Performance comparison of different Artificial Neural Networks for void detection in adhesive joints

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Advanced Joining Processes Unit

Introduction

Adhesive joining is being adopted in sectors such as the automotive or the aerospace industries, to achieve weight reduction and energy efficiency, while guaranteeing that mechanical performance is not compromised [1]. Non-Destructive Tests (NDT) would normally achieve this, but, current testing tools, which are time-consuming and expensive, are not reliable in detecting all damage sources. Structural Health Monitoring (SHM) aims at overcoming these issues by continuously monitoring a structure and to detect, locate and characterize damage.
One such SHM method is the Electromechanical Impedance Spectroscopy (EMIS), where piezoelectric (PZT) elements, acting simultaneously as actuators and sensors, are used due to their coupled electromechanical behaviour. As such, electric impedance readings will depend on both the properties of the adhesive joint and on its integrity. Algorithms can process the electric impedance spectra to detect damage in a structure [2].
Here, numerical simulations based on the Finite Elements (FE) model [3] were done, and the obtained impedance results were processed by two machine learning algorithms: k-Nearest Neighbors (kNN) and Artificial Neural Networks (ANN).

Numerical Models & Simulation Results

Based on the model of Zhuang et al. [3], a direct-steady state linear dynamic analysis was performed over a frequency range between 50 kHz and 2 MHz. A Single Lap Joint (SLJ) with aluminium adherends and a modified-epoxy adhesive were modelled. The piezoelectric sensor is placed on top of an adherend, in the middle of the overlap region.
For each model, a circular void was placed in one of nine positions, with the following diameters

$$\varnothing_V \in \{2, 3, 4, 5, 6, 7, 8\}\ [\mathrm{mm}]$$

SLJ's without voids were also modeled and simulated.

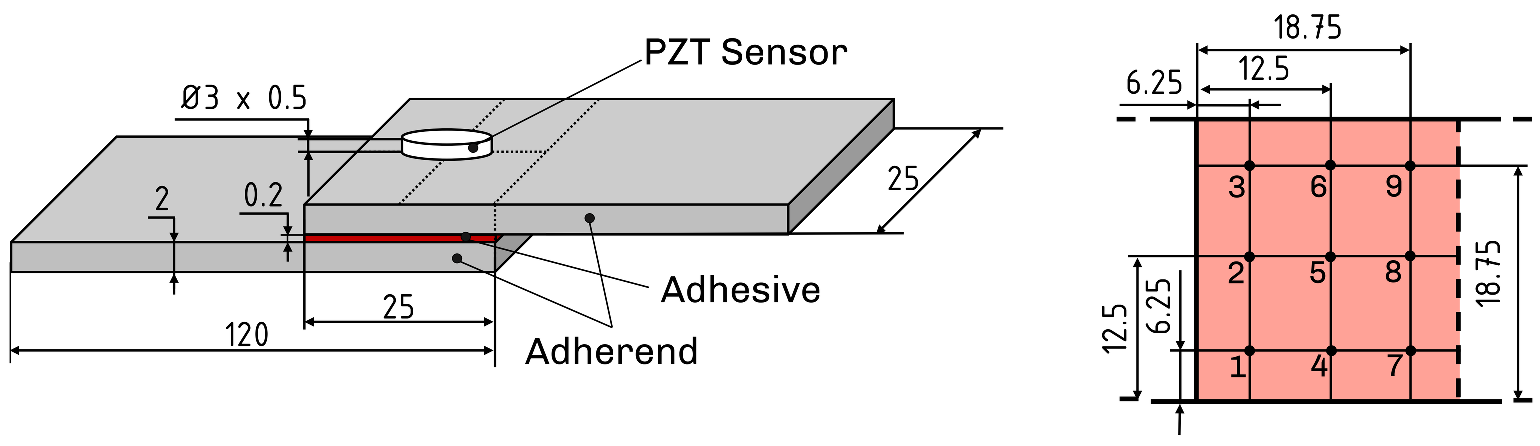

Figure 1 – Numeric FE model: *(a)* Geometric dimensions; *(b)* Position of voids in the overlap region.

A 1 V voltage excitation is created with electric potentials of $E_t = 1{+}0j$ V $E_b = 0{+}0j$ V at the top and bottom surfaces of the PZT sensor.
After running the simulations, the Reactive Electrical Nodal Charges (RCHG) were extracted from all nodes of the top surface and were summed, yielding the generated electric charge, $Q(\omega)$. The electrical impedance, $Z(\omega)$, is obtained through

$$Z(\omega) = \frac{V(\omega)}{I(\omega)} = \frac{E_t - E_b}{j\,\omega\,Q(\omega)}$$

where $V(\omega)$ is the source voltage and $I(\omega)$ is the generated electrical current. To increase the number of cases, electric noise was added.

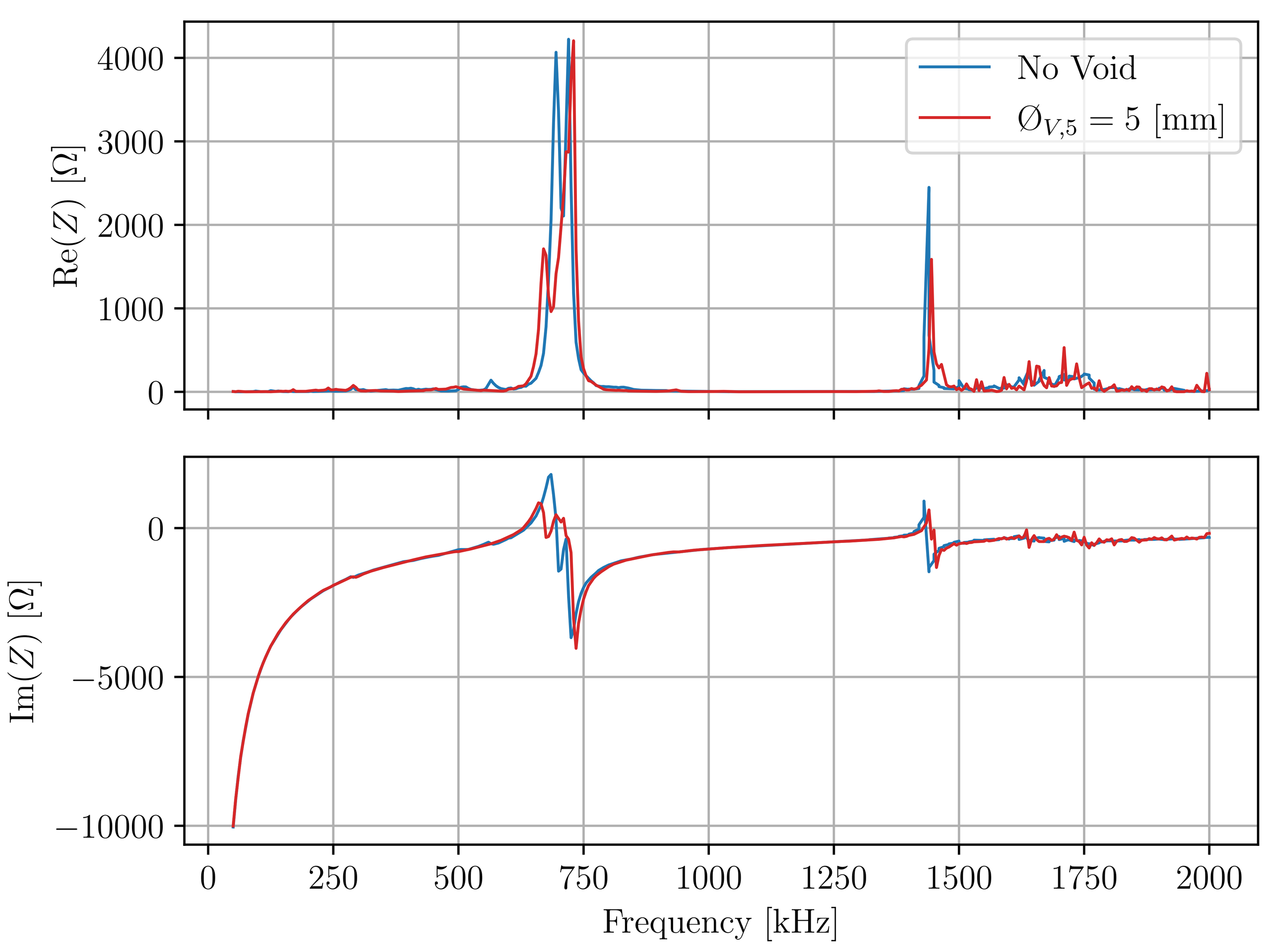

Figure 2 – Impedance spectra for a pristine and a damaged SLJ.

Damage Detection

From the calculated impedance spectra, the three biggest peaks of the real part of the electric impedance, $\mathrm{Re}(Z)_i$ and their respective frequencies, f_i, were extracted, as follows

$$\bar{\mathbf{F}} = [f_1, \mathrm{Re}(Z)_1, f_2, \mathrm{Re}(Z)_2, f_3, \mathrm{Re}(Z)_3]$$

where $i = \{1, 2, 3\}$ is the index identifying the extracted peak. This constitutes the Feature vector, $\bar{\mathbf{F}}$, which is the input to both the kNN and ANN algorithms. In both cases, the output, which is also given as as a reference value in the training phase, corresponds to the instance class (or target), y, such as

$$y = \begin{cases} 0, \text{ if there is no void} \\ 1, \text{ if there is void} \end{cases}$$

1. k-Nearest Neighbors (kNN)

In the kNN algorithm, each new instance is compared with the k nearest data instances.

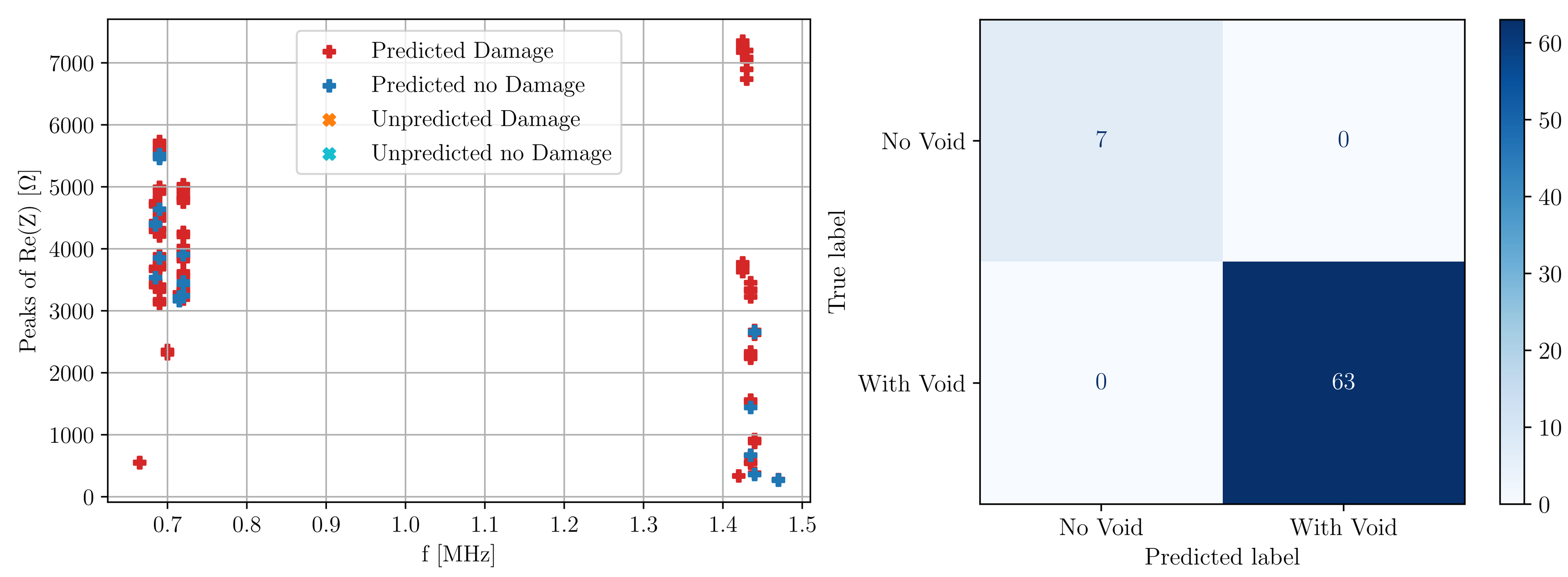

Figure 3 – kNN results from test set, where k = 5: *(a)* Scatter plot with peaks; *(b)* Confusion Matrix.

2. Artificial Neural Network (ANN)

In ANN, a training set is used to define the best internal parameters, the validation set determines when to continue or stop the ANN training, and the testing set validates the ANN.

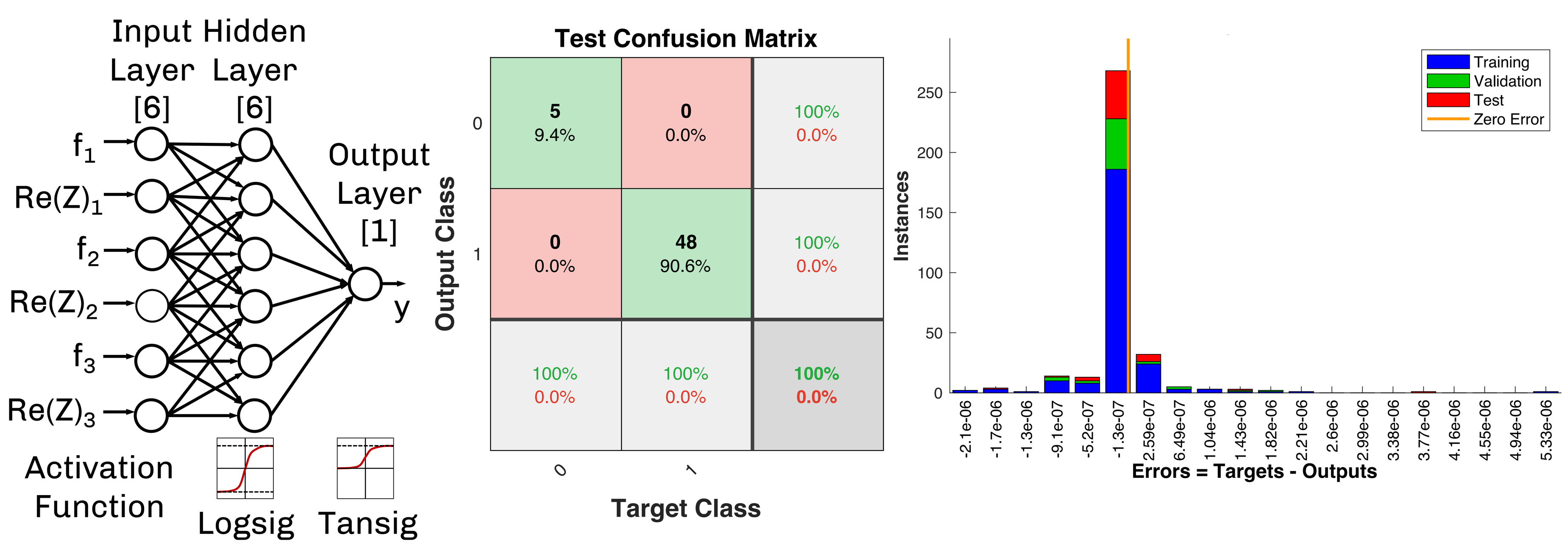

Figure 4 – ANN results: *(a)* ANN structure; *(b)* Test set Confusion Matrix; *(c)* Error Histogram.

References

[1] da Silva, L.F.M, Öchsner, A. and Adams, R.D. Handbook of adhesion technology. 2nd edition. New York: Springer, 2018.
[2] Tenreiro, A.F.G., Lopes, A.M., and da Silva, L.F., "A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy," Structural Health Monitoring, p. 147592172199341, 2021.
[3] Zhuang, Y., Kopsaftopoulos, F., Dugnani, R., and Chang, F.-K., "Integrity monitoring of adhesively bonded joints via an electromechanical impedance-based approach," Structural Health Monitoring, 17(5), pp. 1031–1045, 2018.

Conclusions

Based on the simulations that replicate impedance readings of PZT instrumented SLJ, one can see that the real part of the electric impedance, Re(Z), is sensitive to voids in the adhesive layer. Both ANN and kNN can detect voids from the processed peak information.

Acknowledgements

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