

Smart Concrete with Embedded Sensors for Real-Time Structural Monitoring

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ABSTRACT

Aging infrastructure and increasing demands on bridges, buildings, and pavements require enhanced means for effective and continuous structural health monitoring (SHM). Conventional approaches including visual inspection or the use of external or wired sensors are often laborious, discontinuous, and ineffective in the case of internal defects. Smart concrete, including self-sensing or sensor-embedded solutions, enables structural state assessment from within the structure. The present manuscript aims to identify the state-of-the-art sensing technologies for smart concrete, including piezoresistive composites, fibre Bragg grating, micro electro-mechanical systems, corrosion electrodes, and temperature/humidity sensors. Particular attention is drawn to the operating principles as well as the benefits and limitations of these solutions. Furthermore, the integration of the sensor technologies in an Internet of Things (IoT)-based framework using edge/cloud computing, artificial intelligence (AI), and machine learning is discussed. The applications of smart concrete in bridges, buildings, tunnels, pavements, and other structures are reviewed while considering the current limitations in terms of power supply, durability, data management, and cybersecurity. Overall, it can be concluded that smart concrete is a promising solution as an emerging alternative for conventional SHM technologies.

KEYWORDS: *Smart concrete, embedded sensors, structural health monitoring, self-sensing concrete, Internet of things, artificial intelligence, damage detection, predictive maintenance.*

INTRODUCTION

1. Background

Civil infrastructure, such as bridges, high-rise buildings, tunnels, and pavements, is subject to a permanent load, exposure to the weather, and aging processes. The aging of large infrastructures around the world tends to lead to accidents: fatigue cracks, reinforcement corrosion processes, and stiffness reductions threaten road and rail traffic and cause tremendous costs due to repairs and even complete rebuilds in serious incidents [1], [2]. The importance of timely inspections is evident, as damage that has already occurred can usually be repaired much more cheaply than if the entire structure had to be rebuilt. This has led to tremendous effort in the field of structural health monitoring (SHM) to develop methods that provide continuous information about the condition of the structure in its operational environment throughout its service life [1].

2. Conventional Structural Health Monitoring

Traditional structural health monitoring (SHM) practice has been based on periodic visual inspections performed by qualified personnel, and in some cases, non-destructive evaluation techniques, such as ultrasonic tests and half-cell potential mapping, were used [4], [5]. The former is subjective, tedious, and only provides information about the structural condition at the visual inspection areas. At the same time, only surface-level damage can be detected, while internal defects such as core cracking or rebar corrosion remain undiscovered until they reach an advanced stage [2], [3]. For the latter, most commonly, strain gauges, accelerometers, or displacement transducers are attached to specific points on a structure via a hard-to-install and maintain wired connection [6]. Such a solution is not effective at capturing distributed responses if the damage occurs at locations not equipped with sensors, and the spatial resolution of conventional wired sensor arrays is generally insufficient to detect cracks [11], [12].

3. Emergence of Smart Concrete

To resolve the limitation in terms of coverage and durability due to the external placement of instruments, researchers proposed the concept of smart concrete, a type of construction material that is able to sense its own state (i.e., mechanical or physical condition) [14], [15]. Smart concrete consists of self-sensing (piezoresistive) concrete [14], conductive concrete [15], or sensor embedded concrete [16]. In general, those concretes incorporate various conductive elements such as carbon fibres [15], carbon nanotubes (CNTs) [16], or graphene into the paste-

like structure of cement to allow the final material to be sensitive to strains or cracks, or to embed sensing elements within concrete during the casting process [14], [16]. Smart concrete enables acquiring information from a larger area compared to point measurements from attached sensors.

4. Embedded Sensors

Embedding sensors within the concrete during the casting process can provide several benefits in comparison to conventional approaches of attaching or embedding sensors on the surface or within accessible regions: internal sensors are well-protected against mechanical damage, weathering, and vandalism and can also assess internal conditions such as temperature, humidity, strain, and corrosion that are not available to external measurements [17]–[19]. Placing sensors internally allows for continuous, uninterrupted measurements throughout the structure's service life - from determining the hydration temperatures during curing to evaluating time-dependent loading and environmental effects with far greater utility than periodic measurements based on an assumed schedule, allowing the transition from a time-based to a condition-based maintenance approach [18], [20].

5. IoT and AI Integration

On their own, integrated sensors produce great quantities of raw data that need to be gathered, processed, and evaluated in order to extract value. Smart concrete structural health monitoring systems therefore involve a conceptual pipeline wherein physical quantities are acquired by embedded sensors, converted to digital form and sent via wireless means through an IoT network to an edge or cloud server where artificial intelligence and machine learning algorithms can analyze them, identify patterns, recognize fault conditions, classify problems, issue alerts, and recommend maintenance [11], [24]. Thus, such solutions connect the civil engineering activity of structural health monitoring to the domain of sensors and to the realm of data science.

6. Objectives of the Review

Against this background, this review article has four objectives: (1) to compare embedded-sensor technologies used in smart concrete; (2) to describe the architecture by which data acquired from embedded sensors are sent and processed in IoT, edge, and cloud computing systems; (3) to discuss how artificial intelligence and machine learning algorithms can be

utilized to analyze information from embedded sensors for damage detection and prediction; and (4) to identify research gaps and future trends in embedded-sensor technology.

REVIEW METHODOLOGY

This review has taken a narrative-critical approach rather than a systematic review with screening to fit within the scope of a survey article aimed at a civil engineering and data science audience.

1. Literature Databases

The sources that were used for the research were located through various different scientific databases and repositories, including such resources as Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, the ASCE Library, and Google Scholar, as well as different publishers' websites, among which MDPI and Wiley Online Library are included.

2. Search Strategy

The search queries used combinations of the following keywords: “smart concrete” AND “embedded sensors”; “smart concrete” AND “structural health monitoring”; “self-sensing concrete” AND “damage detection”; “embedded sensors” AND concrete AND IoT; “smart concrete” AND artificial intelligence; “piezoresistive concrete” AND damage detection; and “fiber optic sensor” AND concrete AND structural health monitoring. In addition, the search included specific queries related to individual sensors, communication standards such as LoRaWAN, and machine learning or convolutional neural networks for crack detection.

3. Inclusion and Exclusion Criteria

The review focused on peer-reviewed journal papers, proceedings of relevant conferences, and reviews, and included foundational studies on structural health monitoring (SHM) that continue to be highly cited. The papers were included if they explicitly addressed embedded or self-sensing concrete technologies, wireless or IoT-based SHM concepts, or used artificial intelligence/machine learning to identify or assess structural damage. The papers describing only surface-mounted technologies or irrelevant to concrete structures were excluded, as well as those reporting the same data or results, and non-empirical publications such as white papers. As the review was not registered as a systematic review, this section does not include the number of the considered and excluded papers; rather, the list below provides the reference list for the papers considered in this review.

SMART CONCRETE AND EMBEDDED SENSOR TECHNOLOGIES

1. Smart Concrete

Smart concrete generically refers to enhanced cementitious composites with embedded or compositional features enabling sensing, actuating, or self-repairing capabilities in addition to the standard requirements for construction materials [14], [15]. In the context of structural health monitoring (SHM), the most interesting type of smart concrete is self-sensing (or inherently piezoresistive) concrete, where a certain percentage of conductive agents is added to the cement mix during the curing process. The most common conductive agents include carbon fiber, carbon nanotubes (CNTs), carbon nanofibers, graphene, and steel fibers; their inclusion into the cement results in forming a conductive network, which is then capable of withstanding mechanical deformations typical for concrete structures [15], [16]. For inherently piezoresistive concrete, the degree of deformation is directly linked to the change in the overall resistance of the concrete mix due to the disruption of the conductive network, which can be quantified using the gauge factor – the ratio of the relative change of resistance to strain [15]. Notably, conductive concrete can be utilized in other areas of civil engineering, including de-icing and electromagnetic shielding, but these applications are outside the scope of SHM. Meanwhile, other smart concretes utilizing nanomaterials for mechanical performance improvement also provide additional sensing capabilities, albeit to a lesser extent, than inherently piezoresistive concrete. The critical advantage of self-sensing concrete is the possibility of distributed sensing, as opposed to the use of discrete and often costly sensors.

2. Embedded Sensor Technologies

a) Strain Sensors:

Conventional embedded strain gauges typically consist of a resistive foil or wire mounted on a carrier and encapsulated in concrete, which allows measuring the local strains caused by the applied loads due to the gauge's resistance variation. This type of strain gauges is usually inexpensive and well-established; however, the short gauge length decreases the accuracy of strain measurements, and the metallic leads and adhesives are vulnerable to concrete moisture and highly alkaline chemical environment, leading to a reduced service life and low stability of such strain gauges after installation [2], [3]. Therefore, there is a common need for developing alternative strain sensing technologies, such as fiber optics and self-sensing ones described below.

b) Fiber Bragg Grating Sensors:

Fiber Bragg grating (FBG) sensors are optical fibers with a regular sequence of alternating refractive indices, formed by strain or temperature, along the core. A change of these values will modify the wavelength of a reflected optical signal from the sensor structure, thus enabling simultaneous measurements of strain and temperature, along a single optical fiber with a spatial resolution of several centimeters [17], [20]. Such sensors are highly sensitive, immune to electromagnetic interference, and can be multiplexed on the same transmission link, making them attractive for long-term embedded monitoring of strain and temperature, both during the concrete curing process, and during service loads. However, being optically sensitive, they are mechanically very fragile and require special packaging to survive the pouring process and dynamic loads. Moreover, the required interrogation equipment is relatively expensive, which significantly reduces their practical use despite all the advantages described [17].

c) MEMS Sensors:

Micro-electromechanical systems (MEMS) accelerometers have been used in recent years for detecting the dynamic response of structures such as bridges, due to their low cost, small size, and ability to be incorporated into a wireless sensor node [6], [12]. When implemented in a wireless sensor network, MEMS accelerometers allow eliminating the large amount of wiring needed for connecting a set of accelerometers placed on the structure with a control unit for signal processing [11], [13]. However, being low-cost and small-sized comes at the price of reduced performance in terms of resolution compared to wired accelerometers in laboratory conditions, limited operating time due to battery power, and higher sensitivity to noise and spurious signals masking the desired response [6].

d) Piezoresistive Sensors:

Piezoresistive sensing, either through the use of discrete sensor elements embedded in cement or in a self-sensing concrete as discussed above, relies on the change in resistivity of piezoresistive composites under strain [15], [16]. Since crack opening causes higher resistivity while crack closing lowers it, piezoresistive sensors can be used to indicate incipient cracking and monitor its progress before it becomes apparent on the surface. The main benefits of such a technique are its inherent compatibility with concrete and the relative simplicity and low-cost of the materials used, while its main drawbacks are its

susceptibility to temperature/humidity changes and nonlinearity at higher strains, and the challenge of obtaining a homogenous mix during production [16].

e) Corrosion Sensors:

Reinforcement corrosion due to ingress of chlorides and carbonation is considered to be one of the most economical deterioration mechanisms in reinforced concrete [17]–[19]. The embedded corrosion sensors typically make use of electrochemical principles (half-cell potential, linear polarization resistance, or electrochemical impedance spectroscopy) through reference and counter electrodes embedded in the concrete cover for determining the initiation of reinforcement corrosion before visual indications such as cracking and spalling become apparent [18], [19]. Chloride-specific electrodes and, more recently, fluorescent optical fibers have been proposed to directly measure chloride-ion penetration. The issues of long-term stability of the embedded electrodes in the harsh pore solution environment and the limited information obtainable from a single sensor about the condition of the entire structure are also discussed [17].

f) Temperature and Humidity Sensors:

Internal temperature and relative humidity sensors, typically implemented by thermocouples, thermistors or capacitive humidity elements, can be used to assess the heat of hydration curing process, determine long-term moisture ingress, or provide temperature compensation for strain measurements extracted from either FBG or piezoresistive sensors [16], [20]. Such sensors are usually reliable and inexpensive, though their use in detecting structural status is primarily indirect in nature.

Table 1: Comparison of Embedded Sensor Technologies

Sensor	Main Parameter	Principle	Advantage	Limitation	Application
Strain Gauge	Local strain	Resistive foil deformation	Low cost, well understood	Short lifespan, moisture-sensitive	Localized strain monitoring
FBG Sensor	Strain, temperature	Wavelength shift in optical grating	High sensitivity, EMI-immune, multiplexable	Fragile, costly interrogation unit	Curing & long-term strain monitoring

MEMS Accelerometer	Vibration, acceleration	Micro-machined inertial sensing	Small, low-cost, wireless-ready	Battery-dependent, moderate resolution	Bridge/building dynamic response
Piezoresistive / Self-sensing Concrete	Stress, strain, crack	Resistivity change under deformation	Distributed sensing, low material cost	Nonlinear response, moisture-sensitive	Crack & damage detection
Corrosion Sensor	Corrosion rate, chloride level	Electrochemical (half-cell, LPR, EIS)	Early corrosion detection	Electrode degradation, localized reading	Rebar corrosion monitoring
Temperature/Humidity Sensor	Internal temperature, moisture	Thermocouple / thermistor / capacitive	Robust, low cost	Indirect damage indicator	Curing & durability monitoring

Overall, the discussed technologies demonstrate the trade-off in terms of performance features. Thus, fiber Bragg grating (FBG) sensing allows realizing better sensitivity and multiplexing capacity, though at the expense of complicated and expensive installation. Self-sensing and piezoresistive concretes, in their turn, enable the accomplishment of extensive spatial resolution for a relatively low price, while being highly sensitive to humidity and temperature changes. Accelerometers based on MEMS technology provide excellent insight into global structure behavior, whereas local cracking information is unavailable from such sensors. Finally, sensors for detecting corrosion and environmental effects allow gaining valuable information about the local environment, which other technologies cannot ensure. Thus, for creating a highly performing embedded structural health monitoring (SHM) system, it is essential to combine various solutions, which would complement each other's strengths and weaknesses [6], [16], [17].

REAL-TIME STRUCTURAL HEALTH MONITORING ARCHITECTURE

A complete real-time SHM system based on smart concrete goes far beyond the simple matter of sensors. The information acquired by these devices must be processed through acquisition, communication, computation, and decision support stages in order to provide guidelines for maintenance. Figure 1 shows an example, in which the information acquired by the sensors is sent to a local data acquisition unit, then transmitted through an IoT gateway to cloud and/or edge computing platforms, where predictive analytics based on artificial intelligence

algorithms are performed to, ultimately, detect damage and support maintenance decisions [11], [24], [34].

1. Data Acquisition

Sensor signals, whether resistive, optical, or electrochemical, need to be digitized by local acquisition electronics. Since target signals in a structural monitoring scenario, like ambient vibrations or slowly evolving strains, often exhibit large dynamic ranges, proper acquisition electronics need to have sufficient resolution, appropriate anti aliasing filters, and, in the case of wireless nodes, a reasonable power budget, since signal conditioning and radio transmission often dominate energy consumption in a wireless sensor node [21] , [22].

2. Wireless Communication

Short-range protocols like Wi-Fi and Bluetooth provide high data rates needed for transmitting detailed vibration data but require much higher power and have limited ranges, making them useful for local area monitoring tasks; Zigbee provides lower power consumption but also limited range, previously being used in wireless mesh sensor networks for bridges [11]; Long Range Wide Area Network (LoRaWAN) technology allows for long-range, low-power communications which are useful in sparse sensor networks needed for monitoring of large structures, having been already considered for use with concrete embedded and battery-free sensors with energy harvesting [21], [22]; and 5G cellular network provides high bandwidth and low delay suitable for the use in dense sensor networks. At the same time, concrete, acting as a shielding medium, poses a challenge for radio wave propagation for all of the above-mentioned technologies [21].

3. IoT Integration

An IoT gateway collects information from several sensor nodes, performing the necessary protocol conversion and transmitting the data over regular IT networks to remote servers, enabling engineers to monitor the condition of the observed object remotely and continuously without being tied to the site [34], [35]. IoT can also help coordinate various types of sensors, such as strain, vibration, corrosion, and environmental ones, and enable the unified presentation of their data in the infrastructure or building information modeling management system [21].

4. Cloud and Edge Computing

Cloud computing is typically used for large-scale storage, computation, long-term data warehousing, model training, and structure-wide analytics, is associated with significant communication overheads and costs, and requires uninterrupted Internet access [34], [35]. Edge computing tackles the first two challenges by conducting data preprocessing, feature extraction, or even light-level analytics on-board or in close proximity to the sensor, significantly reducing the data that needs to be transmitted and processed in the cloud and providing faster responses to detected anomalies [34], [36]. In practice, however, most of the cited works employ hybrid edge-to-cloud systems, where edge nodes perform some of the key processing steps, while the cloud is involved in more computationally intensive structure-wide analytics and long-term data warehousing [35], [37].

5. Real-Time Alerts

When sensor readings or edge/cloud analytics identify values outside of expected ranges for any of the monitored parameters, for example, strains beyond design limits, anomalous vibration characteristics or increasing corrosion potentials, an alert could be sent to structural engineers or asset managers so that they could perform a detailed inspection to ensure that no safety-critical degradation has occurred [34]. Alerts require careful consideration to avoid causing too many false alarms that waste resources, but still have an acceptable threshold of detecting early-stage degradation.

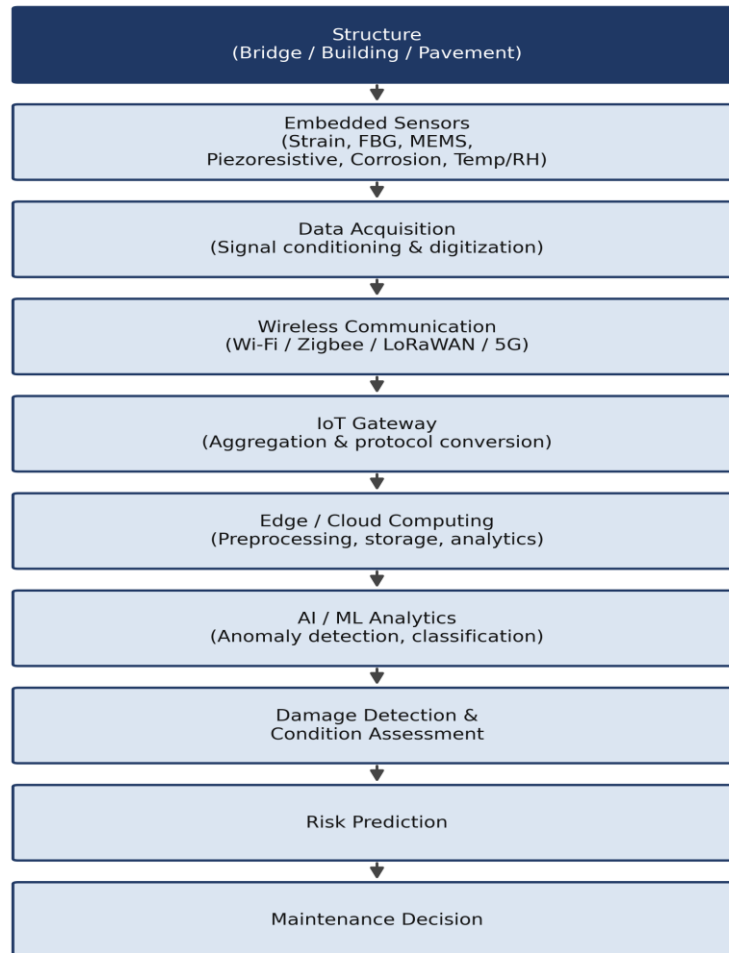


Figure 1: Architecture of an IoT-enabled smart concrete structural health monitoring system.

V. AI AND MACHINE LEARNING FOR DAMAGE DETECTION

A. Machine Learning

Classical machine-learning algorithms are still widely used in the field of SHM classification tasks since they require limited amounts of data and computational power for training. For example, Random Forest classifiers, which train an ensemble of decision trees, have been repeatedly proven to yield highly reliable models for damage/no-damage classification of either vibration- or image-based features [17]; Support Vector Machines (SVM) are known to perform well on linearly separable data sets and have been used for bridge damage diagnosis from acceleration data [26]; and Decision Trees, while not performing as well as random forests, can provide easily interpretable classification rules, which are beneficial for engineering applications. Note that all three methods above typically rely on extracted features from raw sensor data for training and classification.

B. Deep Learning

Deep-learning methods achieve their success by learning representations of the data which can be used discrimination to predict some target output, circumventing the need for extensive manual feature engineering. The convolution neural networks (CNN) in particular have proven to be efficient in the tasks of surface crack detection, either in images [10], [25], or, in the case of one-dimensional convolution, on the raw strain or vibration time series to enable real-time damage detection [8], [9], [28]. The long short-term memory networks (LSTM) and other recurrent architectures were used to model temporal dynamics of the time series and autoencoders were utilized to perform unsupervised detection of damaged sensors based on reconstruction error [7]. The CNNs were shown to significantly outperform the traditional ML methods such as random forest, SVM, or k-nearest neighbours on the task of vibration-based damage classification.

C. Anomaly Detection

Because labelled damage data from real structures is sparse, unsupervised and semi-supervised anomaly detection methods that learn a prototypical healthy-signal distribution and then raise an alarm when measurements deviate significantly therefrom are preferable in practice [7]. These methods can be especially valuable in a resource-constrained setting such as an embedded computing node, where they can provide an initial, computationally inexpensive triage of the sensor data before more intensive analyses are performed in the cloud [34], [36].

D. Damage Classification

The majority of AI/ML-based solutions to the damage detection problem go beyond merely distinguishing between damaged and undamaged components, attempting, instead, to classify the damage as either normal, minor, moderate, or severe in order to prioritize maintenance [29]. Naturally, such multiclass classifications require more data than binary classifications do, and their effectiveness depends on the extent to which the training dataset covers all of the possible damage levels.

E. Failure-Risk Prediction

When sufficient data on the process of their performance degradation are available, regression-based ML and deep-learning models can be trained to predict the future values of the corresponding response variables, such as the corrosion current density or crack width, thus enabling the estimation of when a particular degradation indicator is about to reach a critical value [30]. This, in turn, allows shifting from the traditional paradigm of maintenance based on time or simple response variables to predictive maintenance.

F. Digital Twin Integration

A digital twin utilizes the sensor data stream from a structure in combination with a physics- or data-driven model, such as a finite-element model, to form an updated digital replica of the structure's state [47] [48] [49]. Applied in conjunction with AI-based analytics, digital twins enable the synthesis of information from disparate sensors into structure-wide assessments, allow for what-if analyses and simulations of load cases and repairs, and provide a framework for long-term structure lifecycle management, despite being largely at a research and demonstration level of adoption.

TABLE II AI/ML TECHNIQUES FOR STRUCTURAL DAMAGE DETECTION

AI/ML Method	Input Data	Application	Major Advantage	Limitation
Random Forest	Statistical/vibration features	Damage/no-damage classification	Robust, handles noisy data	Requires feature engineering
Support Vector Machine	Accelerometer/strain features	Binary/multiclass damage classification	Effective on small datasets	Limited scalability to large data
CNN (2D)	Crack images	Surface crack detection/segmentation	High accuracy on image data	Needs large labelled image sets
1D-CNN	Raw vibration/strain time series	Real-time damage detection	No manual feature extraction	Computationally demanding
LSTM	Sequential sensor data	Temporal pattern/trend analysis	Captures long-term dependencies	Long training time
Autoencoder	Multivariate sensor streams	Unsupervised anomaly detection	Works without labelled damage data	Sensitive to baseline drift

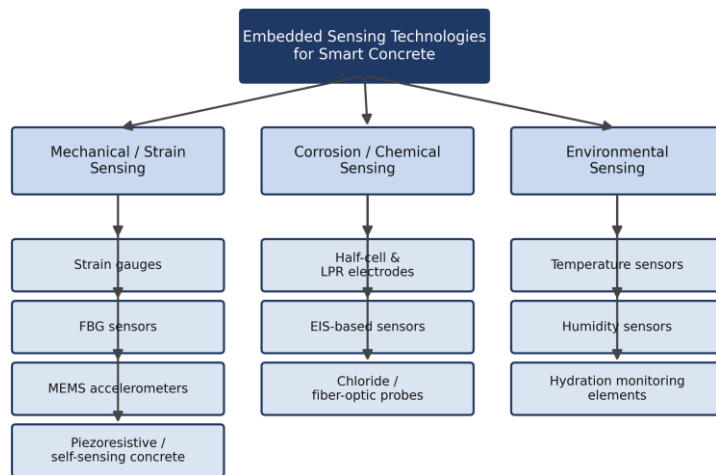


Fig. 2. Classification of embedded sensing technologies for smart concrete.

VI. APPLICATIONS OF SMART CONCRETE

Bridges are the most common engineering structures regarding the application of smart concrete SHM. They include crucial infrastructure for traffic transportation and are constantly subjected to cyclic traffic loading and environmental influences such as extreme climates or, in the case of coastal or de-iced bridges, aggressive chloride containing environments [11], [24].

A. Bridges

MEMS-based wireless accelerometer networks are typically used for monitoring the bridges' modal frequencies and detecting a loss of stiffness, while embedded corrosion and FBG strain sensors can be used for assessing deck and girder condition [12], [17].

B. Buildings

On high-rise and/or critical use buildings, embedded sensing enables both routine condition assessment as well as rapid post-earthquake damage evaluation: with self-sensing concrete elements and/or extensive use of accelerometers, engineers can prioritize building systems and structural elements for inspection before reoccupancy [9], [29]. Additionally, continuous monitoring of structure response (e.g., vibration, strain) can also be used to assess serviceability of a structure subject to wind or other dynamic loading.

C. Flyovers

The roadways of urban flyovers and other overpasses are subject to heavy dynamic loading which is challenging to assess through standard visual inspections on a regular basis due to the obstruction of the view of the lower surface, making the usage of embedded strain and vibration

sensors with IoT capabilities a viable option for continuously assessing the state of the structure without the need to close the road for inspection [11].

D. Tunnels

Tunnel linings can be affected by ground-induced deformations, water ingress and aging processes which are not easily accessible for assessment from the surface; distributed fiber Bragg grating (FBG)-based strain-sensor arrays which are embedded in tunnel linings can monitor the strain distribution of a tunnel lining throughout its lifetime, thus enabling an early recognition of relevant distresses [17].

E. Roads and Pavements

Embedded FBG and piezoresistive sensors can be used for monitoring strain from traffic loads, axle weights, and traffic volumes for pavement structures that incorporate them within their layers [17].

TABLE III APPLICATIONS OF SMART CONCRETE FOR STRUCTURAL MONITORING

Structure	Monitoring Parameter	Suitable Sensors	Main Benefit
Bridges	Strain, vibration, corrosion	MEMS accelerometer, FBG, corrosion sensor	Early detection of fatigue & corrosion
Buildings	Vibration, strain	Self-sensing concrete, accelerometer array	Post-seismic rapid assessment
Flyovers	Strain, vibration	Embedded strain/vibration sensors	Continuous monitoring without lane closure
Tunnels	Strain, deformation	FBG sensor arrays	Early lining distress detection
Roads/Pavements	Strain, axle load	Embedded FBG/piezoresistive sensors	Combined structural & traffic monitoring

VII. CHALLENGES AND RESEARCH GAPS

Despite substantial technical progress, several practical challenges continue to limit the widespread deployment of smart concrete with embedded sensors.

A. Sensor Durability

Embedded sensors must survive for decades in an alkaline, variable-moisture concrete environment; polymer coatings, optical-fiber claddings, and electrode materials may degrade in such an environment, and a sensor that has been embedded cannot be serviced or replaced easily [17], [20].

B. Sensor Survival During Concrete Casting

The mechanical stress on sensitive sensors due to the vibration, pressure, and heat of concrete placement and compaction makes it necessary to use special packaging, which can additionally affect the measurement characteristics of the sensor [17].

C. Sensor–Concrete Compatibility

Achieving good bonding and strain transfer between an embedded sensor and the surrounding cementitious matrix, while avoiding the formation of a local weakness or void, is not a trivial materials-engineering challenge for any class of discrete, nonintrinsic sensors [10].

D. Wireless Communication Through Concrete

Concrete's density, along with embedded reinforcements, tends to limit RF signal propagation, thus constraining sensing range and reliability for sensors located inside reinforced structures [9], [21].

E. Power and Energy Requirements

Battery replacement for sensors permanently encased in concrete is typically impractical; hence, energy needs to be harvested from ambient vibration, solar, or radio frequency sources or consumed via extremely-low-power electronics in order to enable long-term autonomous operation, despite the limited power that can be generated or stored in such systems [21], [22].

F. Signal Noise and Calibration

Structural signals of interest are often embedded in low signal-to-noise ratios and are challenging to distinguish from environmental and electronic noise. Drift due to temperature cross-sensitivity in strain measurements needs to be calibrated regularly to ensure measurement stability [6], [16].

G. Large-Scale Data Management

Continuous monitoring of large infrastructures using multiple sensors produce enormous amounts of data that need to be stored, indexed, and made available for analytical processing. This is a significant challenge to data storage and indexing technologies, as well as costs [34], [35].

H. AI Model Generalization

AI/ML models trained on data from one structure or sensor configuration often fail to generalize to different structures, environments, or damage types, limiting the direct application of trained models to other projects [7].

I. Lack of Real-World Datasets

Much of conventional AI/ML-based structural health monitoring research is based on lab specimens or numerical simulations, as labeled damage states of real-world structures are rarely available, particularly for uncommon, severe damage scenarios, limiting the generalization performance of learned models [4], [7].

J. Cost and Scalability

The sum of sensor costs, interrogators, communications infrastructure, and data repositories represents a significant investment that restricts their use in low-cost infrastructure applications [16].

K. Standardization

The lack of standardized methods for installation, calibration, format, and comparison impairs analysis comparisons and impedes the adoption of these technologies by the industry [11].

L. Cybersecurity

As SHM systems rely increasingly on wireless and cloud technologies, they may be subject to various cybersecurity threats such as eavesdropping, spoofing and denial-of-services that may target critical decision-making algorithms [34].

In addition to the research areas identified in Section 3 there are a number of other areas that require further investigations:

- (1) development of reliable embedded sensor packaging that can survive for the design lifetime of the structure,
- (2) establishment of standardized low-power communication protocols,
- (3) creation of learning-based algorithms that generalize well across structures,
- (4) access to larger and more openly shared field data sets of damaged structures, and
- (5) consideration of cybersecurity issues for such systems.

TABLE IV MAJOR CHALLENGES, RESEARCH GAPS, AND FUTURE SOLUTIONS

Challenge	Current Limitation	Research Gap	Potential Solution
Sensor durability	Degradation in alkaline/moist environment	Lack of multi-decade field validation	Improved protective coatings & packaging

Challenge	Current Limitation	Research Gap	Potential Solution
Wireless transmission through concrete	Signal attenuation, shielding effect	Standardized low-power protocols for concrete	Optimized LoRaWAN/NB-IoT node design
Power supply	Batteries cannot be replaced once embedded	Limited harvestable energy	Vibration/RF/solar energy harvesting
AI generalization	Poor transfer across structures	Absence of universal damage models	Transfer learning, federated learning
Real-world datasets	Reliance on lab/simulated data	Scarcity of labelled in-service damage data	Shared open SHM data repositories
Cost & scalability	High combined system cost	Limited deployment on budget-constrained projects	Low-cost sensor & node design
Cybersecurity	Vulnerability of wireless/cloud links	Lack of SHM-specific security frameworks	Encrypted, authenticated IoT-SHM protocols

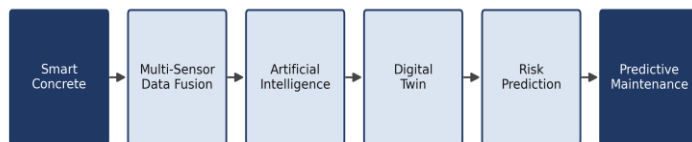


Fig. 3. Future AI-enabled smart infrastructure framework.

VIII. FUTURE RESEARCH DIRECTIONS

The future developments are forecasted to follow several directions, which can be grouped into a few trends. The first one is related to the development of various self-powered methods that can be integrated into the concrete, thus eliminating the need for battery replacement in wireless nodes [21], [22]. The next step will be the enhancement of the standard of the low-power wireless sensor networks specific for the concrete environment [11], [13]. The application of edge artificial intelligence (AI) is also expected to be used, as the increased level of intelligence at the edge can lead to an improved response to the detected damage and a reduction of the data

transmission costs [34], [36]. The trend includes also the development and use of multiple-sensor systems, which can process the data related to not only strain and vibration but also corrosion and other effects, thereby improving the localization accuracy and reducing false alarms [30]. Another trend is related to the improvement of the digital-twin concept, where the automation of data processing from heterogeneous sources and the use of digital twinning with the physics-based analysis will enable moving from research-oriented applications to complex real-life implementations [47]–[49]. The list can be continued with the improvement of smart concrete through the use of nano-modified materials, which can enhance the performance of the embedded sensors [15]. Finally, the implementation of explainable AI will contribute to the process by enabling human-level trust in the decisions made by AI-based automated systems [7]. Altogether, these trends will lead to a concept of intelligent concrete structures, where the use of smart concrete materials, IoT-based interconnected sensors, and the AI-driven data analysis platforms will enable the transition from the current state-of-the-art to an actual forecast-driven maintenance paradigm that will require extensive research and trials before it can be implemented in practice.

IX. CONCLUSION

This review has assessed emerging technologies related to smart concrete with embedded sensors for real-time monitoring of structural integrity. This includes an overview of relevant sensing, wireless communication and control, and machine learning technologies. While the review has found that individual elements of such a system have been demonstrated in laboratory and, in some cases, field settings, the overall system's practical utility appears to be constrained by limitations in sensor lifetime, communication reliability, data annotation challenges, cost, and standardization. At this time, smart concrete appears to be best utilized as emerging and complementary technology to conventional structural health monitoring techniques, offering benefits in select applications such as monitoring of high-value transportation infrastructure elements. Further advances in sensor, communication, and artificial intelligence technologies, as well as reductions in deployment costs, will be needed to fully realize the potential of smart concrete. Interdisciplinary collaboration between civil infrastructure engineers and researchers in wireless communication and data science fields is likely to be critical.

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