Applicability of Loads Estimation Techniques using Sparse Acceleration Sensor Data to Spacecraft Structural Health Monitoring

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Background

- Structural Health Monitoring (SHM) for spacecraft structures can play a crucial role for ensuring the safety, reliability, and longevity of the structure.
- Monitoring for excessive loading at critical interfaces is important as any unexpected structural excitations can cause early unpredicted high structural life consumption and/or damage.
- SHM systems on spacecraft are limited by the availability and cost of flight-certified sensors along with the size and allowable payload mass.
- Developing noise-robust prediction models to assess loads and structural life predictions from a sparse multi-sensor data acquisition system can be a challenging task.

Motivation

- Existing methods for loads estimation for spacecraft center around reconstructing forcing functions using downlinked accelerometer time histories during dynamic events.

- The method for reconstructing forcing functions is a long-standing inverse problem investigated in the aerospace industry

- In recent years, deep learning approaches infused with physics information have also been proposed for recovering loads time histories from kinematic response data

Although these methods can be used for loads estimation during specific events like docking, a more stable, versatile, and noise-resilient method is needed for near real-time monitoring

Objective

- **To evaluate physics-based versus machine learning algorithms for predicting loads and structural life at mission-critical locations on a modular space station using a finite element loads analysis with the application of simulated noise and noise reduction techniques.**

Approach:

Assessed performance of two physics-based algorithms against a machine learning algorithm using simulated sensor data and analytical loads from a finite element model

Finite Element Model

- Model Description:
  - Hurty-Craig-Bampton (HCB) reduced finite element model of a modular space station.
  - Elements equipped with accelerometers modelled as point masses.
  - A loads transformation matrix (LTM) is obtained from the HCB model reduction, which enables a matrix transformation from the reduced model boundary grid displacements to the internal forces and moments.
  - The forces and moments at three mission-critical interface locations on the space station are recovered - two at the solar array interfaces in Element I and one at the docking interface between the two elements.

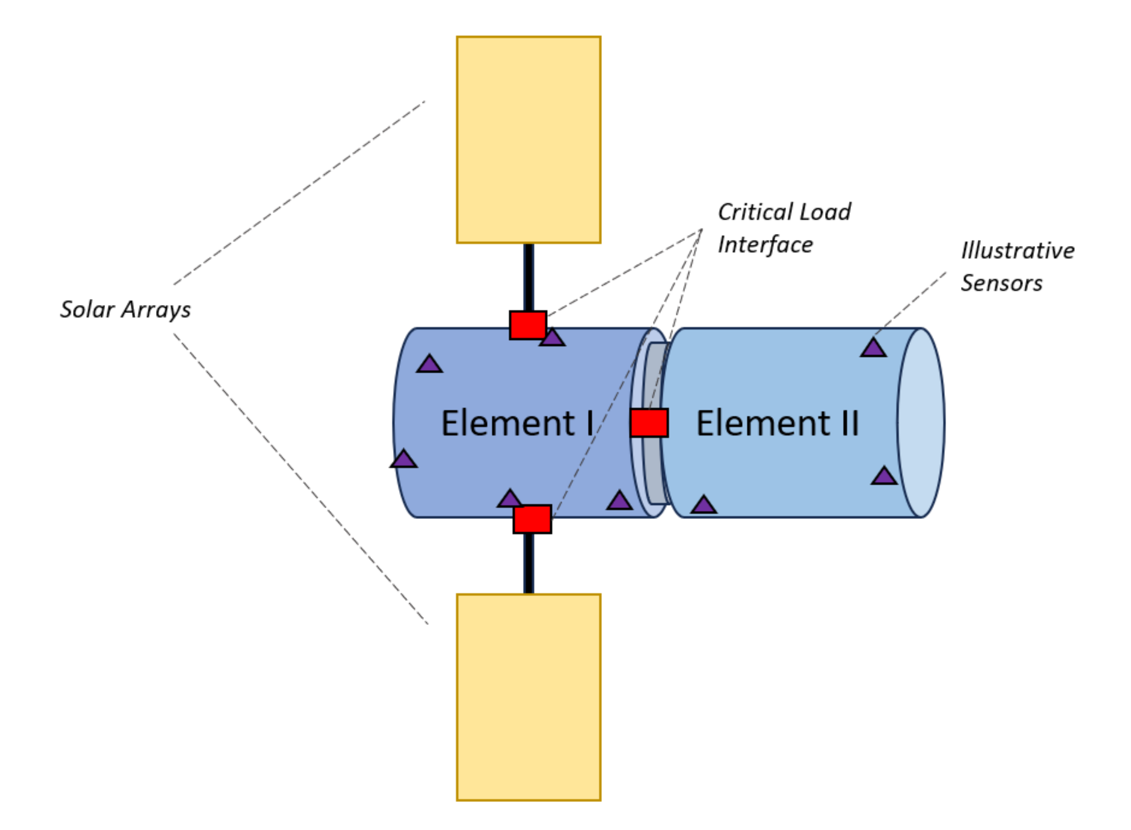

Figure 1. Representative Diagram of the Model with Critical Interfaces Identified.

Finite Element Model Data Generation

- Forcing functions were applied to the finite element model to generate analytical sensor acceleration and interface loads data for algorithm assessment
  - Docking forcing functions were applied at the docking ports of Element II
  - Exhaust plume surface interaction forcing functions applied on the surface elements of the spacecraft model

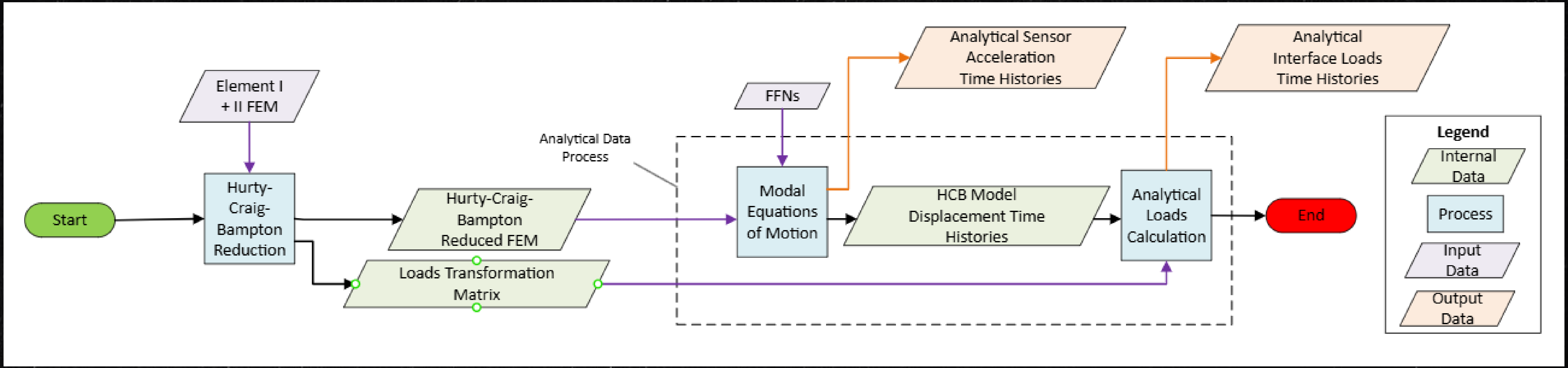

Figure 2. Analytical Acceleration & Loads Generation Process.

Physics-Based Loads Estimation Algorithm

Two approaches are considered for the physics-based algorithm, namely the System Equivalent Reduction Expansion Process (SEREP) and Moore-Penrose pseudo-inverse.

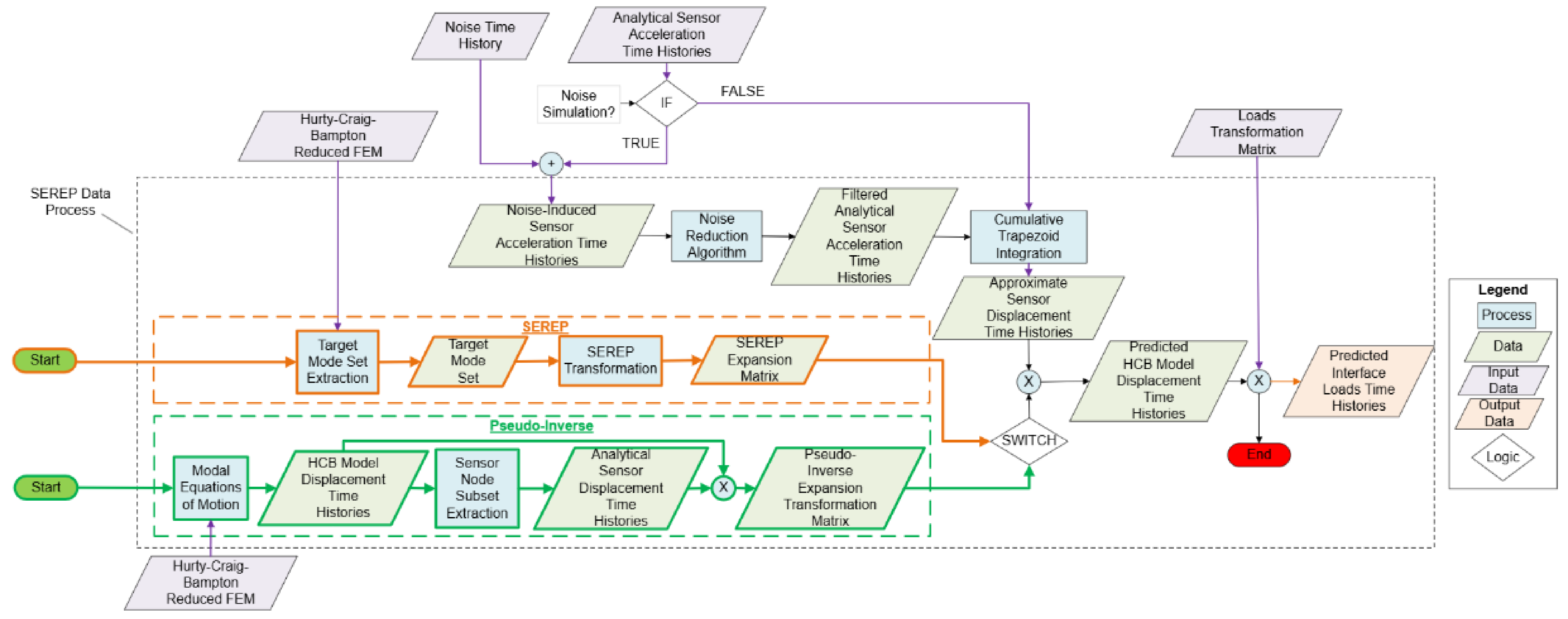

Figure 3. Physics Based Algorithm Process.

Machine Learning Algorithm

- Provides a direct data-driven mapping of the sensor accelerations to the critical interface loads responses using a high dimensionality analysis.
- Methodology:
  - Multi-layer Perceptron (MLP) neural network model training with loads analysis responses of the HCB model to a set of simplified sine wave forcing functions within a limited frequency range applied at two different docking ports of Element II.
  - Input features: Sensor acceleration time history.
  - Output features: Loads time history at critical interfaces.
- Enhancements:
  - Min-max scaling (Linearly scales down the training data into a fixed range).
  - K-means clustering for additional input features.

Algorithm Assessment

- Study I - Physics-Based Algorithm Assessment w/ & w/o Noise
- Study II – Machine Learning Algorithm Assessment w/ & w/o Noise
- Study III – Evaluation of Machine Learning Algorithm with Different Noise Levels & Denoising Methods

- Noise - The baseline noise level to evaluate the performance of these algorithms with noise is based on the sensor accelerometer design maximum allowable spectral noise requirements for a modular space station SHM system.
- Performance Assessment Metric - Normalized Root Mean Square Error (NRMSE) of the analytical & predicted loads time histories

Algorithm Assessment - Study I

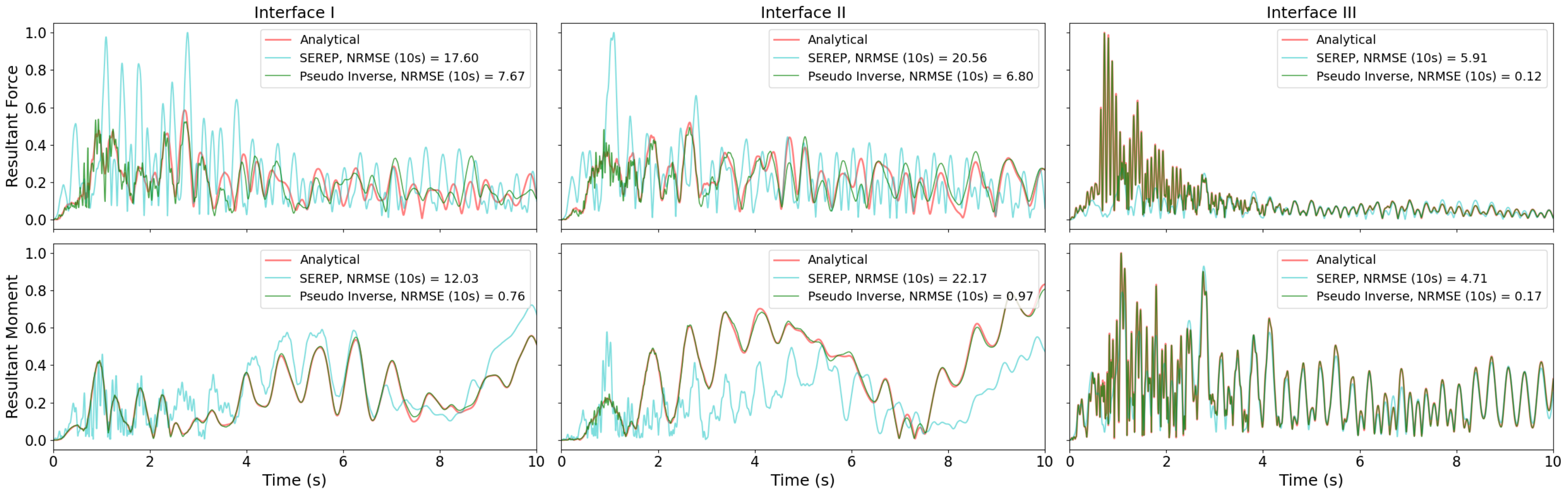

Figure 6. Analytical & Predicted Loads Time History Example with the SEREP & Pseudo Inverse Algorithm w/o Noise.

- The performance of the SEREP algorithm is dependent on the mode set selected for the SEREP expansion but the pseudo inverse algorithm predictions perform better than the SEREP algorithm without noise for all elements except for a few plume forcing functions.

Algorithm Assessment - Study I

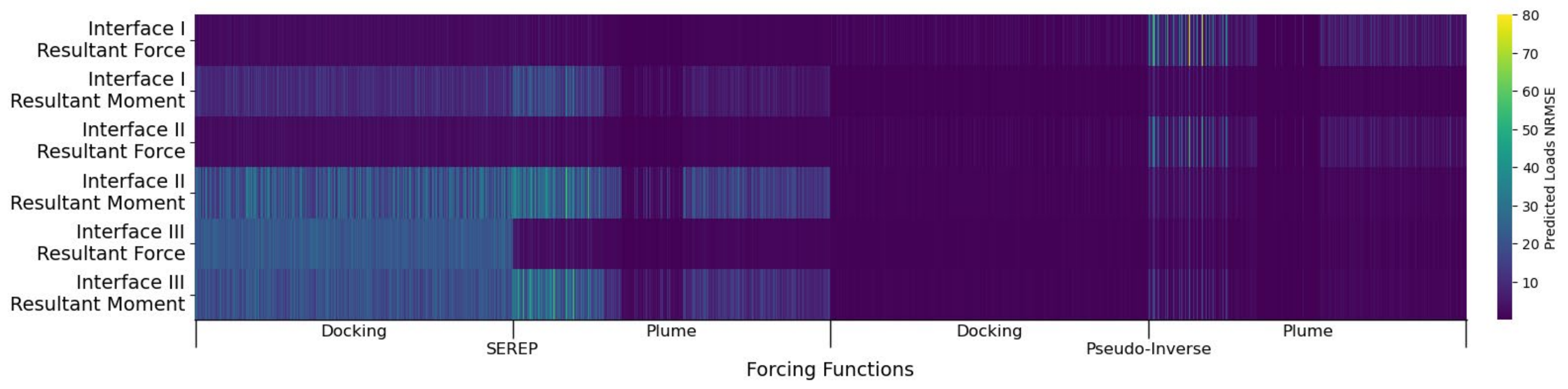

Figure 4. Predicted Loads NRMSE with the SEREP & Pseudo-Inverse Algorithm w/o noise

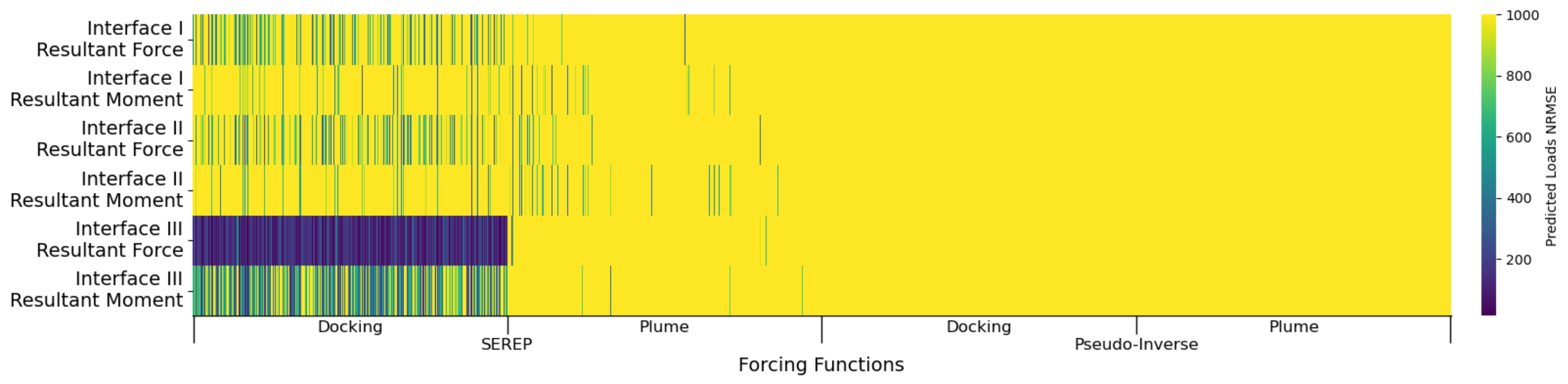

Figure 5. Predicted Loads NRMSE with the SEREP & Pseudo-Inverse Algorithm w/ noise.

Analysis:

- The accumulation of noise in the SEREP and the high sensitivity of the pseudo inverse method to small perturbations causes the predicted loads to be very large and incomparable to the analytical loads.
- Since the predicted interface loads NRMSE are very large for the SEREP and the pseudo inverse algorithms, these physics-based algorithms are unreliable for applications with low signal-to-noise ratios.

Algorithm Assessment - Study II

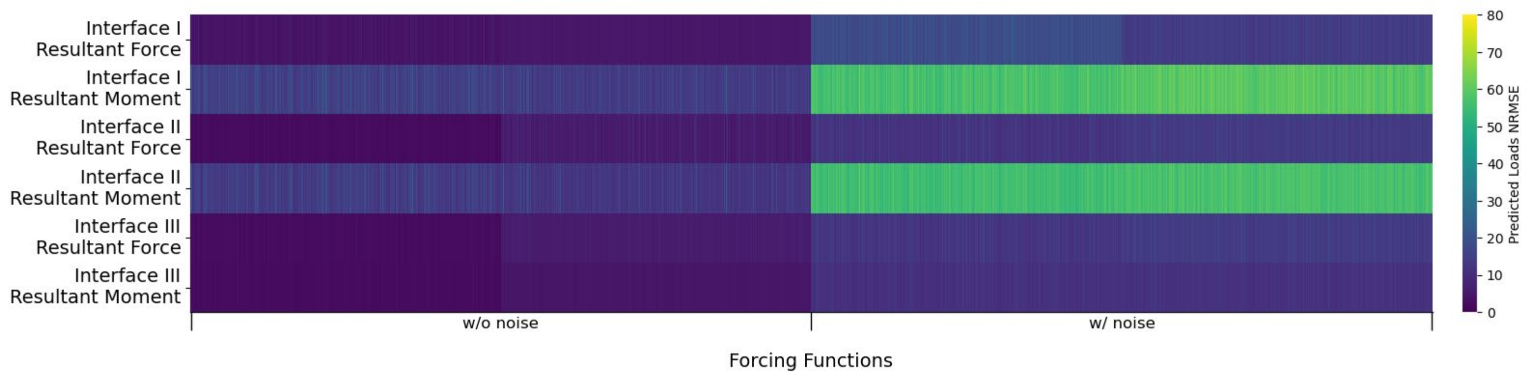

Figure 7. Predicted Loads NRMSE with the ML Model w/o and w/ Noise.

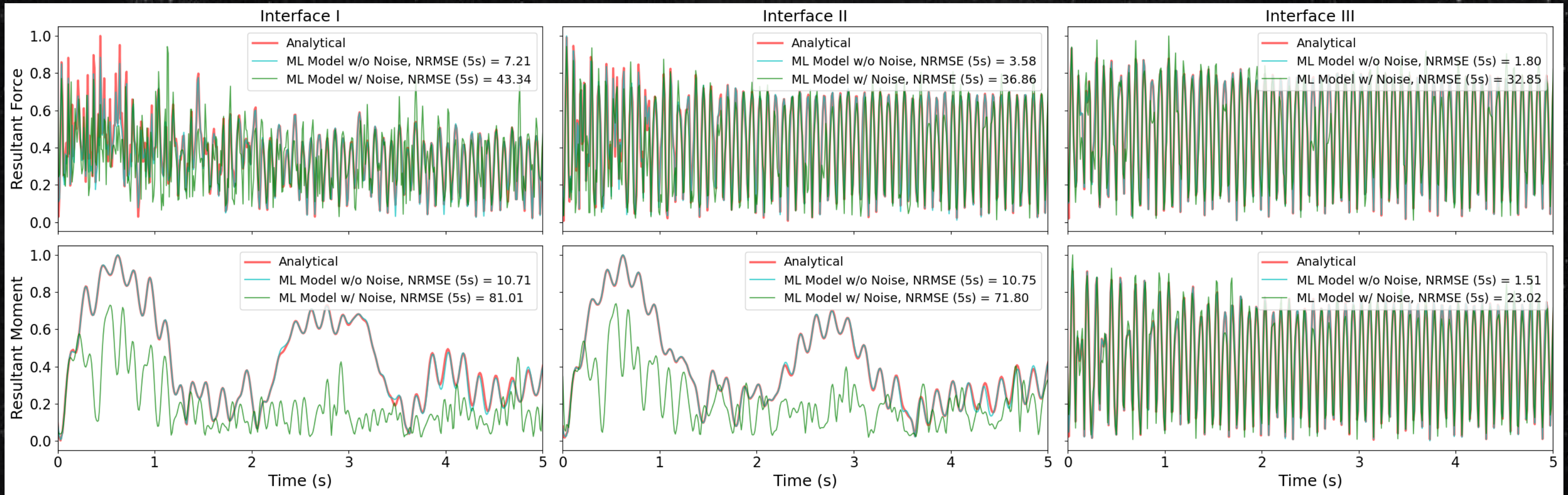

Figure 8. Analytical & Predicted Time History Example with the Machine Learning Algorithm w/ and w/o Noise.

The machine learning algorithm can perform very well without noise and is also able to produce comparable results with noise unlike the physics-based algorithms.

Algorithm Assessment - Study III

Evaluation of Machine Learning Algorithm with different noise levels and with different denoising methods including traditional noise filters & machine learning denoising algorithms.

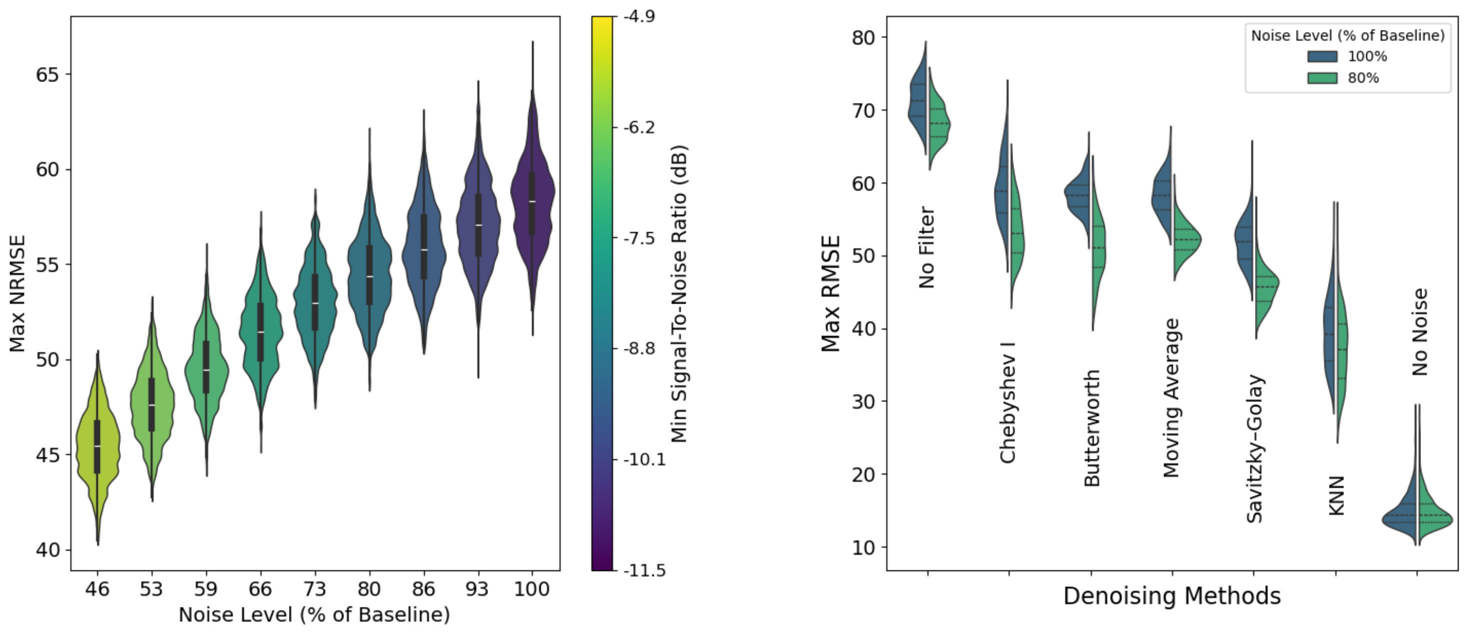

Figure 9. Max NRMSE across all Predicted Loads DOFs for 1,000 forcing functions with a) scaled noise input filtered with a Butterworth IIR Filter b) with the baseline noise with different denoising techniques.

Conclusion

- Assessed the applicability of near-real-time loads estimation algorithms with physics based and machine learning algorithms to predict loads time history responses from sparse acceleration sensor data for the structural health monitoring of a modular space station.
- Although the physics based and machine learning approaches produced comparable loads prediction without noise, the machine learning based algorithm displayed greater resilience to simulated noise as demonstrated in Study I and II.
- Study III findings demonstrates the need for noise-resilient prognostic models and low-noise data acquisition systems on-board spacecraft structures.

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Backup Slides

Physics-Based Loads Estimation Algorithm

- Methodology:
  - Compute sensor displacement using a cumulative trapezoid integration of the sensor accelerations.
  - Employ System Equivalent Reduction Expansion Process (SEREP) for expanding displacements from sensor degrees of freedom to the HCB boundary degrees of freedom.
  - Compute Loads using the Loads Transformation Matrix (LTM) from the HCB boundary displacements
- System Equivalent Reduction Expansion Process (SEREP) :
  - expansion/reduction process to form a mapping between the very large set of finite element degrees of freedom and the relatively small set of sensor degrees of freedom using a modal projection.
  - Performance dependent on selecting an optimal base of modes to achieve a good expansion from the sensor degrees of freedom to the HCB degrees of freedom.
  - Alternative Simplified Process: Moore-Penrose pseudo-inverse approach.
    - $\text{Transformation Matrix} = [\text{HCB Model Displacements}][\text{Sensor Displacements}]^{+}$