Available online at www.eccomasproceedia.org
Eccomas Proceedia COMPDYN (2025) 5016-5024

ECCOMAS
Proceedia

COMPDYN 2025
10th ECCOMAS Thematic Conference on
Computational Methods in Structural Dynamics and Earthquake Engineering
M. Papadrakakis, M. Fragiadakis (eds.)
Rhodes Island, Greece, 15-18 June 2025

USING VIBRATION MEASURES TO ESTIMATE FATIGUE STRESS HISTORIES

Alessandro Menghini[1], Bowen Meng[2], and John Leander[2]

[1] Politecnico di Milano, Department of Architecture, Built Environment and Construction Engineering, Piazza Leonardo da Vinci 32, Milan, 20133, Italy
e-mail: alessandro.menghini@polimi.it

[2] KTH Royal Institute of Technology, Department of Civil and Architectural Engineering, Brinellvägen 23, Stockholm, 100 44, Sweden

Abstract

This study introduces a methodology that integrates two complementary approaches to estimate stress at various locations on a bridge using sparse vibration data. The approach is validated with in-service monitoring data collected from a composite railway bridge in Sweden. Specifically, a deep learning sequence model is used to predict stress histories based on acceleration measurements from multiple locations. Following this, the local response function method is applied, using localized models of the bridge's fatigue critical details to enable precise stress predictions in critical areas. By combining these techniques, the methodology achieves conservative predictions of stress ranges and cycles at instrumented locations, reducing the reliance on extensive instrumentation and offering a more efficient solution for structural health monitoring.

Keywords: Fatigue, SHM, deep-learning

doi: 10.7712/120125.12791.26268

1 INTRODUCTION

Steel railway bridges are increasingly subjected to higher traffic volumes and loading frequencies, often exceeding their original design capacities. This growing demand, combined with the European Green Deal's objective of shifting significant inland freight to rail networks, highlights the urgent need for improved methods to assess their in-service behavior [1-2]. The use of various sensors in bridge health monitoring has become a widely adopted approach to reduce uncertainties about in-service bridge conditions. While strain measurement technologies are effective to estimate load effects, their placement is often restricted to specific locations, leaving critical areas unmonitored. Fatigue-prone areas are often inaccessible, and the high costs and energy requirements of physical sensors additionally constrain data acquisition, transfer, and storage. Moreover, geometric stress concentrations in these areas complicate traditional monitoring, necessitating advanced regression models for reliable stress distribution analysis [3]. Virtual sensing techniques offer a promising alternative by estimating strain responses at unmeasured locations through indirect measurements. These methods have been applied successfully across various structural domains, including civil, offshore, and mechanical systems. Recent advances in this field include data-driven approaches such as Singular Value Decomposition (SVD), artificial neural networks (ANNs), and modal superposition techniques. For example, Akintunde et al. [4] utilized SVD to estimate strain in operational railway bridges, facilitating probabilistic fatigue assessments. Similarly, Maes et al. [5] proposed a virtual sensing methodology combining strain data with longitudinal displacement measurements, while Leander [6] demonstrated that ANNs can accurately predict stress time histories when input variables exhibit consistent variance. However, challenges persist when applying these methods to operational bridges, particularly in addressing uncertainties arising from complex geometries and loading conditions. This paper presents a hybrid methodology that integrates data-driven and model-based techniques to transform sparse acceleration data into stress histories. The approach employs a Temporal Convolutional Network (TCN) for sequence modeling and the Local Response Function Method (LRFM) to extrapolate predictions to unmeasured locations. Validated on the Bryngeån Bridge in Sweden, the methodology offers accurate predictions of stress time histories without requiring extensive direct instrumentation or specific vehicle configuration data. This combined approach significantly enhances the interpretation and extrapolation of sparse monitoring data, providing a cost-effective solution for structural health monitoring. The current paper is an elaborated case study based on the principles first presented in [3].

2 METHODOLOGY

This study proposes a hybrid methodology that integrates data-driven and model-based approaches to convert acceleration measurements into virtual stress data across multiple bridge locations. The process begins with capturing bridge accelerations and translating them into stress histories using a deep learning model. The model, developed using a Temporal Convolutional Network (TCN), is trained with a blend of acceleration and strain data collected from temporary strain gauge installations. Once trained, the strain gauges can be removed as the model will be used to predict strain from accelerometer data. To extend predictions to unmonitored locations, the Local Response Function Method (LRFM) is applied in conjunction with calibrated Finite Element Method (FEM) models. LRFM creates response functions that correlate strain at measurements locations to unmeasured ones [8-9]. This enables real-time extrapolation of strain and stress histories across the structure, even with limited sensor data. By combining TCN and LRFM, the methodology effectively translates train-induced vibrations into detailed structural stress histories, enabling comprehensive and cost-efficient bridge health monitoring. This approach is illustrated in Fig. 1.

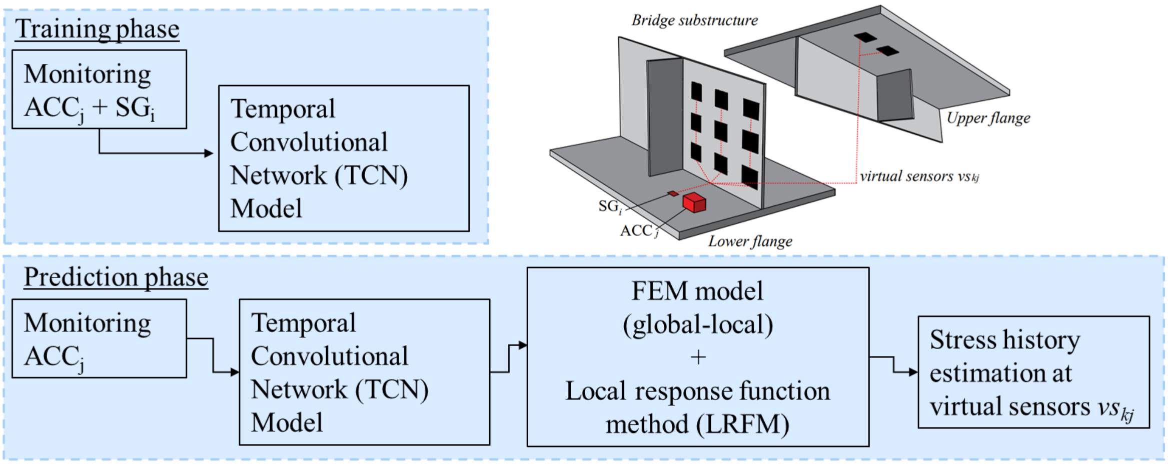


Figure 1: Methodology flowchart: predicting stress histories at remote virtual sensor locations.

In detail, this study employs a deep learning-based sequence model, specifically a Temporal Convolutional Network (TCN), to predict stress histories from acceleration data. While Convolutional Neural Networks (CNNs) are traditionally known for spatial data processing, TCNs extend this capability to sequential time-series data. To handle noise inherent in acceleration signals, a frequency-based decomposition technique is applied, breaking the signals into components representing different frequency ranges. This approach minimizes information loss compared to traditional filtering methods. Additionally, train velocity data—acquired through Weight-in-Motion (WIM) is integrated into the model to enhance its understanding of dynamic bridge responses. The methodology involves data preprocessing, model training, and validation (Fig. 2). Acceleration signals and strain histories are paired with train velocities, obtained via cross-correlation of WIM data, to calculate speeds. The Fast Fourier Transform (FFT) is used for frequency analysis, followed by signal decomposition into fixed-length sequences using a sliding window technique. Each dataset sample includes segmented acceleration sequences and scalar train velocities as inputs, with scalar strain signals as outputs.

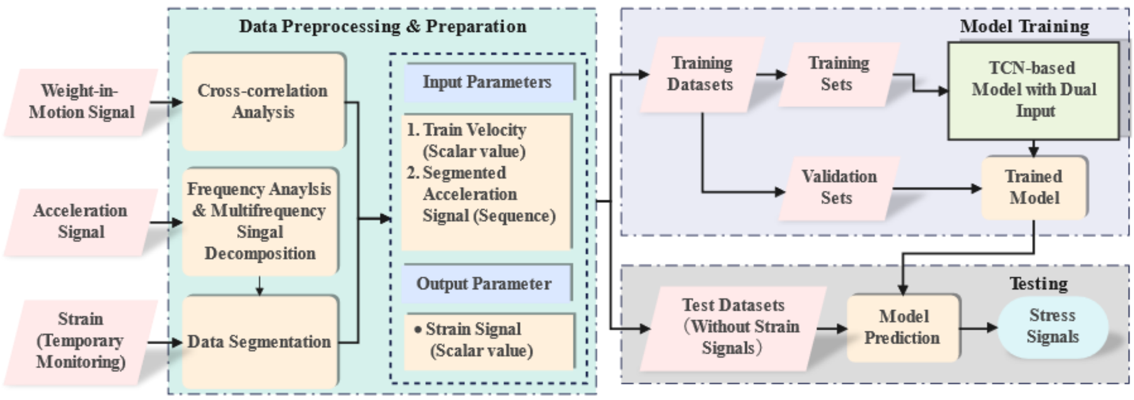


Figure 2: Flowchart of sequence modeling for acceleration and stress history.

During training, the TCN processes acceleration sequences and velocities, passing the outputs through a dense layer to predict strain values. Strain data from temporary sensors are used as labels to align acceleration patterns with structural responses. Validation datasets monitor performance and mitigate overfitting risks. Once trained, the model generates stress histories and stress spectra for unseen acceleration signals and velocities. A more detailed description of the process of signal decomposition and segmentation can be found in [3].
Analyzing the interaction between global and local finite element models (FEMs) of complex bridge geometries often demands extensive computational resources [7]. To address this, the Local Response Function Method (LRFM) is employed as a surrogate model to estimate load effects at sensor-unavailable locations efficiently. As detailed by Menghini et al. [8], the LRFM uses polynomial approximations to represent the implicit relationships between stress responses and controllable variables. Assuming the numerical FEM model accurately replicates the bridge's behavior, the relationship between the two computed stress responses approximates that of the real experimental values. Once the function correlating the two numerical stress responses is estimated, it can be used to predict stress levels at one location based on a single experimentally measured stress at another. The response function is approximated using a third-order polynomial expression, with coefficients determined through a least-squares estimator [8]. This enables the prediction of stress histories at unmeasured locations based on data from other sensor-equipped areas. Mathematically, the system response is defined as a function of controllable variables, with random error assumed to follow a normal distribution. Using these relationships, LRFM predicts stress histories, using reliable numerical models to extend the analysis to locations lacking direct instrumentation. This method provides an efficient solution for estimating stress at critical, inaccessible areas of bridges, supporting comprehensive structural health monitoring with minimal sensor deployment.

3 EXPERIMENTAL AND NUMERICAL MODELING

In the summer of 2021, the Bryngeån bridge was equipped with sensors to measure acceleration, strain, temperature, and displacement, as part of the In2Track3 project under Horizon 2020 [10]. The instrumentation, shown in Fig. 3, included strain gauges, accelerometers, and bridge-weigh-in-motion (BWIM) sensors placed near the mid-span. Accelerometers (A1 to A4) were mounted on the bottom flange of the primary steel beams, while strain gauges SG1 and SG2 were placed to measure nominal strain, avoiding stress concentrations at welds. Data was continuously sampled at 150 Hz, with train events stored for processing through a pre-triggered setup.

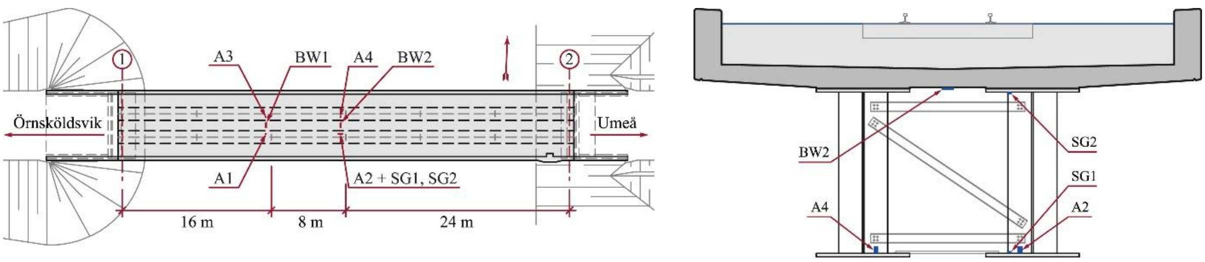
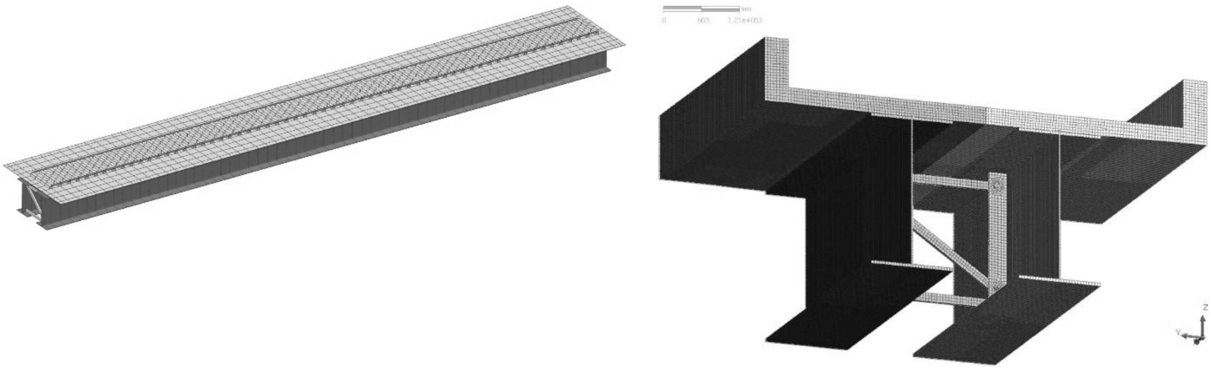


Figure 3: Bridge sensors experimental layout.

For the LRFM, a global numerical model of the bridge was developed using Midas® software (Fig.4-a). Beam elements represent the main girders and bracings, while shell elements model the ballast layer and concrete slab, connected via rigid translational links. The railway tracks, including rails and sleepers, are modeled with beam elements attached to the deck, distributing traffic loads efficiently. Bearings are modeled with fixed translational constraints on one side and rollers on the other. Steel grade S355 is used for the main structure, while concrete C35/45 is used for the sleepers and slab. Local submodels are used to analyze the local principal stress, created using solid elements and based on geometric properties from design drawings and inspections (Fig.4-b). These submodels are connected to the global beam model through master nodes, which carry the displacements from the global model. The master nodes are linked to edge nodes via rigid links in all translations and rotations. The local model of the bridge's span, developed with Midas FEA NX® software, accounts for the typical cross-sectional configuration, connected by horizontal C-shaped struts to stiffeners linking the upper and lower flanges.



a) b)

Figure 4: Bryngeån bridge numerical models: a) Global; b) Local.

4 APPLICATION RESULTS

The TCN-based model was developed to convert acceleration signals into strain and stress histories. The acceleration signals were first decomposed using multifrequency decomposition to isolate high-amplitude noise between 35 and 40 Hz, which is unrelated to the bridge's dynamic response. The optimal segment length for the signals was determined by balancing prediction accuracy and computational efficiency, with signal segments between 70 and 120 samples providing stable results while increasing computational demands by 8%. The model's accuracy improved significantly by including train speed data, as the train speed influences the bridge's dynamic response. A detailed configuration of the TCN model can be found in [3]. The model architecture was optimized to capture temporal dependencies effectively. Training and validation were performed on 80% of the data, with the remaining 20% used for testing. Cross-validation was also carried out to ensure robustness, and the model showed stable performance after 10 epochs. The results were based on 135 train passages, specifically focusing on trains moving at speeds higher than 127 km/h, which showed similar dynamic responses. The most frequently observed train speed was approximately 137 km/h, with the maximum recorded speed reaching 155 km/h. For demonstration, the trained model was used to predict stress histories at SG1's location based on acceleration data from accelerometer A2, with the predictions compared to actual strain gauge measurements (Fig. 5). The predicted and measured stress histories showed a strong correlation, particularly in capturing the amplitude of stress responses over time. However, in some cases (e.g., Fig. 5-b), the model's predicted stress response exhibited lower peak values than the measured data. Out of the 26 tested train passages, 6 showed similar differences. This prediction error was noted to influence the fatigue analysis, where the model tended to predict larger stress ranges than observed, which could lead to conservative estimates of the fatigue life of the bridge.

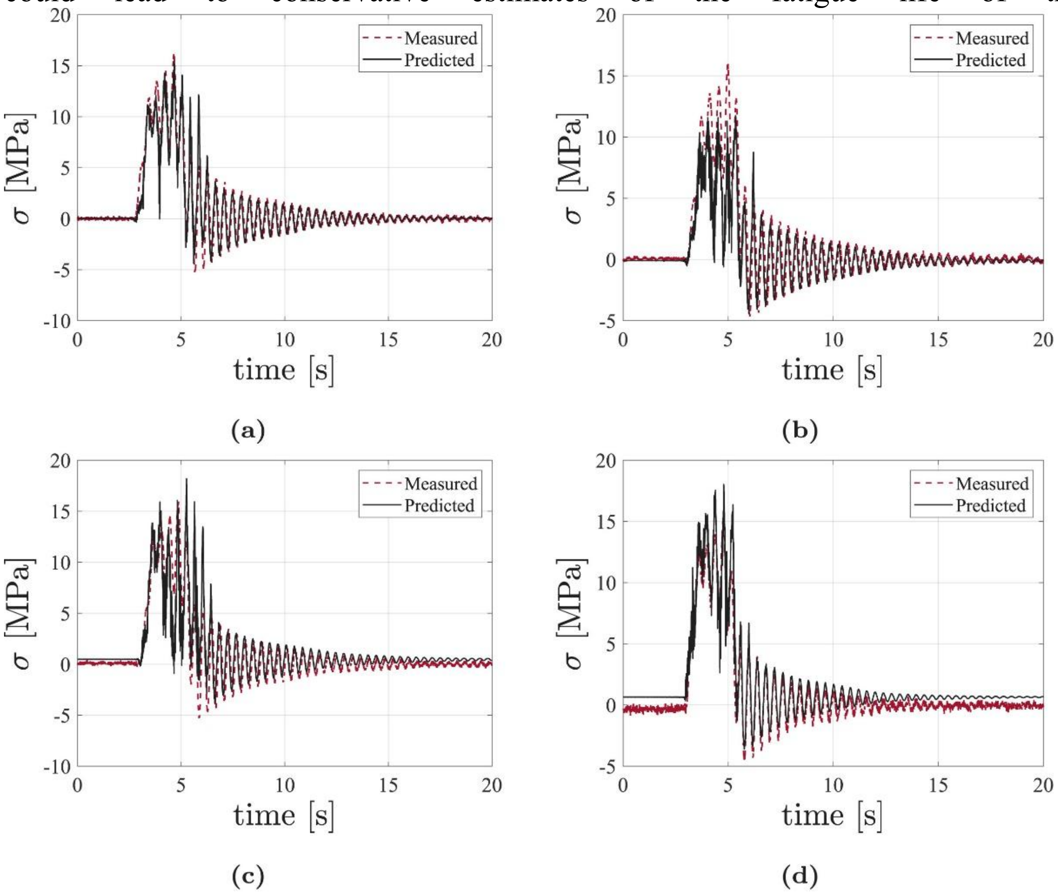


Figure 5: Comparison of predicted histories from A2 and SG1 measurements using the TCN prediction model [3].

Once stress histories were estimated using the TCN model from acceleration data measured at sensor A2, the predicted stress at one sensor (SG1) was used as input to estimate stress histories at other locations by means of the LRFM (e.g., SG2). In this context, the local response function was derived by analyzing the correlation between stress histories predicted by the bridge's numerical local model. The results, shown in Fig. 6, demonstrate a good match with experimental measurements, with the maximum deviation in peak stress values around 14% for one case, while others remained within 6%. More broadly, with a reliable FEM model, the LRFM can predict stress histories at multiple virtual sensors within the locally refined model, using stress histories estimated by the TCN model as input. These analyses were conducted for the virtual sensors shown in Fig. 7-a, positioned on the bridge's midspan cross-section (Fig.7-b). The stress range spectra shown in Fig. 9 can be used to predict the remaining fatigue life using the established Palmgren-Miner rule or more elaborate models based on crack growth, such as linear elastic fracture mechanics (LEFM). However, the low-magnitude stress ranges will be below the fatigue limit, implying an infinite fatigue life. The results indicate that integrating a deep learning algorithm with a well-calibrated numerical model of the structure can effectively predict stress histories at various bridge locations under different railway loading conditions. This approach reduces the need for extensive direct instrumentation, providing a cost-effective and efficient solution for operational structural health monitoring.

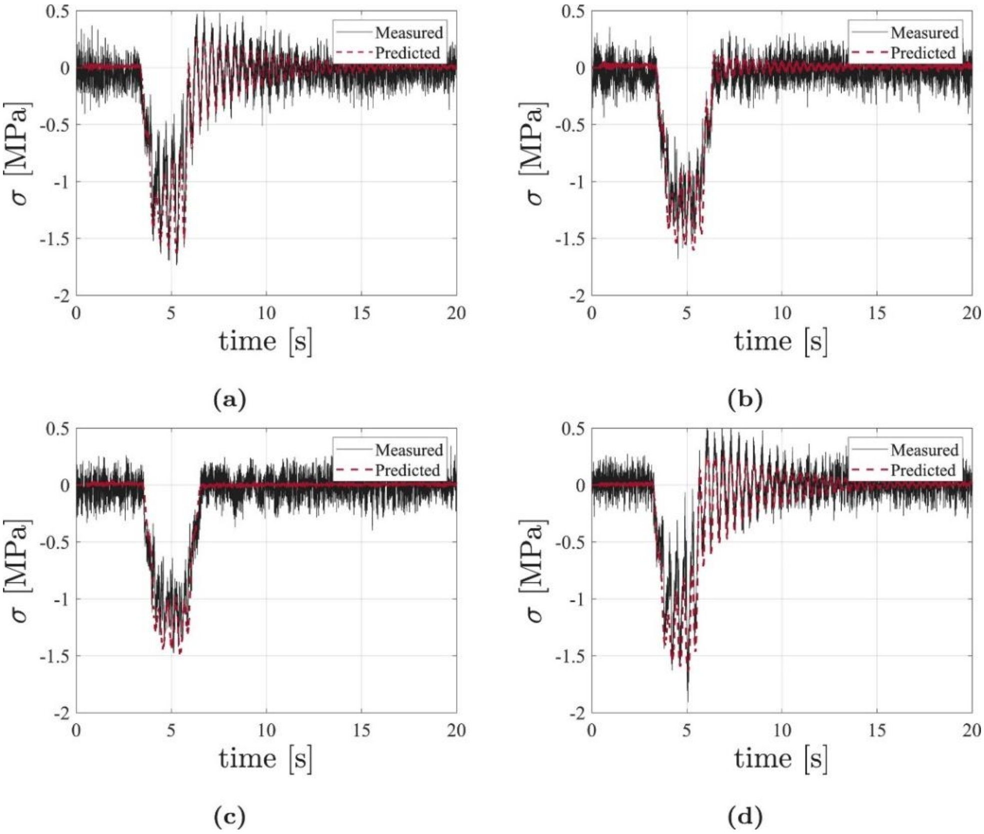


Figure 6: TCN and LRFM sensors prediction: comparison between predicted values and measurements at SG2, reproduced after [3].

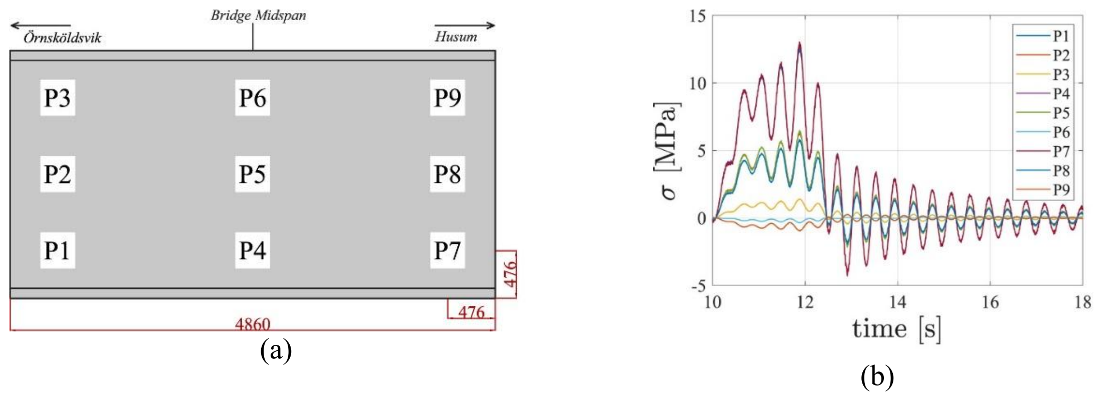


Figure 7: LRFM virtual sensors prediction: a) Virtual sensors locations b) Right girder location, reproduced after [3].

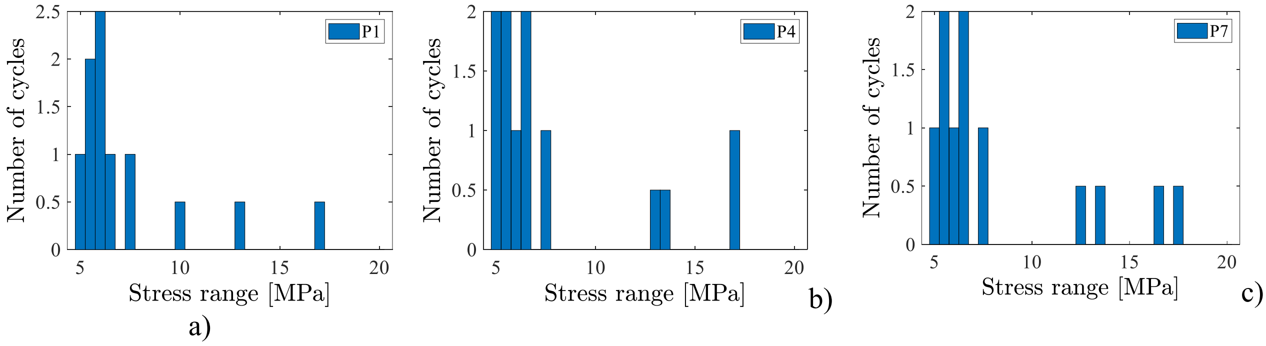


Figure 8: Stress range spectra derived from rainflow counting method.

5 CONCLUSIONS

This study introduced a novel methodology that combines two approaches to predict data across various bridge locations using sparse monitoring. The first approach involved a TCN-based deep learning model to identify correlations between stress histories and acceleration data. The second approach utilized the Local Response Function Method (LRFM) to create a reliable numerical model of the bridge, allowing strain predictions at unmonitored locations. The methodology was validated with experimental data from the Bryngeån Bridge in Sweden. The findings show that the TCN model effectively converted acceleration data into stress histories, providing conservative estimates of fatigue life, especially for higher stress ranges. In conclusion, this methodology presents a cost-effective and efficient solution for enhancing bridge monitoring and maintenance by reducing the need for extensive instrumentation.

REFERENCES

[1] Natali, A., Padalkar, M. G., Messina, V., Salvatore, W., Moreiro, P., Del Bue, A., & Beltrán-González, C. (2022, September 11–15). Artificial intelligence tools to predict the level of defectiveness of existing bridges. *Atti del XIX Convegno ANIDIS & XVII Convegno ASSISi*. Torino, Italy. https://doi.org/10.1016/j.prostr.2023.01.258

[2] Natali, A., Messina, V., Salvatore, W., Gervasi, V., Anzalone, D., Canciani, A., & Severino, F. (2022, September 11–15). A new tailored developed software for the risk classification of bridges according to the Italian Guidelines. *Atti del XIX Convegno ANIDIS & XVII Convegno Assisi*. Torino, Italy. https://doi.org/10.1016/j.prostr.2023.01.257

[3] Menghini, A., Meng, B., Leander, J., & Castiglioni, C. A. (2024). Estimating bridge stress histories at remote locations from vibration sparse monitoring. *Engineering Structures, 318*, 118720. https://doi.org/10.1016/j.engstruct.2024.118720

[4] Akintunde, E., Azam, S. E., & Linzell, D. G. (2023). Probabilistic bridge fatigue evaluation at virtual sensing locations using kernel density estimation. *International Journal of Fatigue, 176*, 107885. https://doi.org/10.1016/j.ijfatigue.2023.107885

[5] Maes, K., & Lombaert, G. (2023). Validation of virtual sensing for the reconstruction of stresses in a railway bridge using field data of the KW51 bridge. *Mechanical Systems and Signal Processing, 190*, 110142. https://doi.org/10.1016/j.ymssp.2023.110142

[6] Leander, J. (2018). *Fatigue life prediction of steel bridges using a small scale monitoring system* (Report No. TRITA-ABE-RPT-2226).

[7] Menghini, A. (2025). Calculation of weld toe stresses from global numerical models: An engineering-oriented approach. *Journal of Constructional Steel Research*. https://doi.org/10.1016/j.jcsr.2025.109431

[8] Menghini, A., Leander, J., & Castiglioni, C. A. (2023). A local response function approach for the stress investigation of a centenarian steel railway bridge. *Engineering Structures, 286*, 116116. https://doi.org/10.1016/j.engstruct.2023.116116

[9] Meng, B., Menghini, A., & Leander, J. (2024). Virtual sensing in steel bridges: Time series deep learning for stress prediction. *Procedia Structural Integrity, 64*, 774–783. https://doi.org/10.1016/j.prostr.2024.09.342

[10] Andersson, A., et al. (n.d.). *High speed low cost bridges, background report, Appendix for D5.6, Task 5.5, In2Track3.*