DINAME 2023 - Proceedings of the XIX International Symposium on Dynamic Problems of Mechanics,
A.S. De Paula, A.T. Fabro and M.R. Machado (Editors), ABCM.
Pirenópolis, Go, Brazil, February 26th to March 3rd, 2023

# A Deep learning approach for interfacial defect identification based on reduced acoustic scattering models

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*Abstract: An inverse scattering problem methodology for identification and recovery of damage fields in laminated structure interfaces from the reflected field is presented. The training procedure of the deep learning method uses stochastic Gaussian fields as output, which are related to interfacial damage fields of the physical problem. We assume prior knowledge of the material properties of the ultrasound incident field and the elastic layers properties. Furthermore, we model the interfaces using the Quasi-Static-Approximation, a method that generates position dependent interfacial stiffness matrices, composed of set of uncoupled normal and tangential springs. This methodology aims to assist ultrasound tests and may be able to detect and recover defects in real time.*

***Keywords: Deep Learning, Acoustic Scattering, Structural Health Monitoring, Laminated Composite, Quasi Static Approximation (QSA)***

## INTRODUCTION

There are many works in literature that uses learning approaches to predict damage. Liu et al. (2017) investigate machine learning methods to predict the length of the path across delamination area in composite materials. Recently, Ritto and Rochinha (2021) tested different classifiers and parameters in order to build a fast digital twin (machine learning), by using a physics-based model, that will be connected to the physical twin to support real time engineering decisions. The computational model consists in approximate a bar structure with actuators and sensors to a 6-DOF lumped parameter, where some parameters are random in order to give the model a stochastic approach. Zobeiry et al. (2020) used a continuum damage finite element model to train interconnected Neural Networks (NN) in series, based on macroscopic load-displacement data in order to characterize damage in quasi-isotropic composite laminates. Then, they used experimental measurements obtained through cumbersome non-destructive testing to validate the predicted damage properties. Santos et al. (2016) investigate and compared the classification performance of four kernel-based algorithms (one-class support vector machine, support vector data description, kernel principal component analysis and greedy kernel principal component analysis) by using measures of an acceleration time-series from an array of accelerometers obtained from a laboratory structure. And Pathirage et al. (2018) propose an autoencoder deep network for structural damage identification in highly non-linear problems. They use the natural frequencies and mode shapes of vibration as input and the structural damage as output in order to train the network.

Chen et al. (2020) mention that deep learning is becoming an increasingly important tool for solving inverse scattering problems (ISPs) in recent years. ISPs can be seen as a problem that consists in determining the nature of an unknown scattering distribution from the measure of the scattered fields. ISPs are challenging to solve because they are intrinsically ill-posed and nonlinear. ISPs can be tackled by either traditional objective-function approaches (as can be seen in Leiderman and Castello (2016), Cakoni et al. (2010), Gaikovich and Gaikovich (2010), to cite a few) or learning approaches, that is the scope of the present work. To avoid using DL as a purely data-driven black-box solver, it is important to address the problem of how profitably is combining DL with the available knowledge on underlying physics as well as traditional objective-function approaches. Many research efforts have been made in this direction to achieve real-time quantitative results. The physical-insight perspective applies not only to ISPs, but also to many other physical regression problems. In fact, in many practical applications, data collected by sensors are automatically governed by physical laws. Some of these physical laws present well-known mathematical properties or analytical formulas, which do not need to be learnt by training with a lot of data as stated by Chen et al. (2020).

In this work, we adopt some concepts presented in Chen et al. (2020), as follows: A DL neural network consists in a neural network with two or more hidden layers, each of which transforms its input to a new representation that is then used as input to the next layer. Although it costs plenty of time for NN in the training stage, the trained network is able to solve typical ISPs in real time. Furthermore, each layer is composed of multiple neurons. There is a vast variety of network architectures, such as fully connected neural network, also referred to as the multilayer perceptron (MLP), convolutional neural network (CNN), recurrent neural network (RNN), generative adversarial network (GAN), long-short term memory network (LSTM) to cite a few. When we solve ISPs, which are a regression task, special caution must be taken when choosing DL architectures, given that architectural choices that work well for a classifier task might be ineffective for solving a regression task. The most used architectures for solving ISPs are CNN and MLP. In MLP, each neuron in a layer is connected to all neurons in the next layer. In comparison, the layer-to-layer connection in CNN is by convolution, which is a local operation. Although theoretically MLP is able to approximate any continuous functions arbitrarily well, it is not suitable to large scale problems due to exceedingly large amount of parameters as a consequence of full connection between layers. In contrast, CNN has much fewer parameters and is more suitable when dealing with images and videos, as they are large scale problems. Here is is worth to highlight that, since we are not dealing with large scale problems involving images or videos, we use a MLP in the present work.

## METHODOLOGY

The methodology of the present work consists in solve the direct scattering problem as an optimization problem for each damage field generated by Gaussian random fields and then use the solution (reflected scattered fields) as input to train a deep neural network, using the Gaussian random fields as output. The whole procedure is shown in Fig. 1.

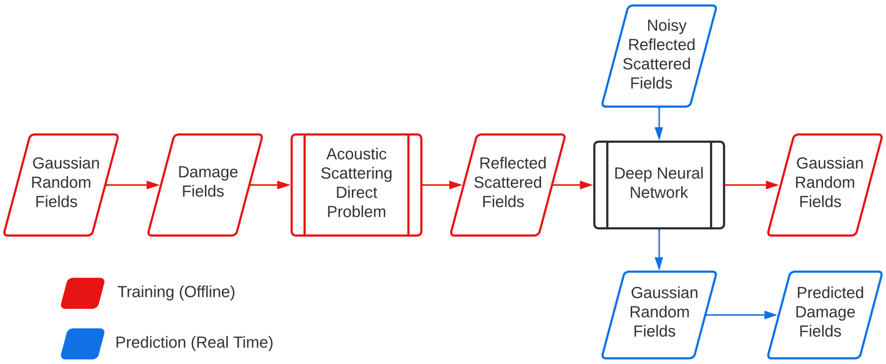


**Figure 1 – The methodology schematically represented.**

It should be noticed that the prediction procedure can be performed with a reduced model, by adjusting the input and output sizes of the neural network.

## RESULTS

The chosen physical system corresponds to a structure composed by stainless steel, copper and aluminum, bonded by thin epoxy adhesives and immersed in water, the whole system and its measures are shown in Fig. 2. Furthermore, the mechanical properties of each constituent material are presented in Tab. 1.

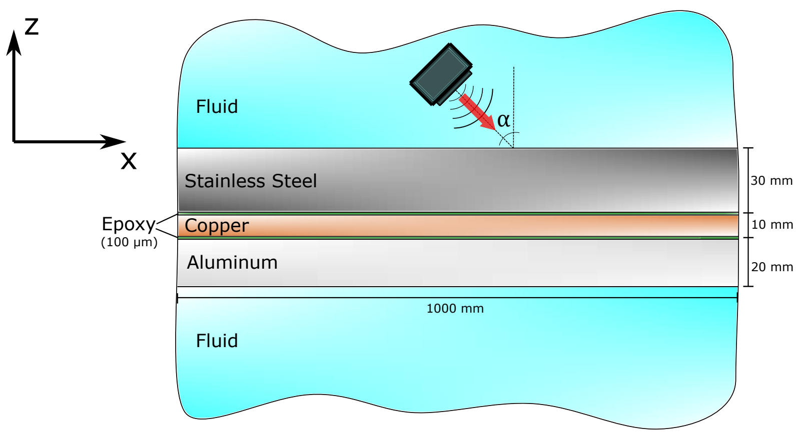


**Figure 2 – The physical system. Where $\alpha$ corresponds to the orientation of the incident field (angle of incidence).**

**Table 1 – Mechanical properties of the constituent materials of the system shown in Fig. 2. Note: $c_p$ and $c_s$ stands for P-wave and S-wave speeds, respectively.**

| Material | $c_p$ $[m/s]$ | $c_s$ $[m/s]$ | $\rho$ $[kg/m^3]$ |
|---|---|---|---|
| Stainless Steel | 5790 | 3100 | 7900 |
| Copper | 4660 | 2660 | 8930 |
| Aluminum | 6320 | 3130 | 2700 |
| Epoxy | 2150 | 1030 | 1200 |
| Water | 1480 | 0 | 1000 |

The prediction of a cohesion field $\hat{\beta}(x) = 1 - \hat{d}(x)$ can be generated independently for each interface and direction ($x$ and $z$) with the procedure shown in Fig. 1. A different NN was trained for each interface and direction, using the reflected scattered field in the z-direction as input. Each realization of the direct problem has 1000 equally spaced measurement points. Furthermore, we have assumed that all wave fields are time harmonic, and the incident field has a rectangular shape. We vary its frequency and angle of incidence for each case chasing an optimum inspection, as can be seen in Leiderman et al. (2018).

Figure 3 shows the cohesion field estimate for a reduced model composed of 50 equally distributed points, i.e., the initial scattered field, composed by 1000 points in space, is now reduced by a factor of 20. Furthermore, we consider defects at the interface between the stainless steel and copper layers, in the $z$-direction.

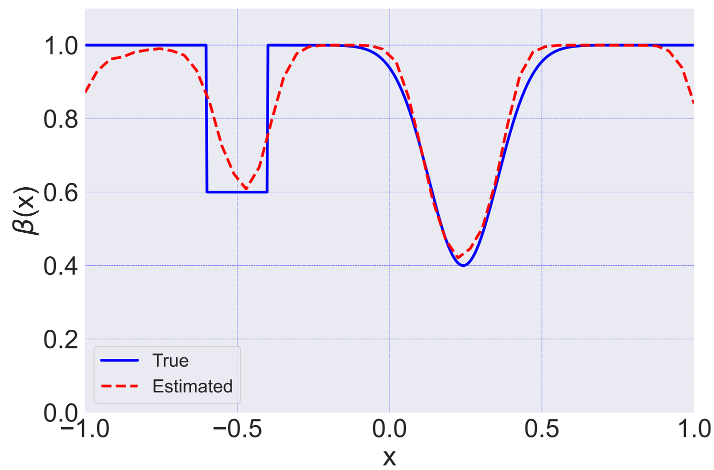


**Figure 3 – Cohesion field recovery for a reduced model with 50 points equally distributed in space. The blue and the dashed red lines represent the true cohesion field and the estimated cohesion field, respectively.**

## CONCLUSIONS

The idea of a deep learning inverse analysis came from the fact that, traditionally, inverse scattering problems with objective-function approach have a very high computational cost, since the direct problem is already an interactive process, i.e., it is costly. Take the work of Leiderman and Castello (2016), as an example, where they adopt a specific parametrization to describe the damage, reducing the computational cost, but not enough to predict defects in a suitable time. In contrast, even though the process of training the deep network demands a considerable time (in the course of a month), once trained the approach has the potential to predict a whole damage field, without the need for parameterization, in real-time.

## REFERENCES

The list of references must be introduced as a new section, located at the end of the paper. The first line of each reference must be aligned at left. All the other lines must be hanging by 1cm from the left margin. All references included in the reference list must have been mentioned in the text. References must be listed in alphabetical order, according to the last name of the first author as in the following examples:

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