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

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ABSTRACT

The use of structural health monitoring systems on spacecraft structures can play a crucial role in ensuring the safety, reliability, and longevity of the structure by gathering and analyzing onboard sensor data. Of specific importance is monitoring for excessive loading at critical interfaces as any unexpected structural excitations experienced by spacecraft structures can cause early unpredicted high structural life consumption and/or damage. The availability and cost of flight-certified sensors along with the size of spacecraft structures and allowable payload mass drives the need for a method to estimate loads using sparsely-located sensors. Numerous approaches such as physics-based, statistical learning, and physics-enhanced statistical learning algorithms have gained popularity among structural prognostics applications. However, 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. This paper discusses the evaluation of physics-based versus machine learning algorithms for predicting loads and structural life at mission-critical locations on the spacecraft structure using a finite element loads analysis with the application of simulated noise and noise reduction techniques. To estimate the loads from accelerations, the physics-based algorithm leverages a loads transformation matrix (LTM) from a Hurty-Craig-Bampton (HCB) reduced finite element model. A System Equivalent Reduction Expansion Process (SEREP) and a pseudo-inverse approach are considered to expand from the onboard sensor degrees of freedom to the HCB model degrees of freedom. The machine learning algorithm provides a data-driven solution/mapping of the sensor accelerations to the loads at the mission-critical locations using a high dimensionality analysis. Although these strategies produce comparable loads prediction without noise, the limitations of these strategies with incorporating simulated noise and noise reduction techniques with low signal to noise ratio signals are evaluated. The study demonstrates the immense potential of statistical learning algorithms for sparse structural prognostic models and enhancing signal denoising techniques. These findings also highlight the need for noise-resilient prognostic models and low-noise data acquisition systems onboard spacecraft structures.

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INTRODUCTION

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 with various estimation techniques proposed based on a sum of the weighted accelerations[1], integrating the sum of the weighted accelerations to obtain velocity and displacement, and solving the equations of motion[2], or using a set of inverse system Markov parameters from a pulse response in which the role of input and output forces are switched[3]. In recent years, deep learning approaches infused with physics information have also been proposed for recovering forcing functions from kinematic response data[4]. Although these methods can be used for loads estimation during specific events like docking, the scope of the investigation of this paper involves assessing a much more stable, versatile, and noise-resilient near-real-time monitoring algorithm of applied loads at multiple critical interface locations from all operational, structurally dynamic activities induced at different locations on the spacecraft structure.

FINITE ELEMENT MODEL DATA GENERATION

To assess the applicability of a structural health monitoring (SHM) loads estimation model for a spacecraft structure, a Hurty-Craig-Bampton (HCB) reduced finite element model[5] of a modular space station structure with 2 primary elements, as shown in Figure 1, is utilized. Elements I & II are equipped with a set of accelerometers which can be modeled as point masses since they are small and lightweight relative to the size and mass of the structure. 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. The HCB reduced model enables the efficient evaluation of sensor acceleration and loads responses to a large variety of forcing functions for various activities, including docking operations and plume impingement due to reaction control system firings from visiting vehicles. The analytical sensor node accelerations and the interface loads data required for the development and validation of the SHM prognostic model is generated by solving for the structural responses to either a set of forcing functions applied at the docking ports of Element II to represent docking and/or a set of exhaust plume surface interaction forcing functions applied on the surface elements of the spacecraft model using the modal equations of motion and the LTM from the HCB reduced model.

The analytical acceleration and loads response data generation process is displayed in Figure 2. A fatigue life consumption indicator is also computed for each critical interface, but evaluation of the fatigue life predictions is not within the scope of this paper.

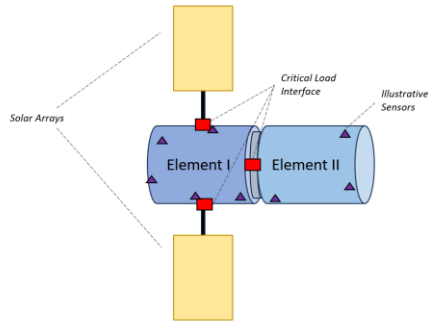

Figure 1. Representative Diagram of the Model with Critical Interfaces Identified.

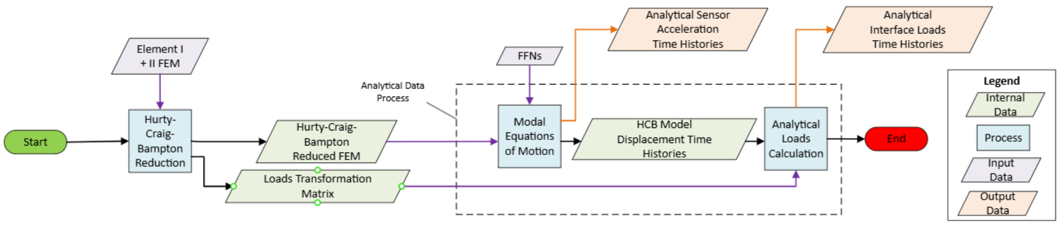

Figure 2. Analytical Acceleration & Loads Generation Process.

LOADS ESTIMATION ALGORITHM

The interface loads time histories and fatigue life consumption indicators must be predicted from onboard sensor accelerometer data for near-real-time structural health monitoring. Therefore, the following physics-based and machine learning algorithms for predicting these loads time histories and fatigue life consumption indicators from the sensor acceleration responses are considered.

Physics-Based Algorithm

The physics-based algorithm leverages the LTM from the HCB reduced finite element model with the employment of a System Equivalent Reduction Expansion Process (SEREP)[6] to predict the interface loads from the onboard sensor accelerations. The LTM from the HCB reduction is used to compute the loads at the critical interfaces from the HCB boundary displacements. The sensor displacements can be computed using a cumulative trapezoid integration from the sensor accelerations, but the sensor accelerations must be expanded from the sensor degrees of freedom to the HCB boundary degrees of freedom to be able to leverage the HCB LTM. SEREP is used to develop a transformation matrix to expand from the sensor degrees of freedom to the HCB boundary degrees of freedom.

SEREP is one of many reduction/expansion schemes 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. The effectiveness of the SEREP expansion depends on selecting an optimal base of modes to achieve a good expansion from the sensor degrees of freedom to the HCB degrees of freedom. This can be a computationally heavy process even with a moderate number of modes. A set of HCB boundary displacement responses to a set of docking and plume forcing functions are generated for the SEREP target mode set selection process. A target mode set for the SEREP expansion is selecting by generating different combinations of the primary modes and selecting the mode set which gives the best displacement expansion from the sensor degrees of freedom to the HCB boundary degrees of freedom.

A simpler alternative to the tedious process of the selection of an optimal target mode set for the SEREP expansion was also evaluated using a Moore–Penrose generalized inverse (pseudo inverse)[9] approach. The transformation matrix is computed using Equation 1 and the HCB model displacement responses from a docking or plume forcing function. Figure 3 outlines the structure and process of the physics-based loads estimation algorithms.

$$\text{Transformation Matrix} = [\text{HCB Model Displacements}][\text{Sensor Displacements}]^{+} \quad (1)$$

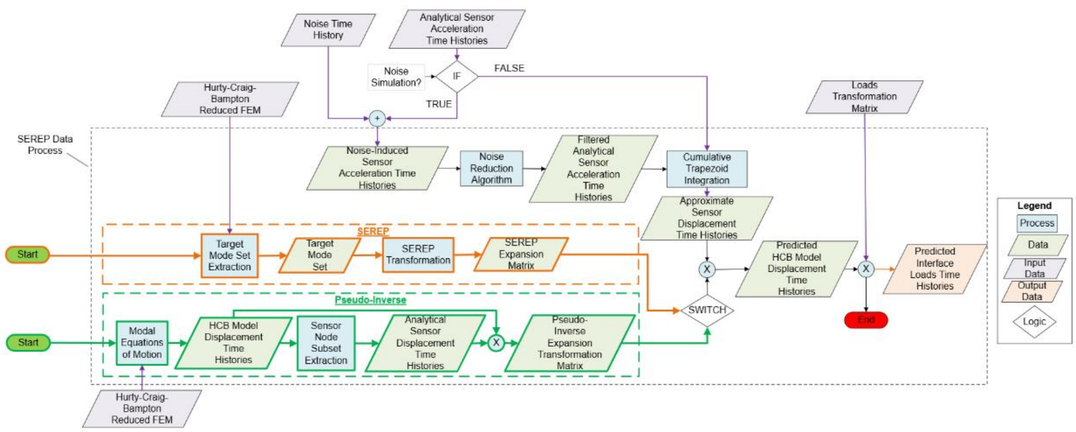

Figure 3. Physics Based Algorithm Process.

Machine Learning Based Algorithm

The machine learning algorithm provides a data-driven mapping of the sensor accelerations to the critical interface loads responses using a high dimensionality analysis. The initial objective of the machine learning based algorithm was to establish whether a mapping can be established under a simplified scenario before applying it to more complex real-world scenarios. 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 are used to train a multi-layer perception (MLP) neural network model. The input features for the machine learning model training are the analytical sensor acceleration time history responses to the simplified sine wave forcing functions. The output features are the loads time history responses at the critical interface locations. To improve the performance of the machine learning model predictions, the training features are scaled by applying a min-max scaler which linearly scales down the training data into a fixed range. Two additional features are also added as input features to the sensor accelerations using the labels generated from a k-means clustering. Labels are assigned based on the sensor acceleration data at each time step and the sensor acceleration data in a 10 second interval. The MLP neural network model is trained with five fully-connected hidden layers and sigmoid activation functions to predict interface loads time histories.

ALGORITHM ASSESSMENT

Three studies will be discussed that were each designed based on findings from the preceding study. The physics-based and machine learning algorithms are assessed with and without the addition of simulated noise to the analytical sensor accelerations by evaluating the predicted interface loads responses. 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.

Study I - The analytical and predicted interface loads time histories at the three interfaces from a set of 500 docking and 500 plume forcing functions are assessed using the SEREP and pseudo inverse algorithms with and without adding simulated noise as displayed in Figure 4 & 5. The forcing function behavior for docking tends to be transient with residual decay, whereas plume tends to be composed of a series of square waves. A 10 second example of the predicted interface loads time histories at the three interfaces from a docking forcing function response using the SEREP and pseudo inverse algorithm is presented in Figure 6. The Normalized Root Mean Square Error (NRMSE) values per each forcing function case were determined using the formula shown in equation 2, where x represents the analytical loads time history, y represents the predicted loads time history, i is each sample, and N is the total number of samples, and X_{max} and X_{min} are the maximum and minimum analytical time history values, respectively.

$$NRMSE = \frac{1}{X_{max} - X_{min}} \sqrt{\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{N}} \tag{2}$$

The performance of the SEREP algorithm is dependent on the mode set selected for the SEREP expansion. A mode set with 11 modes is selected from a set of primary modes for the SEREP expansion to give the best predictions for a large set of plume and docking forcing functions from the assessed mode combinations. A docking forcing function response was used to generate the pseudo inverse expansion matrix. The pseudo inverse algorithm predictions perform better than the SEREP algorithm without noise for all elements except for a few plume forcing functions.

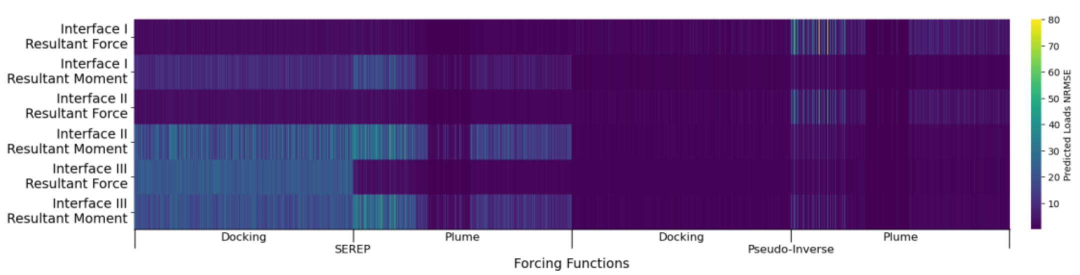

Figure 4. Predicted Loads NRMSE with the SEREP & Pseudo-Inverse Algorithm w/o noise

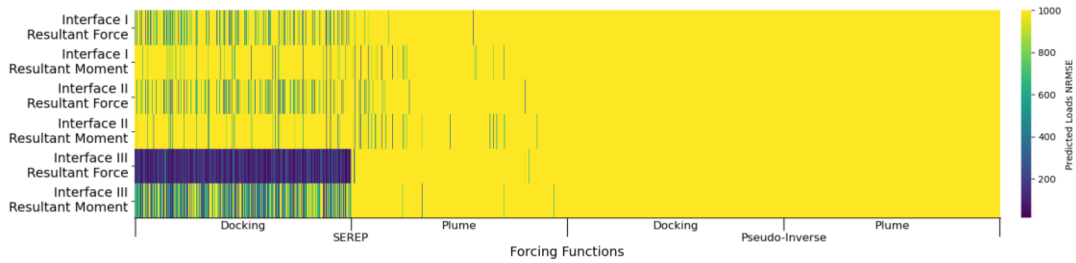

Figure 5. Predicted Loads NRMSE with the SEREP & Pseudo-Inverse Algorithm w/ noise.

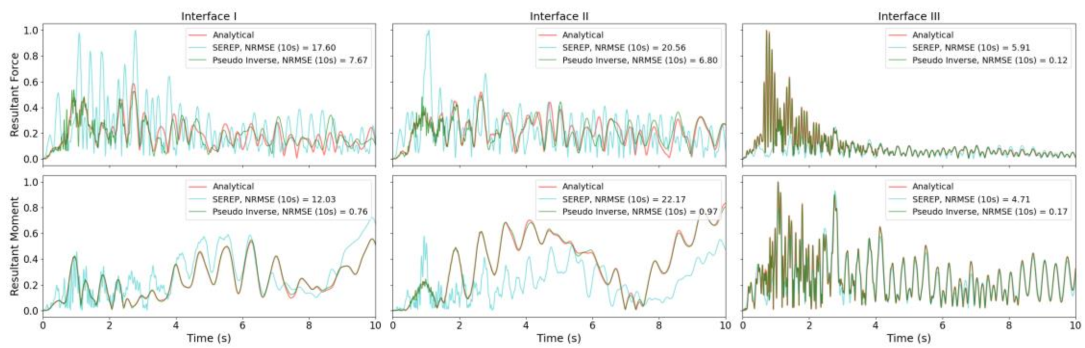

Figure 6. Analytical & Predicted Loads Time History Example with the SEREP & Pseudo Inverse Algorithm w/o Noise.

For the assessment with noise, the noisy sensor accelerations are filtered using a low pass infinite impulse response (IIR) filter but the accumulation of noise in the SEREP from the sensor degrees of freedom to the HCB degrees of freedom causes the predicted loads to be very large and incomparable to the analytical loads. The pseudo inverse method is also generally known to be unstable and highly sensitive to small perturbations in the data therefore even the slightest noise retained or accumulated after the filtering can lead to larger variations in the interface loads predictions. The predicted interface loads NRMSE for all three interfaces are very large for the SEREP and the pseudo inverse algorithms making these physics-based algorithms unreliable for applications with low signal-to-noise ratios.

Study II - The analytical and predicted interface loads time histories at the three interfaces from a set of 1,000 simplified sine wave forcing function responses using the machine learning approach with and without adding simulated noise to the analytical sensor acceleration is assessed in Study II as displayed in Figure 7. A 5 second example of the predicted interface loads time histories at the three interfaces from a simplified sine wave forcing function response using the machine learning approach is presented in Figure 8. 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.

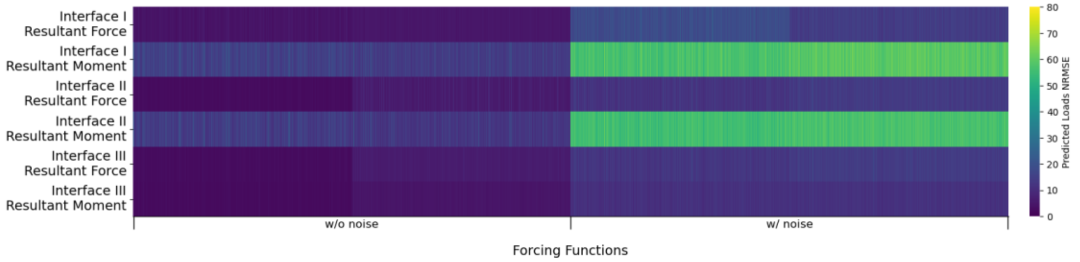

Figure 7. Predicted Loads NRMSE with the ML Model w/o and w/ Noise.

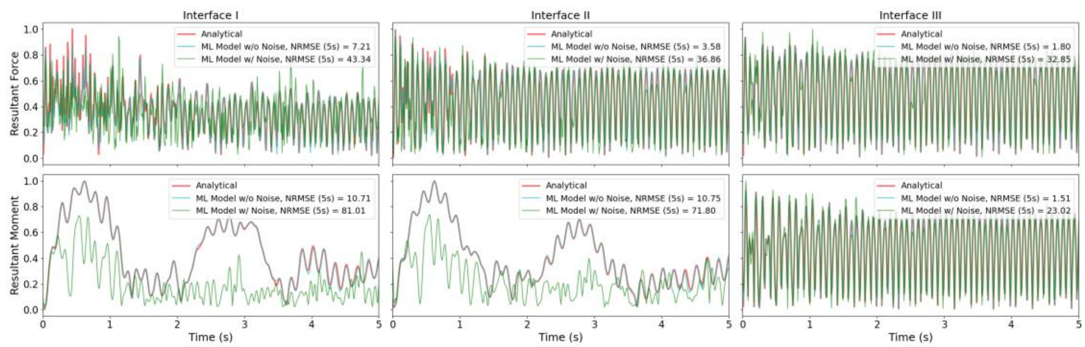

Figure 8. Analytical & Predicted Time History Example with the Machine Learning Algorithm w/ and w/o Noise.

Study III - The machine learning algorithm is also assessed with the simulated noise scaled down from the baseline noise level to evaluate performance at noise levels below the max allowable sensor noise. The predicted interface loads NRMSE across all degrees of freedom (DOF) with the machine learning algorithm assessed at different scales of the gaussian noise standard deviation for 1,000 forcing functions is presented in Figure 9a with the lowest accelerometer signal to noise ratio (SNR) across all degrees of freedom highlighted for each noise level. The SNR is calculated using Equation 3 where TS is the true signal without noise and NS is the noise signal applied to the analytical sensor accelerations.

$$SNR = 10\, log_{10}\left(\frac{mean(|TS|)^2}{mean(|NS|)^2}\right) \tag{3}$$

Different methods for denoising the noisy sensor accelerations with the baseline noise level are also assessed in study III including a k-nearest neighbor (KNN) learning-based approach for denoising the sensor accelerometer along with various conventional filters to improve the performance of the machine learning algorithm with noise[10] as presented in Figure 9b. The KNN denoising method provides the best solution compared to conventional denoising/filtering methods. The KNN model is fitted with noisy sensor accelerations as the input feature and the analytical sensor accelerations as the output features. It stores the training dataset and uses a distance metric to identify nearest neighbors for denoising an unseen signal. The KNN denoising algorithm would require the operational noise profile for practical application. It is also limited by the size of the data fitted and may also be computationally heavy depending on the size of the training data.

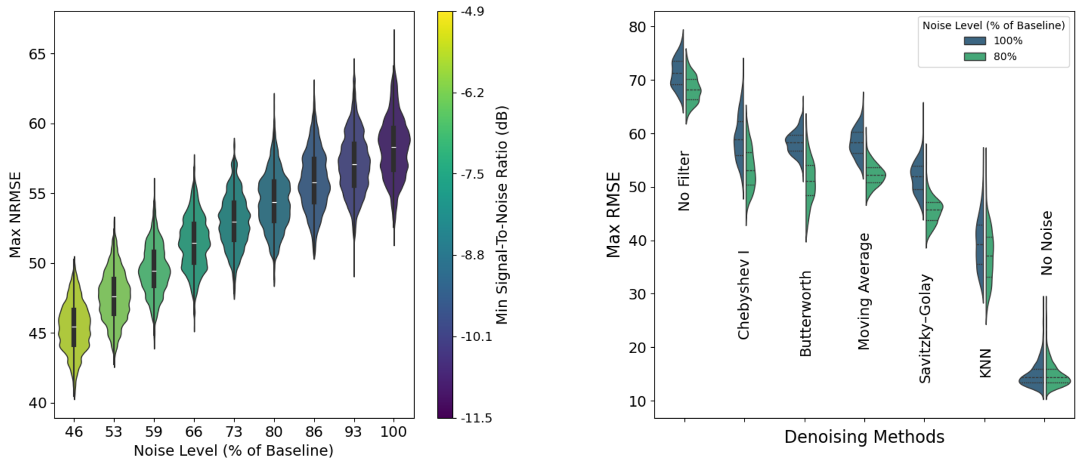

Figure 9. Max NRMSE across all Predicted Loads DOFs for 1,000 forcing functions with a) scaled noise input filtered with a Butterworth IIR Filter b) with the baseline noise with different denoising techniques.

CONCLUSION

The objective of these investigations was to assess the applicability of a near-real-time, continuous, and versatile loads estimation algorithm using sparse acceleration sensor data for the structural health monitoring of a modular space station to predict loads time history responses. Studies I and II demonstrate the applicability of a physics-based and machine learning based loads estimation algorithm from accelerometer data. Although these approaches produced comparable loads prediction without noise, the machine learning based algorithm displayed greater resilience to simulated noise. Studies II & III demonstrate the immense potential in further evaluating statistical learning algorithms for sparse structural prognostic models and signal denoising techniques. These findings also highlight the need for noise-resilient prognostic models and low-noise data acquisition systems on-board spacecraft structures.

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