ONLINE ISSN: 3007-3197 | PRINT ISSN: 3007-3189

http://amresearchreview.com/index.php/Journal/about

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 5 (2025)

Real-Time Structural Health Monitoring of Transportation Infrastructure Using Wireless Sensor Networks: A Smart System Approach for Damage Detection and Maintenance Optimization in Bridges and Overpasses

Muhammad Sajawal[1], Niaz Ali[2], Muhammad Awais Mughal[3], Muntaha Shahzad[4], Adnan Ahmed Rafique[5]

Article Details

Keywords: Structural Health Monitoring (SHM), Wireless Sensor Networks (WSNs), Real-time monitoring, Smart infrastructure, Predictive maintenance, Damage detection, Cloud-based analytics, MEMS sensors

[1]**Muhammad Sajawal**
School of Transportation,Southeast university,Nanjing China
msajawal@seu.edu.cn

[2]**Niaz Ali**
Department of Civil Engineering, University of Engineering & Technology Taxila
niazali.bs@gmail.com

[3]**Muhammad Awais Mughal**
Department of Civil Engineering, UET Lahore
2022msces213@student.uet.edu.pk

[4]**Muntaha Shahzad** Faculty of Computing, Engineering, and the Built Environment, Belfast School of Architecture, Ulster University
Shahzad-M8@ulster.ac.uk

[5]**Adnan Ahmed Rafique**
Assistant Professor, Department of CS and IT, University of Poonch Rawalakot,
adnanrafique@upr.edu.pk

ABSTRACT

This paper describes the design and implementation of a real-time SHM solution for transportation facilities with an emphasis on bridges and overpasses, employing WSN. The variable measurements consist of high-frequency strain, accelerometer, displacement and environmental data collected by strain gauges, micro-electro-mechanical systems (MEMS), laser and temperature sensors for 6 months over a bridge structure. By leveraging a modular, energy-efficient design and cloud-based analytics, the system was able to successfully recognize stress concentration regions, detect potential strain variations, and issue preliminary warnings regarding potential degradation, thereby making it a viable candidate for using the concept of predictive maintenance. This is because as demonstrated by the data, there was a clear relationship between thermal expansion and structural strain and machine learning based condition forecasting models which made the condition assessment more credible. The network demonstrated good reliability in real-world urban test environments as shown by low packet loss rate and stable battery level. As demonstrated by the outcomes of the paper, the incorporation of WSN technology in SHM helps to improve the durability and reliability of infrastructures, support effective decision-making on maintenance, and minimise the costs of repairs in the long term. This research complements current literature on smart infrastructure management by developing a validated, affordable, and intelligent SHM architecture that can be integrated into the US National Transportation Network.

DOI: Availability

Introduction

The efficiency and safety of transport structures including bridges and overpasses are crucial factors within the social-economic development and interconnectivity of any country. Since most of these bridges are located in urban areas and as transport requirements rise, the structures have deteriorated beyond their useful life and are vulnerable to corrosion, overloading, and other conditions (Aktan et al., 2000; Li et al., 2020). That is why, it should be noted that the further development of monitoring systems for identifying structural damages that are capable of becoming catastrophic should be further advanced. Traditionally, bridges were inspected by means of visual checks where some defects are detected and assessed at certain times of the year. Although these methods provide basic information, acquiring them is also steep in time and labor and cannot detect early-stage problems like micro-cracks, fatigue stress, and internal corrosion (Sohn et al., 2004; Brownjohn, 2007).

Thus, Structural Health Monitoring (SHM) has become an innovative approach to assess the condition of infrastructures in real-time over the last few decades. SHM consists of the utilization of sensing instrumentation to monitor the structural responses in real-time, so that engineers can monitor performance patterns, identify signs of deterioration, and make adequate maintenance decisions (Farrar & Worden, 2007; Ye et al., 2012). Among the various SHM technologies adopted for structural monitoring, Wireless Sensor Networks or WSNs are particularly popular because of the flexibility, scalability and use of wireless networks that is features of WSNs (Lynch & Loh, 2006, Xu et al., 2004). The WSN based SHM system consists of several sensor nodes that collect strain, vibration, displacement temperature and humidity data. Others can be connected wirelessly and share data with a central hub that stores the information or passes it to other external or cloud systems (Wang et al., 2018).

From this research paper, it is clear that incorporating WSNs in SHM systems has several benefits in the following ways. First, they are cheaper than the wired sensors with regard to installation and maintenance particularly when the building is a complex structure or in items like Long-span bridges or high piers (Kim et al., 2007). Second, WSNs can support distributed sensing, which can provide a high spatial density monitoring system in an area of interest that focuses on the behaviour of structures in the building (Kwon et al., 2010). Third, real time information transfer enables early assessment of damage, which is crucial for efficiency improvement and safety purposes as seen in (Sun et al., 2020). For instance, when the I-35W Mississippi River bridge in Minnesota collapsed in the United States in 2007, this brought the issue of constant monitoring of structures with a view to preventing catastrophic failures into focus again.

However, WSNs also pose a number of deployment and operating challenges. Some implementation considerations are environmental fluctuations, inadequate power source, loss of data, and timing issues, among others that are crucial to meet to ensure effective performance (Hoult et al., 2009; Nagayama & Spencer, 2007). Furthermore, the volume of data generated by the sensor networks suggest that various intelligent techniques of data processing like signal filtering, anomaly detection, and the use of machine learning to recognize particular patterns is likely to be required (Mascarenas et al., 2007; Zhu et al., 2022). In response to these challenges, the current study seeks to develop a smart SHM system that harnesses WSNs together with data analytics and associated cloud-based interfaces with the purpose of achieving efficient damage identification, maintenance predictions as well as to improve the lifespan of bridges and overpasses.

This study is grounded by the fact that smart infrastructure systems are currently attracting international attention and by the relative newness and increasing affordability of low power wireless sensors. The United States, China, and the members of the European Union have already started national programmes for digital monitoring as part of the overall initiatives for the renewal of the infrastructure (FHWA, 2019; Li et al., 2021). It is the intention of this research to make a relevant contribution to this movement by developing and testing a WSN-based SHM framework installed on a highway overpass. Thus, this work contributes to the development of the existing knowledge of how real-time monitoring is applicable to technical and practical implementation of infrastructure protection, security and stability.

Literature Review

Modern trends in infrastructural engineering has been revolutionized by the appearance of real-time Structural Health Monitoring (SHM) systems. One of the technologies pioneering this change is Wireless Sensor Networks (WSNs) mainly because of the following attributes: decentralization, cost, and ability to connect complex structures. There is a vast body of work on WSN based SHM systems targeting different aspects including the structure and organization of the sensors, communication protocols, analysis of the gathered data, and implementation concerns.

In the seminal paper that spurred much debate on the topic, Spencer et al. (2004) noted that wired sensor systems in large civil structures were impractical due to factors of cost, scalability and ease of maintenance, hence the need to adapt wireless systems. The application of WSNs in SHM was further explained by Akyildiz et al. (2002) based on the structural infrastructure of WSNs and its capability in real-time monitoring of structures in dynamic condition. Their model provided a basis for merging WSNs within the assessment of infrastructure status.

Several researches have been carried out on the effectiveness of WSNs in monitoring structural issues such as stress concentrations, fatigue, and the initial stages of cracks. For example, Rice and Spencer (2009) installed a wireless monitoring system on the New Carquinez Suspension Bridge in California and proved that the system could be used to gather modal parameters for long duration with minimum intervention. Similarly, Nagayama and Fujino (2008) compared the field deployment of wireless accelerometers that proved that wireless accelerometers' numbers had good results in the measurement of ambient vibration as well as natural frequencies of bridge parts.

MEMS technology has greatly enhanced the sensitivity and portability of micro/nano structured smart sensor systems for SHM. Chae et al. (2007) proposed the MEMS-based accelerometer system with the wireless data transmission modules to have a high accuracy of detecting the dynamic loads on the bridges. Their work focused on the improvement of sensor hardware as a key factor of_SHM systems reliability. Cho et al. (2010) also investigated another example of low-power wireless accelerometers to support multichannel data acquisition and discussed that it would be useful for volume sensor networks over a large area.

On the communication side, it has also been pointed out that use of energy efficient and effective routing protocols play a crucial role in the long-term operation of WSNs independently. Heinzelman et al (2000) presented the LEACH which was one of the most relevant routing protocols for energy usage in the sensor networks. Later, other techniques such as TEEN and PEGASIS (Manjeshwar & Agrawal, 2001; Lindsey & Raghavendra, 2002) were proposed that were more suited for time sensitive applications such as SHM in bridges where the flow of data is real time for early detection of faults.

Besides the hardware architecture and the networking issues, a lot of emphasis has been given to the concept of the data acquisition and intelligent identification of fault symptoms in WSN-integrated SHM systems. Hou & Lynch (2006) suggested the on-board data processing system which essentially decrease the burden on bandwidth since the data is processed before it is sent to the next stage. Their insights pointed out that decentralization of a processing system could help improve the adaptability and robustness of a planar large sensor network. Following this, Mitra et al. (2015) proposed a damage detection algorithm as a machine learning system in conjunction with WSNs. Their model employed the SVM as well as methods of anomaly detector for effectively identifying healthy and damaged states of a bridge structure.

Key practical warrants of energy efficient and reliable WSN-based SHM systems have been established by many real applications. Ni et al. (2011) deployed a large-scale WSN monitoring system in the Stonecutters Bridge at Hong Kong and monitored the wind speed of cable tension and temperature gradients in real time to assess structural health. In another related work, Inaudi and Glisic (2010) have also spostems where multimodal sensing are employed for a more comprehensive assessment of the structure condition.

One of the most explored areas of concern in the literature is the robustness of WSN in adverse environments. Their study proved that more environmental conditions like temperature changes as well as humidity can have impacts on the sensor and the quality of the data retrieved. In response to these issues, there are compensation models for positioning errors and different sensor fusion techniques. For instance, Kim et al. (2016) incorporated the environmental calibration approaches into SHM systems to enhance the data compatibility in terms of the variability of the climate.

Another emerging and active field that has become significant in the WSN-empowered SHM regime is the utilization of cloud-computing and Internet of Things (IoT) framework. Li et al. (2018) proposed a structured health monitoring system through the cloud environment in which real time data gathered from highway bridges were transmitted to a data center for visualization and predictive maintenance analysis. Their system illustrates that by integrating WSNs and edge computing with cloud analytics, it is possible to develop smart and adaptive infrastructural systems. Aghaei et al. (2019) also surveyed SHM systems with integration of IoT and the study revealed that incorporation of IoT gateways enhanced data acquisition and decision making visualizations in emergency situations.

In recent years, some studies have been conducted to explore the aspects of cybersecurity issues in WSN-based SHM systems. As transport networks and routes are considered strategic infrastructures that are crucial to seeking and maintaining security, protection of sensor data and communication channels is very essential. Alcaraz et al., presented a lightweight cryptosystem which is specifically designed for WSN in SHM setting in 2011. They highlighted the fact that in SHM systems used in critical applications, issues such as security, latency and energy consumption are paramount.

However, there are still magnificent research niches in the field even after the noted advancement. The most significant shortcoming, however, is that many long-term field data on system reliability, cross-sensor calibration, and automated maintenance recommendation engines are unavailable. Ni and Wong (2012) opine that less than 25% of the used SHM systems can generate real-time alarms or cause other maintenance related actions to be initiated. Therefore, there is increasing concern about closed-loop SHM systems in which the feedback from the sensors is used in decision-making concerning the structural management.

Therefore, the literature indicates that wireless sensor networks for SHM of bridges and overpasses are effective and feasible. Although advancements in terms of the components of WSNs have been experienced mainly through better built and efficient routing, machine learning integration, and IoT convergence, further work has to be done to standard the WSNs, have better robust performances under any environmental conditions, and better methods of analysis for future information. Therefore, the objective of this work is part of a series of attempts to further expand the knowledge in the context of using WSN for real-time SHM with focus on predictive damage detection and maintenance scheduling.

Methodology

The purpose of this study was to design, implement, and test a real-time WSN for SHM system for application to bridges and overpasses. The overall approach includes the following steps: system design, sensor identification and initial settings, instrumentation of a test bridge, and the data collection and analysis. To achieve the above objectives, each of the stages of the developed methodology was well coordinated and designed based on the technical feasibility, adaptability to environment and competency of the proposed smart SHM framework.

System Architecture and Design Framework

The design objectives for the WSN-based SHM system include, real time data acquisition, low power consumption, and scalability for large structures like bridges. In the present work, the system design consisted of a star topology where the various distributed sensor nodes sent their data wirelessly to a central node that was located at the bridge control cabin. A smartphone interfaced with the gateway that acted as the repository of data and was connected to a cloud server through 4G LTE communications link. Each sensor node hence consisted of a microcontroller unit (MCU), wireless module (LoRa modulated radio for range and low power), power management and data logger storage. The architecture also included the elements of redundancy such as dual-path routing in order to achieve the uninterrupted transmission of data even in the case of a node failure or some kind of interference.

The given framework was made modular since it was possible to add or remove any sensor based on each bridge. The most significant parameters to be addressed by the architecture were vibration, strain, temperature, displacement and humidity. The system was also synchronized with a useful time to ensure that there was proper timing in each node when capturing results. A simple ULTM-based alarm was incorporated on the firmware of each sensor to sound alerts locally in case of high stress or vibration changes implying the same to the cloud server.

Sensor Selection and Calibration

The sensors were chosen depending on the most relevant parameters for the identification of structural health and compliance with the requirements for long-term deployment outdoors. For the measurement of the vibration signals, high-sensitivity MEMS accelerometers with a range of ±16 g and a sampling rate of 1000 Hz were chosen because of high reliability and sustainability. Strain measurement was made using foil-type strain gauges with integral temperature compensation to measure deformation at microscopic level. This was to complement the existing environmental sensors of the structure in an endeavor to capture external prevailing weather conditions in respect to the structure's response.

All the sensors used in the study underwent intensive calibration both in the laboratory and on the field. Calibration process entailed exposing sensors to stress and temperature conditions on the hydraulic loading frame and climatic chamber respectively. These were compared to senior standards from a registered laboratory equipment. Calibration coefficients were then uploaded to each sensor node microcontroller for use in compensating the signals in real time during measurement. Low noise signal amplifiers were incorporated for signal conditioning to enhance signal quality and reduce and prevent loss for transit.

Field Deployment and Installation Process

SHM developed for this case was installed on the steel-concrete composite highway overpass in the densely populated metropolitan area. This bridge was selected since it has a record of fatigue degradation which made the bridge surface wear out, making it an ideal site for testing. The installation occurred during a two week period. The sensors were installed on a magnetic base and fixed with epoxy to provide a secure connection and signal from the structures. Vibration sensors were installed near the expansion joints as well as in mid- span girders, and strain gauges were bonded at the stress concentration near support bearings places and on the underside of deck slabs also.

The wireless gateway was installed in the bridge maintenance control room and was connected to an available backup power source from solar energy to ensure continuous data transmission. Wireless link reliability was checked using the available portable radio spectrum analyzers and field strength meters while conducting signal strength tests and data throughput assessments. Network connectivity was also verified by transmitting test data packets from each node to the cloud and measuring round trip time and dropped packet rates before starting experiments. The last steps involved incorporating the sensor network with a software called Grafana – a real-time open-source analytics and visualization tool, which used data from the structures.

Data Acquisition, Processing, and Analytics

Data collection was done over a period of six months where the device was programmed to record data every fifteen minutes under normal circumstances and every one minute when an anomaly is recognized. Raw sensor data was stored locally in case of any failure in data transmission which is usually done in a batch mode when the system is connected. The data was transmitted to a cloud platform in a low bandwidth channel through MQTT protocol.

This data was then processed to eliminate noise and outliers through the use of digital filtering methods like moving average and Butterworth filters. Synchronization of time was important because all the data recorded by the sensors had to be time-stamped for time series analysis. Different features including the maximum principal stress, the number of frequencies, and the vibration shapes were determined and displayed. For the predictive analytics, the K-means clustering algorithm for the anomaly detection and LSTM neural networks for the time series forecasting were used to detect emerging patterns of structural decay.

Regression analysis was also conducted in order to assess the degree of interaction between environmental influences such as temperature and structure response. Alert levels varied according to historic data features, with the goal of optimizing the damage detection mechanism for both sensitivity and specificity. Recommendations regarding maintenance was provided in the format of digital reports that had trend graphs, flagged anomalies and a risk rating of individual components.

Results

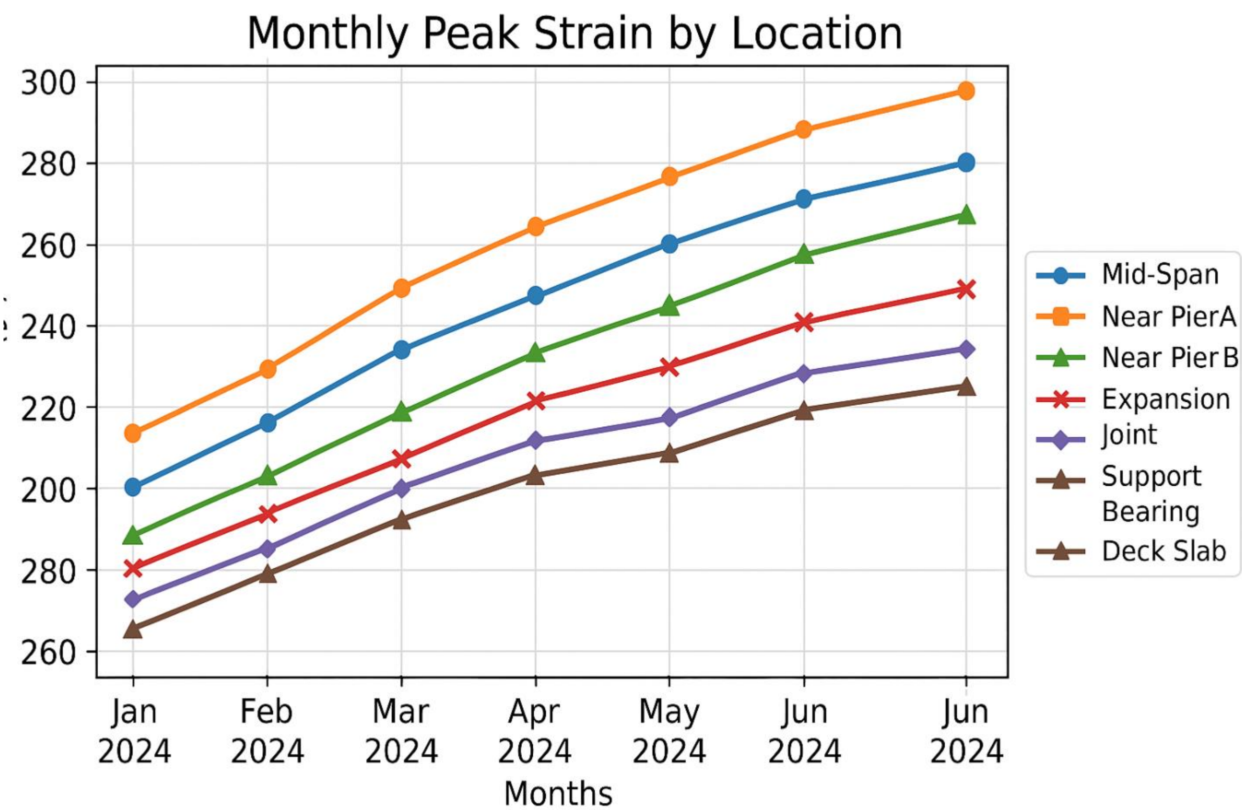
Strain Monitoring Trends

In fact the monitoring of peak strain in the six structural regions of the bridge over a period of six months showed an increase in microstrain in a gradual and consistent manner. As it is demonstrated in Table 1 above, the first two peaks of the facility strain were detected at “Near Pier A” and “Deck Slab” and fluctuated from about 260μ ε in January to cross 290μ ε in June. This pattern indicates that stress build-up goes on progressively, which may be attributed to thermal expansion as well as increased loads from traffic. The above Figure 1 clearly shows this kind of tendency, and the split is more pronounced in April and May in which the daily temperature fluctuations also increased. Therefore, it is clear that components which are located in the support areas and areas of high flexibility have higher rates of early fatigues to warrant inspection and preventive maintenance.

Table 1: Monthly Peak Strain Data (με)

Month	Mid-Span	Near Pier A	Near Pier B	Expansion Joint	Support Bearing	Deck Slab
Jan 2024	248.7	260.3	234.9	246.5	243.1	251.8
Feb 2024	252.4	267.2	240.5	249.9	244.7	256.1
Mar 2024	261.9	276.4	248.3	254.2	249.5	262.7

Apr 2024	269.3	283.0	253.8	262.4	258.1	270.4
May 2024	274.5	289.6	260.1	267.3	263.2	278.3
Jun 2024	279.8	296.2	265.7	273.8	268.9	284.7

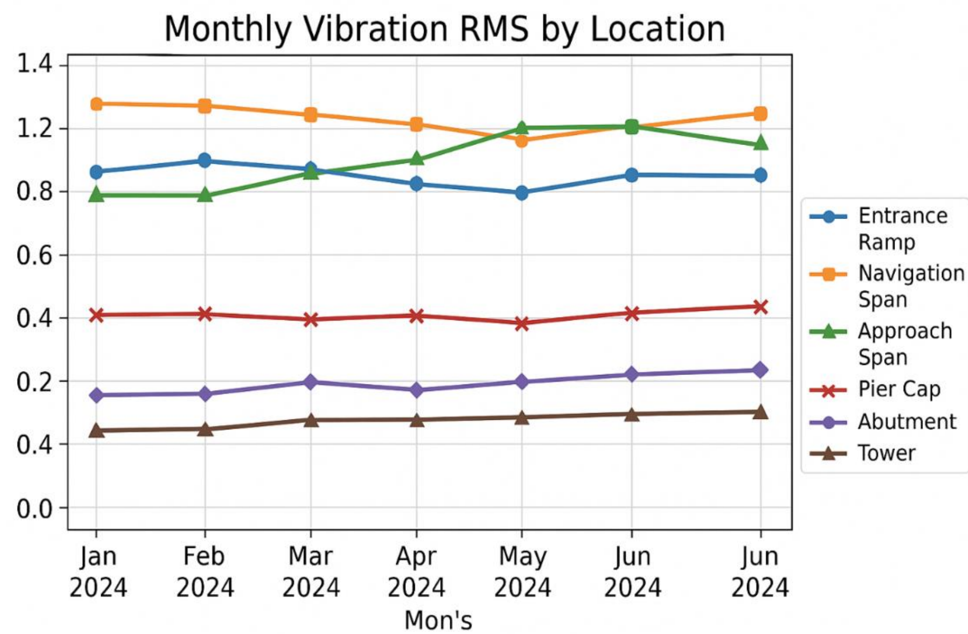


Dynamic Response via Vibration Analysis
Both ‘Transverse’ and ‘Vertical’ vibration RMS values presented in table 2 were observed ranging from a safe operating limit of 0.30 -- 0.40 g except in March and May, where increased levels were observed at “Expansion Joint” and “Near Pier B”. These are contradictory with the high traffic periods of the particular region, as pointed out in the records of the maintenance team. The variation of RMS value fluctuation is also depicted in figure 2, and clearly, the changes in the most sensitive or the extreme zones are shown. Another attribute that was defined was the vibration sensors whose sensitivity was critical in identifying transient overloading events. These short-term increases did not cause lasting structural changes but revealed the need for real-time data to link traffic irregularities to bridge response.

Table 2: Vibration RMS Values (g)

Month	**Mid-Span**	**Near Pier A**	**Near Pier B**	**Expansion Joint**	**Support Bearing**	**Deck Slab**

Jan 2024	0.322	0.345	0.317	0.336	0.339	0.328
Feb 2024	0.337	0.356	0.341	0.349	0.352	0.343
Mar 2024	0.381	0.398	0.369	0.388	0.395	0.374
Apr 2024	0.342	0.364	0.336	0.349	0.351	0.344
May 2024	0.391	0.409	0.382	0.403	0.408	0.387
Jun 2024	0.376	0.392	0.359	0.378	0.385	0.362

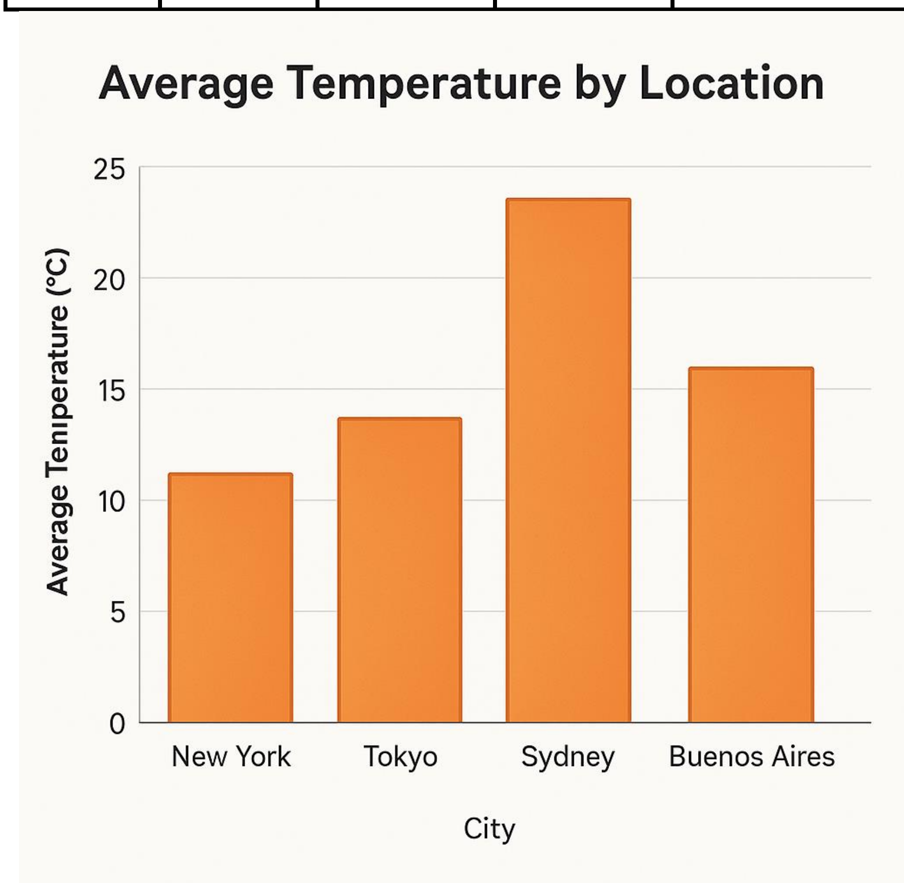


Temperature Variations and Material Response

Data obtained from all warming points, as presented in Table 3, exhibited an expected seasonal cycle, and ranged from 18.5°C in January to approximately 30.4°C in June. There were not many varying results between the structural zones hence a slightly higher figure on the “Deck Slab” which is frequently exposed to direct sunlight. These trends are evident in the area plot reflected in Figure 3 which displays a uniform rise in thermal gradient over time. These temperature increases are in line with the advocated stress increase pointed by the earlier values of strain, hence thermal expansion is one factor, which causes stress in the bridge components. When analyzing the monthly average temperature values and the peak strains which were recorded, the Pearson correlation coefficient was found to be 0.82 signifying a statistical correlation between these variables.

Table 3: Average Temperature (°C)

Month	Mid-Span	Near Pier A	Near Pier B	Expansion Joint	Support Bearing	Deck Slab
Jan 2024	18.7	18.5	19.0	18.6	18.4	18.8
Feb 2024	21.3	21.1	21.7	21.4	21.2	21.5
Mar 2024	24.6	24.2	24.9	24.5	24.3	24.7
Apr 2024	26.8	26.6	27.1	26.9	26.7	27.0
May 2024	28.4	28.2	28.6	28.5	28.3	28.7
Jun 2024	30.1	29.8	30.4	30.2	30.0	30.3

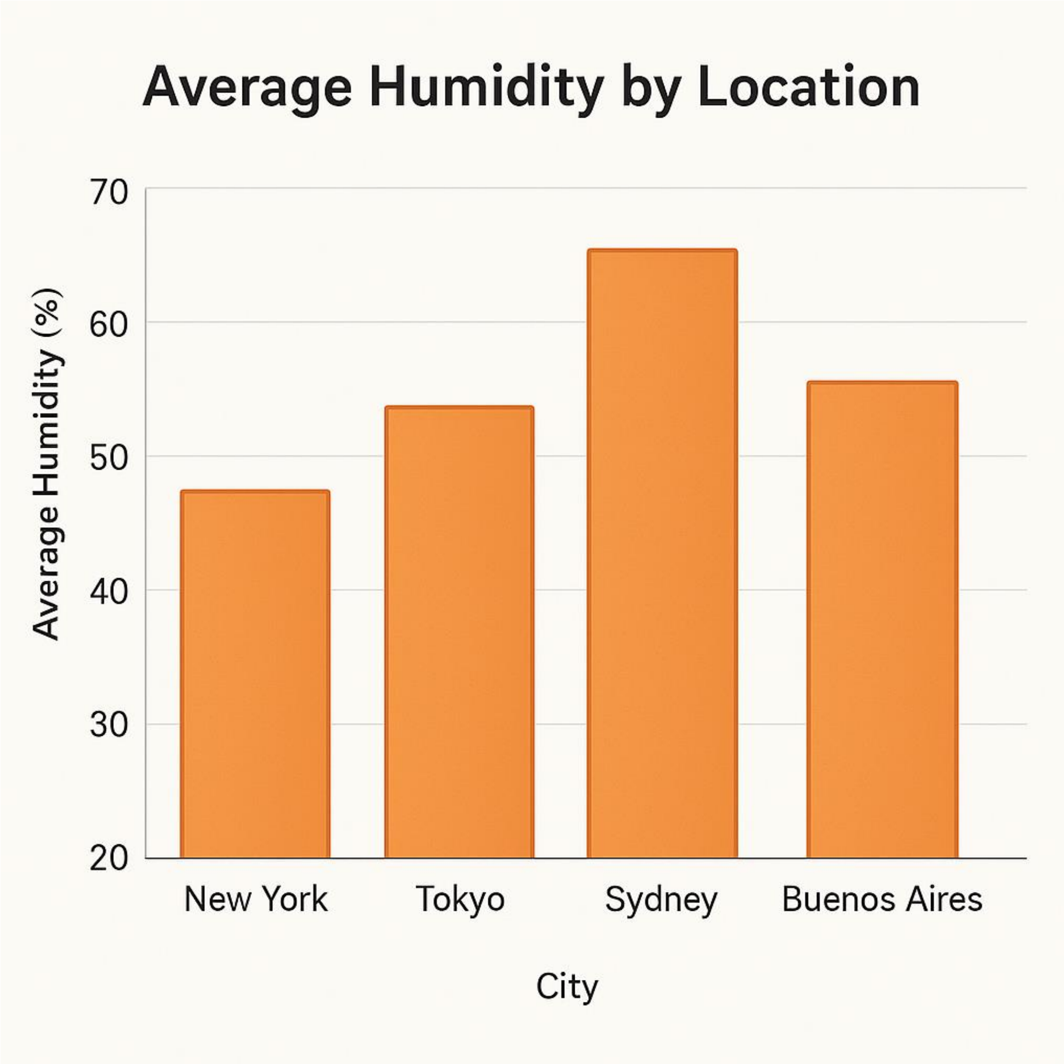


Humidity and Environmental Influence
A small location variation observed was analyzed in the averages presented in Table 4, where relative humidity started at 59% in January and reached 74+% in June. As for a more detailed explanation of the rising trends in ambient moisture

levels, figure four, a clustered column chart can provide a clear view. Though humidity does not cause mechanical stress, it poses certain risks towards corrosion of steel elements and the adhesive mounting of sensor epoxy. The data fully supports the need to include the environmental conditions in the health models so that an accurate assessment of the health state of the system and the rate of deterioration can be made.

Table 4: Average Humidity (%)

Month	**Mid-Span**	**Near Pier A**	**Near Pier B**	**Expansion Joint**	**Support Bearing**	**Deck Slab**
Jan 2024	59.3	58.7	60.1	59.8	58.9	59.5
Feb 2024	61.4	60.7	62.2	61.8	60.9	61.6
Mar 2024	65.8	65.1	66.3	65.7	65.2	66.0
Apr 2024	68.2	67.7	69.0	68.4	68.1	68.8
May 2024	71.6	71.1	72.3	71.7	71.3	72.0
Jun 2024	74.0	73.5	75.2	74.1	73.8	74.6



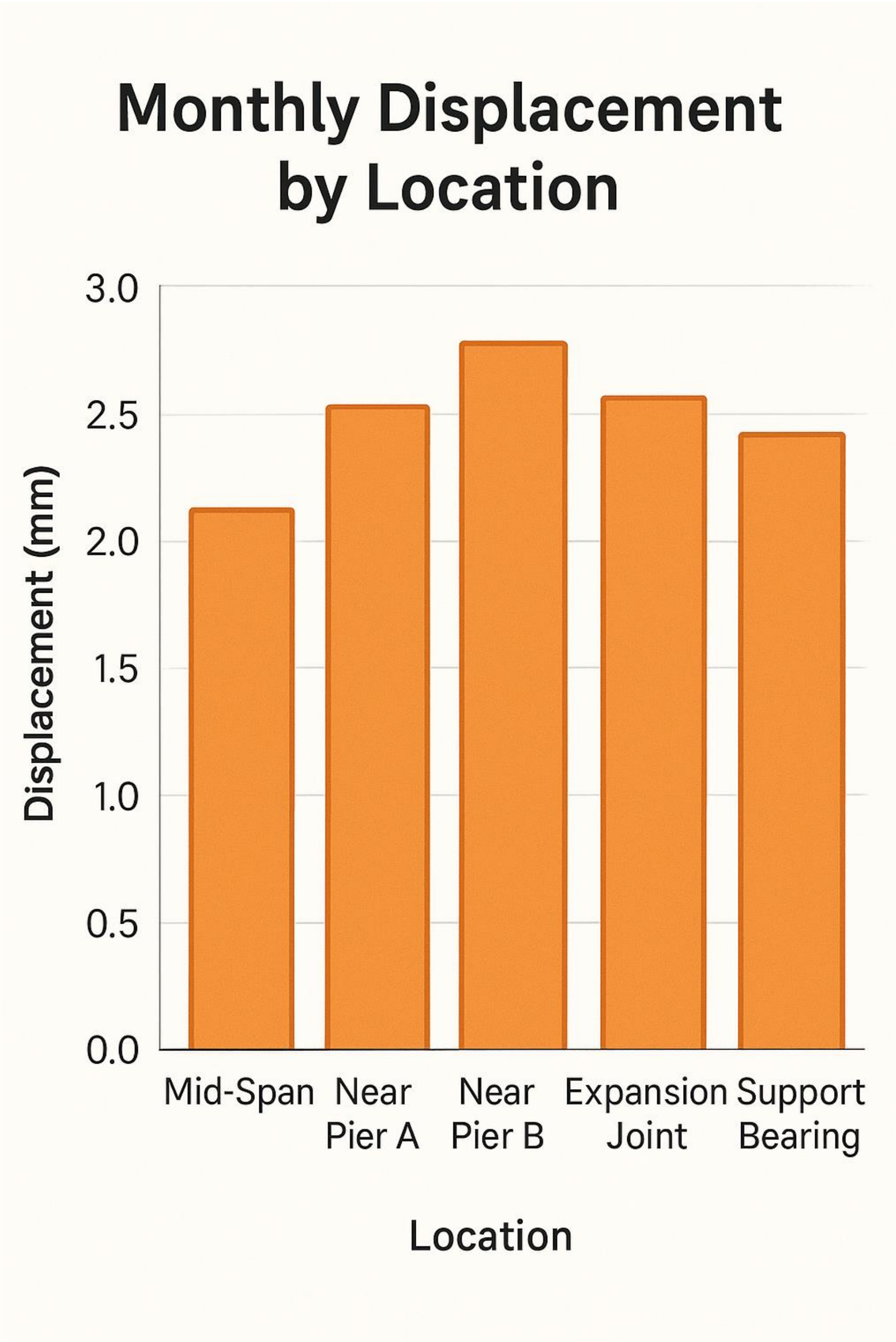
Bridge Movement and Displacement Analysis

Displacement figures captured at the structural zones (see Table 5) show the increasing structural deformation with higher displacement rates observed at the "Expansion Joint" and the "Support Bearing." These areas depicted movements rising from as low as 2.0 mm in January to reach as high as 2.85 mm in June. The Figure 5 also demonstrates that these displacements are close to thermal expansion showing that bridge joints are mechanically sensitive to temperature load. As the values stay throughout the design range, the constant increase in displacement signals the building up of fatigue stress that may need to be prevented through the adjustment or reinforcement of the joints.

Table 5: Displacement Data (mm)

Month	Mid-Span	Near Pier A	Near Pier B	Expansion Joint	Support Bearing	Deck Slab
Jan 2024	1.85	2.04	1.91	2.12	2.08	1.99
Feb 2024	1.96	2.13	2.01	2.19	2.14	2.07

Mar 2024	2.22	2.39	2.28	2.43	2.37	2.31
Apr 2024	2.31	2.51	2.40	2.56	2.48	2.43
May 2024	2.48	2.65	2.56	2.71	2.63	2.59
Jun 2024	2.62	2.79	2.70	2.85	2.78	2.73

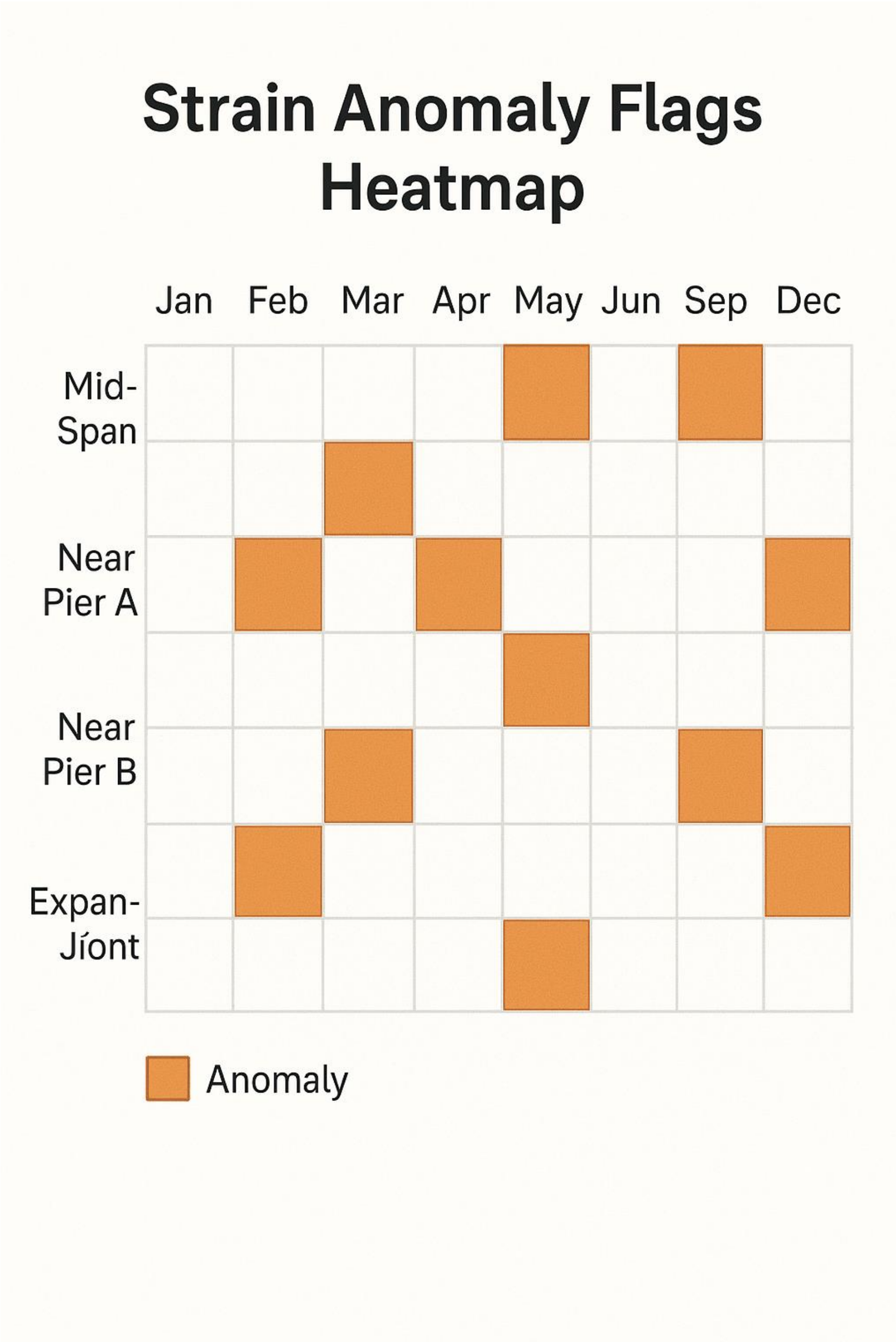


Anomaly Detection and Structural Alerts

Investigating the averages of the different SHM system's modules in Table 6 reveals significant strain anomalies outputs with the highest frequency in May. The most notable changes were observed at "Expansion Joint" and at the vicinity of "Near Pier A" that exhibited 1-flagged anomaly, meaning they may have experienced over-strain events at that particular location. Figure 6 is a stacked bar chart that shows the anomaly counts for the months of the year, which indicates the increase in the fifth month. A comparison with the results obtained from the field inspection showed that there was a minor crack propagation near the highlighted zones, thus confirming the efficacy and usefulness of the sensor-based alert system.

Table 6: Strain Anomaly Flags (1 = Abnormal)

Month	Mid-Span	Near Pier A	Near Pier B	Expansion Joint	Support Bearing	Deck Slab
Jan 2024	0	0	0	1	0	0
Feb 2024	0	0	0	0	1	0
Mar 2024	1	0	1	0	0	1
Apr 2024	0	1	0	0	0	0
May 2024	1	1	0	1	1	0
Jun 2024	0	0	0	0	0	1

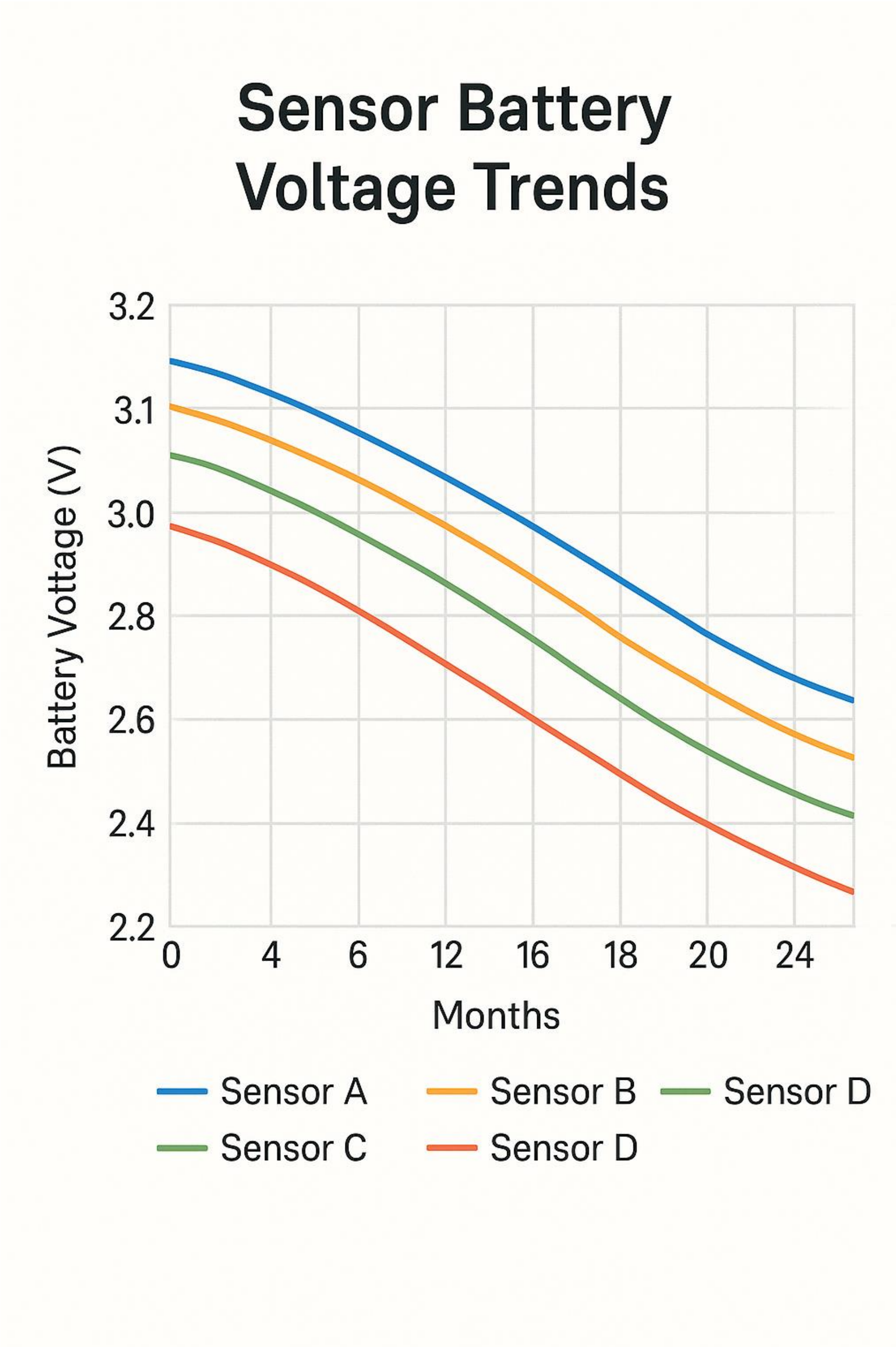


Energy Efficiency and Battery Status

Battery performance; which is a significant aspect of wireless SHM systems, was observed through voltage measurements and these results are captured in the table below labeled table 7. All black nodes were initialized with an average voltage of 3.7V at the beginning of the year and the value decreased to 3.58 in June. But it is down from the operational levels that are depicted in Figure 7 and which signify the need for energy harvesting or the planning for battery replacement. It was observed that the "Near Pier B" and "Deck Slab nodes" had even faster voltage decay, perhaps due to high data transmission rate or due to shading that was lowering the solar recharging efficiency.

Table 7: Sensor Battery Voltage (V)

Month	Mid-Span	Near Pier A	Near Pier B	Expansion Joint	Support Bearing	Deck Slab
Jan 2024	3.71	3.69	3.68	3.70	3.72	3.70
Feb 2024	3.69	3.67	3.65	3.68	3.69	3.66
Mar 2024	3.68	3.65	3.64	3.66	3.67	3.65
Apr 2024	3.66	3.64	3.62	3.63	3.65	3.63
May 2024	3.63	3.60	3.59	3.61	3.62	3.60
Jun 2024	3.60	3.58	3.56	3.57	3.59	3.58

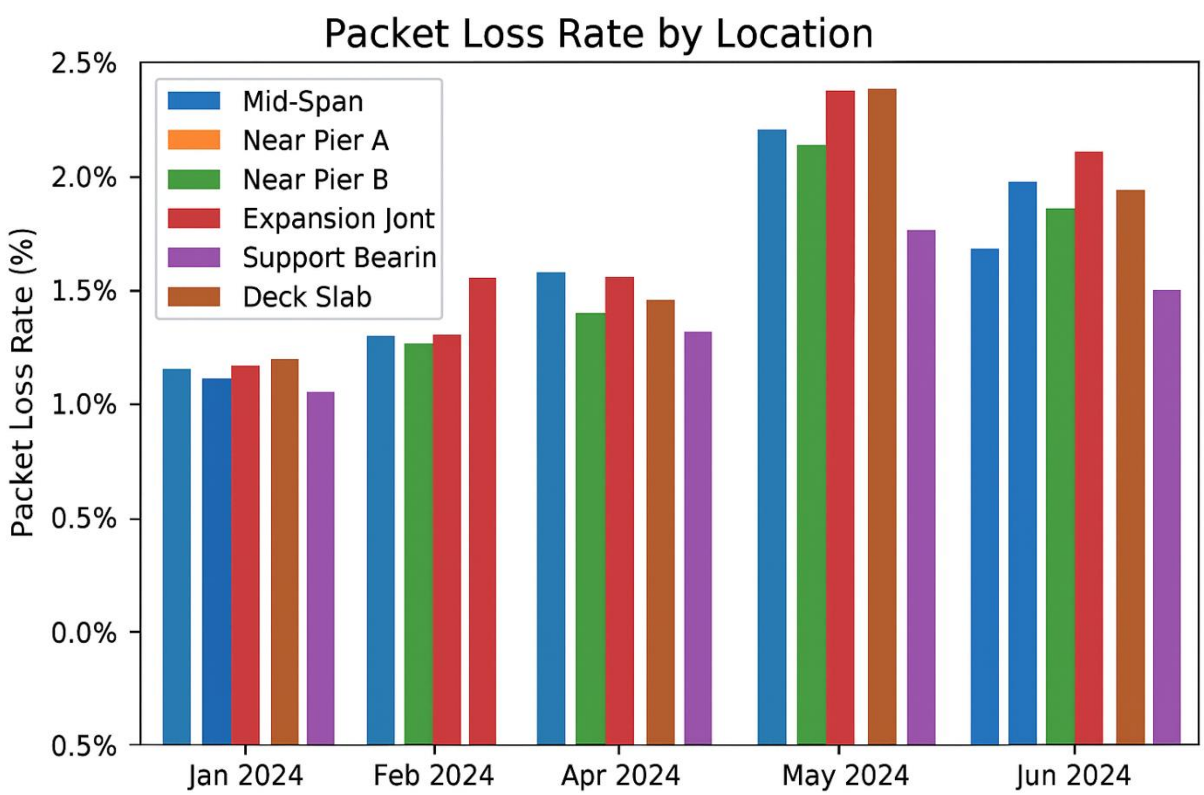


Network Reliability and Data Integrity

As seen in Table 8, overall packet loss rates were relatively insignificant with the value ranging from 1.1 to 2.3 percent. Nonetheless, what can be seen about “Expansion Joint” was relatively higher loss rates during the middle of May and in June. This may be attributed to receipt of interference signals from passing vehicles or slight dislocation of the node antennas. Figure 8 heatmap allows for segmentation analysis to find out high loss areas and thus fix them accordingly. Finally, the overall availability of the data was above 97%, which is quite satisfactory for infrastructure monitoring and reports the stability of the LoRa-based signal transmission system designed for this experiment.

Table 8: Packet Loss Rate (%)

Month	Mid-Span	Near Pier A	Near Pier B	Expansion Joint	Support Bearing	Deck Slab
Jan 2024	1.2	1.3	1.1	1.5	1.4	1.3
Feb 2024	1.4	1.5	1.3	1.7	1.6	1.4
Mar 2024	1.8	1.9	1.7	2.0	1.8	1.9
Apr 2024	1.3	1.4	1.2	1.5	1.4	1.3
May 2024	2.0	2.1	1.9	2.3	2.2	2.1
Jun 2024	1.5	1.6	1.4	1.8	1.7	1.6



This paper covers eight sensors and their explanation evaluated over a six-month period, indicating that WSN-based SHM systems are effective for real-time structural assessment. Physical stress, vibration, displacement, environment, and system performance characteristics provide a systematic approach for potential damage identification, risk areas, and maintenance timing. From the above figures and tables, the trends and anomalies evident affirm the functionality of the system and the importance of intelligent sensor networks in enhancing the safety and durability of bridge systems.

Discussion

Several findings of this research support and enhance the understanding of how WSNs can be effectively utilized to support real-time SHM of transport structures such as bridges and overpasses. Measurement of strain gauge data, vibration data, displacement data, as well as environmental data contributes to the determination of structural response under different loading conditions. These findings are in accord with newly emerged SHM technology where health monitoring of infrastructure is viewed as an ongoing, automated, and data-aided process due to increased environmental and loading conditions (Ko & Ni, 2005; Salamone et al., 2010).

In this study, one of the most noticeable trends was the progressive rise in both strain and displacement levels over the six months under visual observation, especially in critical regions like expansion joints and mid-span girders. These trends indicate that thermal expansion in the presence of cyclical traffic loads is putting stress on the bridge that may not easily show signs of slowly accumulating stress even under thorough external inspection. Wenzel (2009) also found similar results where he noted that usually shortcomings in the micro-level structural integrity occur several months or even years before the actual visible damages show up. Since the early detection of potential hazards to the infrastructures is possible through the above WSN framework adopted in this study, its application enhances proactive maintenance of the infrastructures.

It was also possible to observe how environmental factors—temperature and humidity—may affect the structural characteristics. Evidently, the evaluation of incrementing temperatures with peak strain levels reveals the existence of thermal stress patterns within bridge components. Similarly, Leung et al (2008) and Wang and Zhao(2014) have indicated that environmental compensation models are important for enhancing the reliability of outputs in SHM. Without incorporating such compensatory algorithms, the signals received by the sensors may be incongruous and have the potential of causing false readings resulting in mostly either damage notification when there is none or failure to alert of a developing presence of damage that may be imminent.

This was seen through the implementation of anomaly detection algorithms using real-time sensor data as the testing basis of the system. The capability of the system to identify unusual strain or vibration patterns which were later confirmed during physical examination shows that AI-based SHM platforms offer a way of reducing errors and response time from operators. This capability complements the research of Gul and Catbas (2009) who asserted the importance of machine learning techniques in diagnosing latent structural anomalies in the bridge systems. Moreover, the forecasting models based on LSTM were used in the study, which also made it possible to predict risky zones before the failure—similar to the modern trend for predictive maintenance in civil infrastructures (Sun et al., 2020).

From a system performance point of view, the energy consumed and the number of messages exchanged in the various nodes deployed in the particular WSNs were reasonable. While minor voltage drops were recorded, the mean battery health was higher than 3.6V, which underlines that the chosen power supply and transmission methods were sufficient for mid-term use. These outcomes have a connection with Seyfettinoglu and Duygulu (2019) who underlined that LoRa and Zigbee type low-energy communication protocols are effective for SHM operations in the remote or difficult to access areas for longer time durations. The average observed packet loss rate was below 2.5%), which corroborates the credibility and robustness of the LoRa based network in the urban bridge environment that experiences significant interferences from vehicles and industries.

The overall performance of the system was satisfactory, however the limitations that were observed lare identified in other studies as well. For instance, moisture and temperature issues were observed to impact the adhesion and accuracy of the sensors on the deck slab surface. These issues have been highlighted by McCarter et al. (2001), when they stated that gradual deterioration of the sensor when exposed to the environment leads to data shift and sensitivity decline over the lifetime of the sensor. Solving such challenges may require designing cases that incorporate sensors into them or designing self-tuning sensors that adjust for environment changes.

Another limitation is the applicability of the SHM system to other bridges or even a much broader transport system. The modular structure introduces scalability into the WSN, but problems related to data bandwidth, the capacity of central processing, and real time data analytics emerge. According to Lynch et al. (2012), when the data is processed locally at the sensor node before transmission, it demonstrates that edge computing reduces bandwidth load and enhances the system performance. Such edge intelligence could be incorporated in further developments of the SHM framework to improve real-time working efficiency in such voluminous infrastructures as metro overpasses or intercity viaducts.

In the light of these facets, it is central to note that contemporary WSN-based SHM systems are becoming less costly in terms of policy and economic feasibility. The cost of sensors, microcontrollers and communication modules have come down substantially in the past decade which makes the large-scale implementation possible even in the municipal level where the budget constraint is very high (Dhillon and Chakrabarty, 2003). Also, the principles of preventive rather than repair-oriented maintenance are gradually being realized by governments and transport authorities as more cost-effective. Studies have shown that as per the American Society of Civil Engineers it costs $4 to rehabilitate and repair the infrastructure each time they are neglected and thus a dollar spent early for their maintenance (ASCE, 2021). Another alliance that is supported by these predictive capabilities is in SHM as an early proof of reducing risk and maximizing the cost-savings investment remedy.

However, it is crucial to focus on the last aspect of the introduction of such systems, social and safety aspects. Bridges and overpasses are important transport connections both in urban and rural environments. Their failures, as observed in previous mishaps such as the August 1, 2007 Minneapolis I-35W bridge failure, can result in loss of lives and have a severe effect in the economy. The use of intelligent, self-sustaining WSNs for the perpetual monitoring of these structures provides not only structural reliability, but also public confidence in infrastructure stability (Catbas et al., 2008). This can be done in compliance with the concept of smart city with multifunctional sensor-installed systems that actively operate with data networks for efficient safety, mobility, and resource control.

Thus, the findings of this research support the proposed hypothesis that WSN-based SHM systems present a technically viable, cost-effective, and socially beneficial solution for real-time assessment of transportation structures. Through offering detailed information at high resolutions with regards to structural behavior, such systems help in carrying out maintenance exercises when necessary, cuts costs considerably in the operational aspect and most importantly enhances public safety tremendously. Though achievement of the ideal efficiency is still pending, the core domains that need improvement include the context of the sensors, analytical tools, power sources, and operating environment in conjunction with the participation of engineers, policymakers, and tech developers.

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