessing factors such as structural loads, damage status, defect localisation and quantification, growth rate estimation, future performance prediction, and remaining life estimation [1, 4, 5]. In an ideal SHM system, these evaluations are performed in real-time, providing global insights into the health of a structure as it operates [3].

At its core, SHM involves several essential components, including sensing, load identification, damage detection, damage characterisation, and future performance prediction[1, 6]. SHM systems incorporate continuous or periodic sensing and data collection, allowing for the real-time monitoring of structures under various operational and environmental loads. Sensors, whether passive or active [7], are integrated into the structure during manufacturing or retrofitted for ongoing monitoring. These sensors can be classified as contact-based (e.g., accelerometers, strain gauges, fibre optic sensors, Linear Variable Differential Transformers (LVDT), and thermometers) or non-contact-based (e.g., vision-based systems, infrared thermography, and radar). Both types of sensors capture critical data about the structure's behaviour, environmental conditions, and operational status, transmitting this information to storage systems or cloud-based servers for analysis and decision-making [8, 9].

Contact-based sensors offer high accuracy but often require direct attachment to the structure, periodic maintenance, and replacement, resulting in increased operational costs. Moreover, critical measurement points may be difficult or impossible to access, leading to incomplete or inaccurate data[10, 11]. To address these challenges, non-contact sensors provide an alternative by enabling wide-area and mobile sensing. These sensors operate without requiring direct attachment to structures and are typically positioned at a distance. They capture optical images and videos using technologies such as digital cameras, high-speed cameras, and synthetic aperture radar from satellite sensors. Smartphone-based sensing technologies are also increasingly integrated into SHM systems, expanding their capabilities [9]. By utilising mobile platforms such as unmanned aerial vehicles (UAVs), automobiles, trains, and boats, fly-by, drive-by, tram-by, or sail-by monitoring systems can be deployed, enhancing spatial coverage and reducing data gaps. This more efficient approach enables broader monitoring capabilities across large infrastructure networks, offering a more comprehensive assessment of structural health over time.

As infrastructure becomes more interconnected and intelligent, the need for adaptive, dynamic systems that respond

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in real time to changing conditions is greater than ever. This is where DREAM-SHM as a novel Structural Health Monitoring framework offers a transformative solution. By integrating contact-based and non-contact sensors, Internet of Things (IoT) platforms, and Artificial Intelligence (AI), DREAM-SHM enables structures to not only monitor their health but also adapt dynamically to both environmental and operational changes. The system continuously collects data from sensors and uses AI-driven algorithms to analyse this information, allowing the structure to respond in real time to conditions such as temperature fluctuations, humidity, material stress, and even operational demands. By optimising these factors, DREAM-SHM can maintain both the structural integrity of the building and the comfort of its occupants, while also reducing energy consumption and lowering carbon emissions. Moreover, this integration can help address issues such as overcrowding or traffic congestion by adjusting building operations based on real-time data.

This paper explores the concept of DREAM-SHM, detailing how its combination of advanced sensors, IoT networks, and AI technologies unlocks the next generation of intelligent infrastructure. It reviews the different sensor technologies used in SHM, both contact-based and non-contact, and presents a discussion of the computational aspects that enable DREAM-SHM to adapt to changing conditions. This paper explores the potential of these technologies to revolutionise infrastructure monitoring and maintenance, highlighting their ability to optimise not just structural health but also the environment within and around the infrastructure.

2 SENSOR TECHNOLOGIES FOR STRUCTURAL HEALTH MONITORING

SHM systems depend on sensor technologies to collect continuous or periodic data from infrastructures under operational and environmental conditions. These sensors are typically classified into contact-based and non-contact types, each with unique advantages and limitations [12]. A thorough understanding of both categories is essential for developing a more adaptive and intelligent SHM framework.

2.1 Contact-Based Sensors

Contact-based sensors are physically attached to the structure to capture direct measurements of parameters such as strain, stress, acceleration, displacement, and temperature. These sensors have traditionally formed the backbone of SHM systems, especially in critical and high-risk infrastructure.

2.1.1 Strain Gauges

Strain gauges are widely used to measure strain resulting from applied loads. They are typically bonded to the surface of structural elements and detect minute changes in length as electrical resistance variations. Despite their accuracy, they are susceptible to environmental degradation and require careful installation and protection[13-15].

2.1.2 Accelerometers

Accelerometers are essential in dynamic monitoring, capturing vibrations, modal properties, and transient responses during events such as traffic loading or seismic activity. They can be deployed in arrays across a structure to identify changes in stiffness or detect anomalies associated with damage [10, 16-18].

2.1.3 Fibre Optic Sensors

Fibre optic sensors, including Fibre Bragg Gratings (FBGs), are capable of long-range, high-resolution measurements of strain and temperature. Their immunity to electromagnetic interference and ability to multiplex multiple sensing points along a single fibre make them highly suitable for harsh environments and large-scale infrastructures[19-21].

2.1.4 Linear Variable Differential Transformers (LVDTs)

LVDTs are used to measure displacement and deformation with high precision. These sensors are commonly applied in laboratory tests and long-term monitoring of joints, cracks, and bearing movements in bridges and buildings [22].

2.1.5 Thermocouples and Thermistors

These sensors measure temperature variations, essential for understanding thermal loading effects on structural behaviour. They are often used in combination with other sensors to decouple environmental influences from structural responses.

2.1.6 Limitations of contact-based sensors

Despite their reliability and accuracy, contact-based sensors have several drawbacks, such as installation and maintenance can be labour-intensive and costly. Sensor failure due to environmental exposure requires frequent inspection and replacement. Coverage is often limited to selected points, leading to sparse spatial resolution [23].

2.2 Non-Contact Sensors

Non-contact sensors offer remote sensing capabilities and are particularly valuable for large-scale structures where full-field contact-based monitoring is impractical[24]. These sensors can be deployed on stationary platforms or mobile carriers such as UAVs, vehicles, or boats to conduct “fly-by”, “drive-by”, or “sail-by” inspections.

2.2.1 Vision-Based Methods

Vision-based SHM systems use digital or high-speed cameras to capture visual data from structures[25]. Techniques such as Digital Image Correlation (DIC) [26] and photogrammetry allow for the measurement of displacement, deformation, and surface cracking [27, 28]. These methods are enhanced through artificial intelligence (AI), particularly deep learning algorithms that automate defect detection and characterisation [29].

2.2.2 Infrared Thermography (IRT)

IRT detects subsurface anomalies such as delamination and voids by capturing thermal patterns on a structure’s surface. It is non-invasive and efficient for inspecting large areas. However, it is sensitive to environmental conditions and often requires post-processing with deep learning models to reduce false positives[30-38].

2.2.3 Ultrasound-Based Techniques

Air-coupled ultrasound techniques use high-frequency waves to detect micro-cracks and internal flaws. These are particularly useful in metallic and composite materials where internal

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defects may not be visible externally. Non-contact ultrasound methods allow remote application, reducing the need for physical access[24].

2.2.4 Radar Vibration-Based Methods

Microwave and millimetre-wave radar systems can remotely monitor structural vibrations and dynamic responses with sub-millimetre accuracy. These non-contact methods are particularly effective for tall, slender, or otherwise inaccessible structures such as towers, bridges, and wind turbines. They offer robust performance in challenging environmental conditions, as they are less affected by lighting, fog, or moderate precipitation compared to optical techniques. Radar-based monitoring enables real-time displacement and modal analysis without requiring physical sensor installation on the structure[24].

2.2.5 Magnetic-Based Techniques

Magnetic-based methods such as Magnetic Flux Leakage (MFL) and magnetostrictive sensors are used to detect stress concentrations, cracks, corrosion, and other anomalies in ferromagnetic materials. These techniques work by measuring disturbances in the magnetic field when it encounters defects or discontinuities within the material. They are particularly valuable for monitoring pipelines, prestressed cables, steel-reinforced concrete, and metallic bridge components, offering a non-destructive means of assessing structural integrity in inaccessible or high-risk environments [24].

2.2.6 Wireless Sensor Networks (WSNs)

WSNs use embedded or surface-mounted sensors that wirelessly transmit structural data to remote data acquisition systems. This reduces installation complexity and allows for scalable deployment across large infrastructures. Integration with energy harvesting solutions enhances their long-term viability [24, 39].

2.2.7 Hybrid and Mobile Monitoring Approaches

Combining multiple non-contact methods or integrating them with mobile platforms (e.g., UAVs or autonomous ground vehicles) provides comprehensive spatial and temporal data. These systems are especially useful for structures with limited accessibility or under high traffic loads [9].

2.2.8 Advantages of Non-Contact Sensors

These sensors enable full-field and remote monitoring, reduce maintenance and installation costs, improve safety for inspectors and increase spatial coverage and flexibility.

2.2.9 Challenges of Non-contact Sensors

Environmental conditions (e.g., lighting, humidity, wind) can affect the accuracy of these sensors. Data processing complexity increases with large-scale visual or radar datasets. These sensors are high dependent on robust algorithms for data interpretation.

2.3 Summary and Considerations

The combined application of contact and non-contact sensor technologies can provide complementary insights into structural integrity. While contact sensors offer high accuracy for localised measurements, non-contact sensors excel in wide-area and remote assessments. The integration of AI and the Internet of Things (IoT) further enhances data acquisition, fusion, and interpretation capabilities [40, 41].

A future-forward SHM system, such as DREAM-SHM, should not only integrate these sensors intelligently but also enable self-reflection and prediction, adapting its sensing strategies based on structural performance, environmental changes, and user demands. This vision sets the stage for the next generation of intelligent, adaptive, and sustainable infrastructures.

3 DREAM-SHM: TOWARDS INTELLIGENT, AND ADAPTIVE STRUCTURES

The future of civil infrastructure depends on its capacity to sense, adapt, and evolve, and attributes central to the next generation of intelligent systems. In this context, this paper suggests the DREAM-SHM framework: a novel approach to Structural Health Monitoring that is Dynamic, Real-time, Evaluative, Adaptive (AI-based), Modular, Self-diagnostic, Holistic, and Multi-sensory (Figure 1).

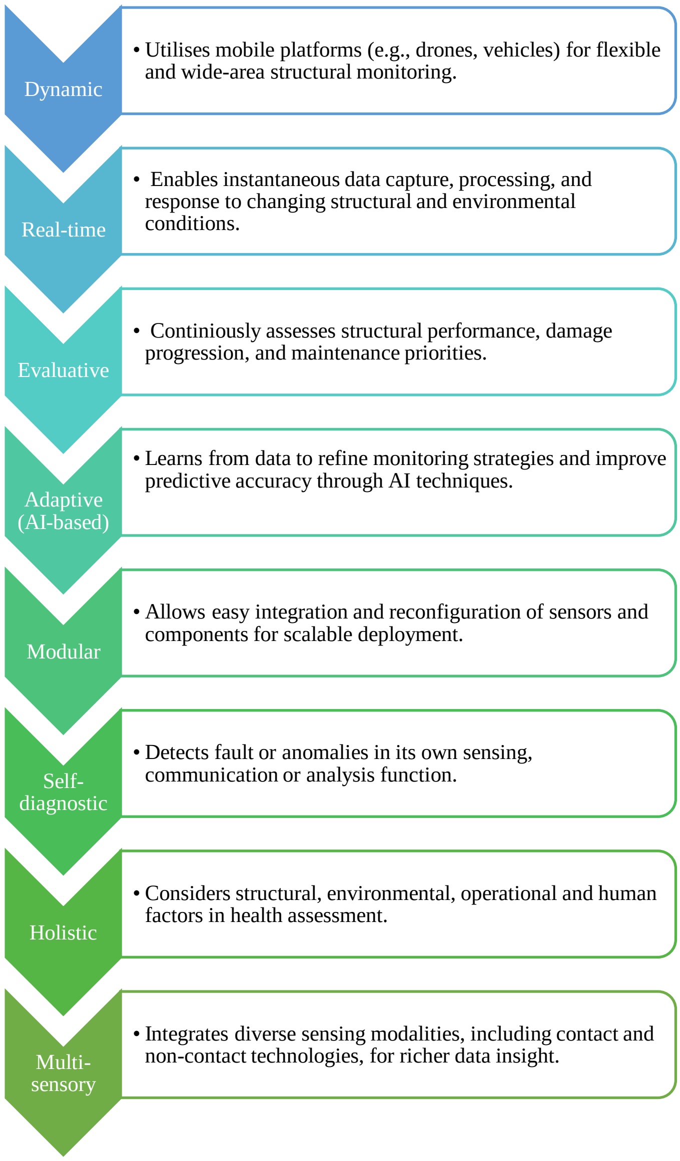

Figure 1. Elements of DREAM-SHM framework

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Rather than functioning as static systems for passive data collection, DREAM-SHM envisions infrastructure as active learning, self-reflective, and responsive entities, capable of anticipating change, optimising performance, and supporting lifecycle decisions with unprecedented insight and autonomy. The DREAM-SHM system is inherently computational, relying on advanced data processing, predictive algorithms, machine learning, and cloud computing to support its highly adaptive and intelligent functionality. It operates through a robust digital backbone that enables the processing of vast amounts of real-time data, the prediction of future conditions, the optimisation of structural health, and the dynamic adjustment of environmental parameters.

3.1 From Traditional to Dreaming Structures

Conventional SHM systems provide snapshots of structural conditions based on sensor data. In contrast, DREAM-SHM envisions a system that continuously "dreams." That is, it reflects on past data, analyses current performance, and simulates future outcomes. Much like human brain consolidates information during sleep [42, 43], DREAM-SHM uses advanced analytics, AI, and IoT integration [44] to consolidate multisource data and learn structural behaviour patterns over time. This cognitive leap transforms infrastructure into living digital twins, constantly updating their condition, adapting to changes in the environment, and providing valuable feedback to engineers and designers.

3.2 Integrating Contact and Non-Contact Sensors with IoT and Data Processing Fusion

In a DREAM-SHM framework, both contact and non-contact sensors are integrated into a broader Internet of Things (IoT) ecosystem. IoT enables sensor networks to communicate, synchronise, and share real-time data through cloud computing or edge processing devices. Contact-based sensors (e.g., strain gauges, accelerometers) provide high-fidelity, localised data critical for detecting internal stress, fatigue, or localised failures, while non-contact sensors (e.g., vision systems, thermography, radar) expand coverage, capture surface conditions, and enable remote inspections.

These sensors generate large, multidimensional datasets that require careful processing and alignment to create a coherent and reliable model of the structure's condition. Advanced data fusion algorithms are applied to integrate multimodal data from multiple sources, resolving discrepancies caused by noise, sensor faults, or varying environmental conditions[39]. Techniques such as Kalman filtering, Bayesian inference, and decision tree models [45] enhance the accuracy of the fused data by accounting for uncertainties and interdependencies across sensor inputs.

IoT platforms facilitate seamless connectivity between sensors, edge devices, data storage, and decision-making systems, enabling real-time alerts, remote diagnostics, distributed data storage, cloud analytics, and cross-sensor data fusion and redundancy to reduce uncertainty. The fusion of contact and non-contact sensor data within this infrastructure supports a comprehensive, context-aware SHM system capable of interpreting data as part of a broader ecosystem influenced by environmental, operational, and human factors [44].

3.3 The Role of AI in Creating Self-Adaptive Structures

AI lies at the core of the DREAM-SHM system, functioning as the central engine that empowers intelligent data interpretation, autonomous decision-making, and adaptive system behaviour. By leveraging machine learning (ML) and deep learning (DL) techniques, the system can extract meaningful patterns, detect anomalies, and respond dynamically to evolving structural and environmental conditions [46].

Deep learning models, particularly Convolutional Neural Networks (CNNs) [12, 46-48], are instrumental in analysing visual inputs from vision-based sensors or thermal imagery from infrared cam eras. These networks can automatically classify and detect structural anomalies such as cracks, deformations, corrosion, or delamination, significantly reducing the reliance on manual inspections. This automation increases the speed and accuracy of damage detection while minimising human error.

AI algorithms are trained on historical and real-time sensor data to enable predictive maintenance, allowing the system to forecast when and where damage is likely to occur. In addition to supervised learning, unsupervised learning approaches are used to uncover previously unseen patterns or emerging failure modes, enhancing the system's adaptability and sensitivity over time.

AI also plays a critical role in fusing data from multiple sensor modalities, including thermal, acoustic, visual, and vibration sources. By integrating these diverse inputs, AI improves fault detection accuracy and reduces false positives. Furthermore, AI enables the autonomous operation of robotic inspection platforms, such as UAVs, which can plan flight paths, adjust actions in real time, and focus on areas of concern based on live feedback.

Reinforcement learning techniques further enhance the self-adaptive capabilities of the DREAM-SHM system. Through continuous learning, the system can optimise its monitoring strategies, improving how it prioritises sensor data, allocates resources, and adapts to changing structural and environmental conditions.

3.4 Dynamic, Self-Reflective, and Adaptable Systems

The DREAM-SHM system represents a significant evolution in how infrastructure is designed, operated, and maintained. At its core, it enables dynamic, self-reflective, and adaptable behaviour through the seamless integration of cloud computing, the IoT, and AI. By combining real-time sensor data with intelligent analytics, the system continuously monitors, analyses, and responds to both internal structural health and external environmental conditions.

IoT-enabled sensor networks form the backbone of this intelligent infrastructure. These networks connect contact and non-contact sensors, environmental monitoring devices, and

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operational systems, allowing continuous data transmission to cloud-based platforms. Cloud computing provides the scalable computational resources needed to handle large volumes of sensor data across wide geographic areas, making it possible for engineers, facility managers, and maintenance teams to access up-to-date structural health reports, plan maintenance, and respond to safety concerns in real time. Edge computing ensures that critical decisions can be made locally and rapidly, particularly when immediate intervention is required. For example, structural anomalies detected by sensors, such as sudden changes in strain or temperature, can trigger instant responses without needing to wait for centralised cloud processing.

This intelligent system also extends to the optimisation of internal environments. By monitoring temperature, humidity, and occupancy levels, DREAM-SHM can automatically adjust heating, ventilation, air conditioning (HVAC), or dehumidification systems. These adjustments not only enhance occupant comfort but also protect structural materials from accelerated degradation, such as corrosion in steel or cracking in concrete, caused by unfavourable environmental conditions.

Moreover, the system adapts to changing operational demands. If a room becomes highly occupied, ventilation can be increased, or air conditioning fine-tuned to maintain air quality and comfort. By learning usage patterns, tracking external weather forecasts, and recognising early signs of material fatigue, AI within the system can anticipate and prepare for future operational needs. This may include adjusting HVAC schedules ahead of temperature drops, deploying shading systems in response to sunlight exposure, or activating safety protocols in anticipation of extreme weather or seismic activity.

Ultimately, DREAM-SHM goes far beyond traditional monitoring. It creates an intelligent feedback loop where data, environment, and structural health are interwoven, enabling buildings and infrastructure to adapt in real time. This not only preserves structural integrity and enhances user wellbeing, but also significantly reduces energy consumption and carbon emissions, contributing to more sustainable and resilient built environments.

3.5 Designing for Longevity Through Predictive Intelligence

One of the transformative aspects of the DREAM-SHM system is its ability to influence future design practices, material selection, and lifecycle strategies through predictive insight. By collecting and analysing long-term structural health monitoring data, the system enables the refinement of design codes based on actual performance under diverse environmental and loading conditions. This data-driven feedback loop allows engineers to make informed decisions, enhancing structural reliability and efficiency over time.

Machine learning algorithms are central to this predictive capability. Trained on historical and real-time data from contact and non-contact sensors, such as accelerometers, infrared thermography, and ultrasound, the system detects early signs of damage and estimates future deterioration, fatigue, and failure. Time-series forecasting models, including autoregressive integrated moving averages (ARIMA) and recurrent neural networks (RNNs) [49, 50], leverage trends in sensor data to guide proactive interventions that extend the service life of the structure.

Supervised learning techniques, including decision trees and support vector machines (SVM), classify structural conditions into actionable states, while reinforcement learning enables continuous model improvement as new data is acquired. By integrating predictive models with real-time monitoring, the system enhances structural safety, minimises operational costs, and maintains optimal performance.

This fusion of predictive analytics with adaptive control transforms infrastructure into self-reflective and intelligent systems. DREAM-SHM further supports generative design processes, where artificial intelligence proposes optimised structural forms and materials tailored to specific environmental and operational conditions. Such insight enables the design of modular, reconfigurable structures that can evolve over time in response to predictive indicators. In doing so, DREAM-SHM contributes to a new generation of infrastructure that is sustainable, resilient, and energy-efficient, with a significantly reduced carbon footprint.

3.6 Unlocking the Next Generation of Intelligent Infrastructure

The implementation of DREAM-SHM signifies a fundamental shift from static to living structures. These infrastructures think through artificial intelligence and predictive modelling, feel through extensive and multimodal sensor networks, communicate through Internet of Things platforms and edge computing, and adapt based on environmental conditions, user demands, and system health. By integrating advanced sensing, communication, and intelligence, future infrastructures will no longer be passive assets, but active participants in their maintenance and evolution.

In doing so, they offer immense societal benefits, including enhanced safety and reliability, reduced maintenance costs and downtime, improved energy efficiency and user comfort, and a deeper understanding of structural behaviour over time. The DREAM-SHM paradigm represents not merely a technological upgrade, but a philosophical reimagining of what infrastructure can be, structures that not only endure but evolve, guided by the very data they produce.

4 DREAM-SHM, CIRCULAR ECONOMY AND NET ZERO GOALS

The transition towards smarter infrastructure must be harmonised with global imperatives such as the circular economy and the pursuit of net zero carbon emissions. The DREAM-SHM framework, defined as Dynamic, Reflective, Evaluative, Adaptive, Modular, Self-diagnostic, Holistic, and Multi-sensory naturally aligns with these objectives by enabling more efficient, resilient, and sustainable infrastructure systems throughout their entire lifecycle.

4.1 Enabling Resource Efficiency and Longevity

One of the primary pillars of the circular economy is resource optimisation through prolonged material use, reusability, and

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reduced waste [51]. DREAM-SHM contributes to this by allowing structures to continuously evaluate their health, detect minor degradations before they escalate, and schedule maintenance proactively. Such real-time diagnostics reduce the need for premature demolition or over-conservative replacement strategies. The *modular* and *adaptive* attributes of DREAM-SHM also support retrofitting and component-based upgrades, enabling structures to evolve without complete reconstruction, an essential strategy in circular design.

4.2 Data-Driven Lifecycle Decision-Making

DREAM-SHM's use of AI and IoT technologies facilitates whole-life performance monitoring. This continuous data stream allows engineers, asset managers, and policymakers to make informed decisions that extend beyond first costs, incorporating embodied energy, operational efficiency, and end-of-life recyclability. For example, the system can inform decisions about optimal repair versus reuse, estimate embodied carbon for design alternatives, or determine the feasibility of adaptive reuse of ageing infrastructure.

4.3 Supporting Carbon Emission Reduction

Smart structures equipped with DREAM-SHM do not only monitor their mechanical performance, they also track environmental parameters such as energy use, indoor temperature, humidity, and CO_2 levels. These insights enable buildings and infrastructures to dynamically adjust internal conditions to optimise comfort and reduce energy consumption, especially under varying occupancy patterns or extreme climate conditions. Integration with renewable energy sources and smart energy grids can further reduce reliance on fossil fuels, directly supporting net zero building operations.

Moreover, DREAM-SHM facilitates operational carbon tracking, where the carbon cost of maintenance activities and material replacements can be quantified in real-time. This capability encourages low-carbon interventions, the use of environmentally friendly materials, and the minimisation of transport or logistical carbon footprints.

4.4 Designing for a Regenerative Future

The holistic nature of DREAM-SHM, combined with its dynamic and evaluative features, can help shift the infrastructure sector from a linear to a regenerative model[52]. Rather than just sustaining performance, future structures can be designed to learn, evolve, and regenerate over time. By treating structures almost like living systems, ones that sense, learn, and adapt, DREAM-SHM lays the foundation for self-regulating and self-improving built environments.

This continuous evolution aligns with the vision of net positive design, where buildings not only minimise harm but actively contribute to ecological and social value. For instance, a bridge equipped with DREAM-SHM could dynamically coordinate traffic to reduce congestion-related emissions or monitor its own runoff water quality and feed data back into environmental management systems.

4.5 Digital Twin Synergies

Another key synergy lies in the integration of DREAM-SHM with digital twins[53, 54], creating a real-time, data-enriched virtual model of the structure. These twins can simulate environmental impacts, forecast degradation under climate stressors, and test low-carbon renovation scenarios before implementation. This predictive capability enhances resilience planning and supports sustainability certification and reporting frameworks.

4.6 Energy Efficiency and Sustainable Power Supply

For DREAM-SHM to be deployed at scale and operate autonomously, it must also be energy-conscious. The system leverages low-power wireless sensor networks (WSNs)[55], which minimise energy usage through efficient communication protocols and duty cycling. Where possible, sensors and edge computing units are powered by renewable sources, including solar panels mounted on structures and wind energy microgenerators integrated into exposed components. Additionally, the framework supports energy harvesting, converting ambient vibrations, thermal gradients, or even electromagnetic noise into small but continuous power sources for embedded sensors. This self-sufficiency allows long-term deployment without frequent battery replacements, reducing both maintenance burdens and electronic waste. By embedding energy-awareness into its architecture, DREAM-SHM aligns itself with net-zero goals not only in terms of what it monitors but how it functions, enabling smarter, cleaner, and more self-reliant infrastructures.

4.7 Example of potential performance of a DREAM-SHM system

To demonstrate the potential of the DREAM-SHM framework, imagine a long-span bridge operating under extreme weather conditions and subject to cyclical loading. During a sudden windstorm, real-time data from accelerometers, fibre optic strain sensors, and vision-based surface monitoring systems are synchronised through the IoT layer and processed at the edge. The AI engine identifies anomalous vibration patterns that signal early-stage fatigue in a critical joint. At the same time, thermal imaging highlights abnormal heat signatures associated with bearing friction. The digital twin continuously simulates the structural state and projects the need for a targeted inspection as conditions stabilise. In response to predictive outputs, the system autonomously modifies traffic flow and delivers a real-time alert to maintenance teams. Concurrently, environmental control systems within nearby infrastructure are adjusted to reduce energy use due to temporary low occupancy. This scenario illustrates how the DREAM-SHM framework functions as an adaptive, multi-sensory, and context-aware system, supporting decision-making under dynamic operational demands.

5 CONCLUSION

This paper presents a conceptual perspective for a future SHM system: DREAM-SHM as summarised in Figure 2.

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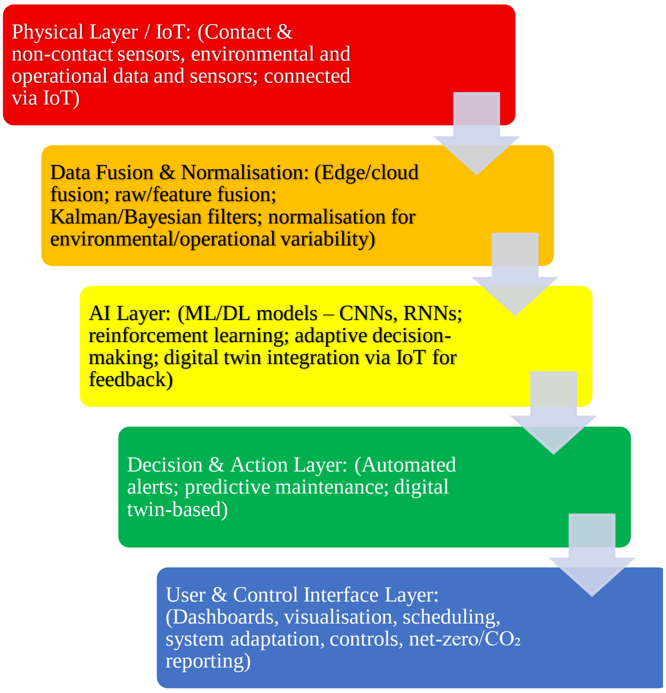

Figure 2. Schematic of the layers of FREAM-SHM framework

This system represents a significant leap forward in structural health monitoring and management. By combining advanced sensor technologies, AI, IoT, and predictive analytics, it provides a comprehensive solution for real-time, adaptive, and sustainable infrastructure management. The computational framework driving the system ensures it can process vast amounts of data, predict future structural performance, and optimise operational conditions dynamically.

While the DREAM-SHM framework offers transformative potential, its implementation at scale presents several challenges primarily rooted in interdisciplinary coordination. Successful deployment requires the integration of diverse expertise across structural engineering, data science, sensor technologies, and artificial intelligence, which demands not only cross-disciplinary collaboration but also specialised training to bridge gaps in knowledge and practice. From an ethical standpoint, careful consideration must be given to the types of human and operational information shared with the system, particularly in contexts involving surveillance, usage patterns, or sensitive infrastructure behaviour. In addition, maintaining cybersecurity and the resilience of communication networks becomes critical, as the framework relies on distributed sensing, edge processing, and cloud-based integration. Despite these challenges, the practical realisation of DREAM-SHM remains promising. The system unlocks the next generation of intelligent infrastructure, where structures are not only monitored but also able to self-adapt and self-maintain. By doing so, DREAM-SHM promotes safety, efficiency, and sustainability in the built environment, while also providing a unifying platform that encourages collaboration between academia and industry. It serves as a compelling motivation for advancing research, developing standards, and forging partnerships that can help turn this vision into reality.

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