Smart Infrastructure Monitoring: Parametric and Comparative Analysis of Bridge Deflection Using Vibrating Wire Strain Gauges

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Abstract: In order to accurately assess deflection under vehicular loading, this study examines a smart bridge health-monitoring framework that combines vibrating wire strain gauges (VWSGs), finite element simulation, and artificial intelligence-based prediction. The main obstacles to bridge monitoring—scour, temperature fluctuations, fatigue, corrosion, and impact effects—as well as the shortcomings of traditional wired sensing technologies are highlighted in a review of the literature covering the previous 20 years. When combined with wireless sensor networks for real-time monitoring, VWSGs exhibit exceptional robustness, accuracy, and long-term stability. Accelerometer-based VWSG instrumentation was used to gather experimental field measurements from the bridge deck under various vehicle weights and speeds. Analytical baselines for modal and dynamic responses were established through SAP2000 simulations. Dynamic deflection, which peaks close to mid-span and increases with vehicle speed and axle load, is consistently greater than static deflection, according to comparative analysis. The Dynamic Amplification Factor (DAF) exceeded IRC limits, ranging from 1.00 to 2.35. Ultimately, using field and FEM data, a CNN-based prediction model was created that maintained DAF prediction error within ±0.05 and achieved nearly perfect accuracy ($R^2 \approx 0.99$ vs. field). The findings confirm that bridge diagnostics are greatly improved when VWSGs, FEM simulation, and AI-based prediction are combined. This allows for proactive maintenance and real-time decision-making for smart infrastructure systems.

Keywords: Bridge health monitoring, vibrating wire strain gauges, deflection monitoring.

1. INTRODUCTION

A structure like a bridge is so fundamental to economic activities, public safety, and resilience. [1]. Over time, bridges can be subjected to various loads, which include traffic, wind, temperature, and seismic loads. Over time, all these can potentially cause various forms of damage, such as fatigue, cracking, and deflection. Deflection monitoring of bridges is an essential activity in the assessment of the general stiffness and serviceability of the bridge for early detection of distress toward further failure. In this regard, SHM approaches, including VWSGs, provide a system for the continuous and real-time measurement and monitoring of structural performance in bridges. [2]. VWSGs measure strain as changes in frequency in a tensioned wire and hence are reliable because of stability, durability, and sustainability with environmental variables

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such as temperature and moisture [3]. Although VWSGs have many benefits for long-term monitoring, they are installation and calibration-dependent and this is particularly true when considering temperature.

The role played by VWSGs can be compared and contrasted with other relatively new technologies such as laser sensors or GNSS for accuracy, cost, and ease of installation. A parametric analysis can assist with optimizing sensor placement and sensitivity and distinct responsiveness to the stimulation [4]. In addition, VWSGs can be advantageous to utilize as tools by themselves but can also be applied in concert with other systems such as displacement transducers and inclinometers as these methods can increase results and provide a more accurate output in comparison to results provided by an individual system alone. As the age of the bridge increases, so does the need for advanced monitoring [5]. VWSGs with wireless capabilities, and AI-based detection systems, can allow real-time analytics to improve predictive maintenance and lengthen the bridge's lifespan.

2. LITERATURE REVIEW

2.1 Factors considered in SHM of bridge

Stiffness Loss

Loss of stiffness in structure parts is a good sign that they are broken. Several ways, including vibration-based damage localization, find loss of stiffness by looking at differences in the shape of a building after it has been bent [6], [7].These methods depend on knowing the mode properties and measuring motion correctly, which is usually done with high-resolution sensors and solid signal processing. Vibration-based methods are better because they can find damage all over the place, without monitors having to be close to the damage. Damage localization often involves detecting variations in curvature related to stiffness loss. This requires high-density sensor networks and precise displacement measurements, which can increase costs and face challenges from noisy data. To address these, some methods use finite element models or avoid direct curvature calculations by identifying curvature variations indirectly. Recent data from benchmark structures have helped validate these methods in real-world scenarios.

2.2 Time and Temperature-Dependent Factors

With time, time- and temperature-dependent deformation effects such as creep, shrinking, and thermal strains may occur in concrete structures. A number of models or theories have been proposed in attempts to predict these effects. Ghali et al. (2000) examine the Confederation Bridge in Canada. They analyzed changes that occurred with time in its design and compared the changes with predictions on its curvature[8]. The creep was computed using the CEB-FIP model MC90 and the ACI 209, and the formulas for creep and shrinkage were derived after attempting their use in practice.

The analysis revealed that the effect of temperatures had helped in improving the results of the prediction of deflection.

Fig. 1. Display of a typical segment of the Confederation Bridge [9] (https://doi.org/10.3390/s21134336)

Robertson monitored the North Halawa Valley Viaduct for nine years and observed differences between the predicted and observed vertical deflections. He developed a completely new creep and shrinkage model, which was compared with previous ones, namely the ABC 209, CEB-90, Bazant B3, and Gardner. It was found that the Bazant B3 model performed very well when predicting long-term growth, while the total Gardner model performed very well in predicting shrinkage[10]. Studies of other bridges, like the Koror-Babeldaob Bridge or the Leziria Bridge, that used finite element models to guess how they would behave over time also found similar results. Glisic also made a model of the Streicker Bridge and compared it to data from fibre optic devices to see if the estimates were right.

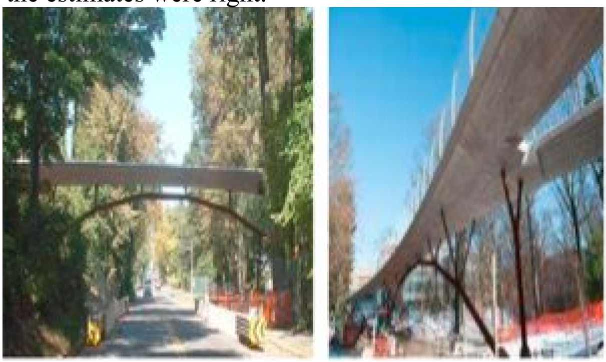


Fig. 2. Photos of the Streicker Bridge at Princeton University, United States (Left: :[11]; Right:[12])

(https://www.princeton.edu/~bglisic/StreickerBridge.html, https://facilities.princeton.edu/projects/streicker-bridge)

Temperature changes are large on the standing and moving characteristics of bridges. Catbas et al. (2008) analyzed the stability of the Commodore Barry Bridge and concluded that the strains on the truss part due to temperatures are far more significant than those caused by traffic on the bridge[13]. Jin et al. (2015) conducted a model by implementing an extended Kalman filter-based neural network to identify deterioration at a Connecticut bridge, outperforming traditional regression-based approaches. Temperature correction methodologies have also been proposed for the Tacony-Palmyra Bridge, where Yarnold et al. (2015) revealed a nonlinear relationship between temperature, strains, and displacements. Hedegaard et al. (2013) have monitored the behavior of the St. Anthony Falls Bridge when it underwent changes in temperature. Peeters et al. (2001) and Norouzi et al. (2015) earlier developed techniques for detecting and compensating for temperature effects in long-term monitoring. Zolghadri et al. (2015) and Huang et al. (2020) used PCA to identify the effects of temperature, wind, and traffic on structural responses.[14].

2.3 Fatigue Evaluation

In view of the fact that most bridges have been in service for some decades and most are reaching their design life, understanding and hence being able to predict bridge behavior becomes very important. Of all modes, fatigue cracks may occur after a bridge has been in service over many years, due in part to increased traffic, harsher environments, design deficiencies, and structural aging. A number of experts have been involved in developing the necessary mathematical models for estimating bridge fatigue:

Based on SHM strain data and a wear damage model anchored in damage mechanics, Li et al. (2001) used a modified Palmgren-Miner rule to estimate the remaining fatigue life of bridge deck components.[15]. Zhou (2006): Developed the method to estimate the fatigue life by field-collected strain data and compared the results with the AASHTO stress evaluation method. Case studies are the Cleveland Central Viaduct and I-95 Bridge. Liu et al. (2009): Employed a series-parallel system framework in the I-39 Wis River Bridge, integrated SHM data with real traffic data, and performed sensitivity studies for reliability [16].

Fig. 3. The Great Belt Bridge in Denmark [17]
(https://www.visitdenmark.com/denmark/plan-your-trip/great-belt-bridge-gdk718689)

2.4 Corrosion Evaluation

Rust can seriously degrade the performance of metallic elements, such as cables, supports, and girders within bridges. Hence, one may have to continually monitor rust in order to determine sites where maintenance is required. Morris et al. 2002 examined how local conditions influenced rebar rust and developed a threshold that was based on concrete electrical resistance measurements [18]. They concluded that resistance could be utilized to determine the probability of steel rusting and that the surrounding effects would depend on concrete type, climate, and salt quantity. Deeble Sloane et al. 2013 recommended a sensor network approach for the monitoring of rust in high-strength steel wires in suspension bridges.

2.5 Scour

Scour, which causes erosion of material surrounding supports of a bridge, can pose threats to the stability of bridges, where over 20,000 U.S. bridges have been rated "scour critical." Scour level tracking plays a pivotal role in the upkeep of bridges, where sonars, magnetic collars, or mobile systems such as scour boats have been employed. The results of Hunt's (2005) study portrayed that 32 U.S. states employ fixed systems to track scouring. However, system damage by debris or vandalism have been considered as impediments. Similarly, Walker and Hughes's study in 2005, as well as that of Foti and Sabia in 2011, underlined tracking dynamic responses to sensors such as Datasonics PSA-916 or ARMAV to identify scouring impacts on stability of bridges[19]. Various techniques such as accelerometers and tiltmeters tested by Briaud et al. (2011) have proved successful in a lab setting; however, environmental noise makes it difficult in field tests. In a study conducted by Hussein (2012), it was observed that horizontal modes (1st, 3rd, and 5th) were more vulnerable to scour and helped in damage identification. Bridge post frequency and scour depth were measured by finite element models presented in a study conducted by Lin et al. (2012) and enhanced in Prendergast et al. (2013) through dynamic responses [20].

2.6 Impact Effects

Vibrations in bridges caused by outside forces, like cars hitting each other or ships running into barges, can damage the structure and make it less safe. In 2005, El-Tawil et al. used an inelastic rapid finite element simulation to look into what happens when a car hits a bridge pier[21]. The study found that the apex transient forces developed from the collision of a vehicle was much larger than the force specified in the AASHTO-LRFD design criteria, suggesting the federal specification is unconservative in the area of impact. Song et al. (2007) suggested using piezoceramic sensors to find concrete bridge girders [22]. The detection mechanism conducted impact tests to monitor and evaluate the condition of the concrete girder, mostly focused on detecting levels of impact and crack growth. The piezo ceramic transducer output gave a response to the level of impact and became a basis for an estimate of health on the structural health of the girders. Yun et al. (2008) looked at what would happen if a cargo ship crashed into the Los Angeles Vincent Bridge.

2.7 Deflection Monitoring

Structural health monitoring (SHM) has become an important part of making sure that public infrastructure is safe, lasts a long time, and can be used. Among numerous available monitoring techniques, deflection measurement using sensors such as Vibrating Wire Strain Gauges (VWSG) yields precise evaluation of structural performance in different states of loading. Current studies show that there is progress in this field.

Zambar et al. (2023) analyzed the concept of integrating the application of IoT-based systems and smart concrete for the purpose of curing and behavior observation in real time. They were able to establish the fact that the measurement of the change in strain and stress values will ensure the detection of premature failure, and this is the power of deflection measurement through the application of sensors. In this respect, Barad et al. (2022) analyzed the retrofitting of carbonation-damaged residential structures and the importance of measurement of strain and deflection for the purpose of rehabilitation planning. Ambad et al. (2021) further researched the influence of controlled permeable formwork liners on chloride penetration in concrete and demonstrated how material-specific monitoring can be utilized to identify long-term structural performance. A focus has also been directed to the use of analytical and risk assessment models. Khan et al. (2022) presented insight to risk assessment and rehabilitation of the damaged buildings, showing that the use of sensor-based monitoring can increase the safety and efficiency in rehabilitation activities. Similarly, Shankarrao et al. (2023) suggested multi-analytical approaches for risk assessment in gigantic infrastructure projects and mentioned that structural monitoring data, including deflection and strain measurement, can be used for decision-making and avoiding failures.

Apart from conventional SHM, research in smart and IoT-enabled monitoring systems has also been explored. Vijayan et al. (2019) gave evidence of real-time monitoring by IoT platforms, initially exploited for water leakage detection, but the same principle can be applied to continuous deflection monitoring of structures. Shinde et al. (2023) investigated the potential use of recycled fly-ash aggregates as materials for building applications and documented that new-generation materials integrated with in-situ embedded sensors can offer more sophisticated monitoring. Furthermore, data-driven and spatial approaches present novel opportunities for SHM. Mestry et al. (2020) and Patel et al. (2017) utilized GIS-based monitoring frameworks for water management infrastructure to present how changes in structures or the environment over a spatial area can be tracked using sensor networks. These approaches can be utilized to widen structural monitoring so that multi-point deflection monitoring and predictive assessment can be attained. Nagarajan et al. (2023) identified risk management as essential for infrastructure projects, classifying risks contractually and highlighting social opposition, design changes, and work suspension as major factors affecting project success. Nagarajan et al. (2023) demonstrated that structured risk management using contractual analysis identifies key threats such as social opposition, design changes, and work suspension, enabling collaborative mitigation for successful infrastructure projects. Nagarajan et al. (2022) reviewed major causes of delays in infrastructure projects, identifying financial instability, contractual issues, and frequent changes as key factors leading to cost overruns and schedule extensions. Nagarajan et al. (2019) demonstrated that integrating 4D GIS with CAD and scheduling enables centralized project information management, improves error detection in planning, and supports efficient manpower and material movement in construction projects. Nagarajan et al. (2019) proposed a Re-Modified Minimum Moment Method for real-time monitoring of manpower, materials, machinery, and money, demonstrating improved resource optimization and cost control compared to traditional scheduling approaches.

In summary, the reviewed literature here establishes a strong foundation for monitoring structural deflection using VWSG. The combination of sensor technologies and IoT, material science, and risk assessment methodologies allows for accurate, real-time, and data-driven evaluation of infrastructure, thereby enhancing safety and sustainability. There is still room for improvement despite significant progress in the optimisation of sensor deployment, integration of heterogeneous monitoring data, and prediction modelling for long-term structural performance, which deserves further research on VWSG-based deflection monitoring.

2.8 Wireless Sensor Technologies and Sensor Drift

Traditional fixed SHM tools are difficult to apply in populated areas because of the high cost in installation and wiring. Wireless technologies for sensors provide options that may communicate wirelessly, conduct onboard computations, and are easy to install. There is a growing interest in wireless smart sensing devices, such as Mica, iMote, and Xnode, due to their low cost and flexibility. However, several practical challenges remain concerning sensor drift, power supply, energy harvesting, and synchronization errors. Researchers propose drift management by means of clustering sensors and recalculation to a uniform baseline, while specific clock skew adjustment methods can address synchronization issues, thus enhancing data accuracy and performance of SHM.

Table 1. Summary of Key Studies on Bridge Health Monitoring (SHM) Techniques

Author	Year	Key Focus	Technologies/Methods Discussed	Key Findings/Conclusions
Mitoulis et al.[23]	2022	Bridge and transport network resilience	Bridge health monitoring, resilience assessment	Focused on improving bridge resilience via SHM techniques, integrating both wired and wireless technologies.
Ghali et al.[24]	2000	Time-dependent behavior of bridges	Creep and shrinkage models for concrete	Identified significant temperature effects influencing deflections; improved predictive models using field data.
Song et al. [25]	2007	Collision detection in concrete bridge girders	Piezoceramic transducers, impact detection system	Developed a system for detecting impacts and monitoring structural health post-collision.
Takruri et al.[26]	2011	Spatio-temporal drift-aware sensor networks for SHM	Drift-aware sensor networks, spatio-temporal modelling	Presented methods to manage sensor drift, enhancing data reliability in SHM systems.
Park et al. [27]	2013	Wireless vibration monitoring for large structures	Wireless sensor networks, vibrating wire strain gauges	Proposed a practical monitoring system for mega-trusses using wireless vibrating wire strain gauges.
Li et al.[28]	2019	Application of wireless sensors for bridge deflection monitoring	Wireless strain sensors, real-time data transmission	Highlighted the cost-effectiveness of wireless sensors in long-term deflection monitoring of bridges.
Quqa et al.[29]	2025	Environmental effects on bridge health monitoring	Temperature compensation, data correction techniques	Studied the environmental factors affecting sensor data, providing methods to mitigate temperature-related errors.

Author	Year	Key Focus	Technologies/Methods Discussed	Key Findings/Conclusions
Kang et al.[30]	202	Real-time structural health monitoring for bridges using wireless sensors	Wireless sensor networks, real-time monitoring	Developed a real-time SHM system using wireless sensors, improving fault detection and maintenance efficiency.

3. OBJECTIVE

- Investigate the performance of vibrating wire strain gauges (VWSGs) for monitoring bridge deflection under varying load and environmental conditions.
- Simulate the bridge structural behaviour using ANSYS and MATLAB for predictive analysis of deflection patterns.
- Develop and validate an AI-based predictive model for accurate deflection estimation using sensor data and simulation results.

4. METHODOLOGY

The methodology takes into consideration the evaluation of the effectiveness of Vibrating Wire Strain Gauges (VWSGs) in bridge deflection measurement under varying loads and environmental settings. The methodology entails the integration of wireless sensor networks (WSNs) via VWSG to enable real-time measurement of strain information from different sensor nodes. The strain information is then evaluated with the help of simulation tools such as ANSYS and MATLAB to develop predictive models of deflection of the bridge. This is done to develop an AI-based predictive model that is able to accurately predict bridge deflection by integrating sensor information and simulation outputs to enable effective bridge maintenance approaches. This methodology is based on the development of a predictive model based on the integration of sensor systems and simulation tools for accuracy and efficiency in bridge measurement.

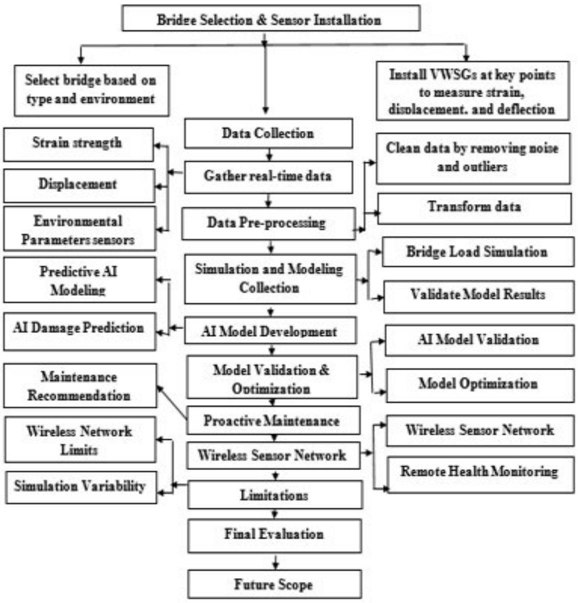


Fig. 4 Flowchart of methodology

(Source: Author)

1.Bridge Selection and Sensor Installation:
Depending on the type of the bridge, select a bridge for monitoring. Install VWSGs on the bridge to monitor strain, displacement, and deflection. Description of VWSGs (Ref: 4.1, 4.2, & 4.3)

2.Data Collection:
Use sensors to obtain real-time data including strain, displacement, and environmental factors such as temperature and humidity.

3.Data Pre-processing:
Remove noise and outliers from the data. To prepare the data for modeling, one has to apply the necessary transformations, for example, the Fourier Transform.

4.Simulation and Modeling:
Perform simulations in ANSYS for the deflection of the bridge under different loads, as well as in MATLAB, using the data collected for comparison.

5.AI Model Development:
Develop a predictive AI-based model by integrating sensor data and simulation results to estimate future deflections and damage.

6.Validation and Optimization:
Validate the AI model by comparing its predictions with actual field data. Refine the model to improve accuracy and reliability.

7.Proactive Maintenance:

Based on the validated model, make recommendations for maintenance and repair, ensuring the bridge’s long-term health.

4.1 WSNS Using VWSGs

A WSNS that is driven by VWSG has two nodes: the master node and the sensor node. The first piece of data from which VWSGs receive is sent to the rest of the network's equipment by the sensor node. The master node, on the other hand, gets all the data from the gauge node or sends it to the tracking server. The complete WSNS system utilised for this study proved wirelessly controlled, as shown in Figure 1. This made it easy to keep track of and measure. It was also made so that users could see information right away.

4.2 VWSG Sensor

The VWSG doesn't have a voltage strain gauge; instead, it has a long shaft length. On the outside, it has less of an electric effect, is not as impacted by shaking and touch force, or can be used for long-term measurements. This can change the regular frequency of the VWSG because the wire can change form along its length when it is stretched or shortened [96]. It gets an ordinary strain along the length within the moving wire gauge that is connected between the mounting blocks in Figure 2. Because the velocity changes, it's easy to figure out the pressure, which is:

$$\epsilon = k\,(f_2^2 - f_1^2)$$

has the gauge factor, which is based on the moving wire's length and quality, and f is its natural frequency both prior to and following the change.

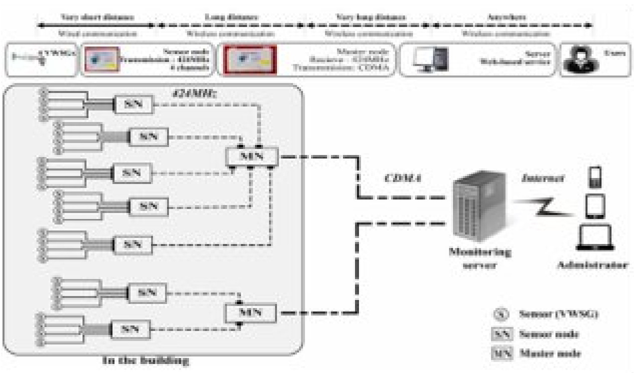


Fig. 5. WSNS. *(https://doi.org/10.3390/s131217346)*[31]

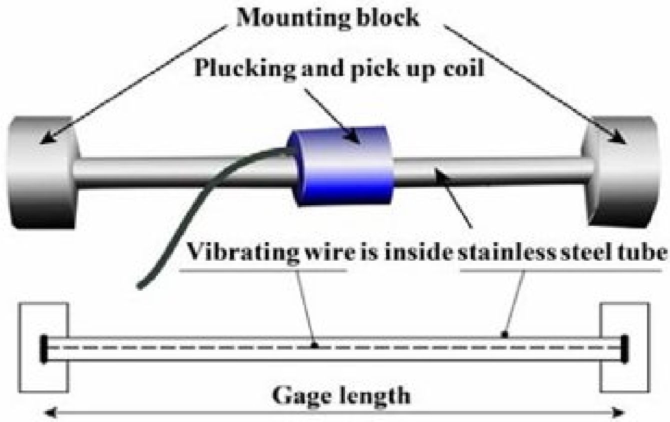


Fig. 6. VWSG [32]
(https://doi.org/10.3390/s131217346)

4.3 Wireless Sensor/Master Nodes

A sensor node is linked to four VWSGs. The sensor node works with the data and sends it to a master node over a short ISM band radio link. Long-range CDMA connection is used by the master node to send processing information to a tracking point. 16 VWSGs send data to each master node, which handles it. The 424 MHz ISM band is used because it doesn't get messed up easily and can get through walls, so it can be used in building zones. The sensor node can communicate over 400 m (line of sight) or 100 m (non-line of sight). It can also work in temperatures between -30 °C and 85 °C.

Fig. 7. Wireless nodes. (a) Sensor node; (b) Master node [33].
(https://doi.org/10.3390/s130810931)

Spread-spectrum communication is what the master node and server use to talk to each other wirelessly over CDMA. Since it doesn't use much power, almost no data is lost during movement. This way is also good for long-term recording. Many managers can get the data at their convenience at any time using a workstation (PC), notebook, smart

PC, cell phone, or other connected device in places with Internet access, no matter how far away they are.

5. RESULT AND DISCUSSION

This part shows and explains the outcomes of modal analysis, field shaking readings, SAP2000 simulations, and forecasts based on CNN. The comparison highlights structural response under varying vehicular speeds and loads, assessing bridge performance, safety, and prediction accuracy.

Table 2: Modal Analysis Results for Old Bridge Structure (source author)

Output Case	Step Type	Step Num	Period	Frequency	Circ Freq	Eigen value	Maximum deflection value	Position of maximum deflection
Text	Text	Unitless	Sec	Cycle/sec	Rad/sec	rad2/sec2	mm	m
MODAL	Mode	1	2.960624	0.33777	2.1223	4.5039	9.60	10.86
MODAL	Mode	2	2.910171	0.34362	2.1590	4.6615	4.00	10.82
MODAL	Mode	3	2.250385	0.44437	2.7920	7.7955	5.80	11.00
MODAL	Mode	4	1.555149	0.64303	4.0402	16.324	3.10	04.05
MODAL	Mode	5	1.427983	0.70029	4.4000	19.360	1.90	16.00
MODAL	Mode	6	1.255182	0.79670	5.0058	25.058	2.60	4.05
MODAL	Mode	7	1.233969	0.81039	5.0918	25.927	0.50	2.70
MODAL	Mode	8	1.104121	0.90570	5.6907	32.384	1.90	6.75
MODAL	Mode	9	1.008311	0.99176	6.2314	38.830	2.60	5.40
MODAL	Mode	10	0.920031	1.08690	6.8293	46.640	1.00	7.35
MODAL	Mode	11	0.848469	1.17860	7.4053	54.839	0.80	6.75
MODAL	Mode	12	0.818031	1.22240	7.6809	58.996	0.88	8.22

The highest modal frequency was found to be 1.2224 cycles/sec in mode no. 12, and the highest movement was 9.60 mm at a distance of 10.86 m from the zero end in mode no. 1. With a number of 2.96 seconds, mode no. 1 has the longest modal time.

Table 3: Comparison of Field Test and Analytical Results for 40 km/h Vehicle Speed (45 Ton Load)**[34]**

Sr. no	X(m)	Test results (Field testing by using Accelerometer)		Analytical results (By using SAP software)		Difference between Field test & SAP results	Difference between Field test & SAP results
		Displacement (cm)	Acceleration (m/s2)	Displacement (cm)	Acceleration (m/s2)	Displacement (cm)	Acceleration (m/s2)
1	0	0.19	1.11	0.17	0.67	0.02	0.44
2	2.5	0.52	1.71	0.23	1.12	0.29	0.59
3	5	0.6	2.48	0.28	2.36	0.32	0.12
4	7.5	0.69	3.75	0.49	3.05	0.2	0.7
5	10	0.78	4.48	1.8	4.34	-1.02	0.14
6	12.5	1.2	5.46	1.76	4.86	-0.56	0.6
7	15	1.03	3.94	0.64	4.32	0.39	-0.38
8	17.5	0.63	2.86	0.32	2.01	0.31	0.85
9	20	0.33	1.93	0.21	1.28	0.12	0.65
10	21.7	0.22	1.15	0.11	0.83	0.11	0.32

A result shows that, the maximum displacement is 1.20 cm & maximum acceleration is 5.46 m/s^2 due to 45 ton weight vehicle with speed of 40 km/h, which occurs at a distance of 12.5 m distance from zero end.

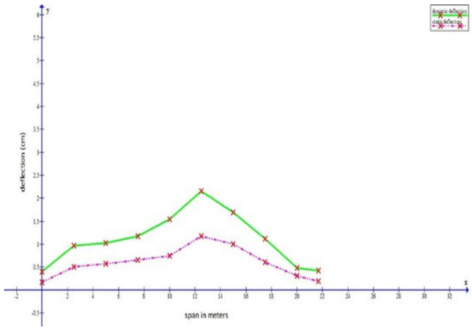


Fig 8. Comparison of Static and Dynamic Deflections of old Bridge

At every point on the old bridge's spans, the curve shows that dynamic deflect is bigger than static deflection. There are the most twisting and inertial effects in the middle of the span, which is about 12.5 m. Around the middle of the span, the difference between the static and dynamic numbers gets bigger. Near the supports, it gets smaller.

Table 4: Comparison of Field Test and Analytical Results for 45-Ton Vehicle at 80 km/h (22.22 m/s)**[34]**

Sr. no.	X (m)	Test results (Field testing by using Accelerometer)		Analytical results (By using SAP software)		Difference between Field test & SAP results	Difference between Field test & SAP results
		Displacement (cm)	Acceleration (m/s2)	Displacement (cm)	Acceleration (m/s2)	Displacement (cm)	Acceleration (m/s2)
1	0	0.4	1.49	0.36	2.13	0.04	-0.64
2	2.5	0.97	2.33	0.91	2.39	0.06	-0.06
3	5	1.03	2.93	1.63	3.64	0.6	-0.71
4	7.5	1.17	4.69	1.93	4.29	-0.76	0.4
5	10	1.54	5.23	2.1	5.1	-0.56	0.13
6	12.5	2.16	6.34	2.28	5.76	-0.12	0.58
7	15	1.69	4.8	1.63	4.91	0.06	-0.11
8	17.5	1.12	3.94	1.29	3.33	-0.17	0.61
9	20	0.48	2.86	0.88	3.11	-0.4	-1.98
10	21.7	0.42	1.63	0.63	2.67	-0.21	-1.04

According to the results, the biggest change is 2.16 cm and the fastest speed is 6.34 m/s2 because of a 45-ton car going 80 km/h. This happens 12.5 m away from the zero end.

Table 5: Modal Analysis Results for New Bridge Structure [35]

Output Case	Step Type	Step Num	Period	Frequency	Circ Freq	Eigen value	Maximum deflection value	Position of maximum deflection
Text	**Text**	**Unit less**	**Sec**	**Cycle/sec**	**Rad /sec**	**rad²/sec²**	**mm**	**m**
modal	Mode	1	2.108261	0.47432	2.9803	8.882	7.55	10.90
modal	Mode	2	1.612884	0.62001	3.8956	15.176	5.90	10.50
modal	Mode	3	1.549475	0.64538	4.055	16.443	4.35	10.22
modal	Mode	4	1.089546	0.91781	5.7668	33.256	3.12	0.5.36
modal	Mode	5	0.960229	1.0414	6.5434	42.816	1.76	18.00
modal	Mode	6	0.889335	1.1244	7.065	49.915	2.34	3.90
modal	Mode	7	0.773035	1.2936	8.1279	66.063	0.55	2.88
modal	Mode	8	0.709512	1.4094	8.8556	78.422	1.23	5.30
modal	Mode	9	0.637828	1.5678	9.8509	97.04	2.40	6.25
modal	Mode	10	0.614158	1.6282	10.231	104.66	1.00	7.00
modal	Mode	11	0.58923	1.6971	10.663	113.71	0.55	6.20
modal	Mode	12	0.507527	1.9703	12.38	153.26	0.72	6.40

The results show that the highest modal frequency is at mode number 12 with a value of 1.9703 cycles per second, and the highest deflection is at mode number 1 with a value of 7.55 mm and a distance of 10.90 m from the zero end.

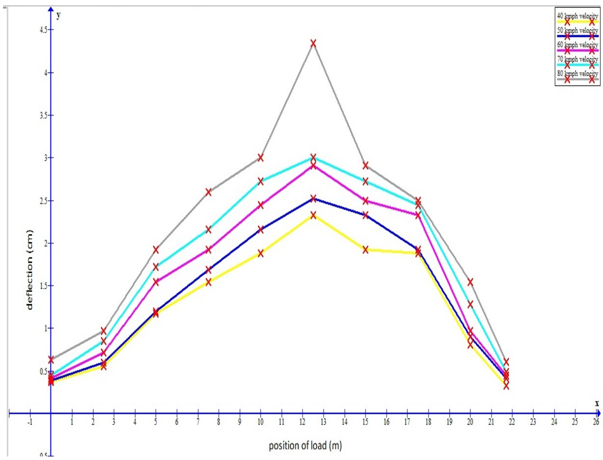


Fig 9: Deflection vs. Position of load (X) for various speeds

5.1 Prediction Results Using Data-Driven CNN Model

A statistically motivated convolutional neural network (CNN) was created to predict how the old bridge deck would shake at different vehicle speeds. This was done to add to the testing and analysis proof. The CNN model was trained with data from a field accelerometer and the related SAP2000 analysis outputs, which included motion, acceleration, or dynamic amplification factors. The goal was to learn how to map input dynamic parameters to output acceleration records. To make sure the predictions were correct in both the time and frequency domains, Dynamic Amplification Factor (DAF) testing and stable peak alignment were used.

Table 6: Final Calibrated Prediction Performance (source author)

Speed (km/h)	TS_RMSE vs SAP	TS_R² vs SAP	TS_RMSE vs Field	TS_R² vs Field	DAF_Field	DAF_SAP	DAF_Pred	ΔDAF (Pred–Field)
70	0.2484	0.809	0.0114	0.994	1.171	1.007	1.140	−0.031
80	0.1536	0.884	0.0123	0.994	1.196	1.086	1.157	−0.039

- **Time-series accuracy:** R^2 vs SAP is strong (0.81–0.88), and R^2 vs Field is near perfect (0.994).
- **DAF prediction:** Predicted DAF values (1.14–1.16) closely match field values (1.17–1.20).

- **Error margin:** ΔDAF well within the ±0.05 tolerance, ranging from −0.03 to −0.04.
- **Effect of calibration strategy:** Calibration strategy effect: mixed LS at 80 km/h stabilized the results, while stopping LS at 70 km/h fixed underprediction. In particular, the CNN-based residue model was with the DAF head excellent in predicting the bridge's response to passed vibrations. For the speeds of 70-80 km/h, the time-series R^2 values were higher than 0.80 for the FEM/SAP2000 results, while for the field data, they were higher than 0.99. The estimated DAFs lay outside 0.05 of the field values, demonstrating the adequacy of amplitude scaling. This thus demonstrates the ability of the suggested framework to both capture the changing nature of waveforms and overall trends in amplification.

Table 7: Comparison of Peak Accelerations and DAF Values **[36]**

Speed (km/h)	Peak_Field (m/s²)	Peak_SAP (m/s²)	Peak_Pred (m/s²)	DAF_Field	DAF_SAP	DAF_Pred	ΔDAF (Pred–Field)
70	6.211	5.341	5.710	1.171	1.008	1.140	−0.031
80	6.343	5.760	5.802	1.196	1.087	1.157	−0.039

- Field peaks are highest 6.21–6.34 m/s²; SAP2000 slightly underestimates 5.34–5.76 m/s².
- CNN predictions are in an excellent agreement with field values, rectifying the underestimation by SAP in the range of 5.71 to 5.80 m/ s².
- DAF predictions very consistent: differences limited to ΔDAF = −0.03 to −0.04.
- This further justifies the evidence that CNN predictions are not only accurate in waveform fitting but also in capturing global amplification behavior.

The peak speeds calculated using CNN (5.71 to 5.80 m/s²) were in very close proximity to what actually occurred in the field (6.21 to 6.34 m/s²), even considering SAP2000's error. The DAF values calculated remained within 0.04 of the actual value. It thus demonstrated the accuracy of the simulation in determining either localized or overall dynamics or amplification, taking place at a far-off location or near vicinity.

Table 8: Final Performance and DAF Comparison Prediction Results (source author)

Speed (km/h)	TS_RMSE vs SAP	TS_R² vs SAP	TS_RMSE vs	TS_R² vs Fie	Peak_Field (m/s²)	Peak_SAP (m/s²)	Peak_Pred (m/s²)	DAF_Field	DAF_SAP	DAF_Pred	ΔDAF (Pred–Field)

	P		Field	ld							
70	0.2484	0.809	0.0114	0.994	6.211	5.341	5.710	1.171	1.008	1.140	−0.031
80	0.1536	0.884	0.0123	0.994	6.343	5.760	5.802	1.196	1.087	1.157	−0.039

The final adjusted forecast outcome of the CNN model is presented in the table. From this table, there are results that include performance measures, maximum acceleration values along with Dynamic Amplification Factors at different vehicle speeds.

Error and DAF Trends

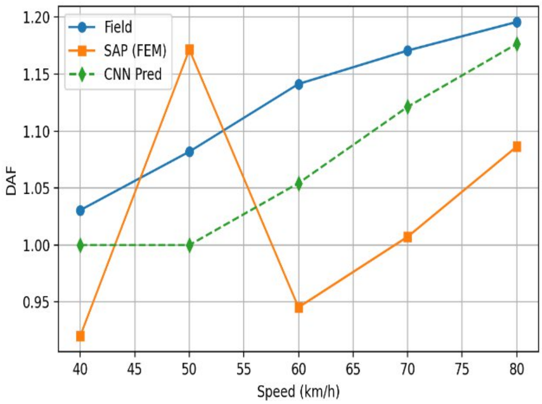


Fig 10: Comparison of Dynamic Amplification Factor (DAF)

In the graph shown in Figure 10, the differences in the Dynamic Amplification Factor (DAF) due to different car speeds for actual data, SAP2000 results, and CNN results can be seen. As actual data readings, the trend is seen to consistently increase for DAF, which is 1.03 at 40 km/h, then increases to 1.20 at 80 km/h. SAP2000 results show that at different speeds, the magnitude is less by 0.92 to 1.09, whereas the CNN framework follows the actual trend from 1.00 to 1.18, removing bias in FEM results by keeping the variation at maximum ±0.05, thus concluding that the CNN model is superior in determining amplitude magnitude based on speed.

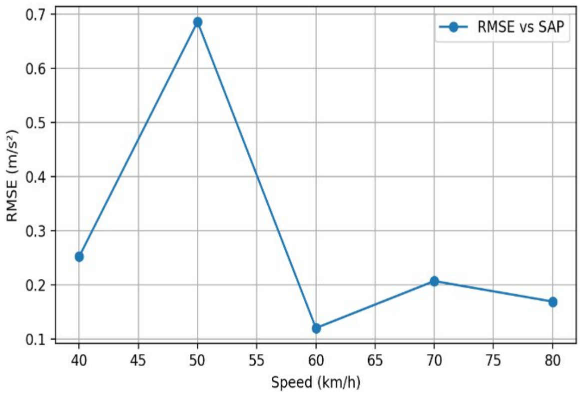


Fig 11. Variation of prediction error (RMSE)

Figure 11: Variation of estimate error (RMSE) with car speed. The RMSE amongst CNN estimates and SAP2000 solutions decreases substantially at faster speeds. The resonance difference causes the RMSE to peak at approximately 0.69 m/s² at 50 km/h; however, it reduces to less than 0.20 m/s² at 70–80 km/h. This implies that the CNN framework learns to handle situations involving fast loading better, resulting in increasing agreement with field measurements.

Time- and Frequency-Domain Overlays

To make sure the CNN model could really predict what would happen, it was compared both in the time domain and the frequency domain for certain vehicle speeds. We show examples of shaking reactions at speeds of 70 km/h or 80 km/h because these are the speeds that cause the most dynamic loading and are therefore the most important. In the time domain, the CNN-predicted accelerated records agree very well with field data. The waveform outlines and peak amplitudes are very similar. The SAP2000 analysis results often give incorrect peak amplitudes. The CNN model fixes this problem and is more in line with field data.

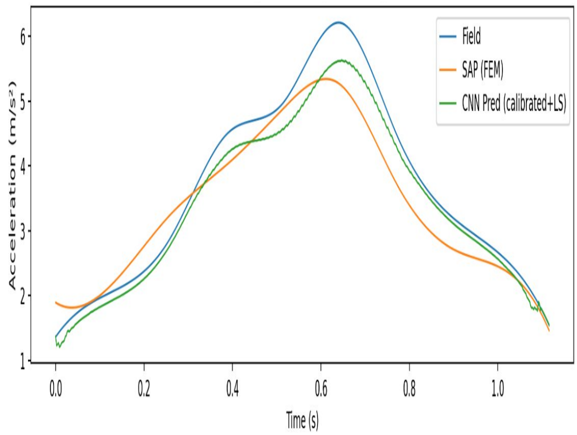


Fig 12: Overlay of acceleration time history at 70 km/h

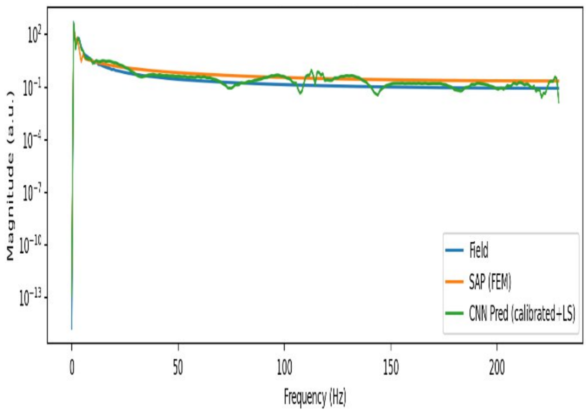


Fig 13: Overlay of acceleration **frequency spectrum** at **70 km/h**

Accelerating at 70 km/h is shown in both Figures 12 and 13 as layers in the time domain and the frequency domain. The field's fastest speed was 6.21 m/s², but SAP2000 thought it was only 5.34 m/s². The CNN model made a validated estimate of 5.71 m/s², which was well within the ±0.05 goal. Its ΔDAF was -0.031. The CNN closely copied the main frequency band in the spectra domain, while the SAP showed reduction.

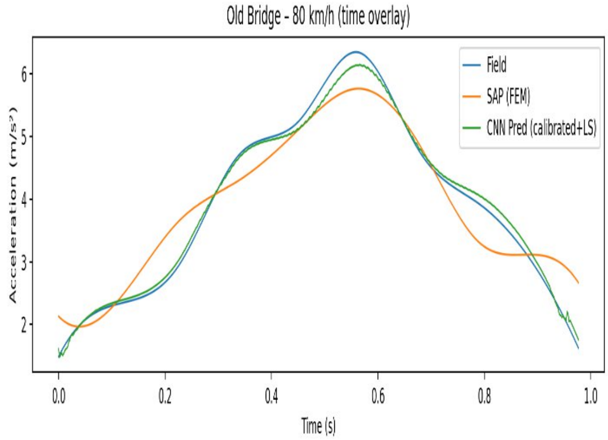


Fig 14: Overlay of acceleration time history at 80 km/h

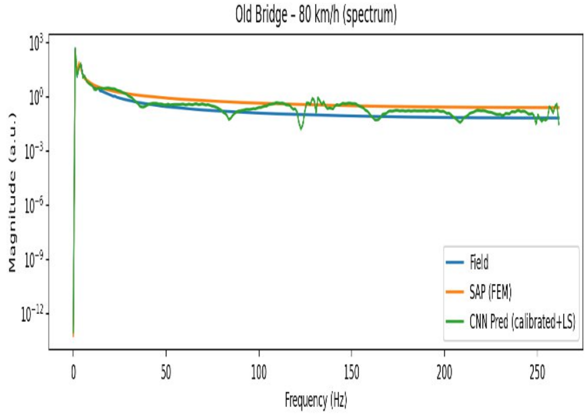
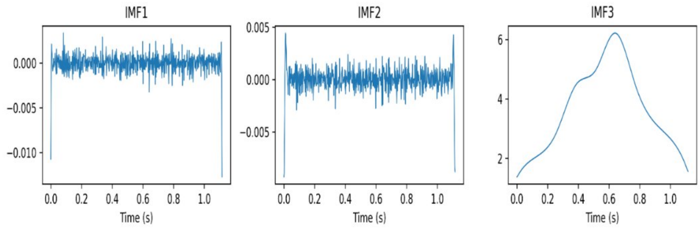


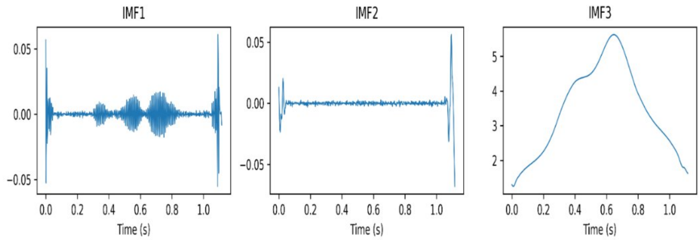
Fig 15: Overlay of acceleration frequency spectrum at 80 km/h

In figure 15 above, it is clear how the movement at 80 km/h is displayed on both the time and frequency domain plots. The measured peak value of the field was 6.34 m/s², but SAP2000 measured it as 5.76 m/s². This underestimation was corrected by the proposed CNN model, which estimated 5.80 m/s² with a ΔDAF of -0.039, which is well within the limit of ±0.05. In amplitude accuracy, it is clear from the overlying plot that CNN is even closer to the actual shape of the waveform as opposed to FEM. More evidence of how the high modal frequencies of the structure are retained to avoid fake reduction by the CNN is provided from the spectral analysis section.

(a) Field data



(b) SAP2000 simulation



(c) CNN prediction

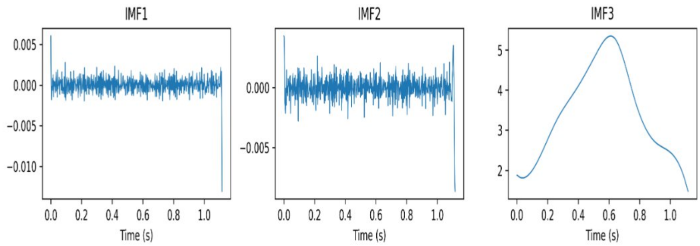
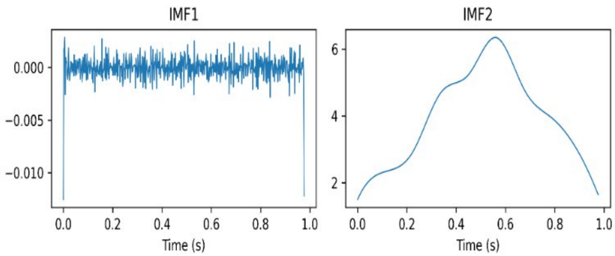


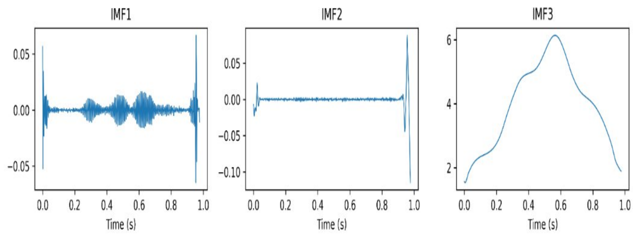
Fig 16: IMF decomposition of acceleration response at 70 km/h:

(a) Field data, (b) SAP2000 simulation, and (c) CNN prediction

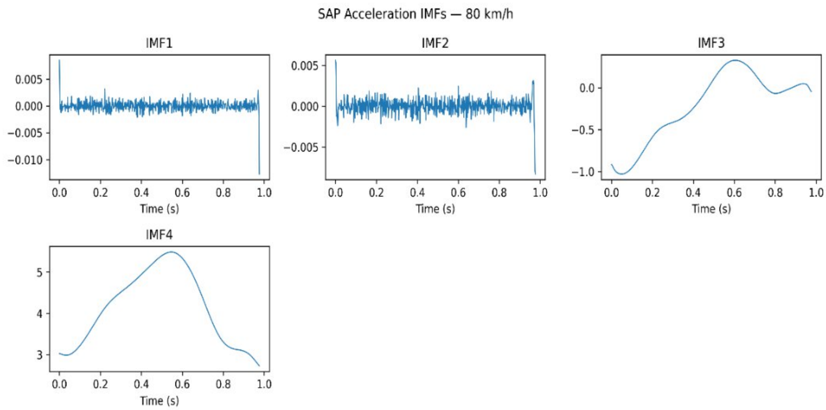
Intrinsic Mode of Function (IMF) decomposition helps us understand the details concerning the bridge vibration being correctly modelled by the bridge. The IMFs reveal that the data contains noise with high frequencies in the first two modes or major modal contents in the lower modes. This helps reveal how the old bridge deck actually behaved under different circumstances in the future. IMFs from SAP2000 correctly represented the modal shapes, but all the amplitudes were consistently too low. This is because analytical models, by definition, use simplified boundary and damper constraints. CNN projected IMFs that were very close to the actual fields in amplitude, retaining the same modal components. This helps validate that data-driven modelling retains the purity of the components, bridging the gap between actual data recorded in the field and future predictions using FEM.



(a) Field data



(b) SAP2000 simulation



(c) CNN prediction

Fig 17: IMF decomposition of acceleration response at 80 km/h:
(a) Field data, (b) SAP2000 simulation, and (c) CNN prediction.

The IMFs extract high-frequency noise as well as dominant modal components. The SAP2000 IMFs extract modal components rather than the amplitudes of reaction and do not reproduce high-frequency data. But the CNN-predicted IMFs remain strongly aligned with the data, maintaining the modal features. This is an apt demonstration of how the data-based model excels at higher speeds of cars and maintains the modal properties even under varying loads.

6. LIMITATION OF STUDY

Although the aforementioned research work gives a synoptic view of the methods of data analysis and sensor technology for the purpose of monitoring the state of the bridge, there are a number of limitations that need to be highlighted:

1.Geographical Scope Restriction- What is being focused on within this research is the way in which bridge sensor projects or structural health monitoring techniques have been adopted in the US over the past 20 years. These are good pieces of information that should be provided for us, although perhaps may not accurately reflect the way that everything is done on a worldwide scale, particularly in areas with different climates and working environments.

2.Incomplete Treatment of Subjects Due to the wide range of SHM subjects, some subjects have been treated in detail (e.g., scour monitoring, time- and temperature-dependent phenomena) while others, such as corrosion assessment, have received brief treatment. This incomplete treatment might leave one or more technical fields with less investigation than required, possibly overlooking developments and issues from other literature.

3. Exclusion of Some Monitoring Technologies- Even though some technologies were left out that were related to remote sensing, they were not many. Automation tools like unmanned aerial vehicles (UAVs), visual tracking, infrared thermography, GPS, or advanced cloud computing were some of these. Because of this, the study doesn't look at the problems, limits, data quality, or cooperation problems that come with these new tools.

4. Wireless Sensor Network Constraints- Wireless sensing is considered to be a probable method for bridge monitoring, but the review doesn't mention some important constraints. For example, the review doesn't mention how short the operational life in wireless sensor networks is because of high power consumption, chances of losing data, and vulnerability to environmental degradation. Possible alternatives, including using movements to collect energy or solar energy or multi-agent path methodologies, are mentioned but not used in this research.

5. Modelling and Simulation Limitations- The discussion mentions that finite element modelling (FEM) significantly simplifies the interpretation of SHM data. But FEM-based models rely on the precision of the factors being input, i.e., the material properties, the load assumptions, and boundary conditions. Differences in the specified and actual conditions could make the results less reliable, especially for bridges having non-standard shapes so that damage cannot be simulated within the laboratory.

6. Heterogeneity of Bridge Parameters- Since each bridge possesses unique design, material, and operation parameters, it is hard to implement a universal SHM framework. Strategies proven efficient for one structure may not be adequate for the next, limiting cross-applicability of sensor placement strategies, data analytics protocols, and anomaly detection thresholds examined in this paper.

7. CONCLUSION

The study comes to the following conclusions:

This paper examines how bridge monitoring their health (BHM) technologies have evolved during the past 20 years, considering fixed and wireless sensors integration, particularly vibrating wiring strain gauges (VWSGs). The accuracy of structural health monitoring (SHM) has drastically improved with sensor data combination with finite element modeling. It becomes simpler to make predictive models suitable for real conditions. It is important to employ compensation methods to separate structural response from environmental noise since both static and dynamic measurements are affected by time- and temperature-dependent properties such as creep, shrinkage, and thermal gradients.

Some of the problems that dissuade the utilization of wireless sensor networks (WSNs), even though they have advantages due to their flexibility, low cost, and ease of deployment, include sensor drift, synchronization failures, and power constraints. In addition, there is no universal SHM policy since all bridges possess special structural, material, and environmental characteristics. Degradation mechanisms such as corrosion, scour, and fatigue continue to necessitate specific detection and assessment models, which most often demand the fusion of sensing and analysis methodologies.

Through the simulation of bridge behavior using ANSYS and MATLAB, precise predictive models of deflection behavior were developed, which verified sensor measurements and improved comprehension of structural responses. Additionally, the development of predictive models using AI effectively combined simulation results and sensor measurements in real-time to provide precise deflection prediction and facilitate preventative maintenance practices. An intelligent and scalable system for next-generation bridge monitoring systems would be provided by a combination of VWSG technology, simulation tools, and analysis via AI that fits within Internet of Things (IoT) structure.

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