DOI: 10.3217/978-3-99161-057-1-192

Physics-Informed Surrogate Modeling of the SCSHM Benchmark

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EXTENDED ABSTRACT

ABSTRACT: This study presents a physics-informed surrogate modeling approach for the SCSHM Benchmark bridge using a dual-path LSTM Autoencoder architecture. By combining synthetic data from a finite element model and real strain measurements, the model effectively reconstructs structural responses under moving truck loads. Results show good agreement between predicted and measured strains. Limitations such as the absence of vehicle–structure interaction effects are discussed, with directions for future improvements.
KEY WORDS: Surrogate modeling, LSTM, SCSHM benchmark, structural health monitoring.

1 INTRODUCTION

This study presents preliminary results obtained using bridge strain data measured on the Society of Civil Structural Health Monitoring (SCSHM) bridge benchmark [1]. The benchmark dataset contains strain measurements and photos collected over nine months by strain gauges and a fixed camera during passages of heavy vehicles. A Finite Element (FE) model of the Benchmark is also made available together with the dataset. In this study, the FE model and the data have been utilized to build a surrogate model of the Benchmark structure.

Traditionally, FE models and detailed simulations have been employed to estimate the structural response with high-fidelity structural properties. While these models are accurate, they are computationally expensive. To address this challenge, surrogate models have emerged as an efficient alternative to approximate the structural response. Surrogate models in structural engineering have gained attention in applications such as response estimation, probabilistic assessment, and damage detection. Among data-driven methods, neural networks have demonstrated strength in capturing nonlinear mappings as well as learning from the data. Deep learning models have successfully predicted the response of the bridges subjected to dynamic train loads, demonstrating the potential of these models in emulating complex structural behavior [2]. Compared to traditional simulations, these models provide rapid and scalable analysis, which is particularly crucial for operational digital twins or near-real-time decision-making support systems.

In this context, Long Short-Term Memory (LSTM) networks have been an especially powerful tool to learn from time series data, thanks to their capabilities to capture long-term temporal dependencies in sequential data. LSTMs have been shown to work well in response prediction for bridge [3]. In addition to the capability to capture the long-term dependencies, LSTM Auto-Encoders (AE) learn an efficient representation of the input space by compressing and reconstructing data, enabling simultaneous learning and data compression. These fusion LSTM-AE models are ideal for surrogate modeling of bridge behavior under vehicle loading.

In this study, two parallel LSTM-AE architectures are combined and trained through strain simulated by the FE model and strain measured on the Benchmark. The architecture is conditioned using specific physical conditions such as gross weight and velocity of the vehicles.

2 METHODOLOGY

The proposed methodology integrates physics-based finite element (FE) simulations with deep learning to accurately predict strain responses of a bridge under moving vehicle loads. A dual-path architecture is built, integrating two parallel LSTM-based Autoencoders (LSTM-AEs). The first is trained using strain responses obtained from a reduced-order FE model, and the second is trained on measured strain data. These parallel encoders are fused in a physics-informed manner to enable robust learning, even in the presence of sparse or noisy real-world measurements.

The reduced-order FE model of the bridge is created using the modal decomposition of mass and stiffness matrices derived from a high-fidelity FE model. Reduced matrices are then used in a state-space formulation to simulate the bridge's dynamic response under moving truck loads. The moving load is applied along the bridge using a defined vehicle path, velocity, and gross vehicle weight (GVW) estimated using the area method [4]. For unique combinations of GVW and velocity observed in the dataset, simulated time series are generated at specific sensor locations using the bending moment and structural geometry. These are then converted into macrostrain using the known strain gauge positions.

The proposed architecture consists of several key components: two parallel encoders, latent representations, conditions, and a decoder, as indicated in Figure 1. The first Encoder encodes the simulated strain signals into a latent representation. These synthetic signals are generated offline for each GVW-velocity pair, corresponding to the conditions observed in the real measurement dataset. The second Encoder encodes the measured strain data into a latent representation. The parameters GVW and vehicle velocity are used as inputs to the FE model and are inherently included in the real bridge measurements, since each truck has its own physical properties. They are also used as condition vectors, as they are fed into the decoder architecture. Finally, the decoder reconstructs the strain measurements using the combined latent representations from both the Encoders and the Condition Vector. The model is trained end-to-end to minimize the reconstruction error between the predicted and the actual measured strain time series.

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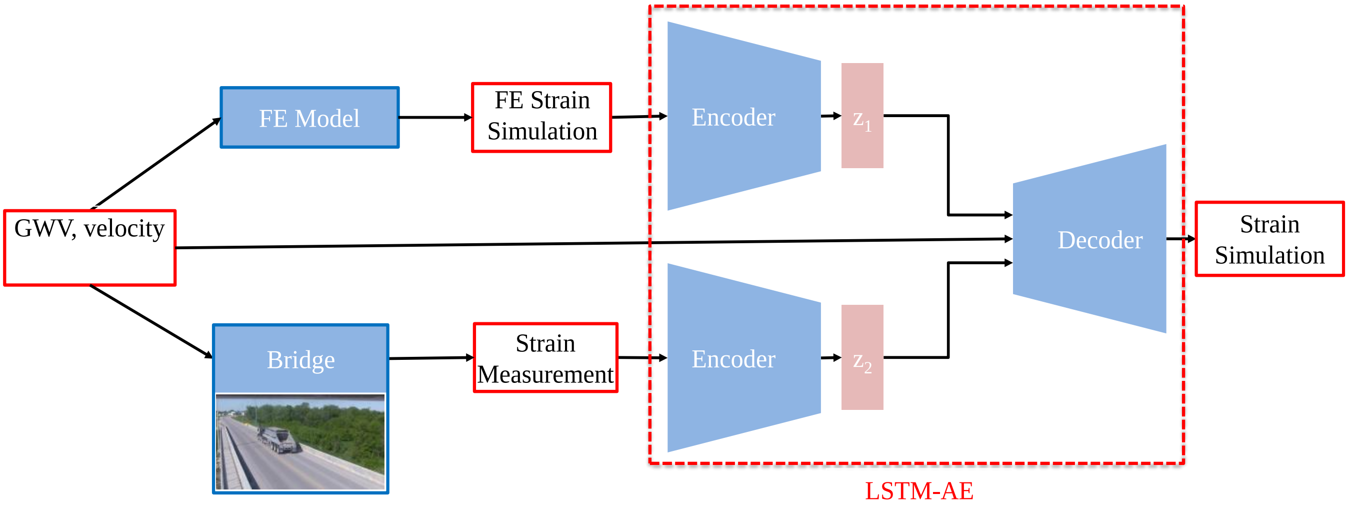

Figure 1. Flowchart of the proposed LSTM-AE architecture.

3 IMPLEMENTATION ON THE SCSHM BENCHMARK

The proposed methodology is implemented using strain data collected as part of the SCSHM bridge benchmark study [1]. The structure is a single-span, simply supported bridge with a length of 22.71 m, carrying two lanes. The selected bridge span is instrumented with 32 electric resistance strain gauges to monitor strains under the deck. Strain gages are placed at several cross-sections (end of spans, midspan, and ¾ of the span) and different locations within each section. The dataset includes measurements recorded during controlled load tests as well as under normal traffic conditions. For this study, operational truck data is utilized due to its high volume and variability, which are essential for effectively training a deep learning-based architecture. To build the surrogate model, the structural responses measured by strain gauges located at the midspan section are selected. These midspan measurements are representative of the critical section where bending moments are typically maximal, making them well-suited for surrogate modeling.

Figure 2 and Figure 3 show the comparison between the predicted and measured strain time series at midspan gauges. They closely align both in shape and amplitude, showing that the model effectively learns the relationship between condition parameters and response evolution. Figure 2 illustrates the model's performance on the training set while Figure 3 on the testing set. The comparison highlights the ability of the LSTM to generalize to unseen data in the test set, where it maintains consistent accuracy even on condition pairs not explicitly encountered during training.

The proposed surrogate model integrating physics-informed simulations and measurement-based encoders via a dual LSTM Autoencoder architecture demonstrates good predictive performance in reconstructing bridge strain responses. Even though the model is trained using the full dual LSTM-AE architecture, only the trained latent representation and decoder, together with condition inputs, are used during prediction, providing a computationally efficient solution. Despite relying on a reduced portion of the architecture for prediction, which enhances computational efficiency, the model successfully captures the dynamic characteristics of the structural response across varying vehicle loading scenarios.

However, it is worth noting that the current model does not account for the effect of the inertia of the moving vehicle, which may explain the absence of the fluctuations observed in the real measurement data. Neglecting this interaction can result in underestimation of transient strain fluctuations or increased scatter in the predicted responses. Therefore, this study should be considered as an initial attempt to build a surrogate model. The future work will focus on incorporating vehicle-bridge interaction into the simulation framework to enhance the fidelity.

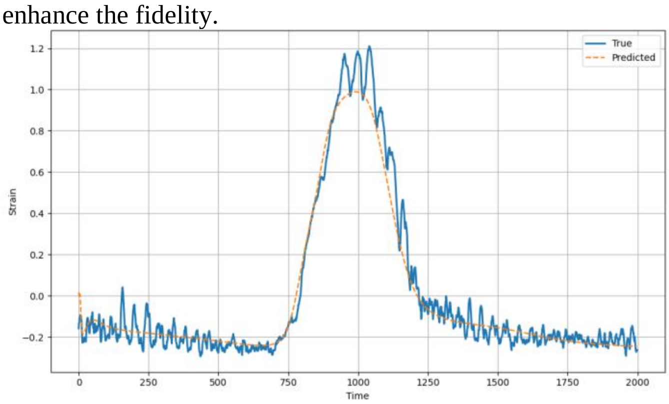

Figure 2. Strain prediction results for the training set.

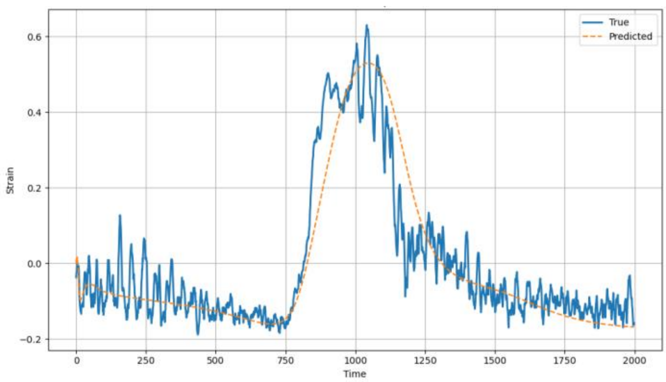

Figure 3. Strain prediction results for the validation set

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