

Feature Engineering for Physics-informed Evaluation of Electromechanical Impedance Measurements for Sandwich Face Layer Debonding Identification

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Abstract. The present research exploits various physically explainable features for the evaluation of electromechanical impedance (EMI) measurements for sandwich face layer debonding identification using a recently published two-step physics- and machine learning (ML)-based approach. In the previous work, the ML approach used employs a One-Class Support Vector Machine and a K-Nearest Neighbor model for debonding detection and size estimation, respectively. Feature engineering was used to compensate for the simplifications of the finite element (FE)-based physical model and a simple data calibration step was used to adapt to distribution shifts. This enabled to train both ML models exclusively with FE simulation-based synthetic EMI spectra data. The efficacy of the method was demonstrated on real-world EMI spectra measurements of a circular aluminum sandwich panel by a piezoelectric transducer. The considered face layer debonding damage was idealized and stepwise increased by a milling process.

In the present work, we explore opportunities for further optimization of our method with respect to data distillation, where we reduce the computational requirements of both training and inference while at the same time preserving essential information. The data preprocessing and ML models are validated by unseen real-world EMI measurement data and benchmarked with the previously published damage evaluation results, considering both reliability and accuracy. The data and the code used in this study are provided in their entirety to enable reproducibility, enhance comprehensibility, and encourage future research.

Keywords: Sandwich Debonding, Damage Quantification, Electromechanical Impedance Method, Physics-informed Machine Learning, Feature Engineering



Introduction

Modern products are increasingly required to be manufactured and operated sustainably. To meet these demands, research is being conducted in various technological fields. One is lightweighting the mechanical structure of a product. This is achieved by an optimal mix of high-performance materials such as fiber-reinforced polymer composites and titanium alloys and modern numerical design methods like the finite element (FE) method. However, high optimization of mechanical structures but also increases the risk of critical failure due to manufacturing and operational uncertainties. Costly maintenance programs are used to address these issues in aircraft operations. Structural health monitoring (SHM), the continuous on-board monitoring of the condition of a mechanical structure during operation by integrated systems of sensors, is a possible approach to reduce maintenance costs while ensuring reliability and integrity [1,2]. In recent years numerous SHM methods have been developed. These use different physical effects for damage identification [3]. Among these, acoustic methods like the EMI method are promising due to their sensitivity to structural change and as the typically used piezoelectric wafer active sensors (PWAS) are small, robust, and lightweight [1-4]. However, this sensitivity makes acoustic methods generally prone to environmental influences, etc. Consequently, widespread industrial application has not been given so far. Particularly the EMI, which evaluates a structure's dynamic response $Z(f)$ to a continuous harmonic voltage excitation $U(f)$ using a single PWAS is challenging, as the response is affected by reflections from distant structural regions and correlated disturbances [5]. Lately, this challenge has been successfully addressed by novel statistical methods like machine learning (ML) [6,7]. However, these methods require large amounts of high-quality data for model training. Real-world data is expensive, thus, efficiently generated physically-based data and the corresponding representative features and ML models are of high scientific interest [6,8,10,11]. A recent publication by the authors addressed these issues [12] and demonstrated sandwich face layer debonding detection and size estimation by EMI measurement evaluation by synthetic data trained ML models. The synthetic data was generated by a strongly simplified FE model. The ML models were shown to evaluate real measurements despite additional environmental influences, indicating robustness and compatibility with cost-effective data. The present work uses a K-nearest neighbors (KNN) regression model (best-performing regression model in [12]) and the same synthetic and real-world data but discusses further opportunities to optimize the proposed sandwich debonding size evaluation approach concerning the reduction of the computational costs of both training and inference while at the same time preserving essential information. This shall enable (i) to handle large training datasets, which are required when further damage types and locations are simultaneously evaluated, and (ii) low energy and close-to-real time EMI measurement evaluation algorithms that may also be used with edge computation and larger sensor arrays. The data preprocessing and KNN models are validated by unseen real-world EMI measurement data and benchmarked with the previously published damage evaluation results [12], considering both reliability and accuracy.

Materials and methods

2.1 Tested specimen and electromechanical impedance data generation

The considered case example is a circular sandwich panel with artificially introduced face layer debonding and a PWAS in the center. The same case example and data were used in a previous publication [12]. Detailed information on the data generation can be found there. Figure 1 shortly summarizes the EMI data generation for synthetic and real-world data.

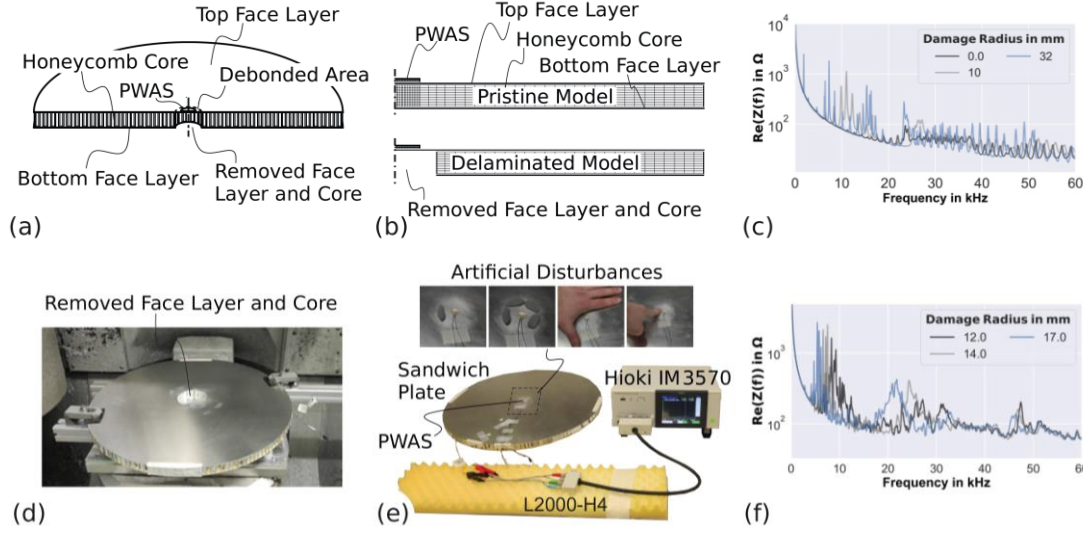


Fig. 1. EMI data generation [12]: (a) schematic sketch of sandwich panel with debonding; (b) FE models; (c) simulated EMI spectra; (d) milling of debonding; (e) measurement setup; (f) measured EMI spectra

Figure 1a presents a schematic sketch of the half-model of the investigated circular aluminum sandwich panel ($500 \times 20 \text{ mm}^2$, 1 mm face layer thickness, 18 mm 3/8–3000–0.0025 honeycomb thickness), including the idealized debonding damage and the PWAS position in the plate center. The synthetic EMI data was simulated by a multi-physics FE model (Solver: Abaqus/Standard Steady-state dynamics) that also included the electrical properties of the PWAS material. The FE models were axisymmetric for efficiency, thereby neglecting the orthotropy of the core material. For every damage state (i.e., debonding size) a separate FE model was used. Figure 1b presents a FE model of the pristine and a FE model of the delaminated sandwich panel. A comprehensive material parameter study was used to overcome the deviations between model and reality. In total 35 FE models (debonding sizes) were used and 10 material parameters (mechanical and electrical properties) were varied, resulting in 34,152 physics-based synthetic EMI spectra. Figure 1c shows exemplary the simulated EMI spectra (801 evenly distributed complex values between 0.004 kHz and 60 kHz) of a pristine model (damage radius 0.0 mm) and two models with debonding (damage radius 10 mm and 32 mm). The real-world EMI spectra are measured with a Hioki IM3570 impedance analyzer at a single sandwich panel. The measurement setup is presented in Figure 1e. The sandwich panel was measured in pristine condition and subsequently, the idealized debonding was introduced and increased step-by-step (25 debonding radii between 0 mm and 40 mm, including not perfectly circular shapes) by milling (cf. Figure 1d), interrupted by further measurements. Every debonding size (radius) was measured undisturbed (lying on foamed polymer) and artificially disturbed. Eight disturbances were used (four examples see Figure 1e), resulting in 225 measured EMI spectra. Figure 1f shows exemplary measured EMI spectra (801 evenly distributed complex values between 0.004 kHz and 60 kHz) of the sandwich panel with three different debondings (damage radius 12 mm, 14 mm and 17 mm).

2.2 Data reduction

The data reduction investigation in the present work is based on the data preprocessing presented in [12], which consists of, (i) eliminating unnecessary frequency ranges from the EMI spectra, (ii) applying a log-scale filterbank, and (iii) applying a discrete cosine transform and using only the first 31 coefficients. Furthermore, the real-world EMI spectra of the pristine sandwich panel were used to calibrate the synthetic data to the real-world data to

compensate for distribution shift. To further reduce the amount of data required to train the KNN algorithm used for debonding size evaluation (compared to [12]), we investigate two approaches. First, we reduced the number of training samples – each representing a single measurement – by selecting a representative subset for each debonding size. Second, we reduced the number of features per sample by identifying those features that contain the most relevant information. Finally, both strategies were applied successively.

2.2.1 Sample reduction

For reducing the number of samples required to train the KNN algorithm, we used a cluster centroids under-sampler (CCU). For implementation, we used a K-Means clustering algorithm to detect a certain number of cluster centers for each debonding size. Figure 2 illustrates a two-dimensional t-distributed stochastic neighbor embedding (t-SNE) of the complete synthetic dataset, where two samples for each damage radius selected by the CCU are highlighted by a black border. As can be seen, they are evenly distributed over the clusters, forming a representative subset of samples from the original dataset.



Fig. 2. 2D t-SNE embedding of synthetic data with two samples per debonding size selected by the CCU algorithm (marked by black border).

2.2.2 Feature reduction

In [12] the authors demonstrated that feature engineering can reduce the 801 features to just 31 features without sacrificing performance. We further reduce these 31 features by selecting the k-best features based on metrics such as mutual information, f-test statistics, and Pearson’s R-value to assess their information content.

Results

Three data reduction experiments were performed on the synthetic training data on top of the used data preprocessing and KNN model proposed in [12]. The first experiment investigates the value of CCU under-sampling. The second experiment investigates the potential of several methods for feature reduction. The third experiment considers both, under-sampling by CCU and feature reduction.

3.1 Sample reduction results

In our first experiment, we compare the KNN results trained on all available synthetic data with the same algorithm trained on the synthetic dataset subsampled using the CCU and the random under-sampler (RU). Both sampling methods draw 2, 8, 40, 181 or 818 samples for each debonding size. The RU randomly selects samples with equal probability. Therefore, the RU is a fair baseline for CCU, since both methods produce the same number of training samples. Figure 3 illustrates the mean squared error (MSE; i.e., the mean squared debonding radius prediction error) of the trained KNN regressor on the synthetic and the real-world data,

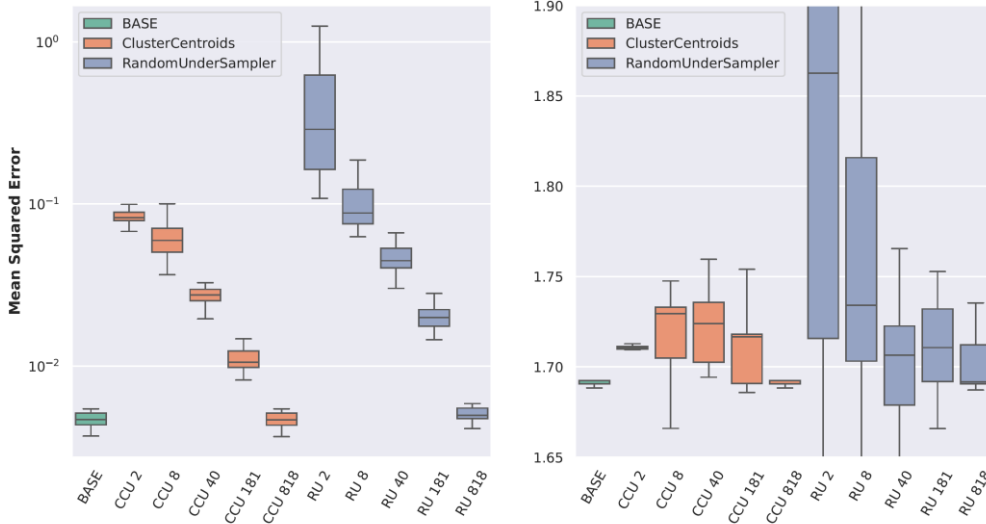


Fig. 3. Regression results on (left) synthetic data, and (right) real-world data. The baseline (BASE) used all available samples (for training approximately 860 per debonding size). The under-sampling methods CCU and RU reduced the dataset to two samples per debonding size.

respectively, over 32 randomly initialized runs. As expected, the predictions on both, synthetic and real-world data get worse the fewer samples are used. Furthermore, the value of the CCU is demonstrated as it clearly outperforms the RU baseline in terms of mean prediction error and scatter. The impact of the under-sampling is much stronger on the synthetic data prediction results, however, on a small scale. For real-world data, the impact on the prediction results is clearly given but small in relation to the BASE and negligible for real applications ($\sqrt{0.05}$ mm size prediction error is not relevant for sandwich debonding).

3.2 Feature reduction results

The debonding size prediction results (over 32 randomly initialized runs) for all samples and the k-best features, selected by mutual information, f-statistics and Pearson's R-value based algorithms, are presented in Figure 4 for synthetic and real-world data, respectively.

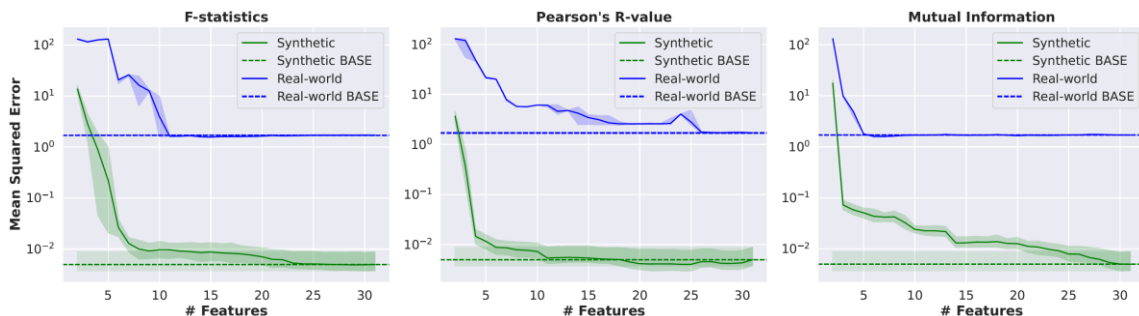


Fig. 4. Regression results (mean and 95%-interval) on synthetic data (green) and real-world data (blue). The baseline (dashed lines) used all 31 features from [12].

Both, synthetic and real-world data enable a strong reduction of features without a significant increase in the mean prediction error or its scatter. For synthetic data, all feature extraction algorithms significantly worsen when reducing below approximately 5 (of 31) features. With more than 5 features the KNN performs best with the f-statistics feature selection but also the Pearson's R-value feature reduction performs well. In contrast, for real-world data, the mutual information feature reduction performs best and the Pearson's R-value feature selection performs worst. For the mutual information algorithm, the features can be reduced to 5, before prediction error and scatter increase. For the f-statistics algorithm, the features can be reduced to 11, before prediction error and scatter increase.

3.3 Sample and feature reduction results

The debonding size prediction results (over 32 randomly initialized runs) for both, sample and feature reduction are presented in Figure 5 for real-world data. The results on synthetic

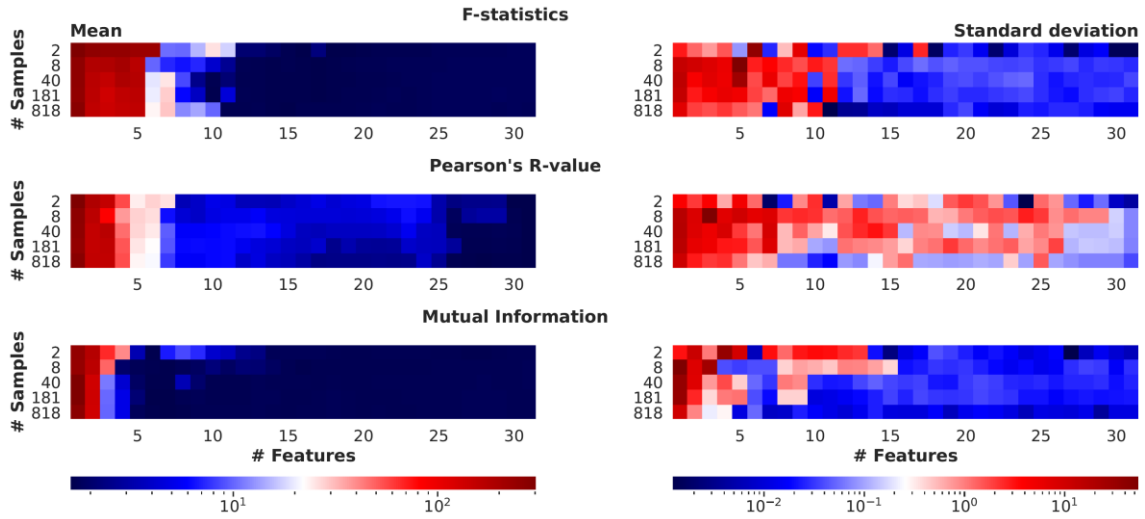


Fig. 5. KNN mean and standard deviation of MSE on real-world data, evaluated based on different combinations of reduced sample and feature numbers for training.

data are not presented as the focus of this work is on real-world data. For sample reduction, only the readily demonstrated CCU algorithm is used. The sequence of sample reduction and feature reduction was not found to have a relevant influence on the results, thus, only the results for CCU before feature reduction are presented. As expected, the regression results generally tend to decrease with the number of samples and features. However, the results for f-statistics and mutual information-based feature reduction are constant over a wide range of sample and feature reduction. For the feature reduction based on Pearson's R-value, the results are significantly worse. In particular, the standard deviation immediately increases with a reduction of features independently of the number of used samples. These results confirm the previously found results for the sole feature reduction (cf. Figure 4). However, the best performance is found for CCU sample reduction with the mutual information feature reduction. This is independent of the number of used samples and features.

3.4 Inference time analysis

The objective of the present work is to reduce the interference time of the proposed damage evaluation approach, thus, Figure 6 presents the real-world sample (measured EMI spectra) evaluation times for CCU reduced sample numbers and different feature reduction

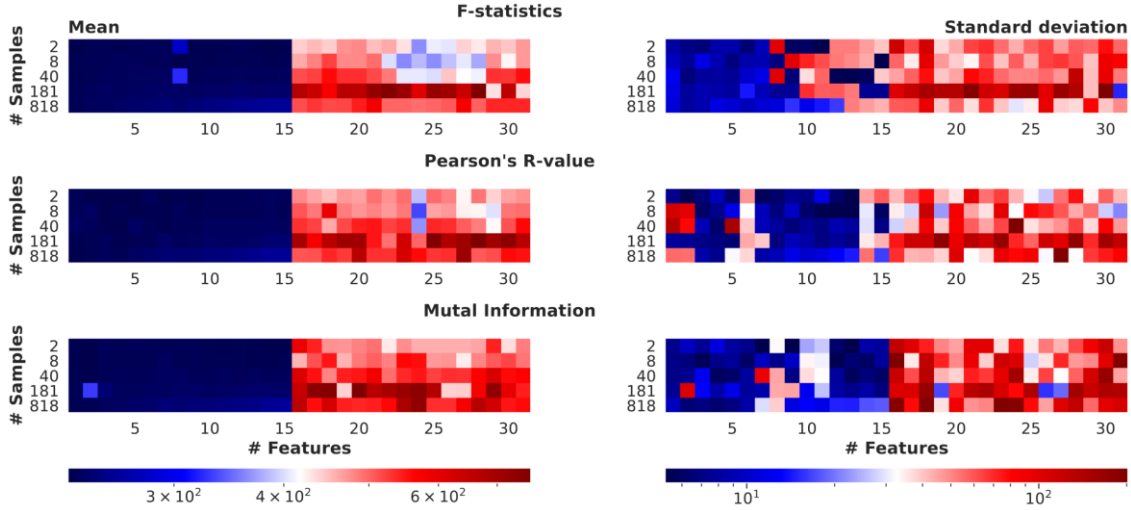


Fig. 6. KNN mean and standard deviation of interference times for single real-world samples, evaluated based on different combinations of reduced sample and feature numbers for training.

algorithms. Again, the CCU sample reduction is done before the feature reduction, and 32 randomly initialized runs are analyzed. Both sample and feature reduction reduce the interference time for the used KNN model. Interference time generally decreases with sample reduction, which is expected since fewer samples need to be iterated to predict a new sample. In contrast, for the feature reduction two interference time plateaus are found, one between 1 and 15, and the second between 16 and 31 features, where a feature number change does not show a clear effect. This can be (at least partly) explained by the KNN implementation in our experiment, which uses a highly efficient KD-tree data structure for the nearest neighbor search. This data structure has an asymptotic complexity of $O(\log n)$ for searching for a neighbor among n training samples. Consequently, we expect further significant speedup potential for a KNN that uses a linear search algorithm with $O(n)$ complexity for finding neighboring samples. Nevertheless, compared to the benchmark presented in [12], the interference time for a single EMI measurement-based debonding size evaluation can be reduced by a mean factor of 1.965 without a relevant loss of prediction accuracy and reliability (CCU reduction to 8 samples and mutual information feature reduction to 10; selection acc. to Figure 4 and Figure 5).

Conclusions

The present work is based on a previously demonstrated physics-informed and ML-based approach for sandwich face layer debonding evaluation by the EMI method [12]. The previously proposed data preprocessing and KNN-based evaluation approach is used as a benchmark. Additional under-sampling and feature reduction methods are investigated for data distillation, i.e., to reduce the computational requirements of both training and inference while at the same time preserving essential information. The used KNN model is trained exclusively with FE simulation-based synthetic EMI spectra data. It is tested on real-world EMI spectra measurements of a circular aluminum sandwich panel by a piezoelectric transducer. Both, under-sampling and feature reduction experiments clearly demonstrate the large potential for saving computational power and energy at the same time with a faster inference. The combination of CCU and mutual information feature reduction thereby reduces the inference time by a factor of about 1.965 compared to the used benchmark, while prevailing reproducibility and accurate debonding size predictions with little scatter. Both, sample and feature reduction contribute to the interference time reduction. Due to the KNN model's KD-tree data structure for searching the nearest neighbor, the full potential of feature

reduction cannot be used. Furthermore, these promising results are demonstrated by only one physical sandwich panel, which was increasingly damaged for the considered EMI measurements. Thus, for reliable general demonstration, the proposed algorithm needs to be tested on further similar sandwich panels. Nevertheless, the highly efficient algorithm may enable future congruent evaluation with more damage parameters, e.g., damage location and type, and the fast evaluation of whole sensor arrays by a single low-tech computation unit. Future research could explore ways to enhance the cost-effectiveness of generating synthetic training examples. Specifically, leveraging the outcomes of under-sampling to minimize the extent of simulating parameter intervals corresponding to material properties.

To enable reproducibility, enhance comprehensibility, and encourage future research, the data and the code used in this study are provided in their entirety under https://github.com/berni-lehner/structural_health_monitoring.

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