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Design of an IoT-Based Structural Health Monitoring System and Its Field Application on Laboratory Columns

He Bai, Heqi Zhang *, Jincheng Li

School of Civil Engineering, Changchun Institute of Technology, Changchun, Jilin, 130012, China

* Corresponding author: Heqi Zhang

Abstract

To address the limitation of manual inspection in achieving real-time, continuous and low-latency perception of structural conditions, an IoT-based structural health monitoring (SHM) system was designed and implemented. The system adopts a four-tier "perception-transmission-platform-application" architecture and relies on an engineering IoT monitoring platform and WH-series sensors to continuously and automatically monitor three categories of structural deformation: cracks, tilt and strain. To verify the effectiveness of the system, 27 measurement points (14 strain, 4 crack and 9 tilt) were deployed on laboratory columns of a university structural laboratory, and continuous monitoring was carried out for about 8.5 months (December 2025 to August 2026), yielding 24710 crack records, 55832 tilt records and 86181 strain records after removal of offline outliers. The results show that: (1) the crack widths remained stable month by month (monthly means of 9.53-9.66 mm), while an obvious anomalous evolution occurred at crack point-3 during 26 April to 7 June 2026 with a peak width of 25.04 mm, which was successfully identified by the system; (2) the mean tilt angles of the 9 tilt points ranged from -2.48° to +2.52° in the X direction and from -0.38° to +1.93° in the Y direction, indicating that the overall tilt state of the structure was safe; (3) the single-step changes of most strain points were concentrated within ±0.5 με, but 1453 sudden-change events exceeding ±200 με occurred at strain point-4, indicating a risk of local abrupt stress variation. Shapiro-Wilk and non-parametric tests confirmed that all the above differences were statistically significant. The tiered early-warning mechanism and typical anomaly cases demonstrate that the proposed system can support automatic structural health monitoring and early anomaly detection, and has practical engineering value.

Keywords

Internet of Things; Structural Health Monitoring; Field Monitoring Data; Statistical Test; Safety Early Warning.

1. Introduction

During long-term service, civil engineering structures are prone to safety risks such as settlement, tilt, cracking and strain accumulation under environmental erosion, repeated loading and extreme events. If such risks are not detected and addressed in time, serious accidents may occur. According to relevant statistics, a considerable number of existing buildings in China have entered the middle and late stages of their service life, and the demand for monitoring and maintaining their structural health is increasingly urgent [1]. Long-term, continuous and automated health monitoring of in-service structures is therefore an important means of ensuring safe operation and reducing maintenance costs.

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Traditional structural health monitoring (SHM) mainly relies on manual inspection and periodic testing. Such approaches involve long monitoring intervals and limited coverage; manual observation can usually only reflect the peripheral condition of a structure and can hardly perceive its internal stress and deformation state, resulting in delayed response to anomalies. With the development of the Internet of Things (IoT), cloud computing and embedded sensing technologies, automated and continuous structural health monitoring based on intelligent sensors has become an important development direction in the SHM field [2,3]. At the sensing-network level, fiber Bragg grating sensors, piezoelectric sensors and wireless sensor networks have been widely applied to high-precision structural state perception [12,13]; at the system level, IoT-based life-cycle safety operation systems for existing buildings and intelligent safety monitoring information models have been proposed [2,3].

However, existing IoT monitoring research still suffers from three deficiencies. First, most studies focus on a single sensing or transmission link, and system-level solutions covering the complete "perception-transmission-platform-application" chain are scarce. Second, systematic verification based on real long-term monitoring data is lacking, and the statistical characteristics of monitoring data and the effectiveness of anomaly identification remain to be demonstrated. Third, the connection between monitoring results and early-warning mechanisms is weak, making it difficult to form a closed loop from data to decision. To address these issues, this paper designs and implements an IoT-based structural health monitoring system and deploys it on laboratory columns of a university structural laboratory for about 8.5 months of continuous field monitoring. The main work includes: (1) designing the four-tier "perception-transmission-platform-application" system architecture and completing sensor selection and measurement-point deployment; (2) performing time-series analysis and statistical tests on the field monitoring data of cracks, tilt and strain to examine structural conditions and data quality; and (3) establishing a tiered early-warning mechanism and verifying the engineering effectiveness of the system through typical cases such as the anomalous evolution of crack point-3.

2. Overall Design of the Structural Health Monitoring System

2.1. System Architecture

The structural health monitoring system developed in this study adopts a four-tier "perception-transmission-platform-application" architecture, realizing a complete closed loop from structural state perception to intelligent decision-making.

The perception layer consists of various structural and environmental monitoring sensors and is the source of structural state information. WH-series sensors provided by the platform are adopted, including crack gauges, intelligent inclinometers and surface strain gauges, which monitor structural cracks, tilt and strain, respectively. The transmission layer is responsible for reliably uploading the monitoring data with low latency, using the DTIOT intelligent IoT system and the DTHUB smart gateway to aggregate sensor data, perform protocol conversion and network transmission, and support remote configuration and device management. The platform layer is an engineering IoT monitoring platform serving as the data processing and storage hub, providing data reception, storage, visualization, alarm and result output capabilities. The application layer is oriented to monitoring data analysis and intelligent decision-making; data visualization and intelligent analysis modules are built on the Python and DTCloud development environments, carrying core algorithms for data preprocessing, time-series anomaly identification and adaptive early warning.

Compared with traditional manual inspection, the proposed system shows significant improvements in monitoring mode, monitoring content, monitoring frequency and anomaly response, as summarized in Table 1.

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Table 1. Comparison between traditional manual inspection and the proposed monitoring system

Item	Manual inspection	Proposed IoT system
Monitoring mode	Manual observation, periodic testing	Automated continuous sensor monitoring
Monitoring content	Mainly structural exterior surfaces	Multi-parameter: cracks, tilt, strain
Monitoring frequency	Once every 20-30 min	Real-time acquisition once per minute
Anomaly response	Manual reporting, delayed response	Real-time early warning, second-level response
Perception capability	Internal stress hardly perceivable	Internal deformation and sudden changes perceivable

2.2. Sensor Selection and Measurement-Point Deployment

Sensor selection needs to balance comprehensiveness of monitoring indices, measurement accuracy and long-term stability. According to the structural health monitoring requirements, a total of 27 sensors of three types are configured on the platform, covering the main parameters of structural deformation monitoring, as listed in Table 2. Among them, 14 surface strain gauges, the largest group, are deployed at key load-bearing locations to monitor strain variation; crack gauges are deployed at existing cracks to monitor crack development; and intelligent inclinometers monitor the tilt deformation of the structure in two orthogonal directions, forming a point-and-plane layout covering the main types of structural deformation. All measurement points are deployed on laboratory columns of a university structural laboratory for systematic field verification.

Table 2. Sensor configuration and monitoring indices of the system

Sensor type	Quantity	Monitoring indices	Measurement points
Surface strain gauge	14	Strain (με), frequency, resistance	Strain-1 to 14
Crack gauge	4	Crack width (mm), variation rate	Crack-1 to 4
Intelligent inclinometer	9	X/Y tilt angle (°)	Tilt-1 to 9

2.3. Data Acquisition and Transmission Design

A data acquisition interval of about 1 minute is adopted, which can capture the dynamic changes of crack, strain and other indices in time while balancing data transmission and storage costs, ensuring the feasibility of long-term continuous monitoring. The platform provides dedicated remote configuration software that supports setting the acquisition interval on demand and exporting data; it also offers alarm configuration, modeling, and result outputs such as daily reports, data tables and curves to meet diverse engineering monitoring needs. Monitoring data are stored and managed in a large network database on cloud servers, and data security is guaranteed through access control and authority management.

3. Field Monitoring and Data Analysis

3.1. Monitoring Object and Data Overview

To verify the application effect of the system in a real engineering environment, 27 measurement points (14 strain, 4 crack and 9 tilt) were deployed on laboratory columns of a university structural laboratory, and continuous monitoring was conducted for about 8.5 months from December 2025 to August 2026 at an acquisition interval of about 1 minute. After

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removing abnormal data caused by device disconnection, a total of 24710 crack records, 55832 tilt records and 86181 strain records were obtained. For indices of different dimensions, statistical quantities at multiple time scales, such as daily and monthly means, were first computed; the Shapiro-Wilk test was then applied to assess normality, and for non-normal data, Wilcoxon-Mann-Whitney and Kruskal-Wallis non-parametric tests were further used to analyze the significance of between-group differences.

3.2. Crack Monitoring Results

The width data of the four crack gauges were aggregated by month, and the monthly variation of the mean crack width is shown in Fig. 1(a). The crack width remained stable overall, with monthly means between 9.53 and 9.66 mm and a fluctuation of less than 2%, showing no sustained growth trend and indicating that the cracked locations were in a controllable state during the monitoring period. Notably, crack point-3 exhibited an obvious anomalous evolution between 26 April and 7 June 2026, with the daily maximum width peaking at 25.04 mm, as shown in Fig. 1(b); the system successfully identified and recorded this anomaly, while in other periods the widths of all crack gauges remained below about 13 mm.

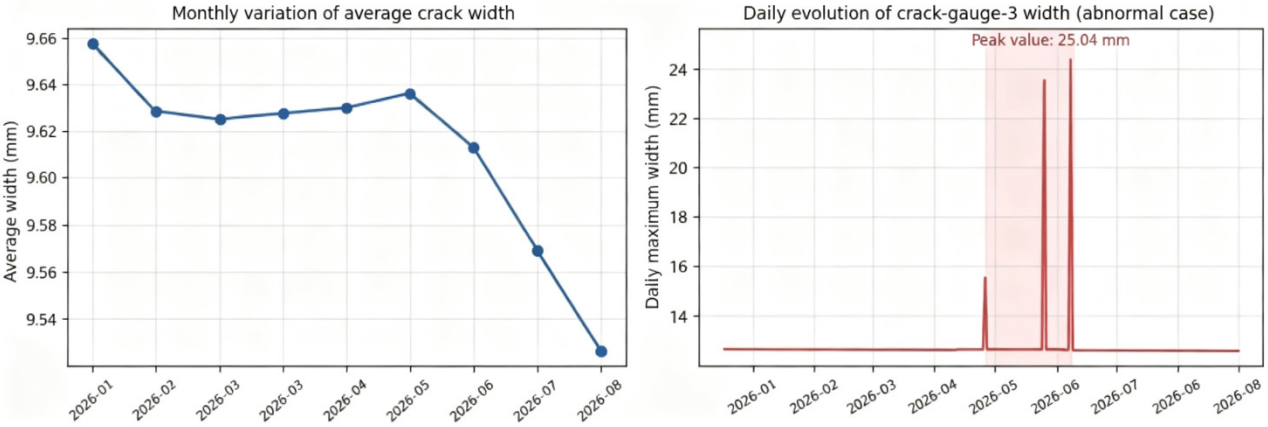


Fig 1. Monthly variation of mean crack width and the anomalous case of crack point-3

3.3. Tilt Monitoring Results

The X-direction and Y-direction tilt data of the nine inclinometers were averaged, and the results are shown in Fig. 2. The mean tilt angles ranged from -2.48° to +2.52° in the X direction and from -0.38° to +1.93° in the Y direction. The X-direction mean tilt angles of tilt points 5 and 6 stabilized at about +2.52° and -2.48°, respectively, while the tilt angles of the remaining points were small, without systematic or sustained tilt trends. Considering the overall service state of the laboratory columns, the overall tilt of the structure can be judged to be within a safe and controllable range.

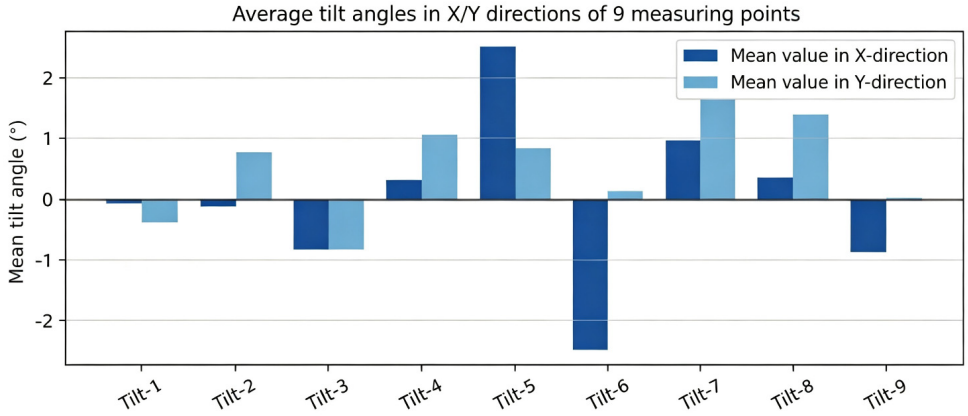


Fig 2. Mean X/Y-direction tilt angles of the nine measurement points

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3.4. Strain Monitoring Results

The single-step changes (με) of the 14 strain points were statistically analyzed. The single-step changes of the vast majority of data were concentrated within ±0.5 με, indicating a stable overall load-bearing state of the structure. However, when sudden-change events were extracted with the criterion |change| > 200 με, a total of 1453 events were identified, whose temporal distribution is shown in Fig. 3. The sudden-change events were mainly concentrated at strain point-4, with a maximum single-step change of -1939.78 με; strain points 5 and 6 each showed one significant sudden change exceeding ±1600 με. These instantaneous changes suggest possible local abrupt stress variation or sensor disturbance, based on which the system triggered alarms and prompted key rechecks, demonstrating its high sensitivity to local anomalies.

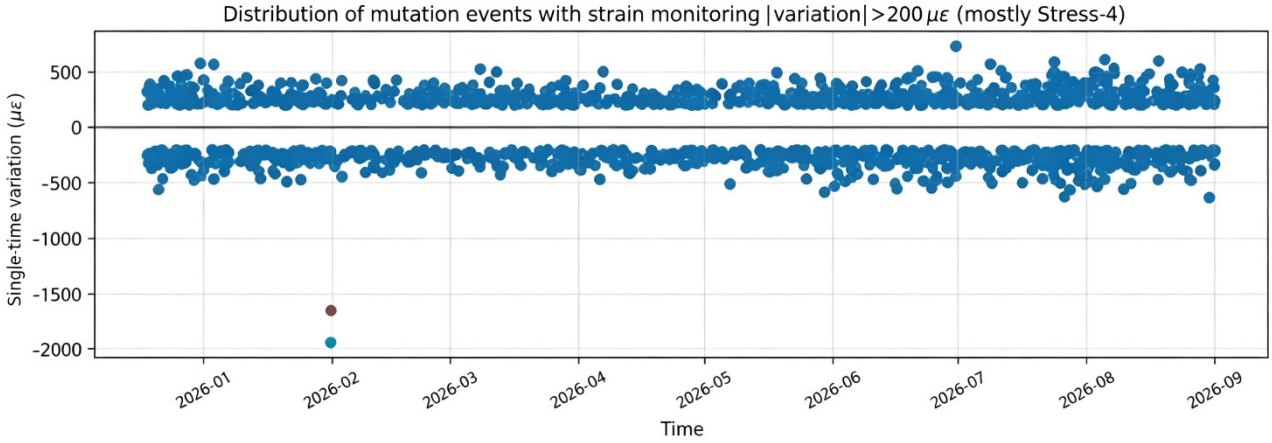


Fig 3. Distribution of strain sudden-change events with |change| > 200 με

3.5. Statistical Tests and Anomaly Identification

To determine whether the differences reflected by the monitoring results are statistically reliable, normality tests were first conducted. The Shapiro-Wilk test was applied to 2000 sampled values of crack width, tilt angle and single-step strain change, and the results are listed in Table 3. The W statistics of the three indices ranged from 0.33 to 0.93 with p values below 0.001, significantly rejecting the normality assumption; therefore, non-parametric tests were adopted for subsequent between-group difference analysis.

Table 3. Shapiro-Wilk normality test results of the monitoring data

Monitoring item	W statistic	p value	Normality
Crack width	0.797	<0.001	Non-normal
Tilt angle (X direction)	0.927	<0.001	Non-normal
Single-step strain change	0.329	<0.001	Non-normal

Under the non-parametric testing framework, significance tests were performed on the three categories of monitoring data, and the results are summarized in Table 4. The crack widths differed extremely significantly among the four gauges (Kruskal-Wallis H = 11251.1, p < 0.001), while the monthly differences of crack point-1 were not significant (p > 0.05); together these results support the judgment of "overall stability with individual anomalies". The Wilcoxon-Mann-Whitney test between the normal and anomalous periods of crack point-3 yielded U = 926957 and p = 3.7e-75, an extremely significant difference confirming that the identified anomalous evolution reflects a genuine structural state change rather than random fluctuation. The tilt angles differed extremely significantly among the nine points in both directions (p <

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0.001), and the single-step strain changes differed extremely significantly among the 14 points ($p < 0.001$), with the amplitude distributions of sudden-change and non-sudden-change samples also differing extremely significantly ($U = 0$, $p < 0.001$), indicating that the instantaneous changes at strain point-4 are statistically distinct from normal fluctuations. In summary, the statistical tests confirm from the data level that the crack anomaly, tilt differences and local strain sudden changes identified by the system are statistically significant and real structural state information, providing a reliable basis for anomaly identification and early warning.

Table 4. Significance test results of the field monitoring data

Test content	Method	Statistic	p value
Cracks: among 4 gauges	Kruskal-Wallis	H = 11251.1	<0.001
Cracks: monthly, crack-1	Kruskal-Wallis	H = 2280.0	<0.001
Cracks: crack-3 normal vs anomalous	Wilcoxon-Mann-Whitney	U = 926957	3.7e-75
Tilt: among 9 points, X	Kruskal-Wallis	H = 17418.9	<0.001
Tilt: among 9 points, Y	Kruskal-Wallis	H = 17779.3	<0.001
Strain: among 14 points	Kruskal-Wallis	H = 189.9	<0.001
Strain: sudden vs non-sudden	Wilcoxon-Mann-Whitney	U = 0	<0.001

4. Tiered Early-Warning Mechanism

A tiered early-warning system was constructed based on the monitoring indices, with multiple warning levels (normal, attention, warning and emergency) defined for the three dimensions of crack, tilt and strain, and an emergency response mechanism for deformation acceleration and sudden damage. The indices and their warning targets are shown in Table 5. When a monitoring index exceeds the corresponding threshold, the system automatically triggers an alarm and pushes it to managers in real time via email and SMS; predefined abnormal data samples are also used to distinguish sensor faults from genuine structural anomalies and quickly locate abnormal nodes, avoiding misjudging equipment faults as structural damage. Taking the anomaly of crack point-3 as an example, the system triggered an "attention"-level alarm at the initial stage of the anomaly, escalated level by level as the width continued to grow and pushed the alerts to managers, realizing early detection and whole-process tracking of the anomaly.

Table 5. Monitoring indices and early-warning targets

Monitoring index	Warning target	Response level
Crack width and variation	Crack development, width sudden change	Multi-level
Tilt angle (X/Y directions)	Overall tilt, differential settlement	Multi-level
Single-step strain change	Local stress concentration, abrupt loading	Multi-level
Variation rate	Accelerated deformation, sudden damage	Emergency

5. Discussion

The pattern of "overall stability with local anomalies" observed at the crack measurement points is consistent with the phenomena reported by Luo et al. [4] in long-term monitoring of spatial structures: deformation indices remain within limited fluctuation under normal service conditions, and anomalies manifest as local evolution deviating from the overall trend at a few points rather than a synchronized drift of all points. This comparison suggests that evaluation criteria based on absolute thresholds of individual points are prone to misjudgment, whereas

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criteria based on relative deviation from the population distribution of measurement points are more robust; the use of non-parametric rank-sum tests in this paper, rather than simple threshold comparison, is precisely a statistical realization of this judgment.

The X-direction mean tilt angles of the tilt points ranged from -2.48° to +2.52° and the Y-direction angles from -0.38° to +1.93°, magnitudes clearly larger than the lower bounds of the sensitive service indices reported by Liu et al. [8] for public buildings, indicating that the laboratory columns have accumulated non-negligible overall tilt during long-term service. Meanwhile, tilt points 5 and 6 exhibited stable offsets rather than continuous growth, suggesting that the tilt is a quasi-steady state under existing installation deviation and environmental actions rather than a developing differential settlement. This judgment implies that subsequent monitoring should incorporate these values as baseline states into the adaptive updating of warning thresholds, rather than directly triggering structural appraisal.

Strain point-4 exhibited 1453 sudden-change events exceeding ±200 με, with a maximum single-step change of -1939.78 με, far exceeding the magnitudes at other points. Two explanations exist: genuine load-bearing sudden changes caused by local stress concentration, or signal drift caused by loose sensor installation or poor contact. Yang et al. [14] proposed using statistical moments of displacement and acceleration as damage indices for single-sampling identification, with the idea of compressing the time series to eliminate transient disturbances; the sudden-change events in this paper illustrate the opposite: for structures monitored with quasi-static deformation quantities, transient spikes are more likely to originate from the measurement chain than from the structure itself. The contrast between crack point-3 and strain point-4 provides direct evidence: the former anomaly lasted 43 days with a monotonically growing pattern, belonging to genuine structural evolution, whereas the latter recurred frequently within 8.5 months with an instantaneous jump pattern, more likely indicating measurement-level disturbance. Therefore, in engineering applications, separability testing (distinguishing sensor faults from genuine anomalies) must be a prerequisite step of the warning process; otherwise, the alarm frequency will overwhelm genuine risks.

6. Conclusion

(1) The system adopts a four-tier "perception-transmission-platform-application" architecture and, relying on an engineering IoT monitoring platform and WH-series sensors, achieves continuous automatic monitoring of cracks, tilt and strain at an interval of about 1 minute, with significant improvements over traditional manual inspection in monitoring frequency, anomaly response speed and perception capability.

(2) The field data analysis shows that the crack measurement points remained stable overall (monthly means of 9.53-9.66 mm), while an anomalous evolution occurred at crack point-3 between 26 April and 7 June 2026 with a peak width of 25.04 mm, which was successfully identified; the tilt points remained within a safe range; and 1453 sudden-change events exceeding ±200 με occurred at strain point-4, indicating a risk of local abrupt loading.

(3) Shapiro-Wilk and non-parametric tests confirm that the three categories of monitoring data are non-normally distributed and that the differences among measurement points and between the anomalous and normal periods are statistically significant, indicating that the anomalies identified by the system are genuine structural state information.

(4) The tiered early-warning mechanism, combined with separability testing, achieves early identification and timely notification of anomalies such as crack evolution and local abrupt loading, verifying the engineering feasibility and application value of IoT technology for automatic structural health monitoring.

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In future work, the coverage of measurement points will be further expanded, and multi-source data fusion and intelligent diagnosis algorithms will be introduced to continuously improve the monitoring accuracy and warning reliability of the system under complex conditions.

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