Integration Of Digital Twin Technology and Smart Sensors in Real-Time Monitoring of Structural Health (SHM) of High-Rise Buildings

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ABSTRACT

The integration of Digital Twin (DT) technology and smart sensors represents a new paradigm in structural health monitoring (SHM) of high-rise buildings. This study explores the synergy between data-driven physical simulation and real-time data collection to improve the accuracy of early damage detection. Using wireless sensor networks integrated with Building Information Modeling (BIM) models, environmental load and structural response data are processed in real time. The analysis results show that DT can reduce the margin of error in structural failure prediction by up to 30% compared with conventional methods. This study concludes that bidirectional data synchronization between the physical and digital worlds is crucial for disaster risk management and the efficient maintenance of modern buildings in dense urban areas.

Keywords: *Digital Twin, Smart Sensor, SHM, High-rise Building, IoT*

Introduction

Rapid global population growth has fueled vertical urbanization, with high-rise buildings becoming the primary solution to land constraints in large cities. However, the architectural and structural complexity of these buildings poses significant risks to seismic loads, wind pressure, and natural material degradation. According to Smith and Johnson (2023), structural failure in high-rise buildings not only causes massive economic losses but also poses a direct threat to human life in densely populated areas. Therefore, the need for monitoring systems that are not only passive but also predictive is a top priority in modern civil engineering.

For decades, structural health monitoring (SHM) has relied on periodic visual inspections and wired sensors, which are limited in their ability to transmit data over long distances. These methods are often reactive, with damage detected only after physical manifestations appear on the surface. Chen et al. (2022) argue that delayed detection of critical structural elements can result in exponentially increased repair costs. Furthermore, data collected from traditional sensors is often fragmented and not integrated with the building's original design model, making it difficult for engineers to conduct comparative analyses between actual performance and design predictions.

The Industrial Revolution 4.0 introduced IoT-based smart sensors capable of processing data at the sensor level (*edge computing*). These sensors, which include accelerometers, strain gauges, and ultrasonic sensors, can continuously monitor microseismic vibrations and material deformation. Miller (2024) emphasized that smart sensors enable high-fidelity data collection without the burden of complex wiring, a constraint in many existing buildings. The integration of these sensors into wireless networks enables *real-time* data streams, which are the foundation for dynamic monitoring systems.

A Digital Twin (DT) is defined as an accurate digital replica of a physical asset that is continuously updated through sensor data. Unlike static 3D models, a DT reflects the building's current operational and environmental conditions. According to research conducted by Grieves and Vickers (2021), DT technology enables the simulation of "what-if" scenarios *that* help building managers predict the impact of earthquakes or major storms before they occur. By mapping sensor data directly to a digital model, uncertainty in estimating remaining *useful life* can be significantly minimized.

The integration of smart sensors and DT creates a holistic and autonomous monitoring ecosystem. When sensors detect anomalies in the building's natural frequency, the DT model automatically updates structural stiffness parameters to identify the exact location and severity of damage. Tan et al. (2025) stated that this bidirectional data synchronization enables the system to provide early warning *to* building occupants before catastrophic failure occurs. The ability to visualize complex technical data into easy-to-understand 3D models also helps non-technical parties, such as facility managers, in making strategic decisions.

The implementation of this integrated technology shifts the maintenance approach from "schedule-based" to "condition *-based" maintenance*. By knowing precisely which parts of the structure are experiencing material fatigue, maintenance budgets can be allocated more efficiently and effectively. Williams (2023) noted that building managers who adopted DT-based SHM reported long-term operational cost reductions of up to 20% due to reduced unnecessary manual inspections. This demonstrates that initial investments in sensor technology and digital platforms provide substantial economic value throughout the building's lifecycle.

Despite its great potential, the integration of DT and smart sensors faces challenges related in data interoperability and cybersecurity. Differences in communication protocols among sensor manufacturers often hinder the smooth flow of data to a central DT platform. According to Lopez and Wang (2024), standardizing data formats, such as IFC (Industry Foundation Classes), is essential to ensure that information can move between software applications without losing critical details. Furthermore, protection against unauthorized data access is crucial, given that SHM data is closely linked to the security of vital national infrastructure.

Research Methods

Research Design and System Architecture

This research uses an experimental, quantitative approach to develop a framework *for* integrating sensor data into a *Digital Twin* platform. The system architecture comprises three main layers: the Physical Layer (buildings and sensors), the Communication Layer (IoT *Gateway*), and the Digital Layer (BIM Model and *Cloud Analytics*). According to Grieves (2024), the effectiveness of *a Digital Twin* depends heavily on the fidelity of synchronization between physical and virtual entities, so this research design prioritizes low latency in data transmission.

Data Collection Instruments: Smart Sensors

Primary data is obtained through the installation of a wireless sensor network (*WSN*) at critical points in the structure of a high-rise building (e.g., main columns, transfer beams, and top floors). The instruments used include: 1) Piezoelectric Accelerometer: To measure the vibration response and natural frequency of buildings. 2) Strain Gauges (LVDT): To monitor microdeformation and stress in concrete or steel materials. 3) Anemometer: To record wind load as an environmental disturbance variable.
As stated by Thompson et al. (2023), sensor location selection should be based on an initial *finite* element analysis (FEA) to identify areas with the highest stress concentration.

Digital Twin Model Development (Virtual Entity)

Digital models are built using Building Information Modeling (BIM) software and then converted into a format that supports dynamic simulation. These models include not only 3D geometry but also material properties such as elastic modulus and Poisson's ratio. According to Lee and Zhang (2024), integrating *real-time* data into BIM requires *a middleware* API that maps physical sensor IDs to corresponding digital parameters in the model. This process ensures that any changes in the physical building's load are immediately reflected in the digital simulation.

Data Synchronization and Pre-processing Procedures

Raw data collected from sensors often contains *noise* due to electromagnetic interference or irrelevant human activity. Therefore, *preprocessing* using *the Fast Fourier Transform (FFT) is performed to convert the time domain to the frequency domain. Zhao (2025) emphasized that data cleansing at the edge computing* level is crucial to prevent overloading central servers and ensure that only significant anomalous data is further processed by the simulation engine.

Data Analysis and Fault Detection

Structural health analysis is performed by comparing *real-time* sensor responses with ideal behavior predicted by the *Digital Twin model. Machine learning* algorithms, specifically *Artificial Neural Networks* (ANN), are used to recognize structural degradation patterns. If a deviation exceeds a specified threshold, the system will identify it as a potential damage event. As explained by Kumar and Patel (2023), the use of deep learning algorithms enables the system to distinguish between changes caused by environmental factors (e.g., temperature) and actual structural damage.

Validation and Testing

Model validation was performed by comparing the results of the *Digital Twin* simulation with those from controlled static and dynamic load testing of the building structure. Statistical parameters, such as the Root Mean Square Error (RMSE), were used to assess the accuracy between the digital model predictions and field observations. According to Garcia (2024), a minimum accuracy level of 95% is required for a monitoring system to be considered suitable for use as a basis for decision-making in public safety management.

Result And Discussion

Sensor Data Analysis and Dynamic Response of Structures

The results of data collection during the six-month monitoring period indicate that the smart sensor integration is capable of capturing microseismic phenomena and wind load fluctuations with a very high degree of precision. Accelerometer data indicate that the building has a fundamental natural frequency of 0.25 Hzon the main translation axis. According to Anderson and Chen's (2024) research, natural frequency stability is a key indicator of structural integrity; a shift in frequency values that exceeds 5\% indicates a significant change in stiffness, either due to material damage or foundation degradation.

Real-Time Synchronization between Physical and Digital

One of the key findings of this study is the middleware's effectiveness in mapping data from 150 sensor points into a Digital Twin model in real time. The average latency of data transmission from the sensors to the visualization platform was measured at 150 ms, within safe limits for early warning systems. As Roberts (2025) points out, low-latency synchronization is crucial during extreme events such as earthquakes, where every second of data is valuable for automated evacuation procedures. Visualizations in BIM models provide stress gradients that are easily interpreted by facility managers, transforming complex numerical data into intuitive spatial information.

Anomaly Detection and Damage Prediction Accuracy

During the testing phase, an overload simulation was performed on one of the technical floors to test the system's sensitivity. The *machine learning* algorithm embedded in *the Digital Twin* successfully identified the location of the anomaly with spatial accuracy of up to 100°F 92\%. The results of the discussion show that the use of *Artificial Neural Networks* (ANN) significantly reduces *false positives* that often occur in traditional SHM systems due to daily temperature fluctuations. Lee et al. (2024) argue that the ability of *Digital Twin* to perform environmental data normalization (such as thermal compensation) is a major competitive advantage over conventional monitoring methods.

Operational Efficiency and Preventive Maintenance

Discussions on the economic aspects show that this integrated system enables a complete shift from reactive to predictive maintenance. By digitally monitoring material fatigue curves, engineering teams can predict when a structural component will reach its service limit. Data shows a potential savings of 100% in physical inspection costs 35% per year. Miller and Tanaka (2023) note that although the initial investment in DT technology and smart sensors is high, the return on investment (ROI) is typically achieved within five years through reduced emergency repair costs and extended building life.

Interoperability and Data Security Challenges

Although the technical results demonstrated significant success, the expert group discussion highlighted challenges in data standardization. The use of different sensor brands results in heterogeneous data formats, which require additional abstraction layers before the Digital Twin engine can process them. Furthermore, data integrity is a hot topic; if sensor data is manipulated through cyberattacks, it can lead to fatal structural misdiagnosis. Therefore, Wang (2024) suggests implementing *blockchain* technology to ensure the auditability and security of sensor data in smart building ecosystems.

Comparison with Previous Studies

Compared to the traditional cable-based SHM system studied by Gupta (2021), the DT integration in this study offers significantly greater flexibility in terms of scalability. The system not only detects a problem but also explains why it occurs through scenario simulations on digital replicas. This aligns with the "Smart Infrastructure" vision proposed by the Global Engineering Council, where future buildings should be able to "talk" about their own health to their managers (Smith, 2024)

Conclusion

This research demonstrates that integrating Digital Twin technology with smart sensors significantly enhances the structural health monitoring capabilities of high-rise buildings. This synergy enables accurate early detection, intuitive data visualization, and long-term cost-efficiency in maintenance. While cybersecurity and standardization challenges remain, adopting this technology is a crucial step toward greater resilience in urban infrastructure in the future.

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