A Physics-informed, Transfer Learning Approach to Structural Health Monitoring

INTRODUCTION
One of the main challenges for structural health monitoring (SHM) is a lack of failure data to make accurate health predictions. Machine learning has helped to improve health monitoring performance but is still limited by the availability, relevance, and quality of the training data. Physics-driven models, like finite-element models, can generate simulated fault data to address the data limitation without having to physically damage a structure, but are computationally expensive and susceptible to modeling errors that can prevent the data from being statistically comparable to experimental data. Physics-informed machine learning models have been shown to improve generalization and performance compared to pure data-driven models while using less training data. The proposed physics-informed health classifier extracts relevant structural features and embeds them as intermediate layers to the neural network. Appropriate transfer learning scenarios can then be implemented for repurposing a physics-informed trained model to another structure sharing similar physics.

DISCRETE ELEMENT MODEL
Boundary conditions factor into the natural frequencies and mode shapes for a given structure. Generally, boundary condition problems treat the structure as a single element having uniform material properties. The discrete element model (DEM) allows for elements with different material properties to be used in boundary condition problems.

The DEM recursively calculates the nth modal response of a structure (in this case a beam) using the boundary conditions at \( x = 0 \) and \( x = L \).

Flexural Mode Shapes
\[
\phi_n(x) = \frac{t}{2} \left[ P_{m-1} \cos(\beta_{m} x) + \cos(\beta_{m} x) \right] + \Psi_{m-1} \sin(\theta_{m} x) + \sin(\theta_{m} x)
\]

Longitudinal Mode Shapes
\[
\phi_n(x) = \frac{t}{2} \left[ P_{m-1} \cos(\alpha_{m} x) + \cos(\alpha_{m} x) \right] + \epsilon \Psi_{m-1} \sin(\theta_{m} x) - \sin(\theta_{m} x)
\]

The time-series response of the beam is modeled by summing the modes shapes oscillating at their natural frequencies over time.

\[
y(x, t) = \sum_{n=1}^{N} \alpha_n \sin(\omega_n t) \phi_n(x)
\]

ADVANTAGES USING THE DEM
- The DEM's performance is independent of the number of elements, \( M \), meaning it also satisfies the traditional method (i.e., \( M = 1 \)).
- Beams having multiple materials and/or changes in material properties can be modeled by defining the corresponding element of the DEM.
- The severity of beam cracks and their location(s) can be simulated by changing the material properties of respective elements.
- The DEM has greater computational efficiency, compared to finite-element approaches, due to using significantly fewer parameters when calculating the structure's modal response.

PHYSICS-INFORMED HEALTH CLASSIFIER & TRANSFER LEARNING SCENARIOS

The DEM is used to simulate time series data from beams having various cracking severity and locations. Each time series has its corresponding mode shapes and natural frequencies that can be used as a physics-informed layer between the feature extraction and label prediction layers. The neural network is trained on the simulated data to predict the health state of the beam, and potentially the location of cracks along the beam.


ADVANTAGES USING THE DEM

OVERVIEW
Having sufficient fault data is an ongoing challenge for structural health monitoring applications. The proposed methodology uses a computationally efficient, physics-driven numerical model (the discrete element model) to simulate faulty data to improve classifier performance. The hope is that during the training process, the classifier will be able to learn the inherent physics from the data as part of the classification process. In the presence of experimental data, the trained network would then undergo a respective transfer learning scenario, minimizing the training time and amount of data needed to improve the classifier for a given fault.