International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Modern Approaches in SHM: Combining AI, UAVs, and 3D Printing for Bridge Monitoring

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Submitted: 25/05/2023 **Revised:** 10/07/2023 **Accepted:** 26/08/2023

Abstract: The challenges of urban management grow as towns, vehicles, and people increase. Making cities smarter is one of the most effective strategies for overcoming urban problems. Today's "smart cities" are distinguished by the use of cutting-edge technology in their infrastructure and services. Smart cities make the most effective use of their resources through meticulous preparation. Smart cities provide their residents with more and better services by lowering costs and upgrading infrastructure. One of the vital municipal services that can be extremely beneficial in municipal administration is structural health monitoring (SHM). Essential urban infrastructure can last longer and operate more effectively by combining cutting-edge new technologies like the Internet of Things (IoT) with structural health monitoring. As a result, a thorough assessment of the latest developments in infrastructure SHM is essential. The construction, upkeep, and development of bridges are among the most important aspects of urban management, and they are one of the essential components of a city's infrastructure. The main goal of this study is to examine how artificial intelligence (AI) and certain technologies, such 3D printers and drone technology, may be used to improve the current state of bridge SHM systems, including conceptual frameworks, advantages and disadvantages, and existing methods. The future role of AI and other technologies in bridge SHM systems was covered in this study. In addition, a few cutting-edge research prospects that are made possible by technology are highlighted, discussed, and described.

Keywords: *Smart Cities; Structural Health Monitoring (SHM); Bridge Infrastructure; Internet of Things (IoT); Artificial Intelligence (AI); Unmanned Aerial Vehicles (UAVs); 3D Printing Technology.*

1. Introduction:

In order to give accurate, real-time data on structural integrity by identifying fractures, stress, and material deterioration, structural health monitoring, or SHM, was initially implemented on long-span bridges in the early 2000s. Although managing and maintaining sensor data presented difficulties for early systems, destructive and non-destructive methods, such as image processing and core sampling, have significantly improved SHM applications. This work suggests a data-driven approach to track the occurrence of cracks and forecast structural deterioration, especially as a result of environmental influences like precipitation, by utilizing embedded sensors and eddy current testing. To inform maintenance choices, an AI program examines the spread of cracks in three dimensions and contrasts sensor data with models that have been trained.

As essential components of urban infrastructure, bridges are essential for removing geographic obstacles and enhancing connectivity. Advanced SHM systems are critical to the durability and safety of smart cities. Conventional monitoring techniques, such vibration analysis, magnetic detection, and technician visual inspections, are frequently constrained, arbitrary, and unable to identify internal or concealed damage. Furthermore, physical inspections may not be possible during times of high traffic and may interfere with bridge operations. These drawbacks emphasize the necessity of more sophisticated, automated monitoring systems.

Recent developments in technology have brought about a change in SHM. In order to facilitate smooth remote data collection and transfer, modern

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systems today integrate wireless sensor networks (WSNs), optical fiber sensors (OFS), scanners, and electromagnetic technologies, all of which are supported by the Internet of Things (IoT). In order to interpret this data and enable more precise evaluations and predictive maintenance, artificial intelligence is essential. These developments promote effective, long-term infrastructure planning in addition to lowering the risk of structural failure. Consequently, SHM is becoming a crucial part of smart urban management, improving the lifetime, safety, and dependability of bridges.

The objective of this study is to examine the potential advantages, challenges, existing techniques, and recent developments in SHM systems for bridges that make use of AI and new technologies. Another aim of this study is to give researchers the tools they need to learn more about the surveillance technologies now used on bridges. AI, drones, and 3D printing technology will be examined and debated in particular as part of the SHM system evaluation process for bridges. It should also be noted that some aspects of these technologies—3D printers, drone technology, AI, and SHM systems—need more research, while others have not been studied as thoroughly, and where the demand for more thorough research is evident. This research attempts to offer a comprehensive and complete picture of AI and current technologies in the SHM of bridges, as well as recent advancements and trends in this area, even though the literature on SHM has been extensively researched and paid attention to. A graphical depiction of the study's framework is shown in Figure 1.

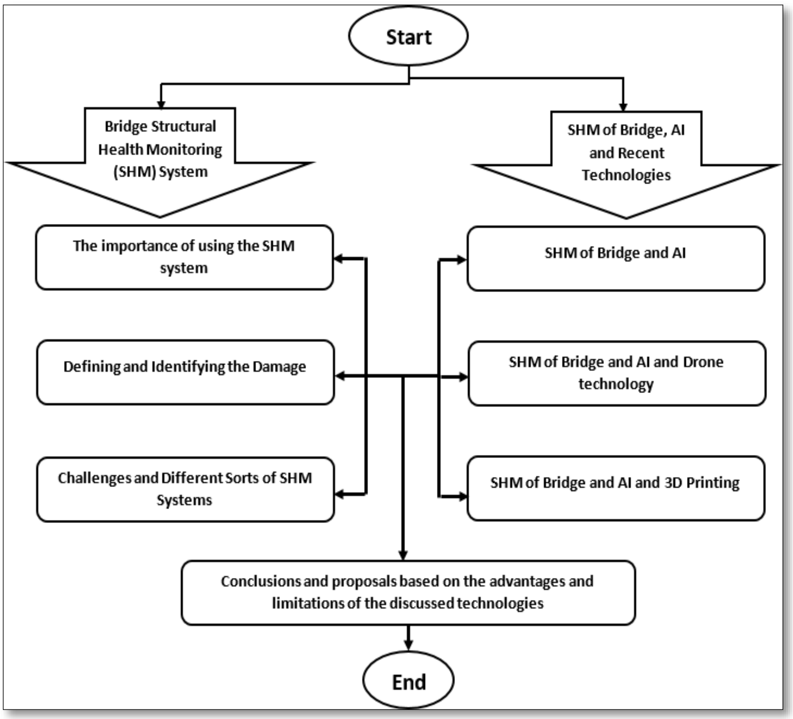

Figure 1. Flow chart of study.

As per the intended format, the remainder of this study is as follows: Section 2 introduces bridge structural health monitoring systems and conceptualizations, while Section 3 covers AI, drone technology, and the 3D printer. Section 4 discusses the latest developments in AI and current bridge structural health monitoring (SHM) technology. Section 5 contains concluding remarks about recent advances in bridge structural health monitoring.

2. Bridge Structural Health Monitoring (SHM) System

2.1 Importance of SHM Systems

Bridges are critical and costly infrastructure assets designed to last for decades. However, many are now handling traffic loads beyond their original design limits, which raises the risk of structural fatigue and failure. To ensure their safety and extend their lifespan, continuous monitoring of their condition is essential. SHM systems help in tracking both static and dynamic responses of a bridge using sensors and data-processing technologies. They allow early detection of structural deterioration, enabling timely maintenance and enhancing performance and safety.

How SHM Works

SHM involves:

1. Collecting data from sensors (e.g., strain, vibration).

2. Processing the data using computer algorithms.

3. Interpreting results to assess structural condition.

This allows informed decision-making regarding bridge maintenance and management.

Recent Developments in SHM

Study / Author	**Key Contribution**
Ko & Ni	New SHM tech: sensors, data mining, signal processing.
Vazquez-Ontiveros et al.	PPP-GNSS + probabilistic SHM = high accuracy monitoring.
Mousa et al.	Vision-based SHM (DIC): detects cracks, vibration, and damage in various bridge types.
AlHamaydeh & Aswad	Identified SHM limitations and future research needs.
Kamal & Mansoor	IoT in SHM: promising, but needs solutions for energy, security, and scalability.
Enshaeian et al.	Reviewed 20 years of SHM on U.S. bridges.
Maroni et al.	Real-time scour risk SHM system using probabilistic models.

Current bridge infrastructure faces significant risks due to damage, inefficiency, and vulnerabilities exacerbated by natural or man-made disasters like earthquakes and explosions. Reliable public infrastructure, especially bridges, is vital for modern society, particularly for disaster response and recovery. To maintain and extend the service life of bridges, Structural Health Monitoring (SHM) is essential. SHM uses sensors, smart materials, data communication, and intelligent analysis to non-destructively evaluate and monitor bridge conditions, enabling early detection of damage, reducing maintenance costs, and preventing catastrophic failures.

Historical bridge collapses, such as the 2007 I-35W bridge in Minneapolis and the 2018 Polcevera (Ponte Morandi) bridge in Genoa, highlighted the consequences of inadequate inspection and maintenance. These tragic incidents, which caused multiple fatalities, underscored the need for improved monitoring and infrastructure management. In response, engineers have increasingly adopted advanced technologies to monitor and maintain bridge safety, aiming to prevent future disasters and improve infrastructure reliability.

A summary of the process of evaluating the performance of bridges under a SHM system is shown in Figure 2.

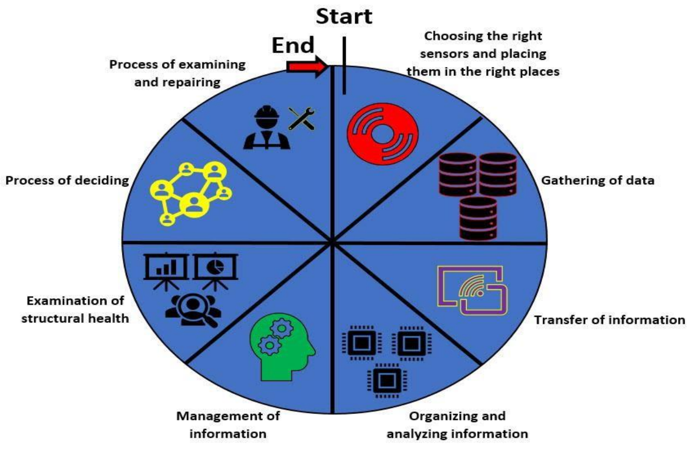

Figure 2. A summary of the procedure of the SHM system to monitor the functioning of bridges.

2.2 Defining and Identifying Damage in Bridge Health Monitoring

Traditional bridge damage identification relies on visual inspections, which allow local, direct observation but face limitations such as difficult access and inability to detect internal damage. Advances in Structural Health Monitoring (SHM) have been made through technologies like artificial intelligence (AI) and the Internet of Things (IoT), enhancing monitoring, control, assessment, and decision-making.

SHM methods are broadly divided into **diagnostic** and **prognostic** approaches. Diagnostic methods locate and measure damage using techniques such as ultrasonic testing, radiography, and magnetic particle inspection. Prognostic methods use diagnostic data to predict the remaining service life of a structure, enabling preventive maintenance.

Damage is any change that reduces a structure's functionality. Detecting damage requires comparing the current condition to its original "initial state." Damage identification often follows a hierarchical system with five levels:

1. **Damage detection** – recognizing that damage has occurred.
2. **Damage location** – determining the damage's position and orientation.
3. **Damage typification** – assessing damage severity and type.
4. **Damage extent** – evaluating the potential to limit or delay damage progression.
5. **Damage prediction** – estimating the remaining useful life or viability of the structure.

This structured approach improves the accuracy and effectiveness of bridge health management.

2.3 Challenges and Types of Structural Health Monitoring (SHM) Systems

Structural Health Monitoring (SHM) of bridges faces several challenges, including inconsistent sensor accuracy, varied data analysis methods, and difficulties in accessing all bridge areas. Traditional visual inspections remain common but have limitations such as high inaccuracy, inability to detect internal damage, and missed localized failures.

Recent technological advances—like optical sensors, lasers, image processing, affordable sensors, blockchain, 5G, and the Internet of Things (IoT)—have improved SHM performance by enabling real-time monitoring, early damage detection, reduced inspection time and costs, and minimized repair expenses. The ideal SHM system is low-cost, non-invasive, fully automated, and does not require bridge closures during installation or operation.

SHM systems generally fall into two categories:

1. **Model-driven SHM**: Uses system models (often via finite element analysis) to analyze vibration data and detect damage by comparing predicted and experimental results. While effective, it is time-consuming, complex, and relies on experimental validation.

2. **Data-driven SHM**: Employs machine learning and artificial intelligence (AI) to manage uncertainties and improve damage detection. AI and computational intelligence have greatly enhanced SHM's effectiveness, sometimes combining data-driven and model-driven approaches.

The study emphasizes the growing role of AI and emerging technologies in improving data-driven SHM systems, setting the stage for further detailed exploration in subsequent sections.

3. Structural Health Monitoring (SHM) of Bridges, AI, and Recent Technologies

Industry 4.0, also called the Fourth Industrial Revolution, combines technologies from traditionally separate fields—biology, computing, and the physical world—leading to enhanced engineering capabilities. This integration has notably improved engineering projects, including the critical field of bridge SHM.

Recent advances in artificial intelligence (AI), driven by more powerful processors and greater data availability, have significantly boosted SHM performance. Additionally, emerging technologies closely related to AI are further enhancing bridge monitoring systems. This study explores how AI and related new technologies work together to improve the effectiveness of SHM in bridges.

Table1 indicates the summary of some of the most important recent research conducted on the structural health monitoring of bridges using new technologies.

Table1.Some recent studies on SHM of bridges vs.new technologies.

Research	ML Technique	Sensors	UAVs	IoT	3D Printers
Lin and Huang					+
Escarcega et al.				+	+
Flah et al.	+	+	+		
Wang et al.	+	+	+	+	
Civera et al.	+	+			
Ghiasi et al.	+	+			
Figueiredo et al.	+	+			
Bud et al.	+	+		+	
Gomez-Cabrera, and Escamilla-Ambrosio	+	+			
Delgadillo and Casas	+	+			
Baba, and Kondoh	+	+			
Zhang, and Yuen	+	+	+	+	
Gordan et al.	+	+			
Bono et al.		+	+		
Zhuge et al.	+		+		
Modir, and Tansel	+	+			+
Overall	+	+	+	+	+

From Table 1 it is clear that sensors and machine learning methods were essential to current research. It is clear that there is a need for additional research on the use of technologies like the IoT, UAVs, and 3D printers, even if other technologies were also considered. The following sections provide a more thorough explanation.

3.1 SHM of Bridges and Artificial Intelligence (AI)

Structural Health Monitoring (SHM) systems leverage innovative technologies such as the Internet of Things (IoT), sensors, and computer processing to provide an advanced, non-destructive way to evaluate bridge integrity. These technologies improve the accuracy of damage detection and reduce maintenance and repair costs.

Traditional SHM methods often rely on finite element modeling and modal features, which require extensive computations and struggle to handle real-world uncertainties. In contrast, data-driven SHM approaches, which do not depend on structural models, offer a practical alternative for damage detection. These can be used alone or combined with model-based methods.

Due to challenges like limited information and signal processing difficulties, AI and machine learning (ML) methods are increasingly valuable in SHM. Research has identified eight stages within the SHM process where AI and ML techniques can play a significant role in enhancing system performance.

Step No.	Process Name	Description
1	Excitation	It is necessary to arouse the existing structure in order to begin looking for signs of deterioration. When determining the technique of excitation, it's important to consider structural response in scenarios like earthquakes and to compare numerical models to actual measurements.
2	Data Acquisition	There may be differing requirements for monitoring dynamic vs static characteristics. It is vital to determine how the data may be gathered and used.
3	Data Normalization	When data has a wide range of scales, normalization is helpful. This step brings all data points to a similar scale due to inconsistencies in data from different sensors.

Step No.	Process Name	Description
4	Data Cleaning	The quality of the data may be harmed by loosely positioned sensors or extraneous influences. Data cleaning involves identifying and removing errors and duplications to create a valid dataset for better decision-making.
5	Data Compression	Encoding, rearranging, or altering data to minimize its size is known as data compression. This reduces the feature size and allows focus on statistically significant and damage-sensitive aspects.
6	Feature Extraction	Reduces the feature space by selecting a subset of the original features to minimize possible features. This step transforms data into a form suitable for machine learning algorithms. Important in detecting damage-sensitive characteristics.
7	Data Fusion	Combines information from multiple sources for higher accuracy, consistency, and usefulness than using data from a single source.
8	Pattern Recognition and Evaluation	Automated identification of patterns using machine learning techniques. This is the final step in the SHM (Structural Health Monitoring) system using ML, helping to evaluate the health of the structure.

Table 2. An outline of the eight stages required to implement a data-driven SHM system.

3.2 SHM of Bridges Using AI and Drone Technology

Artificial intelligence (AI) and drone (UAV/MAV) technology have greatly improved bridge structural health monitoring (SHM) in the modern era. Drones' mobility, maneuverability, and low power consumption make them perfect for checking difficult-to-reach places. They may gather real-time data using pictures, videos, and specialized sensors, such as vibration analysis sensors, and can be operated manually or automatically.

In data analysis, pattern identification, and damage detection, artificial intelligence (AI), especially deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, is essential. Deep learning, as opposed to conventional machine learning, makes it possible to automatically extract features from unprocessed data. For instance, by examining bridge deflection and temperature changes over time, LSTM models have been effectively applied to the detection of structural degradation.

Numerous stationary sensors can be replaced by mobile, intelligent SHM devices when UAVs and AI are combined, according to research, providing a more effective, adaptable, and scalable method of bridge monitoring.

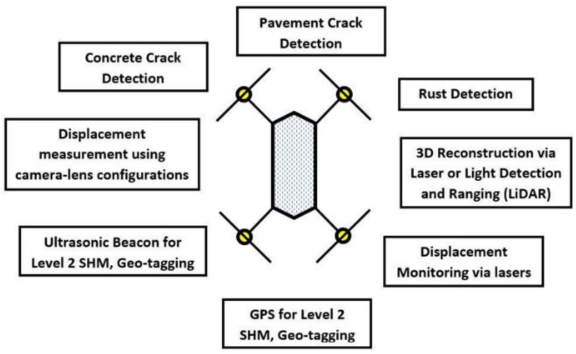

Figure 3. The varied applications of UAVs in the field of damage assessment in SHM systems.

Role of Artificial Intelligence in Drone-Based SHM

Artificial intelligence (AI) plays a **critical role** in enhancing drone-based **Structural Health Monitoring (SHM)** systems from multiple perspectives:

1. **Navigation and Control**: AI is used to develop software that enables **semi-autonomous and fully autonomous** drone navigation, improving efficiency and flight performance.

2. **Data Processing and Management**: Drones collect vast amounts of data (e.g., images, videos), which are **difficult to analyze manually**. AI helps in **automating the processing, analysis,**

and transmission of this data, making it manageable and meaningful for SHM.

3. **Data Transfer**: AI facilitates **the conversion and transfer** of drone-collected data to relevant **sensors and systems,** addressing one of the technical challenges in SHM workflows.

4. **Ground Systems and Airspace Monitoring**: Ground-based systems responsible for safety, security, and **airspace awareness** also rely on AI due to the **complexity** of managing multiple UAV operations.

5. **Integration with Emerging Technologies**: The use of drones in SHM is being **accelerated** by the convergence of AI with technologies like:

- **Advanced image processing**
- **Next-gen deep learning algorithms**
- **IoT devices**
- **5G and 6G networks**
- **New sensor technologies**

This integration is leading to **wider adoption** of drone-based SHM systems, particularly in bridge monitoring.

3.3 SHM of Bridges Using AI and 3D Printing

The integration of **3D printing** (additive manufacturing) with **Artificial Intelligence (AI)** is emerging as a promising advancement in **automated structural maintenance**, especially **in bridge Structural Health Monitoring (SHM)** systems.

- Since the early 1990s, institutions like **Carnegie Mellon University (CMU), University of Texas at Austin,** and **UC Davis** have explored **automated pavement crack sealing** platforms**.**
- Recent progress in 3D printing has led to its application in **automated crack repair**, making **pavement maintenance**—a key indicator of bridge traffic condition—more efficient.
- Two primary types of 3D printing platforms have been developed:
  - **Cartesian table-based platforms**
  - **Robot arm-based platforms**
- Both platforms continue to evolve, contributing to the **automation of bridge maintenance** tasks.
- These technologies, when combined with AI, enable **smart, automated repair processes**, reducing manual labor and improving response times in bridge SHM systems.

4. Discussion and Remarks

1. Role of Artificial Intelligence (AI) in SHM

- **AI has significantly enhanced Structural Health Monitoring (SHM)** by reducing reliance on human interpretation, increasing system efficiency, speeding up monitoring processes, and lowering costs.
- **Machine Learning (ML)** and **Deep Learning (DL)** algorithms are particularly effective for pattern recognition, damage detection, and data analysis, outperforming traditional methods.
- **Deep learning models** improve as more data is introduced, making them well-suited for analyzing the **large datasets** generated by SHM systems.
- **Data-driven approaches** identify patterns in bridge behavior and detect anomalies or failures through statistical methods and AI-enhanced models.

2. Use of Big Data and Cloud Computing

- The **challenges of handling massive SHM datasets** are being addressed through cloud computing and advanced algorithms.
- AI enables **automated pattern recognition**, creation of **decision boundaries** between damaged and undamaged states, and real-time analysis of bridge data.

3. Sensor Optimization and Placement

- **Sensors** are vital for accurate and long-term bridge health monitoring.
- Proper **selection and placement** of sensors are critical due to environmental factors and cost.
- **Optimization algorithms** like genetic algorithms, particle swarm optimization, and harmony search are recommended to find the most effective sensor configurations.

4. Visual Inspection vs. Drones

- Traditional **human-based visual inspections** are time-consuming, costly, and prone to error, though human senses offer certain advantages.
- **Drones (UAVs)** offer a **highly effective alternative**, capable of:

- Inspecting from any angle,
- Operating in diverse weather conditions,
- Being equipped with **high-tech cameras**,
- Providing **real-time condition monitoring**.

- Drones reduce inspection time and cost and increase precision, especially when integrated with **AI, IoT, and 5G/6G** technologies.

5. AI and 3D Printing in Bridge Maintenance

- **3D printing** is playing an increasingly important role in **automated bridge repair**, especially in **pavement crack sealing**.
- Combined with AI, 3D printing systems:
  - Use **machine learning and imaging** (ultrasound, X-ray) to identify damage type and severity.
  - Automatically generate **custom 3D repair models** and convert them into **G-code** for printing.
  - Select and apply **appropriate materials** based on damage characteristics.
- In the **Fourth Industrial Revolution**, AI-driven 3D printing is becoming a **key tool** in predictive and responsive bridge maintenance.

5 Conclusions

This study provides a **comprehensive review** of how **Artificial Intelligence (AI)**particularly **Machine Learning (ML)**along with **drones** and **3D printing**, is transforming **data-driven Structural Health Monitoring (SHM)** systems for bridges.

- **ML algorithms** significantly enhance **pattern recognition** in SHM, though each approach comes with its own challenges.
- **Drones** and **3D printers** have become integral to **data collection, monitoring**, and **automated maintenance** within SHM systems.
- The **integration of AI** with these technologies has led to major **improvements in system performance,** efficiency, and reliability.
- These technologies represent **intelligent, autonomous tools** that are opening up **new opportunities** for bridge engineers and researchers.
- The study highlights the **growing importance of AI in SHM research** and encourages further exploration in this domain.

Future Research Needs:

- There is a notable **gap in understanding how environmental and operational variations (EOV)** impact AI-enhanced SHM system performance.
- More **in-depth studies** are recommended to address this limitation and strengthen the reliability of SHM under varying real-world conditions.

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