Physics-Informed Machine Learning-Driven Structural Digital Twin for Damage Identification

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ABSTRACT

With advancements in AI, data-driven methods such as autoencoders (AEs) have been widely used for damage identification through anomaly detection. However, AE-based methods primarily learn identity mappings from healthy-state data, making them less effective in detecting subtle damage. This study presents a physics-informed, machine learning-driven structural digital twin (SDT) framework for damage identification using anomaly detection. By incorporating physics-informed neural networks (PINNs), the framework reduces discrepancies between finite element model (FEM) predictions and real structural responses, enabling more accurate anomaly detection. The proposed approach is evaluated using the numerical ASCE benchmark structure. It outperforms AE and LSTM-AE baseline methods in comparatively smaller damage scenarios.

INTRODUCTION

In recent years, advancements in Internet-of-Things (IoT) and sensor technology have enabled real-time structural health monitoring (SHM) by integrating diverse sensors that generate vast data streams. Anomalies in these data can indicate structural changes, making anomaly detection suitable for identifying potential damage. The rapid evolution of AI, particularly unsupervised learning techniques, has significantly influenced SHM, with AEs gaining popularity for anomaly detection. However, AE-based methods primarily learn identity mappings from healthy-state data and may struggle to detect subtle structural changes unless the deviation is substantial. To overcome these limitations, this study proposes a physics-informed SDT for damage identification via anomaly detection. Anomalies are identified by comparing the predicted response of the SDT with the actual response of the structure. SDTs integrate a virtual entity, representing the structure via mathematical models, with a physical entity, consisting of the actual structural components. These entities interact through an IoT-enabled connection system that collects real-time sensor data. This research develops a physics-informed, machine learning-driven SDT using a PINN to reduce the residual between FEM predictions and real structural responses. The PINN processes FEM acceleration outputs and predicts ac-

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tual responses under identical loading conditions. The predicted responses are compared to the actual response to detect anomalies. The proposed SDT's performance in damage identification is rigorously evaluated against standard AEs. Additionally, LSTM-AE is employed for comparison.

METHODOLOGY

Figure 1 presents the overview of the proposed method. Let $\boldsymbol{x_t}$ represent the acceleration response of the real structure and $\boldsymbol{x_s}$ the FEM response. While FEM provides an approximation of the real structure's response, inherent modeling uncertainties introduce discrepancies between $\boldsymbol{x_s}$ and $\boldsymbol{x_t}$. The goal is to approximate the mapping: $p(\boldsymbol{x_t} \mid \boldsymbol{x_s})$. To effectively learn the discrepancy, an encoder-decoder architecture is employed. The encoder maps $p(\boldsymbol{x_s})$ to a lower-dimensional latent space $p(\boldsymbol{z})$, capturing essential features of the structural response. The decoder then learns to map the latent representation to the final refined structural response. Training is performed using mean squared error (MSE) in the time domain. By leveraging FEM as a base model and employing a neural network for discrepancy correction, the proposed approach enhances the accuracy of FEM predictions while attempting to preserve interpretability and physical consistency through the model-based response. Since the model is trained on a specific structural state $\mathbf{S_1}$, its learned distribution is $p(\boldsymbol{x}_t \mid \boldsymbol{x}_s, \mathbf{S_1})$. When the structure transitions to a new state, $\mathbf{S_2}$, the true target distribution $\boldsymbol{x'}_t$ shifts accordingly to $p(\boldsymbol{x'}_t \mid \boldsymbol{x}_s, \mathbf{S_2})$ creating the deviation from the output from the model. This discrepancy enhances anomaly detection sensitivity, making even the small structural changes more detectable. It consists of three stacked LSTM layers for both encoder and decoder, with a final fully connected layer producing the output. A skip connection from encoder 1 to decoder 3 mitigates degradation and preserves information. For comparison, a standard AE from Wang et al. [1], which outperforms SCAN and VAE-based methods in anomaly detection, is used. As they adopt a different architecture, a fair comparison is also made against a purely data-driven LSTM-AE with the same architecture as used in this study.

Once the refined response is obtained, the essential aspect of anomaly detection is determining an appropriate threshold beyond which an anomaly is flagged. However, since the model is trained exclusively on healthy-state data, selecting this threshold presents a significant challenge. Based on insights from past studies [1–4], a threshold at the 95th percentile of the reconstruction error was adopted in this study.

CASE SETUP

The proposed approach is applied to the numerical version of the IASC-ASCE SHM benchmark structure [5]. A 12-degree-of-freedom (DOF) model is adopted to represent the FEM and a 120 DOF model is used to simulate the structural response. To evaluate the effect of model updating on the proposed method, an updated 12 DOF model updated through Bayesian model updating has also been used as the source structure. 16 uniaxial accelerometers (eight per X and Y directions) capture responses under hammer impact. To simulate real world conditions, 10% measurement noise and 5% structural uncertainty are introduced in the target structure. As shown in Figure 2, four damage

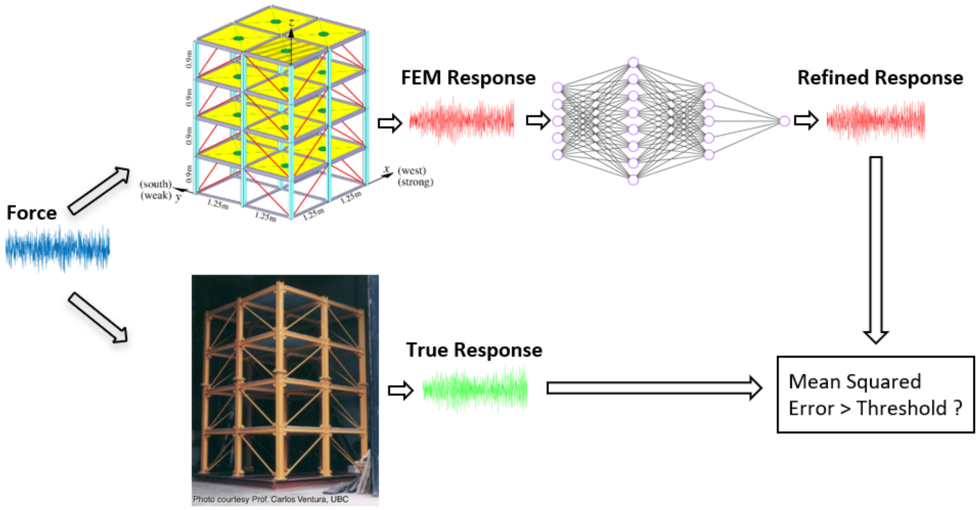

Figure 1. Overview of proposed structural DT based approach for anomaly detection.

states are simulated by removing different number of braces at different locations. Hammer impact data, 4.4s long acceleration time history at 1000 Hz, is generated at forces of 9000–11000N across all floors, yielding 4000 training and 1600 testing samples per scenario.

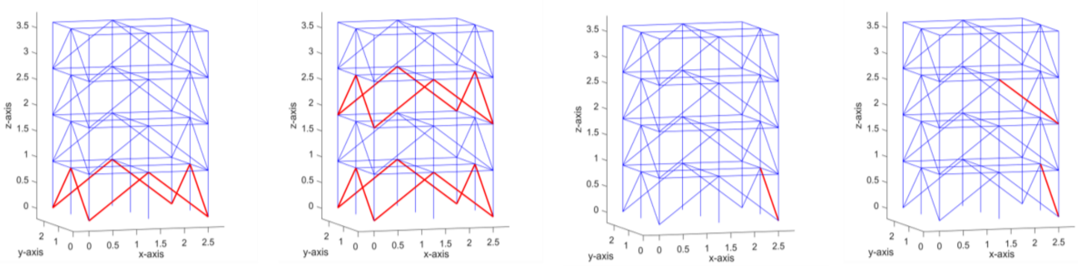

Figure 2. Damage scenarios: DS-1 to DS-4. The unit for the x, y, and z axes is in meters.

RESULTS

Figure 3 compares accuracy from different methods for all the damage cases under hammer excitation. While all methods achieve near-perfect accuracy in DS-1 and DS-2, AE-based methods show performance decline for DS-3 and DS-4, which represent relatively smaller damage scenarios, with the accuracy of standard AE dropping to 84.56% and LSTM-AE to 88.67%. The proposed method, however, maintains the performance.

DISCUSSION AND CONCLUSION

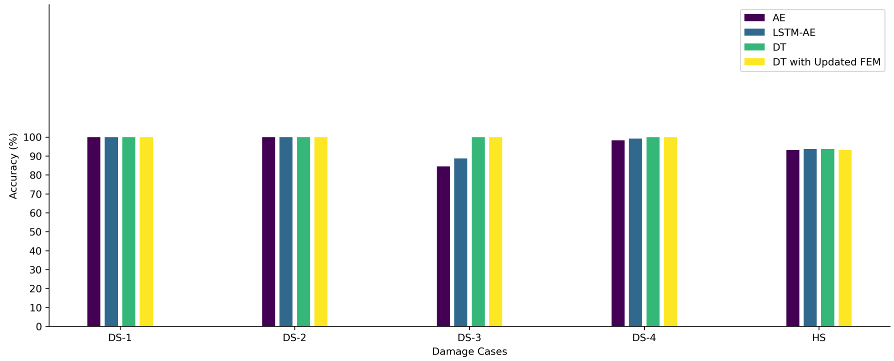

Figure 3. Accuracy comparison of different methods for all damage cases.

This study presents a physics-informed, machine learning-based SDT for damage identification through anomaly detection. The proposed method reduces the discrepancy between FEM predictions and real structural responses and performs anomaly detection using refined responses. The framework is validated using numerical ASCE benchmark structure under hammer impact. Results demonstrate superior performance over AE-based methods, achieving near 100% accuracy for larger damage and also in smaller damage cases where AE-based methods struggle. Moreover, comparable performance was observed when using updated and unupdated 12 DOF model as the source model for the numerical study, suggesting the robustness of the proposed approach at least to some level of modeling uncertainties. However, further studies are required to determine the extent of this observation. This success can be attributed to the nature of the proposed approach, which is trained to map the relationship between the FEM and the real structure, informed by physics. When the structure undergoes a state change, the previously learned relationship becomes invalid causing clear anomalies, unlike other approaches that rely on identity mapping both before and after a state change. While the proposed approach demonstrates superior performance, it has certain limitations. Unlike AE-based methods, it requires a FEM, raising concerns about FEM fidelity. Further studies are needed to assess FEM fidelity impact. Additionally, stronger physical constraints, such as physics-based loss, could enhance the model, and advanced architecture like transformers could be explored. Despite these limitations, the approach presents a promising pathway for effective anomaly-based damage detection with strong real-world potential.

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