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Virtual Sensing in Steel Bridges: Time Series Deep Learning for Stress Prediction

Bowen Meng[a,*], Menghini Alessandro[b], Leander John[a]

[a]*KTH Royal Institute of Technology, Brinellvägen 23, Stockholm 10044, Sweden*
[b]*Politecnico di Milano, Via Giuseppe Ponzio 31, Milano 20133, Italy*

Abstract

This study introduces an innovative approach for predicting stress responses in steel bridges, specifically focusing on a railway bridge in Vänersborg, Sweden. Four deep learning models have been evaluated: Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), Temporal Convolutional Network (TCN), and a hybrid LSTM-TCN. Training on stress history data from a multiscale Finite Element (FE) model and a validation with real-world data from a bridge monitoring system revealed high prediction accuracy near sensor locations, surpassing an R-squared score of 0.9, comparable to the polynomial local response function method.
The comparative analysis provides critical insights into the great potential of deep learning-based sequence models for identifying intricate, temporally dependent stress patterns across the bridge, including predictions at points distant from direct sensor measurements. These models demonstrate a notable capability for capturing highly non-linear relationships between stress histories. While sequence models (LSTM, TCN, and hybrid LSTM-TCN) tended to provide conservative estimates impacting fatigue life predictions, the MLP model occasionally underestimated critical stress cycles.
This research emphasizes the potential of deep learning techniques for time series to enhance bridge monitoring systems, improve virtual sensing, and enable real-time monitoring capabilities. Our proposed methodology provides a comprehensive understanding of stress data in steel bridges, which is crucial for ensuring their maintenance and safety.

Keywords: Fatigue Life Prediction; Virtual Sensing; Time Series Modeling; Deep Learning

* Bowen Meng.
E-mail address: bowenm@kth.se

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1. Introduction

The safety and structural integrity of aged metallic bridges demand heightened attention due to escalating fatigue risks. These risks stem from repetitive and variable loads that bridges endure over time. Fatigue can lead to the development of cracks, degradation of load-carrying capacity, and, in extreme cases, catastrophic outcomes such as the collapse of the Sungsoo Grand Bridge in Seoul in 1994, which resulted in thirty-two fatalities (Cho et al., 2001). Such incidents underscore the need to develop effective monitoring and maintenance strategies for these bridges.

Bridge fatigue assessment has traditionally relied on manual visual inspections and nondestructive testing methods. Sensor-based health monitoring systems increasingly complement these assessment approaches. However, applying monitoring systems to large-scale bridges brings challenges related to hardware costs, maintenance, and operational demands. To overcome these, 'virtual sensing' has emerged as a promising alternative. This concept involves integrating computational models and algorithms to estimate a structure's state using indirect or sparse sensor data. For example, Hajializadeh et al. (2017) demonstrated this concept by using a calibrated finite element (FE) model, combined with weigh-in-motion (WIM) data, to estimate stress ranges and predict cumulative fatigue damages in a steel bridge without strain sensors. Iliopoulos et al. (2017) applied similar virtual sensing techniques in Offshore Wind Turbines (OWTs), addressing sensor installation challenges in hard-to-reach locations. Integrating finite sensor data with calibrated FE models enables stress estimations in physically inaccessible areas.

Despite these advancements, accurately determining loading conditions for each simulation remains a prerequisite for effective stress range calculation using FE models. The substantial computational demands of these simulations also limit their feasibility for real-time monitoring applications. With the advent of machine learning, integrating machine learning methods with FE models for stress prediction has gained significant attention in structural health monitoring. For instance, Leander (2018) utilized theoretical influence lines and artificial neural networks (ANN) to predict stress responses from train passages. The study demonstrates the potential of ANNs in stress predictions, provided the input variables exhibit similar time variance. Akintunde et al. (2023) introduced a data-driven method based on Singular Value Decomposition (SVD) and unsupervised machine learning for strain estimation in operational railroad bridges. However, these studies have not fully explored the temporal dependencies of stress signals, which is critical for accurate stress prediction.

This paper addresses this gap by introducing deep learning techniques for time-series analysis in stress prediction, a novel application in bridge monitoring. The objective is to efficiently predict stresses in specific areas of steel bridges where direct data measurement is challenging, and actual loading conditions are unknown. Building on previous work by Menghini et al. (2023), a multilayer perceptron model (MLP) was initially trained and compared with the local response function method. Subsequently, two machine learning architectures for time-series problems, including Long Short-Term Memory (LSTM) and Temporal Convolutional Networks (TCN), are introduced to develop models trained with stress data from a multiscale FE model. The accuracy of these models is examined against actual bridge stress responses, with a case study conducted on a railway bridge in Vänersborg, Sweden, to validate the proposed methods.

2. Methodology

Fatigue analysis in bridge engineering, particularly using methods based on the S-N curve and Linear Elastic Fracture Mechanics (LEFM), depends heavily on accurately determining the stress range spectrum. Such precision is pivotal for the trustworthy prediction of fatigue life. In response, the subsequent sections will detail methods designed to infer structural information at unmonitored locations, aiming to refine stress range estimation accuracy. These methods incorporate the use of calibrated Finite Element Models (FEMs) in conjunction with direct on-site empirical measurements.

2.1. Local response function method

Rather than depending solely on numerical models for computing stress ranges under variable loading conditions, a local response function approach was employed to examine stress correlations and predict stress variations. This approach facilitates the prediction of stress histories across various elements of a bridge (Menghini et al., 2023). To achieve this, a third-order cubic polynomial function was applied to model the stress correlations. The function is refined using the least-squares regression estimator, incorporating stress data derived from a calibrated FE model.

The resulting correlation function, denoted as f, along with a stochastic error component ϵ, forms the foundation for predicting stress responses. The predicted stress response at a given bridge element $\widehat{S_j}$ is estimated from experimental measurements at location S_i as expressed by Eq (1).

$$\hat{S}_j(S_i) = f(S_i) + \varepsilon \tag{1}$$

The details of the methodology, including the specifics of the function's application and the calibration process of the FEM model, are thoroughly described in Menghini et al. (2023).

2.2. Deep learning architectures

Though the local response function method has proven effective for stress predictions near the sensor locations, it has presented challenges.to predict the stress responses at distant locations where structural behavior significantly differs. By accounting for temporary dependencies of signals, deep learning models were developed and compared to further investigate the complex and implicit stress correlations among different locations. These models include a Multilayer Perceptron (MLP), a Long Short-Term Memory Network (LSTM), a Temporal Convolution Network (TCN), and a hybrid LSTM-TCN model, each featuring distinct architectures and characteristics.

The Multilayer Perceptron, a fundamental form of artificial neural networks, is designed to approximate complex functions using multiple layers of neurons (Rumelhart et al., 1986). Building on the encouraging findings from previous studies, this research explored the MLP's potential to replace the local response function method. Specifically, this study employed an MLP model configured with two hidden layers to approximate stress correlations.

Rather than approaching the prediction of the stress response as a nonlinear regression problem, two sequence modeling architectures were introduced to account for the temporal dependency in stress correlations. Firstly, Long Short-Term Memory Networks (LSTMs) were integrated into the model. LSTMs, as a specialized form of recurrent neural networks (RNNs), are designed to bridge the gap between the need for long sequential processing and memory retention. By leveraging a gated mechanism, LSTMs excel at tasks requiring the preservation of information over time, such as language processing (Sutskever et al., 2014) and time-series prediction (Greff et al., 2017; Kong et al., 2019).

The applied model consists of a two-layer stacked LSTM network. As shown in Fig. 1 (a), the model inputs segmented strain signals, each a sequence of 30 data points, and processes them through a first LSTM layer of 16 cells. A dropout layer is included to prevent overfitting and enhance the model's generalizability. The second LSTM layer, with 16 cells, further processes the temporal features. Finally, a dense layer compiles the outputs from the LSTM layers, producing a single predictive value, $\hat{y}_{n+29}$, which predicts the strain based on the previous thirty data points. A detailed description of the model's configuration and the training procedure will be provided in a later chapter.

To compare with the LSTM model, a Temporal Convolution Network (TCN)-based model with a similar level of parameters was established. As depicted in Fig. 1 (b), the model has two TCN layers, followed by a dense layer that outputs the final prediction.

The Temporal Convolution Network, a tailored convolutional neural network for time series data, was proposed by Bai et al. (2018). It has demonstrated superior performance over canonical recurrent architectures such as LSTMs and GRUs in various standard sequence modeling benchmarks such as word-level and character-level language modeling (Bai et al., 2018). A fundamental aspect of TCNs is the application of causal convolution. This technique ensures that the predicted output at any given time ($\hat{y}_t$) is influenced only by the current and previous inputs ($x_0, x_1, \ldots x_t$), and not by future inputs ($x_{t+1}, x_{t+2}, \ldots$). This design is essential to prevent information leakage from the future to the past, particularly crucial in time-series analysis of sensor data.

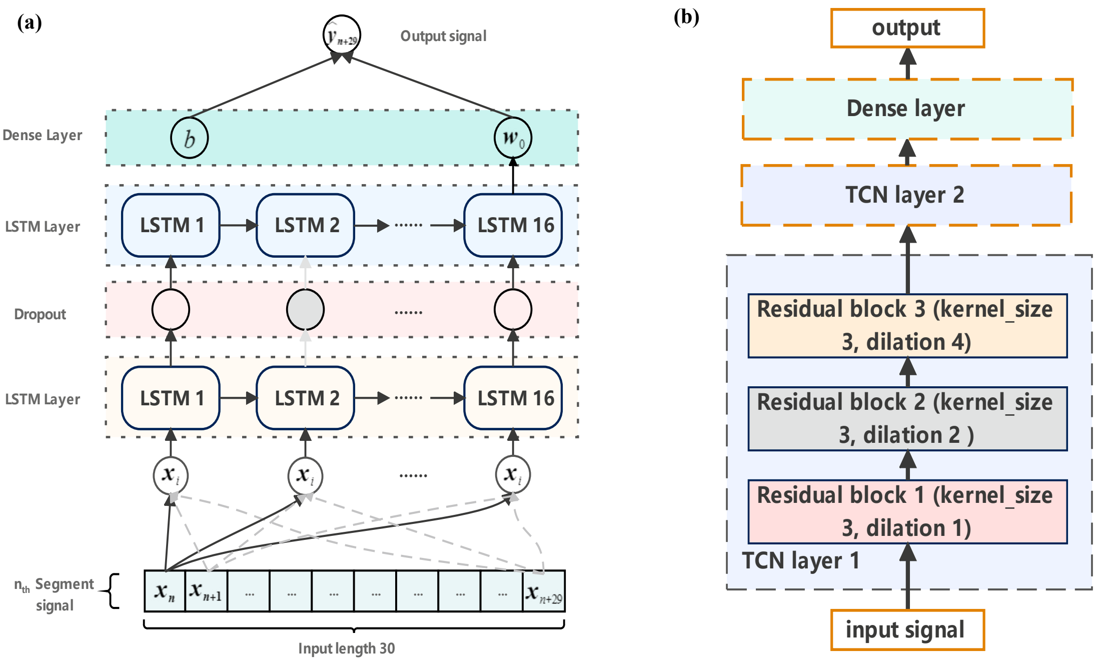

Fig. 1. The architecture of the LSTM model and the TCN model.

Temporal Convolutional Networks (TCNs) leverage dilated convolutions for expanded receptive fields with low computational cost and incorporate residual connections for improved gradient flow, offering computational efficiency and flexibility over traditional RNNs and LSTMs (He et al., 2016; Yu & Koltun, 2015). For further details of mechanisms, see Bai et al. (2018).

The methodology employed in this study, as illustrated in Fig. 2, involves signal analysis and deep learning implementation. Stress histories were extracted from the FE model at points corresponding to the actual locations of strain gauges. These historical data were then organized into pairs: one signal at a specific location is used as the input, and the other from another position is used as the target for prediction outcomes. A sliding window was applied to the input signals to segment the continuous signal into smaller sequences of thirty data points, advancing one point at a time (stride of 1). In parallel, the target signal was also segmented, as depicted by the green blocks in Fig. 2. Zero-padding was introduced at the beginning of the input signal to align the output sequence length with that of the target set. These steps set the stage for deep learning models to learn complex data patterns and predict stress responses that closely match the target signal. After training, the models were validated against stress histories obtained from on-site measurements, determining their effectiveness in real-world scenarios.

To prepare the data to validate the trained models, measured strain signals were transformed into stress histories by multiplying them by Young's modulus (E), valued at 210 GPa. Furthermore, the signals were denoised and synchronized. Fast Fourier Transform (FFT) analysis was first applied to the signals, allowing for identifying the noise frequency range. Then, a low-pass filter with a 5-Hz cutoff frequency was used to mitigate the noisy components. The cross-correlation between signal pairs was examined to determine any time lags and ensure proper alignment and synchronization of the signals before their subsequent use.

The subsequent step involves utilizing the preprocessed input stress history to predict stress responses at different locations. These predictions were compared with actual on-site measurements. Furthermore, stress range spectra were generated using the Rainflow counting algorithm (ASTM, 2017), commonly used in cyclic load analysis. This process provides insights into the distribution of stress ranges, serving as a critical metric for evaluating the accuracy of models.

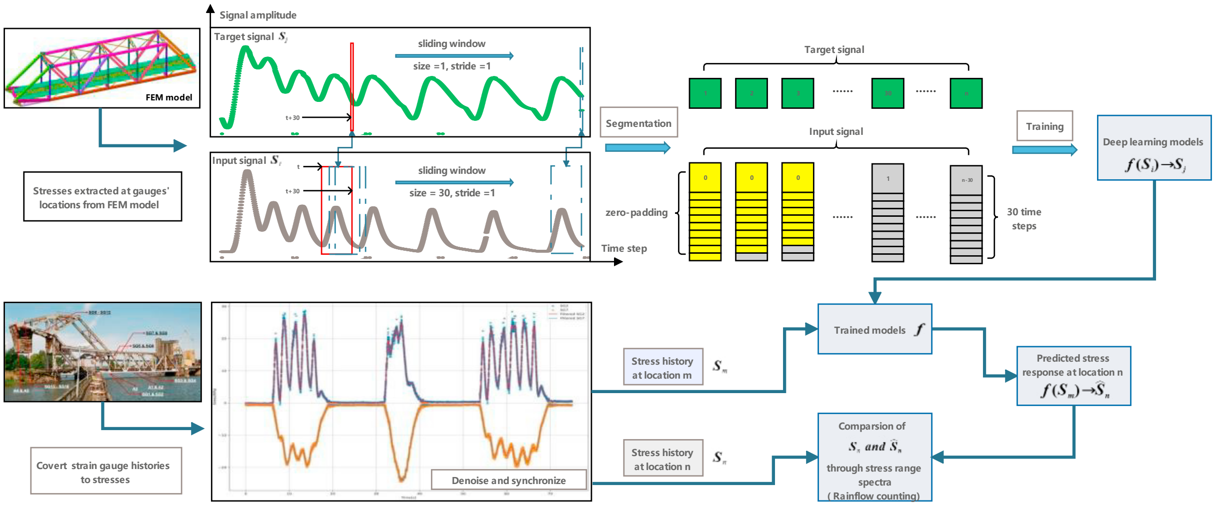

Fig. 2. Illustration of the applied methodology

3. Case Study of the Vänersborg Bridge

3.1. The Vänersborg Bridge and monitoring campaign

The Vänersborg Bridge, situated in the southwest of Sweden over the Trollhätte Canal, is an exemplary model of early 20th-century engineering. In the autumn of 2021, a monitoring campaign was initiated with a set of sensors, including 16 uniaxial strain gauges (SG), 5 uniaxial accelerometers, and an inclinometer for movement tracking of the bascule truss. The strain gauges were strategically positioned to avoid areas susceptible to stress concentrations and provide nominal stress data of the truss elements. The first eight, shown in Fig. 3, were welded to key structural members: SG1 and SG2 on the lower crossbeams, SG3 and SG4 on the adjacent crossbeams, SG5 and SG6 on the truss diagonals, and SG7 and SG8 on the upper chord. The rest of the strain gauges (SG9-SG16) were placed on the counterweight truss. This arrangement was optimized through rigorous visual inspections and preliminary computational evaluations. Together with the strain measurements, five accelerometers are installed at different locations. For instance, A3 recorded vertical acceleration in the first crossbeam. More detailed information on installed sensors, such as sensor types and layout, can be found in Leander et al. (2023).

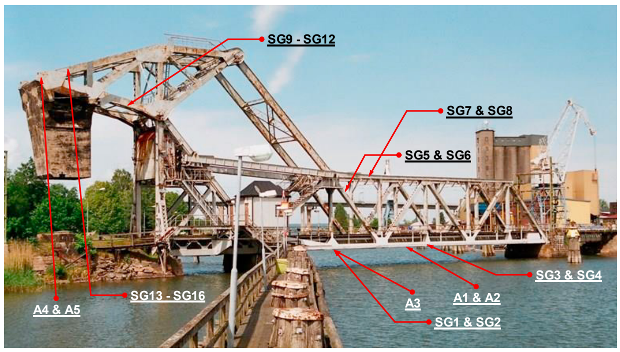

Fig. 3. The sensor layout of the health monitoring system

The collected data, with a sample frequency of 200 Hz and 10-minute events, is systematically archived. From the achieved data, a signal-day strain record containing passages of two different types of trains was used to examine the performance of the trained deep-learning models.

3.2. Numerical modelling procedures

To prepare the training datasets for deep learning models, stress histories must be extracted from a multiscale FE model that encompasses a global model and several local models. The global model uses beam and shell elements for various bridge components. The material properties of steel S275 are assumed for key structural elements. As shown in Fig. 4, the counter-weight system is intentionally excluded from the model, being treated as an independent, statically determined structure (Menghini et al., 2023). Loading conditions were simulated to represent an X55 Regina train transit, employing triangular pulse loads for axle loads and a 10 km/h passing velocity.

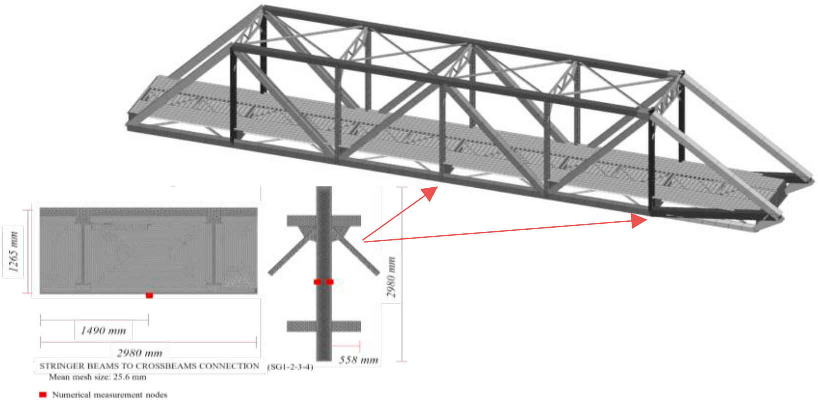

Fig. 4. Global numerical model and local model of the crossbeam (lower).

Once the displacements are obtained from the global model, connections between the local submodels are established through primary nodes according to the procedure in Menghini et al. (2023). A screenshot of the local model for crossbeams is displayed in Fig. 4. The red dots represent the locations of sensors (SG1, SG2, SG3, and SG4). Detailed time-history stress responses were extracted from these locations with the same sample frequency, and these stress histories form the foundation for the subsequent correlation analysis.

3.3. Stress Correlation Exploration

Stress histories of strain gauges SG2, SG5, and SG7 from the FE model were used to train four deep-learning models. To visualize the relationship between each pair of stress values after synchronization, two scatter plots representing correlations of stress responses are shown in Fig. 5.

Fig. 5(a), illustrating the correlation between SG5 and SG7, features a more confined pattern than SG2 and SG7. The former pattern suggests a tighter, more direct association of stresses at two locations. In contrast, Fig. 5(b), depicting SG2 and SG7, displays a less dense, more elongated looping structure, indicating a highly non-linear nature of dependency. The nuanced complexity revealed in the plot is impossible to model with polynomial functions from previous research (Menghini et al., 2023).

Adding time as another dimension, Fig. 6(a) depicts the temporal evolution of two signals, SG2 and SG7, in a three-dimensional space. The color gradient along the data points, ranging from violet to yellow, correlates to the magnitude of SG2. It provides an intuitive visualization of stress variation over time. Furthermore, semi-transparent planes, distinguished by varying hues, divide clusters of data points across different time intervals. These visual aids facilitate the identification of periodic or cyclical patterns in the data with respect to time. As seen in Fig. 6(b), during the specified time intervals of 20.3-29 seconds and 29-38 seconds, the correlation patterns between SG2 and SG7 are remarkably consistent, indicating a non-linear and time-influenced relationship between the two stress measurements. Such insights highlight the potential benefits of employing sequence modeling techniques within deep learning frameworks to capture complex, temporal correlations adeptly. The regularity and predictability implied by these patterns suggest that sequence models, such as LSTMs and TCNs, could be particularly effective in modeling these dynamic relations for predictive analyses.

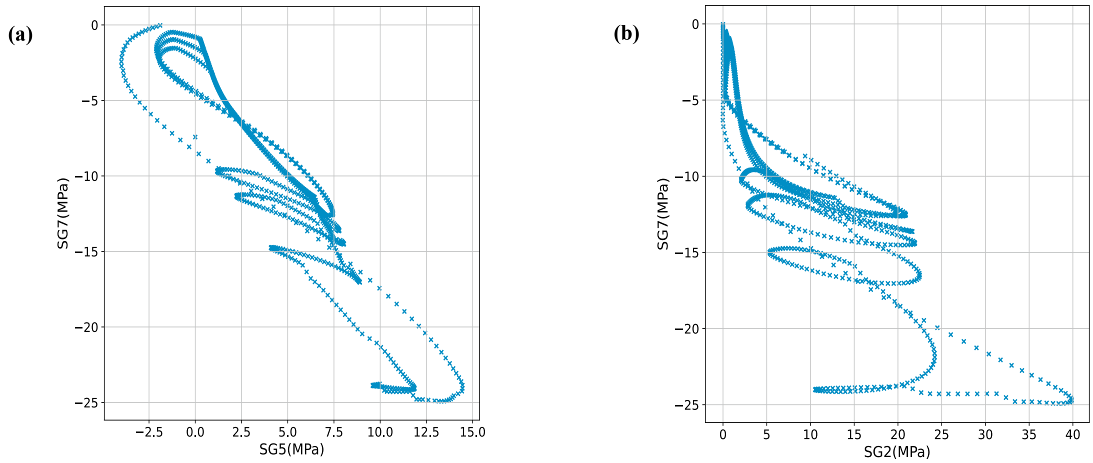

Fig. 5. Stress correlation between SG5 &SG7; and SG2 & SG7.

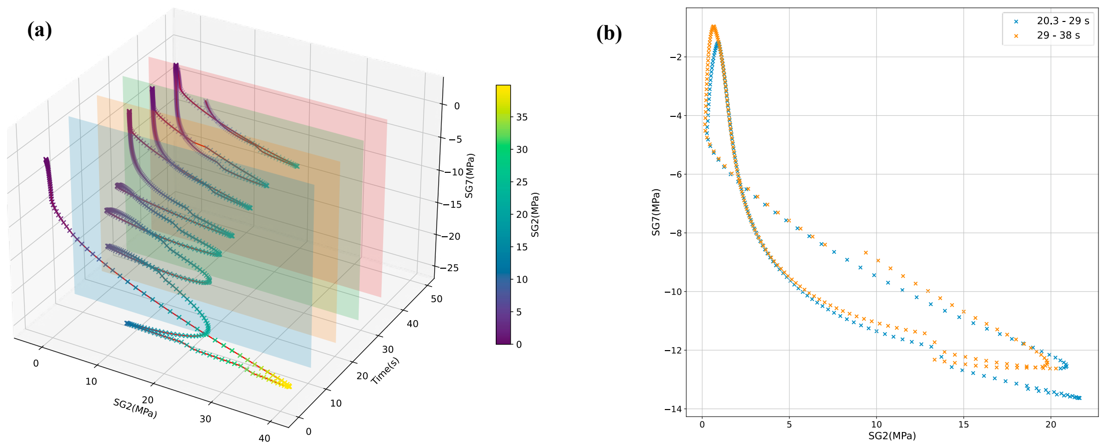

Fig. 6. (a) Temporal dynamics and correlation of stress SG2 and SG7 in three-dimensional space; (b) Stress correlations in time intervals.

3.4. Prediction of stress response

The efficacy of four deep-learning models, including a Multilayer Perceptron, a Long Short-Term Memory network, a Temporal Convolutional Network, and an LSTM-TCN hybrid model, in capturing complex correlations of stress histories was investigated. The configurations and parameters of each model are detailed in Table 1. All models were trained using the Adam optimizer (Kingma & Ba, 2014) and the mean squared error loss function.

Table 1. Configurations of each model with its number of parameters

Model	Input layer	Layer 2	Layer 3	Output layer	Parameters
MLP	1 neuron	64 neurons	64 neurons	1 neuron	4353
LSTM	16 LSTM cells	Dropout 0.1	16 LSTM cells	1 neuron	3281
TCN	TCN 10 filters	TCN 10 filters	N/A	1 neuron	3481
LSTM-TCN	16 LSTM cells	TCN 10 filters	N/A	1 neuron	3993

These models are considered "lightweights" due to their small number of parameters, which are determined through extensive experimental trials. It was observed that the models' performance noticeably declined with a reduced number of layers or cells. Moreover, the dropout layer was omitted in the MLP, LSTM-TCN, and TCN models. This decision was based on the observation that including the dropout layer adversely affects the predictive accuracy of these models.

For training, 90% of the total signal data derived from the FE model was utilized, reserving 10% for validation. This validation aids in determining the appropriate number of training epochs and monitoring overfitting. Once the models are trained, on-site strain signal measurements were employed to evaluate each model's performance. Specifically, two typical trains with distinct stress histories during the passages were selected to test the models' generality. The results are shown in Fig. 7.

On the left column of Fig. 7, the predicted stress response $\widehat{SG}_7$ using SG_5 from each model is depicted for two different train passages. The measured stress response of SG_7 is represented by blue lines, while the yellow lines denote the output from the local response function method. All deep learning models exhibit comparable accuracy, with R-squared scores exceeding 0.9, to the local response function method for the three train signals. However, for train type 2 in Fig. 7(b), the local response function method and MLP model tend to underestimate stress fluctuations caused by train passage. In contrast, LSTM, TCN, and the hybrid models slightly overestimate the peak and trough magnitudes.

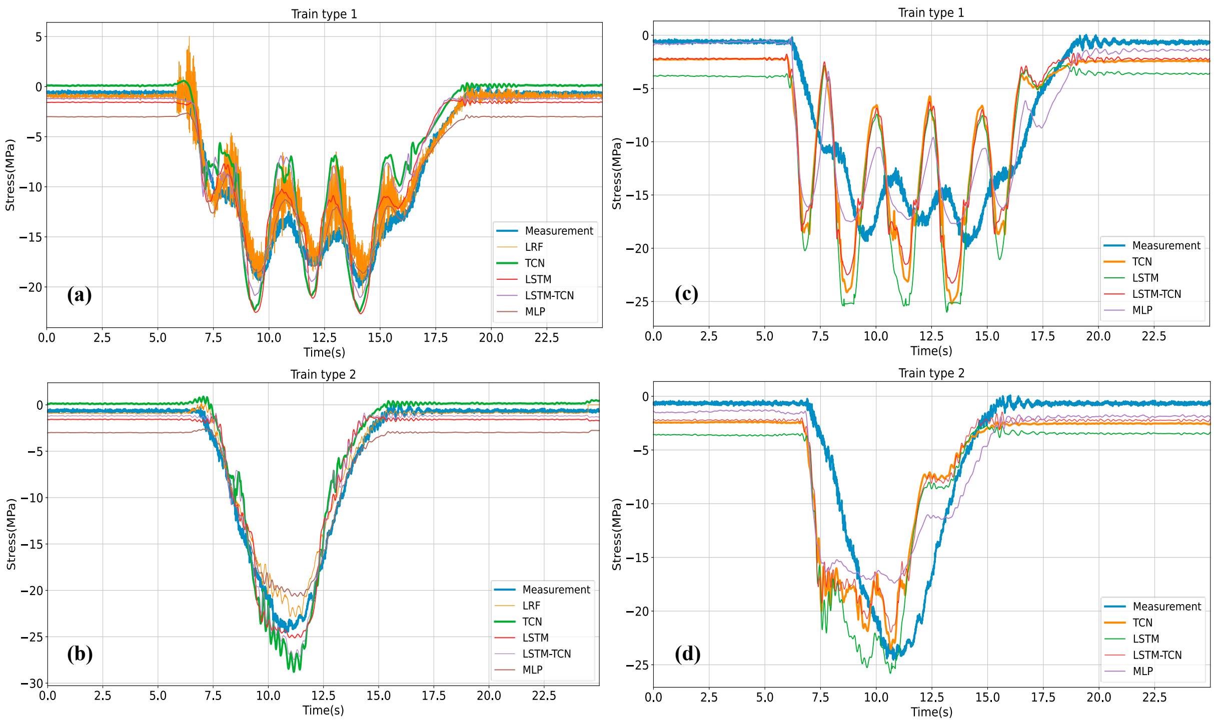

Fig. 7. Predicted stress response of $\widehat{SG}_7$ derived from SG_5(left column) and SG_2 (right column).

Fig. 7(c) and Fig. 7(d) contrast the predictions of $\widehat{SG}_7$ using SG_2 from deep learning models. Given the challenges in approximating the time-dependent correlation with the local response function method, only the results from the deep learning models are presented. All models successfully captured the overall trend of signal variations compared to the true stress response in blue. Except for the MLP model, the other models generally provided amplitudes close to or slightly above the actual measurements. However, the results for train type 1, reveal deviations from the actual response, including two unexpected signal peaks and troughs. Potential causes may include discrepancies in the modeled versus actual axle distance of trains, variations in train speed, and measurement errors from the strain gauges. In fact, the imperfect FEM model can hardly replicate the behaviors of the bridge and thus cause deviations in stress correlations. Furthermore, the axle distance of the train and train speed will influence the time-dependency of stress variations. The trained model with inconsistent loading conditions and biased mapping between stress histories will not give precise predictions. Currently, the FEM model only employs a simple loading condition

(Regina X55 train) as a representative load scenario; expanding the training dataset to include various train configurations could enhance prediction accuracy.

3.5. Stress range spectrum

For fatigue analysis and accurately predicting the remaining life of steel bridges, precise determination of stress range and corresponding cycle count is important. In this pursuit, a rainflow counting algorithm was employed on predicted stress responses from deep learning models to extract stress ranges and cycle counts. To minimize the impact of minor stress fluctuations in the historical data on cycle counting, a threshold of 5 MPa was applied. As a result, stress ranges below this threshold are excluded from the final analysis.

As demonstrated in Fig. 8, a comparative visualization of stress range cycle counts for predicted $\widehat{SG}_7$, obtained based on stress history SG_5 and SG_2, is presented in a three-dimensional representation. Each bar, distinguished by color, represents a predictive model, with the blue bars indicating the actual stress response at the location of strain gauge 7 (SG_7). It is observed that, for most stress ranges, deep learning models overestimate the cycle counts, thus yielding conservative estimates for fatigue life. The MLP model consistently fails to predict cycle counts for stress ranges exceeding 25 MPa. As the studied maximum stress range is below the endurance limit of the material, predictions from MLP will not influence the prediction of bridge fatigue life. However, the results underlined the potential superiority of sequence-based models that incorporate the temporal dependencies of signals for accurate prediction of stress responses.

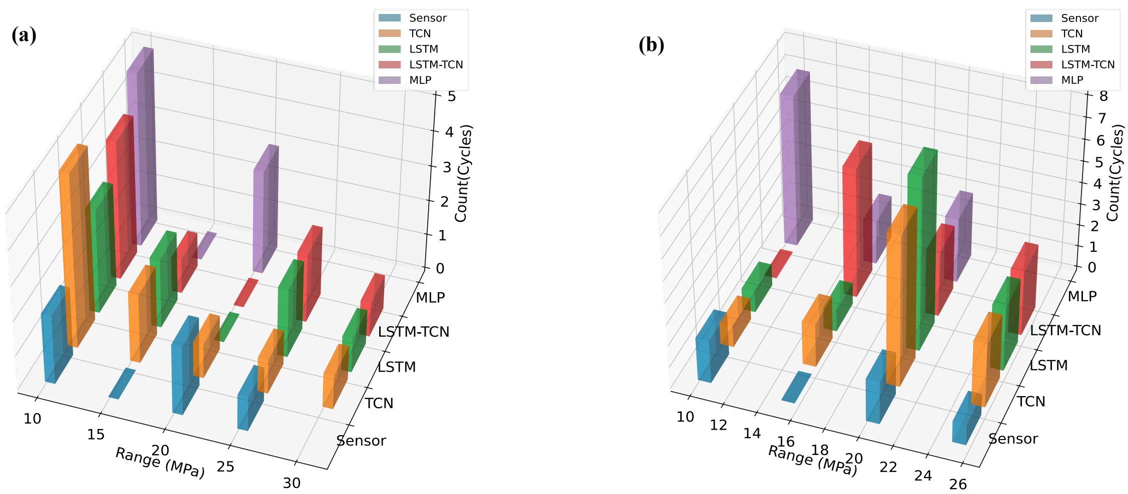

Fig. 8 Comparative analysis of cycle counts: sensor data versus predictive models with $\hat{G}_7$ derived from G_5 (a) and G_2(b).

4. Conclusion

In this research, four deep-learning models were developed and compared. Based on the calibrated FE model, all deep learning models demonstrated high prediction accuracy of stress responses for adjacent bridge elements, with R-squared scores exceeding 0.9. This consistency in performance highlights the models' capability to accurately approximate the stress responses in the vicinity of sensors, particularly in comparison to the traditional polynomial local response function method (Menghini et al., 2023). Notably, the deep learning sequence modeling architectures could capture the time-dependent, non-linear stress correlations at more distant locations where structural behavior significantly differs, which is impossible with the local response function method.

It was observed that the LSTM, TCN, and the hybrid model tended to overestimate stress variations, leading to conservative fatigue life predictions. In contrast, the MLP model, due to its inherent structural limitations and lack of temporal dimension in stress correlation modeling, tended to underestimate predictions. Such underestimation poses a significant concern in fatigue analysis, as it could overlook critical stress cycles, leading to an underestimation of accumulated damage over time.

Interestingly, the study revealed no significant differences in the performance among sequence models, each equipped with roughly 3,500 parameters. This finding suggests that the duration of stress responses elicited by a single train passage does not suffice to highlight the limitations associated with LSTM-based models, specifically their diminished efficacy in handling long-term sequences. Additionally, the TCN model demonstrated remarkable computational efficiency during training, thanks to its parallelized convolutional operations, making it a viable choice when extensive training data is available.

However, it is important to note that this study focused on nominal stress at locations without stress concentrations. Future research should explore the applicability of these models to local stresses around complex geometries. Expanding the training data to include different train configurations is crucial to refine prediction accuracy and ensure more reliable stress responses under various load conditions.

Overall, this study contributes a novel and impactful methodology to bridge virtual sensing, offering a more comprehensive understanding of stress response prediction of steel truss bridges, which is crucial for the long-term maintenance and safety of infrastructures.

Declaration of interests

No known competing financial interests or personal relationships could have appeared to influence the work reported in this paper.

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