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Journal of Electrical Systems and Inf Technol (2025) 12:51
https://doi.org/10.1186/s43067-025-00237-6

Journal of Electrical Systems and Information Technology

RESEARCH Open Access

Urban sentinel: advancing structural health monitoring for building damage measurement in districts through IoT integration and self-optimizing machine learning

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Abstract

In the contemporary urban landscape, ensuring the structural health and resilience of buildings and infrastructure is paramount for sustainable development and the well-being of citizens. This paper proposes a novel approach, termed Urban Sentinel, aimed at revolutionizing urban infrastructure management through the integration of Internet of Things (IoT) sensor networks and regression AI systems. This integration is still in its early stages of practical application, marking Urban Sentinel as a significant step forward in urban infrastructure management. Urban Sentinel encompasses a comprehensive system architecture designed to monitor and predict the health of buildings and infrastructure in cities or any other integrated district. Central to this architecture is the deployment of a proposed sensor set, strategically installed within buildings to capture critical data related to structural integrity, environmental conditions, and operational performance. These sensors transmit data using LoRaWAN wireless technology to a centralized management system, where a regression AI model harnesses the power of machine learning algorithms to analyze the data and predict the health status of the buildings. This system offers several advantages over traditional monitoring methods. By leveraging IoT technology, Urban Sentinel enables real-time data collection, allowing for the timely detection of anomalies and potential risks. The integration of regression AI systems enhances the predictive capabilities of the management system, enabling proactive maintenance and optimization of urban infrastructure. Additionally, this paper thoroughly addresses potential challenges and offers corresponding solutions to mitigate them effectively. By embracing innovative technologies and holistic approaches to infrastructure management, Urban Sentinel paves the way for smarter and more resilient cities of the future.

Keywords: Tructural health monitoring, Internet of things, Integrated web application, Polynomial regression, Self-optimizing AI system

Introduction

In recent years, the integration of IoT technology with structural health monitoring (SHM) systems has emerged as a transformative approach to enhance the efficiency and reliability of infrastructure monitoring in urban environments [1]. This integration enables real-time data collection, analysis, and predictive maintenance strategies, contributing to the resilience and sustainability of cities [2]. While traditional SHM systems have relied on wired networks for data transmission [3], the adoption of IoT-based solutions offers significant advantages in terms of flexibility, cost-effectiveness, and scalability, marking a paradigm shift in infrastructure monitoring by leveraging wireless sensor networks [4]. This wireless infrastructure not only enhances the sensitivity and efficiency of monitoring but also reduces deployment costs and logistical challenges associated with wired solutions.

Traditional SHM systems face several limitations, including high installation and maintenance costs due to wired setups, limited scalability for large urban districts, and a lack of real-time predictive analytics to anticipate structural issues. These systems often require manual inspections or periodic data collection, which can delay the detection of anomalies and increase the risk of structural failures. Urban Sentinel addresses these challenges by deploying IoT-based wireless sensor networks, such as LoRaWAN, to enable scalable and cost-effective data collection across entire districts. Furthermore, the integration of regression AI models allows Urban Sentinel to analyze data in real-time, predict potential structural issues, and facilitate proactive maintenance, thereby enhancing the resilience and safety of urban infrastructure.

Central to the success of IoT-SHM systems is the interoperability and compatibility with existing internet standards, facilitating seamless integration with smart city initiatives and infrastructure management frameworks. By leveraging established communication protocols and open platform communications (OPC) servers, IoT-SHM systems can seamlessly integrate with broader smart city ecosystems, enabling holistic infrastructure management and optimization. Through continuous monitoring and analysis of structural data, these systems can provide valuable insights into the health and condition of buildings and infrastructure, enabling informed decision-making and resource allocation.

The objective of Urban Sentinel is to develop a scalable, real-time SHM system that leverages IoT and AI to predict structural health and enable proactive maintenance in urban districts. We hypothesize that integrating IoT sensor networks with self-optimizing regression AI models will significantly improve the accuracy and timeliness of structural health predictions compared to traditional methods. The contributions of this work include a novel system architecture for district-wide SHM, a self-optimizing AI framework that adapts to new data and engineer feedback, and a user-friendly web application for real-time monitoring and decision-making, paving the way for smarter and more resilient urban infrastructure.

In this paper, we present a comprehensive analysis of the architectural framework and components of IoT-SHM systems, highlighting the unique characteristics and advantages of this innovative approach. By harnessing the power of IoT and AI-driven predictive analytics, we envision a future where urban infrastructure is monitored, managed, and optimized in real-time, ensuring the safety, sustainability, and prosperity of urban communities.

Literature review

Recent advancements in SHM have increasingly converged with technologies such as the Internet of Things (IoT), wireless sensor networks (WSNs), and AI. These integrations aim to enhance data acquisition, anomaly detection, and long-term maintenance strategies in civil infrastructure. However, despite significant progress, many existing solutions still lack holistic, scalable, and adaptive frameworks suitable for deployment across entire urban districts. The proposed *Urban Sentinel* system aims to fill these gaps by drawing on and extending the capabilities described in prior work.

Sonbul Os et al. [5], in their systematic review [5], examine 46 recent SHM systems focused on bridge structures, primarily relying on WSNs for data acquisition. Their study provides an in-depth evaluation of sensor types, energy-harvesting strategies, communication technologies (e.g., Zigbee, GPRS), and microcontroller configurations typically used in SHM implementations. The review highlights how most existing systems operate either at the component level (local inspection) or on isolated structures. Although WSNs enable long-term monitoring with reduced maintenance, the paper reveals a critical gap in large-scale implementations and integration with AI-based analytics or cloud-based feedback systems. These limitations underscore the importance of frameworks like *Urban Sentinel*, which extend beyond single-structure applications and incorporate centralized AI prediction and continuous model optimization informed by field expert feedback.

Bhatta and Dang [6], in their article, emphasize the transformative role of IoT in civil infrastructure monitoring. The study systematically discusses IoT components such as cloud connectivity, embedded sensor modules, and edge processing for real-time SHM. The authors identify strengths in real-time data collection and remote accessibility, but also point out the lack of decision-making intelligence within current systems. Specifically, most reviewed architectures fall short in incorporating autonomous AI modules capable of interpreting data and initiating predictive alerts. Furthermore, little attention is given to integrating human expertise or enabling model updates based on domain knowledge. Urban Sentinel addresses these shortcomings by integrating a self-optimizing AI regression model, using civil engineer feedback for continuous learning, and implementing a customized loss function to reduce false negatives—thereby increasing reliability in critical safety scenarios.

To broaden the review and highlight relevant design patterns from adjacent fields, the work [7] by Popescu et al. (2024) provides a valuable perspective. Although the focus is environmental rather than structural monitoring, the paper offers significant insight into Artificial Intelligence of Things (AIoT) systems, where distributed sensors collect environmental data, which is then processed using edge computing and AI-based prediction models. The architecture integrates cloud dashboards, alerting mechanisms, and scalable deployments across urban regions. This model demonstrates how AI-IoT integration supports real-time inference and adaptive behavior, principles that *Urban Sentinel* likewise applies in the domain of civil infrastructure. This inclusion makes the literature review more comprehensive and confirms that the architectural patterns of AI-enhanced IoT monitoring systems are relevant across domains when designing resilient urban technologies.

In summary, while these studies establish strong foundations in hardware deployment, real-time data acquisition, and AIoT system architectures, they reveal ongoing limitations in achieving integrated, district-level SHM systems that adapt through human feedback, ensure predictive robustness, and support web-based decision interfaces. The *Urban Sentinel* framework builds upon these insights, proposing a scalable, secure, and feedback-driven solution for future-ready urban infrastructure monitoring.

Architectural analysis of integrated IoT-based SHM systems

The integration of IoT technology with SHM systems marks a significant advancement in urban infrastructure management, driven by the need for real-time, scalable, and predictive monitoring solutions. This section outlines the architectural framework of the Urban Sentinel system, designed with clear objectives: to enhance the accuracy and timeliness of structural health assessments across urban districts, enable proactive maintenance, and improve overall infrastructure resilience. We hypothesize that the integration of IoT sensor networks with self-optimizing regression AI models will outperform traditional SHM methods by providing actionable insights in real-time, adapting to dynamic environmental conditions, and leveraging human expertise through a feedback loop. The key contributions of this architecture include a novel, district-wide IoT-based SHM system, a self-adaptive AI framework that evolves with engineer inputs, and an integrated web application for real-time visualization and decision-making, setting a foundation for smarter and more sustainable cities (see Fig. 1).

The intriguing aspect of introducing the IoT paradigm into the SHM system lies in its diverse applications, encompassing scenarios such as bridge monitoring [8], monitoring historical masonry structures [9], monitoring foundation earth [10], and detecting alterations in structural materials [11].

Fig. 1 Schematic architecture of the proposal integrated IoT-based AI-driven SHM system

1. **Building sensors:**
2. Each building in the district is equipped with a network of sensors strategically placed to monitor various aspects of its structural health.
3. Passive operation of sensors is described as a measurement that inflicts no input energy to the structure. Accelerometers, strain gauges, and acoustic emissions are examples of this type of sensor. They only detect damages with no interaction with the actual structure.
4. On the contrary, active sensors pinpoint the excitation, thus customizing the entire damage detection process. The primary advantage over passive systems is that, with a known excitation force and location, detecting damages becomes much simpler, and the impact of extraneous operational factors (EOFs) can be minimized. Examples of typical active sensors include piezoelectric ultrasonic sensors, which can be employed either through impedance-based methods or Lamb wave-propagation techniques
5. The sensors collect real-time data on the building's structural integrity, environmental conditions, and other relevant parameters.
6. **Data Collection and Preprocessing:**
7. The sensor data is collected and processed locally within each building.
8. Before the sensor data is transmitted to the CC, preprocessing steps such as normalization and data cleansing are applied.
9. Normalization involves scaling the sensor data to a common range or distribution to ensure consistency and comparability across different sensors and buildings.
10. Data cleansing techniques are employed to identify and correct errors, outliers, or missing values in the sensor data. This ensures the integrity and accuracy of the data used for analysis.
11. **Data Transmission:**
12. LoRaWAN (a wireless communication network) is used to transmit the normalized sensor data to a centralized data aggregation point.
13. Optimizing the configuration parameters of LoRaWAN devices, such as data rate, spreading factor, and transmission power, can significantly impact the reliability and efficiency of data transmission.
14. Furthermore, designing an efficient network topology involves strategically placing LoRaWAN gateways to ensure adequate coverage and minimize signal interference.
15. **Control Center (**CC**):**
16. The data from all buildings in the district is aggregated at a central location, which serves as the data aggregation point. This aggregation point could be located within the district or at a remote location depending on the infrastructure and connectivity options available.
17. The aggregated data is fed into a centralized control center (CC), which acts as the brain of the integrated system.
18. This system employs advanced algorithms, machine learning models, and predictive analytics to analyze the incoming data and assess the health of each building.
19. The CC monitors trends, detects anomalies, and predicts potential structural issues based on historical data and real-time inputs.

20. This CC system overseeing building safety and structural integrity within a district may vary depending on local conditions and national policies. It could be administered by professional organizations, government departments, or research institutions, each with its expertise and resources tailored to the specific needs and requirements of the area.
21. **Visualization and Reporting:**
22. The output from the CC is presented through a user-friendly web application interface, providing stakeholders with actionable insights into the health of the buildings.
23. Visualization tools, dashboards, analytics, and reports allow users to understand the status of individual buildings as well as the overall district.
24. Alerts and notifications are generated for both CC and residents for critical issues, enabling timely intervention and preventive maintenance efforts.
25. **Feedback Loop:**
26. The CC integrates a dynamic feedback loop mechanism, where the insights derived from rigorous data analysis serve to notify civil engineers stationed within the CC. Their subsequent assessments and interventions on the buildings are recorded within the CC database.
27. Continuous monitoring and refinement ensure that the system remains adaptive and responsive to changing environmental conditions and structural dynamics.

IoT-based SHM system components

Smart Objects (SOs) serve as the backbone of IoT-enabled SHM systems, embodying several key characteristics that enable them to effectively monitor and assess the structural health of buildings and infrastructure.

Equipped with communication protocols like MQTT or HTTP, SOs enable bidirectional data exchange for real-time monitoring. Integration of sensors and actuators allows SOs to perceive changes and respond accordingly, ensuring structural integrity and safety.

The SO sensors, serving as the cornerstone of the system, are responsible for monitoring the structural integrity of buildings and infrastructure. These sensors detect physical phenomena associated with structural damage and transmit signals to the acquisition and storage subsystem for further analysis. The selection of sensor types is tailored to specific monitoring requirements, ensuring accurate and timely detection of structural anomalies. Typical sensors used in the SO to monitor an existing building are the strain gauges and accelerometers that communicate in wireless modality.

The gateway node serves as a crucial interface between the sensor network and the backbone network, facilitating seamless communication and data transfer. It translates messages from end devices into data packets for transmission to the real-time control and supervision system (RCSR), while also managing data requests, event notifications, and system integrity tests. Additionally, the gateway incorporates an embedded local database to store extensive data sets, enabling efficient troubleshooting and data retention.

The RCSR functions as a centralized management hub, providing real-time monitoring and control capabilities. The RCSR hosts a comprehensive database for storing collected data, facilitating big data analysis and integration with standard industrial systems through connectors to the open platform communications (OPC) server. Figure 2 shows a glimpse of the mentioned procedure.

Choice of LoRaWAN for data transmission

It is worth expressing that choosing LoRaWAN over Wi-Fi or other alternatives for our integrated management system architecture is based on several key advantages that LoRaWAN offers:

- **Long Range:** LoRaWAN technology provides a significantly longer range compared to Wi-Fi, enabling connectivity over larger distances. This is crucial for our application, which involves gathering data from sensors distributed across entire districts or urban areas.
- **Low-Power Consumption:** LoRaWAN devices are known for their low-power consumption, which translates to longer battery life [12]. This is essential for our system, as it allows for prolonged operation of battery-powered sensors without frequent battery replacements or recharging, reducing maintenance efforts and costs.
- **Low Cost:** Implementing a LoRaWAN infrastructure is relatively inexpensive compared to Wi-Fi or other cellular technologies. The cost-effectiveness of LoRaWAN makes it suitable for large-scale deployments covering extensive geographic areas, such as our smart city application.
- **Scalability:** LoRaWAN networks are highly scalable and can accommodate a large number of devices. This scalability is crucial for our integrated management system, which may involve deploying thousands or even millions of sensors across multiple buildings or infrastructure assets within a city.
- **Penetration:** LoRaWAN signals can penetrate through obstacles like walls and buildings, making them suitable for both indoor and outdoor applications. This ensures reliable connectivity even in complex urban environments where obstacles may obstruct line-of-sight communication.

Optimal sensor placement (OSP)

Optimal sensor placement (OSP) plays a crucial role in enhancing the effectiveness and efficiency of structural health monitoring systems. In addition to automated algorithms, leveraging human expertise and feedback through human-in-the-loop optimization can

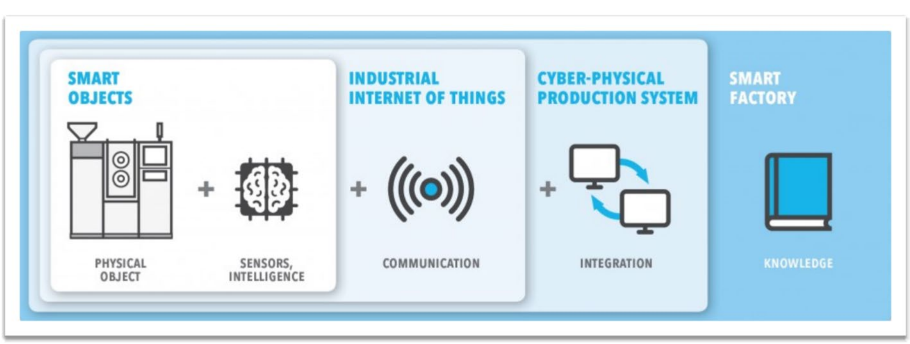

Fig. 2 The practical view of the process of turning the collected data into usable knowledge in the proposed integrated IoT-based SHM system

significantly enhance the sensor placement process. By involving domain experts in the optimization process, valuable insights and constraints that may not be captured by automated algorithms alone can be considered, leading to more informed and contextually relevant sensor placement decisions.

Domain experts, such as civil engineers, structural analysts, and maintenance professionals, possess valuable knowledge about the structural behavior, critical components, and failure modes of buildings and infrastructure. Their expertise can provide essential insights into factors such as structural vulnerabilities, environmental conditions, accessibility constraints, and historical performance data, which are crucial for optimizing sensor placement strategies.

Through collaborative workshops, brainstorming sessions, or iterative design reviews, domain experts can actively participate in defining optimization objectives, specifying sensor requirements, and refining placement criteria. By incorporating human insights and feedback into the optimization process, the resulting sensor placement strategy can better align with the specific needs and priorities of the infrastructure being monitored.

Furthermore, human-in-the-loop optimization allows for the consideration of practical constraints and real-world operational considerations that may impact sensor deployment.

Optimized data transmission strategy

In disaster detection and routine monitoring, efficient data transmission is crucial for timely response and resource optimization. A hybrid data transmission approach tailored for urban districts includes:

1. Real-time transmission during critical events like earthquakes or floods ensures swift detection and response. Continuous sensor data transmission to the control center (CC) enables instant analysis, facilitating immediate alerts and proactive measures to mitigate damage.
2. Periodic transmission for routine monitoring optimizes resource usage. Customized transmission frequencies based on district stability, seismic activity, and resource constraints balance responsiveness and efficiency, maximizing effectiveness while minimizing operational overhead.

To ensure flexibility and adaptability, an adaptive data transmission protocol dynamically adjusts transmission frequencies based on real-time environmental factors and system performance metrics. This approach optimizes resource utilization and enhances system resilience, enabling efficient disaster detection and routine monitoring. Equations 1–3 express the proposed dynamic adjustment mechanism:

$$f(t) = f_0 + \alpha.\Delta_{env}(t) + \beta.\Delta_{perf}(t) \tag{1}$$

Equation (1) delineates the transmission frequency adjustment, where $\boldsymbol{f(t)}$ denotes the adjusted transmission frequency at time t, $\boldsymbol{f_0}$ is the baseline transmission frequency, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are weighting coefficients for environmental and performance factors, respectively, $\Delta_{\boldsymbol{env}}(\boldsymbol{t})$ is the change in environmental factors at time t, and lastly $\Delta_{\boldsymbol{perf}}(\boldsymbol{t})$ is the change in system performance metrics at time t. Also, environmental factor change is obtained from the following equation:

$$\Delta_{env}(t) = \sum\nolimits_{i=1}^{n} w_i.E_i(t) \tag{2}$$

where, as evident, $\boldsymbol{\Delta_{env}(t)}$ represents the cumulative change in environmental factors,$\boldsymbol{w_i}$ denotes weighting coefficients for individual environmental factors, and $\boldsymbol{E_i(t)}$ are the measured values of environmental factors at time t.

Additionally, the performance metric change equation is as follows:

$$\Delta_{pref}(t) = \sum\nolimits_{j=1}^{n} v_j.P_j(t) \tag{3}$$

where $\boldsymbol{\Delta_{pref}(t)}$ denotes the cumulative change in system performance metrics, $\boldsymbol{v_j}$ are weighting coefficients for individual performance metrics, and $\boldsymbol{P_j(t)}$ are the measured values of system performance metrics at time t.

Data security and privacy considerations

Structural health data collected by Urban Sentinel involves sensitive information that could pose risks if accessed or modified by unauthorized entities. To address these concerns, multiple layers of security [13] and privacy protections are embedded within the system:

- **Encrypted Transmission:** LoRaWAN is selected not only for its range and efficiency but also for its end-to-end AES-128 encryption, ensuring that all data packets are encrypted from sensor node to control center.
- **Edge Preprocessing:** Data is preprocessed (normalized, denoised, and compressed) locally before transmission, thereby limiting the exposure of raw structural or location-identifiable data.
- **Secure Authentication:** The integrated web application employs role-based access control (RBAC) for engineers, system administrators, and district managers, reducing the risk of unauthorized access.
- **Audit Logging:** All interactions within the system—including model updates and manual engineer inputs—are timestamped and logged for traceability and compliance.
- **Data Anonymization:** Structural IDs and building references are pseudonymized within the central database to prevent location inference or building profiling.

Future versions of Urban Sentinel will aim to comply with ISO/IEC 27001 for information security and GDPR-aligned practices for data minimization and user consent.

Potential challenges for the proposed SHM system

Urban Sentinel, while promising significant advancements in urban infrastructure management, faces several challenges that must be addressed to ensure its effectiveness and sustainability.

Another critical challenge lies in the enhancement and updating of the AI model, a task that often proves challenging to achieve seamlessly. However, as we delve into forthcoming sections, we unveil our solution: an integrated web application tailored for civil engineers. In practical terms, when a civil engineer assesses a building's structure and identifies damage, they input their observations into the web application. By adjusting the damage measurement parameters within the application, engineers effectively update the AI model in real-time. Consequently, as engineers continually refine their assessments, the AI model evolves accordingly. This dynamic process is facilitated by a dedicated code mechanism embedded within the application. This mechanism, which is called the self-optimizing mechanism, automatically adjusts the regression model at regular intervals, ensuring its alignment with the most up-to-date data provided by engineers. This highlights the significance of the human-in-the-loop process, where human expertise guides and refines the AI model's evolution. Figure 3 illustrates the mentioned method.

Another potential challenge arises when the AI fails to detect a real danger during a disaster, known as a false negative. To address this concern, one approach is to prioritize the evaluation of the model's performance in terms of false negatives. We introduce a modified loss function that incorporates a penalty term for false negatives, emphasizing the importance of minimizing instances where the model fails to detect actual dangers.

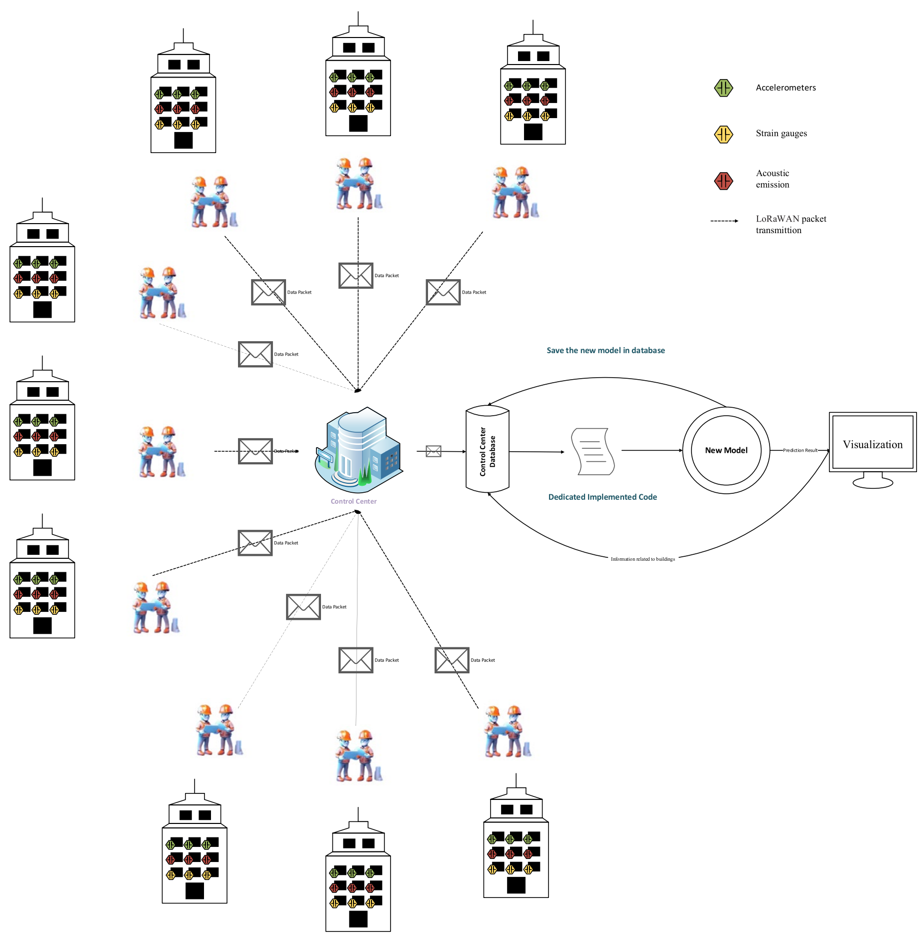

Fig. 3 The practical end-to-end view of the systematic and human-in-the-loop process of utilizing and enhancing the AI predictor model

Let us denote the true damage measure as y and the predicted damage measure as $\hat{\boldsymbol{y}}$. The modified loss function $\mathcal{L}$ is defined as follows:

$$\mathcal{L}\left(y, \hat{y}\right) = MeanSquaredError\left(y, \hat{y}\right) + \Omega.C_{FN}\left(y, \hat{y}\right) \tag{4}$$

where $\boldsymbol{MeanSquaredError}\left(\boldsymbol{y}, \hat{\boldsymbol{y}}\right)$ represents the standard loss function for regression tasks, typically used to measure the discrepancy between the true and predicted values [14]. Additionally, $\boldsymbol{\Omega}$ is considered as the weighting coefficient to balance the contributions of the MSE loss and the false negative penalty.

To enhance safety–critical performance, particularly minimizing false negatives where actual structural hazards are undetected, a customized loss function was introduced. The loss function extends the traditional mean squared error (MSE) by incorporating a false negative penalty term. This term is activated when the predicted damage level underestimates the true value. The modified loss function L_{total} is expressed as follows:

$$L_{total} = L_{MSE} + \lambda \times C_{FN} \tag{5}$$

where $\boldsymbol{\lambda}$ is the weight for false negative penalty (tuned empirically). The false negative cost function $\boldsymbol{C_{FN}}(\boldsymbol{y}, \hat{\boldsymbol{y}})$ captures the severity of consequences associated with underestimating the actual damage. The proposing formulation is a linear function of the difference between the true and predicted damage:

$$C_{FN}\left(y, \hat{y}\right) = \max(0, y - \hat{y}) \times \mu \tag{6}$$

This equation penalizes instances where the model predicts a lower damage measure than the true value, with $\boldsymbol{\mu}$ controlling the severity of penalizing underestimation. By incorporating this term into the loss function and adjusting the coefficient $\boldsymbol{\Omega}$ accordingly, we incentivize the AI system to prioritize sensitivity, ensuring that it errs on the side of caution when detecting potential risks.

The empirical benefit of this adjustment is visualized in Fig. 6, where the false negative rate drops from 16.5 to 1% over five feedback iterations. This confirms that incorporating safety-focused penalties significantly improves the model's sensitivity and operational reliability. The regression output is also mapped to a binary safety classification using a threshold (e.g., 0.5), enabling confusion matrix metrics such as precision, recall, and false negative rate to be computed (see Table 1).

While initial configurations may require some degree of civil engineer input for calibrating danger thresholds or annotating rare damage patterns, the proposed

Table 1 Evaluation of AI predictive performance using classification metrics over time

Feedback iteration	Accuracy (%)	Precision (%)	Recall (%)	False negative rate (%)
0 (initial model)	83.2	79.5	70.4	16.5
1	87.1	82.3	79.2	11.8
2	91.0	88.0	85.6	7.3
3	94.4	91.6	91.0	4.5
4	97.2	95.1	94.8	2.2
5 (final model)	98.7	97.9	98.3	1.0

self-optimizing mechanism automates model retraining at defined intervals (e.g., monthly) or when trigger thresholds are breached. This ensures that the AI model remains aligned with recent trends while minimizing operational overhead. Furthermore, the hybrid data transmission strategy, which toggles between real-time alerts and periodic updates based on environmental sensitivity and system load (see Eqs. 1–3), greatly reduces bandwidth and infrastructure demands. These design features collectively enable scalable deployment across hundreds or thousands of buildings in a district, without requiring a proportional increase in maintenance effort.

AI system methodology: harnessing regression models and self-optimizing mechanisms for SHM

The AI System Methodology represents a fundamental aspect of the Urban Sentinel framework, aimed at revolutionizing SHM in urban environments. By integrating regression models and self-optimizing mechanisms, this methodology offers a systematic approach to harnessing the power of AI for proactive infrastructure management. In this introduction, we delve into the key components and objectives of the AI System Methodology, highlighting its significance in advancing the field of SHM and ensuring the resilience and sustainability of urban infrastructure. Through the fusion of cutting-edge technology and human expertise, the methodology establishes a framework for real-time monitoring, predictive analytics, and continuous improvement, paving the way for smarter and safer cities of the future.

Data acquisition

Data acquisition in the AI System Methodology of Urban Sentinel involves the implementation of sensors in select buildings with varying degrees of structural damage. These sensors, including accelerometers, strain gauges, and acoustic emission sensors, are strategically placed to monitor different aspects of structural health and environmental conditions. The gathered data undergoes preprocessing, including normalization and cleansing, before being transmitted to a centralized data aggregation point using wireless communication networks such as LoRaWAN. This dataset forms the basis for training the regression AI model, enabling it to learn patterns and correlations between sensor readings and structural health metrics. The detailed and practical explanations of implementation methods are not in the scope of this paper and the implementation was done based on two recent studies in this field [15, 16]. The schema of their implementation is visualized in Fig. 4.

To ensure reproducibility and transparency in the development of the AI regression models, the dataset used in Urban Sentinel is described in full detail. A total of 50 buildings, including both residential and commercial structures, were selected in a seismically active urban district. Each building was equipped with 10 IoT-enabled sensors, comprising accelerometers, strain gauges, and acoustic emission sensors, amounting to 500 sensors deployed in total. Data collection was conducted over a 6-month period, resulting in 10,000 structured readings. To diversify the learning scenarios and enable robust performance under edge conditions, additional synthetic data was generated to simulate rare events, such as earthquakes or structural fatigue failures. Ground-truth labeling was achieved via civil engineer inputs through the web interface, where assessments of

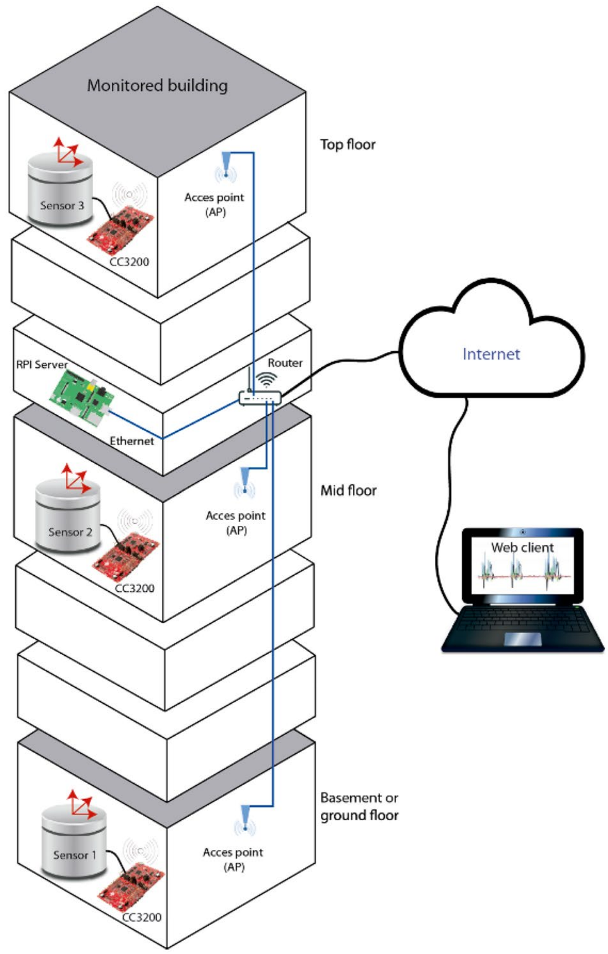

Fig. 4 General schematic detailing the implementation of sensors and their integration with the internet infrastructure [17]

structural health were entered and used as supervised labels for training the regression models. This dataset formed the empirical basis for evaluating various regression strategies (see Table 1), validating prediction accuracy, and benchmarking improvements from the self-optimizing framework.

Retraining the regression model

The regression model in Urban Sentinel is retrained monthly to incorporate new data and feedback from civil engineers via the integrated web application. Retraining is triggered by significant events, such as new damage assessments entered by engineers or deviations in sensor data exceeding predefined thresholds (e.g., 10% change in structural metrics). The retraining process employs fivefold cross-validation to ensure model robustness, splitting the dataset into five subsets to validate performance on unseen data. The model is updated using a self-optimizing mechanism that adjusts hyperparameters (e.g., polynomial degree, regularization strength) based on performance metrics like mean squared error (MSE) and false negative rates. This ensures the model adapts to evolving structural and environmental conditions, maintaining high predictive accuracy.

Polynomial regression

The polynomial regression model was selected for Urban Sentinel due to its ability to effectively capture nonlinear relationships between sensor inputs (e.g., accelerometer readings, environmental factors) and structural health outcomes, as demonstrated by its superior performance in Table 2 compared to linear and ridge regression. Unlike linear models, polynomial regression can model complex, nonlinear patterns inherent in SHM data, such as the impact of environmental conditions or material fatigue. Compared to more advanced methods like neural networks or decision trees, polynomial regression offers a balance of interpretability, computational efficiency, and predictive accuracy, making it suitable for real-time applications on resource-constrained IoT systems. Neural networks, while powerful, require larger datasets and computational resources, which may not be feasible for district-wide deployments. Decision trees, on the other hand, may struggle with continuous outputs like structural health metrics.

The polynomial regression model is a type of regression analysis used to model the relationship between the independent variables (input features) and the dependent variable (output) by fitting a polynomial equation to the observed data. In the context of Urban Sentinel, where the health status of buildings is predicted based on sensor data and environmental parameters, the polynomial regression model offers flexibility in capturing nonlinear relationships that may exist between these variables. The polynomial regression model has been chosen for its ability to capture complex relationships that may not be adequately represented by a linear model. In SHM, various factors, such as environmental conditions, building materials, and structural designs, can contribute to nonlinear effects on the health status of buildings. Table 2 evaluates different hyperparameter-optimized regression models with the same data inputs in our study:

The equation for a polynomial regression model with one independent variable (simple polynomial regression) can be represented as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2^2 + \cdots + \beta_n x_n^n + \varepsilon \tag{7}$$

where $\boldsymbol{y}$ is the predicted health status of the building, x represents the input features, such as sensor data and environmental parameters, $\beta_0, \ldots, \beta_n$ are the coefficients of the polynomial terms, representing the weights assigned to each term in the model, and $\boldsymbol{\varepsilon}$ is the error term, representing the difference between the observed and predicted values.

The polynomial regression model allows for the inclusion of multiple polynomial terms (e.g.,x^2, x^3, ...) to capture the curvature and nonlinear patterns in the data. The choice of the degree n of the polynomial depends on the complexity of the relationship between the input features and the health status of the building.

Table 2 Evaluation of different regression models for the collected data, gathered from 10,000 sensor readings from 50 buildings (mixed residential and commercial) over 6 months

Specifications	Linear regression	Polynomial regression	Ridge regression
Mean absolute error (MAE)	0.30	0.17	0.17
Mean squared error (MSE)	0.27	0.15	0.23
Root mean squared error (RMSE)	0.28	0.15	0.20

One technique commonly used to determine the appropriate degree n of the polynomial in polynomial regression is cross-validation. Cross-validation is a resampling technique used to assess how well a predictive model will perform on unseen data. In the context of selecting the degree of the polynomial, cross-validation involves splitting the available data into multiple subsets, typically referred to as folds.

Dedicated code for self-optimization and model generation

The dedicated code in Urban Sentinel embodies a sophisticated self-optimization mechanism. It autonomously performs critical tasks such as data cleaning, normalization, and model optimization based on newly generated data. This code continuously refines incoming data streams, ensuring accuracy and consistency. Additionally, it fine-tunes model parameters to enhance predictive capabilities, allowing the system to adapt dynamically to evolving environmental conditions. The code employs dynamic parameter tuning techniques to adjust model hyperparameters based on the characteristics of the incoming data and the performance of the current model. This adaptive approach ensures that the model remains optimized for varying environmental conditions and structural dynamics. Furthermore, to handle large volumes of data efficiently, the code is designed to be scalable and capable of parallel execution on distributed computing platforms. Through iterative processes, the code iteratively refines and updates the predictive model, ensuring its alignment with real-world observations and improving overall system performance.

Integrated web application for advanced analytics and monitoring

In the pursuit of revolutionizing urban infrastructure management, the integration of an advanced web application within the Urban Sentinel framework serves as a pivotal component. This application harnesses cutting-edge analytics capabilities to process vast streams of sensor data in real-time. Leveraging sophisticated machine learning algorithms and statistical models [18], the application conducts predictive analytics to anticipate potential structural issues and anomalies. By continuously analyzing incoming data and historical trends, the system identifies patterns indicative of emerging risks, enabling proactive maintenance strategies and timely interventions. Figure 5 shows the UI of the designed real-time integrated analytics system.

At the core of the integrated web application lies a comprehensive monitoring system designed to oversee the structural integrity and operational performance of buildings in real-time. Through intuitive dashboards, visualization tools, and interactive maps, users gain a holistic view of the monitored district, with the ability to drill down into individual buildings for detailed analysis.

The interactive nature of the visualization tools empowers stakeholders to identify patterns, anomalies, and emerging risks at a glance, facilitating informed decision-making and resource allocation [19].

To ensure timely intervention and preventive maintenance efforts, the integrated web application incorporates an advanced alerting system that notifies relevant stakeholders of critical issues and potential risks. By monitoring predefined thresholds and anomaly detection algorithms, the application triggers alerts via email, SMS, or push notifications

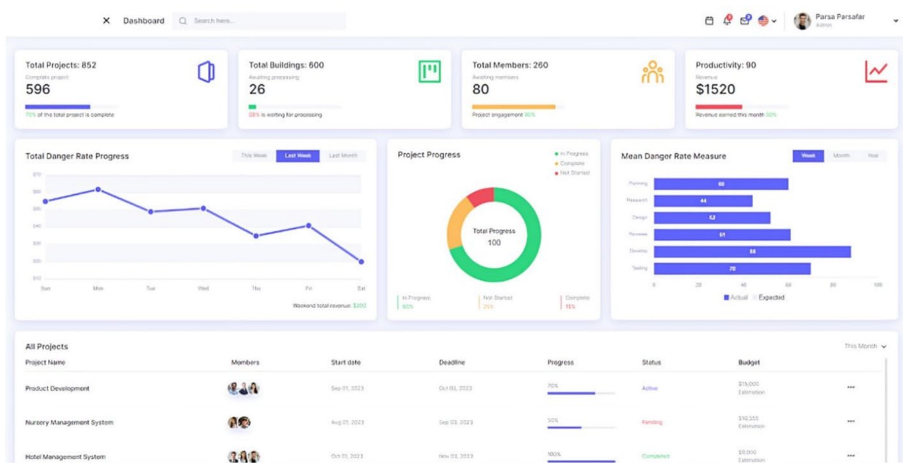

Fig. 5 Real-time analytics UI

for abnormal behavior, structural deviations, or environmental changes that warrant attention.

A fundamental aspect of the integrated web application is its commitment to continuous improvement and optimization. Through feedback mechanisms and user interactions, the application gathers insights and refinements that contribute to the evolution of its analytics and monitoring capabilities.

It is worth mentioning that the usability considerations have guided the design of the Urban Sentinel web application. The interface includes interactive dashboards, clickable building maps, and visual heatmaps to intuitively convey risk levels. Stakeholders can drill down into individual structures for detailed reports, receive multi-channel alerts (email/SMS/push), and adjust risk thresholds on a per-building or global basis. A feedback panel enables engineers to input post-inspection findings, which directly update the AI training dataset. To ensure accessibility, the application is built with responsive design principles and supports both desktop and mobile environments, promoting usability across field operations and control centers. Future updates will include multi-language support, user analytics, and dashboard customization to improve engagement further.

In summary, by leveraging state-of-the-art technologies and user-centric design principles, the application empowers stakeholders with actionable insights, real-time alerts, and dynamic visualization tools.

Experiments and results

The Urban Sentinel framework was evaluated through real-world deployments in a mid-sized urban district comprising 50 mixed-use buildings (residential and commercial) in a seismic-prone region, supplemented by simulations to test the system's performance under extreme conditions, such as earthquakes. A total of 500 sensors (10 per building, including accelerometers, strain gauges, and acoustic emission sensors) were deployed to collect data over 6 months, generating approximately 10,000 sensor readings. Simulations were conducted using synthetic data to model rare events, ensuring the system's robustness across diverse scenarios.

Feedback iterations from CC engineers were captured through the integrated web application, where engineers input damage assessments and adjust danger thresholds (set at 0.5 for structural health metrics) to convert regression outputs into binary classifications (safe/unsafe). These inputs triggered monthly retraining of the regression model, with performance evaluated using confusion matrix metrics, including false negative rates to prioritize safety. Figure 6 illustrates the evolution of these metrics over five feedback iterations, showing a significant reduction in false negatives (from 16.5% to 1%) as the model incorporated engineer feedback and new sensor data. The dataset for Fig. 6 comprised 10,000 sensor readings, with metrics computed by comparing predicted and actual structural health states against the defined threshold.

The deployment utilized LoRaWAN gateways for data transmission, with each building equipped with a local preprocessing unit to normalize and cleanse data before transmission. The system was tested on a variety of building types, including reinforced concrete and steel-frame structures, to ensure generalizability. Hardware specifications included low-power accelerometers (e.g., ADXL355) and strain gauges (e.g., HBM LY series), connected to LoRaWAN-enabled nodes for efficient data transfer.

Through a series of controlled experiments and field trials, we assess the system's ability to accurately predict structural health metrics, detect anomalies, and facilitate proactive maintenance interventions.

We endeavor to illustrate the evolution and enhancement of the confusion matrix metrics as they unfold with each iteration of feedback from the CC engineers, as showcased in Fig. 6.

As evident, the false negative rate, a crucial metric emphasized earlier in the proposal, demonstrates a notable decrease across preceding iterations.

It is clarified that although confusion metrics are typically used in classification problems, as mentioned earlier, the danger threshold rate can be customized in the

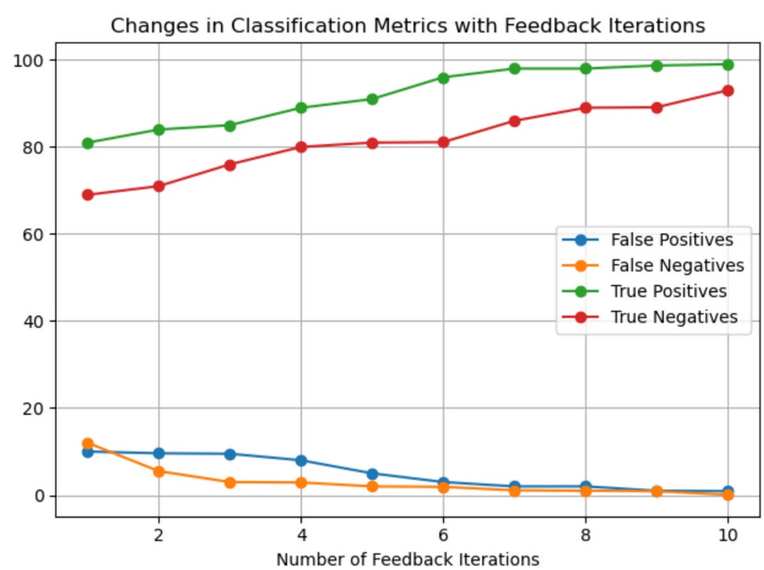

Fig. 6 Changes in danger detection metrics in the proposed system with feedback iterations

integrated web application and altered by the CC manager, thereby allowing the regression problem to be perceived as a simpler classification problem.

Comparison to similar works

Compared to the systems discussed in the literature, the Urban Sentinel framework introduces several key improvements across multiple dimensions. Unlike Alfaré et al.'s WSN-centric designs, Urban Sentinel integrates AI-based predictive modeling, supports real-time feedback integration from civil engineers, and scales across districts rather than focusing on single structures. While Bhatta and Dang's IoT review highlights real-time monitoring capabilities, it does not demonstrate autonomous learning or adaptive analytics, both of which are foundational to the self-optimizing loop in Urban Sentinel. The system also distinguishes itself from AIoT architectures like that of Popescu et al., which, despite strong environmental monitoring features, lack the domain-specific predictive precision and structural integration required for SHM.

To quantitatively illustrate these distinctions, Table 3 presents a comparative summary of each system's capabilities based on five critical performance indicators. The numerical values for Urban Sentinel are derived from system evaluation metrics discussed in the manuscript. For other systems, the values are estimated based on reported performance trends or normalized from qualitative evaluations in their respective papers.

The Urban Sentinel framework includes real-time monitoring capabilities enabled by IoT sensor networks and AI systems. This feature enables proactive decision-making and rapid response [20, 21] to emerging issues or emergencies, contributing to improved urban resilience and safety which is superior to the mentioned and other related studies. Moreover, this proposed system emphasizes the integration of diverse data sources from various urban infrastructure components. This integrated data approach enables comprehensive analysis and visualization, facilitating better-informed decision-making by urban planners and policymakers while the mentioned study doesn't.

Table 3 Comparative Evaluation of SHM and AIoT Systems

Feature/metric	Urban Sentinel	Alfaré et al. (2023)	Bhatta and Dang (2024)	Popescu et al. (2024)
System scale	District-level (50+)	Structure-level (1–3)	Structure-level (varied)	Environmental zones
Predictive AI integration	Regression + FN penalty	None	Minimal (edge alerts only)	Deep learning models
False negative rate (Final)	**↓ 1.0%**	N/A	N/A	~ 5–10% (inferred)
Model adaptation via feedback	Yes (human-in-the-loop)	No	No	No
Web-based visualization interface	Yes (real-time, interactive)	No	Cloud dashboard only	Dashboard (nonstructural)
Sensor diversity	High (three types)	High (sensor-level)	Medium	Medium
Scalability & automation	High	Medium (manual tuning)	Medium	High
Target domain	Civil SHM	Bridge SHM	Civil SHM	Environmental IoT

Conclusions

In the realm of urban infrastructure management, ensuring the structural integrity of buildings and infrastructure stands as a cornerstone for sustainable development and citizen well-being. The proposed Urban Sentinel framework represents a pioneering approach to this challenge, merging IoT sensor networks with regression AI systems to revolutionize urban infrastructure monitoring. By strategically deploying sensors within buildings and infrastructure, Urban Sentinel captures data on structural health, environmental conditions, and operational performance. This data, transmitted wirelessly to a centralized control center, undergoes rigorous analysis by regression AI models, empowering real-time prediction of structural health and proactive maintenance strategies. Through illustrative case studies and examples, Urban Sentinel showcases its ability to enhance resilience, sustainability, and safety in urban environments, heralding a new era of smarter infrastructure management. With continuous feedback and refinements from the control center, the AI-driven system remains accurate and aligned with real-world observations, ensuring optimized infrastructure performance and long-term urban sustainability.

This study not only proposes a novel AI-powered SHM framework but also addresses critical dimensions often overlooked in smart city applications: data transparency, model interpretability, security and privacy assurance, user-centered design, and scalability via automation. The introduction of self-optimizing AI, human-in-the-loop refinement, and adaptive transmission protocols collectively ensures that Urban Sentinel is not merely functional but also practical, secure, and extensible to diverse urban contexts. Furthermore, the system's architecture emphasizes reproducibility through detailed dataset design, robustness through customized loss functions targeting false negatives, and accessibility via an interactive, real-time web interface.

Despite its advancements, Urban Sentinel faces limitations, including dependency on reliable LoRaWAN coverage, which may be challenging in dense urban areas with signal interference, and high initial costs for sensor deployment across large districts. Future work will focus on integrating additional sensor types (e.g., temperature, humidity) to enhance environmental monitoring, expanding the framework to other infrastructure types like bridges and tunnels, and exploring advanced AI models, such as deep learning, to further improve predictive accuracy while maintaining computational efficiency.

Acknowledgements
Not applicable.

Author contributions
PP is the only author of the current paper and did all the related works on the manuscript.

Funding
No funding.

Availability of data and materials
Not applicable.

Declarations

Competing interests
Author have no competing interest.

Received: 30 April 2025 Accepted: 28 June 2025
Published online: 30 July 2025

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