Physically Informed and Data Driven Direct Models for Lamb Waves based SHM: Advantages and Drawbacks of Existing Approaches

MARC REBILLAT, ERIC MONTEIRO and NAZIH MECHBAL

ABSTRACT

Validation and testing of Lamb wave based SHM algorithms requires numerous simulations that require themselves qualitatively and quantitatively consistent models representative of the physical behavior of the monitored structures and that are in agreement with experimental data. Finite elements models appear as an interesting solution to achieve this goal but are associated with large computational costs and low generalization abilities. On the other hand, data driven machine learning approaches are computationally very efficient and can predict fine details but at the cost of low physically interpretability. Original approaches trying to build physically informed models balancing the advantages and drawbacks of physics-based approaches and of machine learning approaches also exist and will be discussed in the context of Lamb waves based SHM of aeronautical structures.

INTRODUCTION

In this article, the objective is to consider how innovative models for the simulation of guided wave propagation in aeronautical structures to monitor using Lamb based can be designed and validated. The requirements associated with such direct models for Lamb waves based SHM are to be able to simulate guided wave propagation in thin structures, to be computationally inexpensive, and to be faithful to the experimental reality. However, the existing models from the litterature are yet not satisfactory: they require too much computation time, they are not representative of the physical phenomena studied, or they are not able to reproduce the experimental measurements faithfully enough.

From a practical point of view, two sources of information are however available to build such models: information from physics, and experimentally obtained data. The expression of *"physically informed"* models will thus be used here in the sense that these two types of information will be combined simultaneously to build these models [1, 2]. This article thus aims at discussing methodologies for the creation of various models for Lamb wave SHM, based on physical knowledge and available experimental data, while ensuring their practical use.

REBILLAT Marc, Associate Professor, Email: marc.rebillat@ensam.eu. Process and Engineering in Mechanics and Materials (PIMM) Laboratory, ENSAM-CNAM-CNRS, Paris, France.

DIRECT MODELS FOR LAMB WAVES BASED SHM

It is first necessary to clarify expectations when the idea of a direct model is raised. In the context of structures monitored by Lamb waves based SHM, the structures are thin and are equipped with active elements. During their life cycle these structures will endure variations in their operational parameters (temperature, mechanical loading, ...) as well as potential damage that will need to be monitored. The so-called *"direct"* models will make it possible to predict the signals received by the active elements bonded on the host structure in function of:

1. *The properties of the input signal* (frequency, number of cycles, amplitude, ...). An input signal applied to the active element $n \in [1, N]$ will be noted as a time series $x(t)$. The resulting signals received by the active elements $k \in [1, N](k \neq n)$ are noted as time series $y_{nk}(t)$. For simplicity, we will note $y_{nn}(t) = x(t)$.
2. *The properties of the host structure* equipped with active elements (geometry, materials, positions, ...). All the parameters related to the host structure and the electro-active elements are grouped in the vector $\mathcal{S}$. The parameters related to the host structure and to the active elements are grouped in the vector $\mathcal{S}$.
3. *The operating environment* where the monitored structure evolves (mechanical loading, temperature, ...). The associated parameters are grouped in the vector $\mathcal{O}$.
4. *Its health status*. The damage parameters are grouped in the vector $\mathcal{D}$.

Thus, a direct model $\mathcal{M}_D[.]$ will be able to estimate for a structure $\mathcal{S}$, in a damaged state $\mathcal{D}$ and under operational conditions $\mathcal{O}$, the set of signals $y_{nk}(t)$ with $n, k \in [1, N]$ for a given $x(t)$ input:

$$\{y_{nk}(t)\}_{n,k\in[1,N]} = \mathcal{M}_D\left[x(t), \mathcal{S}, \mathcal{O}, \mathcal{D}\right] \tag{1}$$

It is important to specify that the objective here is to predict the propagation of guided waves in thin structures, thus in 2D, and that the output is not the displacement field on the whole host structure but simply the resulting electric voltages at the level of the various active elements used as sensors.

DATA, PHYSICS, AND COMPLEXITY

The models described above must now be built on the basis of available information, in a reasonable time, and be usable in practice. Two types of information are available to build these models. Firstly, some knowledge of the physics of the phenomena studied is available via the Lamb wave propagation equations, the waves/damage interaction laws, and the various parameters associated with them, for example. Secondly, it is possible to carry out experimental campaigns on real structures in order to obtain data sets for the studied structures for different frequencies, amplitudes, environmental conditions, state of damage... Finally, the models developed here have a practical purpose: they must be parameterized or learned in an acceptable time and provide estimation results quickly enough to be used in practice. There is thus a compromise to be found between the three

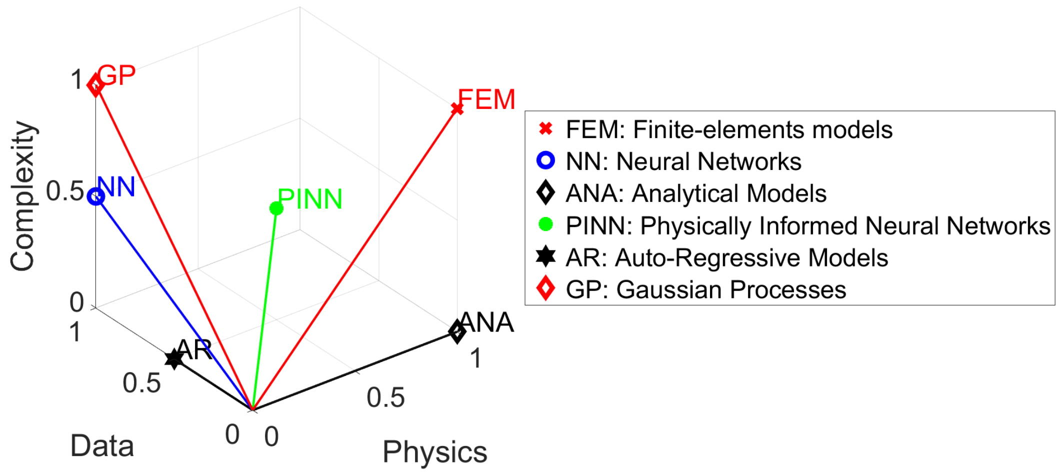

Figure 1. Non-exhaustive categorization of different models according to their needs in terms of physical knowledge, experimental data, and algorithmic complexity.

factors that are physical knowledge, the need for experimental data, and the algorithmic complexity in the construction and choice of these models.

Figure 1 proposes to categorize (in a non-exhaustive way) a certain number of usual models according to their needs in terms of physical knowledge, experimental data, and their algorithmic complexity. Among the models based exclusively on a physical knowledge of the problem, it is possible to quote the finite element models (FEM) or the analytical models (ANA). In contrast to physical approaches, neural networks [3] (NN) are built on a purely data-driven approach and have no preconceived ideas about the physics of the problem studied. Still in this category, the auto-regressive [4] (AR) models are conceptually simpler and less cumbersome to train than the NN models. Finally, Gaussian processes [5] (GP) add to data-based models the possibility of quantifying estimation uncertainties. Between these two extremes gravitate physically informed models. The idea of these models is to propose a solution to these problems based on approaches that not only learn from the data, but also use the knowledge of the physics of Lamb wave propagation, without requiring a complete and fine-grained knowledge of the environment. One of these models from the literature has been applied to the SHM case [6] (*Physically Informed Neural Network* [PINN]).

PHYSICS BASED MODELS

This section first illustrates the strengths and weaknesses of physics-based models in a Lamb waves based SHM context.

Finite-element models (FEM): The FE approach is the most common in the context of SHM [7,8]. It is based on a fine-grained knowledge of the geometry and physical laws within the structure under study. From the geometrical point of view, it relies on a mesh that must be defined in advance and must coincide with the geometry of the host structure. For actual aeronautic structures which cover several meters, this therefore imposes

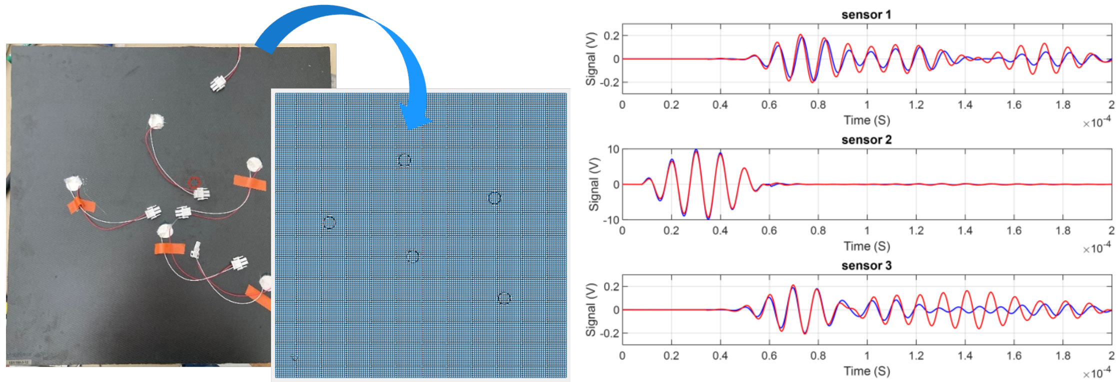

Figure 2. Examples of correlation results between a finite element simulation (in blue) and experimental measurements (in red) (from [6]).

unrealistic meshes from the implementation point of view. Moreover, the frequencies used being quite large, small time steps must also be considered. From a physical point of view, a detailed knowledge of the constitutive laws of the different materials, of the attenuation mechanisms, of the interactions with inhomogeneities, is necessary and must be encoded in the model. In practice, these laws can be more or less well known, which strongly limits the capacity of a finite element model to accurately represent experimental data. Nevertheless, data from finite element models remain an excellent means to validate SHM algorithms. Figure 2 illustrates the quality of correlation that can be obtained between finite element simulations and experimental measurements. The first packet is very well reconstructed, which means that the propagative aspects are well modeled. However, this is not the case for the following packets, which shows the difficulty of modeling the interaction and attenuation laws. In conclusion, even if finite element simulations are interesting from a qualitative point of view, the computational costs and the limitations related to a certain lack of detailed physical knowledge are two major disadvantages of finite element models.

Analytical models (ANA): Analytical models have also been used in the context of SHM [7,9]. They are attractive because they are often very efficient in terms of computational time and have the advantage of allowing a direct interpretation of the effect of different physical parameters on the simulation results. Their main limitation lies in the fact that it is impossible to accurately represent the geometry of a host structure with an analytical model. On the other hand, advanced physical models can be relatively simply included in analytical models, as was presented for example for Lamb wave attenuation. In conclusion, analytical models are very efficient in terms of algorithmic complexity, can potentially include complex physical laws, but unfortunately remain poor in geometrical details and thus incompatible with complex structures.

DATA BASED MODELS

In contrast to the previous section, this section now illustrates the strengths and weaknesses of data-based models in a SHM context.

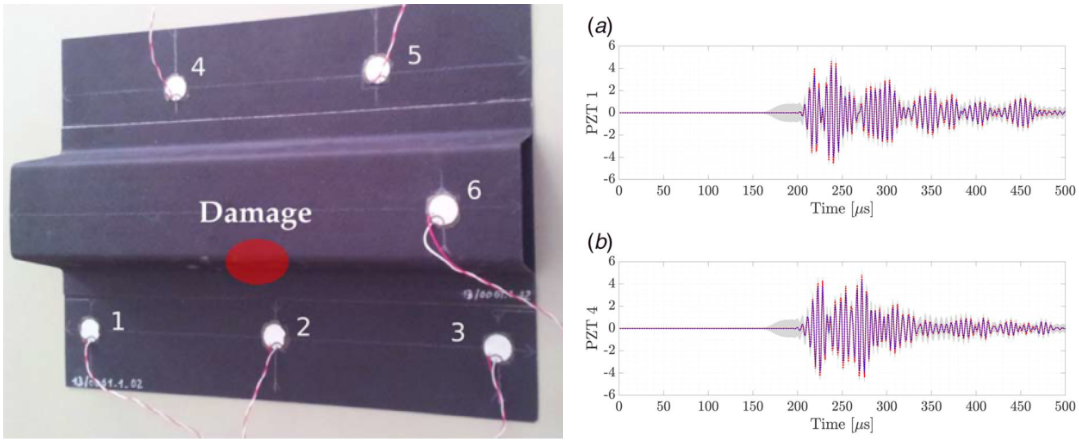

Figure 3. Comparison of temporal signals predicted by an autoregressive model associated with Gaussian processes with those obtained experimentally (from [5]).

Auto-Regressive Models and Gaussian Processes (AR et GP): The idea is now to present a first category of models inherited from signal processing. The AR models are associated with a recurrence equation and allow to model temporal sequences of samples as it is the case in the SHM [4, 5]. These models are linear and are based on relatively few parameters which makes them interesting from the point of view of algorithmic complexity. These models can be easily enriched by Gaussian processes which will consider that their parameters are known via their probability density and will therefore be able to associate a confidence interval to their predictions. Figure 3 illustrates the performances of an auto-regressive model associated with Gaussian processes. The predictions made by these models are of very high quality. On the other hand, the interpretation of the coefficients of these models from a physical point of view remains unfortunately impossible. In conclusion, these models are efficient from an algorithmic point of view and can model geometrically complex cases but it is not possible to easily link them to Lamb wave physics.

Neural Networks (NN): Neural networks are an alternative to legacy signal processing and data-driven models that is widely used in the context of Lamb waves based SHM [6, 10–15]. The universal function approximation theorem indeed establishes that multilayer neural networks have the ability to approximate any continuous function given a sufficient number of hidden units [3]. This suggests that a neural network should thus be able to approximate the solution of the wave equation by learning the appropriate weights from the training data for any geometry and for any damage case. The counterpart of this accuracy is a cost in terms of training data as well as a cost in terms of complexity in the learning phase. In conclusion, these models allow to reach a high degree of accuracy but require a large amount of training data as well as an important training time. Moreover, the physical interpretation of these models remains extremely delicate and their generalization, *i.e.* their use for cases which do not correspond to training cases, is not guaranteed.

PHYSICALLY INFORMED MODELS

The preceding sections thus illustrate the strengths and weaknesses of either data-only or physics-only models. This need to combine physics knowledge with data-driven modeling is the focus of an emerging field called scientific machine learning (SciML) [16] or even theory-guided data science [1, 2]. The underlying idea is to explore synergistic ways that use physical domain knowledge to aid machine learning. Data-driven models will thus be trained to learn from the physical data while respecting certain constraints imposed by the physical domain knowledge under consideration. This hybridization between data and physics can be injected at different levels in the modeling process and be of varying magnitude. Four paths are thus identified as relevant for possible physics-driven approaches in the context of SHM:

1. The physical interpretation of the models built from the data.

2. The respect of the elementary laws of physics underlying the studied problem.

3. The construction of a neural network specialized for the studied problem.

4. The integration of the topology of the problem in the neural network.

The first two levels are briefly detailed in the following and the few works related to Lamb wave SHM at these levels are mentioned. The higher levels have not yet been studied in a SHM context from the authors knowledge.

Level #1 → Explained Artificial Intelligence (XAI): As previously mentioned, data-driven models are very attractive because they are able to accurately predict experimental data. On the other hand, the information captured, via the coefficients of the models, is difficult to interpret from a physical point of view. A field of research called Explained Artificial Intelligence (XAI) seeks to understand, then to physically interpret neural networks and can therefore be interesting in this context [17–20]. Some applications to guided wave SHM of XAI are present in the literature [21–24]. The work done allows for example to analyze among the different actuator-sensor paths available which are the most exploited by the neural networks to perform their prediction, or to determine the portions of measured signals important for damage detection or localization. These XAI approaches for Lamb wave SHM thus mainly provide confidence that the neural networks have learned information that is intuitively relevant from a physical point of view (the first wave packet carries a lot of information or the paths through the damage are informative) but do not really provide a way to act on the models to include more physical meaning.

Level #2 → Physically Informed Neural Networks (PINN): Another popular data-physics hybridization strategy, called Physics Informed Neural Networks (PINN), involves imposing physical constraints, in the form of partial differential equations for example, to act as a regularizer in the cost function of a neural network [25]. Figure 4 shows an example of a comparison between predictions made by a PINN model and an element-finite simulation. In this example taken from [6], time-of-flight information

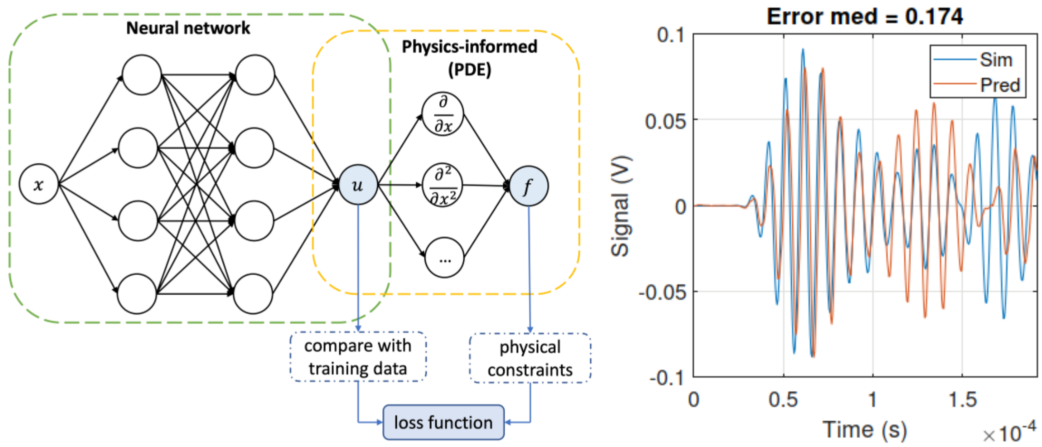

Figure 4. On the left, typical structure of a PINN (from [26]) and on the right example of comparison between predictions made by a PINN model and a finite element simulation (from [6]).

is included in the cost function in order to impose a link between the physics and the learned model. The first two packages are globally well predicted even if their amplitude is not exactly similar between the learned model and the finite element reference used here. This class of models is therefore mainly based on data but allows the addition of physical constraints. However, in the example presented, this addition of physical constraints results in a slight loss of accuracy.

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