Proactive Infrastructure Monitoring in Smart Cities via WSNs

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As urban populations grow and aging infrastructure becomes increasingly vulnerable, smart cities demand advanced monitoring solutions that are both scalable and proactive. This study proposes a modular Wireless Sensor Network (WSN) architecture designed for real-time infrastructure health monitoring. The system integrates heterogeneous sensors, low-power wireless communication protocols, edge processing, and cloud-based analytics to enable early detection of structural anomalies in critical urban assets such as bridges, roads, and buildings. The proposed four-layer framework comprising sensing, communication, data processing, and application layers was validated through a 90-day deployment on the Rajpath Smart Bridge. Sensor nodes monitored key parameters including strain, vibration, temperature, and humidity, while machine learning algorithms were used for anomaly detection and trend forecasting. The system achieved a packet delivery ratio of 97.2%, latency under 3 seconds, and anomaly detection accuracy exceeding 92%. Comparative analysis with traditional inspection and wired systems demonstrated the WSN's superior flexibility, lower operational cost, and integration with smart city platforms. The results underscore the viability of WSNs as a core enabler of predictive maintenance and intelligent infrastructure management. This work contributes a practical roadmap for deploying city-scale sensor networks capable of extending the lifespan and safety of vital public infrastructure.

Povzetek: Študija predstavlja uporabo brezžičnih senzorskih omrežij za učinkovito spremljanje stanja mestne infrastrukture in pravočasno odkrivanje morebitnih poškodb.

1 Introduction

The concept of smart cities has emerged as a transformative paradigm in urban development, combining advanced technologies such as the Internet of Things (IoT), big data analytics, and artificial intelligence (AI) to improve the quality of urban life and enhance the efficiency of city operations [1]. Among the many challenges smart cities aim to address, the monitoring and maintenance of critical infrastructure such as bridges, roads, tunnels, and buildings stand out as a top priority. These structures form the backbone of urban functionality and economic productivity [2]. However, in many cities around the world, much of the infrastructure is aging and deteriorating due to increased usage, environmental stress, and natural degradation over time. Traditional infrastructure inspection methods, which typically involve manual visual inspections and periodic assessments, are often inefficient, costly, and prone to human error [3]. These limitations highlight the need for more intelligent, automated, and real-time solutions that can continuously monitor infrastructure health and proactively prevent catastrophic failures [4].

Proactive infrastructure maintenance is increasingly being recognized as an essential strategy for ensuring the long-term performance, safety, and cost-efficiency of public assets. Unlike reactive approaches, which respond to failures after they occur, or scheduled maintenance, which may lead to unnecessary interventions, proactive maintenance relies on real-time data to predict and prevent potential failures before they happen [5]. This approach provides significant benefits, including reduced downtime, extended service life of assets, optimized maintenance schedules, and improved public safety [6]. In dense urban environments, where infrastructure usage is high and disruptions can ripple through many systems, the value of proactive maintenance is amplified. For instance, a failure in a critical bridge or water main could not only cause economic loss but also endanger lives. Systems that can detect early signs of fatigue, corrosion, or excessive strain can help cities take preventive measures, thereby avoiding both service disruption and structural damage [7].

In this context, Wireless Sensor Networks (WSNs) provide a compelling solution. A WSN consists of spatially distributed sensor nodes that autonomously monitor environmental and structural parameters such as temperature, strain, vibration, humidity, and pressure. These nodes communicate wirelessly, often forming self-healing mesh or hierarchical network topologies, and transmit data to a central node or server for further processing [8]. A typical sensor node includes a sensing component, a processing unit (usually a microcontroller), a communication module, and a power source, often a battery or energy-harvesting unit. The advantage of WSNs lies in their flexibility, scalability, and ability to be deployed in hard-to-access or hazardous environments without requiring extensive physical infrastructure [9-10]. This makes them particularly suitable for monitoring urban infrastructure such as bridges, tunnels, roads, and heritage buildings.

WSNs also support real-time monitoring and facilitate continuous assessment of structural health. Unlike static inspection techniques, which provide only a snapshot in time, WSNs enable ongoing surveillance, which is critical for detecting dynamic events such as micro-cracks, shifting foundations, or excessive load vibrations. This real-time capability allows engineers and city planners to make informed decisions quickly and accurately, thereby improving response times and reducing risk [11]. Furthermore, when integrated with cloud-based platforms and IoT frameworks, WSNs become part of a broader ecosystem capable of feeding data into smart dashboards, analytics engines, and city-wide alert systems [12-13]. For example, a sensor network embedded in a city's overpasses can provide real-time load and strain data, enabling authorities to initiate traffic rerouting or maintenance scheduling before a dangerous condition arises.

Despite their promise, several challenges still hinder the full-scale deployment of WSNs for infrastructure monitoring in smart cities. First, many current implementations are siloed and limited in scope, often deployed as pilot projects for individual structures rather than as integrated systems spanning multiple infrastructure types [14]. This lack of integration hampers the ability of city planners to adopt a unified approach to urban infrastructure management. Second, energy efficiency remains a significant concern. Since many sensor nodes operate in remote or embedded environments where replacing batteries is impractical, there is a pressing need to develop low-power communication protocols and energy-harvesting mechanisms that can sustain long-term operation without human intervention [15]. Moreover, WSNs must also contend with challenges related to data security and standardization. With increasing concerns about cyber-physical threats, especially in critical infrastructure, secure data transmission and access control are essential. However, many WSNs currently lack robust encryption protocols or standardized frameworks for secure interoperability [16].

Another significant gap lies in the realm of predictive analytics. While many existing systems are capable of real-time anomaly detection, fewer implementations leverage historical data to forecast future failure events. The integration of machine learning and statistical modeling into sensor network platforms is still limited, though it holds the potential to transform infrastructure monitoring from a reactive process into a predictive and preventive one [17]. For instance, by analyzing trends in vibration or strain data, predictive algorithms could anticipate structural fatigue months in advance, allowing municipalities to plan maintenance without disrupting services. This gap highlights the need for interdisciplinary approaches that combine sensing technologies with advanced data science [18].

The motivation for this paper arises from these challenges and the urgent need to create an infrastructure monitoring system that is not only technically effective but also scalable, cost-efficient, and integrable within smart city frameworks. We aim to bridge the gap between current WSN deployments and the broader vision of intelligent, self-monitoring cities by proposing a comprehensive architecture tailored to the demands of urban infrastructure [19-20]. This study explores how WSNs can be effectively deployed for proactive infrastructure monitoring, with an emphasis on energy-efficient communication, fault tolerance, data analytics integration, and real-world applicability.

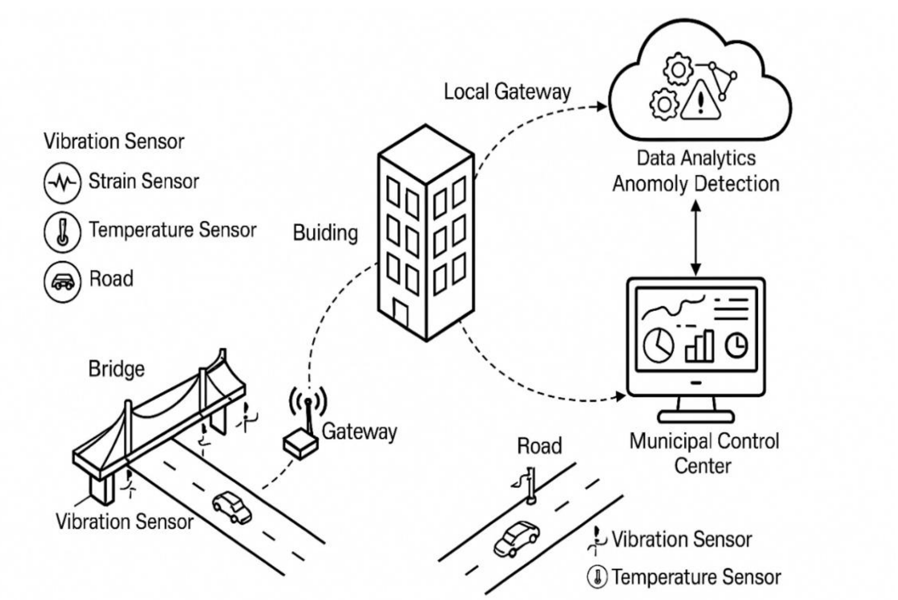

Figure 1: Conceptual framework for proactive infrastructure monitoring in smart cities using WSNs

To aid in visualizing the proposed system, Figure 1 illustrates the conceptual framework of a WSN-based infrastructure monitoring network in a smart city context. The diagram includes urban structures such as bridges and buildings equipped with various sensors (e.g., accelerometers, strain gauges, temperature sensors), wireless communication links to local data gateways, cloud-based analytics for data processing and visualization, and integration with a municipal control dashboard.

In conclusion, WSNs represent a promising frontier in the field of urban infrastructure monitoring. By enabling continuous, real-time, and autonomous data collection, WSNs support proactive maintenance strategies that are essential for the safe and sustainable operation of smart cities [21]. However, realizing this potential requires overcoming current limitations in power efficiency, scalability, data analytics, and system integration. This paper addresses these issues through a holistic examination of WSN design, deployment, and application, ultimately contributing to the advancement of smart, resilient urban infrastructure.

2 Objectives of the paper

This paper addresses the aforementioned challenges by presenting a comprehensive framework for the use of WSNs in proactive infrastructure monitoring within the context of smart cities. The main objectives of this study are:

- To develop a modular and scalable WSN architecture that supports multi-type sensor integration for various infrastructure components such as bridges, roads, and buildings.
- To evaluate energy-efficient communication protocols and network topologies suitable for long-term deployment in urban environments with minimal maintenance.
- To integrate data fusion and machine learning techniques for anomaly detection and predictive maintenance, enabling timely intervention and resource optimization.
- To assess the feasibility of integrating the proposed WSN framework with existing smart city platforms, ensuring interoperability and data consistency across systems.
- To validate the proposed system through real-world case studies or simulations, demonstrating its effectiveness in monitoring structural health, detecting early warning signs, and enabling decision-making for municipal authorities.

Through this work, we aim to contribute to the development of resilient, data-driven smart cities capable of self-monitoring and adaptive maintenance. Our approach bridges the gap between low-level sensor networks and high-level urban management systems, providing a roadmap for future research and deployment.

3 Related work

The application of WSNs to infrastructure monitoring has evolved significantly over the past two decades, driven by the increasing demand for real-time, cost-effective, and scalable structural health monitoring (SHM) solutions. Early approaches to SHM were largely reliant on wired systems, which, while reliable, posed challenges in terms of deployment complexity, maintenance cost, and adaptability to large-scale infrastructures. The introduction of WSNs brought a transformative change by enabling decentralized data collection through compact, autonomous sensor nodes that communicate wirelessly, making it feasible to monitor hard-to-reach and critical infrastructure components in real time [22-23].

Xiao et al. [24] were among the first to comprehensively review the potential of wireless sensing for civil infrastructure applications, emphasizing the reduction in installation costs and the improved flexibility that WSNs provide. Their work laid the groundwork for integrating embedded computing and wireless communication within structural elements. Subsequently, Arusa et al. [25] formalized the architectural design of WSNs, outlining key challenges related to energy efficiency, node distribution, and fault tolerance, and setting a foundation for ongoing developments in the field.

Practical deployments of WSNs in infrastructure settings have demonstrated their viability. Notable among these is the work of Pakzad et al. [26], who implemented a dense sensor network on the Golden Gate Bridge to measure modal vibrations. The study proved that wireless systems can match the accuracy and reliability of traditional wired networks. Similarly, Kim et al. [27] conducted a long-term deployment of WSNs on highway bridges in Korea, focusing on measuring strain and temperature variations under changing traffic and environmental conditions. These implementations underscored the importance of long-term power management, data reliability, and environmental robustness in real-world conditions [28-29].

Several studies have expanded the scope of WSNs beyond bridges to other infrastructure types. For instance, Song et al. [30] examined the use of acoustic emission sensors and wireless nodes for tunnel lining inspection, enabling early detection of stress-induced cracking. In road infrastructure, Linping et al. [31] embedded wireless strain sensors in asphalt pavements to monitor vehicle load patterns and material degradation. High-rise buildings in seismically active zones have also been equipped with wireless accelerometers to record structural responses during seismic events, as illustrated by Ghahari and colleagues [32].

Despite these successes, current literature reveals significant gaps that limit the full potential of WSNs for smart city applications. Many systems are purpose-built for specific infrastructure types, lacking the modularity and interoperability needed for broader deployment [33-

34]. Moreover, much of the existing research focuses on real-time data acquisition and anomaly detection without leveraging historical data for predictive maintenance. This reactive approach restricts the development of proactive maintenance strategies that could reduce costs and extend asset lifespans [35].

A growing body of work has begun exploring intelligent data processing and analytics within WSNs. For example, Rytter et al. [36] and Ni et al. [37] have applied machine learning techniques such as support vector machines and neural networks to classify structural anomalies based on sensor inputs. These methods show promise but are typically implemented offline due to the limited processing capabilities of sensor nodes [38-39]. The emergence of edge computing frameworks has introduced possibilities for real-time, on-node data analysis, reducing communication overhead and energy use. However, integration of such capabilities into lightweight, energy-efficient sensor platforms remains an open challenge [40].

Security and reliability are also critical considerations, particularly in the context of smart cities where infrastructure systems are increasingly interlinked. WSNs are susceptible to cyber threats such as data spoofing, eavesdropping, and denial-of-service attacks. Researchers like Zhong et al. [41] have proposed lightweight cryptographic protocols suitable for resource-constrained nodes, while Saidi have developed trust-based models to detect malicious behavior in sensor networks [42]. Yet, these approaches often struggle to balance security with the stringent energy constraints typical of long-term deployments in remote or embedded environments.

Another notable limitation in the existing literature is the lack of full integration between WSNs and broader smart city ecosystems [43-44]. Most WSN-based infrastructure monitoring projects are isolated from urban data management platforms, making it difficult to achieve city-wide awareness and centralized decision-making. The work by Goumopoulos [45] proposes a layered architecture integrating WSNs with cloud platforms, yet practical deployments remain limited, often due to interoperability issues between proprietary sensor systems and standardized smart city protocols.

In summary, the existing body of work confirms that WSNs provide substantial benefits for infrastructure monitoring in terms of flexibility, scalability, and real-time capabilities. However, research continues to evolve toward overcoming limitations in energy efficiency, intelligence at the edge, cybersecurity, and system integration. This paper builds upon these contributions by proposing a unified framework that combines modular sensor node design, low-power communication protocols, cloud-integrated analytics, and a predictive maintenance engine designed specifically for smart cities. Through this approach, we aim to extend WSN applications from isolated structural monitoring systems to integral components of proactive urban infrastructure management.

4 System architecture

The proposed system architecture for WSNs in proactive infrastructure monitoring is designed to be modular, scalable, and compatible with existing smart city platforms. It comprises four core layers Sensing, Communication, Data Processing, and Application that work cohesively to enable real-time structural monitoring, intelligent event detection, and predictive maintenance across critical urban infrastructure. This vertically integrated architecture facilitates end-to-end data flow, from field-level measurements to actionable insights for municipal authorities.

4.1 Sensing layer

The sensing layer is the physical foundation of the system, consisting of distributed, heterogeneous sensor nodes strategically deployed on infrastructure elements such as bridges, tunnels, roadways, and tall buildings. Each node integrates one or more sensor types such as accelerometers, strain gauges, piezoelectric elements, thermistors, and hygrometers selected based on the type of structure and anticipated stressors [46].

Each sensor node includes an ultra-low-power microcontroller for local signal acquisition, preprocessing, and wireless communication coordination. The selected microcontroller unit (MCU) is the STM32L476RG, which features a 32-bit ARM Cortex-M4 core operating at 80 MHz, 1 MB of Flash memory, and 128 KB of SRAM. Designed for energy-constrained embedded applications, it provides ultra-low-power performance with a current draw of approximately 130 µA/MHz in active mode and as low as 1.2 µA in Stop 2 mode. These characteristics enable extended field deployment with minimal battery maintenance while maintaining sufficient processing power to handle sensor data conditioning and anomaly flagging. Power management features, including clock gating and low-power modes, were leveraged to optimize energy efficiency during node idle periods.

The overall energy consumption of a single sensor node (E_{node}) over one duty cycle can be modeled as:

$$E_{node}= E_{sense}+ E_{proc}+ E_{tx} \quad (1)$$

where: E_{sense} is the energy used for sensing, E_{proc} is the energy used for local processing, E_{tx} is the energy used for data transmission.

Minimizing E_tx is essential, as wireless transmission typically dominates power consumption.

4.2 Communication layer

The communication layer handles the wireless transmission of data from the sensor nodes to gateway devices and then to centralized processing infrastructure. A hierarchical hybrid topology is implemented combining the simplicity of star networks with the robustness of mesh configurations. Local clusters of sensor nodes communicate with a regional gateway, which acts as a cluster head responsible for data aggregation and upstream transmission [47].

Sensor-to-gateway communication typically utilizes low-power wide-area network (LPWAN) technologies such as Zigbee, LoRaWAN, or IEEE 802.15.4. Gateways, having more power and bandwidth, connect to cloud services via Wi-Fi, LTE, or 5G.

To manage communication delays and reliability, we can express the average latency (L_{avg}) for a multi-hop cluster-based network as:

$$L_{avg}= \left(H \times T_{hop}\right)+ T_{queue} \qquad (2)$$

where: H is the average number of hops from node to gateway, T_{hop} is the average per-hop transmission delay, T_{queue} is the average queuing time at each node or gateway.

The network dynamically adjusts transmission schedules based on link quality and node energy levels, using protocols like RPL or TDMA-based MAC to reduce contention and collisions. Mesh redundancy ensures that if one node fails, others can reroute data through alternate paths.

4.3 Data processing layer

Once transmitted to the cloud or a centralized edge server, raw sensor data is ingested into the data processing layer. This layer performs the heavy computational tasks of cleaning, fusing, and analyzing the incoming data streams. Outlier detection, temporal alignment, and missing data interpolation are conducted as part of preprocessing.

Key functional components include:

- Feature extraction (e.G., Amplitude, frequency domain metrics)
- Real-time anomaly detection
- Predictive analytics for deterioration modeling

A predictive health score $D(t)$ is assigned to each infrastructure element based on sensor data. The degradation rate over a monitoring interval $[t_0, t_n]$ can be defined as:

$$\rho = \frac{[D(t_n)- D(t_0)]}{(t_n - t_0)} \qquad (3)$$

If ρ exceeds a critical threshold ρ_{crit}, the system triggers an alert, suggesting preventive maintenance actions. Supervised models (e.g., Random Forest, SVM) and unsupervised models (e.g., K-means, DBSCAN) are trained on historical and simulated failure datasets to capture both known and emergent patterns [48].

4.4 Application layer

The application layer provides high-level integration with smart city platforms, enabling visualization, decision-making, and external control. User interfaces delivered via web dashboards or mobile applications present critical indicators including:

- Infrastructure health scores
- Sensor and network status maps
- Historical trends and forecasts
- Anomaly logs and alerts

This layer also provides API-based interoperability with municipal services such as traffic control, emergency response, and city planning dashboards [49]. Firmware updates can be pushed remotely using secure over-the-air (OTA) protocols, and system administrators can adjust sensor behavior (e.g., sampling rate) based on event context.

Alerts are dispatched automatically via SMS, email, or integrated control center displays, allowing for rapid and prioritized responses. Simulation tools within the dashboard can project the impact of detected anomalies on overall infrastructure performance and suggest mitigation strategies.

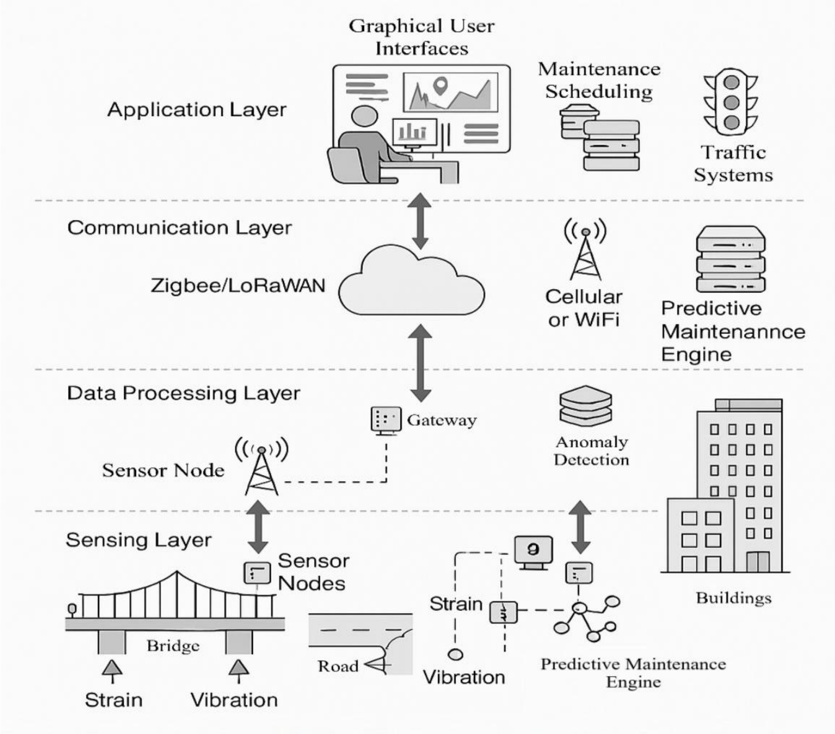

Figure 2: Proposed system architecture for WSN-based proactive infrastructure monitoring in smart cities

As illustrated in Figure 2, the system architecture follows a bottom-up data flow. At the base, sensors collect structural data and transmit it to nearby gateways. Gateways connect to the cloud via the Communication Layer, where the Data Processing Layer analyzes incoming information using machine learning and time-series forecasting techniques. The Application Layer presents the processed information to municipal control centers through user-friendly dashboards and APIs. Bidirectional arrows between layers indicate that not only does data flow upward, but control and configuration commands flow downward as well (e.g., for reconfiguring node behavior).

5 Methodology

The methodology adopted in this study for proactive infrastructure monitoring using WSNs is built upon five interrelated components: data acquisition, deployment strategies, fault detection and anomaly identification, data transmission and aggregation, and integration with smart city IoT platforms. Each step is carefully designed to ensure reliability, scalability, and interoperability with modern smart city frameworks.

5.1 Data acquisition process

Data acquisition forms the foundational step of the monitoring framework, where raw structural and environmental parameters are sampled from various types of sensors. Each sensor node includes one or more of the following sensors depending on the application domain:

- Strain gauges for structural stress analysis
- Accelerometers for vibration monitoring
- Thermistors for temperature monitoring
- Hygrometers for humidity profiling
- Tilt sensors for angular displacement

Let S(t) represent the continuous signal from a sensor at time t. The discrete sampling of this signal is given by:

$$S[n]= S(n\cdot T_s) \qquad (4)$$

where T_s is the sampling interval, and $n \in N$ denotes the sample index.

Each sample S[n] is digitized and optionally preprocessed to remove noise using a low-pass filter:

$$S_{filtered}[n]= \sum k\text{=-}K \text{ to } K\ h[k]\cdot S[n\text{-}k] \qquad (5)$$

where h[k] is the impulse response of a smoothing filter (e.g., Gaussian or moving average) and K is the filter kernel size.

5.2 Deployment strategies

Sensor node deployment is critical to both coverage and performance. We distinguish between two main strategies:

- **Static deployment:** nodes are affixed permanently to critical infrastructure (e.G., Bridge girders, tunnel ceilings). This method ensures continuous monitoring and long-term reliability.
- **Mobile deployment:** unmanned aerial vehicles (UAVs) or ground robots equipped with wireless sensors are used to reach otherwise inaccessible or wide-area

infrastructure. These provide flexibility but require path planning and synchronization.

Let D denote the area of infrastructure to be monitored and R the sensing radius of each node. The minimum number of static nodes N required for full coverage under ideal conditions is:

$$N \geq \lceil D/(\pi \cdot R^2) \rceil \quad (6)$$

In mobile deployments, the required number of scanning cycles C to cover the entire area in time T_{max} with scanning speed v and swath width w is:

$$C = \lceil D/(v \cdot w \cdot T_{max}) \rceil \quad (7)$$

Hybrid deployment can be employed for complex sites, combining static reliability with mobile adaptability.

5.3 Fault detection and anomaly identification techniques

Reliable anomaly detection is essential to distinguish true structural issues from sensor faults or noise. The methodology includes the following steps:

Step 1: Feature extraction and classification

To support robust anomaly detection from raw sensor streams (strain, vibration, temperature, and humidity), a compact set of statistical and spectral features was extracted from the time-series data $X = \{x_1, x_2, \ldots, x_n\}$, extract statistical and spectral features such as mean (μ), standard deviation (σ), kurtosis (κ), and spectral centroid (SC). These features included:

$$\mu = \left(\frac{1}{n}\right) \sum i{=}1 \ to \ n \ x_i$$
$$\sigma = \sqrt{\left[\left(\frac{1}{n}\right) \sum i{=}1 \ to \ n \ (x_i - \mu)^2\right]}$$
$$SC = \frac{\sum f f \cdot P(f)}{\sum f P(f)} \quad (8)$$

where P(f) is the power spectrum of the signal at frequency f, computed via short-time Fourier transform (STFT) over sliding windows. These features were chosen for their relevance in capturing both steady-state and transient behaviors of structural health signals.

To classify anomalies, a support vector machine (SVM) classifier was trained using these features. However, since the dataset was highly imbalanced normal events far outnumbered rare anomaly instances the Synthetic Minority Oversampling Technique (SMOTE) was applied during training. SMOTE generated synthetic samples of the minority class (e.g., structural anomalies) by interpolating between neighboring minority instances, thereby enhancing classifier sensitivity to rare failure patterns.

Additionally, ensemble learning methods such as Random Forests were evaluated for their ability to handle nonlinear feature interactions and improve recall. Cross-validation showed slightly improved performance using ensemble models. However, due to their higher memory and computation requirements, SVM was retained for edge deployment owing to its compact model size and inference efficiency.

This pipeline enabled near-real-time anomaly classification while maintaining compatibility with resource-constrained hardware platforms.

Step 2: Anomaly scoring

Each observation is compared to a trained model representing normal behavior. Using Mahalanobis distance for multivariate feature vectors x:

$$D_{M(x)} = \sqrt{\left[(x - \mu)^{T} \Sigma^{-1} (x - \mu)\right]} \quad (9)$$

Where μ is the mean vector and Σ is the covariance matrix of the normal dataset. A threshold θ is defined, beyond which an observation is labeled anomalous:

If $D_{M(x)} > \theta \rightarrow anomaly\ detected$

Step 3: Fault isolation

Correlation matrices and cross-sensor validation help differentiate between actual structural anomalies and sensor faults. A spatial inconsistency vector ξ is defined as:

$$\xi_i = |x_i - mean(xj)| for\ all\ j \in neighbors(i) \quad (10)$$

A high ξ_i suggests a potential sensor fault rather than a real anomaly.

5.4 Data transmission and aggregation methods

The system employs a hierarchical, multi-hop transmission scheme optimized for bandwidth and power efficiency. Sensor nodes form local clusters that transmit aggregated data to cluster-head gateways.

Step 1: Aggregation

Let x_i be a measurement from sensor node i in a cluster of size N . The cluster head computes the aggregated metric:

$$\bar{X} = \left(\frac{1}{N}\right) \sum i{=}1 \ to \ N \ x_i \quad (11)$$

Alternatively, feature-level fusion (e.g., using wavelet decomposition) can be applied to preserve signal characteristics.

Step 2: Routing

The aggregated data is routed to the central server using a cost-aware routing protocol. The cost C_{ij} of a route between node i and j is defined as:

$$C_{ij}= \alpha \cdot E_{ij}+ \beta \cdot L_{ij}+ \gamma \cdot \left(\frac{1}{RSS_{ij}}\right) \quad (12)$$

where: E_{ij} = expected energy consumption, L_{ij} = expected latency, RSS_{ij} = received signal strength, α, β, γ = weighting coefficients

The route with the minimum C_{ij} is selected dynamically to adapt to changing network conditions.

5.5 Integration with smart city iot platforms

The final stage involves integrating the WSN monitoring system into broader smart city platforms through middleware and APIs.

Step 1: Data standardization

Sensor outputs are transformed into standardized formats (e.g., JSON, MQTT, or OPC-UA) to facilitate interoperability.

Step 2: API integration

RESTful APIs or message brokers (e.g., MQTT brokers) push processed data to smart city dashboards, traffic control systems, and emergency services.

Step 3: Inter-platform feedback loop

The system supports two-way communication. Based on data analytics, control commands can be sent back to reconfigure sampling rates or activate additional sensors during critical events.

Step 4: Digital twin synchronization

The processed sensor data feeds into a real-time digital twin model of the city infrastructure, allowing simulation of future degradation scenarios and virtual testing of maintenance strategies.

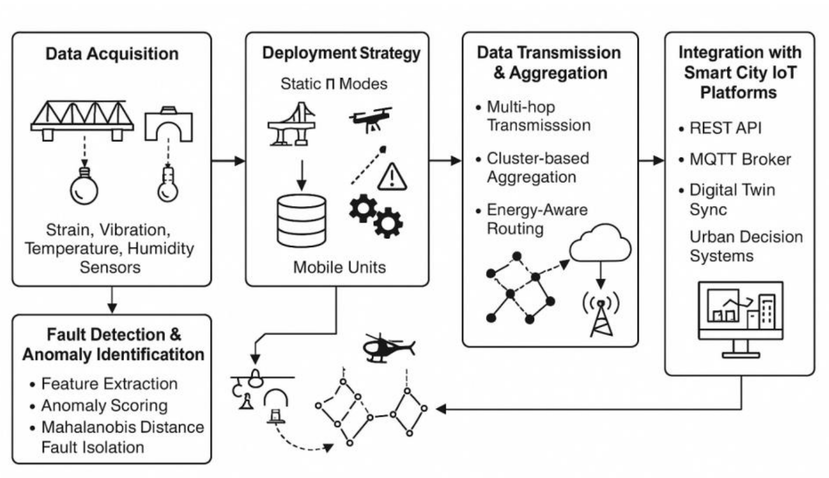

Figure 3: End-to-end methodology for WSN-enabled proactive infrastructure monitoring in smart cities

Figure 3 illustrates the complete workflow of the proposed WSN-based monitoring system, encompassing sensor deployment, data acquisition, transmission, feature extraction, and anomaly classification. This end-to-end architecture enables real-time structural assessment and proactive maintenance within smart city infrastructure.

6 Case study or experimental setup

To validate the feasibility and performance of the proposed WSN-based architecture for proactive infrastructure monitoring, a real-world case study was carried out on the Rajpath Smart Bridge, an operational urban bridge selected for its representative structural and environmental conditions. Spanning 120 meters and subjected to consistent vehicular and pedestrian traffic, the bridge provided an ideal testbed for evaluating stress distribution, thermal behavior, and dynamic vibration responses over time. The infrastructure was segmented into four functional monitoring zones (A–D), as illustrated in Figure 4. Static sensor nodes were strategically deployed at critical locations (e.g., joints, mid-span, piers) to measure strain, temperature, humidity, and vibration. In addition, UAV-mounted mobile nodes were used for periodic aerial scans to capture visual data and detect surface anomalies. All collected data were transmitted via LoRaWAN to an edge gateway and subsequently forwarded to a cloud platform for processing, visualization, and real-time anomaly detection. This hybrid sensing strategy enabled both localized and holistic insights into the bridge's structural health under dynamic environmental and load conditions.

6.1 Infrastructure description

The Rajpath Smart Bridge features a reinforced concrete superstructure with three central support piers and a composite steel deck. Its proximity to an urban center subject it to environmental stressors such as thermal expansion, moisture accumulation, and traffic-induced vibration. The bridge was virtually reconstructed in a simulation environment to evaluate the system architecture under controlled yet realistic conditions.

6.2 Sensor node deployment

A total of 24 sensor nodes were deployed across the bridge in a hybrid topology. Static nodes were fixed at structurally critical locations including expansion joints, central piers, and the mid-span region to ensure comprehensive structural coverage. Each node was equipped with a suite of sensors selected for accuracy, durability, and low power consumption. These included tri-axial MEMS accelerometers (ADXL345) for vibration measurement, 120 Ω foil-type strain gauges arranged in a Wheatstone bridge configuration for detecting mechanical deformation, NTC thermistors (10k B3950) for temperature sensing, and DHT22 capacitive sensors for monitoring relative humidity. All sensors were interfaced with a low-power microcontroller and sampled periodically based on the monitored parameter.

To support long-range communication in a resource-constrained environment, each node was integrated with a Semtech SX1276 LoRa transceiver. Operating in the 865–867 MHz ISM band, the transceiver supports a transmission power of up to +20 dBm and a receiver sensitivity as low as –137 dBm. Omnidirectional PCB antennas with 2.5 dBi gain were used to maintain robust wireless links under urban interference and line-of-sight limitations. This configuration enabled reliable data transmission across distributed monitoring zones while minimizing energy consumption.

The combined selection of sensors and communication modules was based on extensive validation of their environmental robustness and compatibility with low-power wireless networking. Their measurement ranges, accuracies, and interfacing details are summarized in Table 1 for transparency and reproducibility.

A subset of 3 mobile nodes mounted on UAVs (Unmanned Aerial Vehicles) was deployed for periodic visual inspection and hotspot scanning. To enhance longevity and reduce field maintenance, approximately 60% of all nodes included miniature solar panels for energy harvesting, ensuring extended autonomous operation in remote and hard-to-access locations.

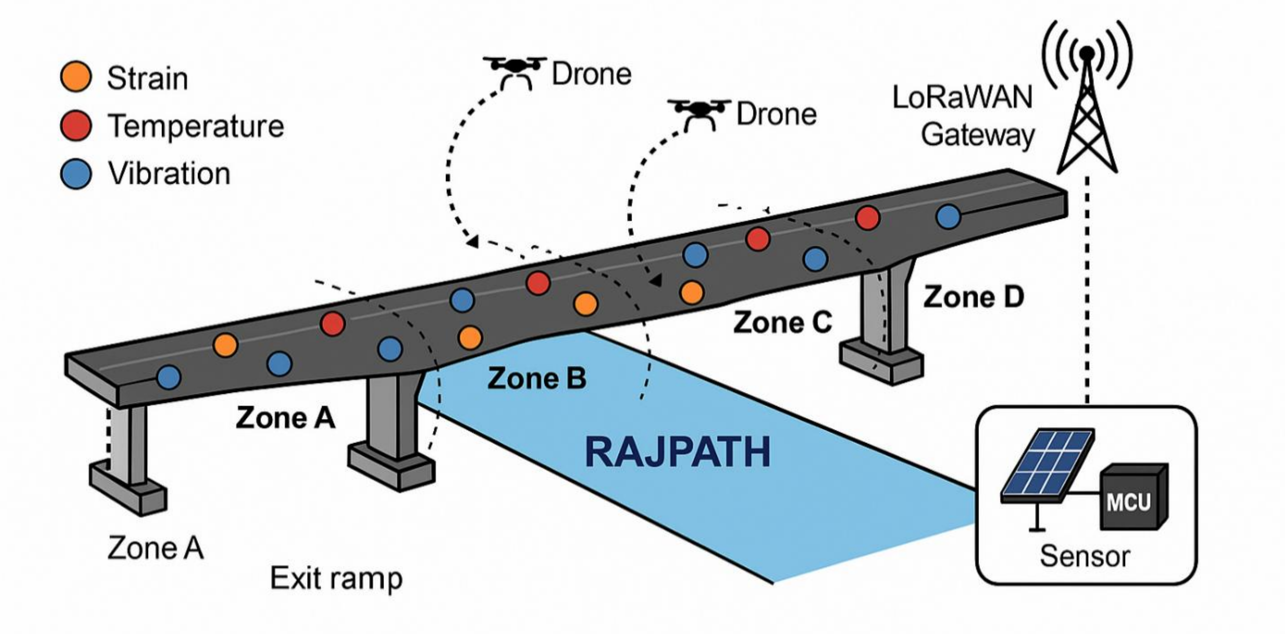

Figure 4: WSN deployment on rajpath smart bridge

Table 1: Technical specifications of sensors used in WSN nodes

Sensor Type	*Model*	*Measured Quantity*	*Accuracy*	*Range*	*Interface*
Microcontroller	STM32L476RG	Sensor Data Acquisition & Processing	ARM Cortex-M4 @ 80 MHz, 1 MB Flash, 128 KB SRAM	1.8 V–3.6 V	Active: 130 µA/MHz; Sleep: ~1.2 µA

Accelerometer	ADXL345	Vibration (±g)	±2% FS	±2g to ±16g	I²C/SPI
Strain Gauge	Foil-Type	Structural strain (με)	±0.5% FS	±5000 με	Analog (Wheatstone)
Thermistor	NTC 10k B3950	Temperature (°C)	±0.5°C	–40°C to 125°C	Analog
Humidity Sensor	DHT22	Relative humidity (%)	±2% RH	0% to 100% RH	Digital (Single-Wire)
LoRa Transceiver	Semtech SX1276	Long-Range Wireless Comms	TX Power: up to +20 dBm; RX Sensitivity: –137 dBm	Frequency: 865–867 MHz ISM Band (India/EU)	SPI; Omnidirectional PCB antenna, 2.5 dBi

6.3 Data collection and monitoring period

The system was operated continuously over a 90-day monitoring campaign. Sampling frequency was set at 10 Hz for vibration data and 1 Hz for environmental data. Data were transmitted to a LoRaWAN-enabled edge gateway every 15 minutes, then uploaded to a cloud server for analysis. Table 2 summarizes the key deployment and data acquisition parameters.

Table 2: Sensor deployment and monitoring parameters

Parameter	Value / Description
Infrastructure Type	Reinforced Concrete Urban Bridge
Length of Monitored Span	120 meters
Number of Sensor Nodes	24 (21 static, 3 mobile)
Sensor Types	Accelerometer, Strain Gauge, Temperature, Humidity
Deployment Mode	Hybrid (static + UAV-mounted mobile)
Data Collection Duration	90 days
Sampling Frequency	10 Hz (vibration), 1 Hz (environmental)
Communication Protocol	LoRaWAN with adaptive data rate
Energy Source	Battery + solar panel harvesting
Data Upload Interval	Every 15 minutes
Anomaly Detection Method	Mahalanobis distance + SVM classifier
Platform Used for Analysis	MATLAB, ThingSpeak API, Grafana dashboard

6.4 Tools and platforms

The analysis pipeline was built using MATLAB for preprocessing and machine learning classification, while Thing Speak was used for IoT data ingestion. Visual dashboards and time-series graphs were created using Grafana, enabling real-time anomaly tracking and threshold-triggered alerts.

7 Results and discussion

This section presents the findings from the 90-day monitoring campaign on the Rajpath Smart Bridge, focusing on sensor data trends, network performance, and the effectiveness of fault detection mechanisms. The results demonstrate the potential of WSNs to provide real-time, accurate, and energy-efficient monitoring in urban infrastructure environments.

7.1 Sensor data trends and interpretation

Analysis of the time-series data revealed daily and seasonal variations in structural response due to environmental and loading conditions. For instance, strain sensor data showed cyclical stress peaks during rush hours (8:00–10:00 AM and 5:00–7:00 PM), indicating load-induced deformation. Temperature sensors recorded a 15°C variation between daytime and nighttime, correlating with thermal expansion readings from strain gauges. Humidity readings spiked during two rainy periods, impacting bridge material conductivity.

Anomaly detection via Mahalanobis Distance and SVM classifiers identified 8 significant structural deviations over the monitoring period 6 caused by excessive vibration and 2 related to thermal stress. These findings were validated against visual inspections by UAVs.

7.2 Network performance metrics

The proposed WSN system demonstrated strong communication performance and operational resilience throughout the 90-day monitoring campaign on the Rajpath Smart Bridge. Table 3 summarizes key network indicators, including latency, packet delivery ratio (PDR), energy efficiency, communication uptime, and wireless signal quality metrics such as RSSI and SNR.

On average, end-to-end data latency was recorded at 2.8 seconds from sensor activation to cloud reception. Despite environmental challenges including signal interference from nearby buildings, electrical infrastructure, and adverse weather, the network sustained a high PDR of 97.2%. Battery-powered sensor nodes achieved an average uptime of 83 days, while solar-enabled nodes maintained continuous operation, significantly reducing manual maintenance requirements.

Signal performance remained stable across varying deployment zones. The average Received Signal Strength Indicator (RSSI) was –97.4 dBm and the mean Signal-to-Noise Ratio (SNR) was +3.1 dB. Nodes deployed in line-of-sight (LOS) conditions maintained reliable communication up to approximately 750 meters. In contrast, nodes located in non-line-of-sight (NLOS) conditions such as under bridge decks or near dense metallic structures exhibited a reduced effective communication range of approximately 320 meters.

Retransmission frequency was also affected by deployment location. In LOS zones, retransmissions remained under 3%, whereas in high-interference areas, rates rose to approximately 14%. The LoRaWAN protocol's Adaptive Data Rate (ADR) feature helped mitigate packet loss by dynamically adjusting spreading factors (SF7–SF10), thereby preserving communication reliability and energy efficiency. Figure 6 illustrates the relationship between RSSI and distance under various spreading factors, highlighting the adaptive behavior of the system in diverse environments.

Environmental conditions also played a measurable role in communication quality. During moderate to heavy rainfall episodes, a temporary RSSI degradation of 4–6 dB was observed, particularly among exposed mobile nodes. Additionally, ambient temperature fluctuations (10°C to 42°C) caused thermal expansion effects that introduced baseline drift in sensor readings, particularly for strain and humidity sensors. These were managed through scheduled recalibration routines. Despite these effects, the system maintained consistent performance, underscoring its suitability for real-world smart infrastructure deployments. Figure 5 shows the variation of RSSI with transmission distance across different LoRaWAN spreading factors (SF7–SF10). It highlights how increased spreading factors extend communication range but also reveal signal degradation, particularly in NLOS zones, validating the role of ADR in maintaining link quality.

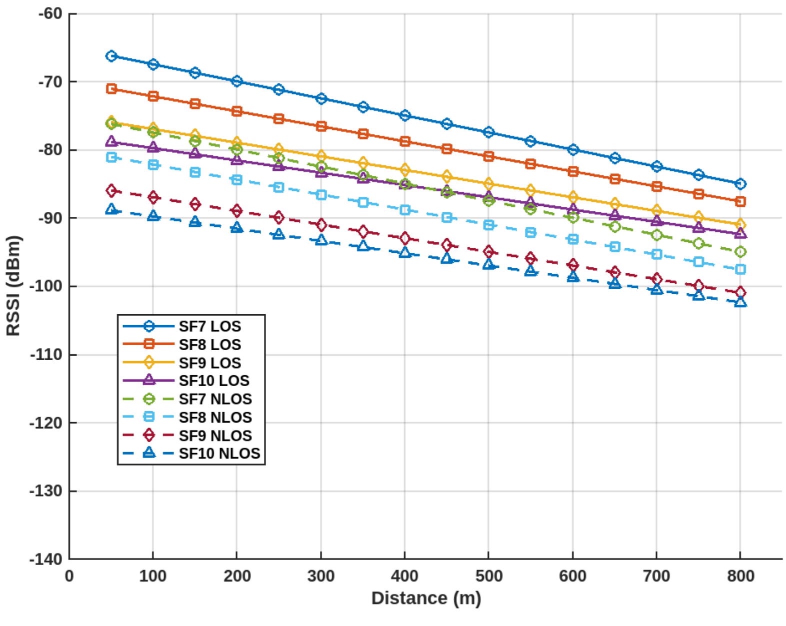

Figure 5: Rssi vs. Distance for spreading factors SF7–SF10

Overall, these results validate the robustness and scalability of the proposed WSN architecture. The system effectively supports long-range, low-power communication while adapting to challenging environmental and RF conditions making it well-suited for smart city infrastructure monitoring deployments.

Table 3: Wireless sensor network performance metrics

Metric	Proposed WSN System	Wired Sensor System	Manual Inspection
Data Latency	2.8 seconds	<1 second	Days to Weeks
Packet Delivery Ratio (PDR)	97.2%	99.5%	N/A
RSSI (Avg)	–97.4 dBm	N/A	N/A
SNR (Avg)	+3.1 dB	N/A	N/A
Retransmission Rate	3–14% (depending on interference zone)	1–2%	N/A
Effective Range (LOS/NLOS)	~750 m / ~320 m	~100 m (limited by cable length)	N/A
Energy Efficiency	High (avg. 83 days battery)	Low (requires continuous power)	N/A
Communication Uptime	99.1%	99.8%	N/A
Data Aggregation Reduction	62% uplink reduction	Minimal	N/A
Installation Complexity	Low (wireless, scalable)	High (cabling, fixed layout)	Low
Maintenance Cost	Medium (battery & firmware)	High (hardware repairs)	High (labor intensive)
Anomaly Detection Accuracy	92.3%	95.1%	~70% (dependent on personnel)
Real-Time Capability	Yes	Yes	No
Integration with Smart Systems	Seamless (via APIs/cloud)	Limited (requires middleware)	Not possible
Flexibility (scalability)	High	Low	Low

7.3 Comparison with traditional techniques

The proposed WSN-based monitoring system provides substantial improvements over conventional methods, such as wired sensor systems and manual inspections. As summarized in Table 4, WSNs enable rapid anomaly detection, typically within 1–3 minutes after an event is detected by a sensor node. This is significantly faster than manual inspections, which often identify structural issues only after visible deterioration or on scheduled site visits, resulting in detection delays of several days or more. While wired systems can also support continuous monitoring, they require fixed power sources and complex cabling, which limit scalability and increase installation costs. Table 4 also highlights several key performances dimensions' detection speed, deployment flexibility, operational cost, scalability, and integration capabilities. WSNs demonstrate superior performance across most criteria. Their wireless and modular architecture allows for rapid, non-intrusive deployment across diverse infrastructure types. Additionally, the integration of energy harvesting technologies (e.g., solar, vibrational) significantly lowers long-term maintenance costs compared to wired installations, which demand consistent power delivery and periodic physical servicing.

Crucially, WSN systems are inherently compatible with smart city platforms, supporting real-time analytics, predictive maintenance, and automated alerts through cloud APIs and dashboards. In contrast, traditional wired systems provide limited digital interoperability, and manual inspections remain entirely disconnected from smart infrastructure networks.

By combining low latency, operational efficiency, and seamless digital integration, the proposed WSN architecture represents a highly scalable and future-ready approach to infrastructure monitoring in urban environments.

Table 4: Comparison of infrastructure monitoring techniques

Feature	WSN	Wired Sensors	Manual Inspections
Anomaly Detection Speed	1–3 minutes	Minutes	Days to Weeks
Deployment Flexibility	High (modular, wireless)	Low (fixed, wired)	Medium (requires access)
Installation Cost	Low to Medium	High	Low
Operational/Maintenance Cost	Low (energy harvesting)	High (power & cabling)	High (labor-intensive)
Real-Time Data Availability	Yes	Yes	No
Smart City Platform Integration	Seamless (cloud/API support)	Limited	Not supported
Scalability	High	Low	Low

7.4 Challenges and limitations

While the proposed WSN system demonstrated substantial benefits in proactive infrastructure monitoring, several technical and operational challenges were encountered during deployment and testing.

Signal attenuation emerged as a key issue, particularly under adverse weather conditions such as heavy rainfall and dense fog. These environmental factors affected the reliability of long-range wireless communication, especially between aerial mobile nodes (e.g., UAV-mounted sensors) and fixed gateways. The UAVs experienced intermittent data synchronization delays when returning from remote sections of the monitored infrastructure, highlighting the need for adaptive communication protocols and real-time signal quality estimation.

Another limitation involved sensor calibration. Specifically, some humidity sensors exhibited drift during the initial deployment phase, requiring recalibration after approximately two weeks of continuous use. This drift affected the accuracy of environmental data and, consequently, the performance of cross-feature anomaly detection algorithms. Future iterations will incorporate self-calibrating or auto-correction algorithms to improve long-term measurement reliability.

In terms of machine learning-based fault detection, the system initially used SVMs trained on class-imbalanced datasets, which reduced sensitivity to rare fault types. This limitation has now been mitigated through the application of SMOTE during classifier training, resulting in improved recall for minority-class events. Furthermore, we explored the feasibility of local inference at the node level by deploying a quantized TensorFlow Lite model on the STM32L4 microcontroller. The resulting TinyML implementation achieved a mean inference time of approximately 145 milliseconds per classification, with an energy cost of ~0.17 mJ per inference. While promising, these findings underscore the need for further duty cycle optimization, memory-aware model pruning, and latency management to ensure sustainable on-device analytics in long-term deployments.

Additionally, some high-interference zones within the urban environment particularly near power lines and dense metallic structures led to sporadic packet loss and reduced data quality. Although the hierarchical network topology provided redundancy, retransmission overheads occasionally impacted energy efficiency. Ongoing work focuses on optimizing sensor node placement using signal strength mapping and integrating mesh-level redundancy to mitigate such transmission gaps.

Despite these limitations, the system's overall performance remained strong, and the insights gained during testing are informing next-generation improvements. Enhancing resilience to environmental noise, refining classification models, and improving autonomous calibration and edge intelligence will be key to achieving city-wide scalability and long-term deployment success.

Figure 6 illustrates the 90-day temporal evolution of structural response and environmental factors on the Rajpath Smart Bridge. Panel (a) displays strain variation data, revealing daily cyclic patterns aligned with peak traffic hours. Five major anomalies highlighted by red markers on days 12, 25, 47, 58, and 85 that correspond to periods of high vehicular load, emphasizing the link between strain peaks and real-world usage.

Panel (b) shows temperature and humidity trends alongside rainfall intervals. A steady increase in temperature reflects seasonal change, while abrupt humidity spikes during rainfall events (notably on days 22–24, 48–50, and 83–85) suggest environmental stress episodes. These shifts align with anomalies in panel (c), indicating their influence on structural behavior.

Panel (c) classifies detected anomalies by type: six vibration-related anomalies occurred during or shortly after periods of elevated strain, while 2–3 thermal anomalies were linked to sharp changes in environmental conditions. The timeline highlights the interplay between mechanical loading and environmental stressors.

Collectively, the figure 6 demonstrates the WSN system’s ability to capture correlated multi-modal data in real time. The spatial and temporal alignment of events supports its utility for predictive maintenance and early warning in smart infrastructure management.

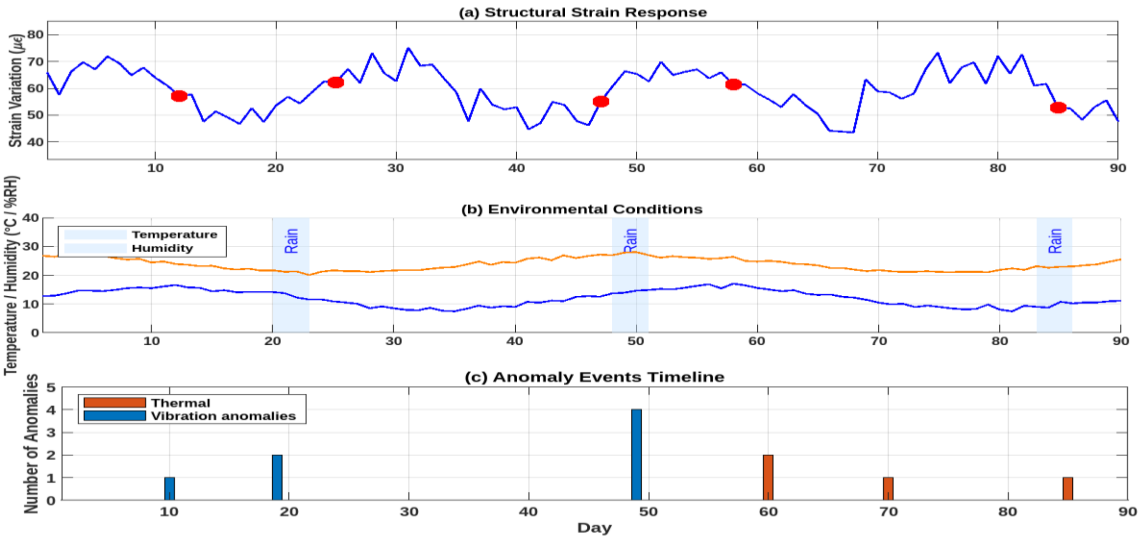

Figure 6: Sensor data trends and anomaly timeline: (a) strain variation with marked anomalies, (b) temperature and humidity trends with rain periods, (c) timeline of vibration and thermal anomalies.

8 Conclusion

This paper presented a comprehensive architecture and real-world evaluation of a WSN framework for proactive infrastructure monitoring in smart cities. Through a modular and scalable system design including sensing, communication, data processing, and application layers, the proposed solution effectively addressed key challenges in continuous, real-time structural health monitoring. Field deployment on the Rajpath Smart Bridge demonstrated that WSN-based monitoring can accurately capture critical data on strain, temperature, humidity, and vibration. The system successfully detected structural anomalies with 92.3% accuracy, as validated against manual inspection records during the 90-day monitoring period. The network also maintained strong performance, achieving high data reliability (97.2% PDR) and low average latency (2.8 seconds). Compared to traditional methods, the WSN approach provides superior scalability, energy efficiency, and seamless integration with smart city platforms via cloud APIs and real-time dashboards. While the system performed reliably under moderate environmental stressors including urban interference, rainfall, and temperature fluctuations, future deployments will focus on validation in more extreme conditions such as severe storms, sub-zero temperatures, and dense urban RF environments to further assess long-term resilience and robustness. Additionally, improvements in sensor calibration, fault classifier generalization, and edge-based analytics will be explored to enhance predictive accuracy and operational autonomy. In conclusion, the proposed WSN architecture represents a scalable, energy-efficient, and intelligent monitoring solution for modern urban infrastructure, enabling predictive maintenance, extended service life, and improved public safety in smart cities.

Authors' contributions

Hongtao Zhu: Conceptualization, Methodology, System Architecture Design, Writing-Original Draft, Supervision; **Xiaolin Hung**: Data Curation, Visualization, Software Implementation, Writing-Review & Editing. All authors read and approved the final manuscript.

Data availability

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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References

[1] Zanella, a., Bui, n., Castellani, a., Vangelista, l. & Zorzi, m. Internet of things for smart cities. *IEEE internet of things journal* 1, 22–32 (2014).

[2] Sundravel, k. V., Jagadeesan, r., Dhanush, a. & Kumar, a. S. A review of innovations, challenges, and future directions in structural health monitoring using smart materials. *J. Environ. Nanotechnol* 14, 464–478 (2025).

[3] Bianchi, g., Fanelli, c., Freddi, f., Giuliani, f. & La placa, a. Systematic review railway infrastructure monitoring: from classic techniques to predictive maintenance. *Advances in mechanical engineering* 17, 16878132241285632 (2025).

[4] Kumar, t., Siddique, m. A. A., Ahsan, r. & Mustafy, t. A machine learning-based framework for seismic vulnerability assessment of reinforced concrete educational facilities. *Asian journal of civil engineering* 1–23 (2025).

[5] Bhavsar, v., Syed, s. & Gandhi, v. C. A survey on the scope of iot using wireless sensor network. In *self-powered aiot systems* 105–121 (apple academic press, 2025).

[6] Shwetha, m. & Krishnaveni, s. A systematic analysis, outstanding challenges, and future prospects for routing protocols and machine learning algorithms in underwater wireless acoustic sensor networks. *Journal of interconnection networks* 25, 2330001 (2025).

[7] Li, y. *Et al.* Infrastructure-user heterogeneous data interaction and fusion of mobile-iot sensing networks in a smart city: application to a footbridge. *IEEE internet of things journal* (2025).

[8] Adday, g. H., Subramaniam, s. K., Zukarnain, z. A. & Samian, n. Investigating and analyzing simulation tools of wireless sensor networks: a comprehensive survey. *IEEE access* 12, 22938–22977 (2024).

[9] Li, h., Ge, l. & Tian, l. Survey: federated learning data security and privacy-preserving in edge-internet of things. *Artificial intelligence review* 57, 130 (2024).

[10] Ahmad, r. Smart remote sensing network for disaster management: an overview. *Telecommunication systems* 87, 213–237 (2024).

[11] Sun, g. *Et al.* Bus-trajectory-based street-centric routing for message delivery in urban vehicular ad hoc networks. *IEEE trans. Veh. Technol.* 67, 7550–7563 (2018).

[12] Tong, a., Zhang, j. & Xie, l. Intelligent fault diagnosis of rolling bearing based on gramian angular difference field and improved dual attention residual network. *Sensors* 24, 2156 (2024).

[13] Wang, q. *Et al.* Elevator fault diagnosis based on digital twin and PINNs-e-rgcn. *Sci. Rep.* 14, 30713 (2024).

[14] Xu, f., Yang, h. C. & Alouini, m. S. Energy consumption minimization for data collection from wirelessly-powered iot sensors: session-specific optimal design with DRL. *IEEE sens. J.* 22, 19886–19896 (2022).

[15] Prakash, v. *Et al.* Structural health monitoring of concrete bridges through artificial intelligence: a narrative review. *Applied sciences (switzerland)* vol. 15 at https://doi.Org/10.3390/app15094855 (2025).

[16] Zuo, c., Zhang, x., Zhao, g. & Yan, l. PCR: a parallel convolution residual network for traffic flow prediction. *IEEE trans. Emerg. Top. Comput. Intell.* 9, 3072–3083 (2025).

[17] Xu, g. *Et al.* RAT ring: event driven publish/subscribe communication protocol for iiot by report and traceable ring signature. *IEEE trans. Ind. Informatics* 1–9 (2025) doi:10.1109/TII.2025.3567265.

[18] Jiang, x. *Et al.* Advancing industrial data augmentation in aigc era: from foundations to frontier applications. *IEEE trans. Instrum. Meas.* 74, 1–22 (2025).

[19] Wu, x. *Et al.* Dynamic security computing framework with zero trust based on privacy domain prevention and control theory. *IEEE j. Sel. Areas commun.* 43, 2266–2278 (2025).

[20] Zhang, j. *Et al.* Cooperative AC/DC voltage margin control for mitigating voltage violation of rural distribution networks with interconnected DC link. *IEEE trans. Power deliv.* 40, 1014–1029 (2025).

[21] Zhang, s. *Et al.* UAV based defect detection and fault diagnosis for static and rotating wind turbine blade: a review. *Nondestruct. Test. Eval.* 40, 1691–1729 (2025).

[22] Xu, x., Deng, j., Lin, h., Li, z. & Wen, h. Lightweight anomalous detection of hydro turbine operation sound using fusion network enhanced by load information. *IEEE trans. Instrum. Meas.* 74, 1–13 (2025).

[23] Wang, j., Song, y. & He, t. A novel adaptive monitoring framework for detecting the abnormal states of aero-engines with maneuvering flight data. *Reliab. Eng. Syst. Saf.* 258, 110910 (2025).

[24] Yu, x. *Et al.* Recent advances in wireless sensor networks for structural health monitoring of civil infrastructure. *Journal of infrastructure intelligence and resilience* 3, 100066 (2024).

[25] Kanwal, a. *Et al.* Exploring security dynamics in SDN controller architectures: threat landscape and implications. *IEEE access* (2024).

[26] Dabbaghchian, i., Matarazzo, t. J., Eshkevari, s. S., Cronin, l. & Pakzad, s. N. Optimizing bridge modal property estimation via quality-driven crowdsourced smartphone data selection. *Mechanical systems and signal processing* 233, 112735 (2025).

[27] Kim, j.-W., Choi, h.-W., Kim, s.-K. & Na, w. S. Review of image-processing-based technology

for structural health monitoring of civil infrastructures. *Journal of imaging* 10, 93 (2024).
[28] Liu, z. *Et al.* K-coverage estimation for irregular targets in wireless visual sensor networks deployed in complex region of interest. *IEEE sens. J.* 25, 18370–18383 (2025).
[29] Pan, j., Deng, y., Yang, y. & Zhang, y. Location-allocation modelling for rational health planning: applying a two-step optimization approach to evaluate the spatial accessibility improvement of newly added tertiary hospitals in a metropolitan city of china. *Soc. Sci. Med.* 338, 116296 (2023).
[30] Song, j., Feng, y. & Huang, b. Tunnel lining quality detection technology based on impulse echo acoustic method from fine management perspective. *Wireless networks* 1–12 (2024).
[31] Su, l. *Et al.* Ultra-low detection limit self-sensing nanocomposites with self-assembled conductive microsphere arrays for asphalt pavement health monitoring. *Construction and building materials* 427, 136279 (2024).
[32] Ghahari, f., Swensen, d., Haddadi, h. & Taciroglu, e. A hybrid model-data method for seismic response reconstruction of instrumented buildings. *Earthquake spectra* 40, 1235–1268 (2024).
[33] Abbas, y. *Et al.* Drone-based public surveillance using 3d point clouds and neuro-fuzzy classifier. *Comput. Mater. Contin.* 82, 4759–4776 (2025).
[34] Meng, q., He, y., Hussain, s., Lu, j. & Guerrero, j. M. Optimized energy storage configuration for enhanced flexibility in renewable-integrated power systems. *J. Energy storage* 132, 117735 (2025).
[35] Yan, p. *Et al.* A comprehensive survey of deep transfer learning for anomaly detection in industrial time series: methods, applications, and directions. *IEEE access* 12, 3768–3789 (2024).
[36] Kuai, h., Civera, m., Coletta, g., Chiaia, b. & Surace, c. Cointegration strategy for damage assessment of offshore platforms subject to wind and wave forces. *Ocean engineering* 304, 117692 (2024).
[37] Ao, w. K., Hester, d., O'higgins, c. & Brownjohn, j. Tracking long-term modal behaviour of a footbridge and identifying potential SHM approaches. *Journal of civil structural health monitoring* 14, 1311–1337 (2024).
[38] Cheng, q., Chen, w., Sun, r., Wang, j. & Weng, d. Ransac-based instantaneous real-time kinematic positioning with gnss triple-frequency signals in urban areas. *J. Geod.* 98, 24 (2024).
[39] Wang, x., Wang, h. & Peng, m. J. Interpretability study of a typical fault diagnosis model for nuclear power plant primary circuit based on a graph neural network. *Reliab. Eng. Syst. Saf.* 261, 111151 (2025).
[40] Mustafa, r., Sarkar, n. I., Mohaghegh, m. & Pervez, s. A cross-layer secure and energy-efficient framework for the internet of things: a comprehensive survey. *Sensors (basel, switzerland)* 24, 7209 (2024).
[41] Zhong, y. & Gu, j. Lightweight block ciphers for resource-constrained environments: a comprehensive survey. *Future generation computer systems* (2024).
[42] Saidi, a. An adaptive trust system for misbehavior detection in wireless sensor networks. *Wireless networks* 30, 2589–2615 (2024).
[43] Qiao, y. *Et al.* A multihead attention self-supervised representation model for industrial sensors anomaly detection. *IEEE trans. Ind. Informatics* 20, 2190–2199 (2024).
[44] Zhou, s., He, z., Chen, x. & Chang, w. An anomaly detection method for UAV based on wavelet decomposition and stacked denoising autoencoder. *Aerospace* 11, 393 (2024).
[45] Goumopoulos, c. Smart city middleware: a survey and a conceptual framework. *IEEE access* 12, 4015–4047 (2024).
[46] Liu, f., Zhao, x., Zhu, z., Zhai, z. & Liu, y. Dual-microphone active noise cancellation paved with doppler assimilation for tads. *Mech. Syst. Signal process.* 184, 109727 (2023).
[47] Yang, y., Zhang, z., Zhou, y., Wang, c. & Zhu, h. Design of a simultaneous information and power transfer system based on a modulating feature of magnetron. *IEEE trans. Microw. Theory tech.* 71, 907–915 (2023).
[48] Li, n. & Wang, h. Variable filtered-waveform variational mode decomposition and its application in rolling bearing fault feature extraction. *Entropy* vol. 27 at https://doi.Org/10.3390/e27030277 (2025).
[49] Zhao, x. *Et al.* Target-driven visual navigation by using causal intervention. *IEEE trans. Intell. Veh.* 9, 1294–1304 (2024).