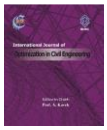
INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2026; 16(2):285-299



PREDICTION OF BRIDGE ACCELERATION RESPONSES USING AN ADAPTIVE AWAN FRAMEWORK

M. Talebi and G. Ghodrati Amiri*, †
School of Civil Engineering, Iran University of Science & Technology, Tehran, Iran

[DOI: 10.22068/ijoce.2026.16.2.678]

ABSTRACT

Bridge Health Monitoring (BHM) plays a vital role in ensuring the safety, reliability, and long-term performance of bridge infrastructure. This study proposes an ARMA–Wavelet–Artificial Neural Network (AWAN) framework for predicting unmeasured bridge deck acceleration responses from limited sensor measurements. The proposed methodology integrates Auto-Regressive Moving Average (ARMA) modeling for temporal feature extraction, Continuous Wavelet Transform (CWT) for signal denoising, and a feed-forward Artificial Neural Network (ANN) for nonlinear response prediction. The combined framework exploits both spatial and short-term temporal correlations to achieve accurate response reconstruction while maintaining computational efficiency. The proposed framework was validated using three bridge models, including a simply supported beam, a two-span steel grid benchmark, and a scaled single-plane cable-stayed bridge. Prediction performance was evaluated using different statistical metrics under multiple loading scenarios. The results demonstrated excellent agreement between the predicted and measured acceleration responses, with higher prediction accuracy generally achieved at mid-span locations than near the supports, reflecting differences in local structural dynamics. In addition, the framework maintained stable performance under moderate temperature variation, demonstrating its robustness for practical bridge health monitoring applications.
The proposed AWAN framework provides an efficient and reliable approach for reconstructing unmeasured structural responses while reducing sensor requirements. Its combination of prediction accuracy, computational efficiency, and robustness makes it a promising tool for data-driven bridge health monitoring and response reconstruction.

Keywords: Bridge Health Monitoring; Acceleration response prediction; ARMA; Wavelet Transform; Neural Network; Response Prediction; Cable-stayed bridge.

Received: 19 March 2026; Accepted: 22 May 2026

---

*Corresponding author: School of Civil Engineering, Iran University of Science & Technology, Tehran, Iran
†E-mail address: ghodrati@iust.ac.ir (G. Ghodrati Amiri)

1. INTRODUCTION

Bridge infrastructure is fundamental to transportation networks and public safety, and systematic performance assessment is essential for ensuring long-term reliability while minimizing maintenance costs. Bridges are continuously subjected to traffic loads, environmental actions such as temperature variations, corrosion, and wind, as well as material aging, all of which contribute to structural deterioration over time. Consequently, regular inspection and continuous monitoring are required to detect early-stage damage before it develops into critical failures. In this context, Structural Health Monitoring (SHM) has emerged as an effective approach that integrates sensing technologies with data acquisition, signal processing, and analytical techniques to continuously evaluate the condition and performance of bridge structures [1-5].

Recent advances in sensing technologies have enabled continuous measurement of bridge dynamic responses, providing valuable information for condition assessment and early damage detection. However, accurately reconstructing the full-field structural response from a limited number of measurement locations remains a major challenge in bridge monitoring. Furthermore, non-stationary responses, environmental and operational variability, and measurement noise often reduce the reliability of conventional assessment techniques. Consequently, modern SHM systems have increasingly incorporated time-series analysis, machine learning, and artificial intelligence (AI) to improve prediction accuracy and automate structural condition assessment [4, 6-9].

The rapid development of AI has significantly expanded the capabilities of data-driven SHM. In addition to conventional machine learning algorithms, deep learning architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNNs), and Transformer-based models have demonstrated excellent capability in learning complex temporal and spatial relationships from structural monitoring data. These approaches have been successfully applied to bridge response prediction, missing-data reconstruction, damage detection, and anomaly identification under varying operational and environmental conditions. Nevertheless, their superior predictive performance is often accompanied by increased computational cost, large training datasets, and extensive hyperparameter tuning, which may limit their practical implementation in real-time bridge monitoring systems. Recent studies and comprehensive reviews have further emphasized the growing role of artificial intelligence and machine learning in civil engineering while highlighting the need for computationally efficient and robust prediction frameworks for practical infrastructure monitoring applications [10-14].

Time-series analysis remains one of the most widely adopted techniques in SHM because of its ability to characterize the dynamic behavior of structures. Among these methods, Autoregressive Moving Average (ARMA) models effectively capture linear temporal dependencies in structural vibration data and have been widely employed for structural response prediction and damage assessment. However, ARMA models alone are insufficient for representing complex nonlinear structural behavior, motivating the development of hybrid prediction approaches that integrate statistical and machine learning techniques [8, 15, 16].

Artificial Neural Networks (ANNs) have demonstrated excellent capability for modeling nonlinear relationships in structural response data and have become an effective alternative to conventional statistical approaches. Their flexibility enables the learning of complex response

[DOI: 10.22068/ijoce.2026.16.2.678]

patterns directly from monitoring data, leading to improved prediction accuracy. More recently, deep learning methods have further enhanced the capability of neural-network-based SHM, particularly for large-scale monitoring applications involving complex structural behavior [8, 15, 16].

Despite these advances, measurement noise, environmental variability, and limited sensor deployment continue to present significant challenges for reliable structural response prediction. Consequently, recent studies have combined ARMA models, Artificial Neural Networks, and Wavelet Transform (WT) techniques to improve signal quality, enhance prediction accuracy, and facilitate early-stage damage detection [9, 17-19].

Although recent sequence-based deep learning models, particularly LSTM and GRU networks, have significantly improved structural response prediction by learning long-term temporal dependencies, their practical implementation generally requires substantial computational resources, extensive monitoring datasets, and careful model calibration. In many bridge monitoring applications, however, sensor availability is limited, measurements are contaminated by environmental noise, and computational efficiency is essential for practical deployment. Motivated by these challenges, this study proposes an ARMA-Wavelet-Artificial Neural Network (AWAN) that integrates wavelet-based signal denoising, ARMA-based temporal feature extraction, and a feed-forward artificial neural network or efficient bridge response reconstruction. By combining robust signal preprocessing with nonlinear data-driven modeling, the proposed methodology exploits the spatial correlation among neighboring sensors and the temporal characteristics of structural responses, providing an effective balance between prediction accuracy, computational efficiency, and practical applicability.

To demonstrate the effectiveness of the proposed methodology, the theoretical foundations of the AWAN framework, including the ARMA model, Artificial Neural Network, and Continuous Wavelet Transform, are first presented. The prediction algorithm is then introduced and evaluated using three bridge models with increasing structural complexity. Finally, the prediction performance is comprehensively assessed to demonstrate the capability of the proposed approach for reconstructing unmeasured bridge responses under different structural and loading conditions.

2. HYBRID AWAN METHODOLOGY

The proposed AWAN framework integrates three complementary techniques ARM, Artificial ANN, and CWT to reconstruct unmeasured structural responses from limited sensor measurements. Within the framework, ARMA captures the temporal characteristics of structural responses, CWT suppresses measurement noise while preserving essential signal features, and ANN models the nonlinear relationships between measured and unmeasured responses. The following subsections describe each component before presenting the integrated AWAN prediction algorithm.

2.1. Autoregressive Moving Average (ARMA) Model

The Autoregressive Moving Average (ARMA) model is a widely used time-series analysis technique for modeling and predicting stationary signals and has been extensively applied to

[DOI: 10.22068/ijoce.2026.16.2.678]

structural response analysis in structural health monitoring (SHM) [20-22]. The ARMA *(p, q)* model combines autoregressive (AR) and moving average (MA) components, as expressed in, as expressed in Eq. 1:

$$x_t = \underbrace{\sum_{i=1}^{p} \phi_i x_{t-i}}_{AR} + \underbrace{\sum_{j=1}^{q} \theta_j e_{t-j}}_{MA} + \underbrace{\varepsilon_t}_{error} \tag{1}$$

where:

- x_t= measured time-series data at time *t*
- p = order of the autoregressive component
- q = order of the moving average component
- ϕ_i = autoregressive coefficients
- θ_j= moving average coefficients
- ε_t = white noise error term at time *t*

The AR component captures the linear dependency of the current value on its previous values. The AR model essentially represents the memory effect of the system. This type of model is particularly useful for capturing the persistence of structural vibrations and the effects of loading over time. Conversely, the MA component models the effect of past noise or shocks on the current value of the time series. This component accounts for the short-term correlation structure in the data and helps to smooth out random fluctuations.

By combining the AR and MA terms, the ARMA model simultaneously captures both the linear dependence on past values and the effect of previous disturbances. The ARMA model is particularly effective in structural health monitoring (SHM) where the structural response exhibits both deterministic and stochastic behavior.

While ARMA models are effective for linear systems, they face limitations when dealing with nonlinear and non-stationary structural responses. To overcome these limitations, ARMA is integrated with ANN and CWT within the proposed AWAN framework, enabling the prediction of nonlinear and noisy structural responses.

2.2. Neural Network-Based Prediction

Artificial Neural Networks (ANNs) have become powerful tools for pattern recognition, function approximation, and system identification in Structural Health Monitoring (SHM). Inspired by the neural structure of the human brain, ANNs consist of interconnected layers of neurons that transform input data into output predictions through successive mathematical operations. Unlike ARMA models, which rely on linear assumptions, ANNs can capture complex nonlinear relationships between inputs and outputs [23].

For a typical feedforward neural network (FNN) with L layers, the mathematical formulation for the output y can be expressed as:

$$y = f_1(W_1 x + b_1) + \cdots + f_L(W_L x + b_L) \tag{2}$$

where:

[DOI: 10.22068/ijoce.2026.16.2.678]

- *x = input vector (e.g., measured acceleration response)*
- *W_i= weight matrix for layer i*
- *b_i = bias vector for layer i*
- *f_i= activation function for layer i*
- *y = predicted output (e.g., predicted response at unmeasured locations)*

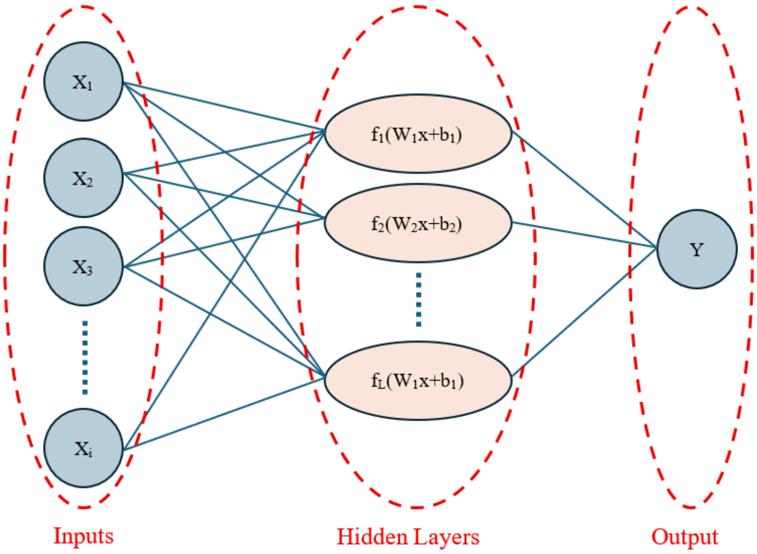


Figure 1: Schematic architecture of a feedforward ANN

The activation function introduces nonlinearity into the model, allowing the network to approximate complex relationships. This capability makes ANNs particularly suitable for modeling complex structural responses and predicting unmeasured responses by learning the spatial and temporal relationships embedded in sensor data.

Although ANNs provide excellent nonlinear modeling capability, their prediction accuracy depends on the quality of the training data and the selection of an appropriate network architecture. Within the AWAN framework, these challenges are mitigated through wavelet-based signal denoising and ARMA-based temporal feature extraction, which improve the quality of the input data while maintaining a lightweight feed-forward network architecture.

2.3. Continuous Wavelet Transform

Wavelet Transform (WT) is a widely used signal processing technique for analyzing non-stationary signals, making it particularly suitable for structural health monitoring (SHM). Unlike the Fourier Transform (FT), which provides only frequency-domain information under the assumption of signal stationarity, WT simultaneously represents the time and frequency characteristics of a signal. This makes it particularly suitable for SHM, where structural responses often vary over time due to environmental effects, loading conditions, and damage events. The continuous wavelet transform (CWT) of a signal *$x(t)$* is defined as [24]:

[DOI: 10.22068/ijoce.2026.16.2.678]

$$W(s,u) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-u}{s}\right) dt \tag{3}$$

where:
- *W (s, u)* = wavelet coefficient at scale s and position u
- *s* = scale factor (related to frequency)
- *u* = translation factor (related to time)
- $\psi^*(t)$= complex conjugate of the mother wavelet
- *x(t)* = input signal

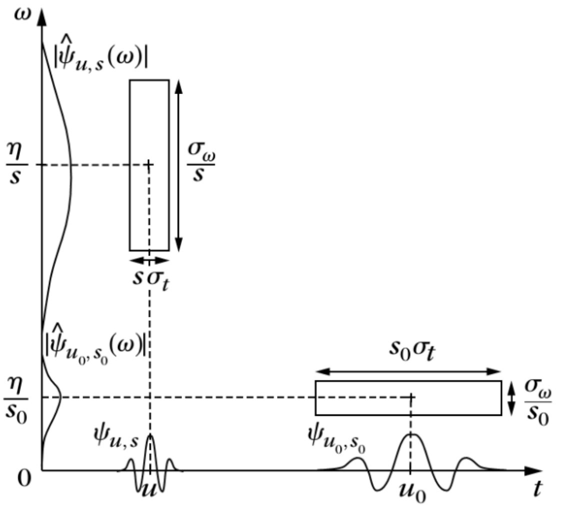


Figure 2: Heisenberg rectangle of $\psi_{u,s}$ for different scale [24]

The mother wavelet $\psi(t)$ serves as the basic analyzing function from which scaled and translated daughter wavelets are generated. The scale factor $s$is inversely related to frequency, with high scales capturing low-frequency trends and low scales representing high-frequency variations. This multi-resolution capability makes CWT particularly effective for analyzing structural responses with mixed frequency content.

Within the AWAN framework, CWT is employed as a preprocessing step to denoise the measured acceleration signals before feature extraction and response prediction.

2.4. AWAN Prediction Algorithm

The proposed AWAN framework integrates CWT, ARMA, and ANN into a unified prediction strategy for reconstructing unmeasured structural responses from a limited number of sensor measurements. Figure 3 illustrates the overall workflow of the proposed methodology. Initially, the measured acceleration responses are preprocessed using CWT to suppress measurement noise while preserving the essential time–frequency characteristics of the structural response. The denoised signals are subsequently converted into lagged input features and used to train a feedforward ANN for predicting the response at the target location. This sequential integration allows the framework to exploit the complementary strengths of signal denoising, temporal feature extraction, and nonlinear mapping.

[DOI: 10.22068/ijoce.2026.16.2.678]

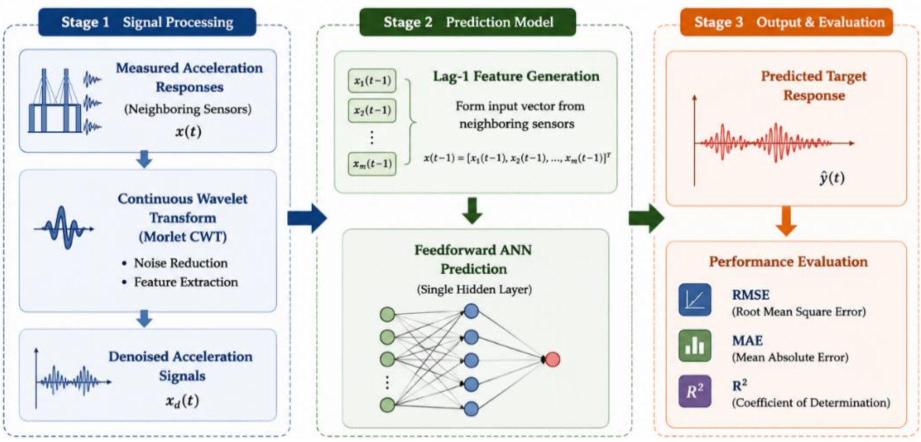


Figure 3: Overall workflow of the proposed AWAN framework.

The ANN employed in the AWAN framework is a feedforward multilayer perceptron (MLP) designed to estimate the acceleration response at an unmeasured location using neighboring sensor measurements. The network receives denoised lag-1 acceleration responses from adjacent measurement points as the input vector, while the output corresponds to the predicted acceleration at the target node. A single hidden layer containing 20 neurons with the Rectified Linear Unit (ReLU) activation function is adopted to model the nonlinear relationship between measured and unmeasured structural responses. Model parameters are optimized using the Adam optimizer with a maximum of 1000 training iterations. The selected architecture provides an effective balance between prediction accuracy and computational efficiency while reducing the risk of overfitting.

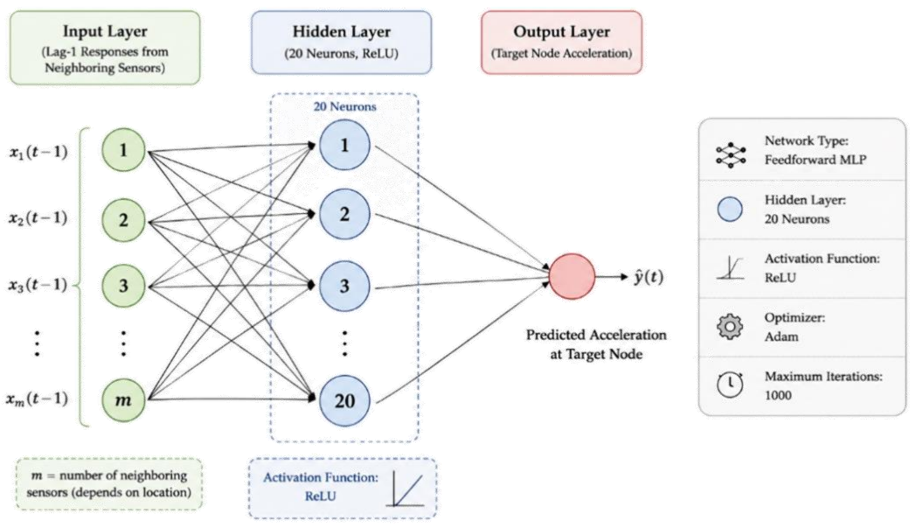


Figure 4: Feedforward ANN architecture adopted in the proposed AWAN framework

Prediction accuracy is assessed by comparing the predicted and measured acceleration responses using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

[DOI: 10.22068/ijoce.2026.16.2.678]

3. VALIDATION OF THE PROPOSED AWAN FRAMEWORK

The proposed AWAN framework was validated using three bridge models representing different structural configurations: a 2D INP beam, a Two-Span Steel Grid benchmark, and a scaled Single-Plane Cable-Stayed bridge. These case studies were selected to evaluate the prediction capability of the proposed framework under progressively more realistic structural conditions.

3.1. 2D INP Beam

This case study considers a simply supported beam with an INP80 cross-section, a total length of 4100 mm, and a clear span of 4000 mm. It is supported by a hinge at one end and a roller at the other. Acceleration responses under various loading scenarios are captured using numerical sensors positioned at 200 mm intervals along the beam [2, 25].

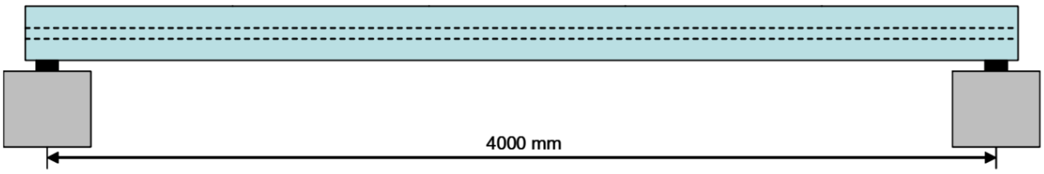


Figure 5: Steel INP beam in 2D model [2, 25]

Figure 6 presents the RMSE at Node 11 for 13 dynamic loading scenarios using the global AWAN model with different time-lag configurations. The gray bars represent the RMSE between the raw measured and predicted responses using a one-lag model, illustrating the influence of measurement noise. The orange bars correspond to predictions based on denoised signals with a one-lag configuration, while the green and blue bars represent the denoised two-lag and three-lag models, respectively. Among the evaluated configurations, the denoised one-lag model consistently achieved the lowest RMSE, whereas the use of additional lag terms resulted in reduced prediction accuracy.

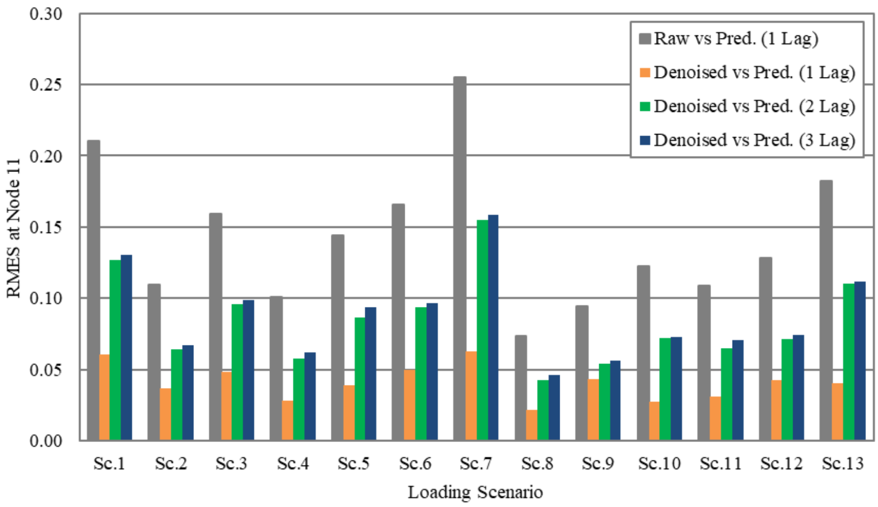


Figure 6: RMSE for different loading scenarios in INP Model

[DOI: 10.22068/ijoce.2026.16.2.678]

Figure 7 compares the AWAN-predicted acceleration response with the denoised measured response at Node 11 under loading scenario Sc.1. The close agreement between the two signals demonstrates the capability of the proposed framework to accurately reproduce the structural response at an unmeasured location.

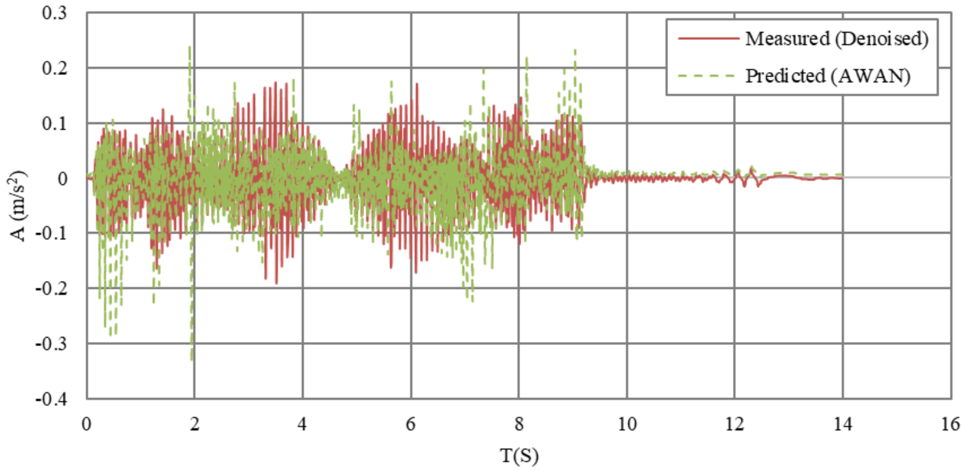


Figure 7: Comparison of predicted and denoised measured acceleration response at Node 11

To investigate the influence of sensor location on prediction accuracy, the performance of the global one-lag AWAN model was further evaluated at Node 11 (mid-span) and Node 5 (approximately one-quarter span) across the 13 loading scenarios. As shown in Figure 8, the RMSE values at Node 11 are consistently lower than those at Node 5, indicating more accurate predictions at the mid-span. This behavior is attributed to the more symmetric vibration characteristics at the beam center, whereas locations closer to the supports are affected by stronger boundary-condition effects and more complex modal interactions, resulting in comparatively higher prediction errors.

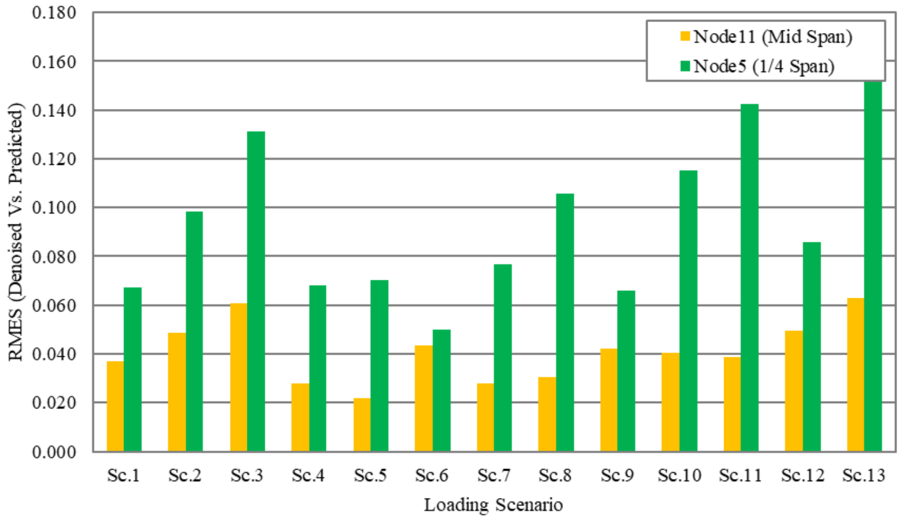


Figure 8: Comparison of prediction accuracy at two sensor locations in INP Model

[DOI: 10.22068/ijoce.2026.16.2.678]

3.2. Two-Span Steel Grid Benchmark

The second case study considers a laboratory-scale two-span steel bridge benchmark. The bridge deck consists of two 18-ft longitudinal beams and seven 3-ft transverse beams constructed from S3×5.7 steel sections and rigidly connected to form an integrated deck system. The deck is supported by six 3.5-ft W12×26 steel columns through hinged connections that permit rotational movement. Acceleration responses under random vertical excitation were obtained at the beam intersections [1, 26].

Figure 9: Two-Span Steel Gride benchmark [26]

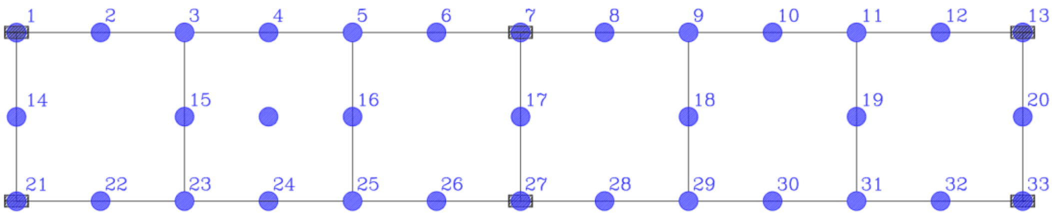


Figure 10: Sensor location at Steel Gride benchmark

Figure 11 presents the RMSE values of the AWAN predictions at Nodes 5 and 16 for seven dynamic loading scenarios. The predicted responses were compared with the wavelet-denoised measured acceleration signals. Across all loading scenarios, the framework maintained satisfactory prediction accuracy, with the lowest RMSE observed under the moderate excitation conditions of Scenarios 3 and 7.

The influence of sensor location on prediction accuracy was further evaluated by comparing the RMSE values at Nodes 5 and 16. As shown in Figure 11, the AWAN framework consistently produced lower prediction errors at Node 16 than at Node 5, indicating that prediction performance depends on the structural response characteristics at the target location.

[DOI: 10.22068/ijoce.2026.16.2.678]

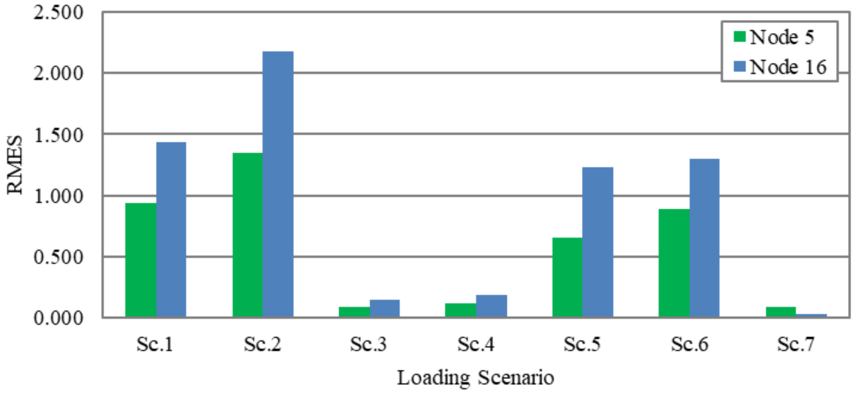


Figure 11: Comparison of prediction accuracy at two sensor locations

To investigate the influence of environmental conditions, Scenario 4 was analyzed with a uniform temperature increase of 20 °C relative to the baseline Scenario 3 while maintaining the same dynamic loading configuration. Figure 12 compares the predicted and wavelet-denoised measured responses at Node 5. The RMSE increased slightly from 0.089 under the baseline condition to 0.113 following the temperature increase. Despite this increase, the prediction accuracy remained high, indicating that the AWAN framework is relatively robust to moderate temperature-induced variations in structural behavior and is therefore suitable for long-term bridge health monitoring under varying environmental conditions.

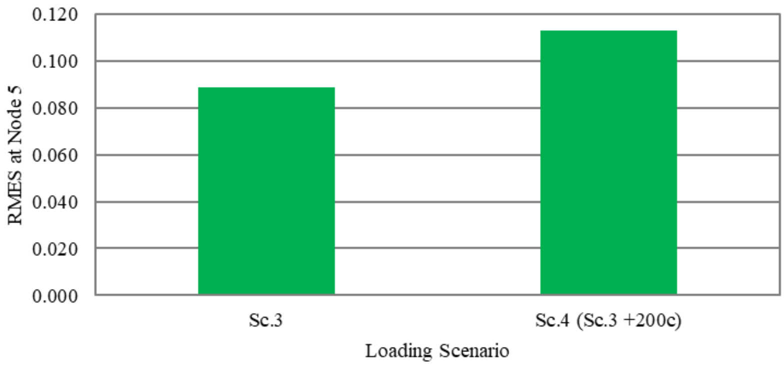


Figure 12: Effect of temperature variation on AWAN prediction accuracy at Node 5

3.3. Scaled Single-Plane Cable-Stayed Bridge

The third case study considers a laboratory-scale single-plane cable-stayed bridge implemented to validate the proposed framework under a more realistic structural configuration. A hollow box steel section was used to represent the bridge deck, while 0.4 mm diameter steel piano wires simulated the stay cables. The pylons were fixed at their bases, and additional steel masses were uniformly distributed along the deck to represent the dead load. Acceleration sensors were assumed at the cable–deck connection points to capture the structural responses under different loading conditions [27-29].

[DOI: 10.22068/ijoce.2026.16.2.678]

Figure 13: Laboratory Cable-Stayed Bridge [27]

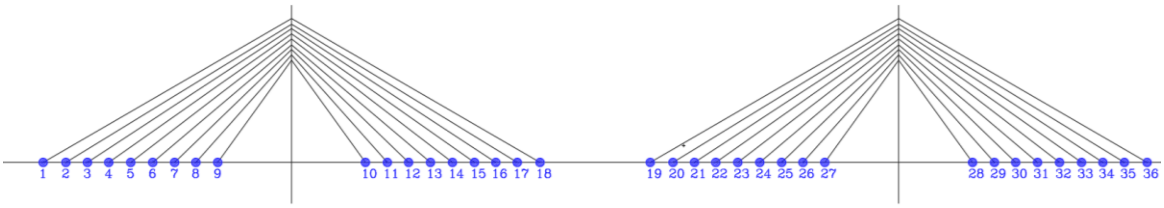


Figure 14: Sensor location at Cable-Stayed Bridge

Figure 15 presents the RMSE values of the AWAN predictions for eleven loading scenarios, demonstrating consistent prediction performance across different loading conditions. Comparing the RMSE values at Nodes 10 and 18, shows that Node 18 generally achieved lower prediction errors than Node 10. The observed difference suggests that local structural characteristics, including cable–deck interaction and stiffness distribution, influence the prediction accuracy at different sensor locations.

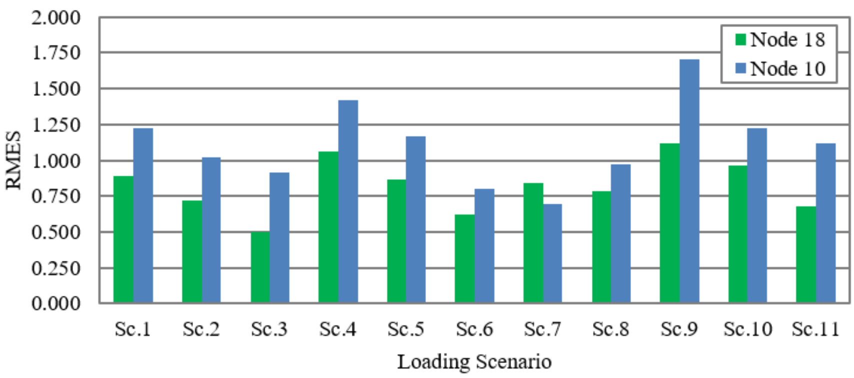


Figure 15: RMSE for different loading scenarios in cable-stayed bridge

To provide a more comprehensive assessment of the prediction performance, MAE and R^2 were also computed for all loading scenarios. The results, summarized in Table 1, show consistently low MAE values and high R^2 values, confirming good agreement between the predicted and measured acceleration responses. Together with the RMSE results, these

[DOI: 10.22068/ijoce.2026.16.2.678]

metrics further demonstrate the reliability of the AWAN framework under different loading conditions.

Table 1: Performance evaluation of AWAN for scaled cable-stayed bridge

Metric	Sc.1	Sc.2	Sc.3	Sc.4	Sc.5	Sc.6	Sc.7	Sc.8	Sc.9	Sc.10	Sc.11
MAE	0.584	0.506	0.343	0.706	0.584	0.451	0.619	0.550	0.730	0.673	0.506
RMSE	0.843	0.732	0.488	1.032	0.846	0.654	0.893	0.798	1.046	0.972	0.723
R^2	0.783	0.800	0.840	0.854	0.713	0.839	0.811	0.786	0.893	0.872	0.741

3.4. General Discussion

Across the three bridge models, the AWAN framework consistently achieved higher prediction accuracy at measurement locations near the mid-span than at locations closer to the supports. This behavior is attributed to the different dynamic characteristics of these regions. Near the supports, boundary effects, localized stiffness variations, and higher-order vibration modes produce less uniform structural responses, making the reconstruction of unmeasured responses more challenging. In contrast, the mid-span response is dominated by global vibration modes, resulting in smoother response distributions and stronger spatial correlations between neighboring sensors, which contribute to improved prediction accuracy.

Despite the slight reduction in prediction accuracy near the supports, the prediction errors remained within acceptable engineering limits for all three case studies. Furthermore, the framework maintained stable performance under different loading scenarios and moderate temperature variations, demonstrating its robustness and practical applicability for reconstructing unmeasured bridge responses in structural health monitoring.

4. CONCLUSIONS

This study presented the Adaptive AWAN framework for predicting unmeasured bridge deck acceleration responses from limited sensor measurements. The proposed methodology was successfully validated using three bridge models with increasing structural complexity. The results demonstrated excellent agreement between the predicted and measured responses under a wide range of loading conditions, confirming the effectiveness and robustness of the framework for structural response reconstruction. Performance evaluation using RMSE, MAE, and R^2 verified the high prediction accuracy achieved across all case studies.

The results also showed that prediction accuracy was generally higher at mid-span locations than near the supports, highlighting the influence of structural boundary conditions and local dynamic behavior on response reconstruction. Furthermore, stable performance under moderate temperature variation demonstrated the potential of the framework for long-term bridge health monitoring. Overall, the consistent performance achieved across different structural configurations and loading scenarios indicates that the AWAN framework provides an efficient and reliable approach for reconstructing unmeasured bridge responses while reducing sensor requirements. Its computationally efficient architecture makes it particularly suitable for practical data-driven bridge health monitoring applications.

Future work will focus on validation using full-scale bridge monitoring data, incorporating

[DOI: 10.22068/ijoce.2026.16.2.678]

broader environmental and operational variability, and enabling real-time implementation through online model updating. In addition, investigating advanced sequence-based deep learning architectures, such as LSTM and GRU, may further improve prediction performance for more complex structural systems while preserving the computational efficiency required for practical structural health monitoring applications.

REFERENCES

1. Ghodrati Amiri G, Talebi M. A novel methodology for structural matrix identification using wavelet transformed optimized by genetic algorithm. *Int J Optim Civ Eng*. 2014;**4**(3):399–413.
2. Talebi M, Tabrizian Z, Ghodrati Amiri G. Bridge deck modal parameters identification using traffic loads. *J Rehabil Civ Eng*. 2025;**13**(2).
3. Li H, Qu J. The state of the art in structural health monitoring of cable-stayed bridges. *J Civ Struct Health Monit*. 2015.
4. Jang S, Spencer BF. Structural health monitoring. *Newmark Struct Eng Lab*. 2015.
5. Zhang L, Qiu G, Chen Z. Structural health monitoring methods of cables in cable-stayed bridge: a review. *Measurement*. 2020;**168**.
6. Arangio S, Bontempi F. Structural health monitoring of a cable-stayed bridge with Bayesian neural networks. *Struct Infrastruct Eng*. 2014.
7. Gordan M, et al. State of the art – review on advancements of data mining in structural. *Measurement*. 2022;**193**.
8. Miao P, et al. Deep learning–based inspection data mining and derived information fusion for enhanced bridge deterioration assessment. *J Bridge Eng*. 2023;**28**.
9. Khanahmadi M, et al. Vibration-based health monitoring and damage detection in beam-like structures with innovative approaches based on signal processing: a numerical and experimental study. *Struct*. 2024;**68**.
10. Kaveh A. *Applications of Artificial Neural Networks and Machine Learning in Civil Engineering*. Springer; 2024.
11. Kaveh A, Eskandari A, Piri M. Metaheuristic-optimized machine learning for mechanical property prediction in eco-friendly rubberized concrete. *Period Polytech Civ Eng*. 2025;**69**(4):1124–48.
12. Li Z, Li D, Sun T. A transformer-based bridge structural response prediction framework. *J Sensors*. 2022;**22**(8).
13. Das T, Guchhait S. A hybrid GRU and LSTM-based deep learning approach for multiclass structural damage identification using dynamic acceleration data. *Eng Fail Anal*. 2025;**170**.
14. Sun B, et al. Hybrid WARIMA-WANN algorithm for data prediction in bridge health monitoring system. *Struct*. 2024;**69**.

[DOI: 10.22068/ijoce.2026.16.2.678]

15. Fadavi Amiri M, Rajabi E, Ghodrati Amiri G. Application of neural network in evaluation of seismic capacity for steel structures under critical successive earthquakes. *Int J Optim Civ Eng*. 2022;**12**(2):171–84.
16. Adrian M, et al. Hybrid approach for supervised machine learning algorithms to identify damage in bridges. *J Bridge Eng*. 2024;**29**(8).
17. Naderpour H, Fakharian P. A synthesis of peak picking method and wavelet packet transform for structural modal identification. *KSCE J Civ Eng*. 2016;**20**(7):2859–67.
18. Khanahmadi M. An effective vibration-based feature extraction method for single and multiple damage localization in thin-walled plates using one-dimensional wavelet transform: a numerical and experimental study. *Thin-Walled Struct*. 2024.
19. Peng Z, et al. Feasibility study of structural damage detection using NARMAX modelling and nonlinear output frequency response function based analysis. *Mech Syst Signal Process*. 2011;**25**.
20. Shumway RH, Stoffer DS. *Time Series Analysis and Its Applications*. Springer; 2011.
21. Kantz H, Schreiber T. *Nonlinear Time Series Analysis*. Cambridge Univ Press; 2011.
22. Lhermitte S, et al. A comparison of time series similarity measures for classification and change detection of ecosystem dynamics. *Remote Sens Environ*. 2011;**115**:3129–52.
23. Farrar CR, Worden K. *Structural Health Monitoring – A Machine Learning Perspective*. Wiley; 2013.
24. Mallat S. *A Wavelet Tour of Signal Processing: The Sparse Way*. Academic Press; 2008.
25. Pedro G, et al. Damage identification of simply-supported beam using modal data. *Proc 14th World Conf Earthq Eng*. 2008.
26. Gül M. Investigation of damage detection methodologies for structural health monitoring. Univ Central Florida; 2009.
27. Elkady AZ, Seleemah MA, Ansari F. Structural response of a cable-stayed bridge subjected to lateral seismic excitations. *J Civ Struct Health Monit*. 2018;**8**:417–30.
28. Haji Agha Mohammad Zarbaf SE, et al. Stay cable tension estimation of cable-stayed bridges using genetic algorithm and particle swarm optimization. *J Bridge Eng*. 2017;**22**(10).
29. Scarella A, et al. Dynamic Brillouin scattering–based condition assessment of cables in cable-stayed bridges. *J Bridge Eng*. 2016;**22**(3).

[DOI: 10.22068/ijoce.2026.16.2.678]