

INTELLIGENT MONITORING OF THE TECHNICAL CONDITION OF BUILDING STRUCTURES

Temirlan Bakhytzhan
Structural Engineer, USA

Abstract

Intelligent monitoring of the technical condition of building structures is one of the most rapidly developing areas of modern civil engineering. Traditional technical inspection systems, based primarily on periodic visual inspections, instrumental measurements, and local non-destructive testing, are gradually being supplemented by continuous data collection, automated diagnostics, and forecasting of structural changes. The current stage of structural monitoring development is characterized by the integration of sensor systems, the Internet of Things, computer vision, machine and deep learning methods, digital twins, and physically informed neural networks.

The purpose of this article is to analytically examine modern approaches to intelligent monitoring of building structures and identify the most promising system architecture that integrates data on the actual condition of the structure, artificial intelligence algorithms, and engineering computational models. This article analyzes current research in the fields of Structural Health Monitoring (SHM), intelligent vibration data analysis, computer vision, IoT monitoring, digital twins, self-diagnosing cementitious composites, and physics-informed machine learning. It is shown that the transition from simple damage detection to intelligent condition assessment requires integrating multiple sources of information and taking into account the physical nature of the structure's operation.

The scientific novelty of this article lies in the proposed conceptual model of intelligent monitoring. The new model comprises six interconnected levels: digital object context generation, multichannel data collection, preliminary data processing and synchronization, intelligent anomaly and damage detection, assessment of the current technical condition, and forecasting of its changes. Particular attention is paid to the need to maintain the engineering interpretability of artificial intelligence results. It is concluded that the most promising approach is a hybrid model in which machine learning methods do not replace computational and expert methods, but are integrated with them into a unified system for supporting engineering decisions.

Keywords: Building structures, technical condition, Structural Health Monitoring, SHM, artificial intelligence, machine learning, deep learning, computer vision, Internet of Things, digital twin, damage prediction, intelligent diagnostics.

Introduction

The reliability and safety of building structures are directly related to the ability to promptly detect degradation processes that occur during the life cycle of a building or structure. Reinforced concrete, metal, masonry, and composite structures are subject to constant and variable loads, temperature changes, moisture, corrosion, cyclic impacts, seismic events, and other factors. As a result, the initial characteristics of the structure gradually change, which can manifest as cracks, reduced rigidity, increased deformations, changes in dynamic characteristics, reinforcement corrosion, and other forms of damage.

The traditional system of technical inspection of building structures is primarily based on periodic inspections. An engineer inspects the structure, records visible defects, takes the necessary measurements, and, based on the data, formulates a conclusion on the technical condition. This approach remains necessary, but its effectiveness is limited by the frequency of inspections and the dependence of the results on the comprehensiveness of the inspection and the specialist's qualifications.

The development of Structural Health Monitoring (SHM) is changing this concept. SHM involves the systematic collection of information on a structure's behavior using sensors and subsequent analysis of the measurements to identify changes in its condition. Modern research is no longer simply considering SHM as a measurement system, but as a complex system encompassing the collection, processing, interpretation, and prediction of a structure's condition [1], [4].

Particularly significant changes have occurred with the active implementation of artificial intelligence methods. Machine learning enables the automatic analysis of large arrays of vibration, deformation, and other measurements, identifying patterns that are difficult to detect using traditional data processing methods. Deep learning expands the capabilities of automatic feature extraction directly from source signals, images, and video streams [1].

A review of current research shows that intelligent monitoring is developing in several directions simultaneously. One is related to the analysis of the dynamic behavior of structures. The second is related to computer vision and the automatic detection of cracks, corrosion, chips, and other visual defects. The third is related to the use of IoT for continuous remote monitoring. The fourth is related to digital twins, which allow for the comparison of the actual state of a structure with its digital model. The fifth direction is related to physics-informed machine learning, where data is combined with physical laws and computational dependencies [1], [3], [4], [5]. Thus, modern intelligent monitoring should be viewed not as a separate software algorithm, but as an integrated engineering system.

From traditional technical inspection to intelligent monitoring. Traditional inspection of building structures can be represented as a sequence: **inspection** → **measurement** → **defect identification** → **engineering analysis** → **condition report**. The main drawback of this approach is its discrete nature. The condition of the structure between two inspections remains essentially unknown. Some damage may develop gradually, while others may develop quite rapidly.

SHM proposes a different approach: information about a structure is collected regularly or continuously. This involves measuring not only directly visible defects, but also parameters that indirectly reflect changes in the mechanical state: acceleration, displacement, deformation, natural frequency, temperature, stress, and other characteristics.

The current stage of SHM development is associated with a transition from the "sensor-measurement-engineer" model to the following: **sensors** → **digital data** → **intelligent processing** → **diagnostics** → **forecast** → **engineering solution**. This change is fundamentally important. A large volume of data does not in itself mean improved monitoring quality. If a system can only accumulate measurements but cannot automatically identify significant changes, its capabilities remain limited. This is why intelligent data processing is becoming a central element of modern SHM. Bao et al. consider machine learning as a means of solving the high-dimensional problem of diagnosing the condition of complex structures, especially in the presence of incomplete and heterogeneous data [4]. The authors note the need to consistently address the problems of data cleaning, identifying dynamic characteristics, detecting damage, updating the digital model, and assessing reliability.

Therefore, intelligent monitoring must answer not only the question: "**What data was obtained?**", but also more important engineering questions: "**What has changed?**", "**Where did the change occur?**", "**How significant is it?**", "**Is it related to damage?**", "**How will the structure's condition change in the future?**", "**Is intervention required?**" This transition from recording to interpretation is the main substantive difference of intelligent monitoring.

The sensory foundation of intelligent monitoring. Any intelligent monitoring system begins with obtaining reliable data. Therefore, the quality of artificial intelligence directly depends on the quality of the measurement infrastructure.

Modern SHM systems utilize accelerometers, strain gauges, displacement sensors, tilt sensors, temperature, humidity, pressure, deformation sensors, and other measuring devices. Wireless sensor networks and IoT infrastructure play a key role.

The state of IoT technologies in SHM is examined in detail by Bhatta and Dang [3]. The authors demonstrate that the proliferation of wireless communications and cloud technologies has created the conditions for the organization of virtually continuous monitoring of construction structures. The IoT enables the connection of distributed sensors to a computing platform where information is accumulated and processed. However, this raises a fundamental problem: the measurement systems themselves can become a source of uncertainty. Sensors are noisy, can lose connection, shift readings, or fail. Therefore, intelligent monitoring must monitor not only the condition of the structure but also the reliability of the measurements themselves. This issue is especially important for long-term monitoring. If a machine learning algorithm interprets a sensor malfunction as a change in the technical condition of the structure, the system may generate a false alarm.

In this regard, the use of digital twins is promising. Manocha et al. propose using digital twins to improve the reliability of SHM data and monitor the reliability of an object's state [6]. This

approach allows for the comparison of sensor data with a model of the structure's behavior and the identification of inconsistencies. Thus, the sensor infrastructure of intelligent monitoring must perform two functions: measure the structure's parameters and ensure the reliability of the measurements.

Intelligent analysis of vibration and dynamic data. Vibration monitoring is a classic area of SHM. The dynamic behavior of a structure contains information about its stiffness, mass, boundary conditions, and damage. Changes in cracks, localized stiffness loss, or changes in connections can lead to changes in natural frequencies, vibration modes, and damping coefficients.

Traditional methods require significant human intervention to identify informative parameters. Machine learning automates this process. Modern algorithms can use time series of accelerations, deformations, and displacements as input. Depending on the task, classification, clustering, regression, autoencoder, convolutional, and recurrent neural networks are used.

A review by Bao et al. shows that modern ML methods are applied at various stages of the diagnostic process, from measurement cleaning to modal feature identification and damage assessment [4].

A key advantage of machine learning is its ability to analyze multidimensional data. For example, a change in a single sensor may be related to temperature or external load and not indicate damage. However, if a group of interrelated parameters changes simultaneously, the likelihood of a true change in condition increases. Therefore, intelligent diagnostics should analyze not a single value, but **a pattern of structural behavior**.

Three levels of analysis can be distinguished: **anomaly detection** (determines whether the current behavior differs from the normal); **diagnostics** (determines the probable type and location of the change); and **condition assessment** (determines the degree of impact of the detected change on serviceability and reliability). Thus, anomaly detection is only the initial stage of intelligent monitoring.

Computer vision as an automated inspection tool. The use of computer vision for monitoring building structures is particularly rapidly developing. Cameras, drones, and mobile devices make it possible to obtain images and videos of large sections of structures without requiring engineers to access each area directly. Modern deep learning models are capable of automatically recognizing cracks, concrete chips, corrosion damage, surface layer destruction, and other visual signs of degradation.

Cha et al., in a comprehensive review of deep learning in SHM, highlight computer vision, UAV, digital twins, vibration monitoring, data recovery, and physically informed methods as interrelated areas of modern intelligent diagnostics [1].

A more detailed analysis of computer vision is presented by Pan et al. [2]. The researchers systematize automatic damage assessment methods into three levels: damage recognition; damage localization; and damage quantification. This division has significant engineering significance. For example, crack detection only answers the question of whether a defect exists.

Engineering assessment requires knowledge of its coordinates, length, width, orientation, and change dynamics. Therefore, computer vision is evolving from simple image classification to semantic and object segmentation. Contemporary research utilizes CNN, U-Net, Transformer family models, and other architectures [2].

However, computer vision cannot yet completely replace engineers. The main reason is that a visual defect does not always directly correspond to a loss of load-bearing capacity. For example, a surface crack in a reinforced concrete element can have different significance depending on its location, direction, width, depth, reinforcement condition, and load type. Therefore, computer vision is most effectively considered as **an automated level of visual diagnostics**, the results of which must be integrated with other measurements and engineering models.

Digital twin of a building structure. The digital twin is becoming one of the most promising elements of intelligent monitoring. A digital twin is a dynamically updated digital model of a real object that receives information from a monitoring system and is used to assess its current and predicted state.

In a traditional computational approach, a model of a building or structure is created, calculations are performed, and the expected behavior is determined. In a digital twin, the process becomes cyclical: **computational model** → **actual structure** → **measurements** → **model update** → **new assessment** → **forecast**.

Huang et al. proposed a practical IoT-based approach to SHM with a digital twin, which involves transmitting data from inexpensive sensors via a cloud platform and automated processing for damage diagnosis [5]. The study demonstrates the feasibility of using a digital twin to reproduce the force and deformation characteristics of a reinforced concrete element. This results in a unified information space for the structure. For a designer or engineer, this means the ability to move from analyzing individual readings to analyzing **the state of the structure as a system**.

Physics-informed machine learning is a field in which machine learning is supplemented with physical laws, differential equations, boundary conditions, or design constraints. This approach is particularly important for building structures, as the behavior of structures is determined by the fundamental laws of mechanics.

Wu et al. demonstrated the application of physics-informed neural networks to reconstruct structural displacements by combining accelerometric and visual measurements [10]. Physical constraints are incorporated directly into the learning function, improving the physical consistency of the results.

of a virtual sensor is particularly interesting. In a real-world design, it's impossible to install sensors at every point. PINN can use information from available measurements and a physical model to estimate the state at points where physical sensors are absent. The resulting principle is: **physical sensors + virtual sensors + computational model**. This allows for a significant

increase in the spatial resolution of monitoring without a proportional increase in the number of equipment.

The physics-informed approach can also be used to assess damage, stiffness parameters, and other characteristics. Its key advantage is its ability to reduce reliance on purely empirical data. Thus, the development of intelligent monitoring is gradually moving from two opposing approaches: **purely computational** and **purely statistical**, to their integration.

Conceptual model of intelligent monitoring Based on the studies reviewed, it is proposed to consider intelligent monitoring of the technical condition of building structures as a six-level system.



Thus, the proposed model has the following structure:

Digital model of the object



Multichannel monitoring



Clearing and synchronizing data



AI diagnostics



Integral assessment of technical condition



Forecasting and engineering solutions

The main result is not just automatic recognition of defects, but the creation of a closed cycle **"measurement - analysis - evaluation - forecast - decision"**.

Comparison of the main technologies of intelligent monitoring

Technology	Basic data	The main task	Advantages	Main limitations
Vibrating SHM	acceleration, deformation	identifying changes in dynamics	continuous monitoring capability	sensitivity to noise and external influences
IoT sensors	multiparameter measurements	remote monitoring	scalability, automation	reliability of communication and sensors
Computer vision	photo, video	detection and localization of defects	contactlessness, automation	dependence on lighting, angle and image quality
Self-sensing materials	electrical parameters	detection of deformations and damage	integration of sensor into material	a calibration, influence of a temperature and humidity
Machine learning	time series and features	diagnostics and classification	processing large amounts of data	the need for high-quality training data
Digital Twin	integrated data	assessment and prognosis of the condition	merging the model and actual data	high complexity of creating and updating the model
PINN/PIML	data + physical limitations	diagnostics and virtual measurement	physical interpretability	the complexity of building and training models

The comparison shows that no single technology is universal. In a promising system, they must be viewed as complementary components.

Shifting from diagnostics to prediction. Traditional monitoring primarily addresses the current state of a structure. Intelligent monitoring must additionally evaluate future dynamics. If the time series shows a gradual increase in deformation or a change in dynamic response, the algorithm can identify a degradation trend. However, forecasting is significantly more complex than diagnostics. It is necessary to take into account changing loads, climatic factors, maintenance impacts, and other circumstances. In this regard, the most promising approach is to combine temporal machine learning models with a digital twin. Conventionally, the process can be represented as follows: **historical data → trend identification → degradation mechanism identification → future state calculation → residual resource assessment → technical intervention planning.**

This approach creates the foundation for the transition from reactive maintenance to **predictive maintenance**. The principle of **"repairing after a serious defect is detected"** is replaced by the principle of **"detecting unfavorable trends in advance."**

Key challenges for further development. Despite significant progress, the widespread adoption of intelligent monitoring is limited by a number of factors. Firstly, there are no universal standards for the preparation and labelling of large data sets on damage to building structures. Secondly, many studies are carried out on laboratory models, while operational designs are characterized by much greater variability. Thirdly, it is necessary to ensure the transferability of models between different objects, materials and climatic conditions. Fourth, the development of explainable artificial intelligence methods is necessary. Engineers must be able to determine which features led the model to its diagnostic conclusion. Fifth, it's necessary to ensure compatibility between different types of data. The image, vibration signal, deformation, and computational model have different structures, so combining them is a separate scientific challenge.

Finally, the problem of integrating intelligent monitoring into existing building inspection and maintenance processes must be addressed. Therefore, a promising research direction lies not so much in creating an even more complex algorithm, but rather in developing an **integrated engineering platform** that integrates various data sources.

A promising scientific concept for intelligent monitoring. An analysis of current research allows us to formulate the following concept. Intelligent monitoring of building structures should be considered as a **multi-level cyber-physical system** in which the real structure is continuously linked to the digital model. Its basic diagram can be represented as follows:

Real building structure

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Sensory and visual information

↓

IoT / digital infrastructure

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Multimodal data fusion

↓

AI diagnostics

↓

Digital twin

↓

Assessment of the current state

↓

Degradation forecast

↓

Engineering solution

↓

Impact on operation and maintenance

↓

New data

Thus, the system becomes self-contained. The transition from individual damage detection algorithms to an integrated model in which **data, artificial intelligence, and the physical model of the structure interact is scientifically significant**. This approach appears to be the most promising for the further development of SHM.

Conclusion

Modern monitoring of the technical condition of building structures is evolving from periodic visual inspection and local instrumental measurements to continuous intelligent diagnostics. Analysis of modern scientific publications shows that key technologies in this transition include machine and deep learning, computer vision, IoT, self-diagnosing building materials, digital twins, and physics-informed machine learning [1]–[10].

Machine learning expands the capabilities of processing large amounts of monitoring data and enables the automatic detection of abnormal changes in structural behavior. Computer vision enables automated visual inspection and defect detection. The IoT creates an infrastructure for continuous data acquisition. Digital twins provide a link between the computational model and the actual state of the object. Physics-informed methods allow the statistical patterns identified by machine learning to be combined with the laws of physics.

However, the analysis shows that using a single technology does not provide comprehensive intelligent monitoring. The most promising approach is a multimodal system that integrates vibration, deformation, visual, temperature, and other data. The proposed conceptual model includes six key stages: generating a digital context for the facility, multichannel data collection, data processing and synchronization, intelligent detection of anomalies and damage, integrated assessment of the technical condition, and forecasting its future development.

A key area for further development is the transition from **detecting existing damage to predicting the progression of degradation**. In this case, intelligent monitoring becomes a tool not only for diagnostics but also for managing the lifecycle of a building structure.

In the future, a digital twin, linked to a sensor system and intelligent algorithms, could become the foundation for continuous digital monitoring of a building or structure. Artificial intelligence should be viewed not as a replacement for an engineer, but rather as an intelligent analytical layer capable of processing large volumes of information, identifying hidden patterns, and supporting engineering solutions.

Thus, the current trend in SHM development is toward the formation of a closed-loop system: **measurement → analysis → diagnostics → assessment → forecast → engineering solution → accumulation of new data**. It is the transition to such an integrated model that defines the promising direction of intelligent monitoring of the technical condition of building structures.

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