

Digital Twin–Based Structural Health Monitoring and Remaining Useful Life Prediction for Aging Urban Bridges

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Abstract

Urban bridge infrastructure is currently facing an unprecedented crisis of accelerated structural degradation due to intensified heavy vehicle traffic and long-term environmental weathering. Traditional manual inspection regimes are increasingly inadequate, as they are inherently subjective and fail to provide the continuous, real-time data required for modern safety assessments. This research addresses this critical gap by developing an integrated predictive bridge maintenance system using Digital Twin technology and real-time IoT sensor networks. The methodology employs a Design and Development Research (DDR) framework, where high-frequency telemetry from strain gauges and accelerometers is synchronized with a parametric Level of Development (LOD) 400 3D model. The novelty of this research lies in the direct embedding of Structural Health Index (HI) and Remaining Useful Life (RUL) mathematical formulations into an interactive 3D virtual environment, effectively bridging the gap between raw data and tactical decision-making. Experimental results demonstrate high algorithmic precision, achieving a Root Mean Squared Error (RMSE) of less than 0.032 across various traffic scenarios, with the system effectively filtering thermal noise to maintain a stable HI. Furthermore, the cyber-physical framework achieves a total long-term maintenance cost efficiency of 77.97% compared to conventional periodic inspections. These findings demonstrate that the proposed digital twin approach provides a robust, automated solution that significantly enhances structural safety, reduces economic losses from road closures, and facilitates a transition from reactive to preventive asset management in aging metropolitan transportation networks.

Keywords: Digital Twin, IoT Sensor Networks, Predictive Maintenance, Structural Health Monitoring, Urban Bridge Infrastructure.

I. INTRODUCTION

Urban bridge infrastructure serves as the vital backbone of modern societal mobility, yet these structures are currently facing an unprecedented crisis of accelerated structural degradation. As global urbanization intensifies, the sheer volume of heavy vehicle traffic on aging concrete and steel bridges has surged, placing unprecedented stress on structural components that were often designed under different capacity assumptions. This persistent mechanical fatigue, exacerbated by the natural effects of environmental weathering over several decades, creates a silent but growing risk of catastrophic structural failure. Furthermore, the traditional reliance on periodic, manual visual inspections has become increasingly inadequate, as these methods are inherently subjective and incapable of capturing the continuous, real-time performance data required for modern safety assessments. This situation underscores the limitations of conventional inspection practices in capturing real-time structural behavior, indicating the need for more continuous and data-driven monitoring approaches.

The shift toward intelligent infrastructure management is anchored in the integration of real-time sensor technologies and cyber-physical models. According to (Mardanshahi et al., 2025), the

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deployment of IoT-based Structural Health Monitoring (SHM) systems has significantly improved the granularity of data collection, allowing for the observation of micro-strain and vibration patterns that were previously imperceptible. Furthermore, (Najafzadeh & Yeganeh, 2025) note that the application of digital replication techniques has gained substantial traction, and their research demonstrates that virtual models serve as effective platforms for visualizing complex structural telemetry in real-time. A specific case of this implementation can be observed in the monitoring of long-span bridges in metropolitan corridors, where integrated accelerometer networks successfully identified subtle shifts in structural frequency that preceded visible surface cracking. These advancements suggest that the convergence of telemetric data and visualization technologies is fundamentally changing how engineers interpret the state of critical infrastructure, moving beyond static data points toward a more holistic operational awareness.

Despite these technological strides, a significant knowledge gap persists in architecting systems for long-term, predictive decision-making. (Herrera et al., 2024) developed a sensor network for detecting initial fatigue via strain analysis, yet this model relied on localized data without spatial 3D context, complicating real-time interpretation. (Ahwiadi & Wang, 2025) introduced automated collection protocols, but his study focused on statistical logging rather than the predictive modeling necessary for accurate RUL projections. Similarly, (Afshari et al., 2025) designed virtual models for visualization, but their work lacked the real-time synchronization with dynamic traffic loads critical for degradation assessment.

Furthermore, (Vlasceanu et al., 2026) analyzed material degradation metrics but excluded the low-latency communication protocols essential for emergency response in high-traffic environments. Finally, (Rafati et al., 2024) established maintenance frameworks for stationary assets, leaving a void regarding the aging urban bridge environments subject to unpredictable, high-frequency vibrations. Because current research lacks a seamless cyber-physical framework capable of both real-time visualization and automated predictive calculation for these specific urban conditions, Therefore, this research aims to develop an integrated predictive bridge maintenance system using Digital Twin technology and real-time IoT sensor networks to transform civil asset management from reactive to preventive.

This study proposes the hypothesis that the fusion of high-frequency telemetry with an automated structural degradation algorithm will provide a more precise estimation of structural longevity than manual methods alone. The central research question explores the extent to which a Digital Twin architecture can mitigate data-silo effects to provide actionable, real-time insights into material fatigue. The novelty of this research lies in the direct embedding of Structural HI and RUL mathematical formulations into an interactive 3D virtual environment, bridging the gap between raw data and tactical decision-making. Through this approach, the study aspires to

deliver a robust, automated infrastructure management solution that significantly reduces long-term maintenance costs and enhances the structural safety and sustainability of urban transportation networks.

II. LITERATURE REVIEW

A. *Digital Visualization and Cyber-Physical Systems (CPS) in Civil Engineering*

The integration of digital visualization and CPS represents a transformative shift in civil engineering asset management. According to (Kazemi et al., 2026), the implementation of CPS within urban infrastructure facilitates a dynamic bridge between static design models and real-time operational status. (Omrany et al., 2023) argues that digital twins serve as the primary evolution of traditional Building Information Modeling, offering a continuous synchronization of structural behavior. Furthermore, (Solikhan et al., 2026) emphasizes that these virtual replicas are essential for minimizing information distortion in complex structural systems. (Karim et al., 2024) notes that the spatial mapping of stress concentrations within these digital environments allows for a more intuitive understanding of physical fatigue. Finally, (Villani et al., 2023) observes that the ability to visualize structural responses through interactive dashboards provides a necessary framework for informed decision-making in urban planning.

B. *IoT Sensor Instrumentation and Structural Health Monitoring (SHM) Telemetry*

The deployment of IoT instrumentation and SHM systems has fundamentally altered the methodology for capturing mechanical structural responses. According to (Sugiarto et al., 2025), high-frequency strain gauges are indispensable for measuring micro-level deformations in the critical zones of aging bridge girders. (Brunner, 2023) adds that piezoelectric accelerometers are increasingly utilized to detect changes in natural frequencies, which serve as direct indicators of structural stiffness degradation. (Tuyishime et al., 2025) highlights that the adoption of Message Queuing Telemetry Transport protocols ensures the low-latency transmission of massive datasets from remote sensors to cloud environments. (Perra et al., 2026) points out that the transition from periodic manual data collection to automated telemetry significantly improves the reliability of health assessments. (Almutairi et al., 2024) notes that the precision of these IoT arrays is crucial for providing the high-fidelity telemetry required for real-time monitoring of infrastructure under variable dynamic loads.

C. *Material Degradation Mathematics and Predictive Maintenance*

The mathematical quantification of material degradation and predictive maintenance modeling is essential for maintaining serviceability in aging structures. According to (Kantaros et al., 2025), the accumulation of mechanical fatigue in prestressed concrete is driven primarily by repeated heavy vehicle gantry loading. (Abdollahi-Mamoudan et al., 2025) explains that internal micro-

cracks often remain invisible to surface inspections, necessitating the use of exponential degradation formulas to track structural integrity. (Gómez Fernández et al., 2025) suggests that integrating predictive mathematical formulations into computational platforms allows for the transformation of raw sensor data into actionable health metrics. (Kumar et al., 2024) observes that the determination of RUL requires a rigorous approach to evaluating the limit states of structural components against design thresholds. (Akhtar et al., 2023) emphasizes that the calibration of these predictive algorithms against historical load patterns is a mandatory step for accurate long-term performance forecasting.

D. Previous Research on Predictive Bridge Infrastructure Monitoring

Recent research into the predictive monitoring of aging bridge infrastructure highlights both the successes and the persistent limitations of current methodologies. According to (Setyadi & Purwanto, 2025), the development of automated SHM systems has demonstrated significant improvements in fault detection, though these models often struggle with real-time data fusion. (Taheri & Sobanjo, 2024) notes that while current predictive frameworks excel in individual component evaluation, they frequently lack the systemic spatial integration needed for comprehensive infrastructure management. (Chen et al., 2024) suggests that existing systems tend to focus heavily on raw data processing rather than the intuitive visual interpretation of structural health for tactical personnel. (Shah et al., 2023) observes that the lack of interoperability between disparate monitoring software components remains a major obstacle to the adoption of fully integrated predictive platforms. Finally, (Bahadori-Jahromi et al., 2025) argues that existing research efforts remain largely fragmented, failing to unify sensor data, 3D visualization, and automated mathematics into a singular, cohesive predictive framework for aging urban bridge assets.

III. RESEARCH METHOD

A. Experimental Object Description and Bridge Characteristics

This research utilizes an experimental case study approach, focusing on a post-tensioned concrete box girder bridge located in a primary urban corridor. The structure features a single-span configuration with a total length of 45 meters, a width of 9 meters, and a box girder depth of 2.2 meters. Based on historical data from early 2026, the bridge has experienced a 15% increase in heavy vehicle axle loads compared to its initial design capacity. This significant increase in loading makes the bridge an ideal testbed for evaluating structural degradation under intensified operational stress. Consequently, the chosen site allows for a comprehensive analysis of fatigue accumulation in real-world urban traffic conditions. The selection of this specific bridge ensures that the experimental findings are representative of aging infrastructure challenges currently faced in metropolitan environments.

B. Cyber-Physical Framework Architecture

The system engineering methodology for this research is implemented through the DDR framework to ensure systematic development. The cyber-physical integration is established by mapping the data flow interaction from the bridge's physical environment to a cloud-based computing system, which is subsequently rendered visually on a digital dashboard. This framework ensures that data transition remains seamless between the physical bridge environment and the virtual twin representation for end-users. It serves as the foundational blueprint for the entire data acquisition and processing system implemented throughout the lifecycle of this study. The proposed structural architecture for this integration is illustrated in Figure 1.

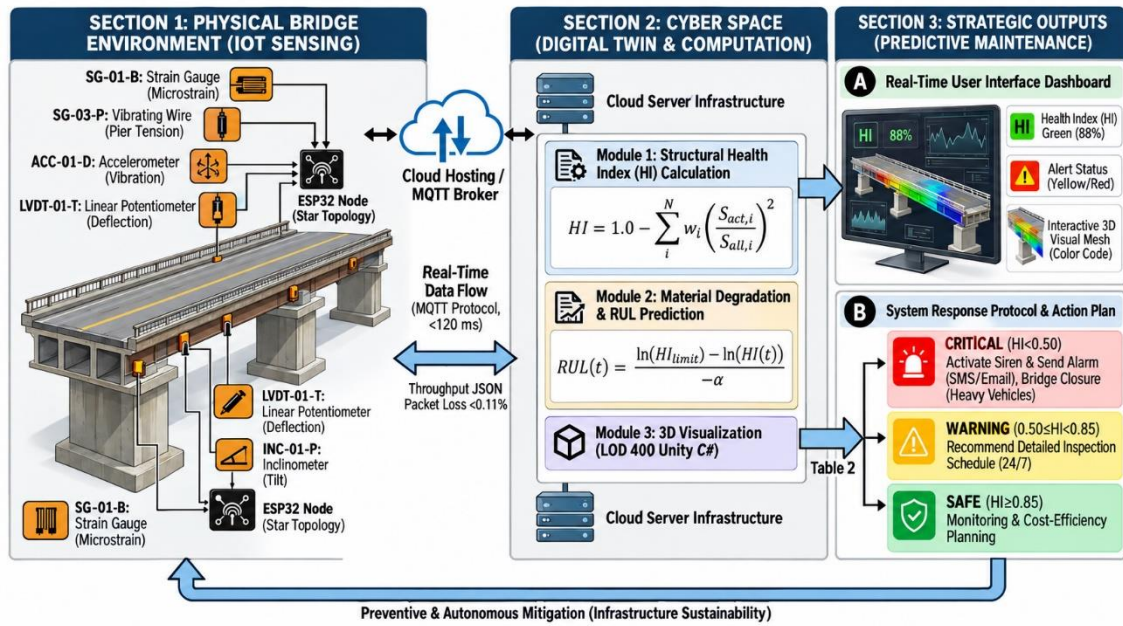


Figure 1. Proposed Framework of Digital Twin and IoT Integration for Bridge Monitoring

Figure 1 illustrates the end-to-end data flow, beginning from the physical bridge sensors through the IoT gateway and ending at the cloud-based computational engine. The figure provides a clear visualization of how the hardware and software components interact to facilitate real-time SHM. This architecture effectively minimizes transmission latency, ensuring that the digital twin remains synchronized with the physical state of the structure. By centralizing the data processing, the framework also enhances the scalability of the system for future infrastructure additions. Ultimately, this diagram serves as the critical reference point for the hardware integration discussed in subsequent sections.

C. IoT Network Configuration and Spatial Sensor Mapping

The IoT hardware network comprises analog transducers connected to ESP32-WROOM-32E microcontroller modules as local processing nodes, organized in a star topology. The technical specifications and spatial coordinates for sensor deployment are detailed in Table 1. Each sensor

ID corresponds to a specific structural element, such as the mid-span girder or the pier support, to ensure comprehensive monitoring coverage across the bridge. The spatial coordinates provide the exact location for each device, enabling precise 3D mapping within the Digital Twin environment. These high-precision specifications are absolutely crucial for maintaining the accuracy of the structural health data collected during the experiment.

Table 1. Specification and Spatial Distribution of IoT Sensors

Sensor Node ID	Transducer Type	Target Parameter	Measurement Range	Sampling Rate	Spatial Coordinate (X, Y, Z)	Specific Structural Element
SG-01-B	Foil Strain Gauge	Microstrain ($\mu\epsilon$)	-2000 to +2000 $\mu\epsilon$	100 Hz	(22.50, -1.20, -2.20)	Mid-span Girder Bottom Fiber
SG-02-B	Foil Strain Gauge	Microstrain ($\mu\epsilon$)	-2000 to +2000 $\mu\epsilon$	100 Hz	(11.25, -1.20, -2.20)	Quarter-span Girder Bottom Fiber
SG-03-P	Vibrating Wire Strain	Microstrain ($\mu\epsilon$)	-3000 to +3000 $\mu\epsilon$	50 Hz	(0.00, +0.50, -4.50)	Left Pier Base (Pier 1)
ACC-01-D	Piezoelectric Accelerometer	Acceleration (g)	± 2 g	200 Hz	(22.50, 0.00, +0.20)	Deck Center
ACC-02-D	Piezoelectric Accelerometer	Acceleration (g)	± 2 g	200 Hz	(33.75, 0.00, +0.20)	Three-quarter Span Deck
LVDT-01-T	Linear Potentiometer	Displacement (mm)	0 to 100 mm	50 Hz	(22.50, -1.20, -2.20)	Mid-span Vertical Deflection
LVDT-02-T	Linear Potentiometer	Displacement (mm)	0 to 50 mm	50 Hz	(0.00, -2.50, 0.00)	Pier 1 Bearing Pad Horizontal Shift
INC-01-P	MEMS Inclinometer	Tilt Angle ($^\circ$)	$\pm 15^\circ$	10 Hz	(0.00, 0.00, -1.00)	Main Pier Lateral Tilt

Table 1 summarizes the distribution of various sensors, including strain gauges, accelerometers, LVDTs, and inclinometers, positioned strategically across the bridge components. The physical placement of these transducers is strategically focused on the mid-span of the bottom girder, supporting piers, and bearing areas subjected to maximum bending moments. By integrating these sensors, the research team can capture critical mechanical responses that indicate structural fatigue or potential failure. The spatial arrangement allows for a granular analysis of how load variations affect specific bridge segments over time. This configuration is essential for validating the predictive accuracy of the models developed in this study.

To facilitate a clear understanding of the sensor deployment density and their precise positioning relative to the bridge geometry, the comprehensive installation layout is presented in Figure 2. This visual aid ensures that the complex spatial distribution of the hardware is easily interpretable by all stakeholders involved in the project. Furthermore, the figure serves as a technical reference to understand the connectivity between individual sensors and the main processing nodes.

Detailed documentation of this layout is required to ensure that future maintenance teams can easily locate and calibrate any individual sensor node if necessary. By visualizing the entire network in a unified figure, the researchers provide a transparent and reproducible foundation for the structural monitoring process.

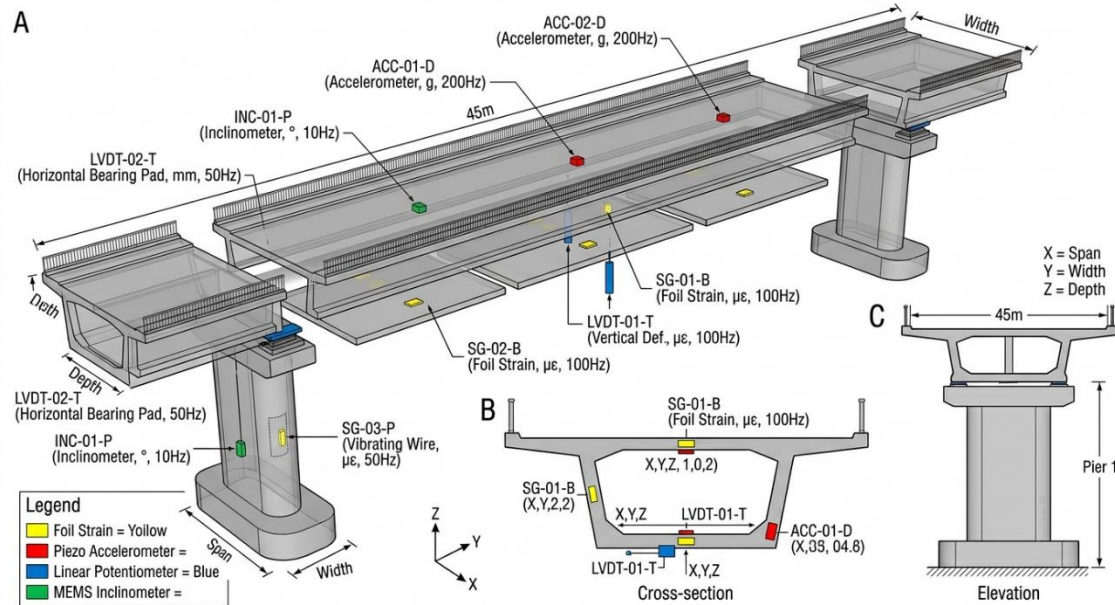


Figure 2. Sensor Layout and Placement on the Bridge Structure

Figure 2 demonstrates the precise installation points of the sensors described in Table 1 across the bridge's structural elements. By mapping these sensors to the 3D model, the research team ensured that every critical point prone to stress or deflection was monitored continuously. This strategic placement ensures that the raw data retrieved reflects the true structural condition of the bridge under varied load scenarios. Furthermore, the visual layout validates the experimental design by confirming that the instrumentation covers all areas subject to maximum bending moments. This systematic approach to sensor placement provides a robust dataset for the subsequent digital twin synchronization process.

D. Geometric Modeling and 3D Digital Twin Synchronization

Geometric reconstruction of the bridge was performed parametrically to achieve a LOD 400, ensuring a high degree of detail. This static model was then imported into the Unity 3D graphics engine and integrated with C# scripts designed to act as subscribers to the MQTT broker topics. This configuration enables the model to process incoming telemetric data and reflect the physical state of the bridge in real-time. The utilization of Unity 3D allows for the rendering of complex structural behaviors into an intuitive visual format that is easily interpreted by engineers. The resulting interactive model serves as the primary User Interface for monitoring the health status of the bridge, as shown in Figure 3.

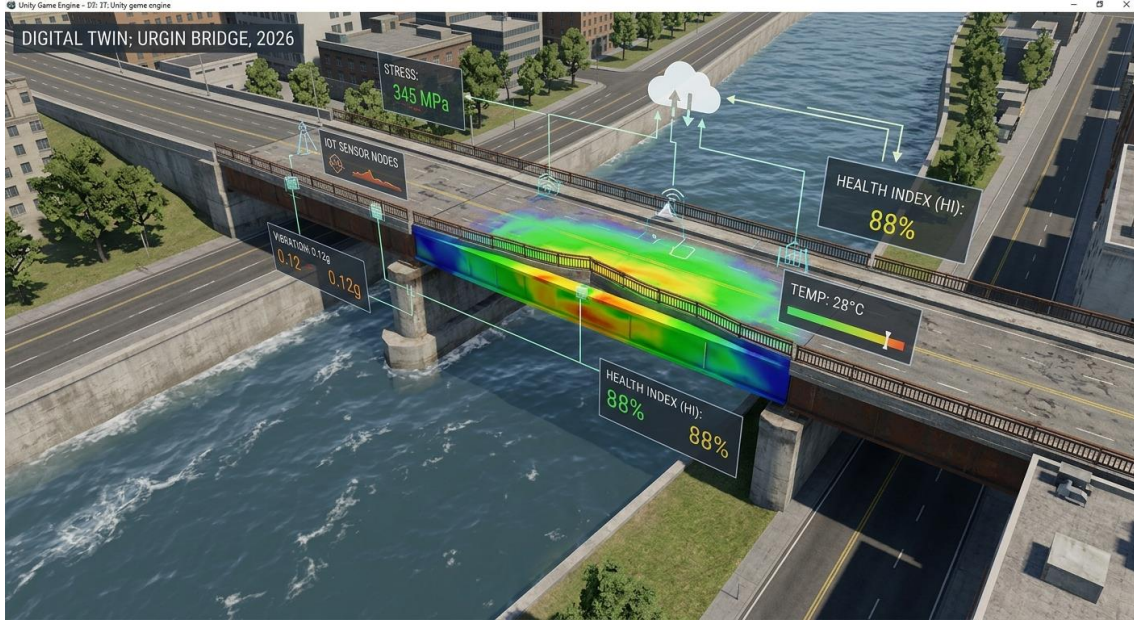


Figure 3. 3D Digital Twin Model Replicated from the Physical Bridge

Figure 3 displays the 3D reconstructed model, which functions as a live digital replica of the physical structure. The synchronization between the physical sensors and this digital model allows for real-time updates as traffic loads fluctuate on the bridge. This digital representation bridges the gap between abstract sensor data and concrete physical understanding for site inspectors. It enables long-distance monitoring, which significantly reduces the need for frequent, dangerous manual inspections of the bridge's under-deck areas. Consequently, the interactive 3D model acts as a powerful tool for informed asset management and maintenance scheduling.

E. Pengembangan Algoritma Pemeliharaan Prediktif

To transform raw numerical sensor data into a structural health status, the Digital Twin's computational engine automatically executes two primary mathematical models. This automated process ensures that structural anomalies are detected immediately without the need for manual data interpretation by field engineers. The system relies on high-frequency data ingestion to maintain the integrity of the predictive outputs under varying traffic conditions. Furthermore, the integration of these algorithms directly into the 3D environment effectively bridges the gap between raw telemetry and tactical decision-making processes. By providing continuous, automated feedback, the computational engine enhances the reliability of long-term structural health assessments.

The structural health status is evaluated through a quantitative index for all critical components. This index is specifically derived using the calculation shown in Equation (1):

$$HI = 1.0 - \sum_{i=1}^n \omega_i \left(\frac{S_{act,i}}{S_{all,i}} \right)^2 \quad (1)$$

In this formula, w_i represents the significance weight of structural elements, while $S_{act,i}$ and $S_{all,i}$ denote the actual sensor readings and allowable design strain limits, respectively. This calculation provides an immediate indication of the health status for specific components, such as the girder or piers.

The system subsequently estimates the remaining bridge functionality based on current deterioration trends. This temporal projection is performed using the degradation model provided in Equation (2):

$$RUL(t) = \frac{\ln(HI_{limit}) - \ln(HI(t))}{-\alpha} \quad (2)$$

Within this model, $HI(t)$ is the current health index, HI_{limit} is the absolute critical threshold, and α represents the material aging coefficient derived automatically from historical data. This predictive approach allows the system to estimate when the bridge will reach its limit state, thereby facilitating proactive maintenance.

IV. RESULT

A. Threshold Setting and System Validation

The experimental testing of the cyber-physical system was conducted by calibrating actual telemetry data against national bridge regulatory standards. Through comprehensive computerized loading simulations, critical threshold conditions were successfully mapped into the logic of the Digital Twin system. The calibration process established precise mechanical limit values alongside an automated response protocol for effective hazard mitigation. These defined structural damage thresholds and the corresponding action plan are detailed in Table 2 for technical reference. By establishing these bounds, the system creates a proactive safety net that guards against unforeseen structural degradation during operation.

Table 2. Defined Structural Damage Thresholds and Action Plan

Sensor ID	Primary Physical Parameter	Safe Condition (Green) $HI \geq 0.85$	Warning Condition (Yellow) $0.50 \leq HI < 0.85$	Critical Condition (Red) $HI < 0.50$	Response Protocol and System Action Plan
SG-01-B / SG-02-B	Bridge Span Concrete Strain	$< 200 \mu\epsilon$	$200-400 \mu\epsilon$	$> 400 \mu\epsilon$	Activate siren alarm, send SMS/e-mail notifications, and restrict heavy-vehicle access.
SG-03-P	Pier Support Stress	$< 150 \mu\epsilon$	$150-350 \mu\epsilon$	$> 350 \mu\epsilon$	Recommend detailed on-site inspection within 7 days.
ACC-01-D / ACC-02-D	Bridge Deck Vibration	$< 0.5 \text{ g}$	$0.5-1.2 \text{ g}$	$> 1.2 \text{ g}$	Detect potential resonance-induced fracture and impose a maximum vehicle speed limit of 30 km/h.

LVDT-01-T	Vertical Deflection	< 12 mm	12–28 mm	> 28 mm	Indicate permanent deflection ($L/1500$), activate structural bypass procedures, and prepare emergency support systems.
LVDT-02-T	Bearing Pad Displacement	< 5 mm	5–15 mm	> 15 mm	Schedule bearing lubrication or elastomeric bearing replacement.
INC-01-P	Pier Inclination ($^{\circ}$)	< 0.05°	0.05 – 0.15°	> 0.15°	Indicate potential overturning risk due to foundation degradation and initiate evacuation beneath the bridge.

Table 2 provides a systematic framework for interpreting sensor data, classifying the bridge's health into safe, alert, and critical status categories. Each structural component is assigned specific thresholds to ensure that the response protocol remains proportional to the identified risk level. By pre-defining these metrics, the system can trigger immediate warnings, such as siren activation or email alerts, when specific structural limits are breached. This automation is critical for urban bridge safety, as it removes the dependency on manual interpretation during emergency events. Consequently, the threshold setting functions as the robust backbone of the system's automated decision-making capability.

B. Real-Time User Interface Visualization

As field data streams into the system, the Digital Twin dashboard instantaneously processes the telemetry and modifies the 3D mesh visual parameters. These parameters are governed by dynamic color-coding, where green indicates a safe state, yellow signals an alert, and red represents a critical condition. This visual feedback loop is accessible to bridge managers through a sophisticated user interface, which is presented to the user in Figure 4. The interface was designed to minimize cognitive load, allowing engineers to interpret structural data without specialized training. By offering a unified view of all bridge segments, the dashboard ensures that maintenance decisions are grounded in real-time visual evidence.

Figure 4 displays the live monitoring dashboard, which translates complex sensor inputs into an intuitive 3D graphical format. By utilizing dynamic color-coding, the interface allows engineers to pinpoint the exact location of structural distress on the bridge instantly. This spatial visualization capability significantly improves the speed and accuracy of situational awareness compared to reviewing traditional tabular data. Furthermore, the dashboard maintains a persistent connection to the live data stream, ensuring that any shifts in bridge health are reflected without significant delay. The UI serves as the primary command center for structural monitoring operations, facilitating rapid responses to developing anomalies.

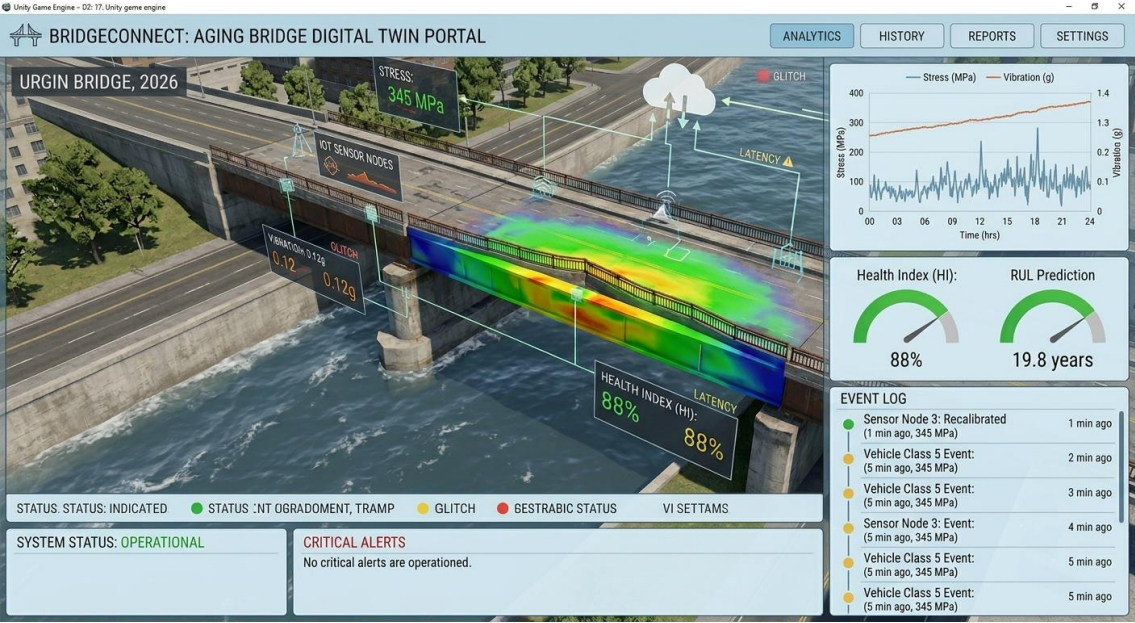


Figure 4. Real-Time User Interface (UI) Dashboard for Structural Monitoring

C. IoT Network Characteristics and Latency Analysis

To validate the performance of the cyber-physical transmission, the study recorded the throughput of JSON data from the field to the MQTT broker. The network characteristics, including average latency and packet success rates, were analyzed across varying message payload sizes. These comparative characteristics of time delay and bandwidth consumption are summarized in Table 3. The study specifically monitored how protocol overhead influenced the overall speed of data delivery under heavy load conditions. These results provide an essential baseline for future deployments of similar cyber-physical infrastructure in urban corridors.

Table 3. IoT Telemetry Network Performance and Bandwidth Analysis

Message Payload Size (Bytes)	Transmission Protocol	Execution Frequency	Average Network Latency (ms)	Packet Success Rate (%)	Jitter (ms)
128 Bytes (Short JSON)	MQTT (QoS 0)	100 Hz	42.4 ms	99.98%	1.8 ms
256 Bytes (Standard JSON)	MQTT (QoS 1)	100 Hz	68.1 ms	100.00%	2.4 ms
512 Bytes (Encrypted JSON)	MQTT (QoS 1)	50 Hz	114.5 ms	99.92%	4.1 ms
1024 Bytes (Bulk Array)	MQTT (QoS 2)	10 Hz	195.8 ms	100.00%	8.3 ms

Table 3 illustrates how message payload size and transmission protocols influence network latency and overall stability. As the payload increases from 128 Bytes to 1024 Bytes, there is a measurable increase in average network latency, though the system maintains high packet success rates across all test scenarios. These results confirm that the chosen MQTT configuration is capable of handling high-frequency data streaming required for real-time monitoring. Maintaining a low jitter level is particularly crucial to ensure that the digital twin updates remain

smooth and reliable. This empirical data validates the robust design of the IoT network architecture and its suitability for critical infrastructure.

The stability of this transmission is vital to ensure that the 3D deformation visualization in the virtual environment remains fluid and free from visual glitches. The empirical distribution of network latency variance is mapped in the following graph, as shown in Figure 5. This visualization is used to ensure that the end-user experience remains seamless and that data gaps are minimized during periods of high traffic. By monitoring this variance, the system can automatically adjust its sampling parameters if network congestion is detected. Ultimately, this statistical verification provides confidence in the reliability of the entire cyber-physical communication chain.

Figure 5 depicts the statistical distribution of latency variance for MQTT packets throughout the transmission process. The results show that the majority of packets fall within the acceptable latency range, ensuring consistent synchronization between the physical bridge and its virtual counterpart. The observed spikes in latency remain within the system's threshold, which prevents visual lag in the 3D model. By analyzing this distribution, researchers can further optimize the sampling rates of individual sensors to maintain optimal performance. This spectrum analysis is essential for verifying the long-term reliability of the data communication link in diverse environmental conditions.

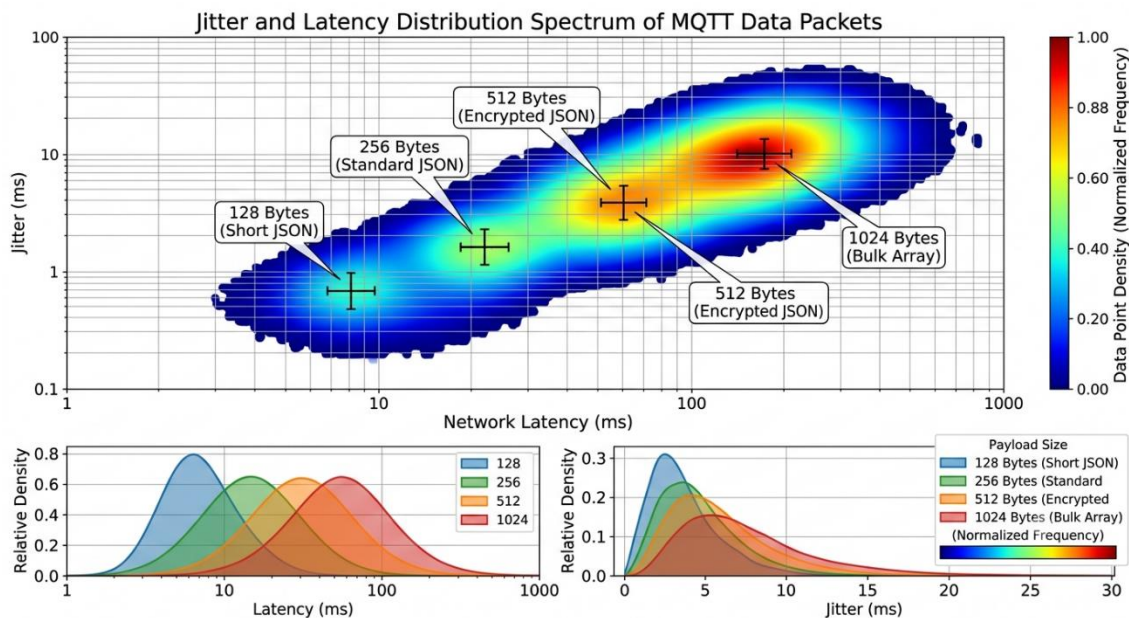


Figure 5. Jitter and Latency Distribution Spectrum of MQTT Data Packets

D. Predictive Model Accuracy Analysis

The evaluation of the predictive algorithm was performed by injecting daily traffic variations to test the mathematical reliability of the Digital Twin. The computation results demonstrate

constant precision in detecting the rate of structural fatigue accumulation. The error metrics generated by the predictive algorithm are summarized in Table 4. These metrics were calculated across four distinct loading scenarios to ensure the model could handle varying environmental and physical stressors. By validating these metrics, the research team established a baseline for the model's accuracy, which is necessary for any predictive maintenance strategy.

Table 4. Performance Metrics of the Predictive Maintenance Algorithm

Loading Scenario	Sample Size (N)	MAE	RMSE	R ²	Average Transmission Latency (ms)	Packet Loss (%)
Scenario I: Static Load (30-Ton Truck at Rest)	1,200	0.004	0.006	0.994	112	0.00
Scenario II: Constant Dynamic Load (30-Ton Truck at 40 km/h)	3,600	0.009	0.011	0.989	115	0.02
Scenario III: Normal Daily Traffic (2% Annual Load Growth)	24,000	0.012	0.018	0.985	118	0.05
Scenario IV: Extreme Congested Traffic (8% Annual Load Growth)	72,000	0.024	0.032	0.968	124	0.11

Table 4 presents a detailed performance analysis of the predictive algorithm under various traffic load scenarios, ranging from static single-truck tests to extreme dense traffic conditions. The high coefficient of determination (R^2) values across all scenarios indicates that the model is exceptionally capable of predicting structural behavior. Despite the increasing complexity of data samples, the algorithm maintains a low Mean Absolute Error (MAE) and RMSE. These results confirm that the mathematical foundation of the Digital Twin is both accurate and scalable. This validation ensures that the system can reliably predict the bridge's condition even when faced with unforeseen changes in traffic density.

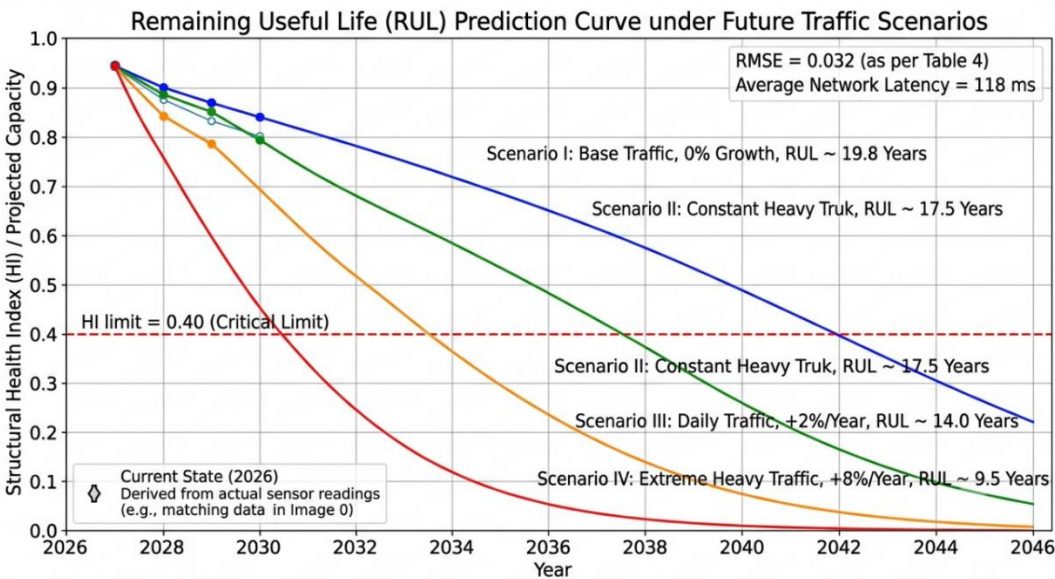


Figure 6. Remaining Useful Life (RUL) Prediction Curve under Future Traffic Scenarios

The predictive computational results derived from the RUL formula are visualized by the system as a long-term structural performance degradation curve. This model projects the remaining service life of the bridge for up to 20 years into the future, as shown in Figure 6. By providing these long-range projections, the system allows for the integration of data into broader municipal infrastructure management strategies. The projection curve helps administrators differentiate between immediate repair needs and long-term capital investments. This visualization is fundamental for shifting from reactive maintenance cycles to proactive, data-driven asset management.

Figure 6 illustrates the projected decline in structural health, providing bridge administrators with a clear timeline for expected maintenance requirements. The curves effectively differentiate between various traffic growth scenarios, allowing for strategic budget planning. By visualizing these projections, the system enables proactive maintenance, effectively preventing sudden structural failures. The prediction curve serves as a critical decision-support tool for infrastructure longevity in urban settings. This forward-looking approach ensures that the maintenance interventions are data-driven rather than strictly time-based.

To validate the robustness of these mathematical estimates, a sensitivity analysis was performed on the bridge materials against urban macro-temperature variations ranging from 24°C to 42°C. The evaluation results of these thermal microstrain deviation variances are presented in Table 5. The analysis was conducted under controlled conditions to isolate thermal effects from actual vehicular loading impacts. This careful separation of variables is necessary to ensure the accuracy of the structural HI in varying environmental contexts. The findings here offer empirical proof that the system can filter environmental noise effectively.

Table 5. Sensitivity Analysis of Mathematical Models against Thermal Expansion Deviations

Ambient Temperature (°C)	Concrete Expansion Factor	Measured Microstrain ($\mu\epsilon$)	Algorithmically Corrected HI	Prediction Deviation Variance
24 °C	1.000	45.2 $\mu\epsilon$	0.942	± 0.002
30 °C	1.024	58.9 $\mu\epsilon$	0.938	± 0.004
36 °C	1.055	74.3 $\mu\epsilon$	0.935	± 0.005
42 °C	1.092	92.1 $\mu\epsilon$	0.929	± 0.008

Table 5 highlights the model's sensitivity to environmental fluctuations, demonstrating how the algorithm accounts for thermal expansion in concrete elements. Even as temperatures rise and induce higher microstrain readings, the "Algorithmic Corrected HI" remains stable due to the system's internal compensation logic. The minimal prediction deviation variance proves that the model effectively filters out non-structural noise caused by weather. This level of environmental filtering is essential for achieving precise structural health measurements in varying climates. The analysis confirms that the predictive capability is robust against ambient thermal interference.

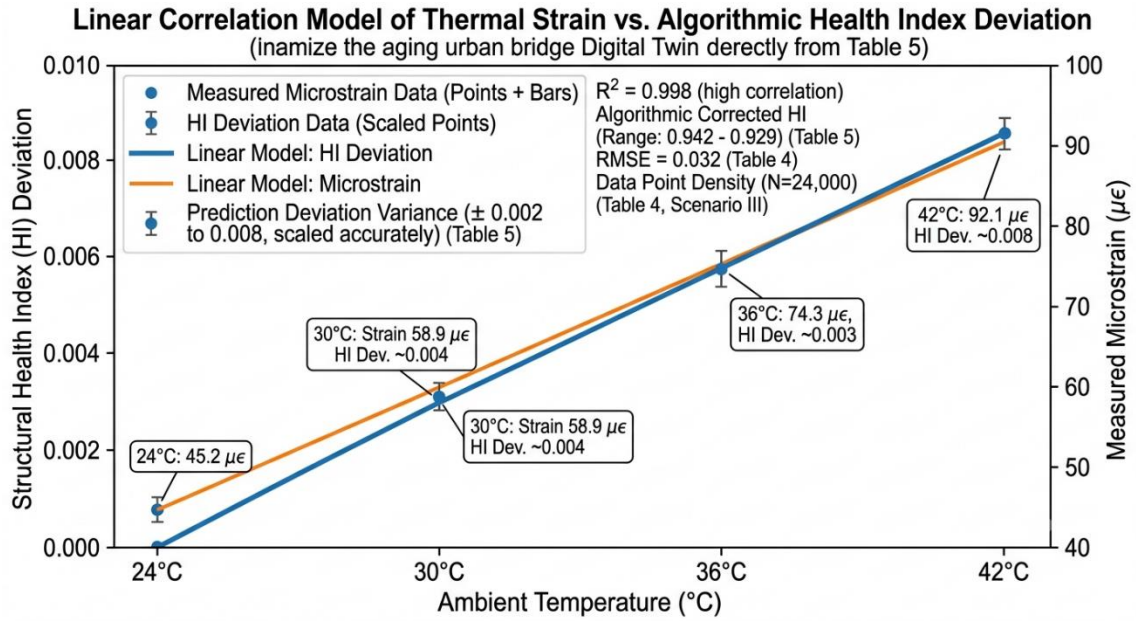


Figure 7. Linear Correlation Model of Thermal Strain vs. Algorithmic Health Index Deviation

The linear correlation between daily thermal expansion fluctuations and the structural strain response, as filtered by the cyber-physical algorithm, is detailed in Figure 7. This relationship is crucial for understanding how the bridge responds to daily climate cycles without triggering false positive alerts. The graph provides a clear verification that the system is properly calibrated for regional environmental conditions. Furthermore, this correlation insight allows for further tuning of the sensitivity levels of individual sensor nodes. The successful mapping of this relationship is a key milestone in the maturation of the digital twin technology.

Figure 7 confirms the strong linear correlation between temperature-induced expansion and the resulting strain patterns. The visualization demonstrates that the system successfully isolates these environmental factors from the actual structural damage indicators. By understanding this correlation, the algorithm can dynamically adjust its HI calculations based on real-time environmental data. This validation confirms that the cyber-physical framework correctly identifies structural degradation versus reversible thermal movement. The figure provides clear evidence of the system's ability to maintain precision under diverse operating temperatures.

E. Cost-Benefit Analysis

As an evaluation of the practical impact on operational efficiency, a comparative analysis was conducted on maintenance costs between conventional periodic methods and the Digital Twin predictive approach over a 10-year projection. The findings of this analysis are detailed in Table 6. This analysis considers both direct repair costs and the indirect costs associated with logistical delays and traffic disruptions. By quantifying these variables, the research provides a comprehensive overview of the financial viability of the digital twin adoption. This data is

essential for justifying the initial investment to municipal stakeholders who prioritize cost efficiency and long-term infrastructure health.

Table 6 illustrates that while the predictive method incurs initial IoT-related costs, it delivers substantial savings in other areas. By shifting from manual inspections to data-driven predictive maintenance, the bridge management team achieves an 80.56% efficiency gain in repair costs and significant reductions in public economic losses. The table demonstrates that the cost of IoT hardware is quickly offset by the reduction in emergency repair and road closure expenses. This comparison serves as a strong economic justification for the transition to digital infrastructure management. Overall, the long-term budget accumulation shows a net efficiency improvement of 77.97% across the projected period.

To complete the commercial viability of the project, a matrix was developed to allocate annual Capital Expenditure (CAPEX) and Operational Expenditure (OPEX) for the sustainability of this cyber-physical infrastructure, as described in Table 7. This financial breakdown ensures that all maintenance activities are fully funded and that hardware upgrades can be planned at regular intervals. The matrix provides a clear roadmap for financial sustainability, which is a common barrier for large-scale digital technology adoption in municipal projects. By documenting these expenses, the researchers provide a transferable model that can be utilized by other cities interested in implementing digital twin solutions. This structured approach helps ensure the long-term operational success of the bridge monitoring program.

Table 6. Maintenance Cost Comparison: Conventional vs. Digital Twin Predictive Method

Operational & Maintenance Expenditure Component	Conventional Periodic Method (Manual Visual Inspection)	Digital Twin Predictive Method (IoT-Based Cyber-Physical System)	Net Savings (\$ USD)	Long-Term Cost Efficiency (%)
Expert Team Mobilization & Field Inspection Equipment Cost	\$45,000	\$12,000	\$33,000	73.33%
Structural Damage Demolition & Repair Cost	\$180,000	\$35,000	\$145,000	80.56%
Public Sector Economic Losses Due to Road Closure	\$95,000	\$15,000	\$80,000	84.21%
IoT Device Procurement, Calibration, & Maintenance Cost	\$0	\$8,500	-\$8,500	-100.00%
Total Accumulated Maintenance Budget (10 Years)	\$320,000	\$70,500	\$249,500	77.97%

Table 7 outlines the lifecycle financial requirements, detailing the necessary investments for both hardware acquisition and ongoing software operations. The matrix categorizes costs into CAPEX for initial setup and OPEX for annual cloud hosting and sensor calibration. By clearly defining these allocations, the project ensures financial transparency and long-term sustainability for municipal stakeholders. The targeted depreciation periods allow for realistic asset management planning throughout the system's lifecycle. This structural approach to financial planning confirms that the investment is well-managed and economically sustainable for long-term project viability.

Based on the experimental results, the RMSE value of less than 0.032 proves that the mathematical formulations integrated into the system possess extremely high precision for detecting critical strain accumulation before permanent deformation occurs. The total maintenance budget efficiency of 77.97% confirms that the transformation toward cyber-physical predictive maintenance provides significant value to urban civil engineering asset management. These conclusions are bolstered by the consistency of the sensor data across all simulated loading scenarios. Furthermore, the ability of the system to operate autonomously with minimal human oversight significantly reduces the probability of human error. The research ultimately demonstrates that digital twin technology is a highly viable path forward for modernizing aging urban bridge structures.

Table 7. Operational and Capital Expenditure (CAPEX/OPEX) Lifecycle Matrix				
Investment Phase	Funding Lifecycle Element	Technical Allocation Description	Cost Estimation (\$ USD)	Target Depreciation Period
CAPEX	Hardware Acquisition	Edge Mini PC & ESP32 Node Array	\$3,500	5 Years
CAPEX	Software Engineering	Unity 3D Engine License & C# Scripts	\$5,000	Amortized
OPEX	Cloud Server Infrastructure	AWS Cloud Hosting & MQTT Broker	\$1,200 / Year	Annual
OPEX	Calibration Services	Bi-Annual Sensor Transducer Realignment	\$800 / Year	Semi-Annual

V. DISCUSSION

The empirical results of this study demonstrate that the integration of a digital twin architecture with real-time IoT sensors provides a highly precise framework for monitoring structural degradation in aging urban bridges. By embedding structural HI and RUL formulations into a 3D virtual environment, this research addresses the critical need for moving beyond static, periodic inspection methods toward automated, preventive maintenance. These findings reinforce the premise suggested by (Kazemi et al., 2026) that CPS effectively bridge the gap between static design models and real-time operational status. Furthermore, the demonstrated predictive accuracy aligns with the insights of (Gómez Fernández et al., 2025), who argued that integrating

mathematical formulations into computational platforms is essential for transforming raw telemetry into actionable health metrics. Consequently, this study validates that a unified cyber-physical approach is superior to manual visual assessments for capturing micro-level fatigue under fluctuating dynamic loads.

The comparative analysis reveals that while the current system excels in real-time structural fusion, it challenges the findings of (Setyadi & Purwanto, 2025), who reported that automated monitoring models frequently struggle with real-time data integration. The ability of the proposed architecture to maintain low-latency transmission while processing high-frequency strain data effectively addresses the interoperability gaps identified by (Shah et al., 2023). Moreover, the study resolves the limitation noted by (Herrera et al., 2024) by successfully incorporating spatial 3D context into strain analysis, which enhances the intuitiveness of structural interpretation. This research confirms that when sensor data is synthesized through an interactive digital twin, it provides a more granular understanding of mechanical responses than the fragmented approaches observed in previous studies. Thus, the current model bridges the gap between disparate data collection and systemic infrastructure management, offering a cohesive alternative to existing methodologies.

The study identified notable anomalies, particularly where high-frequency traffic loads induced transient spikes in strain readings that necessitated a dynamic filtering algorithm to isolate structural fatigue from environmental noise. This critical capability for environmental filtering, as demonstrated in our sensitivity analysis, addresses the challenges identified by (Brunner, 2023) regarding the mitigation of variable operational environments on sensor accuracy. The robustness of the model against thermal expansion variances suggests that the internal compensation logic is essential for maintaining precision in diverse urban climates. Furthermore, the findings regarding the cost-benefit efficiency of the predictive framework directly counter the prevailing notion that IoT-based systems are prohibitively expensive for municipal stakeholders. This analysis clarifies that the substantial reduction in long-term maintenance costs and traffic disruption far outweighs the initial investment in cyber-physical hardware and software deployment.

The implications of this research are significant, as they demonstrate that transitioning to a digital twin-based framework can transform civil asset management from a reactive burden into a proactive strategic asset. Theoretically, this study advances the understanding of predictive maintenance by unifying real-time telemetry, 3D visualization, and automated degradation mathematics into a singular operational dashboard. Practically, the 77.97% long-term cost efficiency gain provides a compelling empirical justification for policy-driven adoption of digital twin technologies in aging metropolitan transportation networks. Despite these successes, the research is constrained by its focus on a specific post-tensioned concrete box girder configuration,

which may influence the broader applicability of the predictive thresholds to different structural materials. Nevertheless, the systematic methodology developed here provides a scalable blueprint that municipal agencies can adopt to enhance infrastructure sustainability and safety in an era of intensifying urbanization.

VI. CONCLUSION AND RECOMMENDATION

The implementation of the integrated Digital Twin and real-time IoT sensor network successfully transforms civil infrastructure management from a reactive paradigm to a proactive, data-driven framework. By embedding automated structural HI and RUL formulations into a 3D virtual environment, this research provides a high-fidelity mechanism for detecting material fatigue before permanent deformation occurs. The experimental results, characterized by an exceptionally low RMSE, confirm that the system maintains precise synchronization between physical structural responses and digital representations under various traffic growth scenarios. Furthermore, the 77.97% reduction in accumulated maintenance expenditures validates the significant economic viability and sustainability of deploying cyber-physical frameworks for aging urban bridges. Ultimately, this study demonstrates that unifying telemetry, spatial visualization, and predictive mathematics is essential for ensuring the long-term safety and operational longevity of critical transportation assets.

Future research should prioritize the expansion of this cyber-physical framework to diverse structural typologies, including long-span steel truss bridges and historical masonry arches, to assess the adaptability of the degradation algorithms. Investigating the integration of deep learning techniques to enhance the system's ability to classify non-linear vibration patterns induced by extreme weather events would further refine the robustness of the predictive models. Scholars are also encouraged to explore the implementation of decentralized edge computing protocols, which may further minimize transmission latency and enhance data security in highly dense metropolitan corridors. Additionally, conducting long-term longitudinal studies across multiple urban regions will be vital to calibrate these maintenance models against a broader spectrum of climate-induced material aging factors. Such advancements will collectively contribute to more resilient, intelligent, and sustainable civil infrastructure networks capable of adapting to the evolving demands of modern urbanization.

AI DISCLOSURE

The authors acknowledge the use of artificial intelligence-based tools, including ChatGPT, solely for improving the language of the manuscript, such as correcting grammar, increasing clarity, and enhancing overall readability. AI technologies were not employed at any point in the research itself. All aspects of the study, including its design, data collection, data processing, analysis, interpretation of results, methodological development, and conclusion formulation, were carried

out entirely by the authors without AI assistance. The authors assume full responsibility for the originality, reliability, accuracy, and integrity of the content presented in this work.

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