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Robustness vs. effectiveness of transfer learning in damage identification depending on feature selection

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ABSTRACT

This paper focuses on the use of transfer learning for training two different Machine Learning algorithms for damage detection and localization, respectively. It is well known that the learning phase benefits from an accurate representation of the intact structure, a realistic noise contamination of the synthetic outputs produced via the virtual experiments and, if needed, the parametric inclusion of damage scenarios. The selected modal features can be advantageously based on those involved in physics-based damage identification to achieve a higher accuracy. In the comparison with more basic features, such as modal shapes and curvatures, less attention has been given to the effects of modeling error. The above principles and analyses are applied to the identification of damage in a rectangular metallic plate for which measured modal data is available from a dedicated experimental campaign in CNR-INM laboratory using accelerometers. The damage is modeled as a stiffness reduction over a small area, being also representative of material thinning due to corrosion. To have meaningful training database, the modal convergence of the FE model to the real structure is guaranteed by a structural optimization process. Experimentally identified noise, representative of real-life applications, is then added to the FE results before algorithm training. Damage existence and position are determined by a Novelty Detection approach and a Regression Neural Network, respectively. It will be shown that basic features always provide less accurate damage estimation in presence of modeling errors on boundary conditions with respect to more structured ones.

Keywords: Damage detection, Machine Learning, Feature engineering, Modal curvatures, Hybrid approach

1. INTRODUCTION

Damage identification is an engineering field focused on assessing the degradation of structures over time. Traditionally, periodic inspections were used, but recent advancements have shifted the focus to continuous health monitoring via permanently installed sensor networks. Identifying damage using data from these sensors presents a significant challenge, as it requires distinguishing between damage effects and variations caused by environmental or operational conditions.

Data-driven methods for damage identification have the ability to detect complex and nonlinear relationships in the data, which may be overlooked or excessively simplified with traditional physics-based approaches. These methods apply Statistical Pattern Recognition techniques directly to system measurements, and are gaining significant attention due to the growth of Artificial Intelligence and Machine Learning (ML) algorithms in recent years [1]. However, a major limitation of data-driven methods is the need for large meaningful datasets to train the algorithms. In practice, especially in the context of damage identification, generating sufficient real-world data is impractical, as it would require to deliberately introduce damage in the structure.

This requirement can be fulfilled using Transfer Learning (TL), where the model is trained on data from a different structure, often derived from simulations, as seen in [2–5]. However, a key issue with TL is the potential discrepancy between the training and testing datasets. When TL is based on synthetic data, modeling errors can cause the algorithms to misinterpret these as damage effects when applied to real structures. Feature Selection can help mitigate this issue by ensuring that the features used in training are both effective and robust. Effectiveness refers to the ability of accurately capture the phenomena of interest, while robustness ensures high performance even when modeling errors are present.

This paper investigates these aspects within the context of a damage identification strategy for thin plates developed in [6]. The strategy aims at detect and localize damage occurring on a thin plate by measurements obtained with an Operational Modal Analysis (OMA) on a given sensor network. Even though the reference paper relies on data from an Experimental Modal Analysis (EMA) conducted in the CNR-INM laboratory, the approach is equally applicable to OMA, which is more suitable for real-world applications. Detection and localization are each addressed by a separate algorithm, namely a Histogram Score Novelty Detection (HSND) and a Regressive Neural Network (RNN). In this paper we compare different features derived from EMA/OMA techniques to identify a set that, despite being more sensitive to measurement noise (and potentially less effective), offers greater robustness against modeling errors.

2. DESCRIPTION OF THE METHODOLOGY

The present methodology for damage detection and localization was already considered in [6] This methodology combines data-driven approaches (in the form of ML algorithms for damage identification) with some knowledge of the physical problem, in a Transfer Learning approach based on simulations and a Physics-Informed choice of the features. In this section a brief overview of the Transfer Learning approach is provided.

The underlying idea is to train the ML algorithms on simulated damage scenarios in order to identify the damage on real data with similar precision. Thus a proper Transfer Learning approach must be implemented. First of all, an optimization of the model parameters must be performed to make the simulated structural behavior close to the target structure. Secondly, the simulated data must be contaminated with the same external influences that affect the real structure. In this paper the only environmental condition considered is the measurement noise on extracted modal data, therefore a proper characterization and inclusion of this effect is introduced. A general overview is provided in Figure 1.

The structure is a thin plate made of 5083 aluminum alloy of dimensions 1.0m$\times$0.5m$\times$0.005m. The plate is supposed clamped at its shortest edges and free at the other two, as shown in Figure 2a. The clamps determine an equivalent constraint in between ideal clamping and simply supported boundary conditions (BCs), and this aspect is the supposed principal source of modeling error. The damage consists in a localized reduction of thickness by 0.002m, covering a square with sides equal to 0.06m, as shown in Figure 2a and 2b.

Experimental data in terms of mode shapes was available from previous experimental campaigns, described in [7]. The grid of points where modal amplitudes were experimentally evaluated is illustrated in Figure 2b. The plate is divided into panels E_{jk} by a grid of points $P(x_j, y_k)$ composed by:

- 9 spaced points in the horizontal direction x with distance $h_x = 0.100$m between points (the points at the edges of the plate coincide with the clamps).
- 7 spaced points y_k in the vertical direction y with distance $h_y = 0.083$m between points.

Such data is used as reference to build an updated FE model of the structure via an optimization procedure. As design variables, the stiffness of the clamped edges (k_1 and k_2) and the actual Young modulus of the aluminum plate (Y) were chosen. The objective function is defined as the product of the relative frequency variation and the Modal Assurance Criterion (MAC) value between the set of numerical and experimental modes:

$$J(Y, k_1, k_2) = \sum_{i=1}^{M} \left(\frac{f_i - f_{exp,i}}{f_{exp,i}} \right)^2 \cdot (1 - \mathrm{MAC}_{i,i})^2 \tag{1}$$

where M is the total number of modes considered, f_i and $f_{exp,i}$ are the resonance frequency of the i-th mode respectively obtained from simulation and experiments, $\mathrm{MAC}_{i,i}$ is the value of the MAC on the mode shape of the i-th mode between simulation and experiment. Only the first four modes are considered because they are adequately separated in the experimental dataset. The model parameters obtained in this way are shown in Table 1.

Table 1: Plate properties obtained by the model updating procedure.

Quantity	Symbol	Unit of Measure	Value
Young modulus	Y	[Gpa]	74.98
Clamp stiffness $x = 0$	k_1	[N/m^2]	$3.63 \cdot 10^{11}$
Clamp stiffness $x = l$	k_2	[N/m^2]	$1.07 \cdot 10^{11}$

Regarding the measurement noise, some important assumptions are made: only random errors are considered here as effects of measurement noise, and these perturbations are assumed to follow a Gaussian probability distributions in their intensity, with a given law. Therefore, for each measurement point and each mode separately, the noisy value of mode shape is given by:

$$\tilde{\phi}^{(i)}_{j,k} = \eta^{(i)}_1 + (1 + \eta^{(i)}_2)\phi^{(i)}_{j,k} \tag{2}$$

where the perturbation terms $\eta^{(i)}_{1,2}$ are governed by a Gaussian probability distribution with zero mean and standard deviation obtained from the reference data and described in Table 2. A noise reduction technique is also considered here to diminish the effect of measurement noise. Such technique consists in performing the average between a set of S measured mode shapes before evaluating the features. It can be demonstrated that the standard deviation due to measurement noise is reduced following the law $\sigma_S = \sigma/\sqrt{S}$, without filtering out the effects of damage.

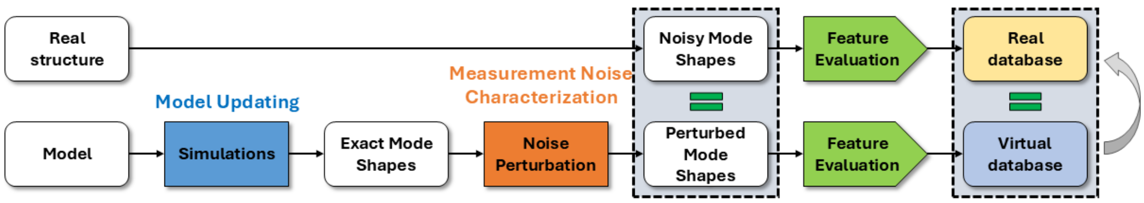
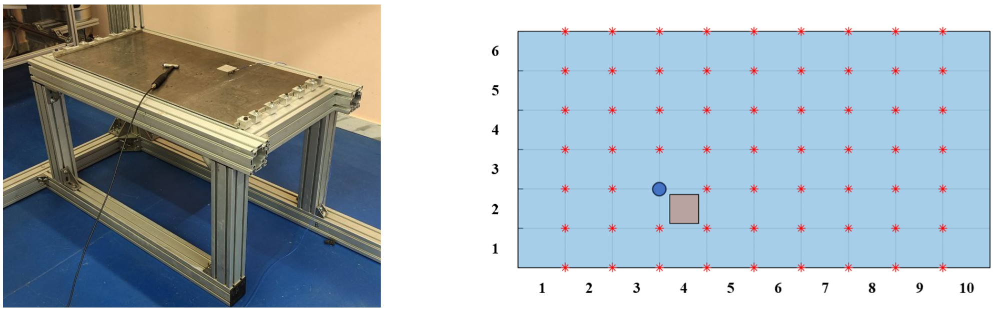


Figure 1: Transfer Learning process logic scheme.



(a) (b)

Figure 2: (a) Plate experimental set up and relative (b) measurement grid (red stars) dividing the plate in panels (orthogonal lines). The blue circle represents the position of the accelerometer used in the experiments, while the gray square represents the damaged area.

Table 2: Standard deviations related to measurement noise description for each mode considered.

Mode	1	2	3	4
$\sigma_1^{(i)}$	0.0011	0.0023	0.0015	0.0068
$\sigma_2^{(i)}$	0.0088	0.0069	0.0024	0.0722

3. INVESTIGATED MODAL FEATURES

Several features are investigated in this paper to solve the damage identification problem. It is worth noting that there is a so-called "mother" feature, the mode shapes, and several "children" features, namely modal curvatures, modal strain energy index and Modified Cornwell's index. The "children" property substantially highlights that these quantities are obtained by arithmetic operations on the original one. In the following the quantities related to the (potentially) damaged configuration are indicated with the superscript *. All the features are obtained from the same grid of accelerometers and are, namely:

1. *Mode shapes*. They consist of the modal amplitudes $\phi_{j,k}^{(i)}$ evaluated on the grid points shown in Figure 2b. To be used as feature, a normalization procedure is implemented based on the intact simulated data, therefore the actual feature vector based on mode shape is

$$\Phi_{j,k}^{(i)} = \frac{\phi_{j,k}^{*(i)} - \mu(\phi_{j,k}^{(i)})}{\sigma(\phi_{j,k}^{(i)})} \tag{3}$$

   where $\mu(\phi_{j,k}^{(i)})$ and $\sigma(\phi_{j,k}^{(i)})$ are the mean and standard deviation, respectively, of the intact simulated mode shapes. For these quantities the variability is provided solely by the measurement noise.

2. *Modal curvatures*. Modal curvatures are evaluated on each grid point from the mode shapes themselves with second order central differences schemes, following Kirchhoff-Love theory for thin plates, as:

$$\kappa_{xx,j,k}^{(i)} = \frac{\phi_{j-1,k}^{(i)} - 2\phi_{j,k}^{(i)} + \phi_{j+1,k}^{(i)}}{h_x^2}, \qquad \kappa_{yy,j,k}^{(i)} = \frac{\phi_{j,k-1}^{(i)} - 2\phi_{j,k}^{(i)} + \phi_{j,k+1}^{(i)}}{h_y^2} \tag{4}$$

   apart from the values on external borders, where hypothesis about BCs are instead used, as described in [6]. The modal twists are instead evaluated on the center of each panel as:

$$\kappa_{x,y,j,k}^{(i)} = \frac{\phi_{j,k}^{(i)} - \phi_{j+1,k}^{(i)} - \phi_{j,k+1}^{(i)} + \phi_{j+1,k+1}^{(i)}}{h_x h_y} \tag{5}$$

   As for the case of mode shapes, a normalization procedure is implemented to obtain the features.

3. *Modal Strain Energy Index (MSEI).* Conrwell's MSEI [8] is used here. As many other MSEI, these indices have a baseline formulation, i.e. they compare the actual configuration with a reference dataset, so that only the changes between the two configurations are highlighted by the indices. With respect to other indices, their formulation directly provides a measure of the stiffness reduction on each panel in which the structure is divided into by the sensor grid:

$$\beta_{Co,j,k} = \frac{\sum_{i=1}^{M} \gamma_{j,k}^{(i)}/\gamma^{(i)}}{\sum_{i=1}^{M} \gamma_{j,k}^{*(i)}/\gamma^{*(i)}} \tag{6}$$

with $\gamma_{j,k}^{(i)} = \int_{x_j}^{x_{j+1}} \int_{y_k}^{y_{k+1}} \left[\kappa_{xx}^{(i)2} + \kappa_{yy}^{(i)2} + 2\nu\kappa_{xx}^{(i)}\kappa_{yy}^{(i)} + 2(1-\nu)\kappa_{xy}^{(i)2} \right] dxdy$. Analogously $\gamma^{(i)}$ is obtained integrating across the whole plate. Integrals are obtained by means of trapezoidal quadrature using the modal curvatures and twist described before.

4. *Modified Cornwell's Index (MCI).* The modified version of Cornwell's MSEI introduced in [6] is used here. With respect to Cornwell's MSEI, the MCI are separately evaluated for each mode, then a transformation is introduced to bound the domain of possible values assumed by the indices:

$$\beta_{j,k}^{(i)} = \frac{\gamma_{j,k}^{(i)}/\gamma^{(i)}}{\gamma_{j,k}^{*(i)}/\gamma^{*(i)}}, \qquad \tilde{\beta}_{j,k}^{(i)} = \begin{cases} \beta_{j,k}^{(i)} & \text{if } \beta_{j,k}^{(i)} \leqslant 1 \\ 2 - \frac{1}{\beta_{j,k}^{(i)}} & \text{if } \beta_{j,k}^{(i)} > 1 \end{cases} \tag{7}$$

4. DEPLOYED MACHINE LEARNING ALGORITHMS

The objective of the damage identification procedure here described is to solve the first two levels of knowledge related to damage [9]: detection and localization. To achieve that, the identification strategy is developed in two steps (as shown in Figure 3), exploiting the most suitable algorithm for each level of damage information. First, damage detection is achieved using a Histogram Score Novelty Detection (HSND) algorithm, and second damage localization is performed via a Regressive Neural Network (RNN).

Performing damage detection using a Novelty Detection approach results in training the algorithm only on intact data, thereby ensuring that any damage can be predicted [10, 11]. The HSND algorithm provides a score for each sample that directly measures the probability of such a sample to be part of the intact class. Such score is based on the histogram built for each element of the feature vector obtained from the intact data. Thus, a threshold is set on the spectrum of score values to distinguish between normal (intact) and novelty (damaged) scenarios. In this work such threshold is obtained by maximizing the accuracy in prediction over a database equally represented by intact and damaged scenarios.

Another advantage that comes from separating detection and localization modules is that it allows for the use of a regression approach for localization, treating the entire structure as a continuous space, and therefore obtaining a tool capable of locating damage anywhere on the structure. A Multi-Layer Perceptron (MLP) is considered here with three hidden layers of N_p, $N_p/2$, $N_p/4$ neurons ($N_p = 192$ represents the number of panels in which the structure is divided by the sensor grid multiplied by the

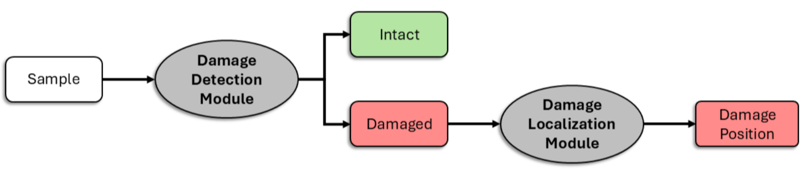


Figure 3: Two-step damage identification strategy.

number of modes considered) and a last regressive output layer with 2 neurons (one for each coordinate on the plate). To avoid overfitting, a dropout layer (dropout probability set at 0.5) is introduced before the third hidden layer. The activation function is a Rectified Linear Unit activation function (ReLU) between hidden layers and a regression function on the output layer. A maximum number of epochs of 20 is imposed, as well as a minibatch size of 500 cases for each epoch, to speed up training. A separation of the dataset in 70%/15%/15% between training/validation/testing is performed, with shuffling between training and validation data for each epoch. Validation is carried out at the end of each epoch. The NN chosen at the end of the training is the one with the lowest RMSE (Root Mean Square Error) validation value. All the aforementioned NN parameters were obtained by means of trial and error tests as the best compromise between performances and training computational costs.

5. RESULTS

The results hereby shown are obtained on data simulated with the model described in Section 2.. The pipeline to build a database is the following: (i) exact mode shapes are simulated with the FE model for each scenario considered (intact or damaged), then (ii) each case is perturbed a certain number of times following the measurement noise characterization illustrated in Table 2, lastly (iii) the various features introduced in Section 3. are evaluated. Since the objective of the algorithms is to detect and localize the damage on the structure, damaged configurations are simulated with the same severity, i.e. the same damage dimensions, but varying positions. To obtain random yet uniform distributions of possible positions, optimized Sobol distributions are used. The numbers of simulations and perturbations for training and testing datasets are illustrated in Table 3.

Table 3: Training and testing database composition.

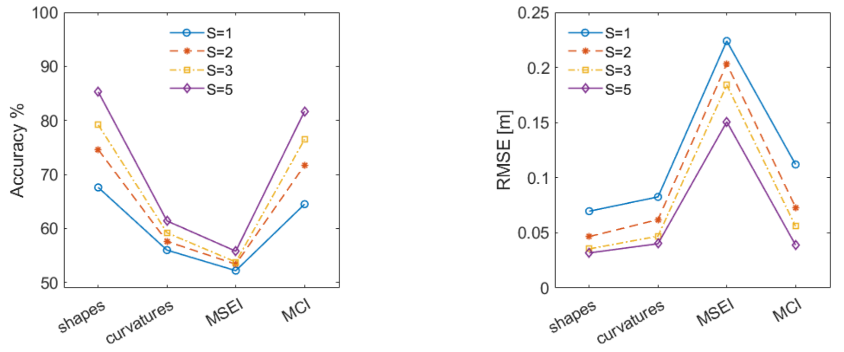
	Training		Testing	
Scenario	Simulations	Perturbations	Simulations	Perturbations
intact	1	30,000	1	10,000
damaged	400	2,000	100	1,000
total samples	830,000		110,000	

5.1. Effectiveness of the features

A first analysis is performed to assess and compare the effectiveness of the various features employed in damage identification. This is studied by measuring the precision of each algorithm varying the feature over which they are trained. Results are shown in Figure 4a for the HSND in terms of accuracy and in Figure 4b for the RNN in terms of RMSE for various intensities of measurement noise (introduced with the noise reduction technique described in Section 2.). As one can see in Figure 4a, mode shapes present the higher accuracy for each noise condition considered, while curvatures and MSEI show a decrease in accuracy that may be related to a detrimental propagation of noise through their numerical calculation. On the other hand, when the MCI set is used, the attained precision is comparable to the one obtained with the mode shapes. For RNN the trends are similar, even though in this case the modal curvatures show a lower RMSE (i.e. a better precision) than the MCI. These results indicate that basic features perform better than more structured ones if both training and testing dataset are coherent. Nonetheless the MCI performances, if compared with those provided by the mode shapes, are quite close, especially when the noise intensity decreases (for larger S).

5.2. Robustness of the features on modeling error

In this section the robustness of the features on modeling error is investigated. In a Transfer Learning strategy based on simulations this is an important issue, because obtaining a numerical model that is an accurate replica of the target object is challenging for several factors: (i) as the structural complexity increases, modeling errors are likely to increase as well, and mitigation by model updating may be less

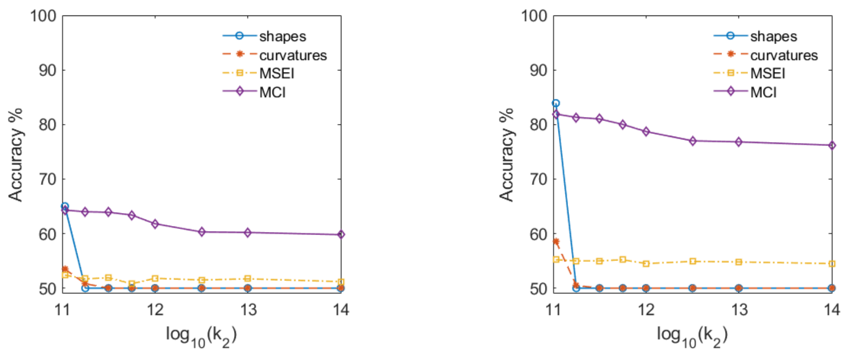


(a) **(b)**

Figure 4: Effectiveness of features for (a) detection with HSND and (b) localization with RNN. S represents the order of noise reduction.

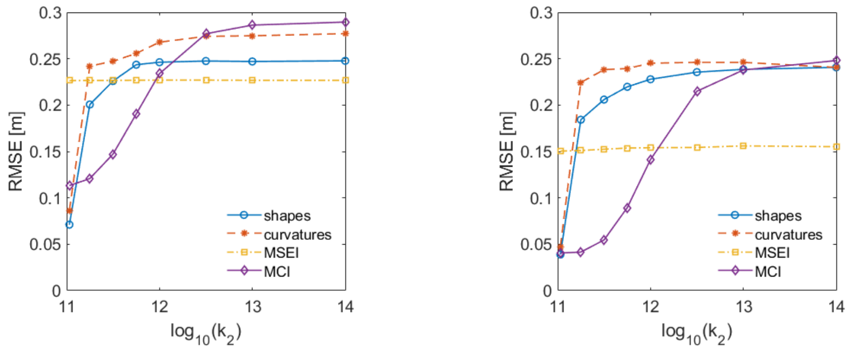
effective; (ii) hypotheses relative to the target damage intrinsically have limitations or, on the other hand, a full damage parametrization is likely to involve a too onerous computational effort; (iii) interaction with the external environment is usually not considered due to its complexity. The previous considerations point out that fully addressing all these aspects is a huge task. Here we limit the analysis to the introduction of a simple but meaningful modeling error by varying, in the test datasets, the plate BCs. In particular, in the FE model there are two stiffnesses (k_1 and k_2) for to the clamped edges, related to uniform elastic foundations covering certain areas of the plate (equal to the clamped areas of the experimental set up). In this section the stiffness k_2 is varied from a reference value ($\log_{10} k_{2,\text{train}} = 11.03$) to generate testing dataset with growing modeling error. Results for the detection module are shown in Figures 5a and 5b for two different orders of noise reduction. As one can see, less structured features as mode shapes and curvatures lose all their effectiveness as a modeling error is introduced, with their accuracy dropping to 50% (every case is recognized as damaged). On the other hand, MSEI and MCI show an almost stable trend thanks to their baseline formulation. In particular, the fact that MCI keeps the modal contribution separate gives an important advantage to the HSND algorithm, thus ensuring very high accuracies even when the modeling error is very high.

Figures 6a and 6b, instead, show the results for the localization module. Similarly to what happened for HSND, the RNN trained on mode shapes and curvatures show an important drop in performances (higher RMSE) as soon as the modeling error is introduced. With respect to the previous module, while MSEI remain quite stable as the error increases, MCI shows a drop in performances as well, even if less intense than the other features.



(a) **(b)**

Figure 5: Robustness of the considered features in the detection module, varying the BC stiffness k_2 of the testing database with respect to the training case for (a) no noise reduction ($S = 1$) and (b) high noise reduction ($S = 5$).



(a) **(b)**

Figure 6: Robustness of the considered features in the localization module, varying the BC stiffness k_2 of the testing database with respect to the training case for (a) no noise reduction ($S = 1$) and (b) high noise reduction ($S = 5$).

6. CONCLUDING REMARKS

This study has explored the effectiveness and robustness of damage identification with respect to different sets of features characterized by increasing complexity. The proposed identification pipeline uses two different algorithms for detection (HSND) and localization (RNN), both of which are tested on the investigated features. Additionally, it leverages Transfer Learning based on simulations with a robustness analysis focused on modeling errors. The features examined were all based on Modal Analysis performed on the same sensor grid. While less structured features, such as mode shapes and, in some cases, curvatures, perform well in prediction when no modeling errors are present, their performance significantly decreases when modeling errors are introduced. By contrast, more structured features, particularly baseline-based features, demonstrate greater robustness to such errors. The main challenge with using MSEI is that the performance in damage detection and localization is unsatisfactory, even in the reference case. However, when MCI are employed as features, the prediction accuracy remains comparable to the one obtained with less structured features, but with greater robustness against modeling errors.

When developing a data-driven approach, the selection of Physics-Informed features can enhance the overall performance of the algorithms. On the other hand, data-driven methods, particularly ML algorithms, can benefit from incorporating less structured features, especially when advanced techniques like Neural Networks are employed. In such cases, the algorithm itself is capable of evaluating and selecting a reduced set of more significant features from the original ones. Nonetheless, this approach often results in overfitting, indicating that the algorithm struggles with generalization and performs optimally only on the data on which it is trained. Therefore, when Transfer Learning is considered to address the issue of data availability, it is crucial not only to assess the effectiveness of the selected features for the chosen method, but also to evaluate their robustness to discrepancies between training and target datasets. In this regard, MCI was specifically designed for this purpose. This study demonstrates both the effectiveness and robustness of MCI when used as a feature for a damage identification problem.

It is noteworthy that this study deals with specific structural configurations, damage characteristics, and sensor layouts. In particular, the latter is composed of a rather dense grid of accelerometers to provide clear insights into the problem of comparing different features. However, the availability of so many sensors may not be easily achievable in practice. It is well known that a high number of sensors is required to provide more features (e.g., vibration modes) and increase the spatial resolution needed for fault localization. To address real applications, a sensitivity analysis of the identification accuracy on the (decreasing) number of sensors is crucial and will be part of future research. The features most affected by sparse information would probably be MCI and MSEI because they depend on finite differentiation on grid point measurements. On the other hand, Dessi et al [12] demonstrated that, for 1D structures, there exists an optimal sensor distance to accurately evaluate the MSEI minimizing truncation errors and noise propagation effects. Thus a compromise between effectiveness and robustness could be achieved with a proper Optimal Sensor Placement strategy, but such analysis falls outside the scope of this preliminary work and will be investigated in the future.

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