

Health monitoring of bonded joints using Electromechanical Impedance Spectroscopy (EMIS)

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Thesis submitted for the degree of Doctor of Philosophy

Doctoral Program in Mechanical Engineering (PRODEM)

Faculdade de Engenharia da Universidade do Porto

Porto, July 2024

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“Study hard what interests you the most in the most undisciplined, irreverent and original manner possible.”

Richard Feynmann

“There’s no point in claiming a system’s job is to do something it consistently fails to do. It functions how it functions. It gives the output it gives.”

Abigail Thorn

“And I say to myself: What a fractional world!”

José António Tenreiro Machado

Abstract

Adhesive bonding of structural components is being progressively adopted in applications, such as aircraft and automobiles, reducing weight and carbon emissions, while guaranteeing mechanical performance. In this manner, one must guarantee the integrity of structural adhesives and consider the appearance of damage foci, either during the manufacturing stage, or the operation of said structure. As per industrial standards and international legislation, a necessary step in integrity evaluation is to perform periodic Non-Destructive Tests (NDT) throughout the useful life. However, these tests are costly, time-consuming and do not guarantee complete adhesive damage detectability. Structural Health Monitoring (SHM) has emerged as an alternative, where sensors continuously monitor a structure by performing physical measurements. A central processing unit stores the measurements and feeds them to algorithms, which will try to tackle damage detection, characterization and estimation of severity to the structure. One such SHM method is the Electromechanical Impedance Spectroscopy (EMIS), which makes use of the coupled electromechanical coupled behaviour of Piezoelectric Wafer Active Sensors (PWAS). Therefore, by measuring the PWAS impedance spectra over a range of frequencies, one is measuring the integrity of the interrogated structure.

Given the potential of SHM in sectors such as the automobile or aeronautic industry, the following work studied the performance of EMIS on Single Lap Joint (SLJ) specimens, where 6000 series aluminium alloy adherends, used in vehicular structures, are connected thanks to a crash-resistant modified epoxy adhesive. This adhesive is specifically formulated for aeronautic applications. Furthermore, preliminary work was also done with SLJ specimens with a silicone adhesive and a Pressure Sensitive Adhesive (PSA). These joints were instrumented with PWAS, and their electrical impedance was measured between 1 kHz and 1 MHz.

Quasi-static tensile tests and Vibrating Cantilever Beam Tests (VCBT) were performed to determine the elastic and dynamic behaviour of both modified epoxy and silicone adhesives. These tests allowed one to estimate average elastic and

damping properties over the wide range of frequencies, which were relevant input on direct-steady state linear perturbation analysis numerical models that can replicate the electrical impedance measurements obtained experimentally. Furthermore, for the case of undamaged adhesive joints, the mechanical impedance was computed with stress and particle velocity results from these simulations. In this manner, the mechanical impedance of the SLJ and electrical impedance of the sensor were correlated.

With this, conventional damage metrics and newly proposed damage metrics were used to ascertain, in a numerically quantifiable manner, damage detectability from the obtained impedance spectra of instrumented modified epoxy SLJ specimens. While conventional damage metrics make use of the real component of the measured impedance, most of the proposed metrics use the active electrical impedance, which is the part of the measured impedance that is sensitive to damage, and enables the use of both real and imaginary components. Likewise, two Machine Learning (ML) approaches were followed. Firstly, Multidimensional Scalling (MDS) ML model performed a dimensionality reduction of the real component of the measured impedance, obtaining a three-dimensional *map*. A second approach made use of the k -Nearest Neighbours (k NN) ML model for classification.

Experimental and numerical results revealed that adhesive elastic and damping dynamic properties contribute to the obtained electrical impedance measurements. Furthermore, artificially created voids influence the measured impedance spectra, given the complex correlation with the mechanical impedance of the adhesive joints. However, no clear trend is observed regarding the void placement and void size, while numerical results show that the adhesive, bonding the PWAS to the SLJ, may also affect the obtained spectra.

The damage metrics results reveal that damage detection is possible, and that the active electrical impedance, which is sensitive to structural parameters, further improves damage detectability. Conversely, the MDS reduced dimensionality *maps* enable not only damage detection, but also damage differentiation between large voids, small voids in the middle of the overlap, and small voids in the corner of the overlap. The k NN approach, used with a defined number of extracted resistive peaks from the measurements, also enable good damage detection and classification.

Keywords: Adhesives; adhesive joints; Structural Health Monitoring; Electromechanical Impedance Spectroscopy; electrical impedance; damage; damage detection; damage quantification.

Resumo

A ligação de componentes estruturais por adesivos está a ser progressivamente adotada em aplicações como aviões e automóveis, reduzindo o peso e as emissões de carbono, mas garantindo o desempenho mecânico. Desta forma, é necessário garantir a integridade dos adesivos estruturais e considerar o aparecimento de focos de danos, quer durante a fase de fabrico, quer durante o funcionamento da estrutura. De acordo com as normas industriais e a legislação internacional, um passo necessário na avaliação da integridade é a realização periódica de Testes Não Destrutivos (NDT) ao longo da vida útil. No entanto, estes testes são dispendiosos, demorados e não garantem a deteção completa de danos em adesivos. A Monitorização da Integridade Estrutural (SHM) surgiu como uma alternativa, em que sensores monitorizam continuamente uma estrutura através da realização de medições físicas. Uma unidade de processamento central armazena as medições e transmite-as a algoritmos, que tentarão abordar a deteção de danos, a caracterização e a estimativa da gravidade da estrutura. Um desses métodos SHM é a Espectroscopia de Impedância Eletromecânica (EMIS), que utiliza o comportamento eletromecânico acoplado dos sensores ativos de pastilha piezoelétrica (PWAS). Logo, ao medir espectros de impedância de PWAS numa gama de frequências, está-se a medir a integridade da estrutura interrogada.

Tendo em conta as potencialidades da SHM em sectores como a indústria automóvel ou aeronáutica, o seguinte trabalho estudou o desempenho do EMIS em provetes de Junta de sobreposição Simples (SLJ), onde aderentes de liga de alumínio da série 6000, utilizados em estruturas veiculares, são ligados graças a um adesivo epóxi modificado, resistente ao choque. Este adesivo foi especificamente formulado para aplicações aeronáuticas. Além disso, foram também realizados trabalhos preliminares com provetes SLJ com um adesivo de silicone e um adesivo sensível à pressão (PSA). Estas juntas foram instrumentadas com PWAS, e a sua impedância eléctrica foi medida entre 1 kHz e 1 MHz.

Foram efetuados testes de tração quase-estáticos e Testes de Vibração de Viga Encastrada (VCBT) para determinar o comportamento elástico e dinâmico do adesivo epóxi modificado e do adesivo silicone. Estes testes permitiram estimar as propriedades elásticas e de amortecimento médias ao longo de uma vasta gama de frequências, que contribuíram para modelos numéricos de análise de perturbações lineares em estado estacionário-direto, que reproduzem as medições de impedância elétrica obtidas experimentalmente. Além disso, para o caso de juntas adesivas não danificadas, a impedância mecânica foi calculada com os resultados de tensão e da velocidade das partículas obtidos nestas simulações. Desta forma, a impedância mecânica de SLJs e a impedância elétrica do sensor foram correlacionadas.

Com isto, métricas de dano convencionais e recentemente propostas foram utilizadas para determinar, de uma forma numericamente quantificável, a detetabilidade de danos a partir dos espectros de impedância obtidos de provetes instrumentados SLJ de epóxi modificado. Enquanto as métricas de danos convencionais utilizam o componente real da impedância medida, a maioria das métricas propostas utiliza a impedância elétrica ativa, que é a parte da impedância medida sensível ao dano, e permite a utilização de componentes reais e imaginários. De igual modo, foram seguidas duas abordagens de aprendizagem automática (ML). Em primeiro lugar, o modelo de ML, Escalonamento Multidimensional (MDS), efetuou uma redução da dimensionalidade da componente real da impedância medida, obtendo um *mapa* tridimensional. Uma segunda abordagem utilizou o modelo de ML, *k*-Vizinhos Mais Próximos (*k*NN), para a classificação.

Os resultados experimentais e numéricos revelaram que as propriedades dinâmicas de elasticidade e amortecimento do adesivo contribuem para as medições de impedância elétrica obtidas. Além disso, os vazios criados artificialmente influenciam os espectros de impedância medidos, dada a complexa correlação com a impedância mecânica das juntas adesivas. No entanto, não se observa uma tendência clara relativamente à posição e ao tamanho dos vazios, enquanto os resultados numéricos mostram que o adesivo, que liga o PWAS à SLJ, também pode afetar os espectros obtidos.

Os resultados das métricas de danos revelam que a deteção de danos é possível e que a impedância elétrica ativa, que é sensível aos parâmetros estruturais, melhora ainda mais a detetabilidade de danos. Por outro lado, os *mapas* de dimensionalidade reduzida, obtidos por MDS, permitem não só a deteção de danos, mas também a diferenciação de danos entre grandes vazios, pequenos vazios no meio da área de sobreposição e pequenos vazios no canto da área de sobreposição. A abor-

dagem por k NN, utilizada com um número definido de picos resistivos extraídos das medições, também permite uma boa detecção e classificação de danos.

Palavras-chave: Adesivos; juntas adesivas; Monitorização da Integridade Estrutural; Espectroscopia de Impedâncias Eletromecânica; impedância elétrica; dano; detecção de dano; quantificação de dano.

Acknowledgments

Firstly, I would like to express my gratitude to my supervisor, Professor António Mendes Lopes, for the academic, technical and personal insights given throughout the project, as well as for the support throughout the various stages of this work. This guidance has helped me flourish in this scientific pursuit and, hopefully, in future pursuits.

I am also very thankful for my co-supervisor, Professor Lucas da Silva, for the feedback given throughout the work, and for giving me the opportunity to work under his supervision and with his research unit, the Advanced Joining Processes Unit.

I also wish to extend my thanks to the Post-Doctoral members of the group, such as Alireza Akhavan-Safar, Ana Queirós, Eduardo Marques (who, in the meantime, became Associate Professor) and Ricardo Carbas, who helped me in this project from the beginning. I am also grateful for the assistance of Nuno Lucas, Vasco Loureiro, Bernardo Moreira and José Cotrim as Master Students, and for our friendly interactions during their work on parallel projects (different from the project of this thesis).

I also would like to thank the help and assistance of Professor Rui Camacho, Professor Manuel Romano Barbosa, Professor Joaquim Gabriel, Professor José Luís Moura Borges and Professor Pedro Leal Ribeiro from Faculty of Engineering of the University of Porto. I would like to extend this acknowledgement to Emília Soares, André Alves, Pedro Alves and José Manuel Fecheira from FEUP, as well as Júlia Meira from INEGI.

A very special thanks should be given to João Amorim, who assisted me in the realization of the VCBT procedure, and also brought very interesting insights during several stages of this project.

This research would also not have been possible without the financial support

Acknowledgments

provided by Fundação para a Ciência e Tecnologia (FCT) through the grant reference number 2021.07689.BD, which is a grant inserted in the Studentships for Doctoral Research program.

A very deep thanks to all members of the Advanced Joining Processes Unit for their constant support and exchange, enabling us to reach our goals and excel in our individual projects. Thank you for the kind friendship, encouragement and spirit of fraternity throughout the time shared together. I am forever grateful.

To all my friends and family for the support given, by lending a hand, by hearing me out when I needed, or by simply hanging out. I special thanks to my mother and my late father, who not only helped me in every step of the way, but also nurtured this fascination for research and helped me have the curious mind that I have today. I could never have done this without you.

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List of Acronyms

AC	Alternating Current
ASTM	American Society for Testing and Materials
BS	British Standard
CFRP	Carbon Fiber Reinforced Polymer
CVM	Comparative Vacuum Monitoring
C3D8R	8-node linear brick and reduced integration elements
DIC	Digital Image Correlation
EIS	Electrical Impedance Spectroscopy
EMIS	Electromechanical Impedance Spectroscopy
EPOT	Electric Potential (nodal variable)
FBG	Fiber Bragg Grating
FEA	Finite Element Analysis
FFT	Fast Fourier Transform
GFRP	Glass Fiber Reinforced Polymers
k NN	k -Nearest Neighbors
MDS	Multidimensional Scaling
ML	Machine Learning
NDT	Non-Destructive Test
NF	Norme Française
PSA	Pressure Sensitive Adhesive
PTFE	Polytetrafluoroethylene
PWAS	Piezoelectric Wafer Active Sensor
RCHG	Reactive Electrical Nodal Charge (nodal variable)
SHM	Structural Health Monitoring
SLJ	Single Lap Joint
S11	Stress component in direction 1
S22	Stress component in direction 2
S33	Stress component in direction 3
VCBT	Vibrating Cantilever Beam Test
V1	Translational velocity in direction 1

List of Acronyms

- V2 Translational velocity in direction 2
- V3 Translational velocity in direction 3

List of Symbols

A	Adimensional parameter (VCBT)
$A_{Pl.}$	Cross section of the methacrilate adhesive
ACD	Average Canberra Distance (damage metric)
B	Adimensional parameter (VCBT)
CC	Correlation Coefficient (damage metric)
cCC	Complex Correlation Coefficient (damage metric)
C_i	Coefficient of fixed-free beam for mode i (VCBT)
$cRMSD$	Complex Root Mean Square Deviation (damage metric)
c_s	Damping of the structure
D	Mass density ratio (VCBT)
D_i	Electrical Displacement in direction i
d_{ij}	Piezoelectric strain coefficient in directions i and j
d_A	Arccosine distance
d_C	Canberra distance
d_E	Euclidean distance
d_M	Manhattan distance
E	Elastic modulus
E_b	Elastic modulus of base beam (VCBT)
E_i	Elastic modulus in direction i
$E_{f,i}$	Electric field component in direction i
e_{ij}	Piezoelectric stress coefficient in directions i and j
F	Force/Mechanical load
f	Ordinary frequency
$f_{b,i}$	Resonance ordinary frequency for mode i of base beam (VCBT)
f_f	Final ordinary frequency
f_i	Initial ordinary frequency
f_i	Resonance ordinary frequency for mode i of specimen (VCBT)
G	Shear modulus
G_{ij}	Shear modulus along direction i , perpendicular to direction j
h_P	Height of the PWAS

List of Symbols

I	Electrical current
j	Unit imaginary number
k_s	Stiffness of the structure
k_p	Coupling factor for the planar radial oscillation
k_t	Coupling factor for the planar thickness oscillation
l_b	Length of beam/specimen (VCBT)
l_P	Length of the PWAS
l_S	Length of substrates
$MAPD$	Mean Absolute Percentage Deviation (damage metric)
$mRMSD$	Modified Root Mean Square Deviation (damage metric)
m_s	Mass of the structure
n	Number of extracted peaks
N	Number of acquired samples
$NCED$	Normalized Complex Euclidean Distance (damage metric)
Q	Electrical Charge
$RMSD$	Root Mean Square Deviation (damage metric)
S	Displacement at the base of the specimen (VCBT)
$\frac{S_{ij}^{E_f}}{S_{ij}^{E_f}}$	Compliance at zero electric field ($E_{f,i} = 0$)
$\frac{S_{ij}^{E_f}}{S_{ij}^{E_f}}$	Complex compliance at zero electric field ($E_{f,i} = 0$)
T	Voltage signal ratio
T_b	Baseline voltage signal ratio
T_c	Curie temperature
TR	Transmissibility
t	Time
t_A	Adhesive layer thickness
t_b	Beam base thickness (VCBT)
U	Displacement at the free end of the specimen (VCBT)
V	Voltage
V_I	Input voltage
V_O	Output voltage
$V_{O,b}$	Baseline output voltage
w_P	Width of the PWAS
$\dot{x}$	Velocity
$\overline{\dot{x}_2}$	Average of V2 (Translational velocity in direction 2)
$\overline{Y_{ii}^{E_f}}$	Complex elastic modulus of PWAS at zero electric field ($E_{f,i} = 0$)
Y_A	Active electrical admittance
Y_P	Passive electrical admittance
Z_e	Electrical impedance
$Z_{e,A}$	Active electrical impedance
$Z_{e,A}^0$	Reference active electrical impedance

Z_e^0	Reference electrical impedance
$Z_{m,P}$	Mechanical Impedance of the PWAS
$Z_{m,s}$	Mechanical impedance of the structure
Δ	Matrix of dissimilarities
Δf_i	Half-power bandwidth of mode i (VCBT)
δ_{ij}	Dissimilarity between instances i and j
δ	Dielectric loss factor
ϵ_{ii}	Permittivity in direction i
ϵ_0	Vacuum permittivity
ϵ_i	Mechanical strain in direction i
ϵ_{ij}^σ	Dielectric constant at zero stress ($\sigma = 0$)
$\overline{\epsilon_{ij}^\sigma}$	Complex dielectric constant at zero stress ($\sigma = 0$)
η	Mechanical loss factor
η_s	Loss factor of sandwich specimen (VCBT)
ν	Poisson's ratio
ν_{ij}	Poisson's ratio along direction i , perpendicular to direction j
ρ	Mass density
ρ_A	Mass density of adhesive (VCBT)
ρ_b	Mass density of base beam (VCBT)
σ_i	Mechanical stress in direction i
$\overline{\sigma_{22}}$	Average of S22 (Stress in direction 2)
σ_r	Raw stress (MDS)
σ_1	Stress-1 (MDS)
τ	Thickness ratio (VCBT)
φ	Signal phase shift
φ_b	Baseline phase shift
$\varnothing_V$	Void diameter
ω	Angular frequency

List of Publications

In the scope of this thesis

- **Tenreiro, A. F. G.**, Lopes, A. M. & da Silva, L. F. M. (2022), A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy. *Structural Health Monitoring*, 21(2), 228-249. DOI: 10.1177/1475921721993419.
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- **Tenreiro, A. F. G.**, Lopes, A. M. & da Silva, L. F. M. (2024), Pattern recognition in electromechanical impedance spectroscopy damage detection of adhesive joints using multidimensional scaling. *Structural Health Monitoring*, Submitted.
- **Tenreiro, A. F. G.**, Lopes, A. M. & da Silva, L. F. M. (2024), Frequency-based k -Nearest Neighbors algorithm for electromechanical impedance based detection of damage in adhesive joints. *Applied Soft Computing*, Submitted.

Publications regarding research on structural health monitoring of adhesive joints

- Loreiro, V., Ramalho, G., **Tenreiro, A. F. G.**, Lopes, A. M. & da Silva, L. (2022), Feature extraction and visualization for damage detection on adhesive joints, utilizing lamb waves and supervised machine learning algorithms. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 236(16), 8842-8855, DOI: 10.1177/09544062221086410.
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Chapter 1

Introduction

In this chapter, the subject of this dissertation is introduced. As such, this chapter contains a brief background, the motivation, the research goals and the dissertation organization.

1.1 Background and Motivation

Adhesive joining has become a viable alternative to other joining methods, and has been gradually replacing more conventional joints in industrial applications, such as rivets, welds or bolts and screws. Welding usually involves the addition of mass, and residual stresses might appear due to the thermal process involved. Conversely, bolting and riveting imply that holes must be created in the joined components, creating stress concentration geometries. In essence, traditional joining methods may induce the premature failure of the structure at hand [1, 2].

This is highly worrying for structural design engineers, whose job is to design structures that can withstand variable loading throughout a long period of time, and whose failure may imply significant monetary costs and the loss of life. One tragic example is the Aloha Airlines Flight 243 that occurred during April 28, 1988, between Hilo and Honolulu in Hawaii. During this flight, the Boeing 737-297 suffered extensive damage with the occurrence of an explosive decompression (sudden decrease of cabin pressure leading to an explosion), which was caused by poor maintenance of metal fuselage and fatigue cracking of the skin, adjacent to rivet holes [3].

Adhesive bonding has shown itself as an interesting alternative joining method, promoting a more uniform stress distribution without stress concentration geometries, higher load transmission, and also enables more freedom of design by allow-

ing the joining of dissimilar materials [1]. Adhesive joint characterization usually involves destructive tests namely tensile tests, shear tests, and others, using specimens such as torsion butt joint, Single Lap Joint (SLJ) or double cantilever beam specimens, just to name a few. With experimental procedures such as these ones, one aims to obtain elastic, plastic and fracture properties of adhesives and of adhesive joints.

This information is usually useful for the design of components and structures [4]. However, if one's aim is to determine the actual strength of a manufactured industrial structure, one cannot perform destructive tests, given that this would imply the destruction of the structure. Given this, Non-Destructive Tests (NDT) are widely used in industrial applications for the inspection of said structures. Despite this, NDT inspection tools do not determine the strength of the adhesive in a given joint. The evaluation of a given joint is done by examining properties, such as mass distribution and stiffness, in a non-destructive manner [5, 6].

This methodology is widely used in many industries for damage detection, either after the manufacture process, or during periodic maintenance procedures. Despite this, defect detection in structural adhesive joints is particularly hard with current NDT technologies, since certain limitations on adhesive defect detection exist, requiring expensive and complex experimental setups [7, 8, 9]. Furthermore, for certain adhesively bonded structures, such as airplanes, regular NDT inspection is mandatory according to international law and company standards, yet they are a time-consuming procedure, inflicting significant financial loss to operational entities, such as airlines [10].

Structural Health Monitoring (SHM) has emerged as an alternative that goes beyond NDT, by performing *in-situ* continuous monitoring of the structural integrity. In this alternative methodology, sensors directly or indirectly measure the mechanical properties of the evaluated component, and the obtained measurements are sent to a computer, where specialized algorithms will try to tackle damage detection and determine information on the detected source of damage [10, 11].

One such SHM is the Electromechanical Impedance Spectroscopy (EMIS), where Piezoelectric Wafer Active Sensor (PWAS) are used simultaneously as actuators and sensors, given their electromechanical coupled behavior. In this monitoring technique, an Alternating Current (AC) voltage signal of low amplitude excites the PWAS, which converts the electric signal into a mechanical vibration. Simultaneously, the coupled electromechanical behavior enables the PWAS to convert the mechanical response of the structure into an electric signal. This signal

is read by an impedance analyzer, which calculates the electric impedance of the PWAS, $Z_e(j\omega)$, in a given range of frequencies, ω . Note also that j is the unit imaginary number, $j = \sqrt{-1}$. In this manner, the measured electrical impedance spectra is influenced by the material properties of structure and, consequently, by the presence of damage [12].

This technology has proven itself capable of performing damage detection and characterization on composite materials [13], aluminium plates [14, 15], or on more complex structures such as bridge components [16], aircraft components [17] and subway infrastructure [18], to name a few. However, integrity monitoring in structural adhesive joints with EMIS is still in its early stages. This work aims to explore the potential of EMIS in adhesive damage detection.

1.2 Problem Definition

Various industries are increasingly adopting structural adhesive bonding for the joining of structural components. However, the unreliability of NDT in examining structural adhesives for damage sources, which may occur either in the production phase, or during the structure's useful life, has hindered the reliability of structural adhesive bonding in the design of structures.

For instance, Federal Aviation Regulation Part 23, Section 23.573(5), entitled *Damage tolerance and fatigue evaluation for any bonded joint*, states that a structural adhesive joint, whose failure will incur in the loss of the airframe, must have guarantees that said joint can withstand a limit load by either:

- Determining the maximum allowable disbond area and preventing the creation of larger disbond areas through design features;
- Proof testing every produced bonded joint;
- Using repeatable and reliable NDT methods to ensure that strength is maintained [19, 20].

Given that NDT is not a repeatable, nor is it a reliable method, for damage detection in adhesive joints, and given that proof testing all joints is economically unfeasible, design of structural components in airplanes also involves the use of other joining methods to guarantee safety requirements [19, 21].

Furthermore, NDT inspections can only be performed during maintenance procedures, where a given structure is not being operated. This means that, while the inspected vehicle is immobile, the company operating it is forcibly incurring a financial loss [10].

In this manner, SHM methods may be an alternative to monitoring structural adhesive joints of primary structures, where defects may hinder the mechanical performance of the whole structure. One such method is the EMIS method, which, as previously stated, has proven itself capable of detecting damage in various materials.

Given the lack of consistent research on the applicability of EMIS on bonded joints, this work aims to research not only the applicability of EMIS-based monitoring of adhesive joints, but also the influence of various parameters on the obtained electrical impedance measurements. Consequently, obtained results may give information to both design engineers and maintenance technicians on the influence of these parameters, and consequently, on the presence of damage.

Furthermore, this dissertation aims to provide more trustworthiness to EMIS, as a repeatable and reliable method, to inspect structures for damage, without requiring a high frequency of maintenance inspections during the useful life of the structure.

1.3 Objectives

The main objective of this dissertation is to perform an in-depth evaluation of EMIS as an integrity monitoring evaluation method for damage detection of structural adhesive joints, where the adhesive is widely used as a structural joining component in vehicular structures. Given that various types of damage may exist in the adhesive layer, adhesive voids are artificially created as the damage source for this work.

This main objective could be divided into two different intermediate objectives. The first objective is the study of various parameters that may influence the obtained electrical impedance measurements. This can be further divided into two sub-objectives, which are:

- To determine the influence of design parameters, such as the geometry of the adhesive joint, or the material properties of the adhesive;
- To evaluate the influence of geometrical properties of the artificial void (i.e., void size and void position in the overlap) on the obtained measurements.

The second intermediate objective is to develop algorithmic and quantitative methods to detect, locate and characterize the artificial void being detected in the adhesive layer. In light of this, this goal can be divided into two other sub-objectives, which are:

- To evaluate the capability of conventional and new damage metrics on the detection of artificial voids in structural adhesive joints, and;
- To develop algorithms that may yield information, not only on the detection of damage, but also on its location and size.

1.4 Research Structure

In this work, various adhesives were used, namely a silicone adhesive, a Pressure Sensitive Adhesive (PSA), and a modified epoxy adhesive, which enabled the joining of aluminium substrates. However, this last adhesive was used as the main adhesive material for this research, given that it was specifically formulated for the aeronautic industry. With these materials, SLJ specimens were manufactured and instrumented with PWAS. The impedance measurements were then used as input to various algorithms for damage detection and characterization. Figure 1.1 presents a schematic structure of the research developed in this project, which is formulated herein.

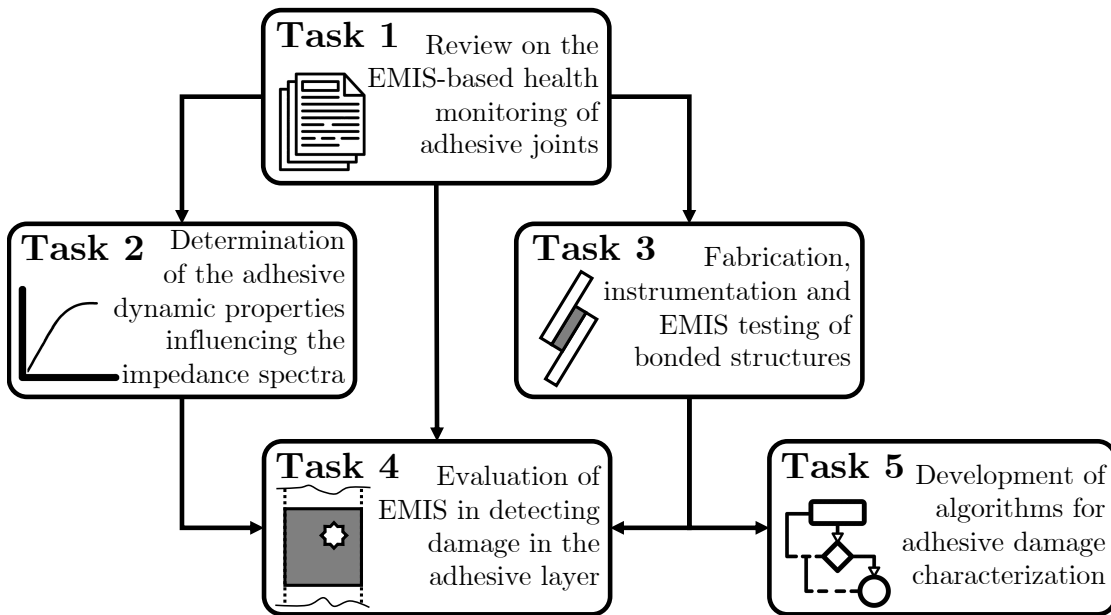


Figure 1.1: Schematic representation of the task workflow performed in this work.

Task 1: Review of the EMIS-based health monitoring of adhesive joints

This task consisted of a review of the EMIS integrity monitoring technique on structures, with special emphasis on adhesive joints. Furthermore, bottlenecks and research opportunities on this field were identified. A study of several damage detection, localization and characterization algorithms was done. This review

also covered both numerical and experimental approaches to determine the EMIS behaviour of adhesive joints.

Task 2: Determination of the adhesive dynamic properties influencing the impedance spectra

The aim of this task was to determine the dynamic properties of adhesive materials that may influence the electrical impedance measurements. In this manner, two adhesives were initially characterized: a silicone adhesive, also employed as a sealant, and a crash-resistant modified epoxy adhesive formulated for bonding of aircraft structural components. In this manner, this task was divided into two different sub-tasks:

- **Task 2.1:** Determining the damping and elastic properties of the adhesives adopted in this work. With this, both properties could be quantifiable. Furthermore, the elastic properties in dynamic conditions were compared with those under quasi-static conditions.
- **Task 2.2:** Numerically modeling instrumented SLJs, to replicate EMIS results in damage-free and damaged bonded joints. In this manner, the obtained elastic and damping properties could be inputted to numerical models, and the obtained simulation results were then compared with the experimentally obtained electrical impedance measurements.

The results from this task work in tandem with Task 4, in better understanding possible influences damage may have on the material properties of the adhesives used here.

Task 3: Fabrication, instrumentation and EMIS testing of bonded structures

In this task, both pristine adhesive SLJs and adhesive SLJs with artificial voids were manufactured, instrumented with PWAS and tested with an impedance analyzer, obtaining several electrical impedance spectra, $Z_e(j\omega)$. The manufacture of damage-free joints followed the best practices. For the cases of damaged SLJs, in order to include voids as adhesive damage, an infill material had to be placed and fixed in the overlap region. Subsequently, the specimens were instrumented with PWAS, and were tested to generate an impedance dataset. This task complements Tasks 4 and 5 by generating impedance data to evaluate the capability of EMIS in damage detection, and to develop algorithms that are capable of both damage detection and characterization.

Task 4: Evaluation of EMIS in detecting damage in the adhesive layer

This fourth task tackles damage detection, which corresponds to the first level a given SHM system must guarantee (as will be explained in section 2.2). In this manner, this assignment aims to use the experimentally obtained impedance spectra from Task 3, as well as knowledge obtained in Task 2, to understand the differences between measurements from pristine and damaged joints. Furthermore, damage metrics, such as the ones found in the literature review of Task 1, are used in EMIS-based damage detection. These damage metrics are mathematical metrics to evaluate the presence of damage, and are calculated by comparing the impedance spectra from a reference pristine adhesive joint, and a joint being inspected for the presence of damage. The results obtained here are compared with the results obtained from the various algorithmic approaches in Task 5.

Task 5: Algorithm development for adhesive damage characterization

This final task made use of the experimental measurements from Task 3, which were used as a database of measurements for algorithm development. A plethora of approaches, that perform an hierarchical approach to determine damage information, are possible. In this manner, two different approaches were followed in this task:

- A first approach made use of unsupervised Machine Learning (ML) models, which received the impedance measurements as inputs, and established patterns from the inputted spectra.
- A second approach used a supervised ML algorithm, more specifically a classification model. In this manner, a proper feature selection procedure was made, guaranteeing accurate classification results.

The results obtained are compared with the damage metrics results from Task 4, when tackling damage detection. However, the results obtained from this task demonstrate that more information can be extracted, namely void location and void size.

1.5 Outline of the Dissertation

This dissertation contains six peer reviewed papers and a summary that contextualizes the research performed. The scientific papers, published in the scope of this research project and tasks presented in section 1.4 and Figure 1.1, are related to each other, as indicated in Figure 1.2.

The summary is divided in six main chapters, the first of which is this intro-

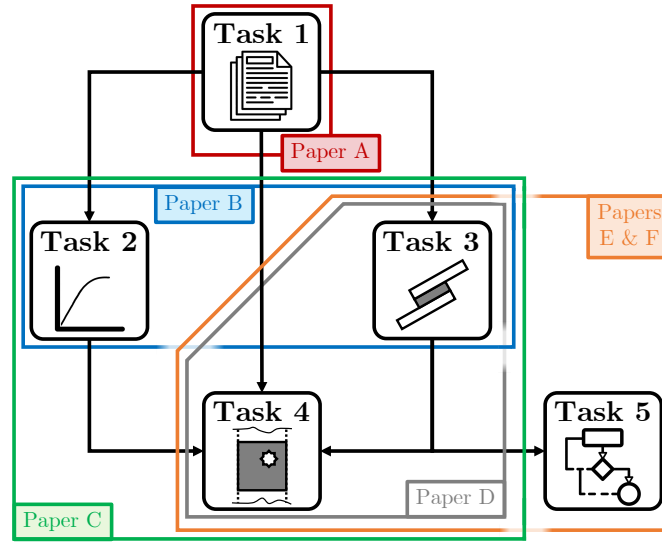


Figure 1.2: Correspondence between the proposed tasks and the scientific papers associated with the research tasks.

ductory chapter that contains a background and motivation, a problem definition, the objectives of this doctoral dissertation and the structure of the research. Additionally, a summary of the scientific papers is presented. Chapter 2 presents a literature review on the performance of NDT of adhesive joints, some advancements and limitations. This chapter also makes an introduction to both SHM and EMIS. Chapter 3 describes the experimental procedures to obtain the experimental spectra, and to measure the elastic and damping properties of the adhesives used, while chapter 4 reports on the numerical Finite Elements Analysis (FEA) models created to replicate the experimentally obtained impedance spectra. Afterwards, chapter 5 presents the algorithmic and computational approaches formulated in this work. These are the damage indices, the Multidimensional Scaling (MDS) and k -Nearest Neighbors (k NN) models, which are, respectively, the unsupervised and supervised models used in this work. Chapter 6 finalizes this work with conclusions regarding the findings, as well as future work in this research topic. Finally, the appendices contain the scientific articles written in the scope of this doctoral research, representing, in detail, the developed research.

Resultant Scientific Papers As previously stated, the appendices contain the scientific publications that represent the research developed in the scope of this doctoral research. In this subsection, these papers are introduced.

Paper A – A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy

Tenreiro, A. F. G., Lopes, A. M. & da Silva, L. F. M. (2022), A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy. *Structural Health Monitoring*, 21(2), 228-249. DOI: 10.1177/1475921721993419. IF: 6.6; Q1; ISI, Indexed in Scopus.

Abstract: The article presents a literature review of electromechanical impedance spectroscopy for structural health monitoring, with emphasis in adhesively bonded joints. The concept behind electromechanical impedance spectroscopy is to use variable high-frequency structural vibrations with piezoelectric elements to monitor the local area of a structure for changes in mechanical impedance that may indicate imminent damage. Various mathematical models that correlate the structural impedance with the electric response of the piezoelectric sensors are presented. Several algorithms and metrics are introduced to detect, localize, and characterize damage when using electromechanical impedance spectroscopy. Applications of electromechanical impedance spectroscopy to study adhesive joints are described. Research and development of alternative hardware for electromechanical impedance spectroscopy is presented. The article ends by presenting future prospects and research of electromechanical impedance spectroscopy-based structural health monitoring, and, while advances have been made in algorithms for damage detection, localization, and characterization, this technology is not mature enough for real-world applications.

Paper B – Effect of mechanical properties and geometric dimensions on electromechanical impedance signatures for adhesive joint integrity monitoring

Tenreiro, A. F. G., Lopes, A. M., da Silva, L. F. M. & Amorim, J. D. P. (2023), Effect of mechanical properties and geometric dimensions on electromechanical impedance signatures for adhesive joint integrity monitoring. *Mechanics of Advanced Materials and Structures*, 30(7), 1437–1452. DOI: 10.1080/15376494.2022.2033891. IF: 2.8; Q2; ISI, Indexed in Scopus.

Abstract: Adhesive joints are prone to damage, which may be difficult to detect using Nondestructive Test. Structural Health Monitoring techniques, such as the Electromechanical Impedance Spectroscopy (EMIS), allow for continuous monitoring and early detection of structural defects. Developing efficient damage detection algorithms requires simulations of adhesive structures, which require elastic and damping properties under high frequency range. Tests were performed

for crash-resistant and silicone adhesives. Numerical simulations with said properties were compared with experimental impedance measurements from Single Lap Joints (SLJ). This allowed for the estimation of adhesive properties, but numerical results for SLJs with silicone adhesive diverged from experimental results.

Paper C – Influence of void damage on the electromechanical impedance spectra of Single Lap Joints

Tenreiro, A. F. G., Lopes, A. M., da Silva, L. F. M. & Carbas, R. J. C. (2023), Influence of void damage on the electromechanical impedance spectra of Single Lap Joints. *NDT & E International*, 138, 102865. DOI: 10.1016/j.ndteint.2023.102865. IF: 4.2; Q1; ISI, Indexed in Scopus.

Abstract: Adhesively bonded joints are susceptible to a variety of damage sources, which may be of difficult detection with current Non-Destructive Testing (NDT) methods. Structural Health Monitoring (SHM) techniques, such as the Electromechanical Impedance Spectroscopy (EMIS), aims to outpace NDT by continuously monitoring structures for defects. However, given the complexity of adhesive joint structures, EMIS capability for damage detection still needs to be thoroughly studied. In this manner, electrical impedance measurements were done to Single Lap Joints (SLJ), with both a modified epoxy adhesive and Pressure Sensitive Adhesive (PSA) for void detection. Void defects could not be detected on adhesive joints with the PSA but, in the case of joints with the modified epoxy adhesive, impedance signatures were significantly altered by the presence of both the artificially created void, and by a second damage source caused during the SLJ manufacture. Experimental measurements from modified epoxy joints were compared with simulation results, yielding good approximation when considering the effect of the second source of damage. An approximation of the mechanical impedance was also computed using numerical results from the pristine SLJ model. In this manner, it is possible to detect damage in the adhesive layer of SLJs with electrical impedance measurements from EMIS.

Paper D – Damage Metrics for Void Detection in Adhesive Single-Lap Joints

Tenreiro, A. F. G., Lopes, A. M. & da Silva, L. F. M. (2023), Damage Metrics for Void Detection in Adhesive Single-Lap Joints. *Mathematics*, 11, 4127. DOI: 10.3390/math11194127. IF: 2.4; Q1; ISI, Indexed in Scopus.

Abstract: Structural Health Monitoring (SHM) techniques, such as Electromechanical Impedance Spectroscopy (EMIS), aim to continuously monitor structures for defects, thus avoiding the need for regular maintenance. While attention has

been given to the application of EMIS in the automatic detection of damage in metallic and composite components, integrity monitoring of structural adhesive joints has been comparatively neglected. This paper investigated the use of damage metrics with electrical impedance measurements to detect defects in Single-Lap Joints (SLJs) bonded with a modified epoxy adhesive. Traditional metrics using statistical and distance-based concepts, such as the Root-Mean Squared Deviation, $RMSD$, or the Correlation Coefficient, CC , are addressed at detecting voids in the adhesive layer and are applied to five different spectral frequency ranges. Furthermore, new damage metrics have been developed, such as the Average Canberra Distance, ACD , which enables a reduction of possible outliers in damage detection, or the complex Root-Mean Squared Deviation, $cRMSD$, which allows for the use of both the real and imaginary components of the impedance, enabling better damage detection in structural adhesive joints. Overall, damage detection is achieved, and for certain spectral conditions, differentiation between certain damage sizes, using specific metrics, such as the $RMSD$ or $cRMSD$, may be possible. Overall, the $RMSD$ or $cRMSD$ values from damaged SLJs tend to be double the metric values from undamaged joints.

Paper E – Pattern recognition in electromechanical impedance spectroscopy damage detection of adhesive joints using multidimensional scaling

Tenreiro, A. F. G., Lopes, A. M. & da Silva, L. F. M. (2024), Pattern recognition in electromechanical impedance spectroscopy damage detection of adhesive joints using multidimensional scaling. *Structural Health Monitoring, Submitted and under revision (Revision 1)*. IF: 6.6; Q1; ISI, Indexed in Scopus.

Abstract: Adhesive joints are prone to various types of damage sources, which may not be identifiable with current Non-Destructive Tests (NDT). Structural Health Monitoring (SHM) techniques, such as those based on Electromechanical Impedance Spectroscopy (EMIS), aim to outperform NDT in damage detection, by continuously monitoring structures. While the EMIS-based algorithmic performance of damage detection has been evaluated on metallic and composite components, integrity monitoring of adhesive joints is yet to be fully determined. Therefore, this paper investigates the use of Multidimensional Scaling (MDS) to cluster and visualize experimental impedance measurements of bonded joints in a 3 dimensional space. With these results, an Euclidean distance *damage metric* is used to try and classify the type of damage. The results show that damage detection is easily performed with the MDS algorithm, but effectiveness is dependent on the spectral measurement conditions. Furthermore, reduced dimensional spaces can yield information regarding the size and location of the damage in the

adhesive layer, yielding increased knowledge on the integrity of structural adhesive joints.

Paper F – Frequency-based k -Nearest Neighbors algorithm for electromechanical impedance based detection of damage in adhesive joints

Tenreiro, A. F. G., Lopes, A. M. & da Silva, L. F. M. (2024), Frequency-based k -Nearest Neighbors algorithm for electromechanical impedance based detection of damage in adhesive joints. *Applied Soft Computing*, Submitted. IF: 8.7; Q1; ISI, Indexed in Scopus.

Abstract: Structural adhesive joints are susceptible to many forms of damage that may not be detectable with currently deployed Non-Destructive Tests (NDT). The Electromechanical Impedance Spectroscopy (EMIS) based Structural Health Monitoring (SHM) methodology constitutes an alternative, where a given structure is continuously monitored for damage, thus outperforming NDT. While much has been done in the applicability of EMIS in metallic and composite structures, only preliminary research has been done on the EMIS-based integrity monitoring of adhesive joints. In this paper, two different k -Nearest Neighbor (k NN) approaches are used for both damage detection and damage quantification. Initially, peaks are extracted from the real component of the measured impedance of instrumented adhesive joint specimens, which are then inputted to either a conventional k NN or a novel parallel k NN model, where each individual model is fed with its respective peak information. For void detection, the parallel classifier approach presents a moderately better performance, with an average accuracy of 98% under optimal conditions, but, for damage quantification, a significant improvement in classification is observed. In all cases, the use of the Canberra distance allows for a significant increase in classification accuracy.

Chapter 2

Literature Review

In this chapter, relevant points of the review are presented, starting with a description of the types of damage found in structural adhesives, as well as a brief overview of several NDT methods applied to adhesive joints. Afterwards, a review of the SHM methodology and the various methods is done. Finally, the EMIS monitoring technique is introduced in detail.

More information on EMIS, its applicability on the monitoring of adhesive joints, and algorithms for damage detection, localization and quantification, can be found in the appended review paper, **Paper A**.

2.1 Non-Destructive Testing of Adhesives

As mentioned in the first chapter, studying the mechanical performance of structural adhesive joints requires destructive tests, which may be methodologically counterproductive to verify for the presence of damage in all manufactured structures. The commonly adopted alternative is to use NDT methods [5, 6, 22].

NDT of bonded joints allows for the examination of the integrity of said adhesive joints, without the need to destroy the examined part. The need for NDT techniques applied to adhesive bonding is of great importance, since, without these, the reliability of the adhesively bonded structures cannot be guaranteed. In fact, national and international regulations on various manufacturing industries exist, specifically stating that one method of corroborating the structural adhesive joint's limit load is to perform repeatable and reliable non-destructive inspection of the joint [19]. One example where such regulations must be applied is the aeronautic industry [20].

Ideally, NDT procedures would monitor the strength of the adhesive bond. However, this can only be performed using destructive tests. As such, the objective of any NDT is to evaluate any physical change that may occur in the overlap, that may indirectly reduce the overall strength, such as the distribution of mass/mass density in the bonded area, or the degree of adhesive cure. By analyzing the variation of the measured parameters, one can correlate the estimated strength of the joint with the presence of defects [1, 6].

In this section, an introduction to the types of defects, found in the adhesive layer of bonded joints, is done. Afterwards, an introduction to several NDT methods is performed, such as the ultrasonic, the shearography and the infrared thermography testing methods. This introduction does not aim to be an extensive work on NDT of adhesively bonded structures, but instead, aims to reveal the applicability and shortcomings of NDT in detecting damage in the adhesive layer.

2.1.1 Damage in Adhesives

To better understand the measurements made by NDT methods, one needs to understand the defects that may be encountered in adhesive bonds. Figure 2.1 presents an illustration of the various defects that may occur in adhesive bonds.

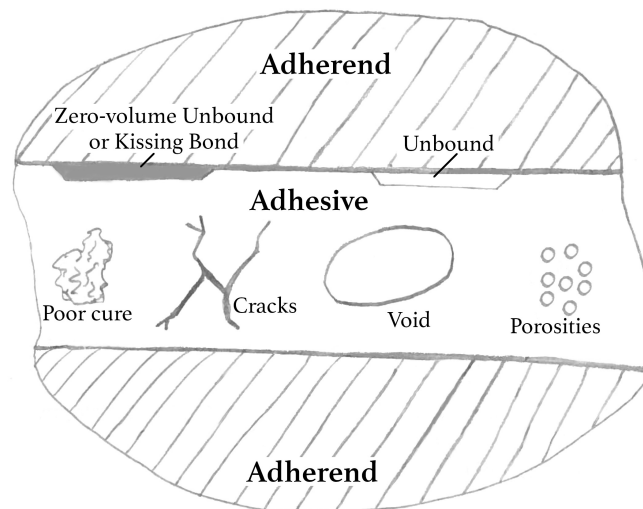


Figure 2.1: Illustration of possible defects present in a bonded joint.

Porosities are pores of microscopic scale, caused by the presence of volatile gases or entrapped air in the adhesive, and are commonly found in adhesive joints. Voids may also be caused when gas, or air, is trapped inside the adhesive. While it is uncommon to find large voids (i.e., pores of millimetric size, which are easily seen if there is adhesive failure) that are caused by the presence of volatiles, these

may occur and may be indicative of bad manufacturing procedures. Relative movement of the adherends can also induce voids in the adhesive layer. It is noted that the presence of a given void may not cause significant change in mechanical performance of the adhesive joint, but may help the ingress of a fluid through the bond, and help fatigue crack initiation. Furthermore, it is known that the presence of voids near the boundaries of the adhesive layer may result in a lowering of the resultant strength [21, 23, 24]. Conversely, porosities do not hinder the mechanical performance of adhesively bonded joints, but may cause greater variation in the overall ultimate strength [25], or a reduction of the fatigue life [26].

Cracks may also be induced in the adhesive layer, if monotonic or fatigue loads are applied, or if incorrect cure, or thermal shrinking, occurs. The adhesive may undergo an incorrect curing cycle or may be poorly mixed, leading to pockets of poorly cured adhesive, which is identified as *poor cure* in Figure 2.1. In some cases, the incorrect chemical formulation of an adhesive may also lead to the creation of pockets of uncured adhesive. The extent of the poor cure throughout the bond depends on the extent of some, or all of these factors. It is noted that some adhesives may cure at room/ambient temperature, and therefore, these pockets of poor cure may disappear, albeit at a slow rate.

Surface unbound is a specific type of void present in the interface layer, and often occurs when the adhesive is unevenly applied to one adherend. This type of defects may originate when the adherend surface is incorrectly clean and, therefore, still contains some unwanted substance. However, the most dangerous defect that may occur is when adhesive and adherend are in physical contact, despite the lack of no bond between them. This defect is called zero-volume unbond, weak adhesion or *kissing-bond*. Such defects may be caused by poor surface preparation, failure to remove the manufacturer's backing film completely, a loose substrate, and so on. This last type of damage is very hard to detect, and might only be possible to detect under very specific conditions. It is known that strains perpendicular to the loading direction in composite SLJs, i.e., strains caused by the Poisson's Ratio, ν , showed a different trend, when compared to strains in pristine SLJs [27].

Hygrothermal aging, while not a defect *per se*, may also lead to the degradation of adhesive mechanical properties. Indeed, this may not be a defect in a stricter sense, since there is no explicit physical form. However, the chemical changes caused by the ingress of water in the adhesive, in the interface, or even in the adherend (depending on the material) [28], or thermal changes [29, 30], may affect the chemical composition of the adhesive. This chemical change is normally correlated with a loss of mechanical properties [31, 32, 33].

2.1.2 Ultrasonic Testing

Ultrasonic-based NDT is widely adopted as a method to evaluate the integrity of adhesively bonded structures, given that it is already widely adopted in the industry to detect damage in many other materials and structures. One common ultrasonic NDT technique is the pulse-echo technique, which is schematically displayed in Figure 2.2, where a probe first generates an ultrasonic pulse. If a given material discontinuity exists, part of the initial wave is reflected backwards, while the remaining portion of the original wave will continue onward, until reaching the opposite end of the joint. Afterwards, the remaining wave is reflected back towards the probe. The two reflected pulse are distinguishable, since the time-of-flight of each pulse is different, as represented in Figure 2.2 [22, 34].

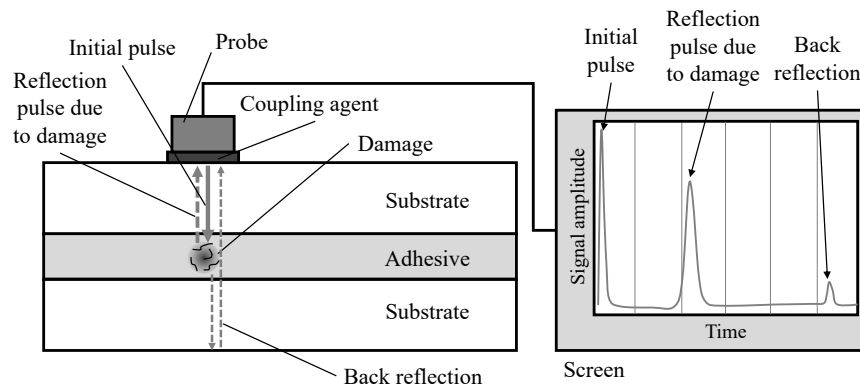


Figure 2.2: Simplified pulse-echo ultrasonic NDT technique, with an A-scan result displayed on the screen.

The through-transmission technique is another ultrasonic NDT technique, which makes use of two perfectly aligned transducers. A transmitter, that generates an ultrasonic pulse traveling towards the opposite end of the adhesive joint, is placed on one side of the joint, and a receiving sensor reads the generated wave on the opposite side. The measured signal amplitude by the receiver should diminish as the size of the damage increases. Consequently, when porosities or microcracks are detected, the measured wave amplitude is smaller than the initial amplitude of the generated wave. Conversely, when large voids or unbounds are present, the pulse wave is blocked, since the damage size is larger than the pulse width. This technique is usually adopted for the inspection of honeycomb structures, airplane fuselage and wings. However, this technique can only be used when access to both sides of the structure is possible. A variation of the through-transmission method exists where a reflecting plate is positioned on the opposite side of the joint.

As previously explained, ultrasonic signals can be presented as an A-scan, or

as a C-Scan, which is a *map* resultant of a surface scan, and may indicate possible defects. As the sensor moves, the echo wave amplitude may change with damage. These amplitudes are then plotted as a function of the position [6, 22, 34].

Traditional ultrasonic NDT methods require a coupling agent, so that the sound wave can be transmitted from the wave generator to the component. This need exists because there is an acoustic impedance mismatch between the air and any solid material. A common coupling agent is water, which allows one to match the acoustic impedances. However, to perform one of these tests, large tanks are needed, so that one can immerse the component in water [34]. This is impractical in some instances, such as in the aeronautic industry, where water jets are employed to avoid using huge water tanks. Alternative ultrasound methods were developed, such as laser-ultrasonics or air-coupled ultrasound [6, 22, 35], but very little has been done to determine their effectiveness in examining adhesive joints. Yilmaz et al. [36] studied the performance of unbound detection on aluminium-epoxy adhesive joints, determining that air-coupled ultrasonic tests performed worse than both water-coupled through-transmission and pulse-echo ultrasonic NDT.

Other shortcomings in defect detection exist, when using ultrasonic NDT. Defect detection in dissimilar adhesive joints is considerably harder, since joints with dissimilar adherends have a larger acoustic impedance mismatch. Therefore, different wave velocities and reflections/transmissions between media will occur [7, 37]. Smagulova et al. [7] developed a signal processing algorithm, where void detection in dissimilar adherend joints is achieved from the measured peaks, observed after multiple reflections and transmission. Jasiūnienė et al. [37] examined dissimilar hybrid joints with the pulse-echo technique, where an additively manufactured titanium alloy substrate, with embedded pins on the substrate, was joined with a Carbon Fiber Reinforced Polymer (CFRP) substrate. Damage detection was possible through both adherends, but sensor scanning could only be performed from the lateral side of the CFRP. Brotherhood et al. [38] studied the detectability of weak adhesion with ultrasonic NDT, and concluded that readings of weak adhesion are sensitive to the exerted contact pressure of the transducer.

2.1.3 Shearography Testing

Shearography is an optical-based non-destructive method for component evaluation, where a small strain excitation is generated on the component with a surface exposed to a laser array. The laser light rays are diffused forward the surface, towards a beam-splitter, which is basically a prism that separates beams of light. These beams are reflected by mirrors and captured by a charge-coupled camera, as schematically represented in Figure 2.3 [39, 40]. Note that this is just one of various existent setups, which are further detailed in reference [39].

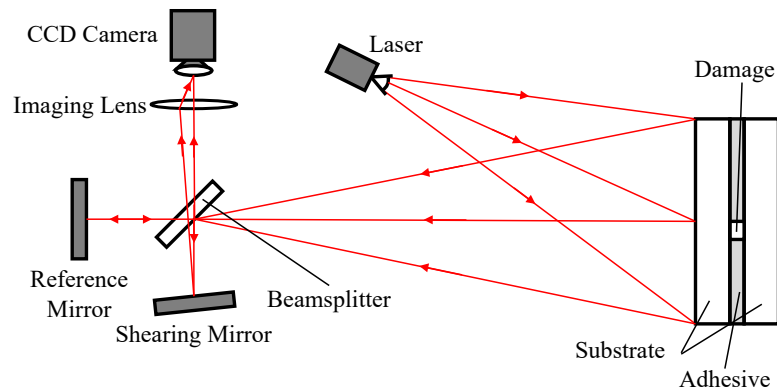


Figure 2.3: Schematic representation of a possible shearography NDT setup for adhesive structure evaluation.

Various strain generation sources exist, such as thermal sources, pressure excitation systems generating either vacuum or a small pressure, or dynamic actuators, like loudspeakers or PWAs [40, 8]. In this procedure, photographs are taken of the component being examined, before and during loading. Changes in lighting are a sign that damage is present [39, 40].

Taillade et al. [41] studied the ability of shearography-based NDT to detect voids in concrete-CFRP adhesive joints, where a vacuum pressure generates strain. With a pressure differential of 10 kPa or less, big voids were detected, but small voids required a pressure difference of 80 kPa. Kryukov and Böhm [8] studied the feasibility of detecting various types of defect in bonded joints, with identical and dissimilar substrates. Damage was easier to detect with substrates of low stiffness, such as aluminium or CFRP adherends. Conversely, only pockets of uncured and unmixed adhesive could be detected when the adhesive joined thick steel substrates. Furthermore, weak adhesion could not be consistently detected. While, in steel joints, this defect was detected, the lack of defined damage boundaries lowered the quality of the resulting image and, therefore, the test accuracy.

Taiber et al. [42] correlated the changes of Terahertz shearography results with the ageing of adhesive joints. Indeed, changes in both polymeric substrates and adhesives are detected by transmission measurements, but it is impossible to assign changes in either refractive or absorption indices to an aging factor.

Shearography is a promising NDT method for structural adhesives, given its applicability in the aeronautic industry [43], and can be automated by using ML or deep learning models, and image processing tools, for defect detection [44].

2.1.4 Infrared Thermography Testing

Another NDT method is to measure the temperature distribution of a free surface of an adhesively bonded structure. The Infrared Thermography NDT method enables this, by having an infrared camera measuring the temperature distribution in a contactless manner. Two different thermography methods exist, one of them being the passive thermography method, where a camera monitors the temperature without the influence of a controlled thermal source. Here, the heat is transferred from outside sources (e.g., sun radiation, convective winds) to the component in examination), and the resultant temperature gradient may indicate the presence of defects. Conversely, active thermography uses a dedicated heat source, and detects damage by measuring the temperature gradients [45].

Active thermography methods can be further subdivided according to various classification criteria, the most common of which is the type of thermal excitation being used during the examination. One such method is the pulsed thermography, where a thermal source generates a pulse excitation, transferring heat in a short amount of time, as schematized in Figure 2.4a. Afterwards, the adhesive joint cools and the resultant temperature gradients enables the location of existent defects. Another approach, represented in Figure 2.4b, is to generate a heat step excitation in stepped infrared thermography. The heating of the bonded component may allow one to obtain inhomogeneous temperature variations, revealing the presence of defects. In lock-in thermography, a thermal excitation is periodically generated, as exemplified in Figure 2.4c, and one analyses the thermal response, with both phase and magnitude components. In other words, one analyses the resultant behaviour in the frequency domain to determine the presence and location of damage. Pulsed phase thermography combines both the pulsed and lock-in thermography methods, such that a heat pulse is generated and the frequency domain phase-response is studied. Figure 2.4d presents an alternative method where the excitation frequency is modulated, thus allowing to extract the phase information in one inspection [9, 41, 45].

Fernando et al. [46] studied the capability of passive thermography in evaluating the degree of bonding of a polyurethane adhesive to fabric materials. This was done by correlating the peel strength, which is dependent on the curing temperature, with metrics from the thermographic images. The standard deviation from the mean temperature correlates well with the observed peel strength. When the peel strength is below 1.6 N mm^{-1} , the standard deviation has values above 0.4, resulting in a measured steep temperature gradient in thermography images. Conversely, when the peel strength is above 1.6 N mm^{-1} , the standard deviation of the average temperature decreases to values between 0.1 and 0.3, thus indicating simultaneously a more homogeneous temperature and adhesive distribution.

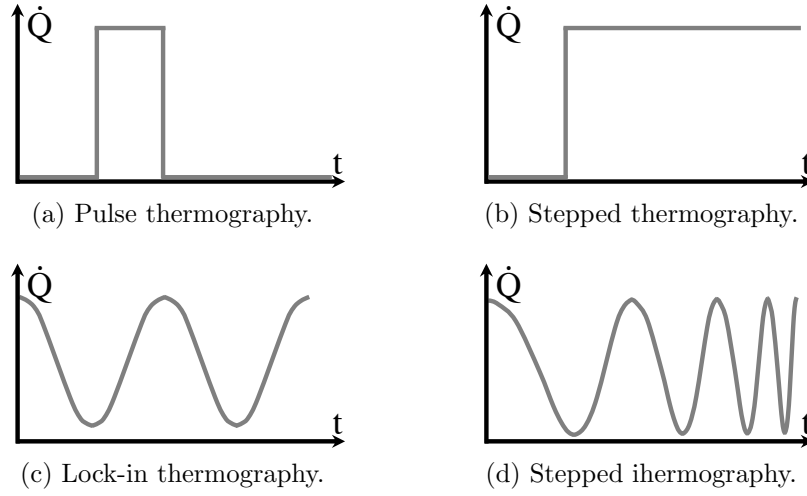


Figure 2.4: Active thermography excitation methods, as a function of time.

Taillade et al. [41] evaluated the capability of pulse thermography in detecting voids in concrete-CFRP bonded structures. With the help of heat transfer modeling, the authors accurately estimated the depth of the defect. Hung et al. [40] also studied the use of pulse thermography to detect voids in dissimilar joints of aluminium and composite substrates. While void detection was possible with both spacial image analysis and logarithmic time-temperature plots, this was only possible with large diameter voids near a substrate. Grosso et al. [47] used the pulsed thermography method to evaluate the detectability of voids in tubular Glass Fiber Reinforced Polymers (GFRP) joints. Various parameters were studied, such as the thickness of the collar connecting both tubular composite components, the heating time and the power used. The authors were able to correlate these with the temperature contrast between the zone with voids and the pristine adhesive zone. In this manner, even there is an increase of both the excitation's heating period and power, there is a thickness limit from which voids are undetectable.

Tighe et al. [9] combined pulsed phase thermography with a thermoelastic stress analysis to detect weak adhesion in CFRP adhesive joints. Thermography images of loaded joints enabled the researchers to locate defect zones. Furthermore, since the use of small loads facilitates the weak adhesion detection process, a small vacuum chamber was built, containing the heat source, thermal camera and the tested joint. The generated vacuum created the desired small loads, enabling the successful detection of weak adhesion. Kurpinski and Fidali [48] successfully used lock-in thermography to evaluate the correct and inadequate distribution of adhesive in bonded joints.

Yilmaz et al. [49] performed a statistical-based study, where both Thermography and Ultrasonic NDT methods were employed on composite adhesive joints with artificially created voids in the adhesive. C-scans and thermal images were combined with the help of data fusion methods. This enabled an easier void detection, but only when there were no contradictions between the obtained measurements.

2.2 Structural Health Monitoring

The previous section reveals that, while NDT technologies are able to detect damage overall, not all damage foci can be reliably detected, leaving doubts regarding its effective capabilities in industrial applications. Even though there are clear signs of improvements in NDT to tackle adhesive damage detection, reliability has yet to reach the desired standards.

SHM has the aim to go beyond NDT, by performing *in-situ* continuous integrity monitoring. This is possible with the use of sensors that directly or indirectly measure the mechanical properties of the monitored structure. The measurements are then processed by a central processing unit with algorithms specialized in damage detection, location, characterization, etc., as shown in Figure 2.5 [10, 11, 50].

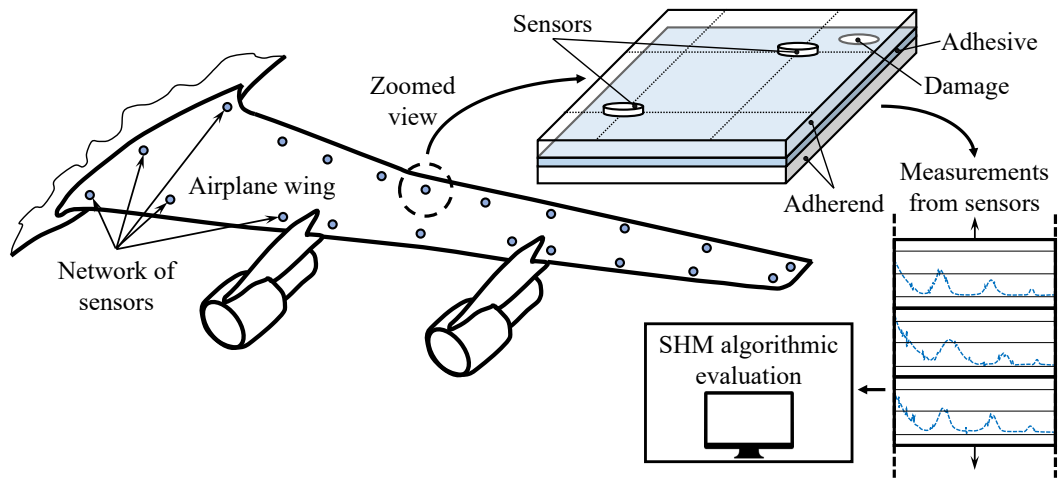


Figure 2.5: Schematic representation of the SHM methodology applied to an airplane wing.

This technology is of particular interest to the aeronautic industry [51, 52], where regular vehicular maintenance is mandated by law and components must be designed with high safety factors. SHM may also be useful to other industrial sectors, where maintenance of structures is excessively expensive and, in certain cases, logistically impossible. This is also true for the specific case of structural

adhesive joints, which, as previously stated, are used in combination with mechanical joining methods to guarantee reliability throughout the entire life-cycle. Furthermore, SHM needs to be versatile, since the algorithmic tools will continuously interrogate the structure for damage, whether it is immobile, or in operation. With this, enterprises should be able to reduce maintenance costs and minimize the need for NDT inspections, while simultaneously being able to perform early detection of damage [10].

2.2.1 Hierarchical Approach to Damage

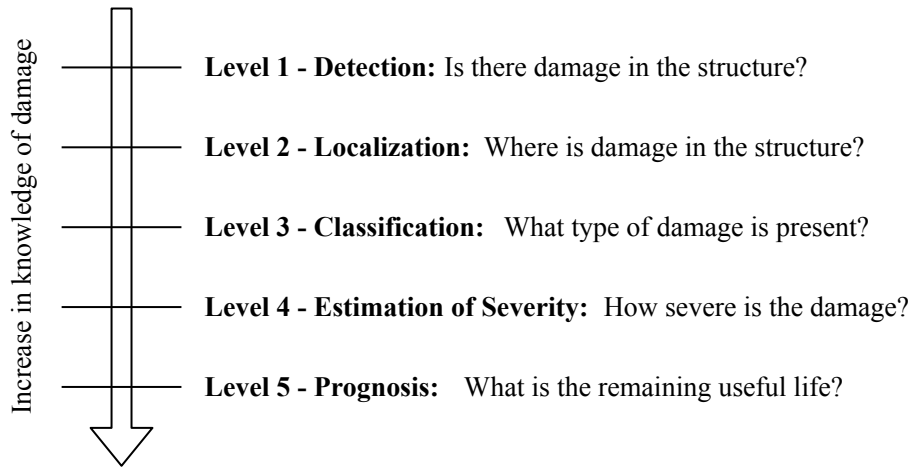


Figure 2.6: Fluxogram showing the SHM hierarchical approach to the analysis of damage.

For the study of damage, a SHM hierarchical approach is required to process information from various sources. This was transferred from the military and medical domains to engineering, forming the field of *Sensor and Data Fusion* [53].

This approach was first proposed by Rytter [54], and resulted in the hierarchy defined in Figure 2.6. One first examines the existence of damage (Detection) in the monitored component. If there is algorithmic confirmation for the presence of damage, the processing unit will proceed with the second level of knowledge, where the damage position is determined (Localization). Afterwards, the employed algorithms should determine the type detected defect (Classification). In essence, for the specific case of adhesively bonded joints, the algorithm should try to classify the detected damage according the type of possible damage sources in adhesives, as described in subsection 2.1.1. In a fourth level, the algorithmic method employed must evaluate the severity of the damage in the structure (Estimation of Severity). Lastly, given all of the obtained information so far, the algorithms must estimate the reliability of the structure until failure (Prognosis) [53, 55, 56]. One must note

that some researchers bundle the third and fourth level into a Characterization level [57]. However, in this work, the *characterization* of damage corresponds to the task of understanding more on the detected damage (Level 2 and beyond).

2.2.2 Classification of SHM methods

Various SHM methods exist, which can be divided into two categories, according to the type of excitation used for the measurement, such as:

- Passive SHM systems, where one does not have an active loading element exciting the structure being inspected. In essence, passive SHM makes exclusive use of sensors, which monitor mechanical wave noise, low-frequency vibrations or transient waves caused by small impacts. Significant changes of the measured oscillations may be indicative of the presence of damage;
- Active SHM systems, where actuators are present, generating a given excitation to the structure, while sensors measure the response of the structure. To assist this operation, the network of actuators and sensors must have a dedicated power supply. The measurements may yield conclusions regarding the presence of damage, or lack thereof [10, 11].

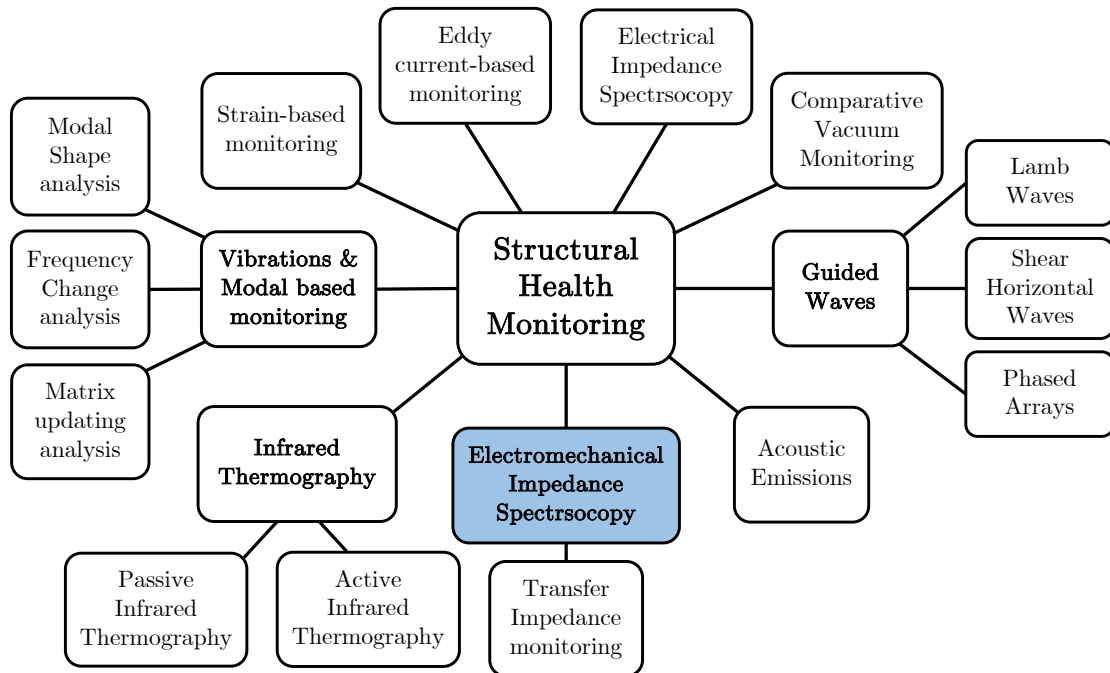


Figure 2.7: Chart subdividing the various SHM methods.

As represented in Figure 2.7, various SHM systems have been developed, and are currently being used in research, which may make use of differing phenomena.

Vibration-based methods are a set of methods that, in essence, make use of mechanical vibrations and modal analysis, and use measurements from accelerometers to determine information on a given source of damage. Changes in structural properties, due to the presence of damage, will result in alterations of both modal frequencies and modal shapes. Other sub-methods perform a continuous optimization of the stiffness, damping and mass matrices in a modeled replica of the structure, to reproduce the measured dynamic response of the structure [58, 59].

Another SHM approach is based on strain measurement, and can be implemented with conventional strain gauges, but its applicability is limited to the size of the structure, and to the number of points where measurements are required. Alternatively, one can make use of accelerometers or optic fiber sensors, such as the Fiber Bragg Grating (FBG) sensors, which suffer a shift in transmitted light wavelength with the presence of a local strain [60, 61].

One can also use guided waves, such as Lamb waves or shear horizontal waves, which are elastic waves that propagate for long distances without significant amplitude loss. This makes such physical methods ideal for integrity monitoring, but the generated waves are complex in nature, requiring the need for complex algorithms and signal processing techniques. In this method, an actuator is required for wave generation. This tends to be a PWAS that is fed a transient signal, such as a Hann window excitation signal. Various transducers can be used, such as PWAS, Laser Doppler vibrometers, magnetostrictive transducers and fiber optic sensors, namely FBG sensors [57, 62, 63]. A sub-variant of the guided waves integrity monitoring method, which is called the Phased Array method, is to use an array of sensors that sequentially excite guided waves. For each instance where a given element acts as an actuator, the remaining elements act as sensors [10, 64, 65].

A different approach is to use the Acoustic Emission passive monitoring method, which also makes use of PWAS elements to measure elastic waves in the instrumented structure. However, these waves are generated by transient small impacts that occur during the regular operation of the structure [11, 50, 66].

Electrical Impedance Spectroscopy (EIS) uses carbon nanotubes, which are a nanoscale smart material that is dispersed onto polymer materials. The small size of carbon nanotubes allows them to be used as small scale sensors. Furthermore, variations in strain are reflected in reversible changes of electrical properties, while irreversible electrical changes occur with the presence and growth of structural damage. In this sense, the measurement of the electrical impedance correlates well with structural changes, which are measured with the help of dedicated equipment, such as a dielectric spectrometer or a potentiostat [67, 68, 69].

The Comparative Vacuum Monitoring (CVM) technique, first developed for the aeronautic industry, makes use of a set of small diameter channels embedded in composite materials, which alternate between having either vacuum or air at ambient pressure. When delamination occurs in the composite, the crack passes through these channels, and pressure sensors that monitor the pressure at each channel, detect an increase in pressure relative to the initial vacuum pressure. With these changes, the SHM system is monitoring the crack growth in a given composite component [70, 71].

Another approach is to use the eddy current monitoring technique. This technique makes use of the fact that an AC signal, passing through a coil, will generate a magnetic field. This magnetic field will generate a secondary electric current, called eddy current, in an electrically conductive component, which is the subject of the integrity evaluation. This eddy current will also influence the magnetic field being generated, thus altering the AC signal in the main electrical circuit. The generated eddy current may be altered with the presence of damage, thus causing changes in the electrical current [72, 73].

Some researchers have discussed the fact that Infrared Thermography, which was discussed in subsection 2.1.4, can be adopted as a SHM method, in the sense that it may be deployed autonomously in a given structure for damage detection and analysis [74, 75].

Lastly, the EMIS method can also be used in the integrity monitoring of components. This last method is the topic of research of this thesis, and, consequently, is introduced in the next section.

2.3 Electromechanical Impedance Spectroscopy

This section presents the EMIS monitoring method, as well as the transfer impedance alternative method.

2.3.1 Conventional Method

EMIS presents itself as an interesting and promising structural inspection method, which makes use of the coupled electromechanical behavior of PWAS. In this manner, these piezoelectric elements work simultaneously as actuators and sensors.

A generated sinusoidal voltage excites the PWAS connected to the structure under examination. This PWAS acts as an actuator and converts the electric voltage into a mechanical load. Simultaneously, as the mechanical load is being generated, the same PWAS, acting as a sensor, converts the mechanical response into an electric signal. This signal is acquired by an impedance analyzer, over

a wide range of frequencies, usually from 1 kHz onwards, since high excitation frequencies are immune to ambient noise and vibration perturbations common in real-world operated structures [76, 77].

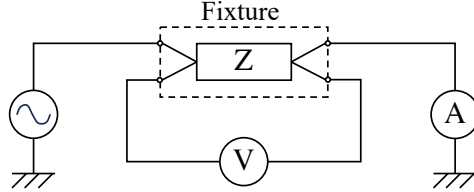


Figure 2.8: Representative electrical circuit of the Impedance Analyzer.

Functionally speaking, the impedance analyzer is connected to one electrical circuit of two meshes, as per the circuit of Figure 2.8, one that measures the electrical current, $I(j\omega)$, and another that measure the voltage, $V(j\omega)$. The first mesh supplies the PWAS with an AC voltage, which also contains an ammeter, while the second one contains a voltmeter. Both, the electrical current and voltage are measured, thus allowing the computation of the electrical impedance [78].

This electromechanical coupled behavior occurs since piezoelectric materials create an electric charge when subjected to mechanical stress, and will generate a mechanical strain under the influence of an electric field. In mathematical terms,

$$\begin{cases} \varepsilon_1 = \overline{s_{11}^{E_f}} \sigma_1 + d_{31} E_{f,3} \\ D_3 = d_{31} \sigma_1 + \overline{\varepsilon_{33}^\sigma} E_{f,3} \end{cases}, \quad (2.1)$$

where ε_1 and σ_1 represent the mechanical strain and the mechanical stress, respectively, while $E_{f,3}$ and D_3 denote the electric field and the electrical displacement (charge per unit area), respectively. Furthermore, $\overline{s_{11}^{E_f}}$ is the mechanical compliance at zero electric field, d_{31} stands for the piezoelectric induced strain coefficient, and $\overline{\varepsilon_{33}^\sigma}$ is the dielectric constant at zero stress. Note that $\overline{\varepsilon_{33}^\sigma}$ may also be referred to as Permittivity in some literature review [11, 79, 80].

The mathematical modeling of the EMIS technique, which has been performed by various authors, always started with equation (2.1), which serves as a starting step to mathematically relate the measured electrical impedance of the sensor, $Z_e(j\omega)$, with the mechanical properties of the structure. The structural properties are described by the mechanical impedance of the structure, $Z_{m,s}(j\omega)$, defined as

$$Z_{m,s}(j\omega) = \frac{F(j\omega)}{\dot{x}(j\omega)}, \quad (2.2)$$

where F and $\dot{x}$ are, respectively, the load and particle velocity.

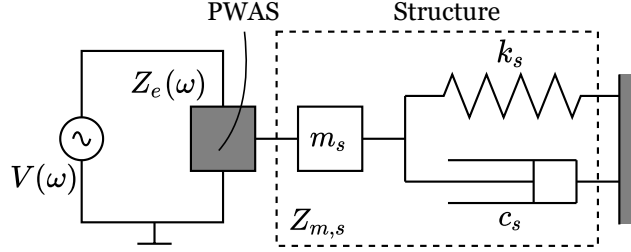


Figure 2.9: Model of interaction between the PWAS and the one-dimensional structure.

Liang et al. [81] proposed the first mathematical model describing this phenomenon, by relating electrical impedance of an instrumented one-dimensional structure with mass, m_s , stiffness, k_s and damping, c_s , of the inspected structure, as shown in Figure 2.9, such that

$$Z_e(j\omega) = \left[j\omega \frac{w_P l_P}{h_P} \left(\overline{\varepsilon_{33}^\sigma} - \frac{Z_{m,s}(j\omega)}{Z_{m,s}(j\omega) + Z_{m,P}(j\omega)} d_{31} \overline{Y_{11}^{E_f}} \right) \right]^{-1}, \quad (2.3)$$

where w_P , l_P and h_P are, respectively, the width, length and thickness of the PWAS, and $Z_{m,P}(j\omega)$ is its mechanical impedance. Once again, variables j and ω correspond to the imaginary number, $j = \sqrt{-1}$, and the angular frequency, respectively. One must note that the variable $\overline{Y_{11}^E}$ is the complex Young's Modulus of the piezoelectric material with a null electric field, and is defined as $\overline{Y_{11}^{E_f}} = |Y_{11}^{E_f}|(1 + j\eta)$, where η is the mechanical loss factor. The dielectric constant at zero stress, $\overline{\varepsilon_{33}^\sigma}$, is expressed as $\overline{\varepsilon_{33}^\sigma} = |\varepsilon_{33}^\sigma|(1 - j\delta)$, where δ corresponds to the dielectric loss factor.

As one can see from equation (2.3), the electric impedance, Z_e , has real and imaginary components, $\text{Re}(Z_e)$ and $\text{Im}(Z_e)$, respectively. However, the real component, $\text{Re}(Z_e)$, is comparatively more sensitive to damage. To demonstrate this, one should actually work with the admittance formulation, which is the inverse of equation (2.3), and can be decomposed into two different components, defined as

$$Y_P(j\omega) = j\omega \frac{w_P l_P}{h_P} \overline{\varepsilon_{33}^\sigma} \quad (2.4a)$$

$$Y_A(j\omega) = j\omega \frac{w_P l_P}{h_P} \frac{Z_{m,s}(j\omega)}{Z_{m,s}(j\omega) + Z_{m,P}(j\omega)} d_{31} \overline{Y_{11}^{E_f}}, \quad (2.4b)$$

where the $Y_P(j\omega)$ corresponds to the passive component, and $Y_A(j\omega)$ to the active component. This separation into two different components was first proposed to demonstrate that a portion of the obtained measurements corresponds to the electrical behaviour of a capacitance, as described by equation (2.4a), which has a comparatively negligible real component. In this manner, the active component, $Y_A(j\omega)$, is more sensitive to damage, and can be directly obtained to determine information from possible damage sources [82].

This method presents interesting advantages over other SHM methods. Firstly, EMIS adopts light-weight and inexpensive piezoelectric transducers, which can be implemented without hindering the stability of the structure. Secondly, and as previously mentioned, EMIS monitors structures in the domain of high frequencies, where ambient noise and vibrations do not influence the obtained readings [76, 79].

2.3.2 Transfer Impedance Method

A sub-variant of the EMIS integrity inspection method is the transfer impedance method. This variant makes use of various PWAS elements, where one PWAS functions as the excitation generator, creating a mechanical vibration, while the remaining piezoelectric elements measure the resultant vibrations.

Much like in EMIS, when the load generator element is excited with a harmonic excitation voltage of frequency ω , $V_I(j\omega)$, the measured voltage in the receiving PWAS, $V_O(j\omega)$, should also be an harmonic signal of the same frequency, but with different amplitude, and a phase shift, such that

$$T(j\omega) = \frac{V_O(j\omega)}{V_I(j\omega)} = |T(j\omega)|e^{j\varphi(j\omega)}. \quad (2.5)$$

Note that $T(j\omega)$ and $\varphi(j\omega)$ represent the ratio and phase shift of both voltage signals, respectively.

While the ratio, $T(j\omega)$, and phase shift, $\varphi(j\omega)$, can provide information on the possible presence of damage, it is hard to quantify. Therefore, a good approach is to compare the obtained ratio and phase shift with a standard baseline ratio, $T_b(j\omega)$, and phase shift, $\varphi_b(j\omega)$, from a structure without damage. In this manner, one can compute the damage metric frequency function, such that

$$\frac{T(j\omega)}{T_b(j\omega)} = \frac{|V_O(j\omega)|}{|V_{O,b}(j\omega)|} e^{j(\varphi(j\omega) - \varphi_b(j\omega))}, \quad (2.6)$$

where $V_{O,b}(j\omega)$ is the baseline output signal, for a damageless structure. This complex function enables a better comparison between a pristine structural condition

and the condition being evaluated [83].

Chapter 3

Experimental Details

In this chapter, both the materials used, and tests performed, are described. The experimental tests are divided into two different sections: mechanical tests and electrical impedance tests. The mechanical tests were performed to determine material properties, while electrical impedance tests were done to obtain the electrical impedance, Z_e , of instrumented adhesive joints.

3.1 Materials

3.1.1 Substrates

In this work, two different aluminium alloy materials were used to manufacture specimens: the 6082-T6 and the 1050-H24 alloys. These will be described herein.

6082 aluminium alloy

The aluminum substrates, used in the majority of the experimental tests of **Papers B & C**, were of the 6082-T6 alloy, and are usually extruded. This alloy belongs to the 6000 series, which contains silicon and magnesium as the main alloying elements. This alloying combination confers good strength, corrosion resistance and ductility [84, 85].

The T6 indication means that this metal was submitted to a temper treatment, starting with a solution heat treatment of approximately 160°C, followed by quenching in water and a precipitation hardening. In this manner, the dissolution of intermetallic phases occurs, improving ductility [84, 86].

1050 aluminium alloy

The 1050-H24 aluminium alloy was used to manufacture specimens in **Paper**

B. This is a 1000 series alloy with over 99% pure aluminium, meaning that there is only a very small percentage of alloying elements. The H24 indication means that this is strain hardened and partially annealed alloy [84, 87].

3.1.2 Adhesives

Three different structural adhesives were used in this research: a modified epoxy adhesive, a silicone adhesive and a PSA. In this case, the term "structural" refers to the adhesive that bonds the aluminium substrates. Other adhesives were used, which are mentioned in their respective subsections.

Modified epoxy adhesive

In **Papers B & C**, the Nagase T-836/R-810 modified epoxy adhesive was used. This is a crash-resistant adhesive, formulated by Nagase ChemteX[®] (Osaka, Japan). This material is a tough one-part modified epoxy adhesive, developed for the joining of structural components in the automotive and aeronautic industries, because of its high strength and resistance to impact. The cure of this adhesive occurs during a 3 hour stage at 160°C.

This adhesive has a glass transition temperature of 136°C. Despite the fact that the manufacturer is still studying the development of this adhesive, it is understood that this adhesive has a mass density, ρ , of approximately 1200 kg m⁻³, similarly to what is commonly found in epoxy adhesives [88].

Silicone adhesive

The silicone adhesive, which was used for the research of **Paper B**, is a commercially available two-part silicone rubber. This adhesive can bond a diverse set of substrates. Furthermore, it has a high heat resistance and long-term stability. This material is recommended for general purpose sealing applications in the automotive and electrical industries.

The manufacturer suggests an adhesive/catalyst ratio of 10:1 and a cure at room temperature for two weeks. However, an alternative curing procedure was followed, as per the work of Borges et al. [89], where an adhesive/catalyst ratio of 1:1 was used, and mixture was performed with a speed mixer. Curing occurred at 120°C for 25 minutes.

This adhesive has a mass density of 1260 kg m⁻³. Borges et al. [89] determined that this adhesive behaves according to the Neo-Hooke hyperelastic model. However, for small strains, one can use an elastic model ($E = 2.44$ MPa, $\nu = 0.495$).

Pressure Sensitive Adhesive (PSA)

The tesa[®] (Norderstedt, Germany) 64620 PSA was also adopted for the research done in **Paper C**. This PSA is a double sided film adhesive, where synthetic rubber hotmelt is placed on both sides of a polypropylene film. This film adhesive has a thickness of approximately 0.1 mm. This adhesive has a good shear resistance under quasi-static conditions at room temperature (23°C), with a tensile strength of 3000 N m⁻¹. However, this mechanical performance decreases with an increase of ambient temperature.

3.1.3 Materials for Void Creation

To manufacture adhesive joints with voids, a Polytetrafluoroethylene (PTFE) circle of diameter, $\varnothing_V \in \{4, 6, 8\}$ mm, was placed in the overlap region of SLJs before the curing procedure. PTFE was adopted as the material to create artificial voids, since this material has a service temperature range varying between -200°C and 260°C . In other words, no chemical change of the PTFE occurs during the curing procedure of the modified epoxy adhesive. Furthermore, this material has a mass density of 2150 kg m⁻³.

To guarantee that the circular infill remains fixed during the cure procedure, these were bonded onto one substrate, with the help of Permabond[®] 825, which is a modified ethyl cyanoacrilate adhesive capable of withstanding high temperatures, since the maximum allowable service temperature is of 200°C.

3.1.4 Materials for Instrumentation

To instrument the adhesive joint specimens, a piezoelectric element was needed. Furthermore, a methacrilate adhesive was used to bond the PWAS element to the adhesive joint.

Methacrilate adhesive

To fix the PWAS element, essential to the EMIS procedure, a Plexus MA 422 methacrilate adhesive, manufactured by TW Performance Polymers (Chicago, Illinois, United States), was used. This adhesive was formulated for the structural assembly of composite, polymeric and metal components. According to the manufacturer, this adhesive is widely employed in composite bonding applications for both transportation and marine industries, since there is no need for previous surface preparation. This adhesive is characterized for its elevated impact resistance and toughness.

This methacrilate adhesive is a two-part adhesive, where one part is the adhesive, and another is the activator. Both parts need to be mixed by a volume proportion of 10:1 (adhesive-activator), and the curing procedure occurs at room

temperature for 24 hours. According to the manufacturer, this adhesive has an elastic modulus varying between 762 and 1031 MPa (for quasi-static tensile testing conditions).

Piezoelectric Wafer Active Sensor (PWAS)

To perform the electric impedance measurements, the adhesive joint specimens were instrumented with PRYY + 1119 piezoelectric sensors, fabricated by PI Ceramics (Lederhose, Germany). This PWAS has a diameter of 10 mm, a thickness of 0.2 mm and an electrical capacitance of 5.24 nF.

The PWAS consist of a PIC 255 piezoceramic material, which is a modified lead zirconate-lead titanate material. This material is characterized for having a high Curie temperature ($T_c = 350^\circ\text{C}$), which means that it has a high service temperature range, before losing its piezoelectric properties. Furthermore, this piezoceramic has a high permittivity, meaning that it has a strong capacitive behaviour, and a high coupling factor, meaning that it has a high piezoelectric effect. In other words, this ceramic material has a high ability of converting mechanical energy into electrical energy, and vice versa. Table 3.1 presents some of the relevant properties of this piezoceramic material. Variables k_p and k_t represent the coupling factor for the planar radial oscillation and of the thickness oscillation of a round disk, respectively, while ρ stands for the mass density of the piezoceramic. Note that ϵ_0 is the vacuum permittivity, and ϵ_{33}^σ is the absolute permittivity of the PWAS in the vertical direction, with null stress. Also note that $s_{11}^{E_f}$ and $s_{33}^{E_f}$ stand for the elastic compliance with null electric field, in the radial and thickness direction, respectively.

Table 3.1: Properties of the piezoceramic material PIC 255.

ρ [g cm ⁻³]	Elastic compliance coefficient		Coupling factor		$\frac{\epsilon_{33}^\sigma}{\epsilon_0}$ [-]
	$s_{11}^{E_f}$ [m ² N ⁻¹]	$s_{33}^{E_f}$ [m ² N ⁻¹]	k_p	k_t	
7.80	$16.1 \cdot 10^{-12}$	$20.7 \cdot 10^{-12}$	0.62	0.47	1750

3.2 Mechanical Tests

3.2.1 Quasi-static Tests

Quasi-static tests were performed in **Paper B**, for the Nagase T-836/R-810 adhesive, in order to determine the elastic quasi-static properties, and to correlate them with the dynamic material properties. Note that this was not done for the silicone adhesive, since this was published in reference [89].

Specimen manufacturing

Bulk tensile tests were performed with conventional "dogbone" specimens fol-

lowing the BS 2782 standard [90]. The specimen geometry is defined in Figure 3.1.

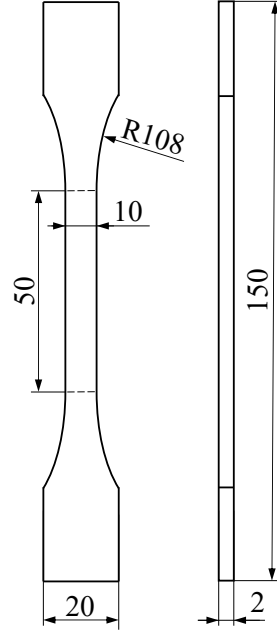


Figure 3.1: Geometry of "dogbone" specimen for bulk tensile testing, with dimensions in mm.

To obtain these specimens, one first needs to produce adhesive plates, as per the NF T 76-142 standard [91]. The process begins by placing a silicone frame of the desired plate thickness inside a mold. This frame is used to guarantee a constant adhesive layer thickness, and, simultaneously, ensures hydrostatic pressure, therefore reducing the number of unwanted defects in the final specimen. Afterwards, the adhesive is deposited inside the silicone frame and the mold is placed inside the hot-plate press, following adequate curing cycle parameters. Finally the bulk specimens are cut from the resultant adhesive plate, thus obtaining the geometry defined in Figure 3.1.

Experimental procedure

To perform the bulk tensile tests, an Instron[®] 3367 universal testing machine was used, which has a load cell capacity of up 30 kN. These tests were performed at room temperature and ambient humidity, and a loading rate of 1 mm/min.

While each specimen was tested, Digital Image Correlation (DIC) was done with the help of a Cannon EOS M5 (Tokyo, Japan) digital camera. Photos of the specimens being loaded were taken every five seconds. DIC measurements were

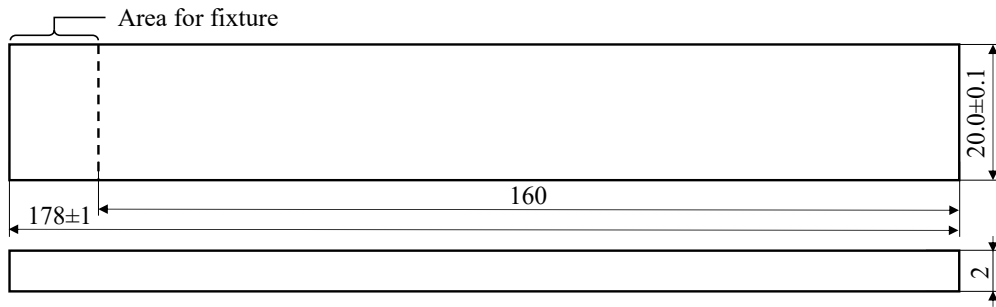
then performed with GOM Correlate[®] software. From this measurements, strains could be extracted to enable the computation of the Poisson's coefficient, ν .

3.2.2 Vibrating Cantilever Beam Tests

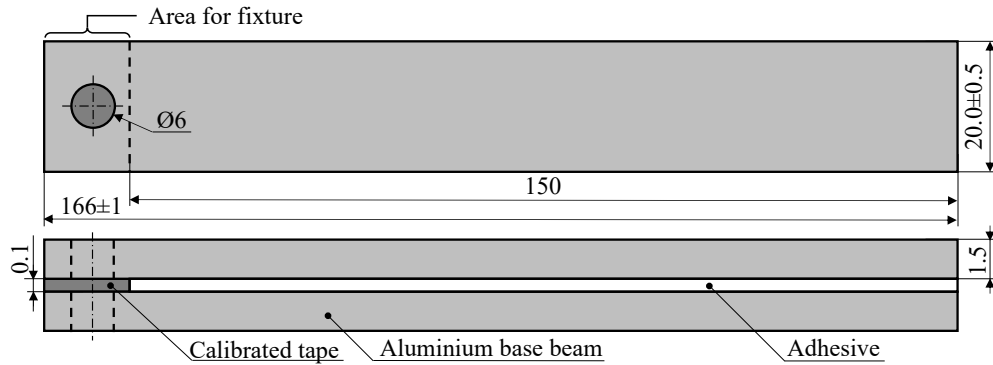
Vibrating Cantilever Beam Tests (VCBT) were performed in **Paper B** for both the Nagase T-836/R-810 adhesive and the silicone adhesive, with the aim of determining the elastic and damping properties, as a function of the excitation frequency, ω .

Specimen manufacturing

Specimens were manufactured to determine the properties of the both adhesives. However, there is a drastic difference in stiffness between them. In this manner, two different specimen geometries are defined in the standard ASTM E 756-05 [92].



(a) Uniform specimen for the modified epoxy adhesive



(b) Sandwich specimen with the silicone adhesive

Figure 3.2: Schematic representation of the specimina used in VCBTs (dimensions in mm).

For the modified epoxy adhesive, uniform specimens were manufactured, which have an identical manufacture procedure to that of the "dogbone" specimens, with

the exception of the geometry, as defined in Figure 3.2a.

For the silicone adhesive, sandwich specimens were manufactured. In this case, 1050 aluminium alloy substrates of 1.5 mm thickness were cut, gritted with sandpaper and then cleaned with acetone. Phosphoric acid anodization was performed by submersing the substrates in a aqueous phosphoric acid solution, with a concentration between 9% and 12% (m/m). An electric current, created by a voltage source of 16 V, passed through the immersed substrates for 25 minutes. In the end, these were removed from the solution and cleaned with distilled water and acetone.

With the surface treatment completed, the substrates were placed on a mold, and adhesive thickness was ensured with a calibrated tape placed on both ends of the specimen. The adhesive was carefully applied to both substrates, in order to avoid the appearance of possible defects. The mold was placed in a hot-plate press to perform adhesive cure. Finally, one of the ends of the sandwich specimen was cut, in order to remove the calibrated tape.

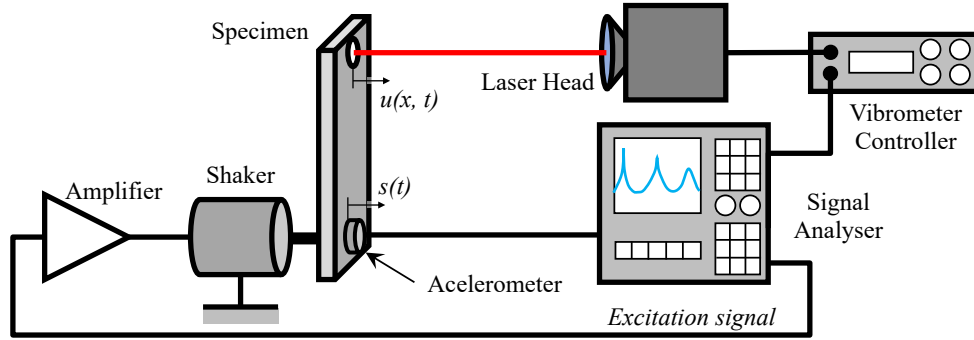


Figure 3.3: Schematic representation of the VCBT setup.

Experimental procedure

The experimental setup used for this test is schematized in Figure 3.3. An excitation signal was generated by Brüel & Kjaer signal analyzer unit type 2035 (Naerum, Denmark), which is a Fast Fourier Transform (FFT) analyzer, and amplified by a shaker amplifier, model LDS PA100E (Brüel & Kjaer). This signal was sent to a shaker (model LDS 401, Brüel & Kjaer), that converts the electrical signal into a mechanical oscillation, so that the specimen undergoes flexural vibration. Due to equipment limitations, this procedure was performed until reaching a maximum frequency of 3.2 kHz. A Brüel & Kjaer 2507-473 accelerometer was placed at the base of the specimen to measure the acceleration. Meanwhile, the velocity at the free end of the specimen was measured with non-contact laser Doppler vibrometer. This laser vibrometer includes the Polytec OFV-303 laser head (Waldbronn,

Germany), that emits and measures a helium laser, and the Polytec OFV 3001 controller, that decodes the signal from the laser head. The measured signals from the accelerometer and the laser doppler vibrometer are processed by the FFT analyzer. The FFT analyzer calculated the transmissibility of the specimen, $TR(j\omega)$, such that

$$TR(j\omega) = \frac{U(j\omega)}{S(j\omega)}, \quad (3.1)$$

where ω is the angular excitation frequency, while $U(j\omega)$ and $S(j\omega)$ stand for the phasors corresponding to the displacement at the free-end (which was obtained by integrating the velocity measurements) and at the base of the specimen (which was imposed by the Shaker), respectively.

With the obtained transmissibility function, one can proceed to compute the elastic and damping properties of the adhesives, as per the ASTM E 756-05 standard [92]. For uniform specimens, the elastic modulus is determined by

$$E = \frac{12\rho l_b^4 f_i^2}{t_A^2 C_i^2} \quad (3.2)$$

$$C_i = \begin{cases} 0.55959, & \text{if } i = 1; \\ 3.5069, & \text{if } i = 2; \\ 9.8194, & \text{if } i = 3; \\ \frac{\pi(i - 0.5)^2}{2}, & \text{if } i > 3, \end{cases} \quad (3.3)$$

where f_i is the experimental resonance frequency for mode i , and C_i is the coefficient for mode i of the uniform specimen, as defined in equation (3.3).

The loss factor, η , that describes the adhesive damping, for the uniform specimen, is computed as

$$\eta = \frac{\Delta f_i}{f_i}, \quad (3.4)$$

where Δf_i is the the half-power bandwidth of mode i .

For the case of the adhesive in the sandwich specimen, one can calculate the

shear modulus, G , such that

$$G = (A - B - 2(A - B)^2 - 2(A\eta_s)^2) \left[\frac{\left(\frac{2\pi E_b C_i t_b t_A}{l_b^2} \right)}{(1 - 2A + 2B) + 4(A\eta_s)^2} \right], \quad (3.5)$$

where η_s is the loss factor of the sandwiched specimen, D is the mass density ratio, τ is the thickness ratio, and A and B are parameters. These variables are defined in the following equations

$$\eta_s = \frac{\Delta f_i}{f_i}, \quad D = \frac{\rho_A}{\rho_b}, \quad \tau = \frac{t_A}{t_b} \quad (3.6)$$

$$A = \frac{f_i}{f_{b,i}} \frac{B}{2} (2 + D\tau), \quad B = \frac{1}{6(1 + \tau)^2}, \quad (3.7)$$

where E_b denotes the elastic modulus of the base beam and l_b is the useful length of the beam, while ρ_A and ρ_b are the mass density of the adhesive and the base beam, respectively. Additionally, parameters t_b and t_A correspond to the thickness of the base beam and of the adhesive material, respectively. One should also note that f_i and $f_{b,i}$ represent the resonance frequencies for mode i of the base beam and the sandwich beam, respectively, while Δf_i is the half-power bandwidth of mode i of sandwich specimen. Also note that C_i is the coefficient for mode i of the fixed-free beam, as defined in equation (3.3).

The loss factor of the silicone adhesive in the sandwich adhesive, η , is determined by

$$\eta = \frac{A\eta_s}{A - B - 2(A - B)^2 - 2(A\eta_s)^2}. \quad (3.8)$$

3.3 Electrical Impedance Tests

SLJ specimens were manufactured and instrumented with a PWAS, so that electrical impedance measurements could be performed. These specimens were chosen for this experimental task, since these resemble certain real world structural joints, while also maintaining some geometrical simplicity [93].

In this manner, various SLJ specimens were manufactured in this work. For **Paper B**, SLJs were manufactured with both the modified epoxy adhesive and the silicone adhesive, where the adhesive thickness varied.

For **Paper C**, modified epoxy adhesive SLJs were manufactured with the same thickness and with artificially created voids in various positions of the overlap region. Boundary conditions were also tested for these adhesive joints. Also for **Paper C**, SLJs with PSA were manufactured and instrumented. A preliminary study was done, where various adhesive thicknesses were adopted. Furthermore, for a specific case of 0.2 mm of adhesive thickness, two different conditions were tested for comparison: one where a void was placed in the middle of the overlap ($\varnothing_V = 8$ mm), and another without any artificial void. Finally, the PSA joints were broken by hand, and the electrical impedance of the instrumented substrate was measured.

Specimen manufacturing

SLJ specimens were manufactured for both **Papers B & C**, with their geometry defined in Figure 3.4. Note that some SLJ dimensions varied.

In **Paper B**, the adhesive thickness, t_A , was altered, such that, $t_A \in \{0.2, 0.5, 1.0\}$ mm. This was done to see if changes in the electrical impedance spectra occur with alteration of adhesive thickness or material properties. Furthermore, the length of the aluminium substrates, l_S , is of 110 mm.

In **Paper C**, the adhesive layer thickness, t_A , was of 0.2 mm for all SLJ specimens with the Nagase T-836/R-810, while for the SLJ specimens with the PSA, the adhesive thickness, t_A , was 0.2 mm when analysing the presence of damage. Furthermore, for the case of undamaged SLJs with PSA, the thickness was altered, such that $t_A \in \{0.2, 0.4, 0.8\}$ mm. This was done to evaluate if there is an influence of the adhesive thickness in the obtained impedance spectra. For these specimens, the length of the substrates, l_S , is of 97.5 mm.

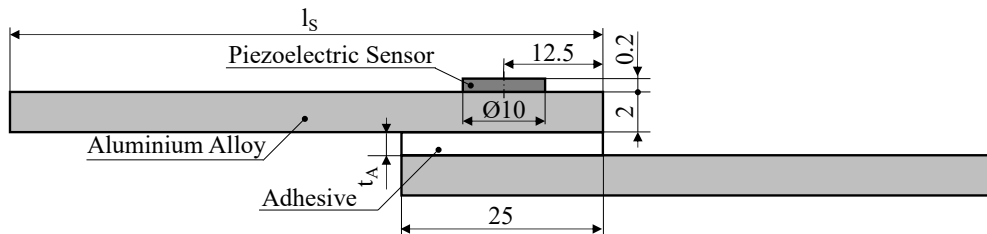


Figure 3.4: Geometry of instrumented SLJ specimens (dimensions in mm).

Initially, surface preparation of the 6082 aluminium alloy substrates was performed. Note that this surface treatment was required for SLJ specimens with either the modified epoxy adhesive or the silicone adhesive. These were initially gritted with sandpaper, and then cleaned with acetone. Afterwards, the anodization process began by submersing the substrates in a aqueous phosphoric acid

solution, with a concentration between 9% and 12% (m/m). An electric current, created by a voltage source of 16 V, passed through the substrates for 25 minutes. These were then removed and cleaned with distilled water and acetone.

With the surface treatment finished, the substrates were placed on a mold and adhesive was spread on the desired overlap area of $25 \times 25 \text{ mm}^2$. To guarantee a well defined and constant adhesive thickness, t_A , shims and calibrated tape were placed on the mold, before adhesive deposition.

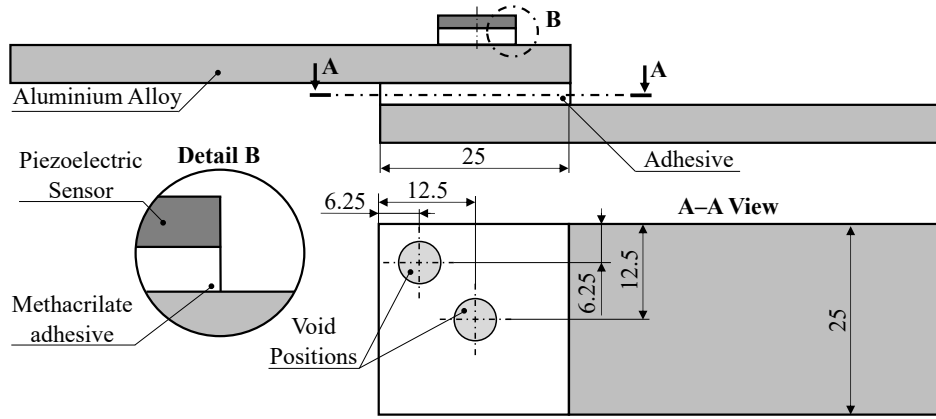


Figure 3.5: Positioning of the artificial voids in the SLJ (dimensions in mm).

Note that, for the case of SLJs with artificial voids, which were manufactured for **Paper C**, an extra step was required. Initially, circular infills were cut from a PTFE sheet with the desired adhesive thickness, which, in the case of the modified epoxy adhesive joints, was $t_A = 0.2 \text{ mm}$. Infills of diameter, $\varnothing_V \in \{4.0, 6.0, 8.0\} \text{ mm}$ were created. These were then fixed on the desired position in the overlap area, as represented in Figure 3.5, with the help of the modified ethyl cyanoacrilate adhesive.

With the mold preparation finished, the mold, with the SLJs, was placed inside a hot-plate press, to perform adhesive curing. For the SLJ specimens with silicone adhesive, manufactured for **Paper B**, the curing cycle was of 120°C at 20 bar, for 25 minutes. For SLJ specimens with modified epoxy adhesive, manufactured for **Papers B & C**, the curing cycle was of 160°C at 20 bar, for 180 minutes.

Conversely, the SLJ specimens with PSA were bonded with previously cut portions of adhesive, and pressure was applied in the overlap area.

Specimen instrumentation

With the manufacture of the SLJ specimens completed, the instrumentation

procedure could begin. Initially, the Plexus MA 422 methacrilate adhesive was placed on top of one of the aluminium substrates, where the overlap is located. Afterwards, a spiral copper wire of 0.2 mm was placed, and the PWAS was placed on top of said copper wire. The methacrilate adhesive cured for 24 hours, as previously mentioned, and, afterwards, a second wire was soldered on the top surface of the sensor.

Experimental procedure

Impedance measurements were done with a Hioki IM 3570 impedance analyzer (Ueda, Japan). The positive crocodile wire was connected to the copper wire soldered onto the upper surface of the piezoelectric sensor, while the negative crocodile was connected to the spiral copper wire placed on the bottom of the PWAS. Note that each crocodile is connected to two wires, as schematically in Figure 2.8, so that the electrical impedance could be computed.

One should note that the Hioki IM 3570 impedance analyzer can perform impedance measurements in a wide range of conditions. The measurement frequency range, which is manually defined by the user, ranges between 4 Hz and 5 MHz, while the voltage supply can be defined with any value between 0.005 V and 5 V.

For **Paper B**, an initial set of experiments were done, where the supply voltage was set to $V \in \{1, 2, 5\}$ V. However, all other experiments in both **Papers B & C** were done under a constant voltage of 1 V. Furthermore, three impedance spectra were directly measured for each specimen:

- In the frequency range $f \in \{1, 1000\}$ kHz, with linearly sampled frequencies;
- In the frequency range $f \in \{1, 1000\}$ kHz, with logarithmic sampled frequencies, and;
- In the frequency range $f \in \{100, 1000\}$ kHz, with linearly sampled frequencies.

Each obtained spectral measurement was stored on a USB pen drive as a comma separated value file. These measurements were then processed by a Python 3 script, in order to convert the electrical impedance from its originally obtained polar coordinates (i.e., magnitude, $|Z_e|$ and phase, $\varphi(Z_e)$), to the respective rectangular coordinates (i.e., real and imaginary components, $\text{Re}(Z_e)$ and $\text{Im}(Z_e)$).

Note that, for **Paper B**, all electrical impedance measurements, Z_e , of instrumented PWAS were done with the lower substrate, i.e., the substrate that is not

instrumented with the PWAS, in contact with a table.

The impedance measurements of the SLJ specimens with the PSA, which were done in **Paper C**, were likewise performed with the lower substrate in contact with a table. However, these were then broken by hand, and the instrumented substrate, which was previously the upper substrate, was used for measurements. In this case, the impedance spectra of the PWAS were obtained for three different conditions:

- The aluminium substrate was on top of a table (hard surface), like in previous cases;
- The aluminium substrate was on top of a foam material (soft surface);
- The aluminium substrate was fixed in one extremity with the help of a clamp, to simulate an encastre. In this part, the substrate was also placed on top of an aluminium material, so that no contact with any other surface occurs. The other extremity of the substrate, where the PWAS is placed, is intended to be free, i.e., without being in physical contact with other surfaces.

Electrical impedance measurements were also performed for SLJs with the modified epoxy adhesive, with two different boundary conditions:

- The lower surface of the SLJ was on top of a table (hard surface);
- Both free ends of the SLJ were fixed with clamps, to simulate encastres. Like in the previous case, the substrates were placed on top of an aluminium material, so that no contact with any other surface occurs, while also guaranteeing that the SLJ remains horizontal.

One must note that the electrical impedance spectra obtained in **Paper C** were then used in **Papers D, E & F**.

Chapter 4

Numerical Details

In this chapter, the main characteristics of the numerical models are presented. In this case, one set of numerical simulations was performed, and are the direct-steady state linear dynamic numerical simulations, which are described in the first section of this chapter. The FEA was performed with the *ABAQUS 2017* software.

4.1 Direct-Steady State Model Definition

In **Papers B & C**, linear perturbation direct-steady state linear dynamic analysis simulations were performed over the frequency range between 1 kHz and 1 MHz, with a linearly spaced frequency interval of 1 kHz, obtaining 1001 frequency sampling points.

The geometric models of the instrumented SLJs were defined by two individual components, which are the PWAS and the SLJ. These two components are then connected by a tie constraint, which means that the bottom surface of the PWAS and the top surface of the Plexus MA 422 methacrilate adhesive are always physically connected for the duration of a simulation. Furthermore, this connection allows for the rapid transition in mesh density between components. These components have the same dimensions that were indicated in section 3.3 and Figures 3.4 and 3.5.

In these simulations, the PWAS element was modeled as an independent component, where the mesh elements used are the piezoelectric type 8-node linear brick and reduced integration elements (C3D8R). These elements have both displacement and electric potential degrees of freedom. The SLJ component, was modeled with three-dimensional stress 8-node linear brick and reduced integration (C3D8R) elements, which are standard volume elements.

In these models, a voltage excitation is created by defining two boundary conditions. One Electric Potential (EPOT) boundary condition is created on the upper circular surface of the PWAS, with a value of $1 + 0j$ V, while a second EPOT boundary condition is created on the lower circular surface, with a value of $0 + 0j$ V. These boundary conditions are equivalent to a voltage signal of 1 V as an oscillatory excitation signal of the PWAS element.

One must note that piezoceramic materials are anisotropic materials. Despite the fact that the manufacturer did not provide relevant material properties to model the PIC 255 piezoceramic material, Krommer et al. [94] provided such properties, which are presented in Table 4.1.

Table 4.1: Electric and mechanical properties of the PIC 255 piezoceramic material used in the numerical model.

Property	Unit	Notation	Value
Elastic Modulus	GPa	E_1	62.89
		E_2	62.89
		E_3	47.69
Shear Modulus	GPa	G_{13}	22.26
		G_{23}	22.26
		G_{12}	23.15
Poisson's Ratio	[—]	ν_{13}	0.46
		ν_{23}	0.46
		ν_{12}	0.36
Permittivity at constant strain	nF m ⁻¹	ϵ_{11}	8.234
		ϵ_{22}	8.234
		ϵ_{33}	7.588
Piezoelectric stress coefficients	C m ⁻²	e_{15}	11.9
		e_{24}	11.9
		e_{31}	-7.15
		e_{32}	-7.15
		e_{33}	13.7
Mass Density	kg m ⁻³	ρ	7800

4.2 Result Extraction

In **Papers B & C**, three different sets of results are extracted from the simulation results: the Reactive Electrical Nodal Charge (RCHG), the stress components in all directions (S11, S22, S33), and the translational velocities in the respective directions (V1, V2, V3).

The obtained simulations enabled one to extract, as a history output, the Re-

active Electrical Nodal Charge (RCHG), which are the simulated charges in the nodes of a given surface. The sum of all nodal charges was extracted for the lower circular surface of the PWAS component, obtaining the equivalent generated electrical charge, $Q(j\omega)$, for each simulated frequency in studied frequency range. The electrical current, $I(j\omega)$, can be defined as the derivative of electrical charge, such that,

$$I = \frac{dQ}{dt}, \quad (4.1)$$

where t stands for time. In the frequency domain, one can relate both, such that, $I(j\omega) = j\omega Q(j\omega)$.

As previously mentioned, the voltage, $V(j\omega)$, is defined as the difference of the electric potential between the upper and lower PWAS surfaces. Hence, one can compute the electrical impedance, $Z_e(j\omega)$, of the piezoelectric component as

$$Z_e(j\omega) = \frac{V(j\omega)}{I(j\omega)} = \frac{1 + 0j}{j\omega Q(j\omega)}. \quad (4.2)$$

In **Paper C**, an approximation of the mechanical impedance, which is defined in equation (2.2), was computed, so as to correlate the mechanical impedance of the SLJ, $Z_{m,s}(j\omega)$, and the electrical impedance of the PWAS, $Z_e(j\omega)$. In this manner, the mechanical impedance was approximated by extracting the average element stress and nodal velocity in the normal direction to the PWAS, which are the average of S22 and V2, respectively, or, in mathematical terms, $\overline{\sigma_{22}}$ and $\overline{\dot{x}_2}$. With this, the mechanical impedance of the SLJ was computed such that

$$Z_{m,s}(j\omega) = \frac{F(j\omega)}{\dot{x}(j\omega)} \approx \frac{\overline{\sigma_{22}} A_{Pl.}}{\overline{\dot{x}_2}}, \quad (4.3)$$

where $A_{Pl.}$ is the cross section of the methacrilate adhesive that is in physical contact with the PWAS.

Chapter 5

Algorithmic Details

This fifth chapter discusses the algorithmic and mathematical approaches adopted herein, to determine if damage can be detected in the adhesive layer, and if information can be extracted from said damage. In this manner, this chapter begins by presenting the damage metrics developed to evaluate EMIS in detecting damage in adhesive joints. Afterwards, a second section presents the ML approaches adopted in this work, relevant mathematical concepts associated with the ML models and the adopted feature extraction procedure.

5.1 Damage Metrics

As per the literature review of **Paper A**, damage metrics are widely adopted in EMIS-based research, to detect damage in structures and to quantify the sensitivity of the SHM method to said damage. In this manner, various damage metrics were used in **Paper D**.

Conventional damage metrics

A first set of metrics, which have been proposed by various researchers and are presented in **Paper A**, were adopted. The first, which is the most widely used damage index in EMIS, is the Root Mean Square Deviation, $RMSD$, and is defined as

$$RMSD = \sqrt{\frac{\sum_{i=f_i}^{f_f} (\text{Re}(Z_e) - \text{Re}(Z_e^0))^2}{\sum_{i=f_i}^{f_f} \text{Re}(Z_e^0)^2}}, \quad (5.1)$$

where $\text{Re}(Z_e)$ and $\text{Re}(Z_e^0)$ are the real components of the impedance signal being

evaluated, and of the reference measurement, respectively. Furthermore, f_i and f_f stand for the initial and final ordinary frequencies of the measured spectra, and are correlated with their respective angular frequencies, such that

$$\omega = 2\pi f.$$

This metric can be viewed as a normalized Euclidean norm (L_2 -space) [95, 96]. Note that the obtained results for this metric, which are present in **Paper D**, are also used for comparison with the results of **Paper E**.

While the *RMSD* metric is widely used in studying the applicability of EMIS in damage detection of adhesive joints, other metrics, that compare impedance spectra, exist and enable damage detection. These are the Mean Absolute Percentage Deviation, *MAPD*, and the Correlation Coefficient, *CC*, which are defined as

$$MAPD = \frac{1}{N} \sum_{i=f_i}^{f_f} \left| \frac{\text{Re}(Z_e) - \text{Re}(Z_e^0)}{\text{Re}(Z_e^0)} \right| \quad (5.2)$$

$$\begin{aligned} CC &= \frac{\text{Cov}(\text{Re}(Z_e), \text{Re}(Z_e^0))}{\sigma[\text{Re}(Z_e)] \sigma[\text{Re}(Z_e^0)]} = \\ &= \frac{1}{N} \frac{\sum_{i=f_i}^{f_f} (\text{Re}(Z_e) - E[\text{Re}(Z_e)]) (\text{Re}(Z_e^0) - E[\text{Re}(Z_e^0)])}{\sqrt{\sum_{i=f_i}^{f_f} (\text{Re}(Z_e) - E[\text{Re}(Z_e)])^2 \sum_{i=f_i}^{f_f} (\text{Re}(Z_e^0) - E[\text{Re}(Z_e^0)])^2}}, \end{aligned} \quad (5.3)$$

where N is the number of acquired samples, while $E[\text{Re}(Z_e^0)]$ and $E[\text{Re}(Z_e)]$ stand for, respectively, the mean value of the measured electric impedance from both the reference pristine joint and the joint under evaluation. Furthermore, $\sigma[\text{Re}(Z_e)]$ and $\sigma[\text{Re}(Z_e^0)]$ are the standard deviation of both aforementioned impedance signals.

The Mean Absolute Percentage Deviation, *MAPD*, is a metric that averages the deviations of $\text{Re}(Z_e)$ at all sampled frequencies [95]. However, given its mathematical formulation, this metric can also be viewed as an averaged and normalized Manhattan distance (L_1 -space) damage index [96].

The Correlation Coefficient, *CC*, is based on the Covariance function, *Cov*, and evaluates the relationship between two impedance signatures, determining whether these two impedance datasets resemble each other. If both signatures peak at the same frequency, then the Covariance is positive. Conversely, if the peak of a dataset is placed where the valley of the other dataset is, then the obtained Covariance is negative. If both signatures are unrelated, then Covariance tends to be null. The *CC* reflects this same pattern, but the value is normalized so that *CC* nears

1 when both signatures are similar, and is equal to -1 when they are opposite to each other [97].

While the indices, presented in equations (5.1), (5.2) and (5.3), are the most important metrics for EMIS-based damage detection, other indices do exist. One such example is the Modified Root Mean Square Deviation, $mRMSD$, which is defined as

$$mRMSD = \sum_{i=f_i}^{f_f} \sqrt{\frac{(\text{Re}(Z_e) - \text{Re}(Z_e^0))^2}{\text{Re}(Z_e^0)^2}}, \quad (5.4)$$

and is usually misidentified as $RMSD$ [98, 99]. Because of this mislabelling, this metric is not presented in **Paper A**. Indeed, this modified metric is similar to the $MAPD$. However, no average is performed, since the summation is not divided by the number of sampled frequencies, N , conversely to equation (5.2). Therefore, this damage metric pertains to the family of metrics inspired by the Euclidean distance (L_2 -space), corresponding to the Pearson χ^2 divergence [100].

Proposed damage metrics

New mathematical damage metrics were proposed in **Paper D**, such as the Averaged Canberra Distance, ACD , which is defined as

$$ACD = \frac{1}{N} \sum_{i=f_i}^{f_f} \frac{|\text{Re}(Z_e) - \text{Re}(Z_e^0)|}{|\text{Re}(Z_e)| + |\text{Re}(Z_e^0)|}. \quad (5.5)$$

This metric is based on the Canberra Distance, which is used in data quantification, especially for data that is scattered near zero, given that it is sensitive to small values [100, 101].

Given the findings of Bhalla et al. [82] on the applicability of the active component of the impedance, which is more sensitive to structural changes, the passive component was removed, as defined in equation (2.4a), yielding only the active component. This component is presented as an admittance (inverse of impedance) in equation (2.4b). In this manner, the active component of the electrical impedance is designated by $Z_{e,A}$. With this, other metrics were also proposed in **Paper D**, such as the Complex Root Mean Square Deviation index, $cRMSD$, which make use of this active impedance. This is an extension of the classical

RMSD damage metric, and is defined as

$$cRMSD = \sqrt{\frac{\sum_{i=f_i}^{f_f} (\text{Re}(Z_{e,A}) - \text{Re}(Z_{e,A}^0))^2}{\sum_{i=f_i}^{f_f} \text{Re}(Z_{e,A}^0)^2}} + \sqrt{\frac{\sum_{i=f_i}^{f_f} (\text{Im}(Z_{e,A}) - \text{Im}(Z_{e,A}^0))^2}{\sum_{i=f_i}^{f_f} \text{Im}(Z_{e,A}^0)^2}}, \quad (5.6)$$

which is the sum of two individual *RMSD* metrics, one using the real components of the active impedance from the evaluated and pristine SLJs, $\text{Re}(Z_{e,A})$ and $\text{Re}(Z_{e,A}^0)$, respectively, and another using the imaginary component of said impedances, $\text{Im}(Z_{e,A})$ and $\text{Im}(Z_{e,A}^0)$.

An alternative to the Correlation Coefficient was proposed to encompass the real and imaginary components of the active impedance, $Z_{e,A}$. This complex Correlation Coefficient, *cCC*, is defined as

$$cCC = \frac{1}{2} \left[\frac{\text{Cov}(\text{Re}(Z_{e,A}), \text{Re}(Z_{e,A}^0))}{\sigma[\text{Re}(Z_{e,A})] \sigma[\text{Re}(Z_{e,A}^0)]} + \frac{\text{Cov}(\text{Im}(Z_{e,A}), \text{Im}(Z_{e,A}^0))}{\sigma[\text{Im}(Z_{e,A})] \sigma[\text{Im}(Z_{e,A}^0)]} \right], \quad (5.7)$$

which are simply the sum of two Correlation Coefficients, one that compares the real component of the impedance, and another that compares the imaginary impedance component. Here, the standard deviations of the real and imaginary components of the active electrical impedance of the pristine joint, $\sigma[\text{Re}(Z_{e,A}^0)]$ and $\sigma[\text{Im}(Z_{e,A}^0)]$, respectively, as well as of the bonded joint under evaluation $\sigma[\text{Re}(Z_{e,A})]$ and $\sigma[\text{Im}(Z_{e,A})]$, respectively, must be computed. Since the summed components yield a value between -2 and 2 , the resultant summation is divided by 2 , so as to have a comparison with the *CC* metric of equation (5.3).

A third proposed metric using both the active resistance and reactance components is the Normalized Complex Euclidean Distance, *NCED*, such that

$$NCED = \sqrt{\frac{\sum_{i=f_i}^{f_f} [(\text{Re}(Z_{e,A}) - \text{Re}(Z_{e,A}^0))^2 + (\text{Im}(Z_{e,A}) - \text{Im}(Z_{e,A}^0))^2]}{\sum_{i=f_i}^{f_f} [\text{Re}(Z_{e,A}^0)^2 + \text{Im}(Z_{e,A}^0)^2]}}. \quad (5.8)$$

This damage index is an alternative proposal of an Euclidean based damage metric, where the normalization is done with the complex active impedance of the damageless adhesive joint.

5.2 Machine Learning Models

In **Papers E & F**, two different ML approaches are implemented. In **Paper E**, an unsupervised ML approach is used, based on the MDS model. Conversely, **Paper F** uses various k NN models, which are supervised ML models, to relate information from the obtained measurements with the respective damage source.

These will be explained in this section. It is noted that both models make use of distances, and, as such, an initial subsection will present the various distances used in this research.

5.2.1 Distance Functions

Both MDS and k NN models make use of distances for dimensionality reduction and classification, respectively. In this manner, various distances were used in both models, which need to verify certain conditions in order to be called as *distances*. Consider a set X with elements A, B, C , such that $\{A, B, C\} \in X$. Function d is a valid distance of set X , if three conditions are verified:

- Non-negativity, $d(A, B) \geq 0$;
- Reflexivity (or identity of indiscernibles), $d(A, B) = 0$, if, and only if $A = B$;
- Symmetry, $d(A, B) = d(B, A)$.

All distances used in both types of ML approaches guarantee these three properties [102].

In **Paper E**, four distances, $\{d_A, d_C, d_E, d_M\}$, are adopted to measure the dissimilarity between two different instances of measurements. Conversely, **Paper F** made use of only three distances, $\{d_C, d_E, d_M\}$, to compute the nearest instances for classification. These distances are computed for each pair of measurements i and k , such that

$$[\text{Re}(Z_{e,i}(j\omega_1)), \text{Re}(Z_{e,i}(j\omega_2)), \dots, \text{Re}(Z_{e,i}(j\omega_f)), \dots, \text{Re}(Z_{e,i}(j\omega_n))]^T$$

$$[\text{Re}(Z_{e,k}(j\omega_1)), \text{Re}(Z_{e,k}(j\omega_2)), \dots, \text{Re}(Z_{e,k}(j\omega_f)), \dots, \text{Re}(Z_{e,k}(j\omega_n))]^T,$$

where $\text{Re}(Z_{e,i}(j\omega_f))$ and $\text{Re}(Z_{e,k}(j\omega_f))$ are the real component of the measured electrical impedance from measurements i and k at the sampled frequency ω_f , where $f \in \{1, 2, \dots, n\}$. The aforementioned distances are the Arccosine distance, d_A , the Canberra distance, d_C , the Euclidean distance, d_E , and the Manhattan

distance, d_M , and are defined by

$$d_A = \arccos \left(\frac{\sum_{f=1}^n \operatorname{Re}(Z_{e,i}(j\omega_f)) \operatorname{Re}(Z_{e,k}(j\omega_f))}{\sqrt{\sum_{f=1}^n \operatorname{Re}(Z_{e,i}(j\omega_f))^2} \sqrt{\sum_{f=1}^n \operatorname{Re}(Z_{e,k}(j\omega_f))^2}} \right) \quad (5.9)$$

$$d_C = \sum_{f=1}^n \frac{|\operatorname{Re}(Z_{e,i}(j\omega_f)) - \operatorname{Re}(Z_{e,k}(j\omega_f))|}{|\operatorname{Re}(Z_{e,i}(j\omega_f))| + |\operatorname{Re}(Z_{e,k}(j\omega_f))|} \quad (5.10)$$

$$d_E = \sum_{f=1}^n [\operatorname{Re}(Z_{e,i}(j\omega_f)) - \operatorname{Re}(Z_{e,k}(j\omega_f))]^2 \quad (5.11)$$

$$d_M = \sum_{f=1}^n |\operatorname{Re}(Z_{e,i}(j\omega_f)) - \operatorname{Re}(Z_{e,k}(j\omega_f))|. \quad (5.12)$$

5.2.2 Feature Selection & Dataset Pre-processing

It is common to perform pre-processing of the dataset in ML. This may mean some transformation of the domain of the input information, (e.g. Z -score normalization, Min-max scaling normalization, etc.), or a feature selection procedure.

For **Paper E**, no feature selection process was done. Some initial data normalization procedures were done, but the obtained results were similar to the ones presented in said paper. In other words, no gain was obtained with such procedures, in the reduced space *maps*.

For **Paper F**, a feature selection routine was created, to avoid the *Curse of Dimensionality* [103]. This means that, if the directly obtained spectra was used as input in a generic ML model, the complexity of the generic model must be forcibly greater, so that pattern learning can be possible, resulting in excessive computational power for the task at hand. Therefore, this feature selection procedure was separated into two steps: (i) measurement uniformization in a frequency range, and, (ii) peak extraction from the real component of the impedance measurements, $\operatorname{Re}(Z_e)$.

For the first step, all of the experimental measurements were processed, with the goal of obtaining several spectra from 1 kHz to 1 MHz. In this manner, the following experimental measurements can be used in the aforementioned methodology:

- $f \in \{1, 1000\}$ kHz, with 801 linearly spaced sampled frequencies, and;

- $f \in \{1, 1000\}$ kHz, with 801 logarithmic spaced frequencies.

These two sets of measurements contribute with 42 effective instances, but more information is presented in the linearly sampled impedance measurement in the range of $f \in \{100, 1000\}$ kHz. Therefore, various combinations of the three experimental spectra were done, such as:

- The combination of the linearly spaced impedance measurements in the range of $f \in \{1, 1000\}$ kHz, and the logarithmically spaced impedance measurements in the same frequency range;
- The combination of the linearly spaced impedance measurements in the range of $f \in \{1, 1000\}$ kHz, with the linearly spaced impedance measurements in the range of $f \in \{100, 1000\}$ kHz;
- The combination of the logarithmically spaced impedance measurements in the range of $f \in \{1, 1000\}$ kHz, with the linearly spaced impedance measurements in the range of $f \in \{100, 1000\}$ kHz, and;
- The combination of all three experimentally obtained impedance spectra.

With this, a total of 126 instances are obtained. Afterwards, the peak extraction process began by performing an iterative process of extracting the peak information. For this, a SciPy module function [104] initially extracted the peaks of $\text{Re}(Z_e)$ with a height of, at least 10Ω , a minimum width of 2 sampled points, and a prominence of 0Ω , and then the height and prominence values were iteratively incremented, until reaching the desired n number of peaks, where $n \in \{3, 20\}$ or $n \in \{3, 25\}$, depending on the task.

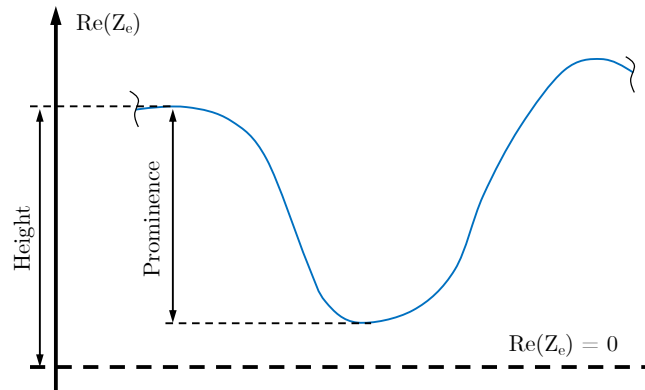


Figure 5.1: Schematic representation of the difference between height and prominence.

Note that height is the vertical distance between the peak value and the reference value of no resistance, i.e., $\text{Re}(Z_e) = 0\ \Omega$, while the prominence is the vertical distance between that same peak and the lowest contour line, i.e., the local minimum between the peak being extracted, and the higher peaks on both sides, as represented in Figure 5.1. If the list of extracted resistive peaks has a smaller number of peaks than the manually inputted value, the width criterion becomes lax, and the peak extraction routine reruns, in order to find all peaks with a minimum width of 1 sampled point. Afterwards, with this initial list of peaks, the minimum required height and prominence values are iteratively incremented, until reaching the desired number of peaks, as initially defined.

In this case, the direct measurements have 801 sampled frequencies, while the combination of measurements have more sampled frequencies. Therefore, for **Paper F**, a range of computational experiments were performed, thus extracting between 3 and 25 resistive peaks, and their respective frequencies. In mathematical terms, $n \in \{3, 25\}$. Note that, for damage detection, no more than 20 peaks were extracted, since more peaks did not lead to any change in classification performance, or, mathematically speaking, $n \in \{3, 20\}$.

5.2.3 Multidimensional Scaling

High-dimensionality datasets are of hard comprehension. While two or three-dimensional plots can show the inherent data structure, higher dimension plots are less intuitive to humans. Therefore, to assist in data structure visualization, the dataset dimensionality needs to be reduced. One approach would be to take a random projection of the data. While this allows for some degree of understanding, the randomness of the choice may not yield any relevant information. Furthermore, some loss of information will always be inevitable.

Another approach is to use manifold learning, which is a set of non-linear dimensionality reduction methods. These methods are based on the fact that the high dimensionality of a dataset is only artificial. Manifold learning generalizes linear frameworks, thus becoming sensitive to non-linear structure in data. This is an unsupervised method that learns the high-dimensional structure of the data, without predetermined classifications.

One such manifold learning method is the MDS model. MDS seeks to compute a low-dimensional representation of a dataset that is originally of high dimension, and where the final distances between instances respect, as best as possible, the distances observed in the original space. In this manner, MDS is used to analyze the similarity or dissimilarity of data [105].

As previously stated, this is an unsupervised ML model, which means that the

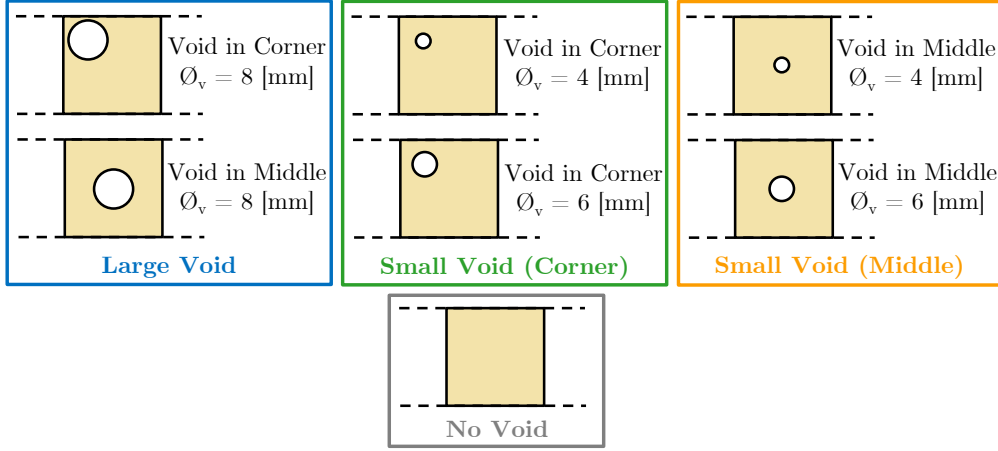


Figure 5.2: Separation of data instances for the MDS approach.

obtained output will always be the same for the same set of inputs, regardless of any possible classification. Nonetheless, one should correlate all points in the reduced dimensionality space with their respective classes, so that data visualization becomes more intuitive. In this manner, the results obtained with the MDS approach followed the classification identified in Figure 5.2.

Mathematical basis of MDS

The MDS starts computing the initial dissimilarities between all pairs of M data instances. Therefore, for instances i and j , one obtains the dissimilarity, δ_{ij} , in the initial m -dimensional space, where $m > 3$, and where each axis of this higher dimension space corresponds to a feature axis. These dissimilarities are then inserted to the matrix of dissimilarities $\Delta = [\delta_{ij}]$, of $M \times M$ dimensions.

In the MDS approach, three properties are observed, which are identical to the properties that define a distance:

- Non-negativity, $\delta_{ij} \geq 0$;
- Reflexivity (or identity of indiscernibles), $\delta_{ii} = 0$;
- Symmetry, $\delta_{ij} = \delta_{ji}$. This means that matrix Δ is symmetric with a principal diagonal of zeros.

Furthermore, a fourth property is observed, which is:

- Triangle inequality, $\delta_{ik} \leq \delta_{ij} + \delta_{jk}$.

After computing the dissimilarities, the model assigns each instance in the $\mathbb{R}^m$ space and tries to estimate its coordinates in a new $\mathbb{R}^r$ space, where $r < m$. This is done in such a manner that the final distances between instance i and all other instances are as close as possible to the ones observed in the initial $\mathbb{R}^m$ space. In other words, the MDS model tries to approximate the initial and final dissimilarities.

In order to obtain a final $\mathbb{R}^r$ space similar to the $\mathbb{R}^m$ space, MDS uses an iterative algorithm that evaluates the configuration obtained in $\mathbb{R}^r$, by minimizing a loss function. Usually this loss function is the raw stress, σ_r , which is defined as

$$\sigma_r = \sum_{i,j=1}^M [d_{ij} - f(\delta_{ij})]^2, \quad (5.13)$$

where δ_{ij} and d_{ij} stand for, respectively, the dissimilarity between instances i and j in the original space, and the distance between said elements in the reduced dimensionality space. Furthermore, $f(\cdot)$ represents some transformation.

However, if one wishes to compare the performance of each distance on the MDS model, one needs to normalize the raw stress. To achieve this, one may compute the Stress-1, σ_1 , which is defined as

$$\sigma_1 = \sqrt{\frac{\sigma_r}{\sum_{i,j=1}^M d_{ij}^2}} = \sqrt{\frac{\sum_{i,j=1}^M [d_{ij} - f(\delta_{ij})]^2}{\sum_{i,j=1}^M d_{ij}^2}}, \quad (5.14)$$

Note that usually, $r = 2$ or $r = 3$, meaning that the final r -dimensional domain is a two or three dimensional space, so that one can visualize the final results in a *map* or plot. The obtained model performs a comparison between the data instances, one can rotate, translate or zoom the final *map*, since the distances the data points remain identical, in either absolute or relative terms.

One can evaluate the final performance of the MDS model with the help of stress or Shepard plots. The stress plot shows the obtained raw stress, σ_r , or Stress-1, σ_1 , with the number of r dimensions, and should decrease with the increase of dimensionality, as exemplified in Figure 5.3. The Shepard plot compares d_{ij} and δ_{ij} for a given dimension r . In this manner, if one observes a narrow scatter of points near the 45° line, then a good fit between the initial dissimilarities, δ_{ij} , and the final distances in the reduced space, d_{ij} , is obtained [101, 105, 106, 107]. An exemplary Shepard plot is presented in Figure 5.4.

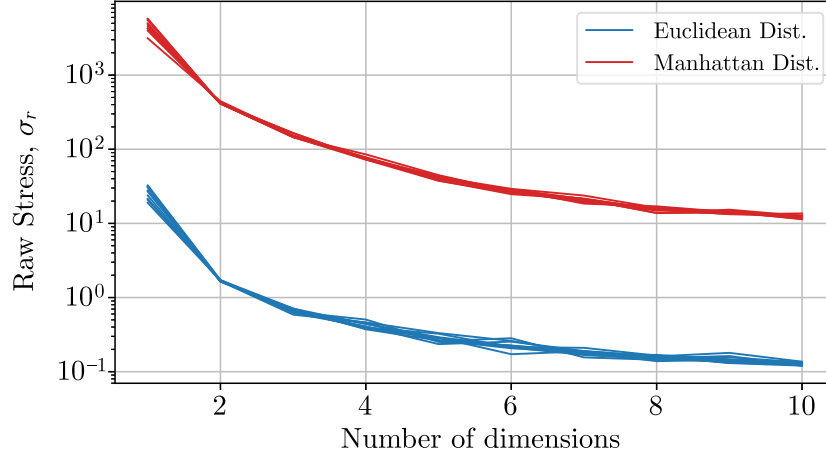


Figure 5.3: Exemplary raw stress, σ_r , plot comparing the performance of various distances.

Distance-based damage classification in the MDS reduced space

Traditional damage detection in SHM may use damage metrics, such as the ones presented in section 5.1, in which one compares the spectrum from a structure under evaluation with a spectrum from a reference structure.

Conversely, by using the MDS model, one is inherently comparing all spectra at the same time. This occurs since the model tries to transpose the original dissimilarities onto the reduced space and, as such, the final co-domain space can yield results regarding the detection and classification of damage. Therefore, in **Paper E**, an algorithm based on the distances between measurement instances is proposed.

Initially, the MDS algorithm performs the task of dimensionality reduction from an initial space that contains the electrical impedance measurements as points, and the dissimilarities are computed. With the reduced dimensionality *map*, a reference needs to be used for comparison. In this manner, the centroid of the cluster containing all instances from undamaged SLJs is calculated, which is done by calculating the average coordinates of all points corresponding to undamaged joints.

Afterwards, the distances between the obtained centroid reference and each dataset points are calculated. Given that humans can better understand the concept of Euclidean distances for dimensional spaces of low dimensions (i.e, two or three-dimensional spaces), the Euclidean distance, d_E , defined in equation (5.11), is used as a *damage metric*, to identify if there is damage, and to classify the type

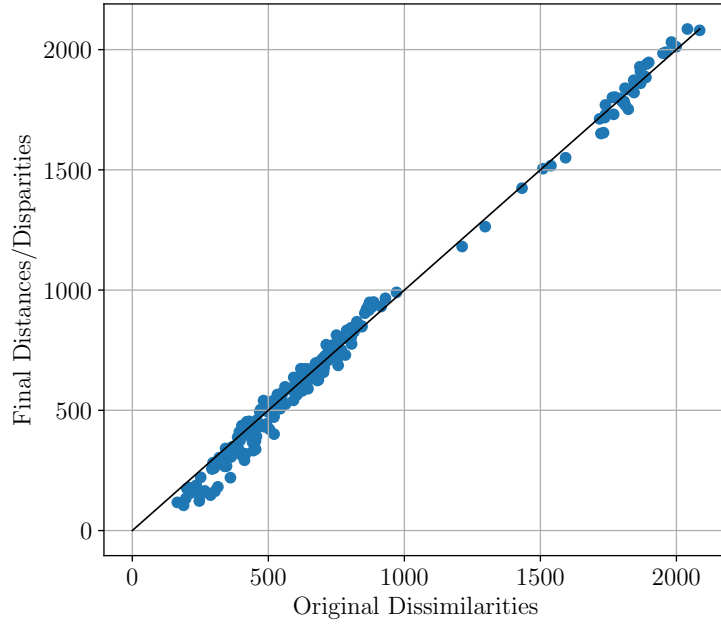


Figure 5.4: Exemplary Shepard plot comparing the initial dissimilarities with the final distances.

of damage.

5.2.4 k -Nearest Neighbors

In **Paper F**, a k NN classification model was used as the supervised ML approach and performed two different tasks, thus requiring two different classifications, as exemplified in Figure 5.5. Firstly, it is used to perform the damage detection task, thus separating all instances into two different classes: the *No Void*, and the *Void* classes, which correspond to measurements from joints without damage, and with a void in the overlap, respectively.

In the second approach, damage differentiation was performed, which is a multiclassification task of labeling the type of void being detected. Here, three different classes exist, where the classes *Small Voids (Corner)* and *Small Voids (Middle)* contain impedance readings from joints with voids of diameter of 4.0 or 6.0 mm, either in the corner or in the middle of the overlap, respectively. The class *Large Voids* contains measurements from SLJs with an 8.0 mm diameter void that is placed either in the middle, or in the corner of the overlap. Note that the instances from the *No Void* class are disregarded for this second task.

In **Paper F**, two different algorithmic methodologies were adopted. The first approach made use of the conventional k NN model, while the second one consists

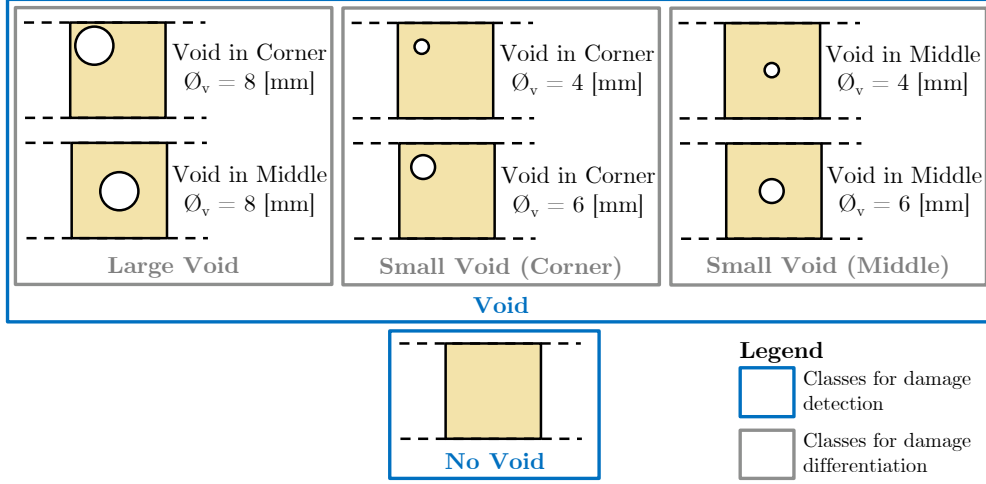


Figure 5.5: Separation of data instances for the two classification tasks.

in using a parallel (or ensemble) k NN approach.

Conventional k NN model

In this first approach, n peaks are extracted and joined to create an array of peaks for a specific measurement instance k , such that

$$[\text{Re}(Z_{e,k})_1, f_{k,1}, \text{Re}(Z_{e,k})_2, f_{k,2}, \dots, \text{Re}(Z_{e,k})_i, f_{k,i}, \dots, \text{Re}(Z_{e,k})_N, f_{k,N}],$$

where $\text{Re}(Z_{e,k})_i$ and $f_{k,i}$ correspond, respectively, to the i -th extracted resistive peak of the impedance measurement, and to its respective frequency. Note that n is the number of extracted peaks, such that $n \in \{3, 25\}$ (or $n \in \{3, 20\}$ for damage detection), as previously mentioned, and i is one of the n extracted peaks, such that $i \in \{3, n\}$.

The dataset was divided into a training subset, which contains 75% of the original dataset, while the testing subset contains the remaining instances. Note that this dataset separation was stratified, i.e., the dataset splitting into training and testing subsets was done so that the relative proportion of classes was maintained, given the large unbalance between classes. From this, the training subset is inputted to the k NN model, which is stored for posterior classification. Afterwards, each element of the testing subset is inputted to the k NN model, which will determine the k nearest instances from the training subset. With this, the testing instance will be classified according to a majority vote. If a tie occurs, the model defines the class of the testing instance [103]. Figure 5.6 schematically presents the aforementioned algorithmic method.

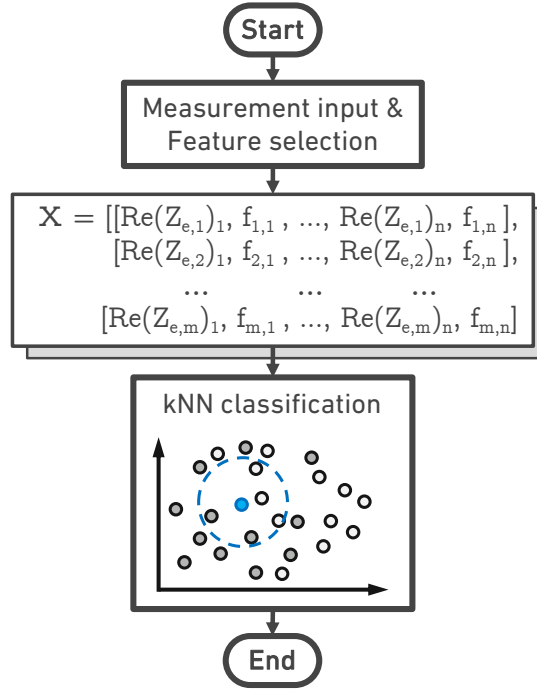


Figure 5.6: Simplified flowchart describing the conventional k NN model.

Parallel k NN model

The second k NN-based classification model developed in this research starts in the definition of the features instances. Much like in the conventional k NN model, the same n peaks, and their respective frequencies, are extracted from the real component of the impedance spectra. However, the extracted information is stored in a list of sub-arrays containing the information of peak i , or, in mathematical terms,

$$[(\text{Re}(Z_{e,k})_1, f_{k,1}), (\text{Re}(Z_{e,k})_2, f_{k,2}), \dots, (\text{Re}(Z_{e,k})_i, f_{k,i}), \dots, (\text{Re}(Z_{e,k})_n, f_{k,n})],$$

where $n \in \{3, 25\}$, (or $n \in \{3, 20\}$) $i \in \{3, n\}$, and where $\text{Re}(Z_{e,k})_i$ and $f_{k,i}$ are the i -th extracted resistive peak of measurement k , and the respective frequency. Similarly to the previous case, 75% of the original dataset is separated into the training subset, while the remainder is stored in the testing subset.

With this, the k NN model is initialized for classification. However, unlike in the previous case, where only one model is instantiated, n models are instantiated, one for each extracted peak. In this manner, the first k NN model is initialized with the first sub-array of extracted peaks from all instances of the training subset, and then, each of the first sub-array of the testing subset is given to said k NN

algorithm for classification. Afterwards, the same procedure is done for the second set of sub-arrays, corresponding to the second extracted peak, and so on, until reaching the n -th peak, and respective set of sub-arrays. Figure 5.7 presents this second algorithmic method. Note that, when there is a tie in the ensemble classification, the closest peak is extracted from all individual k NN models, and a second ensemble-based classification is determined according to the classes of said instances.

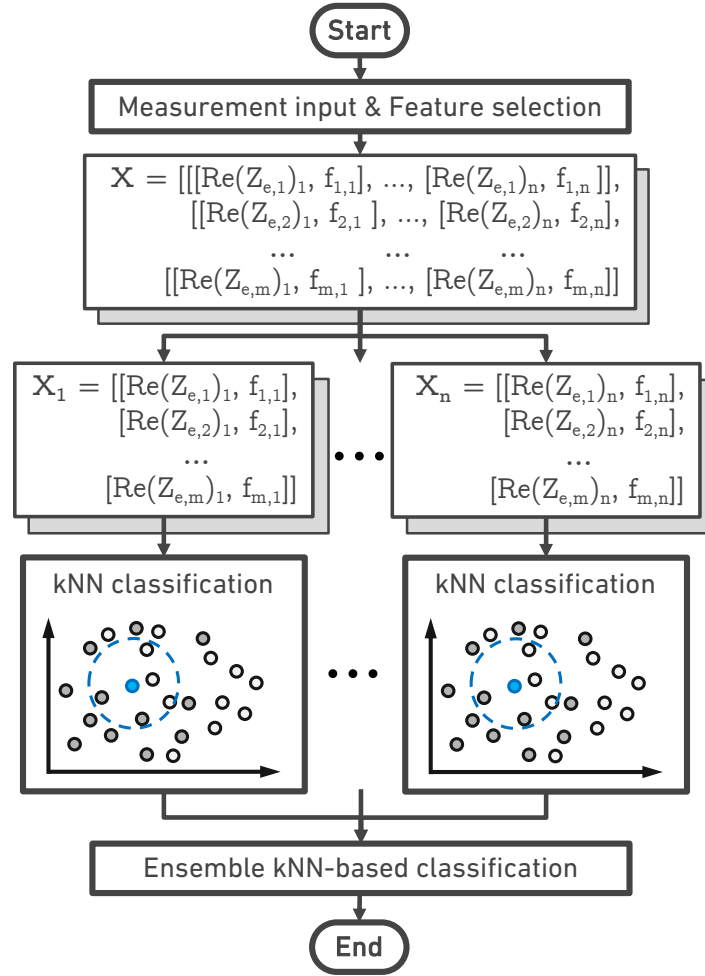


Figure 5.7: Simplified flowchart describing the parallel k NN model.

Chapter 6

Conclusions and Future Work

This work is a combination of the five tasks, as established in chapter 1 of this thesis. This chapter discusses the obtained conclusions of this research work, and presents future topics of research.

6.1 Conclusions

The conclusions are presented in this first section, and are divided in two sections: *(i)* conclusions from the EMIS physical method, and; *(ii)* conclusions from the EMIS-based SHM characterization of damage.

Conclusions from the EMIS physical method

Elastic and damping properties of adhesives (modified epoxy and silicone adhesives), obtained with the VCBT results for a low range of excitation frequencies, enable one to understand the overall trend for the range of excitation frequencies used in EMIS testing.

For small AC voltage excitation signals, the PWAS elements, which are connected to the adhesive joint being inspected, maintain the same impedance spectra. Therefore, PWAS act as linear electric element. However, the fragmentation of PWAS, which may occur during the instrumentation procedure, will result in changes of the obtained electrical impedance.

For modified epoxy adhesive SLJs, an increase of adhesive thickness results in a decrease of the real component subpeaks of the measured impedance, for low frequencies (i.e., below 100 kHz), while also performing an amplitude increase of the the main resistive peaks observed above 100 kHz. These changes may occur due to the alterations of stiffness and, more importantly, of damping, which are

caused by the increase of adhesive thickness.

For silicone adhesive SLJs, the same increase in adhesive thickness also translates in the amplitude decrease of the real component subpeaks of the impedance for low frequencies. However, no clear trend exists regarding the main resistive peaks at high frequencies. This may be caused by the possible presence of a high amount of porosities, which is common with this type of adhesives.

Numerical simulations of both silicone and modified epoxy adhesive SLJs show that the simulated spectra have similar trends and shape to the experimental results. The change in simulated spectra is little, regardless of the change of adhesive material or adhesive thickness. This may be due to the fact that direct steady-state linear perturbation numerical models require the input of constant elastic and damping properties, which is not the case for such a wide range of excitation frequencies.

A similar trend was noticed with experimentally obtained impedance spectra of SLJs with PSA. However, in this case, the changes in electrical impedance were very small throughout the entire frequency range.

Impedance measurements from the instrumented substrate (from broken SLJ specimens with PSA) revealed that there are more resistive subpeaks present in lower studied frequency range, i.e., below 200 kHz, than the impedance spectra from SLJs. Furthermore, these subpeaks may be more pronounced if no boundary conditions exist. A similar trend was observed for both free-free and fixed-fixed SLJ specimens.

The presence of void in modified epoxy adhesive joints do alter impedance spectra, with both significant changes in either the resistive subpeaks observed at lower frequencies, and the main peaks at higher frequencies. However, no clear trend exists with either void size or void placement, and the respective changes in peaks.

Influences in the obtained impedance spectra may be due to three possible factors: *(i)* the presence of the artificially created damage, *(ii)* the appearance of a second unwanted source of damage, which was caused during the manufacture of SLJ with voids, or *(iii)* the fact that the methacrilate adhesive is manually mixed, thus having a wider range of properties than initially proposed. These factors have greater influence in the experimental impedance spectra, thus being harder to quantify in numerical models.

Conclusions from the EMIS-based SHM characterization of damage

Conventional damage metrics, such as the Root Mean Square Deviation, $RMSD$, Mean Absolute Percentage Deviation, $MAPD$, or the Modified Root Mean Square Deviation $mRMSD$, that compare an impedance spectrum from a SLJ under evaluation with an impedance spectra from a reference SLJ, enable the detection of damage. However, damage detection with the Correlation Coefficient metric, CC , is comparatively harder. Such a task is highly influenced by the range of frequencies being examined, and the sampling method. For instance, metrics calculated from logarithmically sampled impedance spectra in the frequency range, $f \in \{1, 1000\}$ kHz present better results than the linearly sampled impedance spectra in the frequency range, $f \in \{100, 1000\}$ kHz.

The Average Canberra Distance metric, ACD , proposed in this work, which makes use of the fact that the Canberra distance allows for a better distinction between elements near themselves, enabled an improvement in damage detection, since less overlap between damaged and undamaged instances occurred.

Proposed damage metrics that make use of the active electrical impedance, $Z_{e,A}$, such as the Complex Root Mean Square Deviation and the Normalized Complex Euclidean Distance metrics, $cRMSD$ and $NCED$, respectively, enabled a significant improvement in damage detection. However, this could only be verified with confidence for higher frequencies, since, for lower frequencies, the real component of the active impedance, $\text{Re}(Z_{e,A})$, yielded negative values. This can only be explained by the fact that the electrical properties of the PWAS change with frequency.

In a second approach, the real component of the measured impedance, $\text{Re}(Z_e)$, was directly used as inputs of a MDS model, which is an unsupervised ML model that performs dimensionality reduction. Therefore, by constructing a three-dimensional *map* that maintains all distances between instances, one can better visualize the obtained patterns. From this, one can differentiate between damaged and undamaged instance, or the type of void being detected.

Damage detection and distinction between the void size and placement was obtained with the reduced three-dimensional spaces, obtained with either the linearly sampled measurements in the frequency range of $f \in \{1, 1000\}$ kHz, or with the logarithmically sampled measurements of the same frequency range. Conversely, there is some overlap between classes, when using the linearly sampled measurements in the frequency range of $f \in \{100, 1000\}$ kHz, which means that there is less relevant information for damage detection in this spectral region.

Furthermore, MDS pattern results show that there is a clear difference between large voids in the overlap, regardless of where it is placed, and small voids in the corner of the overlap, with small voids in the middle of the overlap being somewhat similar to the other two types of instances, given that they tend to neighbor both simultaneously. MDS also enabled the detection of outlier instances, which were previously identified with *RMSD* metric results.

In certain cases, the Euclidean distance between a centroid of all undamaged instances and all measurement instances, in the MDS space, enabled not only the clear differentiation between damaged and undamaged instances, but also the differentiation between the three defined classes of void. Furthermore, this distance-based classification was done without much scatter, meaning that there was considerably less overlap between classes, when compared to the damage metric results.

A k NN model, which is a supervised ML model, was also used to detect and localize damage in the adhesive layer. For this specific case, a feature selection process was developed, such that the n most prominent peaks were extracted from the measurements. These were then inputted into two different k NN architectures, the first being the conventional model architecture, which consists of only one model that compares the entire instance. The second architecture consists of using n k NN models, one per extracted resistive impedance peak, thus performing an ensemble classification, or parallel classification.

Damage detection and quantification can be performed with both algorithmic approaches, with the conventional approach having greater accuracy in the studied hyper-parameter space of n extracted peaks, and k neighbors used for classification. Conversely, the parallel approach has a greater accuracy for low number of k neighboring instances. Furthermore, damage detection and classification with both model approaches is comparatively more accurate when using the Canberra distance, when compared to the same models that use either the Euclidean or Manhattan distances.

6.2 Future Work

While much has been studied, this work can be continued and complemented with other approaches, so that additional topics of this research can be better understood, and so that more information on this SHM method can be obtained. These have been divided into three different subtopics: *(i)* influence of different parameters on EMIS spectra; *(ii)* extension of EMIS on the detectability of damage and; *(iii)* algorithmic development on the EMIS-based adhesive joint monitoring.

Influence of different parameters on EMIS spectra

A first set of studies can be performed regarding the obtained EMIS impedance spectra obtained. Indeed, the obtained results from the VCBT show that adhesive elastic and damping properties increase with the increase of vibration excitation frequency. However, while current results enable one to estimate adhesive properties for such a high and wide range of frequencies, more accurate results should be acquired. This may require the use of other testing methods that can estimate adhesive properties for such a wide range of frequencies.

Associated with this topic, it was also found that FEA modeling of the EMIS method enabled the replication of experimentally obtained impedance spectra, albeit with much less differences, if constant properties are defined. However, this is not the case, and significant differences are observed by comparing experimental and simulated electrical impedance spectra. Therefore, the development of more complex FEA numerical models is a noteworthy scientific endeavor, which may include the use of properties that vary with frequency.

Another aspect that may be analyzed is the study of various adhesives that may be used in bonding the PWAS to the adhesive joint being monitored. While a methacrilate adhesive, that cures at room temperature, was used for this task, not much is known of the influence the adhesive properties have on the impedance measurements. Therefore, various adhesives of different chemical families should be studied, with emphasis on electrically conductive adhesives. A better defined and methodical procedure to instrument adhesive joints may be associated with this topic of research.

In using certain proposed damage metrics to tackle adhesive damage detection, the calculation of the active electrical impedance was performed. In this task, the resultant real component of the impedance is negative, which would imply that, from an electrical point of view, electrical energy is being generated. While this is impossible, this also implies that the electric properties of the piezoceramic material are not constant throughout the whole frequency range. Therefore, a proper study should be done regarding the behaviour of these properties as a function of the excitation frequency.

Extension of EMIS on the detectability of damage

It is noted that, while this work validated that EMIS is able to detect damage in the adhesive layer of bonded joints, this work was confined to the use of modified epoxy adhesive SLJ specimens with artificially created voids. As such, various topics of research can be extended from this research.

In one hand, artificial voids could not only be detected, but also located with ML algorithms, and their size could be estimated. However, the created measurement database was limited to a small overlap region of $25 \times 25 \text{ mm}^2$. Therefore, bigger adhesive joint specimens, with and without defects, should be manufactured. In this manner, one can have a better understanding of the sensibility of EMIS to various forms of damage, as a function of distance between PWAS and damage focus.

On the other hand, adhesive damage detection in this work focused on artificially created voids. Other forms of damage also exist, as presented in subsection 2.1.1, and should be the focus of future research. This task may also require an understanding of how adhesive defects may be created in certain industrial scenarios.

The study on the detectability of damage in adhesively bonded joints was done for a specific set of SLJs of aluminium substrates and modified epoxy adhesive. While these are common materials in aircraft structures, it must be noted that they are not the only ones. As such, this research should also be extended to other materials, namely steel and CFRP adhesive joints, other forms of joining, such as riveting or welding, and other types of structural adhesives. Furthermore, different adhesive joint configurations should also be studied, such as SLJ geometries with dissimilar substrates, or double lap joints, to name a few.

An approach that is yet to be studied for damage detection is the ability of the EMIS-based transfer impedance method in detecting adhesive damage. This alternative may allow for an easier damage detection, but also for a damage localization procedure without the need of complex algorithms. This may also be tested with other SHM methods, such as the Lamb Waves or Phased Array SHM methods.

Algorithmic development on the EMIS-based adhesive joint monitoring

The current work focused on the specific approach to detect artificially created voids in the adhesive layer. As previously mentioned, adhesives are prone to a wide variety of defects, which has implications due to the hierarchical nature of the SHM algorithmic approach. More specifically, this has implications on the third level of understanding, which is *Damage Classification*.

Simultaneously, the proposed future work regarding the sensibility of EMIS to damage as a function of the distance between the damage focus and the PWAS, may also contribute to the development of algorithms that may tackle the second

level of damage knowledge, which is *Damage Localization*.

Another approach, that may be used in tandem with the determination of the piezoelectric properties of the piezoceramic material, is to re-evaluate the use of the active impedance component for damage detection and, simultaneously, the use of damage metrics calculated with both real and imaginary components. These metrics, and others that may be proposed, can then be used in an alternative unsupervised ML approach that may use manifold learning models, such as the MDS algorithm, or others.

These topics of research may be extensive endeavours, which should require a bigger dataset. This may require different approaches, such as the use numerical simulations to develop such a database, or the use of advanced ML algorithms, such as semi-supervised ML models, which may use labeled and unlabeled data instances simultaneously.

Another topic worth studying is the robustness of EMIS as a function of various ambient parameters. One such possible perturbation is the change of ambient temperature, which affects the impedance measurements. In this manner, robust damage detection may require signal processing tools that may compensate the unwanted temperature effects. However, another possible perturbation to the impedance measurements is the hygrothermal aging that adhesives suffer, such as the adhesive that bonds the PWAS to the structural adhesive joint. This may also require specific signal processing tools and dedicated subroutines.

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Appendix A

Paper A

A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy

A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy

Structural Health Monitoring

2022, Vol. 21(2) 228–249

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DOI: 10.1177/1475921721993419

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Abstract

The article presents a literature review of electromechanical impedance spectroscopy for structural health monitoring, with emphasis in adhesively bonded joints. The concept behind electromechanical impedance spectroscopy is to use variable high-frequency structural vibrations with piezoelectric elements to monitor the local area of a structure for changes in mechanical impedance that may indicate imminent damage. Various mathematical models that correlate the structural impedance with the electric response of the piezoelectric sensors are presented. Several algorithms and metrics are introduced to detect, localize, and characterize damage when using electromechanical impedance spectroscopy. Applications of electromechanical impedance spectroscopy to study adhesive joints are described. Research and development of alternative hardware for electromechanical impedance spectroscopy is presented. The article ends by presenting future prospects and research of electromechanical impedance spectroscopy-based structural health monitoring, and, while advances have been made in algorithms for damage detection, localization, and characterization, this technology is not mature enough for real-world applications.

Keywords

Structural health monitoring, electromechanical impedance spectroscopy, piezoelectric wafer active sensors, damage algorithms, adhesive joints

Introduction

Analyzing and monitoring the performance of a given structure, without using destructive evaluation methods, are the underlying ideas of structural health monitoring (SHM). In this field, non-destructive testing (NDT) tools are used to in situ continuously monitor a structure and the measured signals are processed by a damage identification algorithm to determine the presence of a given fault. The implemented algorithm has the objective of detecting the existence of damage, its location, type, and the degree of severity to the structure's well-being.^{1–6} SHM is a vast field of study with many applications, such as aeronautic,^{7,8} aerospace,⁹ naval,¹⁰ and civil structures.^{11–13}

When studying damage identification and characterization, one must know what constitutes a damage for the monitoring setup. In this context, damage is the change of material and/or geometric properties in the observed system, which may negatively impact the structural performance. In Material Science and Engineering, this is referred to as a defect, and it

appears in a progressive or sudden manner, such as fatigue solicitations or impact conditions. If no action is taken, damage propagation may occur until failure is attained and the structural system can no longer operate.¹ However, one cannot conclude that all material defects are damage in the structure, as some material imperfections may not negatively impact its performance.²

In general, an SHM setup includes a set of sensors and actuators. The actuating elements are connected to a function generator that creates the input signal excitation, while the sensors are connected to a

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data-acquisition equipment that stores and processes the measured signals. In some cases, passive SHM systems make use of only sensors, which measure ambient signals to detect damage, meaning that there is no need for actuation elements and associated power driving systems. Nonetheless, both setups will always require a central unit to properly process the measured signals for de-noising, compensate for environmental factors, and extract damage signature.^{5,7} In this last stage, damage identification, localization, and characterization algorithms, based on physical modeling or statistical and machine learning techniques¹⁴ are required.

A variety of NDT methods have been used in the scope of SHM to monitor and evaluate structural integrity, such as guided waves,^{5,15,16} acoustic emissions,^{17,18} and infrared thermography,¹⁹ among others. Particular attention was paid to several vibration-based SHM methods, where one can monitor changes in the system's stiffness, mass, and energy dissipation properties.^{20,21}

One promising vibration-based SHM method is the so-called electromechanical impedance spectroscopy (EMIS). EMIS makes use of the coupled electromechanical behavior of piezoelectric wafer active sensors (PWASs), which can work both as actuators or sensors. An electric AC voltage, generated by a function generator, is sent to the PWAS, acting as an actuator, and converts the electric voltage signal into a mechanical stress solicitation. At the same time, the PWAS acts as a sensor, converting the structure's mechanical response to an electric signal, which is then sent to a data-acquisition unit, such as a computer or an impedance analyzer. This experiment is tested for a wide range of frequencies, usually going from 1 kHz onward. A schematic representation of the following setup in adhesive joints is presented in Figure 1. This online monitoring technique seems advantageous over other methods since (a) the used transducers are light-weight,

inexpensive, and can be implemented without negatively impacting the structure's performance; (b) the high frequencies used are immune to ambient noise and vibrations commonly present in real-world applications; and (c) with a wide frequency spectrum, one can detect minute damage foci.^{4,13} In fact, EMIS is considered such a robust measuring method that it is also starting to be used for industrial monitoring of system properties, such as fluid viscosity monitoring.²²

It must be noted that SHM systems for adhesively bonded joints, where two mechanical components are joined together with a structural adhesive, are uncommon and in an early stage of research. Furthermore, traditional NDT technologies used for adhesive connections, such as the Ultrasound, Acoustic Emissions and Infrared Thermography are time-consuming and incapable of detecting all types of damage.^{23–27} Among the various defects present in adhesive joints, weak adhesion, alternatively known as kissing-bonds or zero-volume unbound, is extremely difficult to detect with conventional NDT methods.^{28,29} Weak adhesion is presented as a defect in the interface between the adhesive and the adherend, where there may be physical contact between the two, but there is no bonding of the adhesive on the component to be connected.^{28,30} Therefore, the electromechanical impedance method has great potential for damage detection and characterization for adhesively bonded joints.

Although several reviews were published on this topic,^{4,31–33} the following article presents an updated literature review of the EMIS-based monitoring research, with focus on adhesively bonded joints, and is organized as follows. Section “Theoretical background of EMIS” introduces a theoretical background regarding the electromechanical coupling that occurs in the electromechanical impedance method. Section “Algorithms for damage detection, localization, and quantification” presents an overview of algorithms and indices used to detect, locate, and quantify damage in a given structure. Section “EMIS-based monitoring of adhesive joints” presents a review of the research of electromechanical impedance monitoring applied to adhesively bonded joints. Section “Hardware for impedance measurement” gives an overview of the hardware equipment used with EMIS measurements. Section “Challenges for EMIS-based SHM” discusses the main challenges and trends in EMIS research. Finally, the concluding remarks are presented in section “Conclusion.”

Theoretical background of EMIS

EMIS is an NDT method that takes advantage of the fact that PWAS elements can convert electrical signals into a mechanical actuation and vice versa. This is due

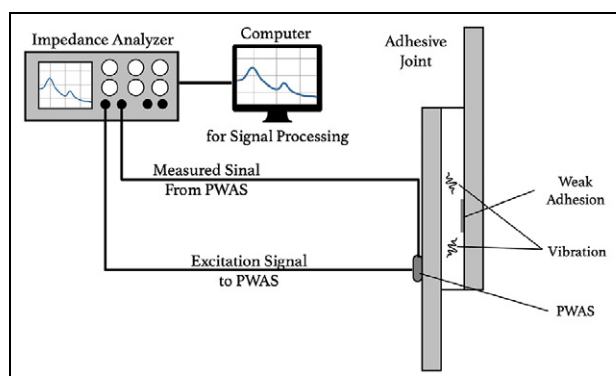


Figure 1. Schematic representation of the electromechanical impedance setup in a bonded joint.

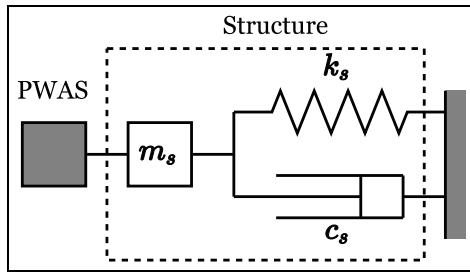


Figure 2. Model of interaction between the piezoelectric element and the monitored structure made by Liang et al.³⁵

to electromechanical coupling property of piezoelectric elements. In other words, this element can generate an electric charge when subjected to a mechanical stress, or can generate a mechanical strain when under the influence of an electric field, as described by

$$S_1 = \bar{s}_{11}^E T_1 + d_{31} E_3 \quad (1)$$

$$D_3 = d_{31} T_1 + \bar{\epsilon}_{33}^T E_3 \quad (2)$$

where S_1 represents the mechanical strain, T_1 is the mechanical stress, E_3 denotes the electric field, D_3 is the electrical displacement (charge per unit area), $\bar{s}_{11}^E$ is the mechanical compliance at zero electric field, d_{31} stands for the piezoelectric induced strain coefficient, and $\bar{\epsilon}_{33}^T$ is the dielectric constant at zero stress.^{3,4,34} These relations constitute the backbone of all modeling of EMIS.

Liang et al.³⁵ developed a one-dimensional (1D) model for the electromechanical coupling, based on equations (1) and (2), where a piezoelectric element is connected to a structure of stiffness, k ; mass, m ; and damping coefficient, c , as presented in Figure 2. The researchers demonstrated that the electrical admittance, $Y(\omega)$ (or the electric impedance, $Z(\omega)$), as a function of the angular frequency, ω , is related to the structure's mechanical impedance, Z_s , as per equation (4)

$$Z(\omega) = Y(\omega)^{-1} \quad (3)$$

$$Y(\omega) = j\omega \frac{w_P l_P}{h_P} \left(\bar{\epsilon}_{33}^T - \frac{Z_s(\omega)}{Z_s(\omega) + Z_P(\omega)} d_{31} \bar{Y}_{11}^E \right) \quad (4)$$

The variables w_P , l_P , and h_P are the width, length, and thickness of the piezoelectric element, Z_P corresponds to the piezoelectric element's mechanical impedance, and $\bar{Y}_{11}^E$ is the complex Young's Modulus of the piezoelectric material, defined as $\bar{Y}_{11}^E = |Y_{11}^E|(1 + j\eta)$, where η is the mechanical loss factor. The dielectric constant at zero stress, $\bar{\epsilon}_{33}^T$, is affected by a dielectric loss factor, δ , such that $\bar{\epsilon}_{33}^T = |\epsilon_{33}^T|(1 - j\delta)$. It should be noted that both Z_s and Z_P are mechanical impedances that are defined as the ratio between the load

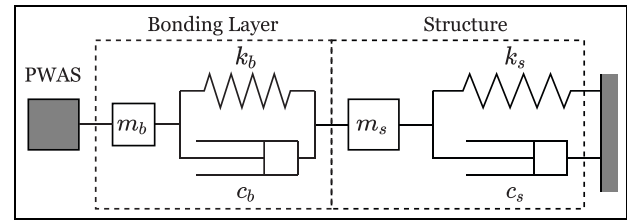


Figure 3. Model of interaction between the piezoelectric element and the monitored structure made by Xu and Liu.⁴⁰

excitation, F , and the velocity of a particle excited by the load, $\dot{x}$, so that, $Z = F/\dot{x}$.

This model was developed on the fact that the actuator force is not constant under variable frequency excitation, as first established by the static and early dynamic finite element approaches.³⁶ This model formed the basis of extensive research on structural monitoring. Giurgiutiu and Zagari³⁷ used the model presented in equation (4) to detect axial and flexural resonance frequencies. Sun et al.³⁸ tested various algorithms based on this model to determine the system frequency behavior. Zhou et al.³⁹ extended the presented model and proposed a two-dimensional (2D) system, with the structural impedance depending on the position.

Xu and Liu⁴⁰ improved the 1D model in equation (4), by adding a bonding layer between the PWAS and the monitored structure, as per Figure 3, obtaining

$$Y(\omega) = j\omega \frac{w_P l_P}{h_P} \left(\bar{\epsilon}_{33}^T - d_{31} \bar{Y}_{11}^E + \frac{Z_P(\omega) d_{31} \bar{Y}_{11}^E \tan(\kappa l_P)}{Z_P(\omega) + \xi Z_s(\omega) \kappa l_P} \right) \quad (5)$$

$$\xi = \frac{1}{1 + \frac{K_s}{K_b}} = \frac{1}{1 + \frac{-m_s \omega^2 + j\omega c_s + k_s}{-m_b \omega^2 + j\omega c_b + k_b}} \quad (6)$$

where ξ is a parameter relating the structure's dynamic stiffness, K_s , with that of the bond layer, K_b , as described by equation (6). The parameter ξ modifies the dynamic behavior of the structure. If $\xi = 1$, then one obtains the model formulated in equation (4), which means that K_b is much higher than K_s and perfect adhesion of the PWAS is achieved. In practice, this may be difficult to achieve, since bonding operations occur manually and are inherently susceptible of variations. Therefore, the quality of the adhesive greatly influences the obtained electrical admittance.

Zagari and Giurgiutiu^{41,42} proposed a 2D model of an isotropic circular plate coupled with a PWAS, where both the axial and flexural components of the natural vibrations are considered. The model was validated with experimental results, and can be written as

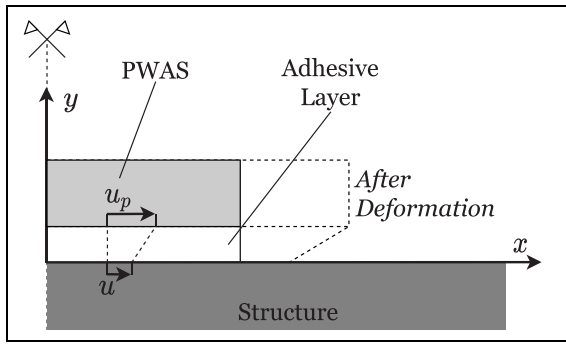


Figure 4. Shear lag effect phenomenon due to the adhesive bonding the PWAS to the structure.⁴³

$$Z(\omega) = \left\{ j\omega C(1 - k_p^2) \left[1 + \frac{k_p^2}{1 - k_p^2} \times \frac{(1 + \nu)J_1(\varphi_a)}{\varphi_a J_0(\varphi) - (1 - \nu)J_1(\varphi_a) - \chi(\omega)(1 + \nu)J_1(\varphi_a)} \right] \right\}^{-1} \quad (7)$$

where κ represents the wave number, ν is Poisson's coefficient, k_p is the planar coupling factor, and $\chi(\omega) = \frac{k_s(\omega)}{k_p}$ denotes the dynamic stiffness ratio between the structure, $k_s(\omega)$, and the piezoelectric element, k_p . This model was defined with Bessel functions, $J_0(\varphi)$ and $J_1(\varphi)$, of order zero and one, respectively, where $\varphi = \frac{\omega r}{c}$, c being the sound speed in the PWAS and r being the radius. The variable φ_a is defined for the disk radius r_a .

Bhalla et al.⁴³ proposed a simplified 2D impedance model considering shear lag effect, as presented in equation (8). This effect occurs in the adhesive layer that connects the piezoelectric sensor to the monitored structure, and is defined as the lag (or difference) in displacement between the structure's and the PWAS's surfaces, as shown in Figure 4. The model states that the electrical admittance, $Y(\omega)$, is given by

$$Y(\omega) = 4j\omega \frac{l_p^2}{h_p} \left[\bar{\epsilon}_{33}^T - \frac{2d_{31}^2 \bar{Y}_{11}^E}{1 - \nu} + \frac{2d_{31}^2 \bar{Y}_{11}^E}{1 - \nu} \times \frac{\tan(\kappa l_p)}{\kappa l_p} \left(\frac{Z_{p,eff}}{Z_{s,eff}(\omega) + Z_{p,eff}(\omega)} \right) \right] \quad (8)$$

where $Z_{p,eff}$ and $Z_{s,eff}$ are the effective mechanical impedance of the piezoelectric element and of the structure, respectively, which combine the bidirectional impedance behavior. It must be mentioned that Bhalla and Soh⁴⁴ previously developed a similar model, but their approach differed from this one since they did not consider an averaged shear strain along the structure's length (x direction in Figure 4). Moharana and Bhulla⁴⁵ refined the model, similar to that of Equation (8), where inertial and shear terms are included. Wang et al.⁴⁶ and Zuo et al.⁴⁷ extended this approach and developed a three-dimensional (3D) electromechanical impedance

model using the concept of effective mechanical impedance.

Pavelko⁴⁸ developed an electromechanical impedance model for PWAS–structure interaction that can be applied for 1D, 2D, or 3D cases. However, such a model becomes more complex, and, consequently, cumbersome for SHM applications. Furthermore, this model only presents adequate results for large structures and loses accuracy for high frequencies. Annamdas and Soh^{49–51} conceived a semi-analytic 3D electromechanical model for a broad class of structures, with any spatial distribution of PWAS and with the sensor's mass also in consideration. However, the

model is quite complex, requiring numerical data to calculate model parameters.

Several authors developed models of electromechanical coupling between a specific structure and the PWAS, such as for beams structures,^{52–55} axial rods,^{54,56} shell,⁵⁷ and plaque geometries.⁵⁸ However, no analytical model relating the mechanical impedance of adhesively bonded structures with PWAS was made so far. While this approach provides a good estimation of the electrical impedance measurements at high frequencies, one is limited to structures with simple geometries. Furthermore, in order to accurately predict the measured electrical impedance of a damaged structure, the model used must include the influence of the damage.

Algorithms for damage detection, localization, and quantification

The objective of SHM is to detect the presence of damage in a given structure, pinpoint its location, classify the type

of damage, evaluate its severity, and establish a prognosis on the structure's lifetime based on the data collected. These tasks require advanced statistical and algorithmic approaches that may not be able to fully accomplish all of these tasks. As such, most research on SHM is focused on developing more robust and complex algorithms. This section reviews statistical metrics and algorithms for EMIS-based structural monitoring for performing damage detection, localization, and characterization. However, no discussion on algorithms that estimate the remaining useful life of the structure is presented.

Damage detection

When the properties of the monitored structure change due to the presence of some damage, so does the measured impedance signature. Therefore, once the impedance signatures are acquired, metrics and algorithms are required to determine whether there is damage in the structure. Most research makes use of damage metrics/indices, which allow the comparison of impedance (or admittance) readings of a pristine structure (as a baseline/reference) with the in situ impedance readings. Various metrics have been proposed in the literature. The most commonly used are the root mean square deviation, *RMSD*; the mean absolute percentage deviation, *MAPD*; the Covariance, *Cov*; the Correlation Coefficient, *CC*; and the Correlation Coefficient Deviation, *CCD*, defined as

$$RMSD = \sqrt{\frac{\sum_{i=\omega_i}^{\omega_f} (Re(Z_i) - Re(Z_i^0))^2}{\sum_{i=\omega_i}^{\omega_f} Re(Z_i^0)^2}} \quad (9)$$

$$MAPD = \frac{1}{N} \sum_{i=\omega_i}^{\omega_f} \left| \frac{Re(Z_i) - Re(Z_i^0)}{Re(Z_i^0)} \right| \quad (10)$$

$$Cov = \frac{1}{N} \sum_{i=\omega_i}^{\omega_f} (Re(Z_i) - \overline{Z_{Re}}) (Re(Z_i^0) - \overline{Z_{Re}^0}) \quad (11)$$

$$CC = \frac{Cov}{\sigma_Z \sigma_Z^0}$$

$$= \frac{1}{N} \frac{\sum_{i=\omega_i}^{\omega_f} (Re(Z_i) - \overline{Z_{Re}}) (Re(Z_i^0) - \overline{Z_{Re}^0})}{\sqrt{\sum_{i=\omega_i}^{\omega_f} (Re(Z_i) - \overline{Z_{Re}})^2 \sum_{i=\omega_i}^{\omega_f} (Re(Z_i^0) - \overline{Z_{Re}^0})^2}}$$

$$CCD = 1 - CC \quad (13)$$

where Z_i^0 is the baseline electrical impedance of the pristine structure, Z_i is the measured electrical impedance, and N is the number of acquired samples. The variables $\overline{Z_{Re}}$ and $\overline{Z_{Re}^0}$ are the average of the measured and pristine impedance, while σ_Z and σ_Z^0 are the standard deviation of the measured and pristine impedance, respectively. It is noted that, usually, these indices are calculated using only the real component of the electrical impedance, since it is more sensitive to damage.^{3,33} However, research has shown that, after some processing, the imaginary component can be used as well.⁵⁹

The root mean square deviation, *RMSD*, which is based on the euclidean norm, allows one to see, for a given frequency range, if the two impedance spectra are similar or not. If they are similar, then *RMSD* tends to

be null.^{60–62} Oliveira et al.⁶³ adopted the Principal Component Analysis to process time-domain readings. Then, these results were used to calculate the *RMSD*. It was verified that they were more sensitive than those obtained directly with EMIS. The mean absolute percentage deviation, *MAPD*, evaluates the average of the absolute values of the deviations at each individual data point of the signatures. If the deviations between spectra are small, then *MAPD* is nearly zero, thus reflecting that there is no damage.^{62,64} The Covariance, *Cov*, evaluates the relationship between two impedance signatures and determines whether these two impedance datasets resemble each other or not. If both signatures peak at the same frequency, then the Covariance is positive. Conversely, if the peak of a dataset is placed where the valley of the other dataset is, then the Covariance is negative. If both signatures are unrelated, then covariance tends to be null. The *CC* reflects the same information as the Covariance, but the value is normalized so that, *CC* nears 1 when both signatures are similar, and is equal to -1 when they are opposite to each other. The correlation coefficient deviation, *CCD*, also represents the same information as the correlation coefficient, *CC*. However, it better reflects how much different the two impedance spectra are: if they are similar, *CCD* nears zero.^{61,62}

While these are the most commonly used damage indices, other metrics have been developed. Tinoco and Marulanda^{65,66} developed the ellipse damage index, *EDI*, which correlates the impedance readings from a reference/pristine structure, Z^0 , and a damaged structure, Z . These impedance readings can be described by two Gaussian distributions, one for the reference values, $N(\mu_{Z^0}, \sigma_{Z^0}^2)$ and another for the measured readings $N(\mu_Z, \sigma_Z^2)$. From the covariance matrix that relates these two distributions, one can determine the eigenvalues, λ_{min} and λ_{max} , that describes an ellipsis, as represented in Figure 5. From these parameters, one can define *EDI* as

$$EDI = 2.4477 \frac{\pi \lambda_{min} \lambda_{max}}{\max(Z^0) \max(Z)} \quad (14)$$

Enciu et al.⁶⁷ developed a normalized entropy index, *H*, based on the statistical concept of entropy, which is the logarithm of a probability, and is defined as

$$H = - \frac{\sum_{i=\omega_i}^{\omega_f} p_i \log_2 p_i}{\log_2 n} \quad (15)$$

where n is the number of datapoints in the impedance signature, and p_i is a probability associated with the electrical impedance measurement at frequency ω_i , defined as

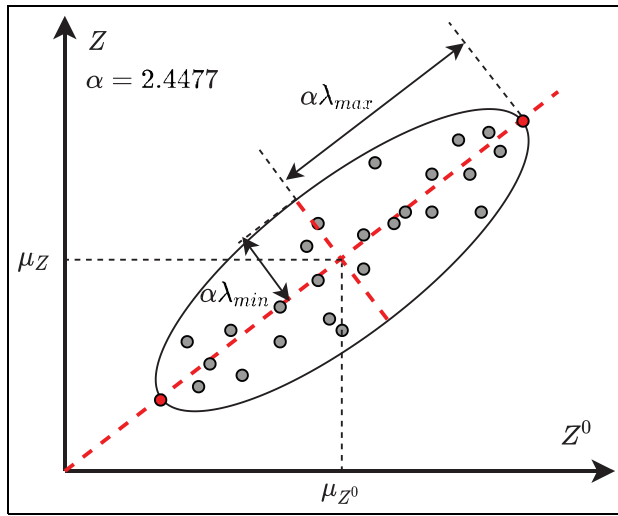


Figure 5. Ellipse obtained from the Covariance matrix and respective eigenvalues.⁶⁵

$$p_i = \frac{Re(Z_i)}{\sum_{i=\omega_i}^{\omega_f} Re(Z_i)} \quad (16)$$

The difference between a baseline entropy index, H^0 , and the entropy index of the damaged specimen impedance readings allowed to determine the presence of damage in a circular aluminum plate.

Other approaches based on statistical and machine learning algorithms have been proposed. Based on the work of Sohn and Farrar,⁶⁸ Park et al.⁶⁹ developed an unsupervised learning auto-regressive model with exogenous inputs in the frequency domain for damage identification in structures. de Oliveira et al.⁷⁰ developed a convolutional neural network (CNN) that was able to detect the presence of one of three possible damage foci in an aluminum plate. Their results provided 100% accurate results in the Testing phase when using three epochs, but also require a longer training time period than other methods.

Damage localization

For a more robust damage algorithm, detection may not be sufficient to characterize the defect, especially for large structures. It is also of importance to locate the focus of damage. Hence, damage localization algorithms are of interest.

Cherrier et al.⁷¹ developed a damage detection and localization algorithm, where acoustic attenuation, $A_{i,j}$, was used as a tool for damage localization, and is defined as

$$A_{i,j} = \frac{a_t}{a_0} = e^{-m(\omega)x_{i,j}} \quad (17)$$

where a_0 denotes the incident wave/vibration amplitude, a_t is the received wave/vibration amplitude after propagation from the actuator has occurred, and $m(\omega)$ is the acoustic attenuation coefficient. Since this method requires spatial discretization, a meshing of the component being monitored is necessary, and, therefore, the variable $x_{i,j}$ translates the distance between the transducer at position i and the center of the mesh j . The value of acoustic attenuation $A_{i,j}$ is used to calculate a position dependent damage index, DI_j . The following damage metrics were proposed

$$DI_{j(RMSD)} = \left[\sum_{i=1}^N \left(\frac{RMSD_i}{A_{i,j}} \right) \right]^{-1} \quad (18)$$

$$DI_{j(\overline{\Delta f})} = \left[\sum_{i=1}^N \left(\frac{\overline{\Delta f}_i}{A_{i,j}} \right) \right]^{-1} \quad (19)$$

where $RMSD_i$ is the calculated root mean square deviation for the signatures obtained with sensor i , $\overline{\Delta f}_i$ is the averaged shift in frequency peaks for obtained signatures from sensor i , and N stands for the total number of piezoelectric sensors. These damage indices were used to detect small impact damage in a composite I-beam (1D geometry) and a clamped composite plate (2D geometry). It was verified that the algorithm was able to detect and locate the damage foci.

Kralovec et al.⁷² developed a triangulation algorithm for damage localization in an aluminum plate, based on both experimental and finite elements method (FEM) numerical results. Magnets were used to simulate damage. These experiments determined the impedance spectrum for baseline and damaged plates (21 damages were considered). Then the $RMSD$ and $MAPD$ values were calculated. These indices are function of the distance between PWAS and damage location. As such, it was found that the results could be fitted using either an exponential law or a two-term Hankel function of the first kind. These empirical relations were able to detect other damage foci.

Dragan et al.⁷³ combined the reconstruction algorithm for probabilistic identification of damage (RAPID) imaging algorithm with the EMIS transfer impedance approach to locate damage. In EMIS, transfer impedance is an experimental procedure where one PWAS acts as a vibration actuator, and another PWAS acts as vibration sensor. The impedance transfer function, $T(\omega)$, is defined as

$$T(\omega) = \frac{U_s(\omega)}{U_a(\omega)} = \frac{|U_s|}{|U_a|} e^{j\varphi(\omega)} = |T(\omega)| e^{j\varphi(\omega)} \quad (20)$$

where U_s and U_a are the measured voltage signals from the PWAS sensor and the PWAS actuator, respectively, and $\varphi(\omega)$ is the phase shift between the two signals. The

RAPID algorithm, which is extensively used for Lamb wave-based SHM,^{74,75} calculates a damage intensity probability, I , which can be generically calculated as

$$I = \sum_{a=1}^{N_a} \sum_{s=1}^{N_s} DI(a, s) R_{a,s} \quad (21)$$

where N_a and N_s are the total number of actuators and sensors, respectively, DI is the obtained damage index for the combination of actuator a and sensor s , and $R_{a,s}$ is a function that represents the range between actuator a and sensor s . The impedance transfer function, $T(\omega)$, is used as the damage index, $DI(a, s)$, to calculate the damage intensity probability.

Giurgiutiu and Kropas-Hughes⁷⁶ performed the training and validation of a probabilistic neural network (PNN) to detect damage in a 2024T3 aluminum plate of 100 mm diameter, where the sensor was placed at the center. Two high-frequency bands were considered: 10–40 kHz and 10–150 kHz. In this approach, the researchers defined five groups of damage: pristine (no crack), slight damage (crack at 40 mm from PWAS), intermediate damage I (crack at 25 mm from PWAS), intermediate damage II (crack at 10 mm from PWAS), and strong damage (crack at 3 mm from PWAS). First, a feature extraction algorithm was developed that extracted the resonant peak frequencies and amplitudes, as well as the corresponding log-amplitudes. However, only the resonant peak frequencies were considered as input for the PNN. This was essential, since it allowed for dimensionality reduction of the problem at hand, and, consequently, a more efficient and less time-consuming PNN training procedure. In the 10–40 kHz frequency range, 4 frequency features (major peaks only) were not enough for accurate classification of the damage location, while 6 and 11 features provided good results. For the 10–150 kHz range, 22 frequencies were required in order to accurately classify the damage in the aluminum disk.

Selva et al.⁷⁷ also developed a PNN for damage localization on a carbon fiber-reinforced polymer (CFRP) instrumented with three PWASs. FEM simulation results obtained from various models were used, with damage being placed at various locations. In their work, the simulated damage corresponds to an impact damage caused by a drop-weight impact tower with a mass of 2 kg and energy of 20 J. Various metrics were considered for the input of the PNN, such as correlation coefficient of $Re(Z)$, area subtraction of $Re(Z)$ and $Im(Z)$, RMS or quadratic mean of $Re(Z)$ and $Im(Z)$, and root mean square deviation using $Re(Z)$ and $Im(Z)$. Afterward, the neural network was tested with experimental data results to see if it was properly trained. The PNN provided good results for locating damage with 600 mm² of area, and placed correctly three of five

damages. However, its performance was unsatisfactory for 225 mm², since the experimental data used for this case had damaged surfaces with a larger area.

Loendersloot et al.⁷⁵ used a combination of EMIS and Lamb wave to detect and localize damage caused by fatigue loading in glass-fiber reinforced polymer. In a first stage, damage detection was performed using EMIS readings from PWAS. It was found that both the *RMSD* and *MAPD* indices allowed the detection of damage and index values increased with the number of load cycles. Afterward, Lamb waves were generated and the RAPID algorithm was used to locate the damage with accuracy.

Rabiei et al.⁷⁸ developed an EMIS-based algorithm for damage detection and localization on a replica of an aluminum mobile bridge structure. In a first step, the damage indices *RMSD*, *CC*, and *CCD* were used to detect damage. Afterward, the damage location map was made using a mixture of Gaussian kernels, where impedance spectra for the various PWASs were inputted. Gonzalez et al.⁷⁹ performed a variability analysis using an ANOVA approach and Tukey's multiple comparison tests. *RMSD* values were obtained from impedance signatures of an aluminium aeronautical panel instrumented with eight PWAS. Additionally, six structural scenarios were considered: pristine condition, three cases with a loosened bolt in different locations, one consisting of three bolts simultaneously loosened, and one where all the bolts were re-tightened. The ANOVA approach proved to be effective in detecting and locating the damage. However, this method requires the determination of the frequency bandwidth over which the impedance signatures are obtained.

Damage quantification

Given the high and ever-increasing complex computing advancements, algorithms have been developed that can detect, locate, and characterize damage. These will be presented here.

Khodaei and Aliabadi⁸⁰ developed a three-layered algorithm to detect, localize, and quantify, to some extent, the damage in a curved composite fuselage panel with composite stiffeners. Their approach made use of guided waves and the electromechanical impedance method, and a network of 16 PWAS elements. In the first level of the diagnosis algorithm, the existence of damage was evaluated by processing Lamb wave measurements from the sensor network, using the maximum value of the energy envelopes difference, $E(R_{ij})$, between the pristine and the current states, given by

$$E(R_{ij}) = |R_{ij} - jH(R_{ij})| \quad (22)$$

where $R_{ij}(t)$ is the residual that is calculated as the energy envelope difference between the pristine state

and the measured state, and $H(R_{ij})$ is the Hilbert transform of the residual signal. Various thresholds were defined to determine whether damage was present and which path between sensors best detects the damage. The second level of the algorithm considered the EMIS signatures to determine an approximate localization of the damage. To easily process the signatures, the correlation coefficient, CC , was used to determine which sensors were the most sensitive to the presence of damage. Afterward, in the third level of the algorithm, an accurate damage localization and characterization was performed. The two most sensitive sensors were selected to execute triangulation of the damage. In order to choose a sensor for accurate localization, various guided wave paths were analyzed using the energy envelopes difference, as in Level 1, where the previously chosen sensors from Level 2 acted as actuators, and the others were considered as sensors. With the third sensor chosen, the weighted energy arrival method (WEAM) was used to accurately detect the location and size of the damage, and is defined as

$$DI(x, y) = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^N E(R_{ij}(t_{ij}(x, y))) w_{ij}(\sigma, \nu) \quad (23)$$

where $E(R_{ij}(t_{ij}(x, y)))$ is the energy envelope determined in equation (22), for coordinates x and y and time t , and $w_{ij}(\sigma, \nu)$ denotes a window centered at the first peak of the residual signal to reduce the effect of reflections and mode superposition. The presented algorithm led to accurate results both in location of damage and in estimation of damage size.

Fan et al.⁸¹ developed a damage identification, localization, and quantification methodology using sparse information from resonant frequency shifts of impedance spectra. Given that the number of measured frequency shifts is smaller than the number of structural parameters, l_1 regularization method is used to solve the underdetermined inverse problem. This method allowed for the detection and localization of damage, and determined the severity of the damage, but its accuracy is limited to small structures. For larger structures or structures with multiple damage foci, this technique underestimates the severity of the damage.

He et al.⁸² trained and tested an artificial neural network (ANN) to detect, localize, and quantify damage in a truss structure. Damage was simulated by loosening the screws to various levels, and thereby creating various damage intensities. The measured impedance spectra were divided into various sub-bands, and $RMSD$ values were calculated for each portion of the spectrum. These values are then inputted into the ANN, and three output neurons indicated the damage location (i.e. the rod and joint where the screw is loosened) and severity.

Palomino et al.⁸³ trained a PNN for detection, localization, and classification of damage in both an aluminum

aircraft panel with and without window, with defects such as cracks and rivet loss as present in the structures in question. Concurrently, the authors also developed a Gustafson-Kessel fuzzy cluster algorithm to classify the type of damage. Both algorithms were able to detect and classify the damage with minimal error if the sensors are placed near the damage, hence also presenting an approximated form of damage localization. However, no accurate damage localization is performed. De Moura and Steffen⁸⁴ developed a Statistical Meta-modeling technique of surface responses involving Correlation Coefficients, CC , of impedance measurements from an aluminium airplane fin. These results were used to characterize damage, such as the radial distance from the fault to the sensor, and the severity of damage. Their experimental procedures were also used to train a PNN to detect damage without the need for determining the impedance signal peaks in the monitored frequency band.

Zahedi and Huang⁸⁵ developed an interesting approach based on the combination of EMIS and Lamb waves. The excited waves are generated by a Hanning windowed tone-burst signal, like traditional Lamb waves SHM method, but the same piezoelectric elements that excite the structure also measure the response. Afterward, both the electric admittance, $Y(\omega)$, and the current of the generated signal, $I(\omega)$, are used to calculate the frequency domain response of the PWAS, $O(\omega)$, such that

$$O(\omega) = Y(\omega)I(\omega) \quad (24)$$

which is then converted to the time-domain by using the inverse Fast Fourier Transform (FFT). Finally, the time-domain signal envelope, $O(t, f)$, is calculated with the Hilbert–Huang transform. With this procedure, the amplitude can be represented as a function of frequency and time. While this does not enable the detection or direct characterization of damage, the transient EMIS time–frequency analysis allows the detection of damage and, in an indirect manner, the sensitivity of the PWAS to damage by measuring echoes.

As a final remark, one can see that damage metrics are commonly used in EMIS for damage detection, of which, the most commonly used are the $RMSD$; the $MAPD$; the Covariance, Cov ; the CC ; and CCD . These can also be used for more complex algorithms that are able to determine damage localization or characterization. However, in this stage, researchers tend to focus more on either complex physics-based model-driven approaches, or ANN to perform damage localization and/or quantification.

EMIS-based monitoring of adhesive joints

EMIS is an ever-growing field of research since the first articles were published in the mid 1990s. However, research on its application to adhesively bonded joints has only started in this last decade. This section

presents a review of the most relevant work performed so far by the scientific community.

Experimentation

The backbone of any progress or innovative approach in SHM, in general, and in EMIS-based SHM, in particular, has been the use of experimental testbeds for concept validation and discovery. This subsection discusses the experimental work where EMIS is used to monitor adhesive joints.

In one of the earliest works, Na et al.^{86,87} monitored adhesively bonded joints immersed in corrosive environments, such as water and acetone, using reusable PWAS sensors, where the piezoelectric element is attached to a neodymium magnet. Their findings showed that this adapted sensor was able to detect debonds occurring in the adhesive due to the nature of the environment. A comparative analysis between the performance of these sensors and the traditional PWAS noted that, despite still being able to detect damage in the adhesive, sensitivity to damage was sacrificed at the cost of measurability simplicity.

Lim et al.⁸⁸ performed a more comprehensive and thorough monitoring research of epoxy-based adhesive cure for 21 days. First, an analysis of the PWAS resonances was made. For the first 6 h, as the adhesive became more viscous, a dampening effect occurred reducing the PWAS resonance magnitude and frequency. Afterward, between 6 and 24 h, as the adhesive became progressively more solid, the frequency peak shape gradually altered, and several smaller peaks appeared due to the adhesive stiffness. At the same time, a rightward shift of the piezoelectric resonance frequency was observed. From 1 to 7 days, there is still some hardening of the adhesive, and a slight rightward movement of the PWAS resonant frequency was observed. Finally, from 7 to 21 days, the hardening of the adhesive was almost indiscernible. One drawback of this approach was the fact that, for high frequencies, the EMIS sensing zone was highly localized and, therefore, the repeatability between different sensors was less satisfactory. A second analysis approach using the structural resonance peaks as indicators yielded similar conclusions. These results were corroborated with Lamb wave monitoring results.

Dugnani et al.⁸⁹ studied the influence of bad adhesion, more commonly known as kissing-bonds, in epoxy-based adhesive single lap joints (SLJs) under static testing conditions, where the SLJ was cyclically loaded with incremental load differences, until failure. Using the cross-correlation function, $A_n(\omega)$, defined as

$$A_n(\omega) = \int_{-\infty}^{\infty} G_0(\omega) * G_n(\omega + 2\pi\tau) d\omega \quad (25)$$

where $G_0(\omega)$ is the reference conductance, $G_n(\omega)$ is conductance after the n th loading cycle, τ is the frequency lag, and $*$ is the convolution operator. From this, the authors used $A_n(\omega)/A_0(0)$ as a damage metric. A normalized resonant frequency shift, $\Delta f_R/f_R$, was also used as a damage metric. Using FEM numerical simulations, the authors observed that both indices augmented slightly when the lack of adhesion originated in the extremities of the interface layer between the adhesive and the adherend. Then the indices reached a local minimum when the damage neared the PWAS, and, finally, the indices augmented exponentially until failure occurred. However, this was only experimentally verified for $\Delta f_R/f_R$. Despite not reporting the difference of numerical and experimental behavior of the cross-correlation function ratio, $A_n(\omega)/A_0(0)$, the researchers deduced that: (a) the adhesive's loss factor, η_b , might influence conductance signals due to environmental perturbations and (b) the local minimum might occur near the SLJ stress failure. Either way, this damage metric is unreliable for damage detection.

Zhuang et al.⁹⁰ studied the EMIS performance of a modified epoxy-based adhesive SLJ with distinct levels of bad adhesion, and having piezoelectric sensors embedded inside the adhesive layer. SLJ specimen were cyclically loaded with increasing load steps of 111 N, and every time load ceased to be applied, impedance measurements were performed. Damage index, *RMSD*, of the measured impedance did not increase significantly until the stress values were roughly at 80% to 90 % of the failure stress (with a threshold value of *RMSD*=0.2). The parasitic effect of having an embedded sensor in the adhesive was studied, concluding that, given the small size of the sensor, no significant effect on the mechanical performance was observed. This seems coherent with research on mechanical behavior of adhesive joints with artificially placed voids^{91,92} which concluded that, for small defects, failure is controlled by the adherends' plasticity. Zhuang et al.⁹³ also performed fatigue testing of the SLJ specimen, and periodically stopped the test to perform EMIS monitoring. They found that only at 75% of its full fatigue life (i.e. at 36,000 of 48,000 load cycles), some change of the measured impedance spectrum occurred, and only at 88% of its life (i.e. at 42,000 of 48,000 load cycles) did the *RMSD* increase significantly.

Malinowski et al.^{94,95} compared the electromechanical impedance readings of pristine joints with various defective adhesive joints in a high-frequency range (3–5 MHz) and used the *RMSD* damage index and the frequency shift to measure the bond degradation. Three different defect causes were studied: (a) contamination with a silicon release agent, (b) moisture contamination, and (c) lower adhesive curing temperature. They concluded that bad

curing caused greater decrease in *RMSD* values and frequency shifts. Meanwhile, weak adhesion caused by either release agents or moisture presence resulted in a big variations of *RMSD* and a small variation of frequency peaks.

In a more recent study, Malinowski et al.⁹⁶ performed mechanical, ultrasound, and EMIS testing on adhesive joints with CFRP. In their experiments, the joint specimen were subject to (a) varying of thermal treatment temperature, (b) contamination with potassium formate-based de-icing fluid, and (c) combined modification due to thermal treatment and de-icer contamination. Ultrasonic testing was unable to detect damage or bond weakening, but was able to detect delamination in the CFRP due to excessive temperature for thermal treatment. However, the EMIS monitoring in a high-frequency range (4.25–4.7 MHz) could unravel information regarding the bond quality. Indeed, the reduction in *RMSD* values for each contaminated specimen could be correlated with a reduction in both mode I and mode II fracture-toughness results.

Gulizzi et al.⁹⁷ first studied the applicability of monitoring the adhesive's curing process at ambient temperature by means of EMIS, using a simple data acquisition setup, with a chirp signal exciting the PWAS, as proposed by Baptista and Filho.⁹⁸ Their findings revealed that, as the cure progresses, the adhesive gains stiffness and the impedance amplitudes are increased. In the first 6 h of curing, significant changes in the impedance spectrum were observed, and resonant peaks started to appear. Afterward, changes in the impedance spectrum were less significant. In a second study,^{99,100} the same authors analyzed the repeatability of monitoring the cure of adhesives, using the same setup. They concluded that no significant changes in the impedance readings took place. They also found that the ratio of resin/hardener had a significant influence on the curing time and on the resultant stiffness. As the percentage of resin in the mixture increased, resulting in a higher ratio, the increment of *RMSD* with time became less significant. Furthermore, one could observe when *RMSD* became constant and, consequently, when the curing stopped.

Cuc and Giurgiutiu¹⁰¹ studied the applicability of using EMIS for monitoring adhesively bonded titanium C-sections for helicopter rotor blades. A comparison between pristine and debonded rotor blades revealed that significant changes in the frequency spectrum were observed in the lower frequencies (below 200 kHz). In this region of the frequency spectrum, the resonant peaks shifted leftward to lower frequencies.

Rautela and Bijudas¹⁰² developed an EMIS-based SHM system to detect damage in adhesively bonded joints. Two ANN, one for FEM simulation and another for experimental results, are trained to detect

and quantify both the debond in the structural adhesive layer (SD for structural debond), as well as the debond in the adhesive layer connecting the PWAS to the adhesive joint (TD for transducer debond). Impedance spectra from cases where TD, SD, and a combination of TD and SD, where the debonded lengths varied, were used to train the ANN. The neural network obtained interesting results, especially in estimating the length of TD. However, in order to have better results, apparently more data should have been used to train the ANN, in order to better estimate the length of SD.

It must be noted, once again, that only in recent years has EMIS been used to study adhesive joints. While some research has proven that this method can detect issues like weak adhesion and debond, no systematic analysis of the effects in impedance signatures caused by various defects in adhesive joints has been made.

Simulation

Often, the EMIS behavior of a given structure is validated or predicted using the finite elements approach. This allows to have a basic understanding of the structural response to EMIS monitoring and to optimize SHM parameters.¹⁰³ This subsection, reviews the use of FEM as a tool to study the EMIS behavior in adhesively bonded joints.

Zhuang et al.⁹⁰ performed a direct steady-state linear dynamic type FEA simulation using ABAQUS to minimize the parasitic effect on the mechanical behavior of a bonded joint with an embedded sensor, and to optimize its ability to detect damage. Therefore, a parametric analysis of the dimensions of the sensor was made. The researchers concluded that reducing the thickness of the sensor would optimize its sensitivity to damage, while an optimal diameter of 3 mm would maximize its ability to detect bad adhesion.

Roth and Giurgiutiu^{104,105} proposed an FEM methodology with two types of numerical simulations to determine the best frequency range and location of the sensors on an adhesively bounded doubler, using ANSYS. In a first stage, a modal analysis determined the best mode shapes to evaluate the presence of an artificial debond in the adhesive. In order to avoid interpretation errors, a numerical algorithm was developed by the authors. A mode-matching index between the pristine and damaged simulation models was calculated, where the dot product of the normalized nodal displacements for the pristine and debond model was calculated and then the mean of all dot products for each node is determined. To choose the pristine mode, which best matches a given debond mode, the maximum of the mode-matching index for the *n*th mode was determined. Afterward, local debond displacements

were compared through the root mean square deviation, *RMSD*. The obtained results were then ranked in descending order, thus easily detecting the mode shapes of largest value. Once having the frequency range determined, a finite element sensitivity study both on the pristine and debonded models estimated the best sensor placement. The simulations results were finally verified experimentally, both using the EMIS method as well as with laser Doppler velocimetry.

Rautela and Bijudas¹⁰² compared the impedance spectra obtained from a 1D analytic model, FEM simulations, and experimental results. Both numerical simulations and experimental procedures of the bonded structure were made, where two steel adherends were bonded with an epoxy-based adhesive. Conversely, the analytical model considered only a medium composed of steel, and, therefore, damping effects caused by the adhesive were not included in the formulation. Resonant peaks in experimental and FEM results were closely matched. However, the peak amplitudes of the experiments are smaller than the ones from the analytical or numerical results. This discrepancy may be due to factors like thickness of the adhesive layer, or its variation, temperature dependence of piezoelectric parameters, among others.

FEM numerical simulation is commonly used by researchers for (a) determining the placement of sensors for optimal performance in damage detection in the monitored structure, (b) estimate the behavior of the electrical impedance signatures in a wide frequency range, and, therefore, determine the optimal frequency range for structural monitoring using EMIS, or (c) gather data from numerical models to train advanced damage algorithms like, for example, ANN. This is also the case for bonded joints. Nonetheless, given that only recently has EMIS been used for SHM of adhesive joints, few cases of FEM simulation has been found in the literature.

Hardware for impedance measurement

An EMIS system designed for the continuous surveillance of structural health is composed of one or more PWAS, as described in section "Introduction," and an impedance analyzer that derives the measured electrical impedance, or admittance, in a frequency spectrum. However, while this is the conventional equipment setup in EMIS-based SHM, various alternatives have been put forth. It must be noted that these alternatives have been made for monitoring of any structure, and, as such, some of these techniques have also been employed to monitor adhesive joints. However, no hardware setup has been developed for exclusive monitoring of bonded structures.

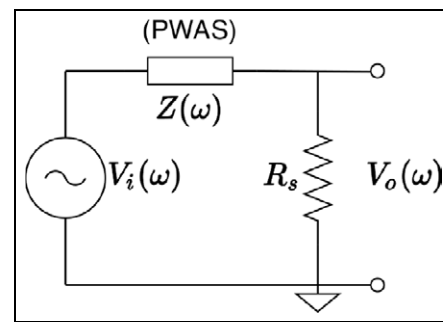


Figure 6. Voltage divider used by Peairs et al.¹⁰⁶

Given that impedance analyzers are expensive, bulky, and may be over-weighted for some applications, Peairs et al.¹⁰⁶ proposed an alternative composed of a simple and low-cost voltage divider in conjunction with an FFT analyzer. By using this approach, the measured electrical impedance can be approximated by dividing the input voltage, V_i with the current passing through the sensing resistor, $I = V_o/R_s$, as presented in Figure 6, where V_o is the output voltage and R_s is the sensing resistor. Panigrahi et al.¹⁰⁷ improved this experimental setup by using a function generator as pure sine signal generator and an oscilloscope to measure V_o . Bhalla et al.¹⁰⁸ implemented a simple impedance measurement setup using piezoelectric elements, a function generator, and a digital multimeter. This setup proved to be effective in detecting changes in structural behavior due to damage, but the measured results are quite different from those obtained with conventional equipment.

Xu and Giurgiutiu¹⁰⁹ have also developed a low-cost setup that included a function generator with a linear chirp signal source and a frequency-swept signal source, while the measurements were acquired by a data-acquisition (DAQ) board and a computer. Baptista and Filho⁹⁸ used a chirp signal to excite the piezoelectric actuator, and used a DAQ board connected to a computer with LabView, as well as an auxiliary circuit for the EMIS readings. The reported results show that measurements acquired by this system are quite similar to the ones obtained by an impedance analyzer (model HP4219A). This setup was then used by Gulizzi et al.^{97,99,100}

Wang and You¹¹⁰ developed an impedance measuring system based on a Wheatstone bridge, where one of the impedances is the piezoelectric sensor, Z_{PWAS} , and an adjustable digital resistor, Z_p , is placed parallel to the PWAS, to balance the bridge, as presented in Figure 7. Kim and Wang¹¹¹ used an array of bi-stable circuits integrated with the structure and piezoelectric transducers to obtain measurements less sensitive to noise and to allow for better localization of the damage. Maruo et al.¹¹² developed a hardware and firmware system based on a microcontroller for measuring the electromechanical impedance of multiplexed bonded

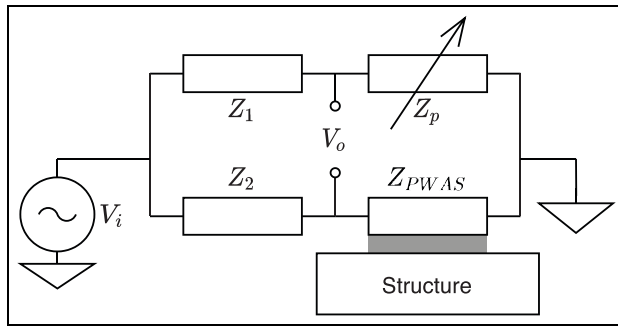


Figure 7. Wheatstone bridge proposed by Wang and You.¹¹⁰

PWAS, without making use of expensive FFT analyzers or algorithms and without need for high-speed data-acquisition equipment. The results obtained in this case were almost identical to those obtained by an HP4194A impedance analyzer.

In the meantime, new piezoelectric sensors have also been developed by several researchers. Based on a Lamb wave mode decomposition sensor setup to identify individual modes,¹¹³ Song et al.¹¹⁴ applied a dual piezoelectric transducer composed of a piezoelectric ring and a piezoelectric disk contained inside the ring, where the top and bottom surfaces are coated with nickel. These elements can work both as actuators and sensors simultaneously, or can act separately as a sensor and as an actuator. Experimental results revealed that the measured amplitudes are higher than those achieved with conventional PWAS. Furthermore, the imaginary component of the measured impedance is only sensitive to the structural impedance, and is not influenced by dielectric constant, ϵ_{33}^T .

Piezoelectric diaphragms, also known as “buzzers,” are a sound component normally used for producing alarms and sound elements in electronics, but have also recently been candidate for SHM sensors.¹¹⁵ This component, which is a circular piezoelectric ceramic bounded to a circular metallic plate, seems an interesting alternative sensor for the electromechanical impedance monitoring of structures, since it acts similar to a conventional PWAS.^{116,117} de Freitas et al.¹¹⁸ developed an equivalent circuit model to physically describe the electromechanical coupling in a 1D medium, and experimentally evaluated its sensitivity.

PWAS are basically ceramic components with mechanically brittle behavior and are susceptible to fracture in real-world applications, where one cannot control the environment. Furthermore, these elements cannot be fixed to non-planar surfaces, given their lack of mechanical flexibility. For this reason, NASA researchers developed a macro-fiber composite (MFC) sensor, which is a piezocomposite composed of a sheet of aligned piezoceramic fiber, a couple of thin polymer layers with conductive electrode patterns, and a matrix material.¹¹⁹ This

piezocomposite is comparatively stiffer and has more flexibility, allowing it to be mounted in curve geometries, and, as such, researchers have used it in experimental setups.^{120–123} However, it is noted that, with high temperatures, post-curing of the matrix may occur, leading to unwanted changes in impedance readings.¹²⁴

EMIS is an effective local damage detection method, however it has the disadvantage of requiring the implementation of a network of sensors for health monitoring of large structures, and therefore, of establishing a complex hardware architecture for signal generation and data acquisition, with a multitude of electric cables. An alternative to this is to use wireless sensors in SHM.^{125,126} This strategy was put forth as an alternative to EMIS-based SHM.^{123,127–129} This is done so with the help of the AD5933 impedance measurement evaluation board (manufactured by Analog Devices, Inc.), and allows for impedance measurements for frequencies up to 100 kHz.¹³⁰ It is reported that the use of this equipment is in EMIS-based research.^{123,127,129,131}

Challenges for EMIS-based SHM

SHM is a field where intensive research has been made in the last two decades, but real-world implementation of such systems are rare, only being present in niche applications. Among these are NASA’s Shuttle Modal Inspection System for subsystem’s inspection,¹³² and the Israeli’s Air Force unmanned aerial vehicle (UAV) planes for damage detection during flight operations.¹³³ Recently, the first real-world application of EMIS-based SHM was documented in Singapore, where monitoring of a mass rapid transit (MRT) heavy metro station’s structure is performed during construction operations.¹³⁴ However, despite these efforts, SHM systems are far from commercial use. Therefore, in this section, current EMIS-based SHM research, development and implementation issues, and challenges are presented.

Temperature effects and compensation algorithms

One of the main problems faced by EMIS-based monitoring systems is that the measured signals are susceptible to unwanted variations with temperature changes. This happens because the dielectric constant, ϵ_{33}^T (see section “Theoretical background of EMIS”), varies significantly with temperature, and consequently, changes the capacitive component of the measured electrical impedance.^{135,136} However, the piezoelectric-induced strain coefficient, d_{31} , of certain piezoelectric materials is also temperature sensitive.¹³⁵ Furthermore, material properties of the monitored structure may also vary

significantly with temperature. As such, the structural mechanical impedance may vary.⁶¹

Several studies show that the measured impedance amplitude decreases with increasing temperature, when plotted versus the excitation frequency, while the phase remains unaffected.^{135,136} Baptista et al. corroborated these findings and verified that the measured resonance peaks reveal a shift toward lower frequencies. This shift is a function of both the temperature and the baseline frequency of the resonance peak.⁶¹ The frequency shifts and variations of the impedance amplitude may be significant enough to jeopardize the detection algorithms, leading to false positive detection.

Several algorithms have been proposed to fix this issue. Krishnamurthy et al.¹³⁵ proposed the formulation of a frequency-independent temperature coefficient, δ^T , that can be used to establish a linear relationship in order to determine a compensated impedance, Z_{comp} , at a given reference temperature, T_{ref}

$$Z_{comp} = Z_m [1 + \delta^T (T - T_{ref})] \quad (26)$$

where Z_m is the measured impedance at temperature T . However, this type of approach can only be approximately defined for a given temperature range, since the piezoelectric parameters do not vary linearly with temperature. Park et al.¹³⁶ followed a similar approach to shift the measured frequency readings until it matched the baseline measurements. Baptista et al.⁶¹ developed an automatic method, using the linear shifting compensation method, where the measured impedance was incrementally compensated in a loop until the correlation coefficient, CC , between the measured and the reference impedance was maximized (nearly unit, $CC \approx 1$). However, such a procedure was only feasible without errors for readings of small frequency spectra. Koo et al.¹³⁷ demonstrated that CC values of measured and frequency-shifted impedance signals have fluctuations, which may result in false damage characterization, and propose the use of an outlier analysis with the frequency shifted measurements. Siebel and Lilov¹³⁸ have shown that temperature compensated impedance measurements using the CC is effective for excitation frequencies below 30 kHz, but may not be sensitive to detection of impact damage with temperature fluctuations.

Sun et al.¹³⁹ used a probability correlation function to perform temperature compensation. This approach also enables damage detection, but it can only be performed by measuring the differences in the resonant peak amplitudes, since the measurement of frequency shift is no longer possible.

Bastani et al.¹³¹ conjectured that, if the monitored structure has more than one PWAS, then the changes in the electric impedance measurements due to temperature would be reflected in all PWAS

measurements, while changes in the measured impedance due to damage are local to the nearest sensors. Therefore, comparing statistics, such as the mean square root deviation, $RMSD$, between two different PWAS readings, would indicate that, if both values are identical, then impedance changes are due to temperature changes. Otherwise, values differ if changes are due to the detection of damage. However, one must note that this method is only effective when various sensors are used.

Standard EMIS-based SHM systems may require the detection and compensation of temperature variations in impedance readings, however, some applications should include the temperature effect. Kundu et al.⁵⁵ examined the electromechanical impedance behavior of continuous welded rails with axial loads and temperature variations, which may cause thermal stresses, and, consequently, may affect impedance readings.

Given the research conducted so far, advances are needed to improve the compensation of temperature influence upon impedance spectroscopy measurements. The approach of Bastani et al., based on the comparison between readings of different piezoelectric sensors, allow to see whether significant impedance changes are either due to temperature or due to damage. However, such procedure needs to be extended by including other statistical indices for comparison. Another approach is to develop temperature compensation algorithms without potentially losing damage information, such as the resonant peak frequency shift.

Research on the temperature effects on EMIS readings of adhesively bonded joints have been performed. Temperature can have a much stronger impact on the impedance readings, since the adhesive's mechanical behavior can be temperature dependent, and can change drastically if the ambient temperature is superior to the adhesive's glass transition temperature, T_g .^{140,141} As such, electrical impedance measurements are highly susceptible to variations due to both variations of piezoelectric properties, as well as variations of adhesive properties, as demonstrated by Bilgunde and Bond.¹⁴²

Issues for real-world applications

The temperature perturbation on electromechanical impedance signatures is recognized as the most influential variable that may cause false positives. Nonetheless, other factors may also influence the measured signals.

As previously discussed, piezoelectric elements need to be connected to the structure using adhesives. However, the bonding procedure is manually made, and, consequently, may lead to imperfect adhesion of the PWAS. This is of great importance, since a badly connected sensor may lead to either the false detection of damage, or the inability of detecting real damage.

Knowing this problem, procedures need to be designed in order to evaluate the quality of the bond. Giurgiutiu et al.¹⁴³ found that, when the sensor is detached from the structure, the sensor's resonant frequencies can be easily detected from the electrical reactance, $Im(Z(\omega))$, measurements. Park et al.¹⁴⁴ further analyzed the feasibility of using the imaginary component of the electric admittance (the inverse of the impedance) to determine the sensor's integrity to accurately conduct structural monitoring. They concluded that breakage of PWAS would result in a downward shift of the slope of the imaginary part of the admittance, while, on the other hand, bonding defects would cause an upward shift in the slope. Park et al.¹⁴⁵ also compared the performance of piezoceramic and MFC sensors and concluded the composite sensors could still perform monitoring, since they are more robust and reliable than PWAS. As previously mentioned, Xu and Liu⁴⁰ developed a mathematical formulation of the electromechanical impedance behavior, where the adhesive bond between the structure and the sensor could be adjusted. Mulligan et al.¹⁴⁶ studied the performance of PWAS in structural excitation and sensing, and found that both non-uniform adhesion and degradation of the adhesive properties influence the PWAS behavior, both as an actuator and sensor. Ai et al.¹⁴⁷ developed an EMIS-based damage detection SHM system that was able to detect if there was deterioration in the bond layer or in the sensor, as well as breakage. Following these ideas, new advances should focus on developing an automated method for controlling the bonding of PWAS to any given structure.

It was also reported that piezoelectric ceramics are sensitive to humidity, thus affecting the measured impedance spectra. Bhalla et al.¹⁴⁸ determined that protecting the sensor with silica gel could mitigate this problem, but it would render the piezoelectric sensor less sensitive to damage. Furthermore, humidity also affects the adhesives and composites and it has been shown that water uptake will have a negative effect on the mechanical behavior of adhesive joints.^{149,150} To the authors' best knowledge, the monitoring of adhesive joints under the effect of hygrothermal aging was not yet tackled and recognize this as an interesting topic, especially when considering the effects of water on the piezoelectric properties of PWAS.

Another important issue with EMIS-based SHM systems is the existence of wire resistance, which, if long, may negatively impact the measurements of the electrical impedance, $Z(\omega)$. Annamdas and Yang¹³⁴ viewed that the addition of the wire resistance caused a shift of resonance peaks to lower frequencies. As such, wire length is limited. Alternatively, to avoid this problem, one can use wireless transmission of data as presented in section "Hardware for impedance measurement." Another alternative is to use drones

that can connect to the PWAS and acquire the impedance spectrum.³³ Loading conditions may also affect the impedance measurements, since they have influence on the mechanical properties of the structure being examined. Ding et al.¹⁵¹ verified that a downwards and rightwards shift of impedance peaks were observed for concrete structures. Neuschwander et al.¹⁵² developed a load compensation algorithm that related the strain suffered by a CFRP structure with the impedance signatures. Furthermore, this strategy allowed one to determine when the structure became damaged or reached failure. However, loading conditions need to be further studied, particularly when knowing that external loading may have similar effects to those resulting from the influence of temperature.

New algorithms and metrics for SHM

SHM is a field where data are a key component and, therefore, data processing and interpretation tools are of the utmost importance. Unlike traditional NDT methods, SHM may yield huge amounts of data in a short period of time. Therefore, it is vital to develop data compression tools and efficient damage detection algorithms for future commercial use.¹⁵³

Commonly, EMIS-based health monitoring systems use statistical metrics for damage detection, such as the mean square root deviation, *RMSD*, or the correlation coefficient, *CC*. These indices use the real part of the measured electric impedance, which is sensitive to damage. Bhalla et al.⁵⁹ demonstrated that the measured electric admittance can be divided in passive, $Y_P(\omega)$, and active components, $Y_A(\omega)$, respectively as

$$Y_P(\omega) = j\omega \frac{w_P l_P}{h_P} \epsilon_{33}^T \quad (27)$$

$$Y_A(\omega) = j\omega \frac{w_P l_P}{h_P} \frac{Z_s(\omega)}{Z_s(\omega) + Z_P(\omega)} d_{31} \bar{Y}_{11}^E \quad (28)$$

where $Y_P(\omega)$ and $Y_A(\omega)$ were deduced from the model proposed by Liang et al.³⁵ It can be noted that the passive component does not contribute to the detection of damage, since it is not dependent on the structural mechanical impedance, Z_s . Therefore, the passive component from experimental measurements was not considered and merely the imaginary part of the measured impedance was used for structural damage monitoring. However, since their works publication, there has been very little follow-up research that the authors have seen. As such, the authors find that potential application of these data can be useful for damage detection, localization, and quantification, either by the development of new algorithms or by the conception of new statistical metrics.

Various algorithms have been developed in order to detect, localize, and characterize damage. Most either

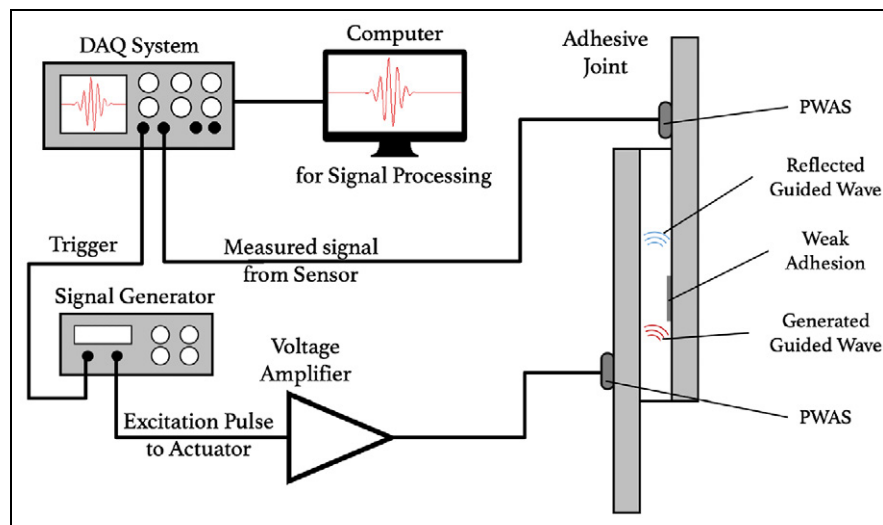


Figure 8. Schematic representation of the guided wave setup in a bonded joint.

use a model-based approach, meaning that their development is based on physical phenomena, or take advantage of simple damage metrics. In recent years, some researchers developed ANN to process electromechanical impedance signatures, with varying degrees of success. However, further research is still needed, since most algorithms have only been tested for simple structures in a laboratory environment. Furthermore, other data-driven and machine learning approaches, besides CNN and PNN, can be used.^{14,154} As an example, Gu et al.¹⁵⁵ developed a fuzzy-logic system that could correlate EMIS measurements with the compressive strength of concrete structures during the curing process.

Another unexplored alternative in the study and modeling of EMIS signatures is using fractional calculus, which is a generalization of the classical differential calculus. This mathematical tool has been used to model complex and nonlinear systems and components,^{156,157} and recently has been used in conjunction with electrical impedance spectroscopy to characterize the electrical behavior of an epoxy adhesive in SLJs.¹⁵⁸

EMIS-based SHM with other systems

Piezoelectric elements are an essential part of EMIS-based monitoring of structures. However, these sensors can also be used in other SHM systems, such as guided waves (Lamb, Shear Horizontal, etc.), and Acoustic Emissions,^{3,143,159} or even in structural control of vibrations.^{119,160} These systems will be discussed herein.

Guided waves are a family of ultrasonic elastic waves that propagate through a bounded medium, which may result in multi-modal, dispersive waves. These waves have a special relevance in SHM, since they can propagate over large distances and inside curved walls.

Rayleigh waves, which are also known as surface acoustic waves or surface-guided waves, are a type of elastic guided wave that travels close to the surface with almost no penetration through the solid's depth. Shear horizontal waves are horizontally polarized waves, meaning that the particle motion is parallel to the surface and perpendicular to the wave's propagation direction. Lamb waves are more complex in nature and can be subdivided as (a) symmetric lamb waves, which are quasi-axial waves and (b) antisymmetric lamb waves, which behave as quasi-flexural waves. For a given value of the quantity frequency–thickness product, that is, of ωh , a combination of symmetric (S_0 , S_1 , S_2 , ...) and antisymmetric (A_0 , A_1 , A_2 , ...) waves may coexist. However, given the complex nature of these waves, research tends to use lower frequencies, obtaining therefore only the fundamental modes (S_0 and A_0).^{3,5}

For the creation and measurement of guided waves, one can use various types of actuators and sensors, among which, one of the most popular is the PWAS. The EMIS- and guided wave-based SHM systems can coexist, as discussed in a number of studies.^{75,88,143,160–162} In fact, one can use EMIS health monitoring to monitor near-sensor incipient damage, and, at the same time, use guided wave-based SHM for monitoring of distant damage. However, one must note that extra equipment is required for the generation of guided waves, such as a voltage amplifier and a dedicated DAQ system. A schematic diagram of the guided wave SHM setup for adhesive joints is presented in Figure 8.

Acoustic emission is an SHM and NDT method where elastic waves are generated by small impacts and instantaneous solicitations on the monitored structure.^{17,18} Therefore, unlike guided wave SHM systems, structural integrity monitoring using acoustic emissions does not

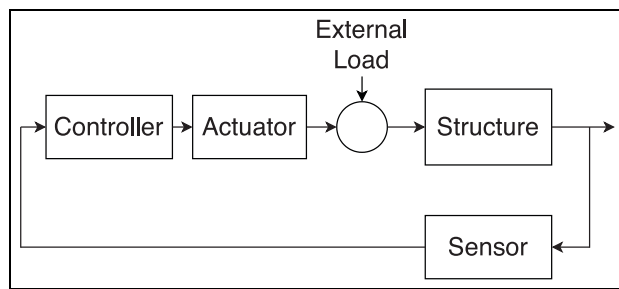


Figure 9. Block diagram of an active vibration control system.

require signal generation hardware. It is also noted that PWAS sensors can be used in acoustic emission-based SHM systems. Therefore, since acoustic emission and EMIS systems are similar in what concerns the hardware implementation, they can work concurrently to synergistically detect damage in structures.^{115,121,163}

Piezoelectric elements have also been used in the control of vibrations in structures, or, in other words, in the design of control systems to monitor and reduce/nullify vibration loads in structures.^{119,160,164,165} There are two types of vibration control systems: passive and active control systems. Active control systems use a controller and a power source to control the actuators that apply a force to the monitored structure, as illustrated in Figure 9. Conversely, passive control systems do not require a power system and are activated by the resultant motion from the vibration.¹⁶⁰

Conclusion

This article reviewed EMIS as a vibration-based SHM method, with emphasis in adhesively bonded joints. SHM is seen as the successor of NDT to mechanical structures, and aims to perform the tasks of detecting, localizing, and characterizing damage on a structure as well as determining the severity of the damage and the remaining useful life of its lifecycle. Up to the present day, no EMIS-based SHM system has been able to perform all of these tasks. This is particularly true for adhesively bonded structures, where research with EMIS-monitoring only began to take place in this last decade, focusing on the adhesive curing process and the monitoring of the joint's mechanical behavior. Meanwhile the detection of damage and defects in bonded joints still requires much attention.

The EMIS method has been an ever-growing field of research in SHM, and several approaches have been made to study structures. One of the first methods is the mathematical modeling of the PWAS interaction with the structure and, consequently, of the connection between the electrical behavior of the piezoelectric element and the mechanical impedance of the structure. Another possible approach is to use damage metrics or

specialized algorithms to detect, locate, and characterize damage in a given structure.

Another important aspect of this technique is the development of special hardware and signal processing tools for implementation of an EMIS-based SHM system. Here, the main focus has been on developing cheaper alternatives, and more robust systems allowing for (a) the design of signal processing with lower complexity, (b) the implementation of a wide sensor network, and (c) the transmission of data by means of wireless communication systems.

However, despite such progress, further groundbreaking research still needs to occur in order to reach a broad implementation of EMIS as a feasible and reliable structural monitoring tool. Among these issues, robust compensation methods for ambient perturbations on electromechanical impedance readings need to be developed, as well as the development of novel and innovative damage detection, localization, and characterization algorithms.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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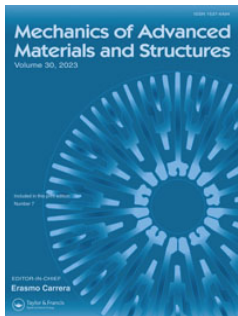
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Appendix B

Paper B

Effect of mechanical properties and geometric dimensions on electromechanical impedance signatures for adhesive joint integrity monitoring



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To cite this article: A. Francisco G. Tenreiro, António M. Lopes, Lucas F. M. da Silva & João D. P. Amorim (2023) Effect of mechanical properties and geometric dimensions on electromechanical impedance signatures for adhesive joint integrity monitoring, *Mechanics of Advanced Materials and Structures*, 30:7, 1437-1452, DOI: [10.1080/15376494.2022.2033891](https://doi.org/10.1080/15376494.2022.2033891)

To link to this article: <https://doi.org/10.1080/15376494.2022.2033891>



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Effect of mechanical properties and geometric dimensions on electromechanical impedance signatures for adhesive joint integrity monitoring

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ABSTRACT

Adhesive joints are prone to damage, which may be difficult to detect using Nondestructive Test. Structural Health Monitoring techniques, such as the Electromechanical Impedance Spectroscopy (EMIS), allow for continuous monitoring and early detection of structural defects. Developing efficient damage detection algorithms requires simulations of adhesive structures, which require elastic and damping properties under high frequency range. Tests were performed for crash-resistant and silicone adhesives. Numerical simulations with said properties were compared with experimental impedance measurements from Single Lap Joints (SLJ). This allowed for the estimation of adhesive properties, but numerical results for SLJs with silicone adhesive diverged from experimental results.

ARTICLE HISTORY

Received 31 October 2021
Accepted 21 January 2022

KEYWORDS

Structural Health Monitoring;
Electromechanical Impedance Spectroscopy;
adhesive joints; material properties; geometric dimensions; Single Lap Joint

1. Introduction

Adhesive bonding of structural components is being increasingly used in a variety of structures, such as in airplane and automobile structures. This transition of joining methods is caused by a societal and industrial drive in reducing overall structural weight and carbon emissions, while guaranteeing that mechanical performance is not compromised [1, 2]. As such, it is of great importance to ensure the integrity of adhesive joints throughout the structure's useful life. This is especially true when considering possible performance issues caused by environmental effects (i.e., thermal or aging effects) [3, 4], loading solicitations of various types (i.e., high strain-rate or fatigue conditions) [2, 5–7] and the possibility of introducing unwanted contamination during the manufacturing stage [8].

Nondestructive Tests (NDT) have been employed to evaluate the integrity of adhesive bonding [9, 10]. Unlike destructive tests, which directly evaluate the strength of the bonded joint, NDT methods do not inform on the strength of the joint, but rather on the stiffness and on the bond area. This goal is achieved by detecting possible damage foci. These can be voids, cracks, porosities, pockets of poorly cured adhesive or regions of the interface layer with weak adhesion, also known as kissing-bond [1].

Despite this, the use of NDT techniques for damage detection in adhesively bonded joints is somewhat limited, since current testing tools are not reliable in detecting all damage sources. This is even more drastic for weak

adhesion, which is virtually undetectable with current NDT used in industrial environment and, by consequence, requires complex and expensive tools [11–13]. Furthermore, in several industries (e.g., aeronautics), safety regulations and legislation demand that companies perform inspection of vehicular structures on a regular basis. This philosophy of time-scheduled maintenance is followed in order to detect possible origins of structural failure as early as possible, but forces companies to lose on potential revenue and on maintenance costs [14].

Structural Health Monitoring (SHM) is a scientific field that evolved from NDT, triggered by the aforementioned shortcomings, and consists in continuously monitoring a given structure to automatically detect and characterize any source of damage. A network of sensors continuously examines the structure and the measured signals are sent and stored in a central hardware unit. Here, an algorithm processes the obtained data and compares it to stored signals of readings from an equivalent pristine structure, that is, a structure without any source of damage [15–17].

A SHM method that has been conceived to monitor structures is the Electromechanical Impedance Spectroscopy (EMIS), where piezoelectric sensors, acting simultaneously as actuator and sensors, are used due to their coupled electromechanical behavior. In EMIS, an AC signal is sent to a Piezoelectric Wafer Active Sensor (PWAS), acting as an actuator, and the piezoelectric element converts the electric signal into a mechanical vibration. Conversely, at the same time, the PWAS behaves as a sensor by converting the

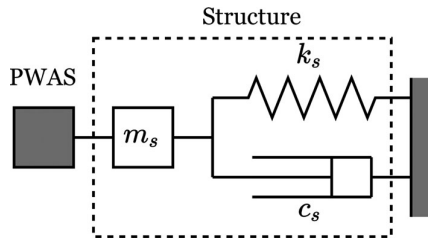


Figure 1. Model of interaction between the PWAS and the 1-D structure, as proposed by Liang et al. [25].

mechanical response of the structure into an electric signal. Afterwards, the measured signal is read by an Impedance Analyzer, which computes the electric impedance of the PWAS, which, in turn, is a function of the structural properties [17–19].

Several mathematical models have been developed to analytically determine the measured electric impedance of the PWAS, Z , as a function of the piezoceramic properties of the sensor and of the mechanical impedance of the structure, $Z_{m,s}$ [20–24]. One must note that the mechanical impedance is defined as $Z_m = F/\dot{x}$, where F is the load excitation and $\dot{x}$ is the velocity of an excited particle. The first model, which is presented in Eq. (1), was proposed by Liang et al. [25], and estimates the measured impedance for a one-dimensional structure with mass, m_s , stiffness, k_s , and damping coefficient c_s , as shown in Figure 1.

$$Z(\omega) = \left[j\omega \frac{w_p l_p}{h_p} \left(\bar{\epsilon}_{33}^T - \frac{Z_{m,s}(\omega)}{Z_{m,s}(\omega) + Z_{m,p}(\omega)} d_{31} \bar{Y}_{11}^E \right) \right]^{-1} \quad (1)$$

In Eq. (1), the width, length and thickness of the piezoelectric element are the variables w_p , l_p and h_p , respectively, and $Z_{m,p}$ is the mechanical impedance of the PWAS. The complex Young's Modulus of the piezoelectric material with a null electric field ($E=0$), $\bar{Y}_{11}^E$, is defined as $\bar{Y}_{11}^E = |Y_{11}^E|(1+j\eta)$, where η is the mechanical loss factor. The dielectric constant at zero stress, $\bar{\epsilon}_{33}^T$, is expressed as $\bar{\epsilon}_{33}^T = |\epsilon_{33}^T|(1-j\delta)$, where δ is the dielectric loss factor. Furthermore, d_{31} stands for the piezoelectric induced strain coefficient, and j corresponds to the imaginary number, $j = \sqrt{-1}$.

Note that the measured electric impedance, Z_e , has real and imaginary components, corresponding to resistive and reactance elements, respectively, in an equivalent circuit. However, only the real component is sensitive to damage and some signal processing is required to obtain a damage sensitive reactance, as shown by Bhalla et al. [26].

Research has been done using the EMIS technique to monitor adhesive joints. Na et al. [27] studied the feasibility of detecting unbonds in the interface of adhesively joined glass-fibre reinforced polymers when immersed in corrosive fluids. Damage could be detected using both glued PWAS and attaching piezoelectric sensors to the structure with neodymium magnet. Malinowski et al. [28] performed experiments at high frequency ranges (3–5 MHz) with damageless and damaged bonded joints, and used the Root Mean Square Deviation, *RMSD*, and peak frequency shift metrics to evaluate damage. Three different causes of damage were

created: (a) moisture contamination, (b) contamination with a release agent and (c) insufficient curing. From these results, bad cure could be observed by a decrease of both the *RMSD* and frequency shift decrease, while both the release agent or moisture contamination caused significant changes in the *RMSD* values.

Zhuang et al. [29] analyzed the effectiveness of EMIS-based SHM in detecting weak adhesion on epoxy adhesive joints. In their work, the Single Lap Joint (SLJ) specimens were cyclically loaded with increasing load steps of 111 N and, between each cycle, impedance readings were performed. The *RMSD* damage index was used as an estimator for the specimen's integrity. Results showed that the measured impedance did not significantly shift from the pristine specimen's values until roughly at 80% to 90% of the failure stress, which corresponds to the threshold value of *RMSD* = 0.2. Roth and Giurgiutiu [30] performed an analysis on the local detection of voids in adhesive joints using EMIS. In order to estimate the range of frequencies for impedance measurements, a Finite Element Method (FEM) methodology with two types of numerical simulations was proposed. First, a modal analysis simulation determines the best mode shapes for disbond detection. Afterwards, a FEM study assessed the sensitivity of sensor placement for both the pristine and debonded structures.

The work of Malinowski et al. [31] appears to be the only one up to the present date, where mechanical performance of adhesive joints, with and without damage, was compared with impedance measurements. Damage was created either by (a) varying the thermal treatment temperature, (b) introducing contamination with a deicing fluid, or (c) combining the temperature modification with deicing contamination. Impedance readings in a frequency range of 4.25 to 4.7 MHz revealed information regarding the bond quality of damaged and undamaged specimens. *RMSD* index values were calculated and the results showed a correlation with the experimental values for Mode I and Mode II fracture-toughness.

To the best knowledge of the authors, no parametric studies on EMIS readings of adhesive joints were performed so far, and a study on FEM numerical simulations of EMIS measurements of adhesive joints is not yet available. This occurs despite the fact that structural mechanical properties have been recognized of extreme importance for vibration-based SHM, such as, for example, EMIS [32, 33]. Therefore, it is the aim of this work to perform an analysis of the influence of geometric dimensions and different types of adhesives on the electric impedance readings in EMIS-based SHM.

Quasi-static and Vibrating Cantilever Beam Test (VCBT) were performed for a ductile adhesive and a crash resistant adhesive, with the aim of determining the elastic and damping properties of the adhesives. Single Lap Joints (SLJ) were manufactured and instrumented with PWAS, in order to perform EMIS monitoring tests. The manufactured SLJs have aluminum adherends and can have an adhesive layer of 0.2, 0.5 or 1.0 mm thickness. The adhesive used in these specimens are either the ductile or the crash resistant

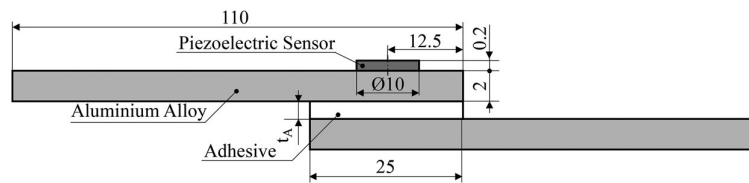


Figure 2. Schematic representation of a SLJ specimen with dimensions in mm.

adhesives. From the results obtained from VCBT, damping and elastic values were estimated. With these results, numerical models were created to replicate the experimental results obtained from the impedance spectroscopy measurements. Simulation results correlate with the impedance measurements, especially with the epoxy-modified adhesive.

Given this description, the paper is organized as follows.

Section 2 describes the experimental procedures adopted in this research. In Section 3, the results and measurements obtained from the experimental tests are presented. Afterwards, Section 4 describes the developed numerical model, whose aim is to replicate the impedance measurements shown in Section 3. Section 4 also presents the obtained simulation results and a comparison with the experimental data. Finally, Section 5 draws the conclusions of this work.

2. Experimental details

2.1. Materials

In this work, two adhesive materials, with different mechanical behavior, were used for the experimental procedures. The first consisted of the Nagase T-836/R-810 crash-resistant adhesive, which is manufactured by Nagase ChemteX® (Osaka, Japan). This material is a tough one-part modified epoxy adhesive, developed for the automotive and aeronautic industries, because of its high strength and resistance to impact. The cure cycle of this crash-resistant adhesive consists of a 3 hour stage at 160° C. This adhesive has a mass density of 1200 kg·m⁻³.

A two-part silicone rubber adhesive was also used in this investigation. The two components were mixed according to a mass proportion of 1 to 1. This adhesive requires a curing cycle of 120° C for 25 minutes. This material is recommended for general purpose sealing applications in the automotive and electrical industries. This adhesive has a mass density of 1260 kg·m⁻³. The mechanical properties of the adhesive were studied by Borges et al. [34], and determined that this adhesive behaves according to the Neo-Hooke hyperelastic model. However, for small strains, one can use an elastic model ($E = 2.44$ MPa, $\nu = 0.495$).

In the experimental tests, various aluminum alloys were used. For the EMIS testing, SLJ specimens were manufactured with 6082 aluminum alloy adherends. These substrates have a thickness of 2 mm and a mass density of 2710 kg·m⁻³. Regarding the elastic properties, this alloy has a Young's Modulus of 70 GPa, and a Poisson's Ratio of 0.33.

The 1050 aluminum alloy was also used in the fabrication of sandwich specimens for the vibrating cantilever beam

tests. In this case, the aluminum substrates have a thickness of 1.5 mm and a mass density of 2700 kg·m⁻³. This alloy has an Elastic Modulus of 69 GPa and a Poisson's Ratio of 0.33.

2.2. Specimina fabrication

2.2.1. Dogbone specimen

For the quasi-static tests, *dogbone* specimens were manufactured. One should note that, since the properties of the silicone rubber adhesive were determined in [34], only *dogbone* specimens of the crash-resistant adhesive were fabricated. The T-836/R-810 adhesive bulk plate was produced in accordance with the French standard NF T 76-142 [35]. From this plate, *dogbone* specimens were manufactured in accordance with British standard BS 2782 [36]. Digital Image Correlation (DIC) analysis is done during the quasi-static testing of the *dogbone* specimens. To guarantee correct tracking of points, black paint was sprayed onto the bulk *dogbone* specimens, thus creating a slight dotted pattern.

2.2.2. Single lap joints

The SLJs were manufactured according to ASTM D 3933-98 standard [37]. Firstly, the 6082 aluminum alloy substrates were gritted and anodized. In the anodization procedure, the substrates were submerged on a mixture of phosphoric acid and distilled water, with a mass proportion of 1 part of acid per 10 of distilled water. Then, an electric current (with a voltage source of 16 V) passed through the substrates and the acid mix for 25 minutes. The anodized substrates were first cleaned with acetone and distilled water and then dried. After completing the surface preparation, the SLJs were produced following the curing cycle defined in Section 2.1 for both adhesives. The geometry of the SLJ specimen is presented in Figure 2.

The SLJ specimens were instrumented with PRYY + 1119 piezoelectric disk sensors from PI Ceramics (Lederhose, Germany) for the EMIS Testing, which is detailed in subsection 2.3.3. These sensors have a diameter of 10 mm and a thickness of 0.2 mm, and are made of PIC 255, which is a soft piezoceramic material with a high Curie temperature ($T_C = 350^\circ\text{C}$). The material properties are presented in Table 1. The PWAS was attached to an adherend of the SLJ with the two-part methacrylate adhesive Plexus MA 422, which is manufactured by ITW Performance Polymers (Chicago, Illinois, United States). A copper wire, with a spiral pattern, was placed under the piezoelectric sensor, and the methacrylate adhesive curing was performed in 8 hours

Table 1. Properties of the soft piezoceramic material.

	Elastic compliance coefficient		Coupling factor	
	s_{11}^E	s_{33}^E	k_p	k_t
Mass density 7.80 g/cm^{-3}	$16.1 \cdot 10^{-12} \text{ m}^2 \text{N}^{-1}$	$20.7 \cdot 10^{-12} \text{ m}^2 \text{N}^{-1}$	0.62	0.47

at room temperature. Afterwards, another copper wire was soldered at the top surface of the piezoceramic transducer.

2.2.3. Uniform and sandwich specimens

Several specimens were manufactured to determine elastic and damping properties of the both the crash-resistant and the silicone adhesives. However, given that the stiffness is significantly different for both adhesives, two different types of specimens were manufactured, with their geometry defined in the ASTM E 756-05 standard [38]. For the Nagase T-836/R-810, uniform specimens were produced, as presented in Figure 3a.

Conversely, sandwich specimens, which are schematically presented in Figure 3b, were manufactured to determine the properties of the rubber adhesive. This was done, since a uniform specimen of silicone adhesive is not stiff enough for these testing procedures. In order to manufacture these specimens, 1050 aluminum alloy base beams were used. The manufacturing process for this type of specimen is similar to the SLJ fabrication procedure, which is described in subsection 2.2.2. These specimens were produced following the curing cycle defined in Section 2.1. The relevant dimensions are presented in Figure 3.

2.3. Testing procedures

2.3.1. Quasi-static testing procedure

Quasi-static tests were performed to determine the elastic properties of the adopted adhesive materials. For this purpose, an INSTRON® 3367 (Norwood, Massachusetts, USA) universal testing machine, with a load cell of 30 kN, was employed. The quasi-static tests were performed at a constant velocity of 1 mm/min, and only for *dogbone* specimens of the crash-resistant adhesive, since the properties of the silicone rubber adhesive were determined in [34].

To determine the Poisson's ratio of the T-836/R-810 adhesive, measurements were also done using optical extensometry. In this procedure, digital images were recorded every five seconds with the help of a digital camera, and a DIC analysis was done using the software GOM Correlate, which is developed by GOM (Braunschweig, Germany).

2.3.2. Vibrating Cantilever beam testing procedure

The obtained results from quasi-static experiments can only yield information regarding the elastic properties of the adhesives under static conditions. Therefore, other experimental procedures were required to determine the adhesive properties in dynamic conditions. The vibrating cantilever beam test method was used for this purpose. Figure 4 presents the adopted experimental setup.

An excitation signal, created by the Fast Fourier Transform (FFT) analyzer (Brüel & Kjaer Signal Analyzer Unit Type 2035, Naerum, Denmark) was first amplified by a Shaker Amplifier, model LDS PA100E (Brüel & Kjaer). This signal was sent to a Shaker (model LDS 401, Brüel & Kjaer), that converts the signal into a mechanical solicitation, so that the attached specimen undergoes flexural vibration. This procedure was performed for a given range of excitation frequencies. An accelerometer (model, 2507-473, Brüel & Kjaer) was placed at the base of the specimen to measure the acceleration. Meanwhile, the velocity at the free end of the beam specimen was measured with non-contact laser Doppler vibrometer. This laser vibrometer includes the Polytec OFV-303 laser head (Waldbronn, Germany), that emits and measures a helium laser, and the Polytec OFV 3001 controller, that decodes the signal from the laser head. The measured signals from the accelerometer and the laser doppler vibrometer are processed by the FFT analyzer. The FFT analyzer calculated the transmissibility of the specimen, TR , such that

$$TR(\omega) = \frac{U(\omega)}{S(\omega)} \quad (2)$$

where ω is the harmonic excitation frequency, and $U(\omega)$ and $S(\omega)$ are the phasors corresponding to the displacement at the free-end (which was obtained through the integration of the velocity measurements) and at the base of the specimen (which was imposed by the Shaker), respectively.

2.3.3. EMIS testing procedure

The main objective of this test was to evaluate the influence of the adhesive properties and the adhesive thickness on the impedance measurements obtained from EMIS testing. The impedance spectrum was measured with a Hioki IM 3570 impedance analyzer (Ueda, Japan). A schematic representation of the experimental setup for impedance measurements is present in Figure 5.

3. Experimental results

3.1. Quasi-static test results

A characteristic stress-strain curve obtained from a quasi-static tensile test of Nagase T-836/R-810 adhesive bulk specimens is presented in Figure 6.

One can observe that this adhesive is simultaneously stiff and ductile, since it has a high elastic modulus and a high maximum strength, while, at the same time, having a considerable maximum tensile strain for an epoxy adhesive. This mechanical performance results from the crash-resistant adhesive, since it is a modified epoxy. The obtained values from three experimental results are listed in Table 2.

As previously mentioned, the tensile tests were recorded with the help of a digital camera and the resultant footage

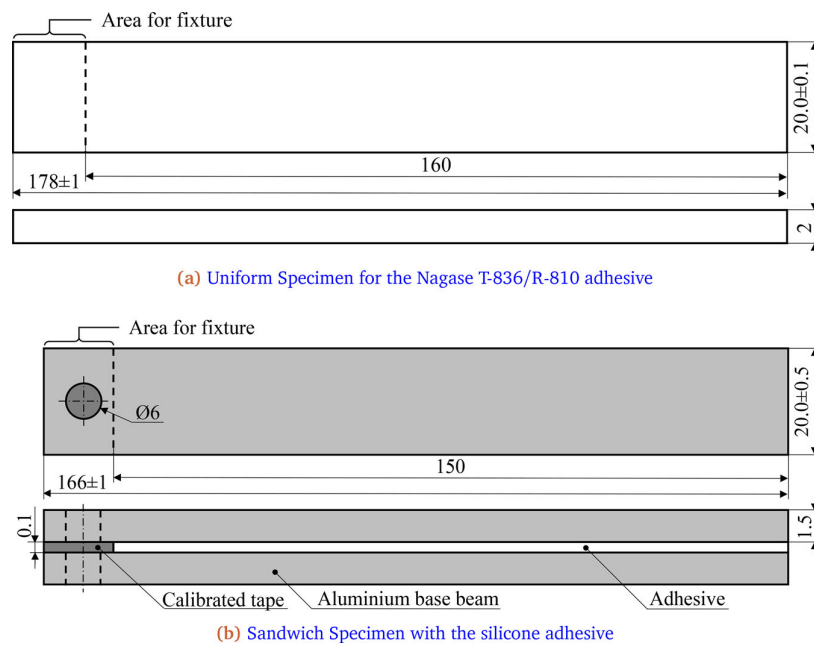


Figure 3. Schematic representation of the specimens used in vibrating cantilever beam tests with dimensions in mm.

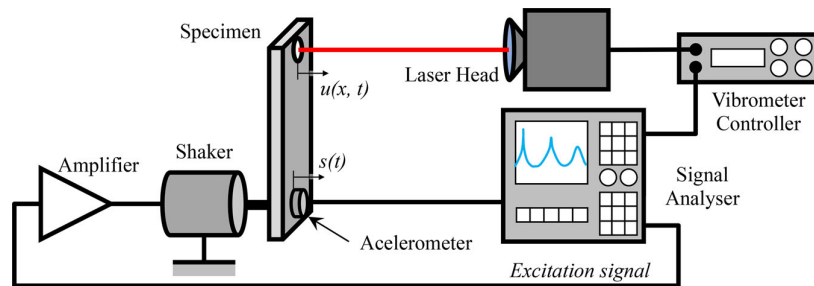


Figure 4. Schematic representation of the experimental VCBT setup.

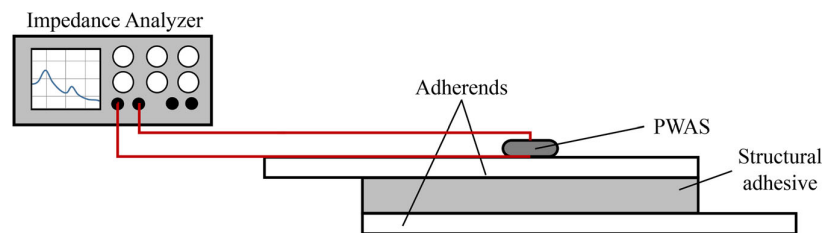


Figure 5. Schematic representation of the experimental impedance measurement setup.

was used in the DIC analysis to obtain the Poisson's ratio, ν . It must be noted that one obtains the elongation suffered by each specimen. Consequently, to calculate the Poisson's ratio, one first needs to compute the longitudinal and transversal strains, ε_l and ε_t , respectively. A typical plot of the strains, ε_l and ε_t , and of the Poisson's ratio, ν , is portrayed in Figure 7 as a function of the measured longitudinal displacement, Δl . It is noteworthy to mention that the first three measured points were disregarded, since the obtained elongations in the transversal direction are prone to error from the image resolution. The obtained value for the Poisson's Ratio, ν , is listed in Table 2, which were determined from the three tested specimens.

3.2. Vibrating Cantilever beam test results

Vibrating Cantilever Beam Tests were performed with the crash-resistant and silicone adhesives, using uniform and sandwich specimens, respectively. Figure 8a and b present the measured transmissibility versus the excitation frequency. Since a uniform specimen behaves as a cantilever beam under flexural vibration, the natural frequency of mode i , f_i^t , was calculated [39] with the Young's Modulus, E , yielded from the quasi-static tests. Conversely, the estimation of the natural frequencies was not considered for the sandwich specimens. As such, only the experimental transmissibility is plotted in Figure 8b.

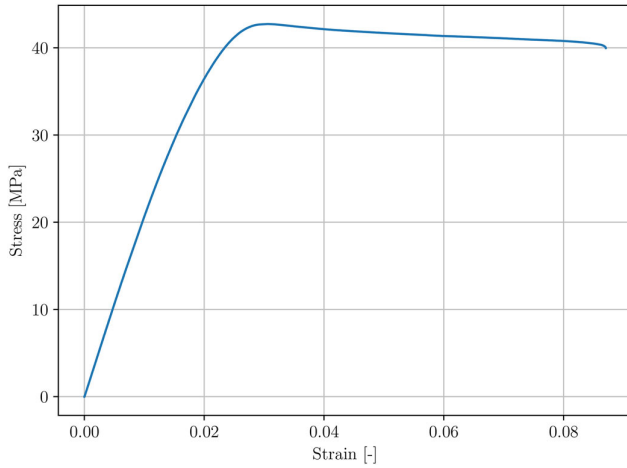


Figure 6. Example of a stress-strain curve obtained for the tensile test of a T-836/R-810 adhesive *dogbone* specimen tested at room temperature and at quasi-static conditions (1 mm/min).

Observing **Figure 8a**, one can see that the transmissibility peaks occur at a higher frequency than predicted. This phenomena could explained by the fact that the stiffness of the crash-resistant adhesive increases with the excitation frequency. According to the ASTM E 756-05 standard [38], the elastic modulus can be calculated as follows

$$E = \frac{12\rho h_u^4 f_i^2}{t^2 C_i^2} \quad (3)$$

$$C_i = \begin{cases} 0.55959, & \text{if } i = 1; \\ 3.5069, & \text{if } i = 2; \\ 9.8194, & \text{if } i = 3; \\ \frac{\pi(i - 0.5)^2}{2}, & \text{if } i > 3 \end{cases} \quad (4)$$

where f_i^e is the experimental resonance frequency for mode i (which are the transmissibility peaks), and C_i is the coefficient for mode i of the cantilever beam (fixed uniform specimen, as shown in **Figure 4**), which is presented in **Eq. (4)**. Furthermore, h_u and t are the useful length of the specimen (which is 160 mm), and the thickness of the specimen, respectively. The results are plotted in **Figure 9a**, which shows that the Young's Modulus augments with the frequency of vibration, f .

The loss factor, η , that describes the damping of the adhesive, is obtained as

$$\eta = \frac{\Delta f_i}{f_i^e} \quad (5)$$

where Δf_i is the half-power bandwidth of mode i .

As one can see, damping decreases with the increase of the vibration frequency, until reaching the third natural mode at around 300 Hz. Afterwards, the loss factor, η , increases significantly as the vibration frequency rises. Additional tests were carried out with higher excitation frequencies, showing that the loss factor increases further. However, one could not calculate η based on the obtained experimental results, since the amplitudes of the transmissibility peaks for the following

Table 2. Mechanical properties of the crash-resistant adhesive *dogbone* specimens at room temperature.

Young's Modulus, E [MPa]	2095.08 ± 83.52
Max. tensile strength, σ_m [MPa]	43.01 ± 1.14
Poisson's ratio, ν [—]	0.4182 ± 0.0174

natural modes became exponentially smaller, thus making infeasible the use of **Eq. (5)**.

One should also remark that the obtained loss factor values are descriptive of the adhesive's behavior for a frequency range between $1 \cdot 10^1$ and $3 \cdot 10^3$ Hz. While one can infer the increase of the loss factor, η , with frequency of up to approximately 10^4 Hz, one cannot foresee with certainty that this trend remains constant for higher frequencies.

As per ASTM E 756-05 standard [38], one can also determine elastic and damping properties from the transmissibility of the two-part silicone adhesive, as presented in **Figure 8b**. From this, one can calculate the shear modulus of the adhesive, G , such that

$$G = (A - B - 2(A - B)^2 - 2(A\eta_s)^2) \left[\frac{\left(\frac{2\pi E_b C_i t_b t}{h_u^2} \right)}{(1 - 2A + 2B) + 4(A\eta_s)^2} \right] \quad (6)$$

where η_s is the loss factor of the sandwiched specimen, D is the mass density ratio, T is the thickness ratio, and A and B are parameters. These variables are defined in the following equations:

$$\eta_s = \frac{\Delta f_{s,i}}{f_{s,i}}, \quad D = \frac{\rho}{\rho_b}, \quad T = \frac{t}{t_b} \quad (7)$$

$$A = \frac{f_{s,i}}{f_{b,i}} \frac{B}{2} (2 + DT), \quad B = \frac{1}{6(1 + T)^2} \quad (8)$$

where E_b denotes the elastic modulus of the base beam and h_u is the useful length of the beam, while ρ and ρ_b are the mass density of the adhesive and the base beam, respectively. Additionally, the parameters t_b and t correspond to the thickness of the base beam and of the adhesive material, respectively, while C_i is the coefficient for mode i of the cantilever beam, as defined in **Eq. (4)**. One should also note that $f_{b,i}$ and $f_{s,i}$ represent the resonance frequencies for mode i of the base beam and the sandwich beam, respectively, while $\Delta f_{s,i}$ is the half-power bandwidth of mode i of sandwich specimen. The values for $f_{s,i}$ were extracted from the Transmissibility plot of **Figure 8b**, while $f_{b,i}$ was estimated with the help of the theoretical formula that determines the natural frequencies of flexural vibration of beams. This simplification can be done, since the obtained values are an extremely good approximation of the experimental values for the natural frequencies of the base aluminum beam.

The obtained results from this calculation are represented in **Figure 10a**. One can observe that, for low frequencies, there is a sharp increase of the shear modulus, until reaching a frequency of approximately 600 Hz. Afterwards, the shear modulus remains almost constant at circa 10 MPa.

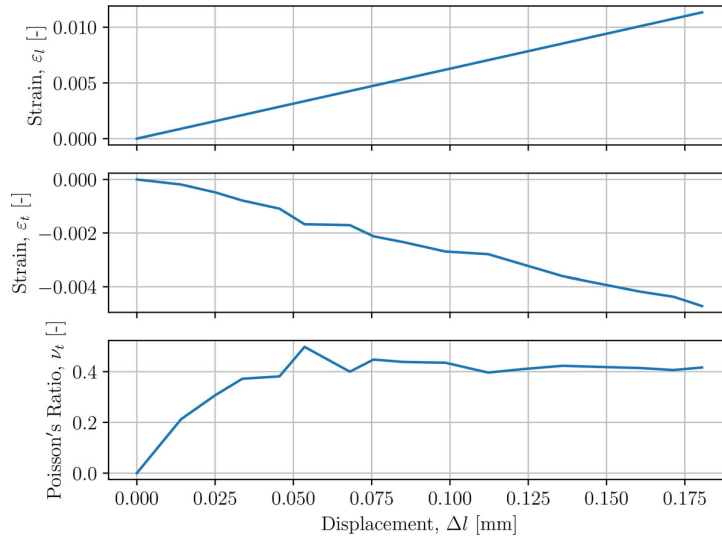
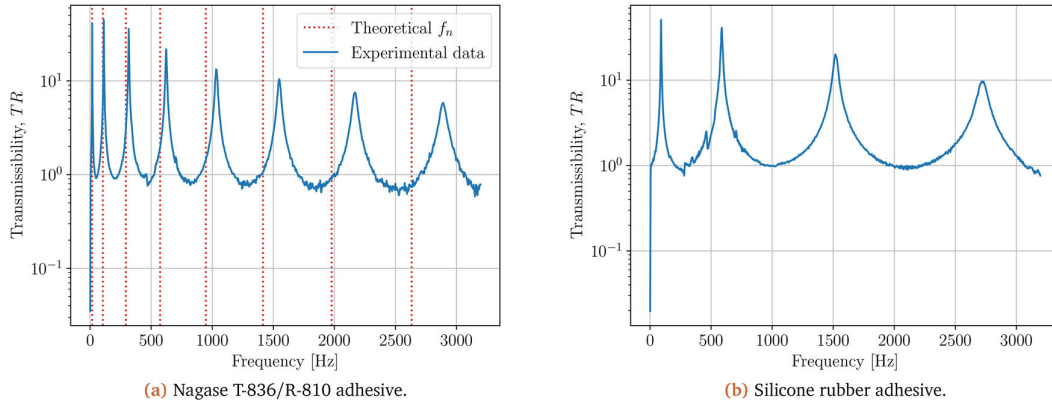


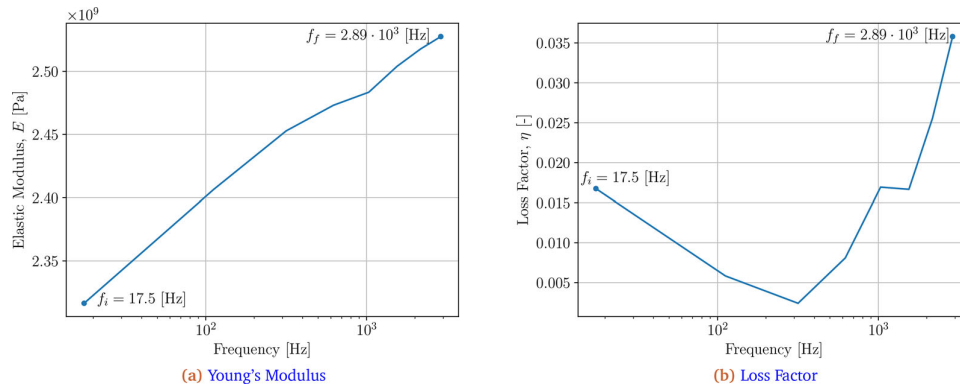
Figure 7. Example of the strains, ε_l and ε_t , and of the Poisson's ratio, ν , from the DIC analysis of the tensile test of the T-836/R-810 adhesive *dogbone* specimen.



(a) Nagase T-836/R-810 adhesive.

(b) Silicone rubber adhesive.

Figure 8. Transmissibility of a uniform (crash-resistant) and sandwich (silicone) specimen, respectively.



(a) Young's Modulus

(b) Loss Factor

Figure 9. Parameters of the Nagase T-836/R-810 adhesive as a function of frequency, f .

The shear loss factor of the silicone adhesive, η , is determined by

$$\eta = \frac{A\eta_s}{A - B - 2(A - B)^2 - 2(A\eta_s)^2} \quad (9)$$

Note that the parameters A , B and η_s have already been defined in Eqs. (7) and (8). The corresponding results are plotted in Figure 10b. One can clearly see that first a small decrease of the shear loss is observed for low excitation

frequencies. However, after reaching 600 Hz, the loss factor increases monotonically.

3.3. Impedance measurements

Influence of the voltage supply

Figure 11 presents the Bode plot of the measured impedance spectra for a SLJ specimen for voltage supply values of 1.0,

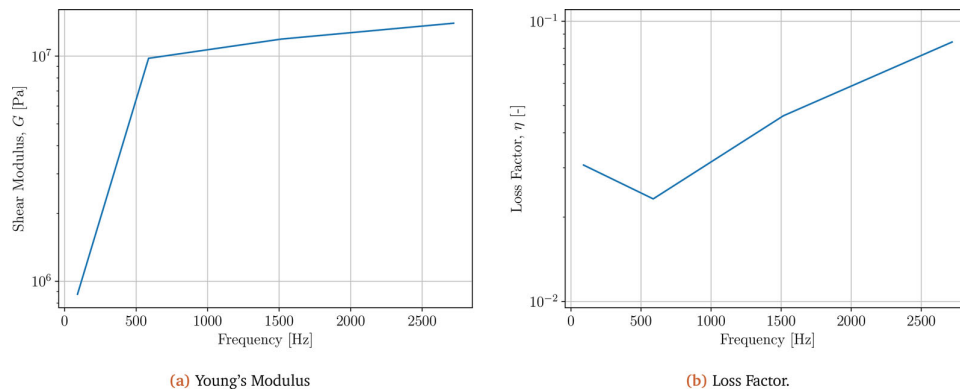


Figure 10. Material parameters of the silicone adhesive as a function of frequency, f .

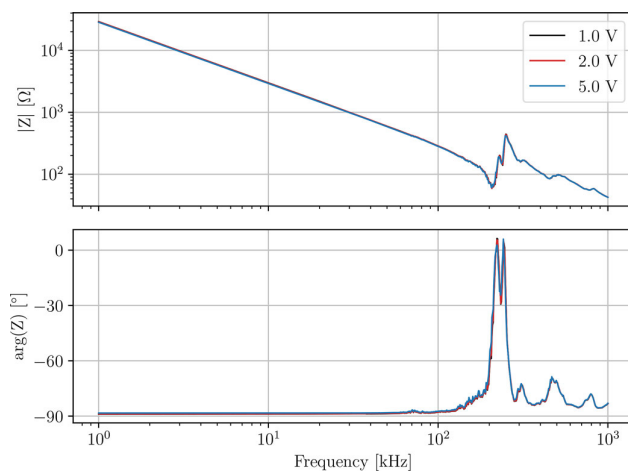


Figure 11. Bode plot of the impedance measurements of a Nagase crash-resistant adhesive SLJ specimen with adhesive thickness of 0.2 mm, with source voltage values of 1.0, 2.0 and 5.0 V.

2.0 or 5.0 V. The measurements were performed for a frequency range between 1 kHz and 1 MHz. In this analysis, the specimen used was made using the crash-resistant adhesive with an adhesive layer of 0.2 mm thickness.

One can observe that there is almost no difference between the obtained experimental data. Only minor variations in the peaks of the impedance occur, in both the magnitude and phase of the peaks near 200 kHz. This difference is more pronounced for the measurements with a voltage of 5.0 V. These differences may be caused by minor variations in the properties of the piezoceramic sensor, such as the complex elastic modulus, $\bar{Y}$.

Influence of sensor integrity and adhesion to SLJ

Measurements were done for various SLJs with identical parameters (same adhesive material and identical adhesive thickness). Figure 12a and b present the readings for specimens with 0.2 and 1.0 mm thickness of the Nagase T-836/R-810 adhesive. Note that, for each condition, three SLJs were manufactured.

From Figure 12a, one can see that the measured impedance spectra of SLJs 2 and 3 are considerably similar. In fact, merely small differences are observed in the small peaks

present in the frequency range of 10 kHz to 100 kHz, and in the main peaks between 100 kHz and 1 MHz. Several reasons can be put forward for the variations. Firstly, small voids could occur due to non uniform methacrilate adhesive spreading. Concurrently, the copper wire deposited between the sensor and the adhesive joint may not always have the same spiral, i.e., the same number of turns, the same diameter, etc. This observation is also applicable for the impedance spectra of SLJs 2 and 3, which were manufactured with the crash-resistant adhesive and an adhesive thickness of 1.0 mm, as seen in Figure 12b.

Conversely, the impedance spectrum of SLJ 1, depicted in Figure 12a, which corresponds to the measurements for the SLJ with the Nagase T-836/R-810 adhesive of thickness of 0.2 mm, is considerably different from the other two spectra. Firstly, the peaks of the real component, $\text{Re}(Z)$, which are present in the readings of SLJs 2 and 3 in the frequency range of 10 kHz to 100 kHz, do not exist in the impedance readings of SLJ 1. Second, the main resonance, which occurs at approximately 300 kHz for SLJs 2 and 3, had a leftward shift, shifting to approximately 250 kHz. Furthermore, an increase of the peak amplitude also occurs. These variations are observed when the sensor is not completely bonded to the structure, which leads to a decrease of the dynamic stiffness of the sensor bonding layer [40].

The impedance spectrum of SLJ 1, shown in Figure 12b, is considerably different from the other impedance measurements of the crash-resistant bonded specimens ($t_A = 1.0$ mm). At low frequencies, the impedance magnitude is considerably higher than those of SLJs 2 and 3, and at higher frequencies, the main measured peaks do not align with the measured peaks from the other adhesively bonded specimens.

Influence of adhesive thickness for the crash-resistant adhesive

Figure 13 compares the measured impedance spectra of the modified-epoxy bonded SLJ with adhesive thicknesses, t_A , of 0.2, 0.5 and 1.0 mm. Figure 13a displays the log-log plot of the experimental results for 1 kHz to 1 MHz in Cartesian coordinates, while Figure 13b displays the Nyquist plot of the measured impedances between 400 kHz and 1 MHz.

One verifies that the main impedance peaks observed at higher frequencies (above 100 kHz) increase with a bigger

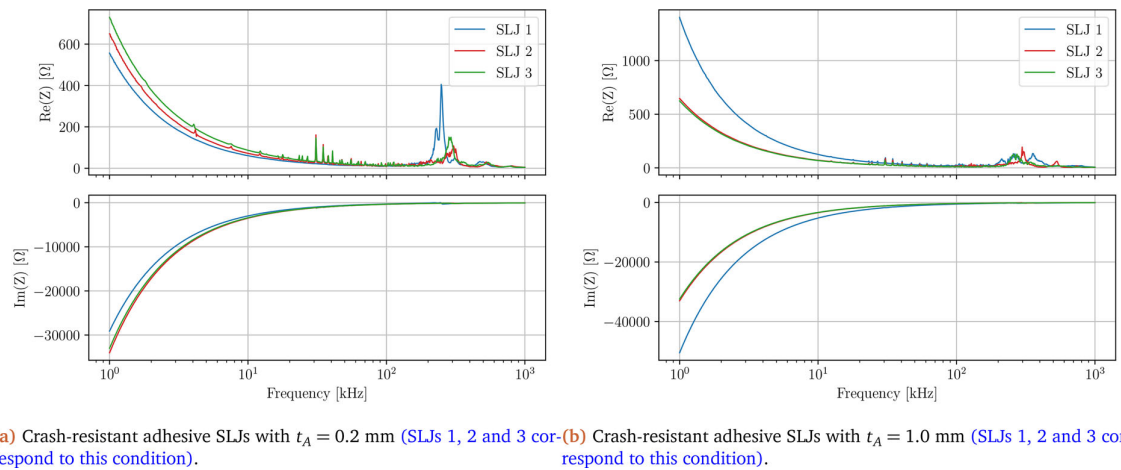


Figure 12. Impedance spectra of various SLJs.

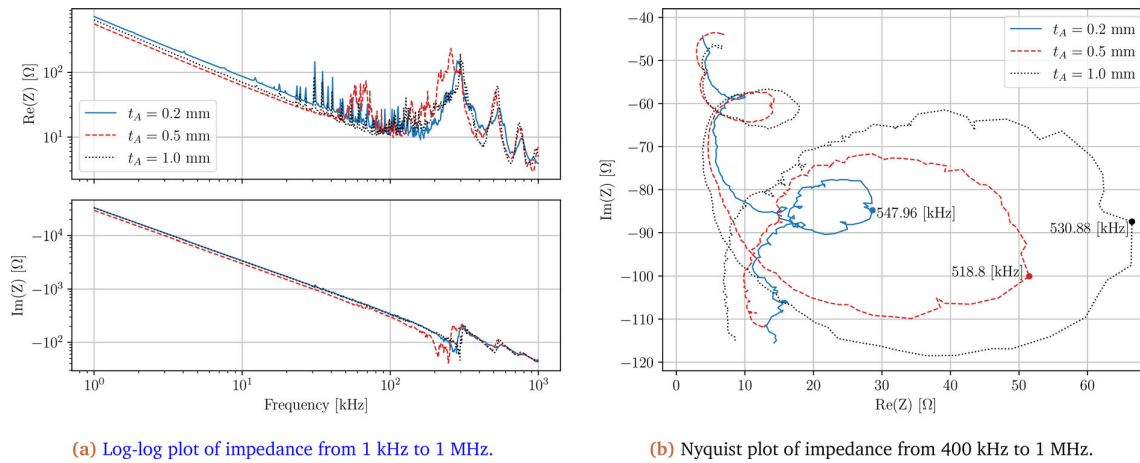


Figure 13. Impedance spectra of SLJs with crash-resistant adhesive with thicknesses $t_A \in \{0.2, 0.5, 1.0\}$ mm.

thickness of the adhesive layer. This is more easily seen for the real component of the impedance, $\text{Re}(Z)$, since this component is not greatly affected by the electrical properties. However, the Nyquist plot presented in Figure 13b shows that these changes in the imaginary part, $\text{Im}(Z)$, also increase. Conversely, the observed peaks occur at approximately the same frequency, meaning that the adhesive thickness does not result in a frequency shift of the observed peaks.

Impedance measurements of the SLJ with adhesive thickness of 0.5 mm showed a significant change in the frequencies ranging from 50 to 80 kHz, when compared to the other two impedance spectra. This change is only visible in the real part of the impedance, $\text{Re}(Z)$, since the exponential increase of $\text{Im}(Z)$ still occurs in this frequency range. This is quite different than the obtained impedance measurements for the SLJs with adhesive thickness of 0.2 and 1.0 mm.

Influence of adhesive thickness for the silicone adhesive

Figure 14 compares the measured impedance spectra of the SLJ specimens with two-part silicone adhesive and with adhesive thicknesses, t_A , of 0.2, 0.5 and 1.0 mm. Figure 14a presents the log-log plot of the experimental results for 1 kHz to 1 MHz in Cartesian coordinates, while Figure 14b

gives the Nyquist plot of the measured impedances between 400 kHz and 1 MHz.

For low frequencies, i.e., between 1 kHz and 100 kHz, one can see that small peaks occur in the spectra of $\text{Re}(Z)$, and that their amplitude tends to decrease with an increase of the adhesive thickness. Furthermore, for the case when $t_A = 1.0$ mm, these peaks have a negligible amplitude. However, despite this, one must note that the peaks start occurring at lower frequencies than those observed for the SLJ specimens bonded with the Nagase adhesive.

For higher frequencies, i.e., 100 kHz above, one can see that the impedance spectrum starts to diverge between SLJs of different adhesive thicknesses. This effect is stronger when $t_A = 1.0$ mm. Apparently, no straightforward reason explains this outcome. However, from the authors experience, the silicone adhesive can easily develop porosities during the curing procedure, which may hypothetically cause a significant influence on the impedance measurements. This effect can be observed when comparing the Nyquist plots of Figures 13b and 14b.

Comparing the impedance results of both the ductile and crash-resistant adhesives, one can see that the impedance spectra obtained for the SLJs with crash-resistant adhesive

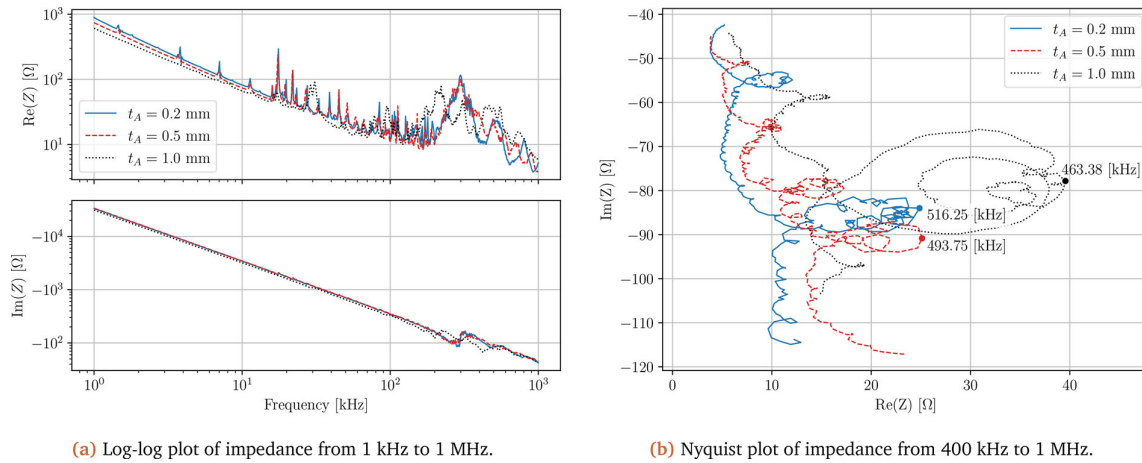


Figure 14. Impedance spectra of SLJs with silicone adhesive with thicknesses $t_A \in \{0.2, 0.5, 1.0\}$ mm.

are more pronounced, than for SLJs with the silicone adhesive. This occurs because the epoxy-modified adhesive is considerably stiffer than the ductile adhesive, while its damping is smaller.

4. Numerical simulations

The main purpose of the numerical models developed in this work is to create models that can accurately recreate the behavior observed experimentally from the impedance measurements. Therefore, a set of numerical simulations were developed using ABAQUS 2017. First, the definition of the numerical models is done, and, afterwards, the simulation results were compared with experimental measurements.

4.1. Numerical models

A direct-steady state linear dynamic analysis was performed over a frequency range between 1 kHz and 1 MHz, with a linearly spaced frequency interval of 1 kHz, thus requiring the calculation of the impedance at 1001 sampling points. Figure 15 shows the 3D assembly model used for the simulations. One should note that Plexus MA 255 methacrilate adhesive was also included in the simulations, since it was verified that the adhesive significantly affected the impedance measurements. The piezoelectric sensor was independently modeled from the remainder of the SLJ. Both parts were then connected with a tie constraint interaction, thus guaranteeing no relative movement between the distinct components, while avoiding any separation between them due to dissimilar meshing.

The mechanical and electrical properties of PIC 255 piezoelectric transducer are presented in Table 3 [41]. The modeled sensor has a diameter of 10 mm and a thickness of 0.2 mm. A mesh control of approximately $7.66 \cdot 10^{-4}$ m was defined at the perimeter of the piezoelectric element. For this component, piezoelectric type 8-node linear brick and reduced integration elements (C3D8R) were used.

To create a voltage excitation of 1 V, two electric potentials were defined at the circular surfaces of the sensor, with

an electric filed potential of $E_t = 1 + 0j$ V at the top surface and of $E_b = 0 + 0j$ V at the bottom surface. 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

$$Z(\omega) = \frac{V(\omega)}{I(\omega)} = \frac{E_t - E_b}{j \omega Q(\omega)} \quad (10)$$

where $V(\omega)$ is the source voltage and $I(\omega)$ is the generated electrical current.

The SLJ component has the dimensions indicated in Figure 2, with the exception of the methacrilate adhesive layer that bonds the sensor to the specimen. This layer is placed on the top surface of an aluminum adherend in the middle of the overlap area. Furthermore, this layer has a cylindrical shape with the same diameter as the PWAS, and a thickness of $3 \cdot 10^{-4}$ m (which corresponds to the diameter of the copper wire used in the experimental specimen). Table 4 lists the mechanical properties of the aluminum alloy and the adhesives included in the models. It is noted that, for both the T-836/R-810 and the silicone adhesives, the inputted elastic and damping properties were based on the obtained VCBT experimental results. Simulations were done with elastic moduli obtained from the quasi-static tests, but the results diverged from the experimentally obtained impedance results.

The model of the SLJ part has a general mesh size of $1 \cdot 10^{-3}$ m. However, several geometries required some mesh refinement. As such, a mesh size of $5 \cdot 10^{-4}$ m was defined along the thickness of both the adhesive and the aluminum adherends. A mesh control of approximately $7.66 \cdot 10^{-4}$ m was defined at the circumference created by the methacrilate adhesive layer. Note also that the entire overlap region was sectioned by the midpoints and the diagonals, as presented in Figure 15, to simplify the meshing. Also, a single bias mesh control was defined in the adherends, fromwards of the overlap area, starting from a mesh size of $1 \cdot 10^{-3}$ m to a mesh size of $5 \cdot 10^{-3}$ m at the free ends.

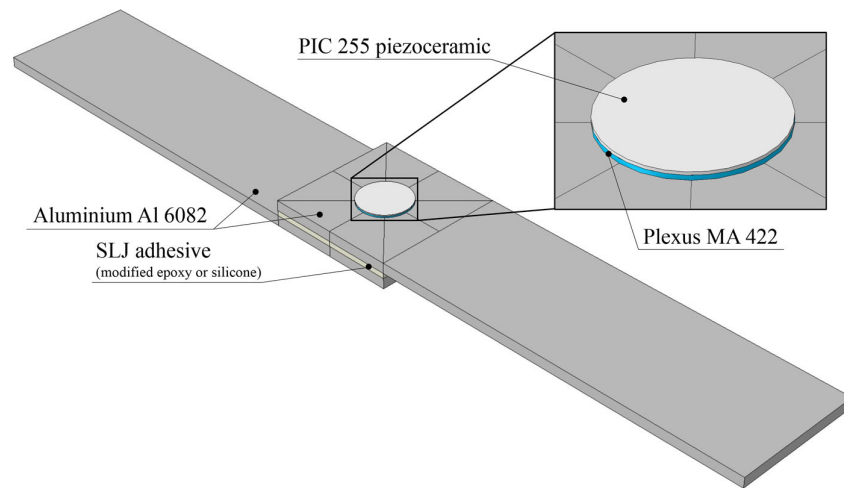


Figure 15. Schematic representation of the 3D model used to replicate the impedance measurements obtained experimentally.

Table 3. Electric and mechanical properties of the PIC 255 piezoceramic material used in the finite element model.

Property	Unit	Notation	Value
Elastic modulus	GPa	E_1	62.89
		E_2	62.89
		E_3	47.69
Shear modulus	GPa	G_{13}	22.26
		G_{23}	22.26
		G_{12}	23.15
Poisson's ratio	[-]	ν_{13}	0.46
		ν_{23}	0.46
		ν_{12}	0.36
Permittivity at constant strain	nF m ⁻¹	ϵ_1	8.234
		ϵ_2	8.234
		ϵ_3	7.588
Piezoelectric stress coefficients	C m ⁻²	e_{15}	11.9
		e_{24}	11.9
		e_{31}	-7.15
		e_{32}	-7.15
		e_{33}	13.7
Mass density	kg m ⁻³	ρ	7800

Table 4. Properties of the adhesives and adherend used in the finite element model.

Material	E [GPa]	ν [-]	η [-]	ρ [kg m ⁻³]
Aluminum Al 6082	70.0	0.33	$5.0 \cdot 10^{-4}$	2710
Plexus MA 422	0.994	0.31	0.45	960
Nagase T-836/R-810	2.55	0.41	0.10	1200
Silicone adhesive	$29.95 \cdot 10^{-3}$	0.495	1	1260

4.2. Simulation results

Results for the crash-resistant adhesive and comparison with experimental results

Figure 16a and b present, respectively, the log-log and the Nyquist plots of the processed electrical impedance results, $Z(\omega)$, from the direct-steady state linear simulations of the crash-resistant bonded SLJ, with adhesive thickness, t_A , of 0.2, 0.5 and 1.0 mm.

Comparing these results, one can merely see a small deviation of the overall impedance spectra. The four main resonance peaks observed in the frequency range between 100 kHz and 1 MHz occur at the approximately at the same frequency. The frequencies of the first to peaks of the real part of the simulated electrical impedance, $\text{Re}(Z)$, which are

indicated in Figure 16b, have a difference of up to 3 kHz. Furthermore, there is no clear trend in the evolution of the real and imaginary components of the impedance with an increase of the thickness of the adhesive layer, unlike what was observed experimentally in Figure 13. One can only note that the amplitude of the real and imaginary parts of the impedance decrease with an increase of excitation frequency. This can be seen in the Nyquist plot present in Figure 16b, since the loop trajectories become smaller when increasing the input voltage frequency.

Figures 17–19 compare the experimental and simulation results for the SLJs bonded using the Nagase adhesive with an adhesive thickness, t_A , of 0.2, 0.5 and 1.0 mm, respectively.

From this comparison, one can say that the simulation results match fairly well with the experimental measurements. First off, the main peaks of the real and imaginary components of the electric impedance, $\text{Re}(Z)$ and $\text{Im}(Z)$, occur at approximately the same frequency as the peaks observed in the measured impedance spectra. In the particular case of the SLJ with an adhesive thickness, $t_A = 0.5$ mm, the peaks occur at a slightly higher frequency than those recorded in the experimental results. Conversely, the peaks of the simulated electrical impedance in SLJs with adhesive thickness, t_A , of 0.2 and 1.0 mm occur at a lower frequency than those observed in the experimental results. This is more noticeable in the log-log plots, since the electric impedance decreases exponentially with an increase of the signal's frequency.

This being said, the aforementioned peaks that occur at higher frequencies (above 100 kHz), apparently have higher amplitudes than the ones obtained experimentally. This occurs both for the real and imaginary components, $\text{Re}(Z)$ and $\text{Im}(Z)$. Furthermore, the difference between the amplitudes of the experimental and numerical results increases from peak to peak. Meanwhile, the simulated real component values between consecutive peaks is considerably lower than the measured values. Consequently, one can deduce that the loss factor, η , of one, or of both adhesives (the

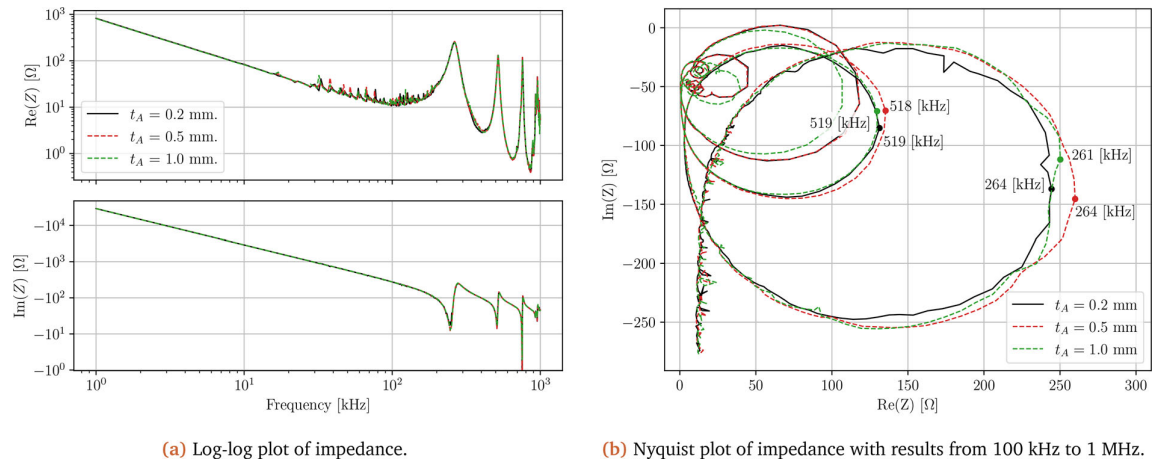


Figure 16. Simulated impedance spectra of SLJs with crash-resistant adhesive with thicknesses $t_A \in \{0.2, 0.5, 1.0\}$ mm.

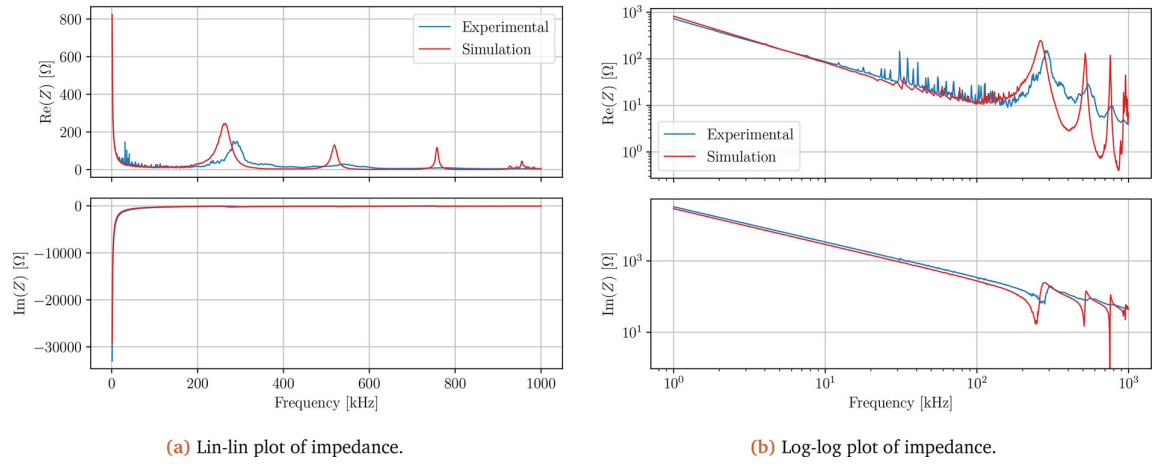


Figure 17. Comparison between the experimental measurements and simulation results for the crash-resistant adhesive SLJ with an adhesive thickness of 0.2 mm.

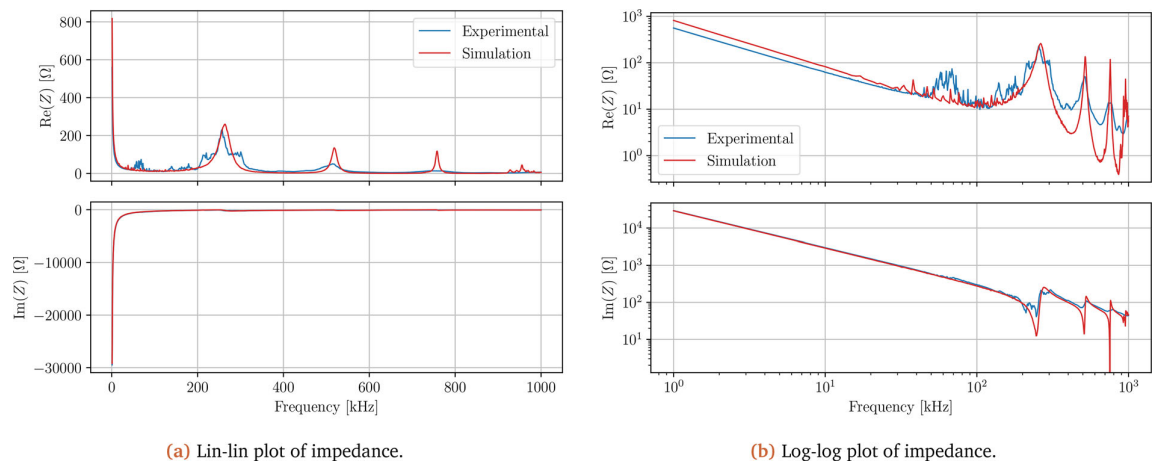


Figure 18. Comparison between the experimental measurements and simulation results for the crash-resistant adhesive SLJ with and adhesive thickness of 0.5 mm.

epoxy-modified and methacrilate adhesives) may vary with excitation frequency.

The small peaks in the real component of the impedance, $\text{Re}(Z)$, which are present in the frequency range of 10 kHz to 200 kHz, are also recreated with numerical simulations.

However, the sub-peaks amplitude from the simulation results are somewhat smaller than those obtained in the experimental measurements. One can adjust this by increasing the mesh size. Furthermore, these peaks do not occur at the same frequencies as for the experiments. This issue can

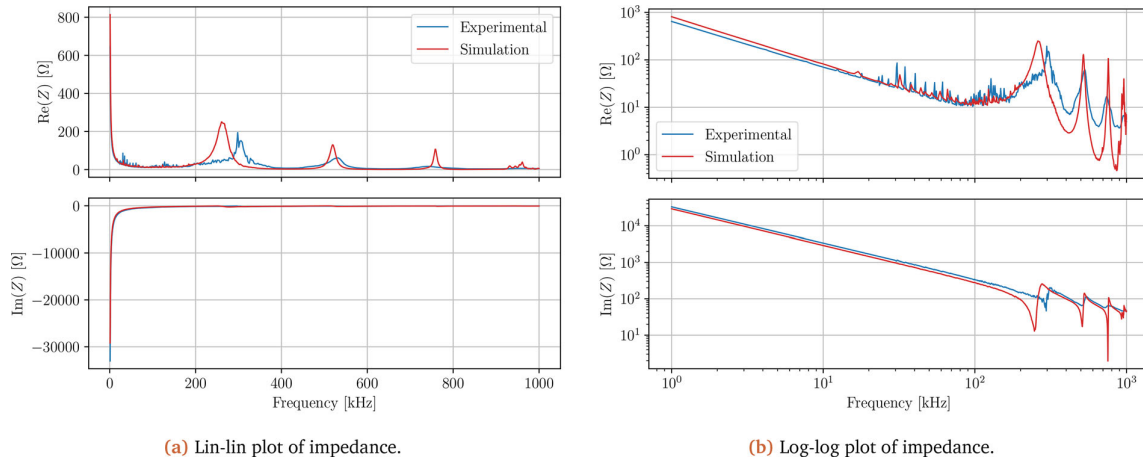


Figure 19. Comparison between the experimental measurements and simulation results for the crash-resistant adhesive SLJ with an adhesive thickness of 1.0 mm.

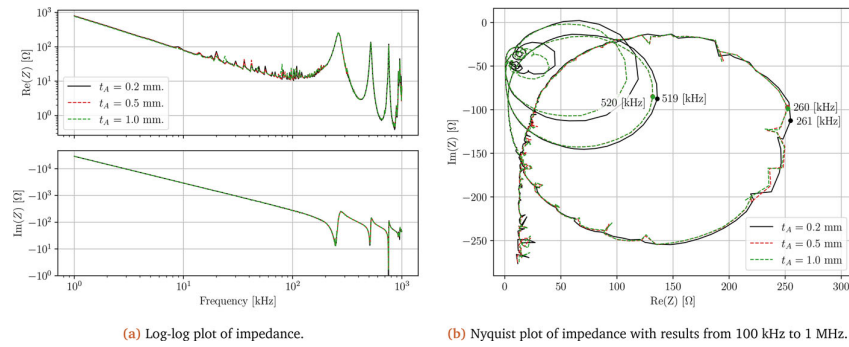


Figure 20. Simulated impedance spectra of SLJs with silicone adhesive with thicknesses $t_A \in \{0.2, 0.5, 1.0\}$ mm.

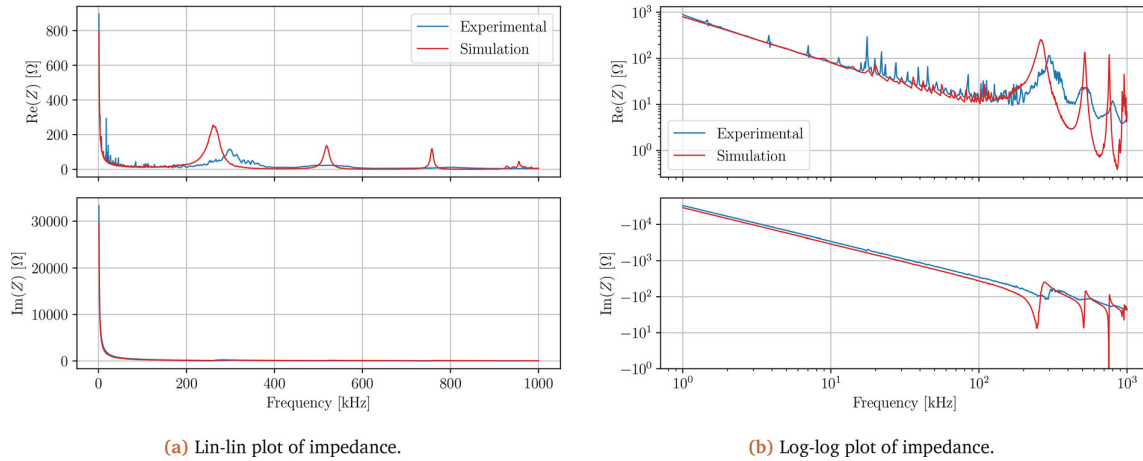


Figure 21. Comparison between the experimental measurements and simulation results for the silicone adhesive SLJ with an adhesive thickness of 0.2 mm.

be mitigated by increasing the number of sampling instances for which impedances are calculated.

Results for the silicone adhesive and comparison with experimental results

Figure 20a and b present, respectively, the log-log plot and the Nyquist plot of the processed electrical impedance results, $Z(\omega)$, from the direct-steady state linear simulations

of the silicone adhesive bonded SLJ, with adhesive thickness, t_A , of 0.2, 0.5 and 1.0 mm.

Comparing these results, there is little difference in the overall impedance spectra, just like for the previously presented simulation results. Once again, the four main resonance peaks observed in the frequency range between 100 kHz and 1 MHz occur approximately at the same frequency, as indicated in Figure 20b. Also, the three simulated impedance spectra are similar to each other, as well as to the simulated impedance spectra of the crash-resistant bonded SLJs. This

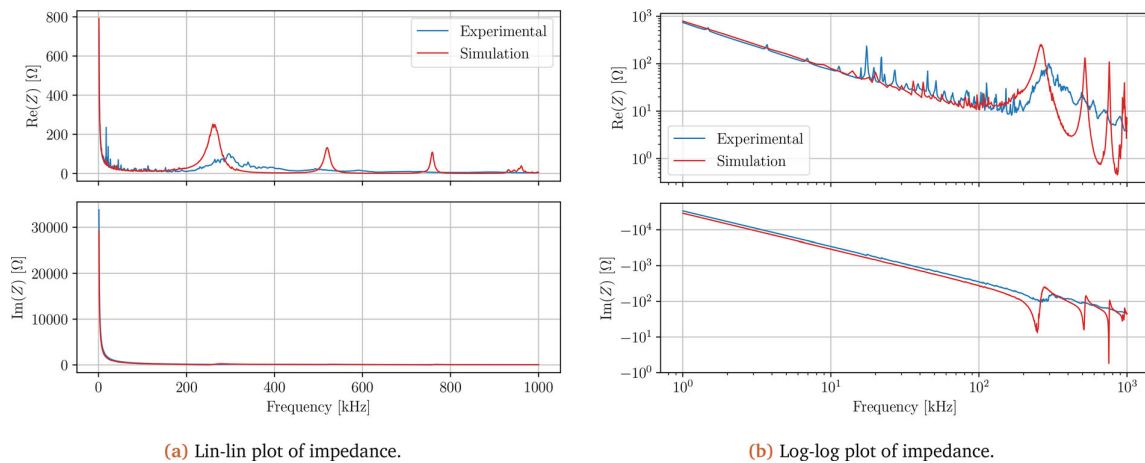


Figure 22. Comparison between the experimental measurements and simulation results for the silicone adhesive SLJ with an adhesive thickness of 0.5 mm.

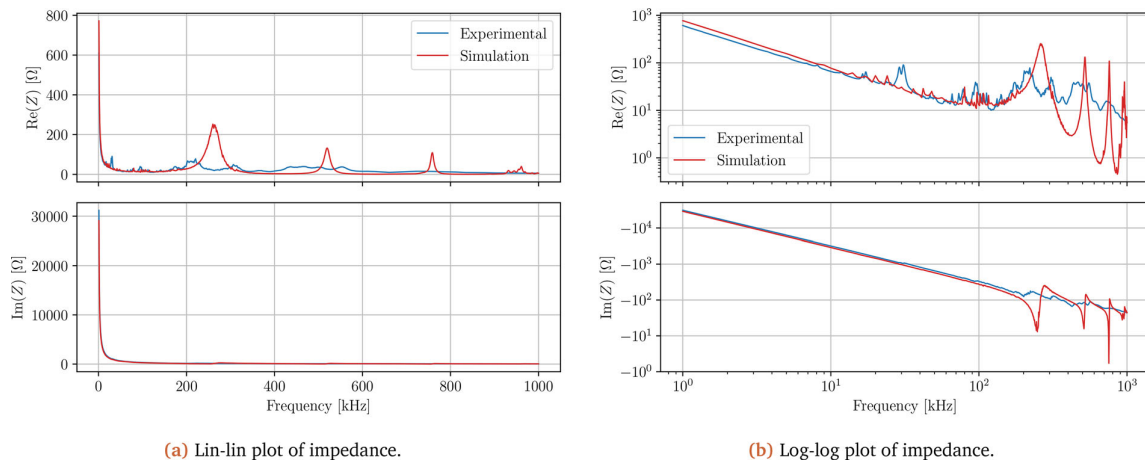


Figure 23. Comparison between the experimental measurements and simulation results for the silicone adhesive SLJ with an adhesive thickness of 1.0 mm.

seems to imply that the obtained measurements are very dependent on the loss factor of the methacrilate adhesive that bonds the piezoelectric element to the specimen. Therefore, two conclusions can be drawn from this: first, the loss factor of the methacrilate adhesive varies with the excitation frequency and second, adhesives with smaller damping may be more adequate to bond piezoelectric sensors on SLJs.

Figures 21–23 compare the experimental measurements and the simulation results for the SLJs bonded using the two-part silicone adhesive with an adhesive thickness, t_A , of 0.2, 0.5 and 1.0 mm, respectively.

Comparing these results, one sees that the simulation results have similarities with experimental measurements, but, overall, these results are more divergent, when compared with obtained impedance results for the modified epoxy adhesive, as presented in Figures 17–19. As with the previous comparison, one can see that the major peaks observed after 100 kHz still occur at approximately the same frequency, and, at the same time, the amplitude values obtained from the numeric simulations are considerably higher than those observed experimentally. However, the difference between the observed amplitudes in both the real and imaginary components are higher in this case than in

the previous case where SLJs were bonded with the crash-resistant adhesive.

Also, one can see that the numerically simulated impedance subpeaks obtained at low frequencies, as in bellow 100 kHz, start appearing at higher frequencies than the ones observed experimentally. When viewing Figures 17 and 18, one sees that the experimental results show subpeaks appearing right in the 1 kHz range, while numerical results show that these peaks start appearing at frequencies above 10 kHz.

Some of these discrepancies between the numeric and experimental results may be due to the fact that the silicone adhesive was modeled as an elastic material, despite actually exhibiting an hyperelastic mechanical behavior. As such, a possible future line of research may be to investigate possible model hyperelastic models with damping to simulate in a more accurate manner silicone adhesives.

5. Conclusion

In this paper, an experimental framework was developed using vibrating cantilever beam tests to obtain the elastic and damping properties of adhesives for a given range of frequencies. The results were compared with elastic

properties obtained from quasi-static tensile test results. Vibrating cantilever beam experiments allow a better estimation of the elastic properties in a range of frequencies and enable an accurate determination of the loss factor of adhesives. The experimental setup used was limited to the quantification of the elastic and damping properties of adhesives for low vibration frequencies. These results allow one to estimate the material properties for high frequencies, but research is still needed to accurately validate this.

Impedance measurements were performed with SLJ specimens which were bonded with a crash-resistant adhesive and a silicone adhesive, with the adhesive thickness, t_A , varying between 0.2 and 1.0 mm. There is a small variation of impedance values with the adhesive thickness at frequencies below 100 kHz. At higher frequencies, the impedance variations are more significant, in particular for the epoxy-modified adhesive. In these SLJ specimens, the amplitude of the measured impedance peaks ($\text{Re}(Z)$ and $\text{Im}(Z)$) increases as the adhesive thickness increases. However, for the impedance spectra of the silicone adhesive bonded SLJs, no clear trend could be defined.

Direct-steady state linear dynamic models were designed to simulate the electrical impedance measurements for SLJs with both the modified-epoxy and the silicone adhesives. The simulation results agree with the experiments, despite not allowing a clear distinction between the adhesive materials and thicknesses. This is due to the fact that the damping of the methacrylate adhesive, used to bond the piezoelectric sensor to the specimen, is considerably high and, consequently, influences the electric impedance simulation results. Therefore, further study is required to evaluate and quantify the influence of this adhesive in the impedance readings, and to evaluate which adhesive is better suited for this application. The simulations of the SLJs bonded with the crash-resistant adhesive better matched the measurements than those for the silicone adhesive. This may be due to the fact that the silicone material behaves as an hyperelastic material.

Disclosure statement

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors gratefully acknowledge the funding of grant 2021.07689.BD, which is provided by Fundação para a Ciência e Tecnologia (FCT).

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Appendix C

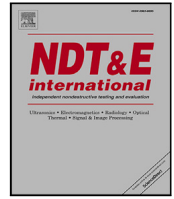
Paper C

Influence of void damage on the electromechanical impedance spectra of Single Lap Joints



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Influence of void damage on the electromechanical impedance spectra of Single Lap Joints

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ARTICLE INFO

Keywords:

Structural Health Monitoring
Electromechanical Impedance Spectroscopy
Adhesive joints
Void
Electrical impedance
Void detection

ABSTRACT

Adhesively bonded joints are susceptible to a variety of damage sources, which may be of difficult detection with current Non-Destructive Testing (NDT) methods. Structural Health Monitoring (SHM) techniques, such as the Electromechanical Impedance Spectroscopy (EMIS), aims to outpace NDT by continuously monitoring structures for defects. However, given the complexity of adhesive joint structures, EMIS capability for damage detection still needs to be thoroughly studied. In this manner, electrical impedance measurements were done to Single Lap Joints (SLJ), with both a modified epoxy adhesive and Pressure Sensitive Adhesive (PSA) for void detection. Void defects could not be detected on adhesive joints with the PSA but, in the case of joints with the modified epoxy adhesive, impedance signatures were significantly altered by the presence of both the artificially created void, and by a second damage source caused during the SLJ manufacture. Experimental measurements from modified epoxy joints were compared with simulation results, yielding good approximation when considering the effect of the second source of damage. An approximation of the mechanical impedance was also computed using numerical results from the pristine SLJ model. In this manner, it is possible to detect damage in the adhesive layer of SLJs with electrical impedance measurements from EMIS.

1. Introduction

Structural adhesive bonding has been replacing conventional joining methods such as welding, riveting or bolting. This is particularly true for vehicular structures, since mechanical connections require the addition of weld material or the use of rivets, bolts and nuts, which increase structural weight and vehicular fuel consumption. Furthermore, by using structural adhesives, holes are avoided, which induce possible notching effects [1]. Despite this, adhesive joints are prone to thermal or aging effects [2,3], diverse loading solicitations (e.g., high strain-rate or fatigue conditions) [4–7] and the introduction of contaminants during the manufacture [8]. These phenomena negatively impact the mechanical performance of structural joints, thus requiring adequate damage detection methods.

Non-Destructive Tests (NDT) are industrially employed to inspect the bond integrity of adhesive joints [9,10]. These testing methods cannot quantify the joint strength, as this would entail the destruction of the joint. Instead, NDT detect possible defects by mapping the stiffness, bond area and mass density distribution. However, damage detection in adhesive joints is limited, and measurements may require advanced signal processing and algorithmic tools [11], or special laboratory set-ups [12,13]. Moreover, industry specific safety regulations

and legislation mandate regular inspection of vehicular structures and their time-scheduled maintenance. In this manner, maintenance aims to detect any signal of early structural failure, despite the loss on potential revenue and the high maintenance costs associated with such procedures [14].

Evolving from NDT, Structural Health Monitoring (SHM) methods automatically and continuously monitor a given structure to detect and characterize damage. In SHM, sensors electrically measure and digitally store specific structural behavior. Afterwards, features are extracted from said signals and are inputted to algorithms that will detect, locate and quantify a given damage source [15–18].

Various SHM techniques exist, such as the Electromechanical Impedance Spectroscopy (EMIS), which uses piezoelectric elements for their electromechanical coupled behavior. Structural examination with EMIS starts by generating a low voltage AC signal that excites the Piezoelectric Wafer Active Sensor (PWAS). This piezoelectric element converts the electric signal into a mechanical vibration. Concurrently, the PWAS behaves as a sensor by converting the mechanical response of the structure into an electric signal. The signal is read by an Impedance Analyzer, which calculates the electric impedance of the PWAS, $Z_e(j\omega)$. This electrical impedance is influenced by the material properties of

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<https://doi.org/10.1016/j.ndteint.2023.102865>

Received 9 February 2023; Received in revised form 26 April 2023; Accepted 29 April 2023

Available online 6 May 2023

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$$Z_e(j\omega) = \left[j\omega \frac{w_p l_p}{h_p} \left(\bar{\epsilon}_{33}^T + \frac{d_{31}^2 \bar{Y}_{11}^E}{1 - \nu} \left(\frac{\sin(\kappa l_p) \sin(\kappa w_p)}{l_p w_p} - 2 \right) \right. \right. \\ \left. \left. \begin{bmatrix} \kappa \cos(\kappa l_p) \left(1 + \frac{Z_{s,xx}}{Z_{p,xx}} - \frac{\nu w_p Z_{s,xy}}{l_p Z_{p,xx}} \right) & \frac{\kappa \cos(\kappa w_p)}{Z_{p,yy}} \left(\frac{l_p Z_{s,yx}}{w_p} - \nu Z_{s,yy} \right) \\ \frac{\kappa \cos(\kappa w_p)}{Z_{p,xx}} \left(\frac{w_p Z_{s,xy}}{l_p} - \nu Z_{s,xx} \right) & \kappa \cos(\kappa w_p) \left(1 + \frac{Z_{s,yy}}{Z_{p,yy}} - \frac{\nu l_p Z_{s,yx}}{w_p Z_{p,yy}} \right) \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right]^{-1} \right]^{-1} \quad (4)$$

Box I.

the structure, which can be described by its mechanical impedance, $Z_{m,s}(j\omega)$ [17,19].

Various analytical models allow the estimation of the measured electric impedance, $Z_e(j\omega)$, as a function of the piezoceramic properties and of the mechanical impedance, $Z_{m,s}(j\omega) = F/\dot{x}$, where F and $\dot{x}$ are the load excitation and the velocity of the excited structure, respectively [20–22].

Liang et al. [23] presented the first and simplest analytical electromechanical impedance model, which is presented in Eq. (1). This model corresponds to the excitation of an one-dimensional structure with concentrated mass, damping and stiffness, m_s , k_s and c_s respectively, yielding

$$Z_e(j\omega) = \left[j\omega \frac{w_p l_p}{h_p} \left(\bar{\epsilon}_{33}^T - \frac{Z_{m,s}(j\omega)}{Z_{m,s}(j\omega) + Z_{m,p}(j\omega)} d_{31} \bar{Y}_{11}^E \right) \right]^{-1} \quad (1)$$

where w_p , l_p and h_p are the width, length and thickness of the piezoelectric element, respectively, and $Z_{m,p}(j\omega)$ is the piezoelectric mechanical impedance. The variable d_{31} corresponds to the piezoelectric induced strain coefficient, and j is the imaginary number, $j = \sqrt{-1}$. The variables $\bar{Y}_{11}^E$ and $\bar{\epsilon}_{33}^T$ stand for the complex Young's Modulus of the piezoceramic material with a null electric field ($E = 0$), and for the dielectric constant at zero stress, and are defined as

$$\bar{Y}_{11}^E = |Y_{11}^E|(1 + j\eta) \quad (2a)$$

$$\bar{\epsilon}_{33}^T = |\epsilon_{33}^T|(1 - j\delta) \quad (2b)$$

where η is the mechanical loss factor, and δ corresponds to the dielectric loss factor.

Other models were put forth to consider other physical effects occurring during the structural inquiry performed by the PWAS. Xu and Liu [24] added the effect of the adhesive layer bonding the sensor on the electrical impedance measurements. As such, the influence of both the structure's dynamic stiffness and the sensor's adhesive layer dynamic stiffness were added to the one-dimensional model first proposed by Liang et al.

Zhu et al. [25] also extended the model, by considering that the electrical impedance measurements of a two-dimensional structure are caused by a matrix of mechanical impedances, such that,

$$\begin{bmatrix} F_x \\ F_y \end{bmatrix} = - \begin{bmatrix} Z_{s,xx}(j\omega) & Z_{s,xy}(j\omega) \\ Z_{s,yx}(j\omega) & Z_{s,yy}(j\omega) \end{bmatrix} \begin{bmatrix} \dot{x}_x \\ \dot{x}_y \end{bmatrix} \quad (3)$$

where F_x and F_y are the loads being applied in directions x and y , respectively, and the variables $\dot{x}_x$ and $\dot{x}_y$ correspond to the velocity in the x and y direction, of the structure being excited. Furthermore, mechanical impedance components $Z_{s,xx}$ and $Z_{s,xy}$ quantify the difficulty of force F_x in causing movement described by $\dot{x}_x$ and $\dot{x}_y$, respectively, while $Z_{s,yx}$ and $Z_{s,yy}$ describe the structure's resistance to movement caused by force F_y . As such, the electrical impedance would be resultant of a bi-dimensional electromechanical coupling, such that the equation in Box I holds.

The variables $Z_{p,xx}$ and $Z_{p,yy}$ are the mechanical impedance of the PWAS in directions x and y , respectively, while ν and κ are the Poisson coefficient and the two-dimensional wave number. Eq. (4) involves extremely complex calculations, especially given that the four complex mechanical impedance variables, $Z_{xx}(j\omega)$, $Z_{xy}(j\omega)$, $Z_{yx}(j\omega)$ and $Z_{yy}(j\omega)$, need to be determined. Note that these are just some mathematical models describing the relation between the structure's mechanical impedance and the measured electrical impedance. For more information on these, and other models, please consult the following Refs [17,26]. While EMIS is being widely used in monitoring various structures, research on its use to monitor adhesive joints is still in an early stage [17]. Na et al. [27] studied the detectability of interface unbonds in glass-fiber reinforced polymer adhesive joints, when immersed in corrosive fluids. Damage could be detected using both glued and magnetically attached PWAS. Malinowski et al. [28] performed experiments at 3 to 5 MHz with damageless and damaged bonded joints, and used the Root Mean Square Deviation, *RMSD*, and peak frequency shift metrics to evaluate damage. Damage was created with either moisture contamination, release agent contamination and insufficient curing. Measurements from joints with insufficient cure yielded a decrease of both the *RMSD* and frequency shifts, while both the release agent or moisture contamination caused changes only in the *RMSD* values.

Zhuang et al. [29] analyzed the ability of EMIS to detect weak adhesion on epoxy Single Lap Joint (SLJ), which were cyclically loaded with increasing load steps. Between each loading cycle, the electric impedance was measured, and the *RMSD* index was computed. Throughout most of the cyclic loading period, the measured impedance spectra remained virtually unchanged, until reaching roughly 80% to 90% of the failure stress, where a *RMSD* threshold value of 0.2 was surpassed. Roth and Giurgiutiu [30] performed a local void detection in adhesive joints using EMIS. To estimate the measurement frequency range, a Finite Element Method (FEM) workflow with two numerical models was proposed: an initial modal analysis evaluated the best mode shapes for disbond detection, and a second FEM simulation assessed the sensitivity of sensor placement for both the intact and debonded adhesive joints.

Malinowski et al. [31] compared the mechanical behavior of damaged and intact adhesive joints, and EMIS measurements. Impedance signatures from 4.25 to 4.7 MHz changed according to the bond quality of damaged and undamaged specimens, and calculated *RMSD* values correlated well with experimental values for Mode I and Mode II fracture-toughness. Tenreiro et al. [32] performed a study of the elastic and damping properties of adhesive materials, which are relevant to the electromechanical coupling that yield the measured electric impedance. Electric impedance measurements were done for SLJ specimens, where both the influence of adhesive thickness and the adhesive material on the experimental spectra were analyzed.

This paper aims to evaluate the detectability of voids in the adhesive layer of bonded joints with the EMIS monitoring technique. To achieve this, SLJs with either a Pressure Sensitive Adhesive (PSA), and a modified epoxy adhesive were manufactured with and without voids, and were then instrumented with PWAS. Accidentally, a second source

of damage was created in the SLJ specimens with artificial voids. Also, other parameters were studied, such as the thickness of the PSA, or the boundary conditions. Furthermore, numerical simulations were performed to guarantee that the experimentally obtained measurements indeed detect damage in the adhesive layer.

Note that no data processing was done to the electrical impedance measurements, nor were features extracted from the electrical impedances. This may be useful in the development of damage metrics, mathematical models or algorithms for damage detection and quantification.

In this manner, Section 2 presents the experiments performed in this work, while Section 3 discusses the experimentally obtained electrical impedance measurements. Section 4 describes the developed numerical models and presents the numerically obtained electrical impedance, as well as an approximation of the mechanical impedance from pristine bonded joints. Finally, Section 5 provides the conclusions of this research.

2. Experimental details

2.1. Materials

In this work, adhesive joint specimens were manufactured using 6082 aluminum alloy adherends, with a thickness of 2 mm. This alloy has an elastic modulus of 70 GPa, a Poisson's ratio of 0.33, and a mass density of 2710 kg m^{-3} .

Furthermore, two different adhesive materials were used. The Nagase T-836/R-810 crash-resistant adhesive, that is manufactured by Nagase ChemteX® (Osaka, Japan) and is adopted for the better part of this research, is a one-part modified epoxy adhesive. This polymeric adhesive is conceived specifically for the automotive and aeronautic industries, due to its high strength and impact resistance. This epoxy adhesive has a curing cycle of 3 hours at 160°C . In a previous study [32], the authors concluded that the elastic modulus and loss factor changed with the excitation frequency. However, one can approximate these values for the range of 1 kHz to 1 MHz. As such, this adhesive has a Young Modulus of 2.55 GPa, a Poisson Ratio of 0.41 and a loss factor of 0.10.

The tesa® (Norderstedt, Germany) 64620 Pressure Sensitive Adhesive (PSA) was also used in this research. This PSA is a double sided film adhesive, where synthetic rubber hotmelt is placed on both sides of a polypropylene film. This film adhesive has a thickness of approximately 0.1 mm. Note that the PSA was only used for part of the experimental work, and was not adopted in the numerical models.

2.2. Specimen fabrication

Adhesive SLJ specimens were manufactured using either the modified epoxy adhesive or the PSA. For the case of modified epoxy adhesive joints, the 6082 aluminum substrates were first grinded with sandpaper and then anodized, following the procedure in standard ASTM D 3933-98 [33]. Therefore, the substrates were submerged on a solution of 10% phosphoric acid and 90% distilled water (m/m), and an electric current, created by a voltage source of 16 V, passed through the immersed aluminum substrates for 25 min. Afterwards, these were removed and cleaned with distilled water and acetone. After completing the surface preparation, the SLJs were produced following the curing cycle defined in Section 2.1, and with adhesive thickness, $t_A = 0.2 \text{ mm}$. In some SLJs, voids of diameter $\varnothing_V \in \{4, 6, 8\} \text{ mm}$ were created by placing a Polytetrafluoroethylene (PTFE) infill in the overlap region before the curing procedure. SLJ dimensions and possible void positions are presented in Fig. 1.

Concurrently, SLJs were manufactured with the PSA. Adhesive thicknesses of $t_A \in \{0.2, 0.4, 0.8\} \text{ mm}$ were created by stacking different layers of the film adhesive, which corresponds to having two, four and

Table 1

Properties of the soft piezoceramic material PIC 255.

Mass density	Elastic compliance coefficient		Coupling factor	
	s_{11}^E	s_{33}^E	k_p	k_t
7.80 g/cm^{-3}	$16.1 \cdot 10^{-12} \text{ m}^2 \text{ N}^{-1}$	$20.7 \cdot 10^{-12} \text{ m}^2 \text{ N}^{-1}$	0.62	0.47

eight film tapes, respectively. These were then adhered onto the aluminum substrates, which were only cleaned with acetone. Afterwards, a small uniform pressure was exerted onto the overlap of the SLJs. In this case, SLJs with void were created by punching a hole onto the film adhesive with a punch, before bonding it to the substrates. Note that these SLJs were first manufactured and instrumented. However, after performing measurements, the PSA was removed and a new film adhesive was used to create a new SLJ specimen.

2.3. Specimen instrumentation & testing

PRYY + 1119 piezoelectric sensors, which are manufactured by PI Ceramics (Lederhose, Germany), are used to instrument the SLJ specimens. These circular sensors are made of the piezoceramic material PIC 255, which has a high Curie temperature ($T_C = 350^\circ\text{C}$), and whose material properties are presented in Table 1. The diameter and thickness of the piezoelectric element are, respectively, 10 mm and 0.2 mm.

The PWAS was fixed on top of the upper adherend of the SLJ, in the middle of the overlap region, with the help of a manually mixed two-component methacrylate adhesive Plexus MA 422, manufactured by ITW Performance Polymers (Chicago, Illinois, United States). This adhesive cures at room temperature for 24 hours. Before the curing period, a copper wire, with a spiral pattern, was placed under the piezoelectric sensor. A second copper wire was soldered on the upper surface of the PWAS. These specimens were used to perform impedance measurement testing. For this, a Hioki IM 3570 impedance analyzer (Ueda, Japan) was used.

Impedance measurements were done under various conditions, in order to impose different boundary conditions. Measurements of SLJs with modified epoxy adhesive were made with the SLJ on top of a table and fixed on the extremities of the adherends, as shown in Figs. 2(a) and 2(b) respectively. Impedance measurements from SLJs with PSA were only done with the specimen being placed on top of a table. However, these adhesively bonded joints were broken and the film adhesive was removed. With this, only the instrumented substrate was used, and measurements were done with the aluminum substrate on top of a table (hard surface), on top of a foam (soft surface), and in a fixed-free position (fixed on the free end, and free on the instrumented end), as schematized in Figs. 3(a) to 3(c), respectively. Note that only the adhesive joints with film adhesive were broken, since the modified epoxy adhesive required extreme temperature in order to have adhesive failure, which is impractical.

3. Experimental results

Given the variety of experiments done in this work, the first subsection will present the impedance measurements from SLJs with the PSA, while the second subsection will present the experimental results obtained from the adhesive joints using the modified epoxy adhesive.

3.1. Measurements from SLJs with PSA

Void detectability. Electrical impedance measurements were performed for SLJ specimens, where the adherends were joined with the tesa® 64620 double sided film adhesive. Fig. 4 presents the measured impedance results for SLJs with adhesive thickness of 0.2 mm, without void and with a void of 8 mm diameter in the center of the overlap.

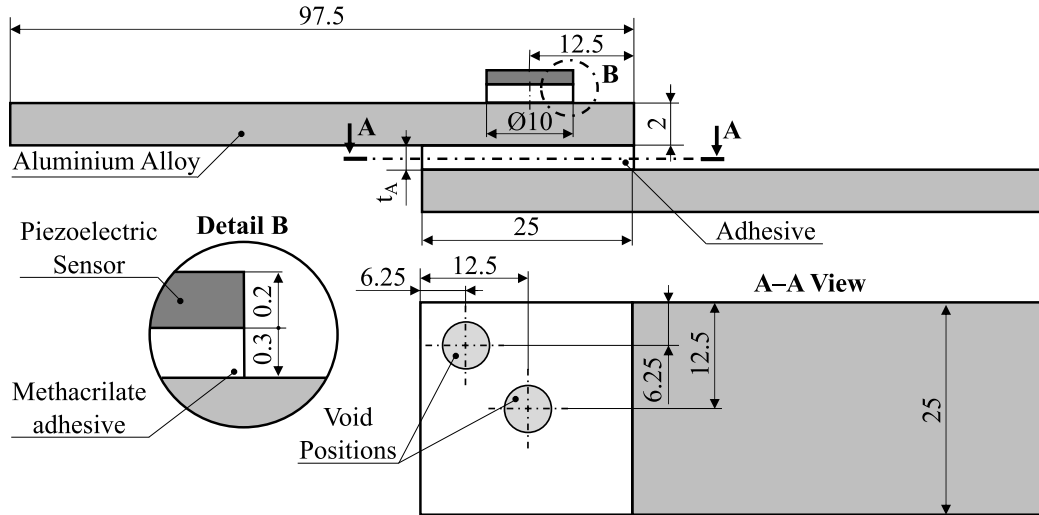


Fig. 1. Schematic representation of a SLJ specimen (with dimensions in mm).

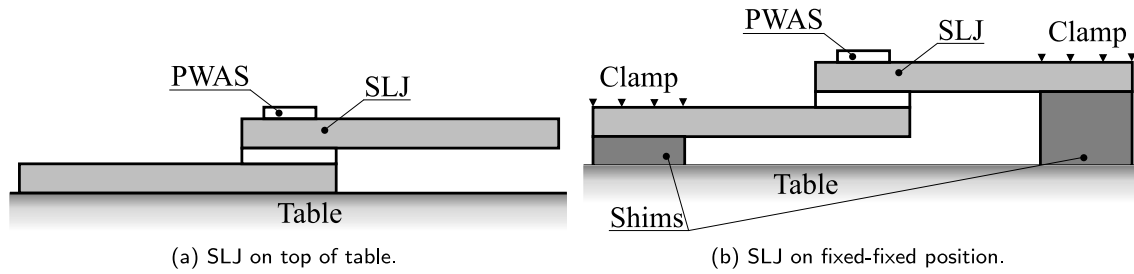


Fig. 2. Measurement setups for instrumented SLJs.

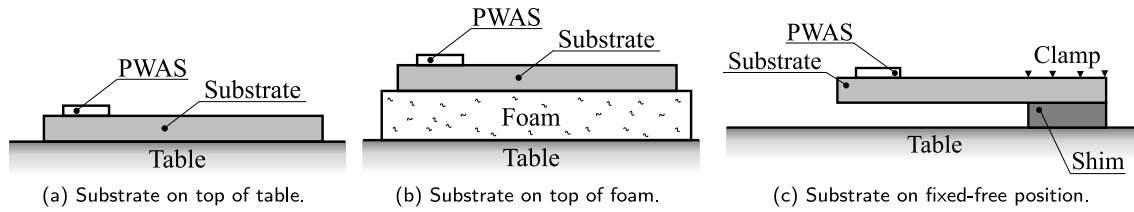


Fig. 3. Measurement setups for instrumented substrate.

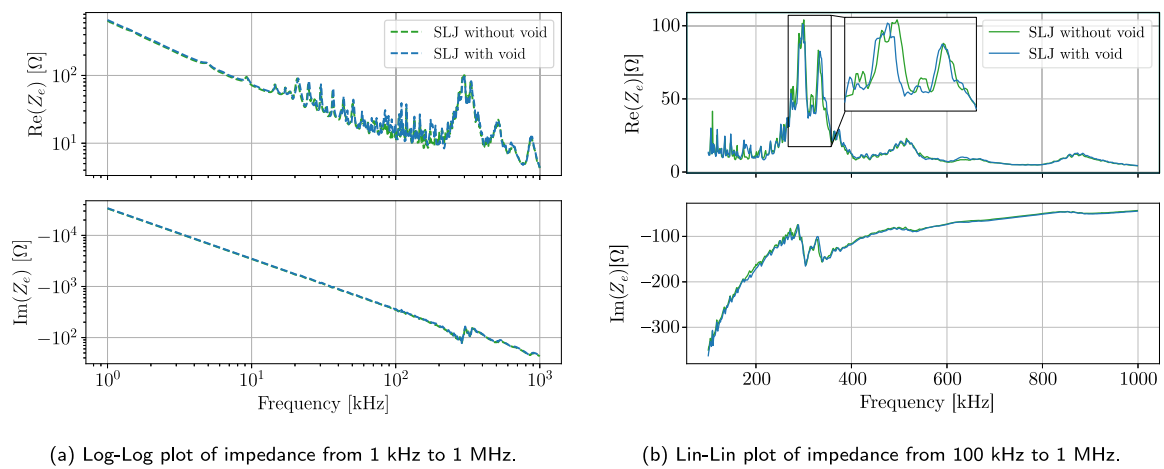


Fig. 4. Impedance spectra of SLJs with PSA without void, and with a 8 mm diameter void in the center of the overlap.

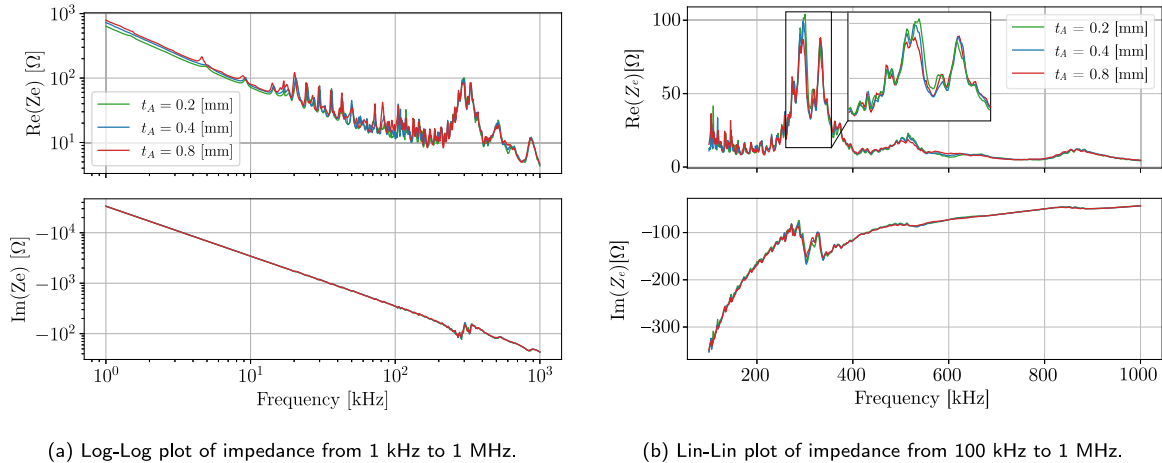


Fig. 5. Impedance spectra of SLJs with PSA with adhesive thicknesses, $t_A \in \{0.2, 0.4, 0.8\}$ mm.

Fig. 4(a), which presents a Log-Log plot of the electrical impedances from 1 kHz to 1 MHz, shows almost no difference between the measured spectra from both SLJs with and without void. Indeed, the only noticeable difference regards the change of the small peaks of $\text{Re}(Z_e)$, observed between 80 kHz and 100 kHz. Fig. 5(b) plots the same electrical impedance signals in a Lin-Lin scale from 100 kHz to 1 MHz, yielding the same conclusions. Indeed, only by zooming in the first two main peaks that occur between 300 kHz and 320 kHz, does one notice any difference at all. Given this, one may conclude that EMIS appears to be insensitive to damage in PSA adhesive joints.

Influence of film adhesive thickness. Given the aforementioned results, a comparison of the influence of film adhesive thickness on the impedance measurements was done. Fig. 5 presents a comparison of the electrical impedance spectra for SLJs with adhesive thicknesses $t_A \in \{0.2, 0.4, 0.8\}$ mm. Note that these joints do not have artificial voids.

In the Log-Log plot shown in Fig. 5(a), one sees that, overall, the influence of adhesive thickness does not cause major changes to the measured spectra. This contrasts with previous work from the authors, where, for modified epoxy adhesive joints, the peak amplitude of the real part of the electrical impedance, $\text{Re}(Z_e)$, increases with an increase of adhesive thickness [32]. However, when observing the impedance values for lower frequencies, the initial exponential trend of the electrical impedance starts at slightly higher values with the increase of thickness, t_A .

Fig. 5(b) plots the same spectra on linear scales for a frequency range between 100 kHz and 1 MHz. Similarly to the void detectability results, the electrical impedance spectra does not change in a significant manner with adhesive thickness. Indeed, the only significant change in the measured spectra occurs in the first two main peaks, at approximately 300 kHz and 330 kHz, respectively. The first observed peak of $\text{Re}(Z_e)$ decreases with the increase of film adhesive thickness, while the second one increases.

Influence of boundary conditions of instrumented substrate. Given that voids in the film adhesive joints appear to be undetectable with EMIS, and given that the influence of adhesive thickness is considerably less perceptible than what was observed with modified epoxy adhesive joints [32], the double film adhesive was removed and the substrate surface was cleaned, as stated in Section 2.2. However, impedance measurements were done for the instrumented substrates, as mentioned in Section 2.3. Fig. 6 showcases the obtained experimental measurements.

In the Log-Log plot of Fig. 6(a), one notices that, overall, the electric impedance spectra of the instrumented substrates placed on top of a table, and on top of a foam (corresponding to conditions schematized in Figs. 3(a) and 3(b), respectively) are very similar. Indeed, some small variations are observed in the peaks of $\text{Re}(Z_e)$ for frequencies below 200 kHz. This is even more clear in the Lin-Lin plot of Fig. 6(b).

Conversely, significant changes in the impedance spectra are noticed when the substrate is fixed in one end, and free to move in the opposite end, where the PWAS was placed, as per Fig. 3(c). Overall, the resistive peaks, which occur at frequencies below 200 kHz, are less pronounced than for the previous cases. Concurrently, in the same frequency range, the imaginary component has less noticeable inflection points.

Furthermore, the bigger peaks of $\text{Re}(Z_e)$ (observed at 300 kHz, 500 kHz and 850 kHz, in Fig. 6(b)) are comparatively *more monotonous*, or, in other words, these wider peaks are not influenced by the sub-peaks that occur in the other substrate measurements. This can be better observed in the Nyquist plot of Fig. 6(c). These results show the influence of boundary conditions on the mechanical impedance of the aluminum substrate, $Z_{m,s}(j\omega)$, and, consequently, on the measured electrical impedance, $Z_e(j\omega)$. In this manner, one can conclude that no body present on the lower surface of the substrate influences the structural modes of vibration, and consequent measurements. Furthermore, the big variation between the measured spectrum from the substrate fixed in one end, and the other two spectra shows that the sub-peaks observed throughout the frequency range is not due to any *electrical interference* or *noise*. It is, in fact, caused by the dynamic mechanical behavior of the specimens, which is influenced by the mechanical properties, and by the boundary conditions.

3.2. Measurements from SLJs with a modified epoxy adhesive

Influence of boundary conditions on SLJ. Electrical impedance spectra were also obtained for adhesive joints with the modified epoxy adhesive. Figs. 7 and 7(a) present a Log-Log plot of the impedance spectra for two SLJ specimens with adhesive thickness, $t_A = 0.2$ mm, without void and with a void of 8 mm diameter in the center of the overlap, respectively. Note that each plot compares the measurements for both cases where the adhesive joint is on top of a table and when the same joint is fixed on both ends, as per Figs. 2(a) and 2(b), respectively.

One can observe that, just like for the substrate measurements of Fig. 6, the resistive peaks observed at frequencies below 200 kHz are more pronounced when the joint is on top of a table, rather than when the joint is rigidly fixed on both ends. This phenomenon is more pronounced when there is a void in the adhesive layer, which can be caused by the fact that, with the presence of a void, the stiffness of the joint decreases. In this manner, the indirectly measured modes of vibration tend to resemble that of the substrate.

Figs. 8(a) and 8(b) present the Lin-Lin and Nyquist plots, respectively, of the measured electrical impedance from the SLJ without void in the adhesive layer. Similarly to what occurred in the measurements of the instrumented substrates, the boundary conditions influence the

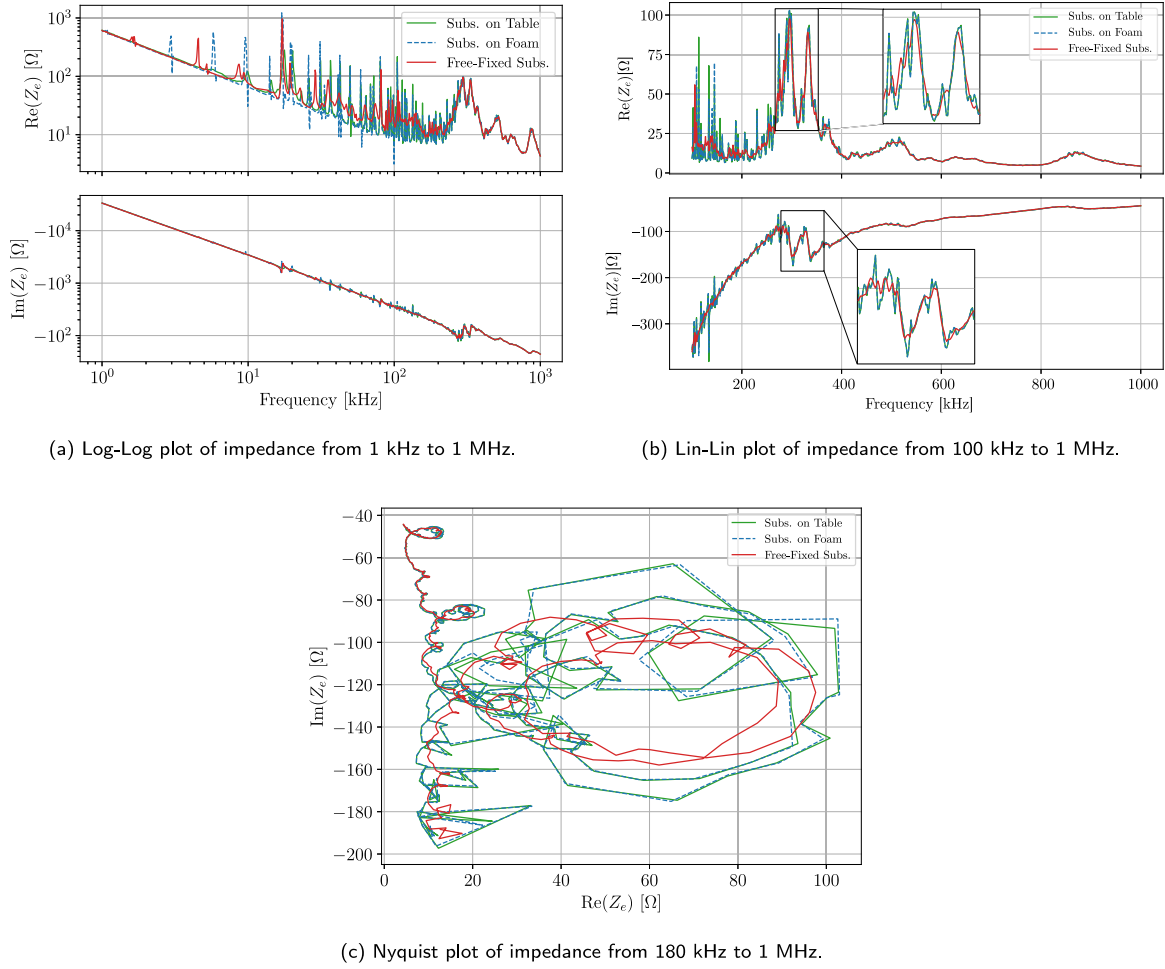


Fig. 6. Impedance spectra of instrumented substrate from SLJs with PSA.

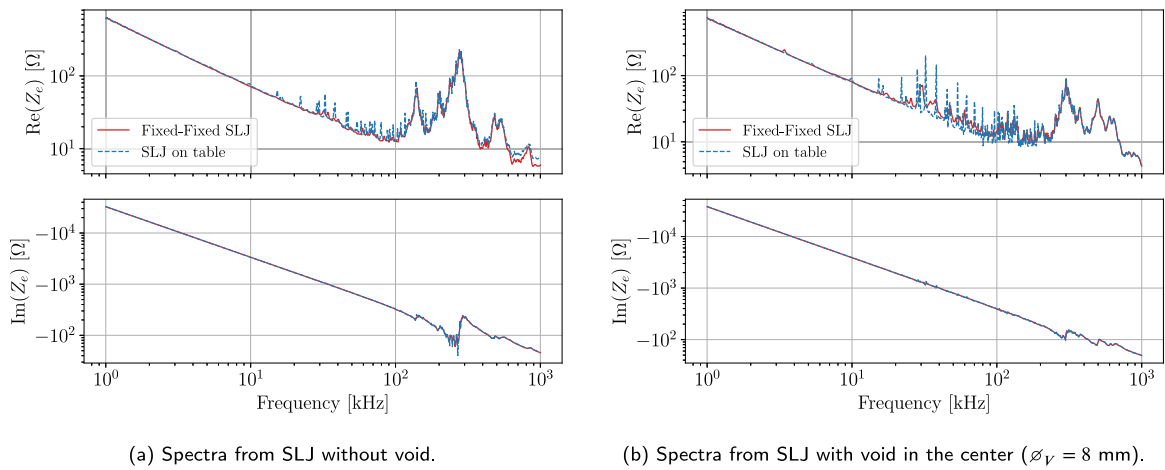
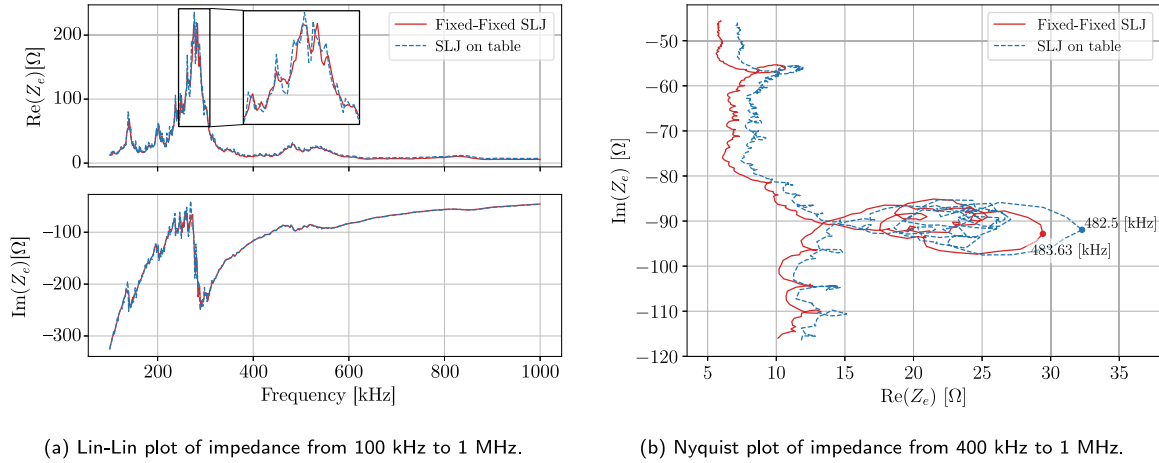


Fig. 7. Log-Log plots of electrical impedance spectra from SLJs with and without void (1 kHz–1 MHz).

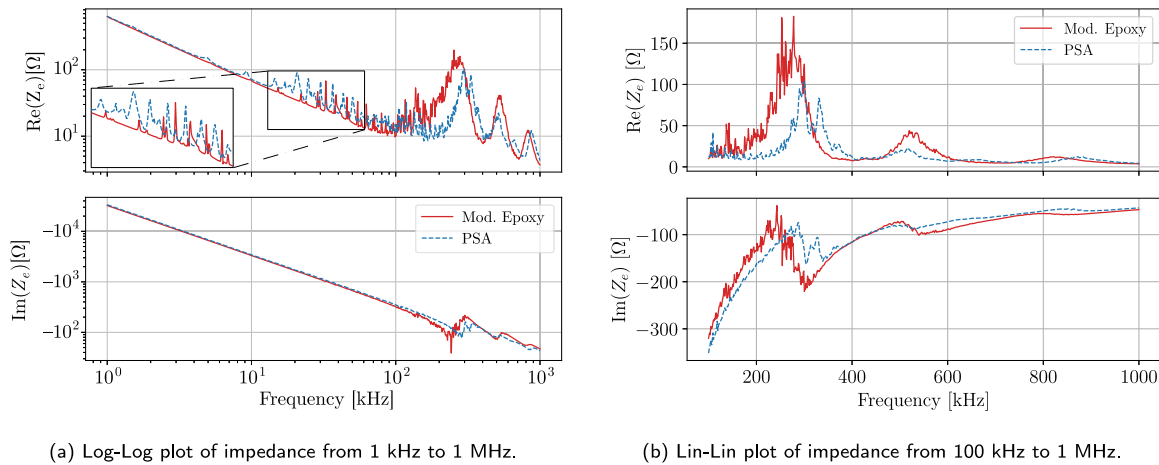
larger peaks of $\text{Re}(Z_e)$, and the respective inflection points in $\text{Im}(Z_e)$. When the adhesive joint is cantilevered on both free ends, these major peaks and inflection points are *more monotonous*, and are less affected by the subpeaks that occur when the adhesive joint is on top of the table.

Comparison with measurements from SLJs with PSA. Before proceeding with a study of the capability of EMIS to detect voids in crash-resistant adhesive joints, a comparison was done between impedance measurements from Single Lap Joints (SLJ) using both the Pressure Sensitive Adhesive (PSA) and the modified epoxy adhesive. Note that the



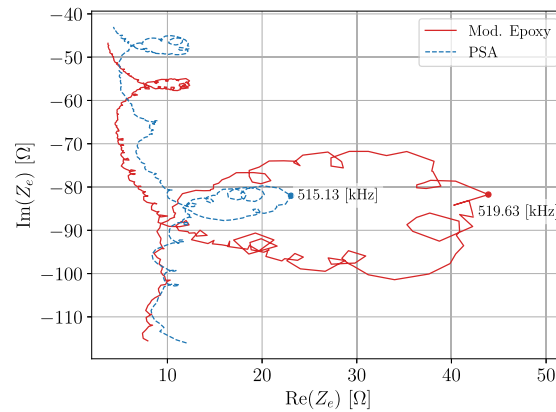
(a) Lin-Lin plot of impedance from 100 kHz to 1 MHz.

(b) Nyquist plot of impedance from 400 kHz to 1 MHz.

Fig. 8. Impedance spectra of a pristine SLJ with the cash resistant adhesive under different Boundary Conditions.

(a) Log-Log plot of impedance from 1 kHz to 1 MHz.

(b) Lin-Lin plot of impedance from 100 kHz to 1 MHz.



(c) Nyquist plot of impedance from 400 kHz to 1 MHz.

Fig. 9. Impedance spectra of SLJs with both the modified epoxy and the double film adhesives.

measured spectra originate from adhesive joints without void. Figs. 9(a) and 9(b) compare the experimentally obtained impedance spectra for one joint of each condition, on both a Log-Log and Lin-Lin plot.

From Fig. 9(a) alone, one notices that peaks of $\text{Re}(Z_e)$ at frequencies below 100 kHz do not coincide. This means that, with a different adhesive, the stiffness, damping and mass density of the structure changes to the point that the resonances change significantly.

Furthermore, the larger peaks of the resistive part and the corresponding inflection point of $\text{Im}(Z_e)$, which occur at higher frequencies

(above 100 kHz), change significantly, as plotted in Fig. 9(b). The first resistive peak shifts from the 290–340 kHz window for joints with the PSA, to the 240–300 kHz range for modified epoxy adhesive joints, and increases its amplitude, from 100 Ω to almost 200 Ω . The next major peaks, which occur at 515 kHz and 519 kHz for both joints with the PSA and the crash-resistant adhesives, respectively, also have a similar amplitude discrepancy. This difference is clearly noticed in the Nyquist plot of Fig. 9(c). The last observed peak of $\text{Re}(Z_e)$ does not differ with adhesives, but its respective inflection point does, occurring

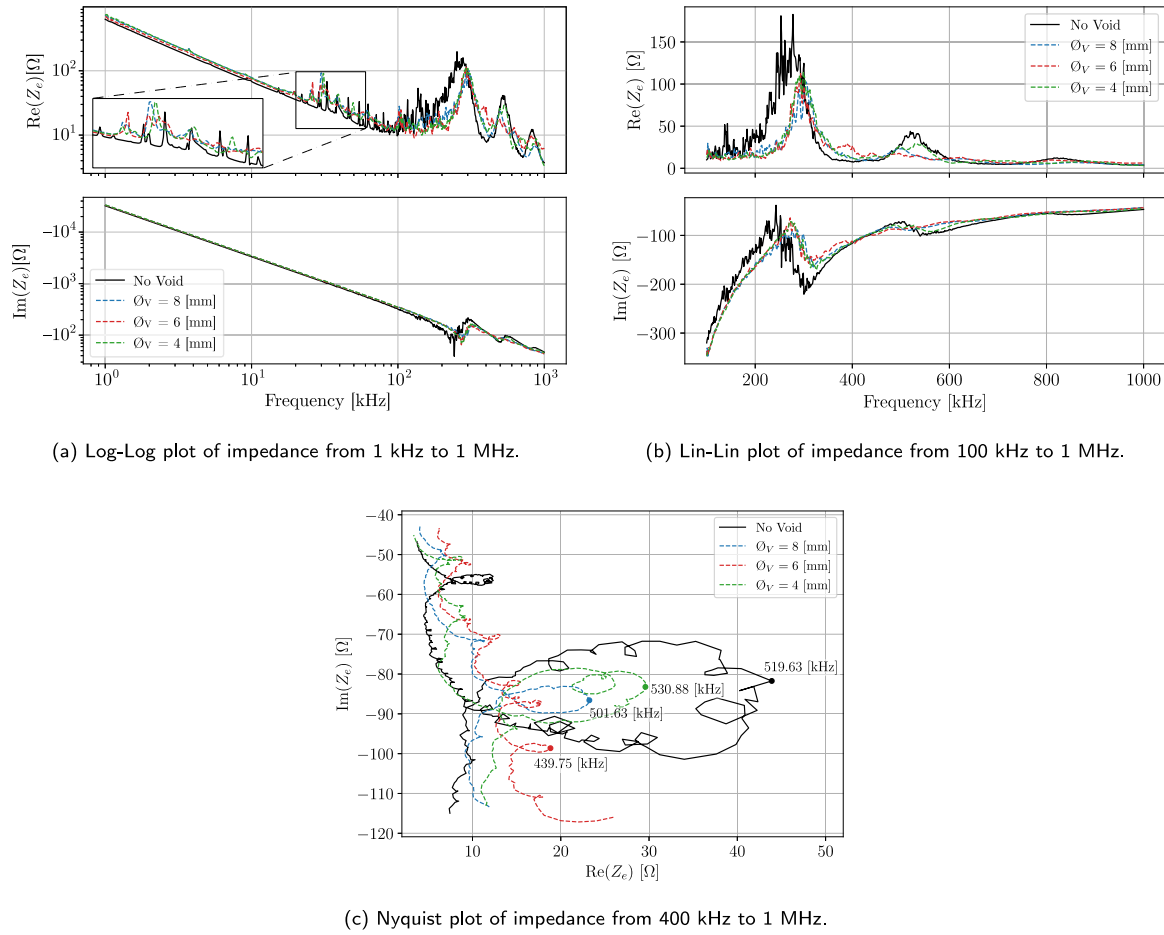


Fig. 10. Comparison of impedance spectra from crash resistant adhesive joints without void and with void in the middle of the overlap ($\phi_V \in \{4, 6, 8\}$ mm).

at somewhat lower values of $\text{Im}(Z_e)$ for the joint specimen with the Nagase T-836/R-810 adhesive.

Influence of void size in damage detection. Fig. 10 compares the measured electrical impedance for modified epoxy bonded joint of 0.2 mm adhesive thickness, with and without void in the middle of the overlap. The cases of damaged joint have voids of diameters, $\phi_V \in \{4, 6, 8\}$ mm, placed in the middle of the adhesive layer, as presented in Fig. 1.

While examining the Log-Log plot shown in Fig. 10(a), one clearly sees that the first measured resistive peaks, at lower frequencies (below 100 kHz), shift to slightly lower frequencies with the presence of void. The first two peaks of $\text{Re}(Z_e)$ from SLJs with voids, which were observed between 20 and 30 kHz, occur at exactly the same frequencies. Conversely, the remaining peaks occurring in this range, for spectra from defective adhesive joints, do not coincide with each other. However, when comparing these with the spectrum from an undamaged adhesive joint, the peaks of the $\text{Re}(Z_e)$ are defined for specific frequencies, and have higher amplitudes (relative to the exponentially decreasing trend), which is not the case for damaged joints.

For higher frequencies (above 100 kHz), both the $\text{Re}(Z_e)$ of bigger amplitude, and their respective inflection points in $\text{Im}(Z_e)$, which are plotted in Fig. 10(b), shift significantly, despite still being able to denote a trend. The first major resistive peak (and respective reactive inflection point) is shifted from approximately 280 to 300 kHz. Note also that, for the electrical measurements originating from the pristine adhesive joint, the smaller peaks are still present in the impedance measurements, until reaching this first major peak. Conversely, while these peaks are also present in the spectra of damaged specimens, these have a comparatively smaller amplitude. This can be explained by the fact that the presence of void alters the stiffness and damping,

thus decreasing the resonance amplitudes, and the respective peaks of $\text{Re}(Z_e)$.

The remaining peaks and inflection points, that occur at higher frequencies, can be observed in Figs. 10(b) and 10(c). As stated, no clear trend exists regarding the major peaks observed at higher frequencies. However, when comparing the case where no void is present with the cases where void exists in the adhesive layer, one sees that the peaks of $\text{Re}(Z_e)$ are considerably smaller for defective joints. The same can be said for the relative maximum and minimum points near the inflection points of the imaginary part of Z_e . The electric impedance spectrum from the SLJ specimen with a void, $\phi_V = 6$ mm, is considered the extreme scenario, since the peak of $\text{Re}(Z_e)$ and inflection point of $\text{Im}(Z_e)$, typically observed between 500 and 530 kHz, is almost non-existent.

To verify that the differences observed in the impedance measurements were caused by the existence of a void, some SLJs were broken, which are shown in Fig. 11. One could see that, for joints without induced damage, the adhesive layer is comparatively uniform, with only minor porosities (smaller than 1 mm). Conversely, the bonded joint with an artificially created void contains two types of damage — the artificially created void, and a larger burned area of the overlap, composed of non-uniform voids and degraded adhesive. This second defect was caused a possible unwanted chemical reaction of a high temperature resistant adhesive, used specifically to guarantee the positioning of the PTFE inlet that creates the artificial void. Indeed, the PTFE circular shape is also present in Fig. 11(b), outside of the overlap area. The authors do not know why this high temperature resistant glue caused this second source of damage, but they believe this may be due to chemical incompatibility with the modified-epoxy adhesive.

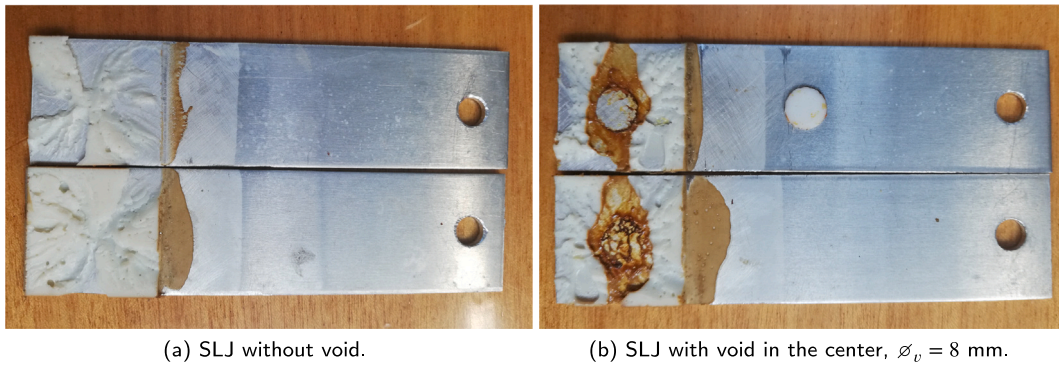


Fig. 11. Photos of manually broken SLJs with the crash-resistant adhesive.

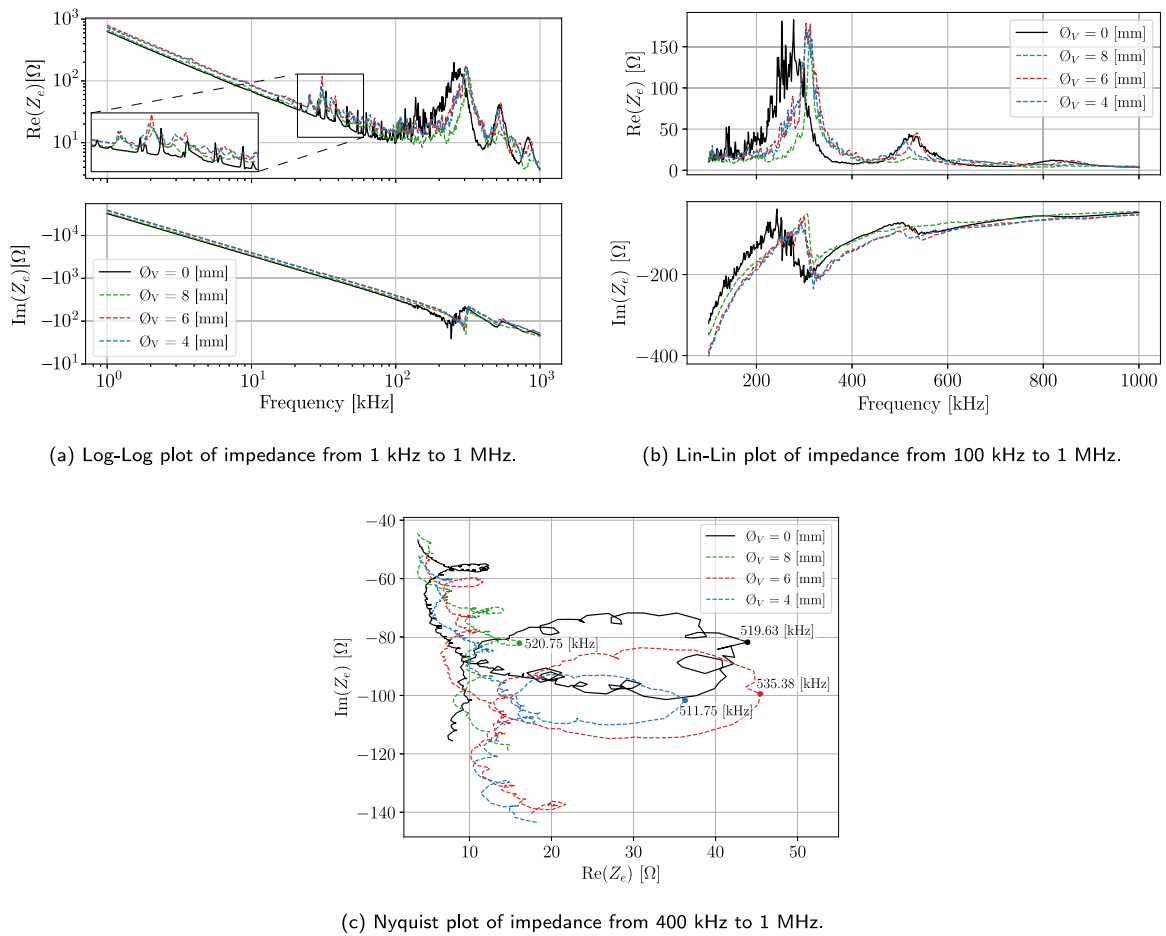
Fig. 12. Comparison of impedance spectra from crash resistant adhesive joints without void and with void in the corner of the overlap ($\varnothing_v \in \{4, 6, 8\}$ mm).

Fig. 12 compares the measured electrical impedance from adhesive thickness with and without void in the corner of the overlap. Once again, the damaged SLJ specimens have voids of diameter $\varnothing_v \in \{4, 6, 8\}$ mm, and are placed in the corner of the adhesive layer, as indicated in Fig. 1.

From Fig. 12(a), which shows the Log-Log plot of the aforementioned impedance spectra, one sees once again that, for spectra of damaged joints, the first two measured resistive peaks, observed between 20 and 30 kHz, coincide, similarly to the case where the void was

in the center of the overlap. Likewise, the remaining peaks occurring below 100 kHz, for spectra from defective SLJs, do not coincide with each other.

Furthermore, for higher frequencies (above 100 kHz), both the first major peak of $\text{Re}(Z_e)$ and its respective inflection points of $\text{Im}(Z_e)$, plotted in Fig. 12(b), shift to higher frequencies (from approximately 280 to 300 kHz). The remaining peaks and inflection points, which are also present in the Nyquist plot of Fig. 12(c), are normally smaller than the measured peaks and inflection points observed from undamaged

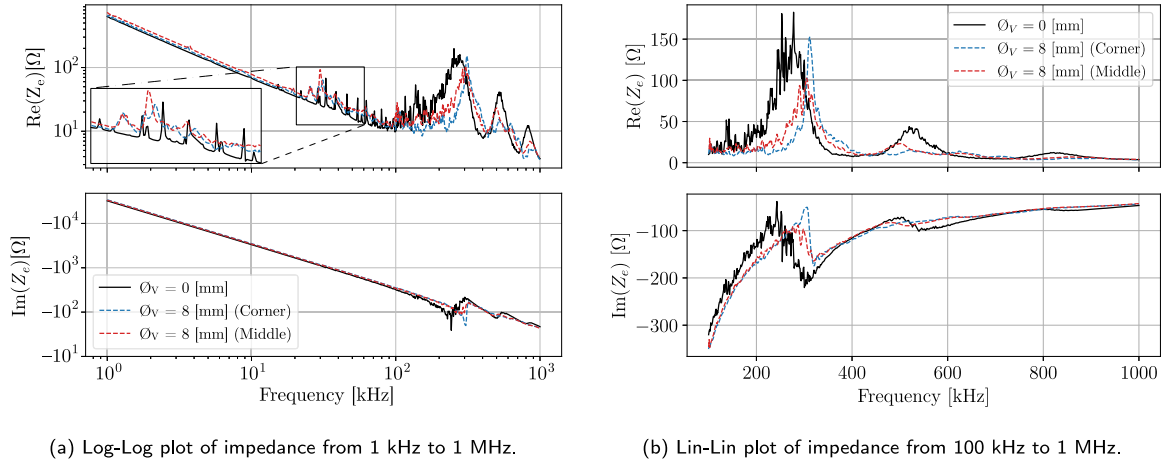


Fig. 13. Comparison of impedance spectra from crash resistant adhesive joints without void and with voids ($\varnothing_V = 8$ mm) in either the center or the corner position.

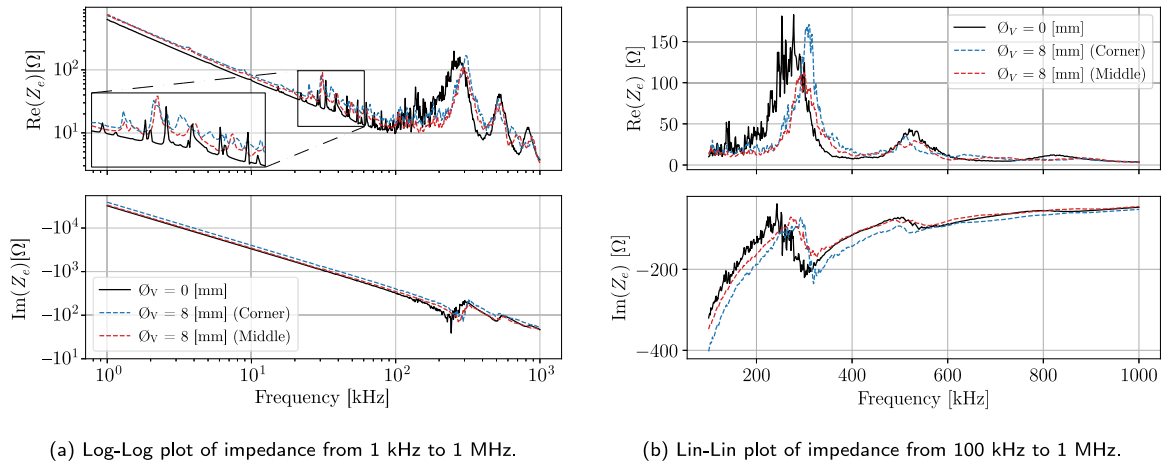


Fig. 14. Comparison of impedance spectra from crash resistant adhesive joints without void and with voids ($\varnothing_V = 4$ mm) in either the center or the corner position.

adhesive joints. However, a different pattern is observed, when comparing with impedance spectra from joints with void in either the corner or middle of the overlap. The SLJ instance with a void diameter, $\varnothing_V = 8$ mm has an almost non-existent maximum value of $\text{Re}(Z_e)$, as well as inflection point of $\text{Im}(Z_e)$, with relative maximum and minimum values very near each other. However, for $\varnothing_V \in \{4, 6\}$ mm, both resistive peak and reactive inflection points increase. This being said, no clear trend was observed with the decrease of void diameter, $\varnothing_V$.

Influence of void position in damage detection. Fig. 13 compares the measured electrical impedance of adhesive joints without void and with a 8 mm diameter void either in the center or in the corner of the overlap. Fig. 14 presents the same comparison for SLJs without void and with a void ($\varnothing_V = 4$ mm). Most observations that were stated previously are repeated here. However, other patterns are noticed, which can yield information on void placement.

Both Figs. 13 and 14 show that the amplitude of the first major peak of $\text{Re}(Z_e)$, and respective difference between the local maximum and minimum of $\text{Im}(Z_e)$, decrease with the proximity of the void to the sensor. In other words, when the void is in the middle of the overlap, which is as near as possible to the PWAS, the amplitude of the $\text{Re}(Z_e)$ peak occurring at 300 kHz decreases. Also, when analyzing the spectra at lower frequencies (below 100 kHz), one sees that, as previously stated, the first smaller resistive peaks from damaged joints

coincide. However, for SLJs with void, $\varnothing_V = 8$ mm, the remaining peaks are considerably similar. Conversely, when the void is of 4 mm, this difference is more pronounced.

4. Numerical simulations

Numerical models were developed to accurately recreate the coupled electromechanical behavior experimentally observed with the electrical impedance measurements. In this manner, numerical simulations were performed using ABAQUS 2017, as explained in this section.

4.1. Numerical models

A linear perturbation direct-steady state dynamic analysis was done in a frequency interval between 1 kHz and 1 MHz, with a linearly spaced frequency interval of 1 kHz, yielding a total of 1000 sampling points. The geometric models were defined by two components, the piezoelectric element and the SLJ. The mechanical and electrical properties of PIC 255 piezoceramic material are presented in Table 2 [34]. The modeled sensor has a diameter and thickness of 10 mm and 0.2 mm, respectively. For this component, piezoelectric type 8-node linear brick and reduced integration elements (C3D8R) were used, with

Table 2

Electric and mechanical properties of the PIC 255 piezoceramic material used in the finite element model [34].

Property	Unit	Notation	Value
Elastic Modulus	GPa	E_1	62.89
		E_2	62.89
		E_3	47.69
Shear Modulus	GPa	G_{13}	22.26
		G_{23}	22.26
		G_{12}	23.15
Poisson's Ratio	[-]	ν_{13}	0.46
		ν_{23}	0.46
		ν_{12}	0.36
Permittivity at constant strain	nF m ⁻¹	ϵ_1	8.234
		ϵ_2	8.234
		ϵ_3	7.588
Piezoelectric stress coefficients	C m ⁻²	e_{15}	11.9
		e_{24}	11.9
		e_{31}	-7.15
		e_{32}	-7.15
		e_{33}	13.7
Mass Density	kg m ⁻³	ρ	7800

a general mesh size of $5 \cdot 10^{-4}$ m and a mesh control of $1 \cdot 10^{-4}$ m in the thickness direction of the sensor.

The 1 V voltage excitation is defined with an electric field potential of $E_t = 1 + 0j$ V at the top circular surface of the PWAS, and an electric field potential of $E_b = 0 + 0j$ V at the bottom surface of the sensor. After running the simulations, the Reactive Electrical Nodal Charges (RCHG) were extracted from the nodes at the bottom surface and were summed to compute the generated electric charge, $Q(j\omega)$. The electrical impedance, $Z_e(j\omega)$, is then obtained through

$$Z_e(j\omega) = \frac{V(j\omega)}{I(j\omega)} = \frac{E_t - E_b}{j\omega Q(j\omega)} \quad (5)$$

where $V(j\omega)$ is the source voltage and $I(j\omega)$ is the electrical current passing through the piezoelectric element.

The SLJ component was geometrically modeled with the indicated dimensions of Fig. 1, with an adhesive thickness, $t_A = 0.2$ mm, and with one void either in the center or in the corner of the overlap, with diameter $\varnothing_v \in \{4, 6, 8\}$ mm. Note also that a numerical model of a pristine SLJ was done. Table 3 lists the reference mechanical properties of the aluminum alloy and the adhesives included in the models. However, given that (i) the two components of the Plexus MA 422 adhesive were manually mixed before bonding the sensor and (ii) a second damage source was induced in the adhesive layer of the SLJ, the elastic modulus, E , and loss factor, η , were altered to replicate the experimentally obtained electrical impedance spectra, $Z_e(j\omega)$.

The model of the SLJ part has a general mesh size of $5 \cdot 10^{-4}$ m, with a single bias mesh control in the free end of each adherend, starting near the overlap area with a mesh size of $5 \cdot 10^{-4}$ m to a mesh size of $5 \cdot 10^{-3}$ m at the free ends. Furthermore, a mesh size of $1 \cdot 10^{-4}$ m was defined along the thickness of the adhesive layer. A mesh control of approximately $5 \cdot 10^{-4}$ m was defined at the circumference created by the methacrylate adhesive layer and at the void circumference. Note also that the entire overlap region was sectioned by the midpoints and the diagonals, to simplify the meshing.

As stated in Ref. [32], the Plexus MA 255 methacrylate adhesive layer bonding the PWAS, was also modeled, since this adhesive influences the impedance measurements. The PWAS component was connected to the methacrylate adhesive geometry in the SLJ part with a tie constraint interaction. With this interaction, no relative movement between both components occurs, while also avoiding any separation caused by dissimilar part meshing.

The average nodal translational velocity components, $\bar{x}_x$, $\bar{x}_y$, $\bar{x}_z$, as well as the average element normal stresses, $\bar{\sigma}_{xx}$, $\bar{\sigma}_{yy}$, $\bar{\sigma}_{zz}$, of top circular surface of the Plexus MA 422 adhesive were extracted to

Table 3

Properties of the adhesives and adherend used in the finite element model.

Material	E [GPa]	ν [-]	η [-]	ρ [kg m ⁻³]
Aluminum Al 6082	70.0	0.33	$5.0 \cdot 10^{-4}$	2710
Plexus MA 422	0.994	0.31	0.45	960
Nagase T-836/R-810	2.55	0.41	0.10	1200

compute the mechanical impedance of the SLJ, $Z_{m,s}(j\omega)$, which, as presented in Eq. (1), influences the electrical impedance measurements. An approximation of the mechanical impedance, $Z_{m,s}(j\omega)$, is computed with

$$Z_{m,s}(j\omega) = \frac{F}{\dot{x}} \approx \frac{\overline{\sigma_{yy}} A_{Pl}}{\dot{x}_y} \quad (6)$$

where A_{Pl} is the area of the aforementioned circular surface. The computed impedance, $Z_{m,s}(j\omega)$, is only an approximation, given that average component values were extracted. Furthermore, only the average vertical normal stress, $\overline{\sigma_{yy}}$, and the average velocity component in the same direction, $\dot{x}_y$, were used in this calculation.

One should consider that the estimation of the mechanical impedance was done using only data from the numerical simulation of the adhesive joint without damage. This was done since the second source of damage is not controlled, thus leading to small variations in the degree of damage of the joint. Furthermore, the modification of the loss factor, η , is hard to establish in the numerical simulations without an experimental quantification of such a property. Therefore, an approximation of the mechanical impedance from the pristine SLJ numerical model is presented.

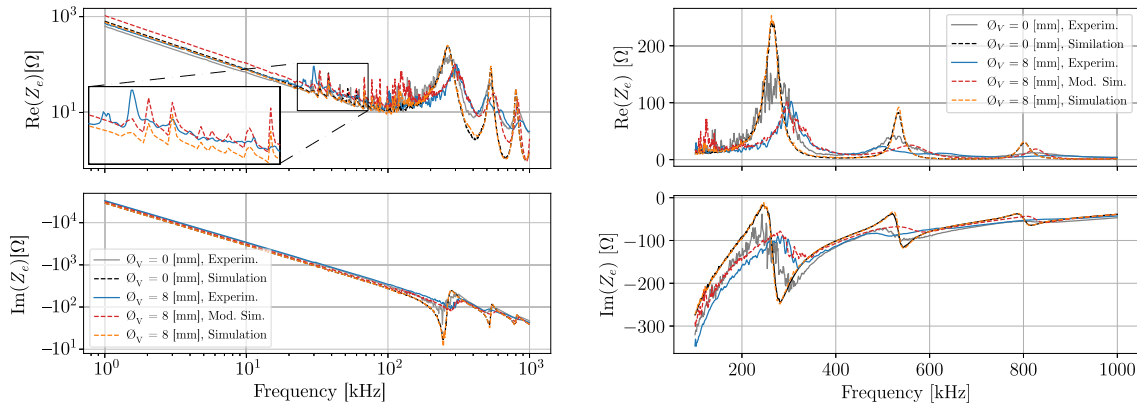
4.2. Simulation results

Simulated electrical impedance and comparison with experimental results. Figs. 15(a) and 15(b) present a comparison between the experimental and simulation spectra from adhesive joints without void and with a void of diameter, $\varnothing_v = 8$ mm in the middle of the overlap. The numerically obtained impedance spectra of undamaged joints are in agreement with experimental measurements, with only minor deviations in the peak amplitudes of $\text{Re}(Z_e)$. This is explained by the fact that the loss factor, η , of the adhesive may change with the frequency excitation, ω .

When analyzing the simulation results from the SLJ with a 8 mm void in the middle of the overlap, one observes that the peaks of $\text{Re}(Z_e)$ occurring at lower frequencies concur with the experimentally obtained results, especially when considering that the amplitude of most peaks decrease, as seen in the zoomed subplot of Fig. 15(a). Conversely, the correspondent resistive peaks and inflection points of $\text{Im}(Z_e)$ of the experimental signature occurring above 100 kHz suffer a bigger shift to higher frequencies. This change is believed to occur mostly due to the accidentally induced damage shown in Fig. 11. In this manner, the burned and porous region present around the artificially created void changes the properties of the crash-resistant adhesive in an unwanted heterogeneous manner.

However, the observed shifts may also occur due to small changes in the properties of the methacrylate adhesive used to bond the PWAS to the adhesive joint, as stated in Section 2. This two-component adhesive is manually mixed, as mentioned in Section 2 and, therefore, it is hard to guarantee consistent mechanical properties. Furthermore, according to the literature [22,24], mechanical properties of the adhesive that bonds the piezoceramic element will significantly influence the obtained electric impedance signatures.

Given these two factors, it is hard to correctly quantify the variations of the mechanical properties of both adhesives, in an exact manner. In this manner, modifications were done in the Plexus MA 422 adhesive to try and replicate the experimentally obtained measurements. In this manner, both the elastic and damping properties were



(a) Log-Log plot of impedance from 1 kHz to 1 MHz (zoom of $\phi_v = 8$ mm curves only).

(b) Lin-Lin plot of impedance from 100 kHz to 1 MHz.

Fig. 15. Comparison of numerically and experimentally obtained impedance spectra from adhesive joints without void and with voids ($\phi_v = 8$ mm) in the middle position.

altered. It is noted that the damping increased significantly, and, for damaged joint (void in the middle of the overlap with 8 mm diameter), a loss factor of 0.55 was defined. This alteration yielded better results, which are presented in Figs. 15(a) and 15(b) as a modified numerical model (Mod. Sim.).

Fig. 16 presents a comparison between the experimentally obtained impedance measurements and the numerically simulated electrical impedance. Overall, the simulated electrical impedance of SLJs with voids match relatively well with the experimentally measured PWAS impedance, for low frequencies (below 100 kHz), and for the first major peak at approximately 300 kHz. For the three cases where a void is placed in the corner of the overlap, the numerically observed resistive peaks are considerably more pronounced than the ones observed experimentally. This difference may be due to the presence of the second source of damage, where the chemical incompatibility has caused the creation of a bigger void area. In this manner, the damaged area of the overlap area is bigger than what is actually simulated.

Conversely, for higher frequencies, the major resistive peaks observed numerically, which are similar to the ones observed both experimentally and numerically for the undamaged adhesive joint, differ from the spectra experimentally obtained. Indeed, this appears to be caused by the presence of the second source of damage, or by possible differences in the properties of the methacrilate adhesive used to bond the PWAS. However, the numerical models already have considered a loss factor varying between 0.5 and 0.55 (this parametric variation can be explained by the non-uniform manner in which this second source of damage appears in the adhesive layer). Therefore, one may deduce that the second source of damage in the structural adhesive layer may alter the impedance signatures in a non-linear manner, since this effect only occurs on impedance signatures from damaged adhesive joints.

Simulated mechanical impedance. As previously explained, this section will only present the numerical estimation of the mechanical impedance, $Z_{m,s}(j\omega)$, of the adhesive joint without the two damage sources (artificial void and burned region near the aforementioned void). Therefore, Figs. 17 and 17(b) present the average element normal stresses and the average nodal velocities, respectively, along with the numerically obtained electrical impedance, $Z_e(j\omega)$. Note that the average element shear stresses are not presented here, given that they are orders of magnitude smaller than the average normal stresses.

From Fig. 17(b), one clearly sees that the average velocity in the vertical direction, $\bar{x}_y$, is considerably bigger than the other two velocity components, $\bar{x}_x$ and $\bar{x}_z$, which is expected, given that the main excitation should be in the y direction. However, while comparing the average normal stresses, as plotted in Fig. 17, one observes that the average normal stress in the y direction is only considerably bigger than

the other components at lower frequencies. This is more noticeable for the first major peak occurring between 200 kHz and 300 kHz. For the other major peaks, this difference decreases significantly. Given these findings one would expect that the major resistive peaks, $\text{Re}(Z_e)$, and reactance peaks near the inflection points, $\text{Im}(Z_e)$, should not decrease in a significant manner, which is not the case. Therefore, the electrical impedance should be mostly a function of the normal stress component $\bar{\sigma}_{yy}$, as presented in Eq. (6).

Figs. 18(a) and 18(b) plot both the electrical and mechanical impedance, $Z_e(j\omega)$ and $Z_{m,s}(j\omega)$ respectively, which were computed according to Eqs. (5) and (6). The black markers of Fig. 18(b) correspond to the values of Z_e and $Z_{m,s}$ where the maximum magnitude of Z_e occurs, while the blue markers placed on both the curves of Z_e and $Z_{m,s}$ of the same figure correspond to the values of Z_e and $Z_{m,s}$ where the maximum magnitude of the approximate mechanical impedance, $Z_{m,s}$, occurs.

From these figures, one first notices that the peaks normally observed at lower frequencies (below 100 kHz) are significantly expressive in the calculated mechanical impedance, $Z_{m,s}(j\omega)$. These are not clearly reflected in the magnitude of the electrical impedance, and can only be seen in its real component, $\text{Re}(Z_e)$, since the reactance, $\text{Im}(Z_e)$, is considerably larger than the resistive part, and since $\text{Im}(Z_e)$ is also dependent on the piezoelectric and mechanical properties of the piezoceramic material, as demonstrated by Bhalla et al. [35].

One also notices from Fig. 18(a) that, at higher frequencies (above 100 kHz), the major peaks of the electrical impedance are accompanied by their respective peaks of the structure's impedance, $Z_{m,s}$. However, these occurs at slightly higher frequencies than the ones observed for the measured electrical impedance. In this manner, the polar plot shown in Fig. 18(b) is more informative, since the frequencies where both Z_e and $Z_{m,s}$ maxima occur are not that distant. However, this difference is explained by two facts. Firstly, the computed mechanical impedance is an approximation, given that an average of the nodal velocities in the vertical direction, $\bar{x}_y$, and of the normal stress, $\bar{\sigma}_{yy}$, were used. Secondly, the mathematical definition of the mechanical impedance used is based on the works of [23,24], and corresponds to the structural impedance of a one dimensional structure. However, as presented by other researchers, such as Zhu et al. [25], the concept of mechanical impedance is not one-dimensional. Therefore, the occurrence of peaks at slightly different frequencies may result from the fact that other components of the mechanical impedance may contribute to electrical impedance signatures.

Also, Figs. 18(a) and 18(b) show that the estimated mechanical impedance peaks occur when the argument, $\arg(Z_{m,s})$ nears -180° , which means that the average velocity, $\bar{x}_y$, and the average normal stress in the y direction, $\bar{\sigma}_{yy}$, have opposite phases.

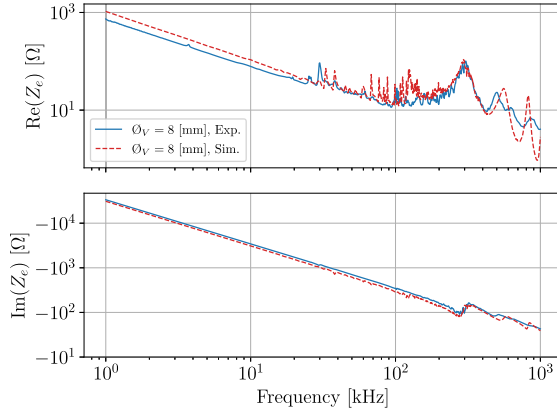
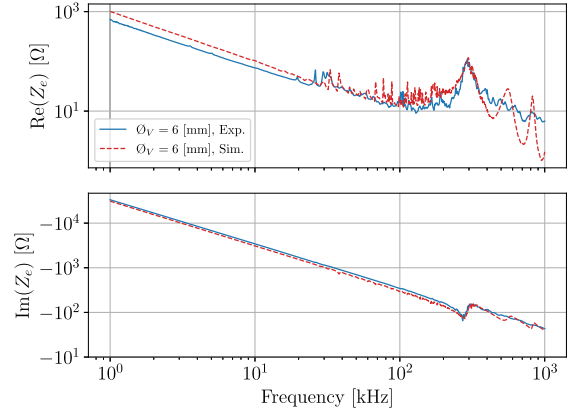
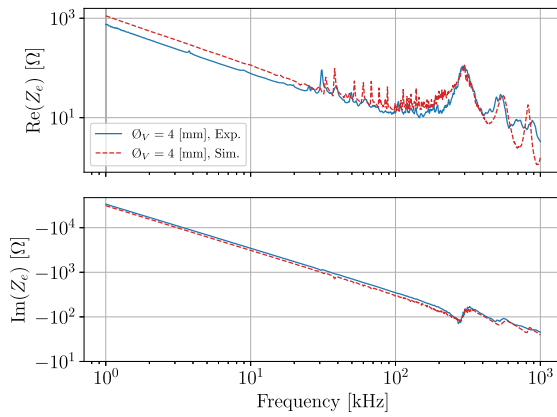
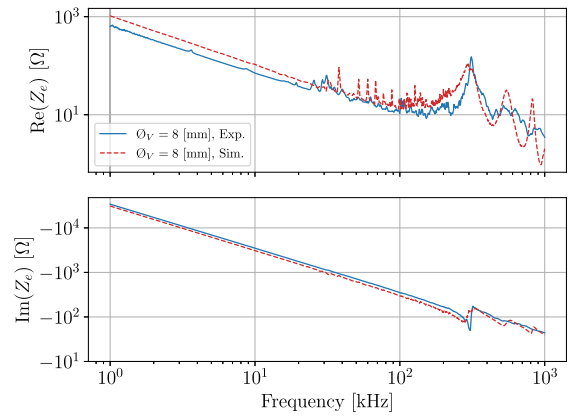
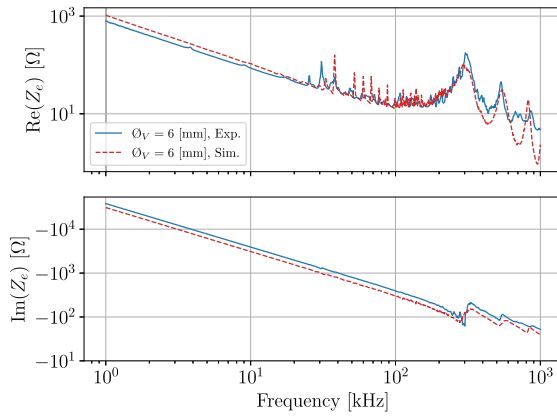
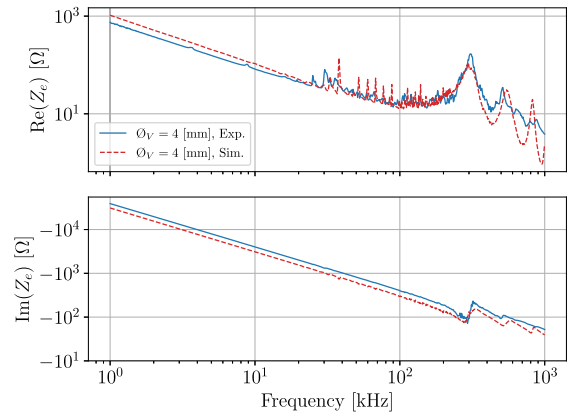
(a) Comparison for middle void of $\varnothing_V = 8$ [mm].(b) Comparison for middle void of $\varnothing_V = 6$ [mm].(c) Comparison for middle void of $\varnothing_V = 4$ [mm].(d) Comparison for corner void of $\varnothing_V = 8$ [mm].(e) Comparison for corner void of $\varnothing_V = 6$ [mm].(f) Comparison for corner void of $\varnothing_V = 4$ [mm].

Fig. 16. Comparison of numerically and experimentally obtained impedance spectra from adhesive joints with voids in the middle and corner positions.

5. Conclusions

This paper presents an experimental comparison of electric impedance signatures from instrumented SLJs with a Pressure Sensitive Adhesive (PSA) and a modified epoxy crash-resistant adhesive, as well as from instrumented substrates. From these measurements, one can see that void detection in joints with a PSA is impractical, since only very small differences occur in the obtained spectra. Further analysis determined that, after breaking these joints, the instrumented substrates yielded similar spectra to the SLJs with PSA, but have considerably

more $\text{Re}(Z_e)$ peaks. Furthermore, boundary conditions significantly influenced the impedance signatures. This was also verified for SLJs with the crash-resistant adhesive, but to a lesser degree.

Conversely, void detection was successfully performed in SLJs with modified epoxy adhesive, with significant changes in both the smaller resistive peaks observed at frequencies below 100 kHz, and in $\text{Re}(Z_e)$ and $\text{Im}(Z_e)$ signatures at higher frequencies. However, these changes occurred due to (i) the presence of artificially created voids, (ii) the unwanted creation of a second source of damage in the manufacturing process of the adhesive joints with voids and (iii) possible variations of

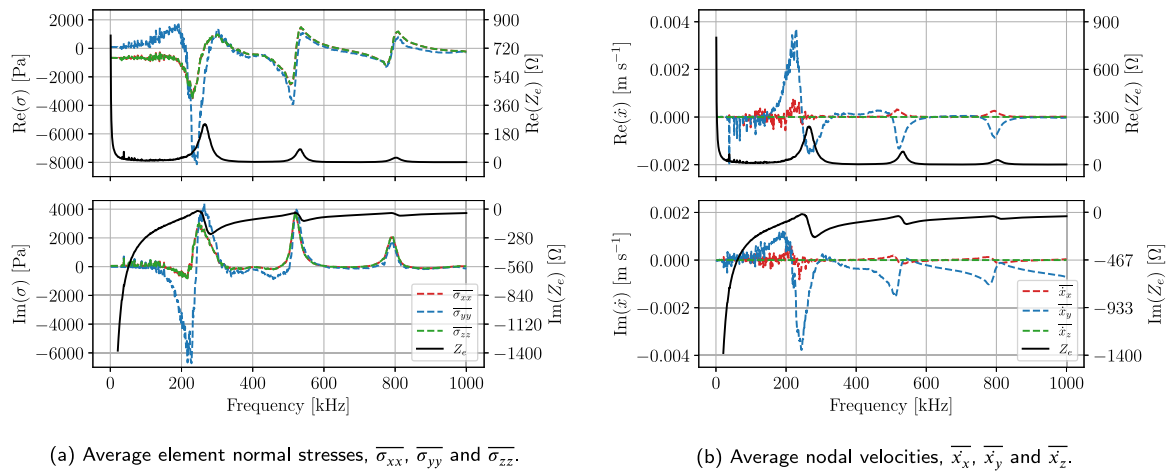


Fig. 17. Spectrum comparing the mechanical response of the undamaged SLJ and the electrical impedance.

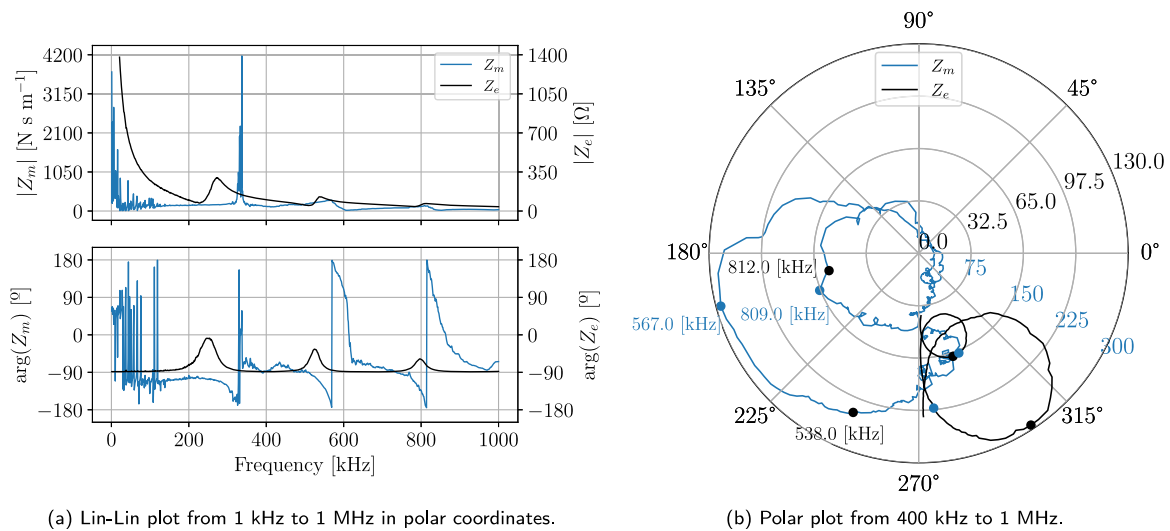


Fig. 18. Spectrum comparing the mechanical and electrical impedances, $Z_{m,s}$ and Z_e , respectively.

mechanical properties (mainly damping) properties of the methacrilate adhesive used to bond the piezoelectric element.

Numerical simulations were performed to try and replicate the experimentally obtained impedance spectra. Numerical results agree with experimental measurements, but this requires the alteration of the loss factor, η , of at least one of the adhesive materials. Given the possible causes for property alterations, modifications were only done to one damping property (loss factor of the methacrilate adhesive). Further study requires an analysis of the damping properties of this adhesive, in order to verify if such large alterations are also caused by this adhesive. A numerical approximation of the mechanical impedance, $Z_{m,s}$, was also computed, yielding a good correlation with the electrical impedance spectra.

CRedit authorship contribution statement

A. Francisco G. Tenreiro: Writing – original draft, Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Experiment. **António M. Lopes:** Writing – review & editing, Supervision, Methodology, Project administration, Resources. **Lucas F.M. da Silva:** Writing – review & editing, Supervision, Methodology, Project administration, Resources. **Ricardo J.C. Carbas:** Experiment, Methodology, Resources.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: A. Francisco G. Tenreiro reports financial support was provided by Foundation for Science and Technology. Ricardo J. C. Carbas reports financial support was provided by Foundation for Science and Technology.

Funding

The authors gratefully acknowledge the funding of grants 2021.07689.BD and CEEDIND/03276/2018, which are provided by Fundação para a Ciência e Tecnologia (FCT), Portugal.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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Appendix D

Paper D

Damage Metrics for Void Detection in Adhesive Single-Lap Joints

Article

Damage Metrics for Void Detection in Adhesive Single-Lap Joints

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Abstract: Structural Health Monitoring (SHM) techniques, such as Electromechanical Impedance Spectroscopy (EMIS), aim to continuously monitor structures for defects, thus avoiding the need for regular maintenance. While attention has been given to the application of EMIS in the automatic detection of damage in metallic and composite components, integrity monitoring of structural adhesive joints has been comparatively neglected. This paper investigated the use of damage metrics with electrical impedance measurements to detect defects in Single-Lap Joints (SLJs) bonded with a modified epoxy adhesive. Traditional metrics using statistical and distance-based concepts, such as the Root-Mean-Squared Deviation, *RMSD*, or the Correlation Coefficient, *CC*, are addressed at detecting voids in the adhesive layer and are applied to five different spectral frequency ranges. Furthermore, new damage metrics have been developed, such as the Average Canberra Distance, *ACD*, which enables a reduction of possible outliers in damage detection, or the complex Root-Mean-Squared Deviation, *cRMSD*, which allows for the use of both the real and imaginary components of the impedance, enabling better damage detection in structural adhesive joints. Overall, damage detection is achieved, and for certain spectral conditions, differentiation between certain damage sizes, using specific metrics, such as the *RMSD* or *cRMSD*, may be possible. Overall, the *RMSD* or *cRMSD* values from damaged SLJs tend to be double the metric values from undamaged joints.



Citation: Tenreiro, A.F.G.; Lopes, A.M.; da Silva, L.F.M. Damage Metrics for Void Detection in Adhesive Single-Lap Joints.

Mathematics **2023**, *11*, 4127. <https://doi.org/10.3390/math11194127>

Academic Editor: Francesc Pozo

Received: 6 September 2023

Revised: 20 September 2023

Accepted: 26 September 2023

Published: 29 September 2023



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Keywords: structural health monitoring; electromechanical impedance spectroscopy; adhesive joints; damage metrics; piezoelectric sensors; void

MSC: 68M18

1. Introduction

Structural Health Monitoring (SHM) is the scientific and engineering domain of automatic and continuous inspection of damage in structures. In this manner, sensors are placed in a given structure and measure dynamic physical quantities that are influenced by material and structural properties. If damage is present, these properties will vary, and therefore, the dynamic behavior being measured will also change. Given this, a computer will acquire these measurements and input them into algorithms for damage detection and evaluation [1,2]. The use of SHM may reduce the number of out-of-service operations and possibly eliminate the need for alternative tools for damage detection, namely Non-Destructive Testing (NDT) [2,3].

Various integrity-monitoring techniques exist, some of which are based on the coupled electromechanical behavior of Piezoelectric Wafer Active Sensors (PWAS) [1,2,4–6]. One such method is the Electromechanical Impedance Spectroscopy (EMIS) monitoring technique, where a PWAS is supplied by an AC voltage source, with a sweep of the signal frequency, ω , across a range of values, normally above 1 kHz. In this manner, for each frequency, ω_i , the PWAS will convert the voltage signal, $V(j\omega_i)$, into a mechanical force,

$F(j\omega_i)$, and particle velocity, $\dot{x}(j\omega_i)$. Concurrently, the stress–strain vibrations influence the electrical current, $I(j\omega_i)$. Consequently, the PWAS behaves simultaneously as a vibration actuator and sensor, but the associated mechanical variables, $F(j\omega)$ and $\dot{x}(j\omega)$, are indirectly measured, given that an impedance analyzer captures the electrical impedance of the PWAS for the examined frequency spectrum, $Z_e(j\omega) = V(j\omega)/I(j\omega)$ [6].

Various studies have proposed mathematical models relating the mechanical load and velocity, $F(j\omega)$ and $\dot{x}(j\omega)$, respectively, or the mechanical impedance of the structure, $Z_{m,s}(j\omega) = F(j\omega)/\dot{x}(j\omega)$, with the electrical impedance measurements [7–11]. One such model, formulated by Liang et al. [7], correlates the electrical impedance with the impedance of a one-dimensional structure with concentrated mass, m_s , stiffness, k_s , and damping, c_s , like the one in Figure 1, yielding

$$Z_e(j\omega) = \left[j\omega \frac{w_P l_P}{h_P} \left(\overline{\varepsilon_{33}^T} - \frac{Z_{m,s}(j\omega)}{Z_{m,s}(j\omega) + Z_{m,P}(j\omega)} d_{31} \overline{Y_{11}^E} \right) \right]^{-1}, \quad (1)$$

where the width, length, and thickness of the piezoelectric element are w_P , l_P , and h_P , respectively. The variable $Z_{m,P}(j\omega)$ stands for the mechanical impedance of the PWAS, while j and d_{31} correspond to the imaginary number, $j = \sqrt{-1}$, and the piezoelectric-induced strain coefficient, respectively. The complex Young's Modulus of the PWAS material with a null electric field ($E = 0$), $\overline{Y_{11}^E}$, is defined as $\overline{Y_{11}^E} = |Y_{11}^E|(1 + j\eta)$, where η is the mechanical loss factor, and the dielectric constant at zero stress, $\overline{\varepsilon_{33}^T}$, is expressed as $\overline{\varepsilon_{33}^T} = |\varepsilon_{33}^T|(1 - j\delta)$, where δ is the dielectric loss factor. It is noted that, in these models, structural damping and stiffness are considered constant throughout the inspection frequency range, which may not always be true, as shown in [12].

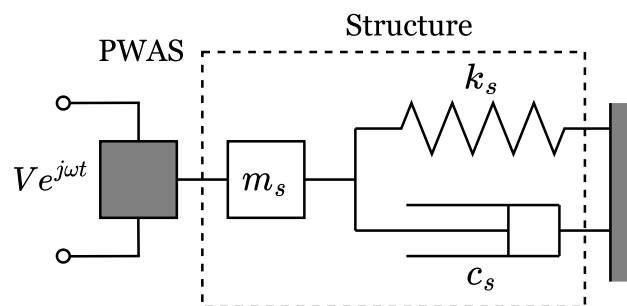


Figure 1. Model of interaction between the PWAS and a one-dimensional structure that occurs in the EMIS method, proposed by Liang et al. [7].

One should consider that the impedance of the sensor, $Z_e(j\omega)$, has real and imaginary components, corresponding, respectively, to the resistive and reactance elements of an equivalent electrical circuit. However, the imaginary component is mainly dominated by the dielectric constant $\overline{\varepsilon_{33}^T}$, which is passive in the sense that it is independent of the structural parameters, i.e., mechanical impedance, $Z_{m,s}(j\omega)$. In mathematical terms,

$$Z_e(j\omega)^{-1} = Y_e(j\omega) = Y_{e,P}(j\omega) + Y_{e,A}(j\omega) \quad (2)$$

where $Y_e(j\omega)$ is the electrical admittance, which is the inverse of the electrical impedance. This admittance can be decomposed into a passive and active admittance, $Y_{e,P}(j\omega)$ and $Y_{e,A}(j\omega)$, respectively.

$$Y_P(j\omega) = j\omega \frac{w_P l_P}{h_P} \overline{\varepsilon_{33}^T} \quad (3a)$$

$$Y_A(j\omega) = j\omega \frac{w_P l_P}{h_P} \frac{Z_{m,s}(j\omega)}{Z_{m,s}(j\omega) + Z_{m,P}(j\omega)} d_{31} \overline{Y_{11}^E} \quad (3b)$$

From this formulation, one can deduce that the passive component, $Y_P(j\omega)$, corresponds to the electrical admittance of a parallel plate capacitor and consists of a complex vector mainly contributing to the reactance [13]. In this manner, the active component $Y_A(j\omega)$ is the main contributor to the real component of the measured electrical impedance, which is more sensitive to damage, as shown by Bhalla et al. [14].

Research on NDT methods, to examine the bondline integrity of structural adhesive joints, has been considerably small in nature and scope [5,6,15–18], especially given the widespread use of structural adhesives in vehicular structures [19–23], e.g., airplanes, automobiles, boats, etc. Indeed, recent studies on NDT inspection of adhesive joints show that not all types of adhesive defects are detectable, requiring the combined use of various NDT techniques, complex signal processing tools, and expensive testing apparatuses [24–28]. In this manner, SHM methods, such as EMIS, can gain scientific and industrial relevance for damage detection.

One manner of evaluating if a given SHM method is able to detect a given form of damage in a type of structure or material is to compare measurements between damaged and undamaged structures. This is performed with the help of damage metrics, given that they have a simple computation, and for the specific case of EMIS, these make use of the real component of the measured electrical impedance, $\text{Re}(Z_e)$. Some metrics are adopted in this field, such as the Mean Absolute Percentage Deviation, *MAPD*, or Pearson's Correlation Coefficient, *CC*. However, the most-widely adopted damage metric is the Root-Mean-Squared Deviation, *RMSD*, and for the specific case of adhesive joint integrity monitoring, this is the only damage index being used in scientific research [6].

Na, Tawie, and Lee [29] studied the detectability of adhesive mass loss in glass-fiber-reinforced polymer adhesive joints, after immersion in acetone, which is considered a corrosive solution. Damage could be detected by computing the Root-Mean-Squared Deviation damage metric, *RMSD*, which is defined as

$$RMSD = \sqrt{\frac{\sum_{i=\omega_i}^{\omega_f} (\text{Re}(Z_e) - \text{Re}(Z_e^0))^2}{\sum_{i=\omega_i}^{\omega_f} \text{Re}(Z_e^0)^2}} \quad (4)$$

where $\text{Re}(Z_e)$ and $\text{Re}(Z_e^0)$ are the real impedance components of the signal under evaluation and of a reference/pristine measurement, respectively. Note also that ω_i and ω_f stand, respectively, for the initial and final sampled angular frequencies of both measurements. These frequencies are related to the initial and final frequency variables, f_i and f_f , respectively, such that $\omega = 2\pi f$. Malinowski et al. [30] used a combination of both the *RMSD* and the peak frequency shift as dimensional metrics to detect damage in Single-Lap Joints (SLJs). Damage was created using either pockets of uncured adhesive (by reducing the curing cycle), release agent contamination, or moisture contamination. For both the joints with release agent contamination and damage caused by moisture, only the *RMSD* values changed. However, when analyzing measurements from joints with pockets of uncured adhesive, a decrease of both metrics occurred.

Roth and Girgiutiu [31] evaluated the sensitivity of EMIS to detect voids in adhesive joints. To achieve this, an initial finite element modal analysis determined the best mode shapes for damage detection, and posteriorly, a second simulation yielded the optimal PWAS placement for intact and debonded joints.

Zhuang et al. [32] performed cyclic load testing, with increasing load steps, on epoxy SLJ specimens with artificially created weak adhesion (also known as *kissing bond*). Between each load cycle, PWAS impedance was measured and the *RMSD* damage metric was computed. In an initial stage, the damage metric remained unchanged, until reaching a threshold value of 0.2, where one would reach approximately 80% of the specimen's failure stress. Malinowski et al. [33] correlated the mechanical performance of adhesive joints with electrical impedance measurements and verified that the spectra from 4.25 to 4.7 MHz

changed according to the bond quality of the adhesive joint. The authors also verified that the *RMSD* values were in agreement with Mode I and Mode II fracture-toughness values.

This paper evaluated EMIS's capability to monitor the integrity of aluminum adhesive joints, whose electrical measurements were studied in [34]. This was performed by computing damage metrics that made use of both the measured electrical impedance, as well as the active impedance. In this manner, the different metrics may have differing results, which may improve the performance of damage detection, depending on the type of damage and on the type of structure. When using the measurements directly, only the real component of the electrical impedance, $\text{Re}(Z_e|_m)$, was used in damage detection. In this case, the Root-Mean-Squared Deviation, *RMSD*, the modified Root-Mean-Squared Deviation, *mRMSD*, the Mean Absolute Percentage Deviation, *MAPD*, and the Correlation Coefficient, *CC*, were used as traditional EMIS damage metrics. Furthermore, a new damage index—the Average Canberra Distance, *ACD*—is also proposed and tested, enabling a reduction of outliers in damage detection. Conversely, new damage metrics are also proposed that make use of the active electrical impedance, thus including both the real and imaginary components, $\text{Re}(Z_e|_A)$ and $\text{Im}(Z_e|_A)$, respectively. These metrics include the complex Root-Mean-Squared Deviation, *cRMSD*, the Complex Correlation Coefficient, *cCC*, and the Normalized Complex Euclidean Distance, *NCED*.

In this manner, Section 2 presents and defines the aforementioned damage metrics, while Section 3 describes the manufacturing and instrumentation of the SLJ specimens, as well as the measurement procedure and spectral conditions for this investigation. Section 4 presents and discusses the obtained results on the application of these metrics for void detection in adhesive joints. Finally, Section 5 presents the concluding remarks of this research.

2. Damage Metrics

Various damage metrics have been proposed for EMIS-based damage detection. However, while studying the viability of EMIS-based integrity evaluation of adhesive joints, the Root-Mean-Squared Deviation metric, *RMSD*, appears to be the only defect metric adopted. In this manner, the most-commonly used EMIS damage metric indices are listed here, as well as the proposed alternatives that make use of the real component of the measured impedance, $\text{Re}(Z_e|_m)$.

Furthermore, it is known that the measured impedance contains a passive component (different from the complex rectangular coordinate impedance components), which is insensitive to damage and is mainly observed in the imaginary component, $\text{Im}(Z_e|_m)$. However, to the best of the authors' knowledge, no previous work has been performed where this passive impedance component is removed for damage detection. In this manner, new damage metrics are proposed, where the passive component has been removed.

2.1. Conventional Damage Metrics

While the *RMSD* damage metric, as presented in Equation (4), normally correlates well with damage present in adhesive joints, it has so far been the main metric used to evaluate the applicability of EMIS in defect detection of adhesive joints. Note that this metric can be viewed as a normalized Euclidean norm, L_2 [35,36].

However, other metrics have also been employed in comparing impedance spectra to determine the presence of damage [6], such as the Mean Absolute Percentage Deviation, *MAPD*, and the Correlation Coefficient, *CC*, which are defined as

$$MAPD = \frac{1}{N} \sum_{i=\omega_i}^{\omega_f} \left| \frac{\text{Re}(Z_e|_m) - \text{Re}(Z_e^0|_m)}{\text{Re}(Z_e^0|_m)} \right| \quad (5)$$

$$CC = \frac{\text{Cov}(\text{Re}(Z_e|_m), \text{Re}(Z_e^0|_m))}{\sigma_{\text{Re}(Z_e|_m)} \sigma_{\text{Re}(Z_e^0|_m)}} = \frac{1}{N} \frac{\sum_{i=\omega_i}^{\omega_f} (\text{Re}(Z_e|_m) - \overline{\text{Re}(Z_e|_m)}) (\text{Re}(Z_e^0|_m) - \overline{\text{Re}(Z_e^0|_m)})}{\sqrt{\sum_{i=\omega_i}^{\omega_f} (\text{Re}(Z_e|_m) - \overline{\text{Re}(Z_e|_m)})^2} \sqrt{\sum_{i=\omega_i}^{\omega_f} (\text{Re}(Z_e^0|_m) - \overline{\text{Re}(Z_e^0|_m)})^2}} \quad (6)$$

where N is the number of acquired samples. Furthermore, the variables $\overline{\text{Re}(Z_e^0|_m)}$ and $\overline{\text{Re}(Z_e|_m)}$ stand for, respectively, the mean value of the measured electric impedance from both the reference pristine joint and the joint under evaluation, while $\sigma_{\text{Re}(Z_e|_m)}$ and $\sigma_{\text{Re}(Z_e^0|_m)}$ are the standard deviation of both aforementioned impedances [6].

The Mean Absolute Percentage Deviation, *MAPD*, is a metric that averages the deviations of $\text{Re}(Z_e|_m)$ at all sampled frequencies [35]. However, given its mathematical formulation, this metric can also be viewed as an averaged and normalized Manhattan distance (L_1 distance) damage index, which makes use of the real component of the measured impedance [36].

The Correlation Coefficient, *CC*, is based on the Covariance, $\text{Cov}(\text{Re}(Z_e|_m), \text{Re}(Z_e^0|_m))$, and therefore, the authors chose to only include the *CC* metric in this investigation [6]. The Covariance, *Cov*, evaluates the relationship between two impedance signatures and determines whether these two impedance datasets resemble each other or not. If both signatures peak at the same frequency, then the covariance is positive. Conversely, if the peak of a dataset is placed where the valley of the other dataset is, then the covariance is negative. If both signatures are unrelated, then the covariance tends to be null. The *CC* reflects the same information as the covariance, but the value is normalized so that *CC* nears 1 when both signatures are similar and is equal to 1 when they are opposite each other [6,37].

While these are the main damage indices used in EMIS, others do exist. One such example is the modified Root-Mean-Squared Deviation damage metric, *mRMSD*, which is defined as

$$mRMSD = \sum_{i=\omega_i}^{\omega_f} \sqrt{\frac{(\text{Re}(Z_e|_m) - \text{Re}(Z_e^0|_m))^2}{\text{Re}(Z_e^0|_m)^2}} \quad (7)$$

and is usually misidentified as the *RMSD* [38,39]. Indeed, this modified metric is equivalent to the *MAPD*, despite the fact that no averaging is performed, since the summation is not divided by the number of sampled frequencies, N , converse to what occurs in Equation (5). Therefore, this damage metric pertains to the family of metrics inspired by the Euclidean distance, L_2 , corresponding to the Pearson χ^2 divergence [40].

2.2. Proposed Damage Metrics

In this work, new damage metrics are also proposed, to try and obtain other methods of damage detection. One proposed metric is the Averaged Canberra Distance, *ACD*, which is defined as

$$ACD = \frac{1}{N} \sum_{i=\omega_i}^{\omega_f} \frac{|\text{Re}(Z_e|_m) - \text{Re}(Z_e^0|_m)|}{|\text{Re}(Z_e|_m)| + |\text{Re}(Z_e^0|_m)|} \quad (8)$$

This metric is based on the Canberra distance, which is used in data quantification, especially for data that are scattered near zero, given that it is sensitive to small values [40,41].

Given the considerations of Bhalla et al. [14], regarding the usefulness of using the active component of the measured impedance, the passive component was removed, which is defined in Equation (3a), yielding only the active component, which, in this paper, is identified by the notation $Z_{e,A}$.

A complex Root-Mean-Squared Deviation index, *cRMSD*, is proposed as an extension of the classical *RMSD* damage metric and is defined as

$$cRMSD = \sqrt{\frac{\sum_{i=\omega_i}^{\omega_f} (\text{Re}(Z_{e,A}) - \text{Re}(Z_{e,A}^0))^2}{\sum_{i=\omega_i}^{\omega_f} \text{Re}(Z_{e,A}^0)^2}} + \sqrt{\frac{\sum_{i=\omega_i}^{\omega_f} (\text{Im}(Z_{e,A}) - \text{Im}(Z_{e,A}^0))^2}{\sum_{i=\omega_i}^{\omega_f} \text{Im}(Z_{e,A}^0)^2}} \quad (9)$$

which, in simple terms, is the sum of two individual *RMSD* metrics, where one uses the real components of the active impedance from the evaluated and pristine SLJs, $\text{Re}(Z_{e,A})$ and $\text{Re}(Z_{e,A}^0)$, respectively, and the second part is computed with the imaginary component of said impedances, $\text{Im}(Z_{e,A})$ and $\text{Im}(Z_{e,A}^0)$.

A modification of the correlation coefficient is proposed to encompass the real and imaginary components of the active impedance, $Z_{e,A}$. This complex Correlation Coefficient, cCC , is defined as

$$cCC = \frac{1}{2} \left[\frac{\text{Cov}(\text{Re}(Z_{e,A}), \text{Re}(Z_{e,A}^0))}{\sigma_{\text{Re}(Z_{e,A})} \sigma_{\text{Re}(Z_{e,A}^0)}} + \frac{\text{Cov}(\text{Im}(Z_{e,A}), \text{Im}(Z_{e,A}^0))}{\sigma_{\text{Im}(Z_{e,A})} \sigma_{\text{Im}(Z_{e,A}^0)}} \right] \quad (10)$$

which can be viewed as the sum of two individual correlation coefficients, one that only compares the real component of the impedance signals and another that compares the imaginary impedance component. In this manner, the standard deviations of the real and imaginary components of the active electrical impedance of the pristine joint, $\sigma_{\text{Re}(Z_{e,A}^0)}$ and $\sigma_{\text{Im}(Z_{e,A}^0)}$, respectively, as well as of the bonded joint under evaluation $\sigma_{\text{Re}(Z_{e,A})}$ and $\sigma_{\text{Im}(Z_{e,A})}$, respectively, must be computed. Note that the summed components yield a value between -2 and 2 . Therefore, to have an accurate comparison with the traditional CC metric defined in Equation (6), the resultant summation was divided by 2 .

A third proposed metric that makes use of both the active resistance and reactance of the PWAS is the Normalized Complex Euclidean Distance, $NCED$, such that

$$NCED = \sqrt{\frac{\sum_{i=\omega_i}^{\omega_f} [(\text{Re}(Z_{e,A}) - \text{Re}(Z_{e,A}^0))^2 + (\text{Im}(Z_{e,A}) - \text{Im}(Z_{e,A}^0))^2]}{\sum_{i=\omega_i}^{\omega_f} [\text{Re}(Z_{e,A}^0)^2 + \text{Im}(Z_{e,A}^0)^2]}} \quad (11)$$

This damage index is an alternative proposal of a Euclidean-based damage metric. For this index, the normalization was performed with the complex active impedance of the damageless adhesive joint.

3. Experimental Details

This section presents the specimen materials, their manufacturing procedure, and their measurement conditions. It is noted that this work used the specimens manufactured and studied in [34]. In this manner, the production of the specimens will be briefly described here.

3.1. Materials and Manufacture

The SLJ specimens were manufactured with 6082 aluminum alloy adherends of a 2 mm thickness. The adhesive for SLJ production was the Nagase T-836/R-810 crash-resistant adhesive, which is a modified epoxy adhesive specially conceived of for automobile and aeronautical structures and is manufactured by Nagase Chemtex[®] (Osaka, Japan). This adhesive cures at a temperature of 160 °C for 3 h. The properties of both materials are presented in Table 1.

Table 1. Properties of the adhesives and adherend used in SLJ manufacturing [12].

	E (GPa)	ν (-)	ρ (kg m ⁻³)	η (-)
Aluminum Al 6082	70.0	0.33	2710	$5.0 \cdot 10^{-4}$
Nagase T-836/R-810	2.55	0.41	1200	0.10

The substrates were initially roughened with sand paper. Anodization was performed, as per the standard ASTM D 393398 [42], where the aluminum substrates were submerged in a solution of 10% phosphoric acid and 90% distilled water (m/m), and a current, created by a 16 V voltage, passed through the substrates for 25 min. Afterwards, the substrates were rinsed with distilled water and acetone.

For void creation, Polytetrafluoroethylene (PTFE) infills were placed in the overlap region, before applying the structural crash-resistant adhesive. Subsequently, the mold, with the SLJs, was placed in a hot press, where the aforementioned curing cycle was

performed. Note that the infills of diameters $\varnothing_V \in \{4, 6, 8\}$ mm were placed in either the corner or the center of the overlap layer, as per Figure 2, with the help of a cyanoacrilate adhesive capable of withstanding high temperatures ($T_{\text{service}} = 200^\circ\text{C}$).

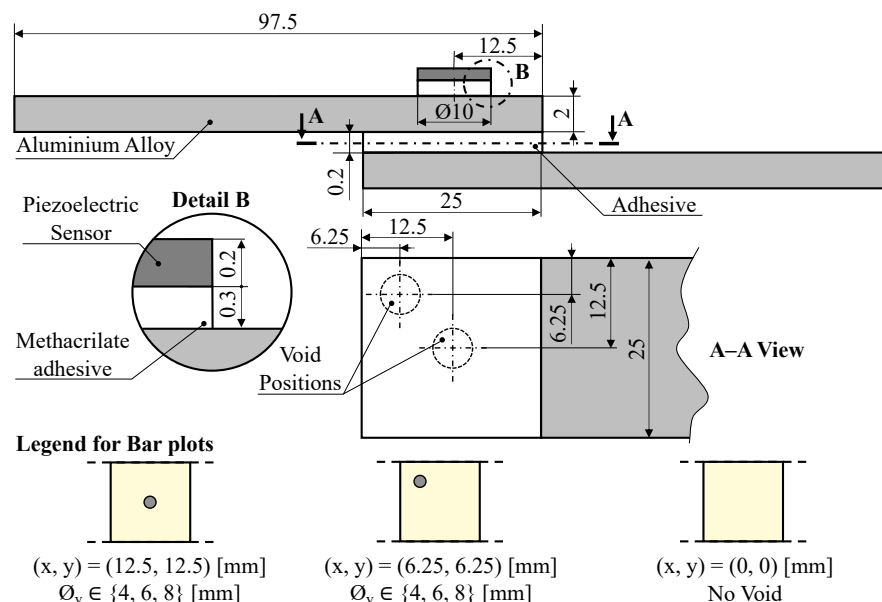


Figure 2. Schematic representation of an SLJ specimen (with dimensions in mm).

After the manufacture of these adhesive joint specimens, the authors observed that a second source of damage was unintentionally created, as stated in [34]. In this manner, the actual void present in the adhesive layer was constituted by the infill material and a region surrounding this infill, which was unintentionally created. The authors believe that this second source of defect was caused by an unwanted chemical reaction between the modified epoxy adhesive and the cyanoacrilate adhesive. Nonetheless, the main damage to be detected should be the circular void, given that it defines the majority of the damaged area in the overlap.

3.2. Specimen Instrumentation and Measurements

After the manufacturing of the SLJ specimens, PRYY + 1119 piezoelectric sensors, fabricated by PI Ceramics (Lederhose, Germany), were used to instrument said joints. These elements, whose dimensions are indicated in Figure 2, are made of PIC 255 piezoceramic, which has a high Curie temperature ($T_c = 350^\circ\text{C}$) and whose material properties are presented in Table 2. Note that ρ is the mass density of the piezoceramic, while $\frac{\epsilon_{33}^T}{\epsilon_0}$ is the relative permittivity in the polarization direction. The PWAS was fixed on the free side of the upper substrate, in the center of the overlap, with the help of a manually mixed methacrylate adhesive Plexus MA 422, manufactured by ITW Performance Polymers (Chicago, Illinois, United States), which cures at room temperature for 24 h. The mechanical properties of this adhesive are present in Table 3. Before this cure, a spiral copper wire was placed under the piezoelectric element, and afterwards, a second wire was soldered on top of said element.

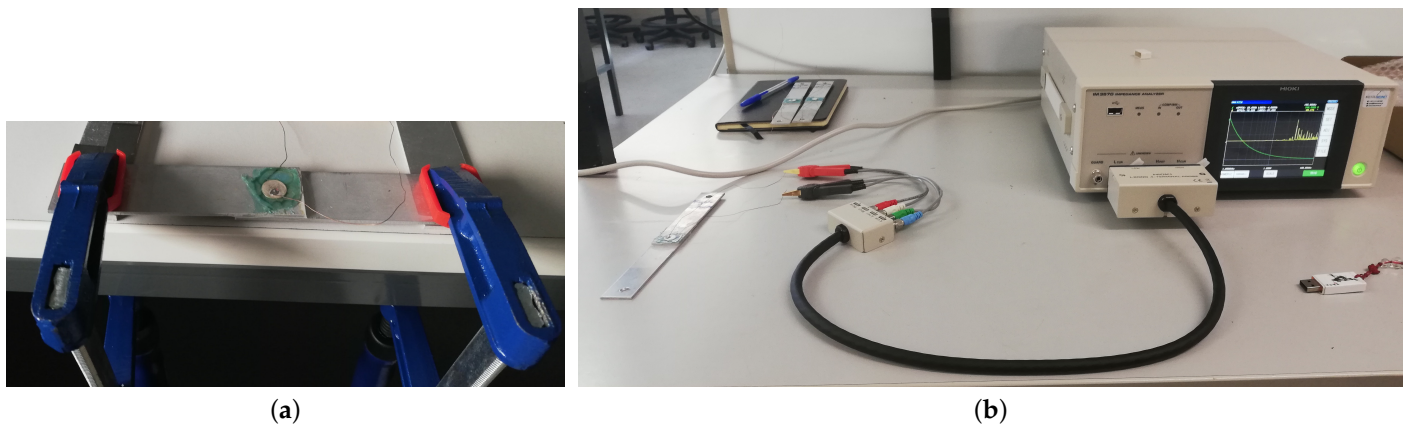
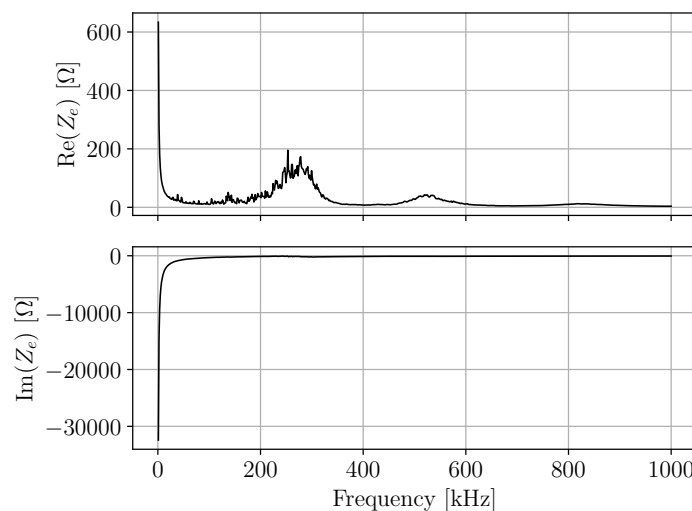
Table 2. Properties of the soft piezoceramic material PIC 255.

ρ (g cm ⁻³)	Elastic Compliance Coefficient		Coupling Factor		$\frac{\epsilon_{33}^T}{\epsilon_0}$ (-)
	s_{11}^E (m ² N ⁻¹)	s_{33}^E (m ² N ⁻¹)	k_p	k_t	
7.80	16.1×10^{-12}	20.7×10^{-12}	0.62	0.47	1750

Table 3. Properties of the adhesive used in the SLJ instrumentation [12].

	E (GPa)	ν (-)	ρ (kg m ⁻³)	η (-)
Plexus MA 422	0.994	0.31	960	0.45

Impedance measurements were performed with a Hioki IM 3570 impedance analyzer (Ueda, Japan), where the adhesive joints were fixed on both free ends with clamps, as demonstrated in Figure 3. This was performed since the boundary conditions influence the measured electrical impedance, $Z_e(j\omega)$. Three impedance spectra were directly measured for each specimen: (i) from $f_i = 1$ kHz to $f_f = 1$ MHz, with linearly spaced sampled frequencies, (ii) from $f_i = 1$ kHz to $f_f = 1$ MHz, with logarithmically spaced frequencies, and (iii) from $f_i = 100$ kHz to $f_f = 1$ MHz, with linearly spaced sampled frequencies. Each measurement yielded 801 sampled frequency points. A plot of the measurements is given in Figure 4.

**Figure 3.** Experimental setup. (a) Fixed adhesive joint specimen. (b) Impedance analyzer with SLJ.**Figure 4.** Plot showing the measured electrical impedance from an undamaged SLJ, with 801 linearly spaced points, from $f_i = 1$ kHz to $f_f = 1$ MHz.

These measurements were then processed by a Python 3 script that computes the damage metrics for each spectral condition. During this processing, two other spectra were created: (iv) the three spectra were combined to yield a spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz with 2389 sampled points; (v) a sub-spectrum was also created from the experimentally obtained spectrum (ii), containing all sampled points between $f_i = 10$ kHz to $f_f = 200$ kHz. Note that, for Spectra (iv), all repeated sampled frequencies were removed.

The aforementioned damage metrics were calculated for all SLJs. However, this required a pristine/reference measurement. In this manner, each pristine SLJ impedance measurement was used as a reference, and all other measurements from all other damaged and damageless joints were considered as measurements from joints under inspection. Therefore, for each reference joint, a total of 20 metrics were computed (3 for each damage case and 2 for the case of SLJs without a void).

4. Damage Metric Results and Discussion

Given the number of metrics developed for this work, the following section is divided in two subsections. The first subsection will tackle the obtained results for the metrics using exclusively the real component of the measured impedance. Afterwards, the second subsection will present and discuss the obtained metric results for the active electrical impedance, which contains both real and imaginary components. Please note that, given the huge amount of different damage metrics calculated for different spectral conditions, the exact numerical values are presented in Appendix A.

One must point out that the obtained metric results were a function of various aspects, such as the number of sampled points or the spectral measurement conditions, i.e., logarithmically or linearly spaced sampled points. Given this, there was no clear manner of establishing a fixed threshold between values from damaged and undamaged adhesive joints.

4.1. Metrics Using the Real Component of the Impedance

4.1.1. Linearly Spaced Spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz

Figure 5 presents the average and standard deviation of the obtained damage indices using only the real component of the measured impedance, $\text{Re}(Z_e|_m)$. Given the fact that the five metrics defined in Section 2 have different ranges, different vertical scales are presented.

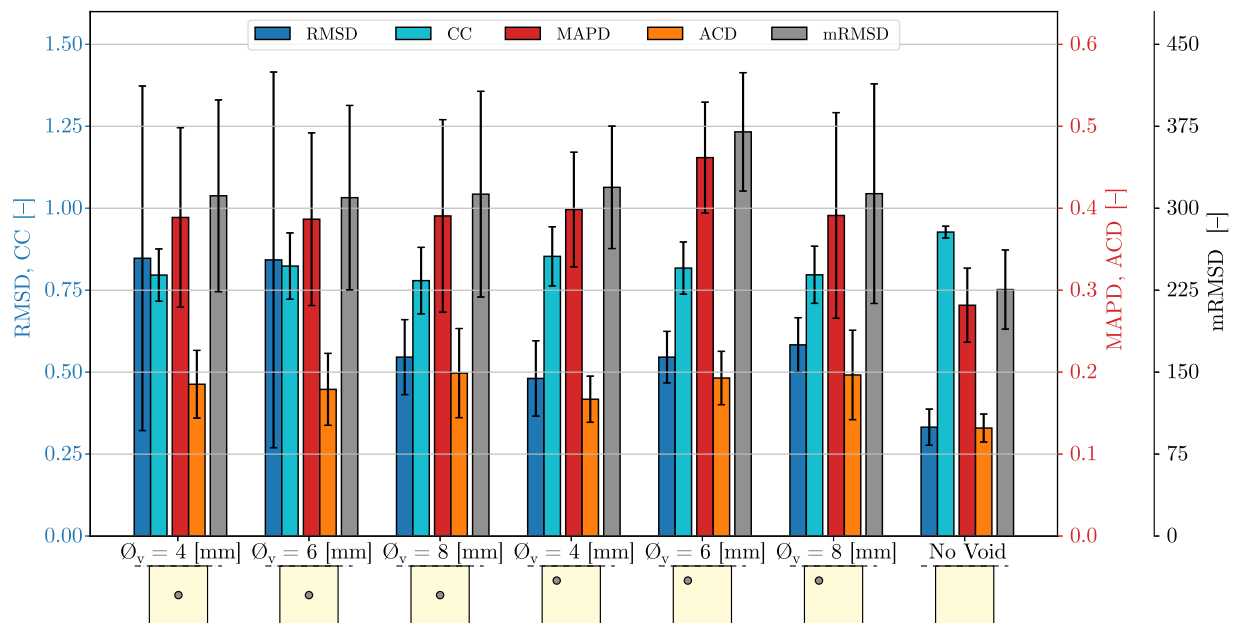


Figure 5. Bar plot comparing the average and standard deviation of the obtained damage metrics, computed using the real component of the measured impedance from $f_i = 1$ kHz to $f_f = 1$ MHz (801 linearly spaced points).

Overall, one sees that all damage metrics increased significantly when damage was present, with the exception of the Correlation Coefficient, CC. This occurred because, as expected from its mathematical definition, the obtained metric values tended towards the unit value when the spectra being compared were similar in trend. Therefore, the CC,

for the case where there was no void, had values between 0.90 and 0.95, while overall, the metric values from the damaged SLJs tended to be lower than 0.90.

This being said, there were some outlier values, originating from joints containing voids, that were superior to 0.90. These values tended to originate from the comparison between any given damaged joint specimen and the pristine SLJ₀ 2 specimen, which was used as the reference baseline specimen for comparison. This can be explained by the fact that the spectra of the reference undamaged joint SLJ₀ 2 were similar to some spectra from joints with voids. This was the case of specimen SLJ 1, which had a void in the corner of the overlap adhesive layer, and $\varnothing_V = 4$ mm, as can be seen in Figure 6a, yielding $CC = 0.9615$. Conversely, Figure 6b shows a similar comparison of the spectra from the reference SLJ₀ 1 with specimen SLJ 2, which had a $\varnothing_V = 4$ mm void in the center of the overlap, obtaining a value of $CC = 0.6914$, which is to be expected.

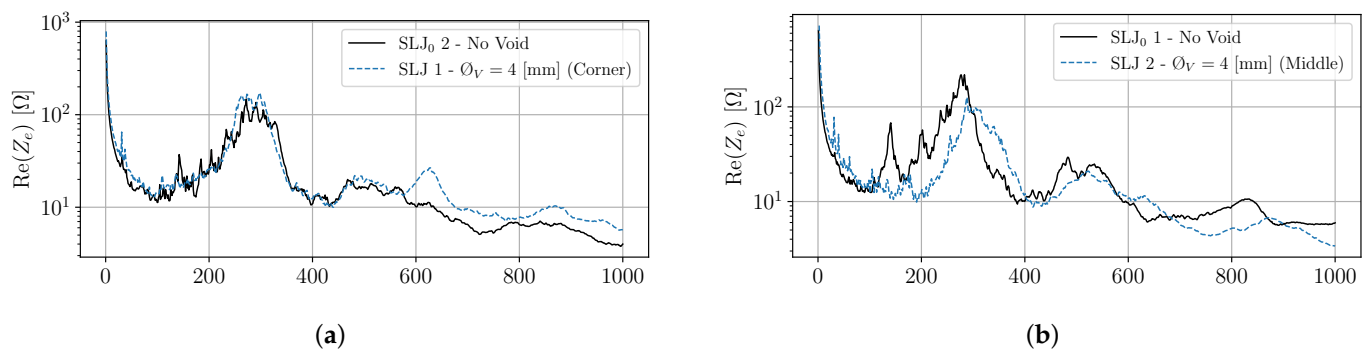


Figure 6. Lin-Log plot comparing the $Re(Z_e|_m)$ spectra between pristine SLJs and SLJs with voids. (a) Reference SLJ₀ 2 and SLJ 1 (corner $\varnothing_V = 4$ mm void) specimens. (b) Reference SLJ₀ 1 and SLJ 2 (middle $\varnothing_V = 4$ mm void) specimens.

As previously stated, the other four damage metrics—Root-Mean-Squared Deviation, *RMSD*, Mean Absolute Percentage Deviation, *MAPD*, modified Root-Mean-Squared Deviation, *mRMSD*, and Averaged Canberra Distance, *ACD*—increased with the presence of damage. This is to be expected, since bigger changes in the spectra translated into bigger distances between the sampled impedance values. Overall, the obtained metrics for damaged cases tended to have values between one- and two-times the metric values for undamaged joints, as shown in Figure 7. This is explained by the fact that the damage caused significant changes in the obtained spectra, as shown in Figure 6b. However, even with these four distance-based damage indices, there was some overlap between the undamaged and damaged adhesive joints, precisely in the case where undamaged SLJ₀ 2 was used as a reference.

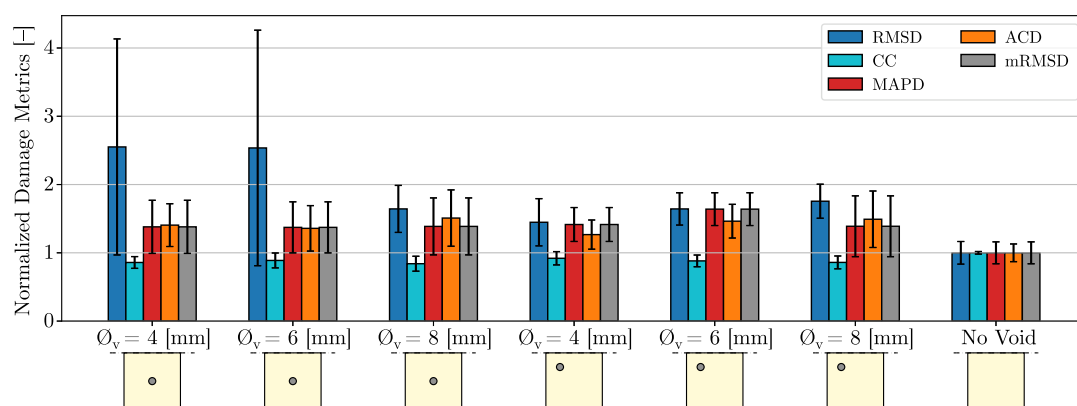


Figure 7. Bar plot comparing the normalized average and standard deviation of the obtained damage metrics, computed using the real component of the measured impedance from $f_i = 1$ kHz to $f_f = 1$ MHz (801 linearly spaced points).

One must also note that the *RMSD* metric had a somewhat better performance in damage detection, when compared with the other three damage metrics. Normally, the *RMSD* metric values for the damaged SLJs tended to be between one- to two-times the observed values from the undamaged joints. However, some *RMSD* values were approximately five-times what was observed for undamaged joints, hence the large standard deviation bars observed in the cases of voids with a diameter $\varnothing_V \in 4, 6$ mm, which were placed in the middle of the overlap. This can only be caused by the fact that the second uncontrolled source of damage (increasing the overall void area) occupied a bigger area of the overlap and, thus, caused a bigger change in the impedance spectrum. Furthermore, one must point out that the *RMSD* metric overall had a better performance in damage detection. This is noted by the fact that, in other cases of void size and placement, there was a smaller, but significant improvement in damage detection ((12.5, 12.5) mm, $\varnothing_V = 8$ mm, or (6.25, 6.25) mm, $\varnothing_V = 8$ mm damage cases), when compared to the other three distance-based damage indices.

4.1.2. Logarithmically Spaced Spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz

Figure 8 plots the average and standard deviation of the damage indices that were computed with logarithmically spaced measured impedance, from $f_i = 1$ kHz to $f_f = 1$ MHz.

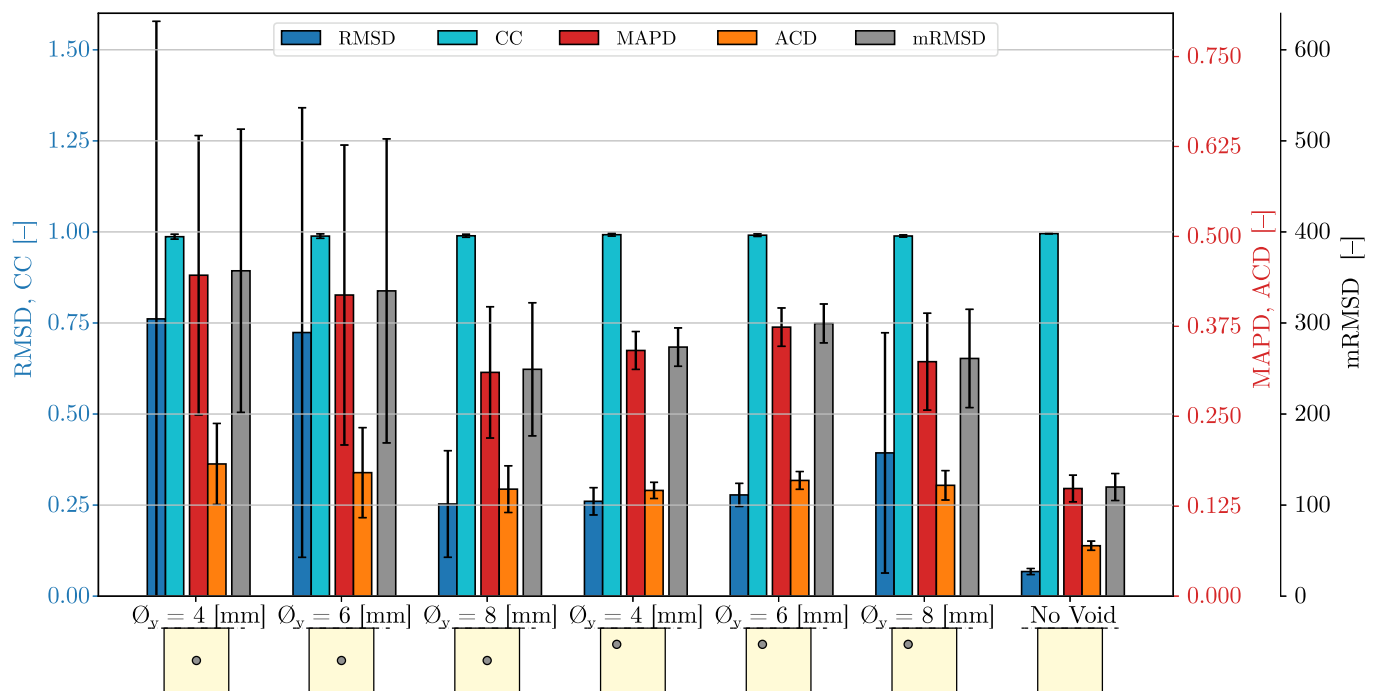


Figure 8. Plot comparing the average and standard deviation of the obtained damage metrics, computed using the real component of the measured impedance from $f_i = 1$ kHz to $f_f = 1$ MHz (801 logarithmically spaced points).

In an initial analysis, one sees that the *CC* metric appeared to have very little changes between damage cases. Upon closer attention, one can verify that the metrics from the pristine SLJs were indeed very close to the average value of $\overline{CC}(\text{NoVoid}) = 0.9954$ with very little variation ($\sigma_{CC}(\text{NoVoid}) = 6.789 \cdot 10^{-4}$). Conversely, all of the computed *CC* for the damaged cases yielded values between 0.9792 and 0.9972, which means that some overlap still existed. Furthermore, all six classes of damaged joints had larger standard deviation. The smallest standard deviation for damaged adhesive joints was from the joints that had a void of diameter $\varnothing_v = 8$ mm in the corner of the overlap, i.e., $(x, y) = (6.25, 6.25)$ mm, where $\sigma_{CC} = 3.053 \cdot 10^{-3}$. In essence, the correlation coefficient was unreliable in the damage detection, when using this spectral measurement condition.

All distance-based damage metrics (*RMSD*, *mRMSD*, *MAPD*, and *ACD*) had a clearer distinction between joints with and without artificially created voids. Indeed, the average values for all six damage cases tended to be two- to three-times higher than the average value observed for the pristine case. This is shown in Figure 9, with a zoomed view of the *mRMSD*, *MAPD*, and *ACD* for one case (void in $(x, y) = (6.25, 6.25)$ mm, with $\varnothing_v = 8$ mm) as an example. Overall, for these three mathematical metrics, all values from the damaged joints tended to have values between 1.5- and 4-times the values observed for the undamaged adhesive joint specimens.

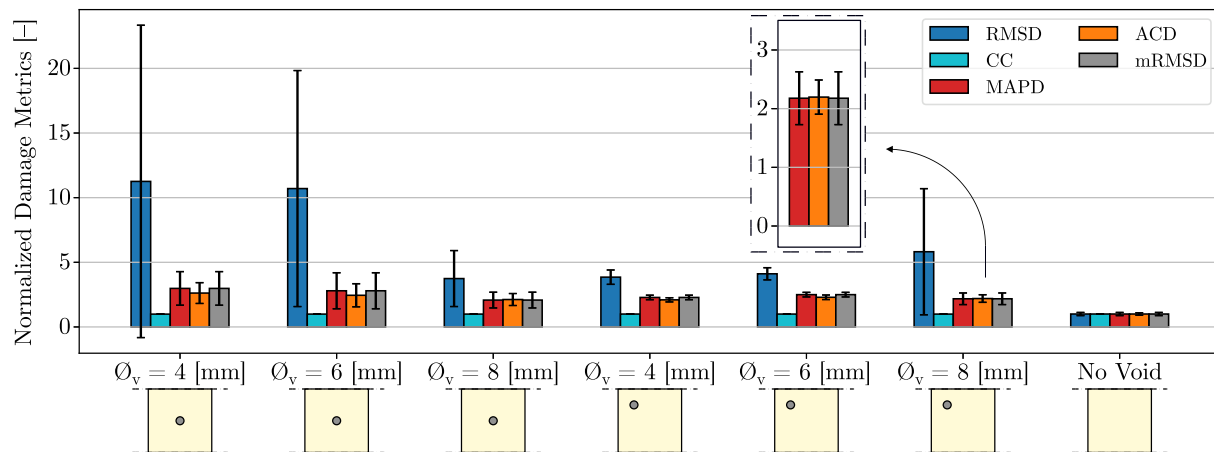


Figure 9. Bar plot comparing the normalized average and standard deviation of the obtained damage metrics, computed using the real component of the impedance from $f_i = 1$ kHz to $f_f = 1$ MHz (801 logarithmically spaced points).

A similar behavior was observed for the *RMSD* index values. However, the gap in values between measurements of the damaged and pristine SLJs was starker, since, as shown for the previous case, this damage metric appeared to have a better performance in damage detection. This can be seen by the fact that all average *RMSD* values for damaged instances were at least four-times higher than the average for the undamaged case. In part, this can be explained by the mathematical definition of the *RMSD* damage index, which enables a better detection of damage, as previously stated. However, one must point out that all four distance-based damage metrics were computed from measurements with 801 logarithmically spaced sampling points, which means that each order of magnitude of the frequency had 267 sampled impedance points. This equal distribution of the sampled points enabled the lower frequency range (i.e., below 100 kHz) of the measured real component of impedance, $\text{Re}(Z_e|_m)$, to have a bigger impact on damage detection.

It is noted that the average and standard deviation of the *MAPD*, *mRMSD*, and *RMSD* values, for the two cases where voids of $\varnothing_v \in \{4, 6\}$ mm, placed in the middle of the overlap (i.e., void in $(x, y) = (12.5, 12.5)$ mm), were higher than for the remaining damaged joint classes. This was caused by the fact that some SLJs in these classes had a larger overall damaged area due to the unwanted creation of a second defect in the adhesive layer. However, with the use of logarithmically spaced impedance spectra, the differences occurring at lower frequencies were more pronounced, and the *MAPD* and *mRMSD* metrics also became more sensitive to the impedance alterations.

4.1.3. Linearly Spaced Spectrum from $f_i = 100$ kHz to $f_f = 1$ MHz

Figure 10 shows the average and standard deviation of the computed damage indices from the linearly spaced measured impedance, from $f_i = 100$ kHz to $f_f = 1$ MHz.

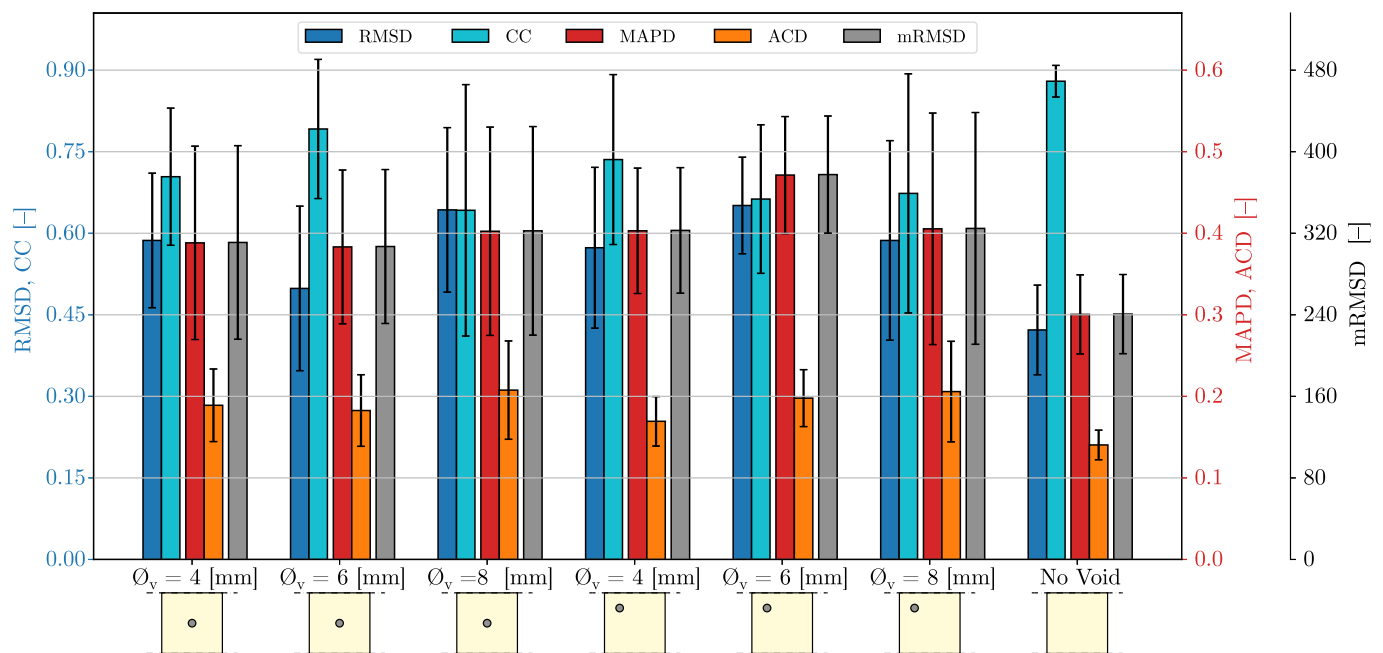


Figure 10. Plot comparing the average and standard deviation of the obtained damage metrics, computed using the real component of the measured impedance from $f_i = 100$ kHz to $f_f = 1$ MHz (801 linearly spaced points).

Much like in the previous cases, the CC metric decreased with an increasing change in the spectra of $\text{Re}(Z_e|_m)$, according to its mathematical definition. Furthermore, the global average of all CC metrics clearly showed the presence of damage, since the average $\overline{CC}$ value for the undamaged joints was $\overline{CC}(\text{no void}) = 0.8796$, while all of the average values for the damaged SLJs were below 0.80, $\overline{CC}(\text{Void}) < 0.80$. Despite this, some outlier values existed, much in the same line as seen in the metrics of the linearly spaced sampled frequencies from $f_i = 1$ kHz to $f_f = 1$ MHz, meaning that some of the computed CC metric values for the damaged joints fell within the value range of the undamaged SLJ specimens. This overlap can be visualized in the bar plot of Figure 11, which shows the normalized metrics according to the average value of the *no void* case.

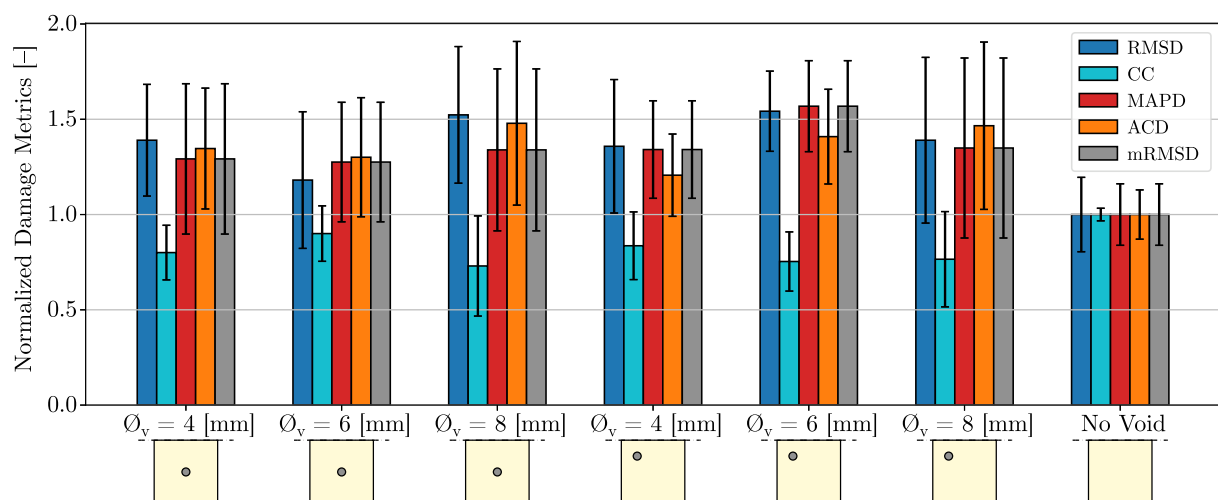


Figure 11. Bar plot comparing the normalized average and standard deviation of the obtained damage metrics, computed using the real component of the measured impedance from $f_i = 100$ kHz to $f_f = 1$ MHz (801 linearly spaced points).

Furthermore, similar to the metric results from the 801 linearly spaced sampled frequencies from $f_i = 1$ kHz to $f_f = 1$ MHz, there was an overlap in the metric values between the undamaged and damaged cases when using the *RMSD*, *mRMSD*, *MAPD*, and *ACD* distance-based metrics. Likewise, this can be seen in the normalized damage metric bar plot of Figure 11, where there is an overlap of the various standard deviation bars between most cases of the joints with voids and the case of the undamaged joints. These similarities in trends between both spectral cases were due to the fact that a significant portion of the linearly sampled measured impedance spectra between $f_i = 1$ kHz and $f_f = 1$ MHz was equivalent to the direct spectral measurements from $f_i = 100$ kHz to $f_f = 1$ MHz. Therefore, the obtained metrics should be similar to the ones obtained in the first analyzed spectral case, as was the case when comparing Figures 5 and 10. The only difference between both cases that impacted the computed metrics was the fact that this spectral condition did not have the initial exponential decrease of $\text{Re}(Z_e|_m)$, thus leading to a slight decrease of the metric values when compared to the first studied case.

Upon closer comparison between the Averaged Canberra Distance, *ACD*, and the other three distance-based metrics, one sees that there were fewer cases of damaged joints with overlapping values with the undamaged adhesive joints. This can be attributed to one of the base properties of the Canberra distance as a mathematical index, which is the fact that it is sensitive to alterations near zero [40,41]. Consequently, the *ACD* is a somewhat more-robust damage index when compared to the *RMSD*, *mRMSD*, and *MAPD*.

4.1.4. Logarithmically Spaced Spectrum from $f_i = 10$ kHz to $f_f = 200$ kHz

Figure 12 shows the average and standard deviation of the computed damage indices from the logarithmically spaced measured impedance, from $f_i = 10$ kHz to $f_f = 200$ kHz. Note that this impedance spectrum was obtained by cropping the measured logarithmically spaced impedance spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz, obtaining a sub-spectrum with 347 sampled points.

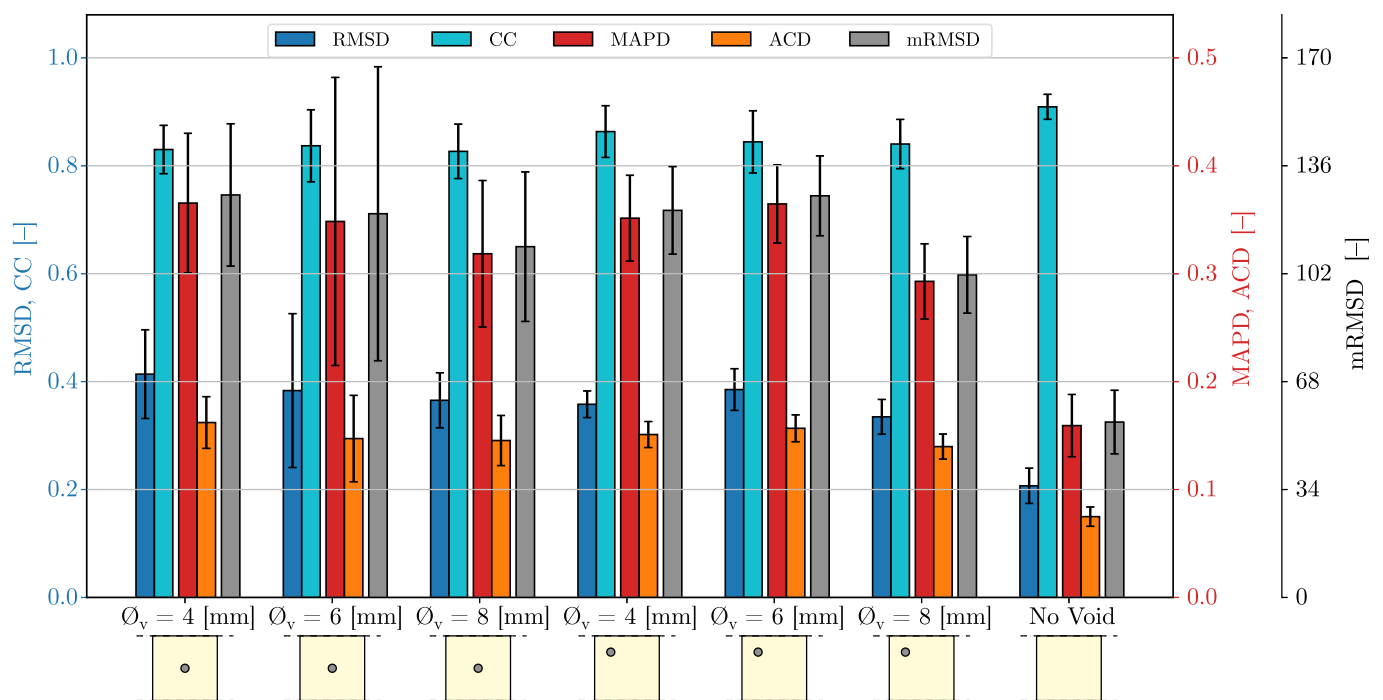


Figure 12. Plot comparing the average and standard deviation of the obtained damage metrics, computed using the real component of the measured impedance from $f_i = 10$ kHz to $f_f = 200$ kHz (347 logarithmically spaced points).

An initial observation showed that, once again, as per the mathematical definition, a comparison of the undamaged joints with a reference joint yielded higher CC values, when compared to the CC metrics obtained for the damaged joints as a whole. In this manner, the mean value for the pristine SLJs was of $\overline{CC}(\text{no void}) = 0.909189$, while the average values for all three damaged cases tended to be below 0.865. However, upon closer observation, a significant portion of the computed correlation coefficient values for the damaged bonded joints, using the SLJ₀ 2 specimen as a reference, overlapped significantly with the values obtained for the undamaged joints. Comparatively speaking, there was no overlap between the damaged and undamaged joints when using SLJ₀ 1 as a reference, and three values of the damaged joints overlapped with the undamaged values when SLJ₀ 3 was used as a reference. Alternatively, Figure 13, which presents the normalized average damage metrics for this spectral condition, shows that there was a clear overlap between the undamaged and damaged CC metrics, which corroborated the obtained results.

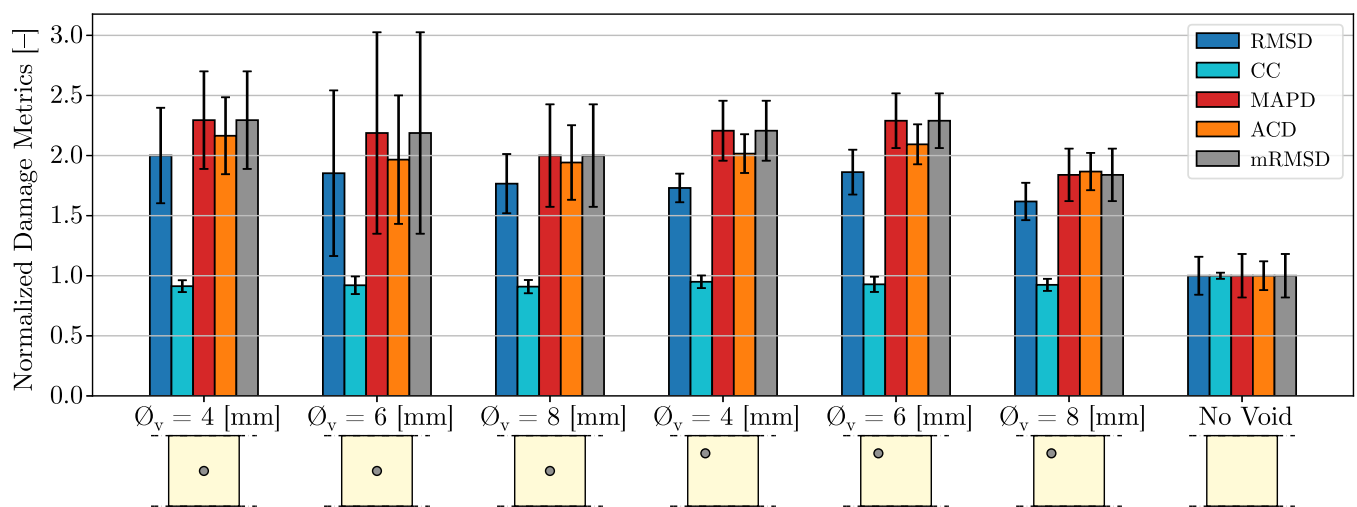


Figure 13. Bar plot comparing the normalized average and standard deviation of the obtained damage metrics, computed using the real component of the measured impedance from $f_i = 10$ kHz to $f_f = 200$ kHz (347 logarithmically spaced points).

Converse to the CC statistical damage metric, there was no overlap between the damaged and undamaged joints when using all four distance-based metrics—*RMSD*, *mRMSD*, *MAPD*, and *ACD*. While inspecting these four metrics, one sees that both the average *mRMSD* and *MAPD* values for all six different void positions tended to be at least double those of the undamaged SLJs.

Furthermore, while the overall differentiation between the damaged and undamaged cases was less noticeable when using the Averaged Canberra Distance, *ACD*, one sees that, when examining all individual values, there was a bigger gap between the maximum value from an undamaged joint and the minimum value from a damaged joint. In this manner, all metrics from the damaged joints were closer together, and consequently, the standard deviations for each void placement were smaller, as seen in Figures 12 and 13. This was further proof that the *ACD* damage index is sensitive to alterations near zero [40,41], thus proving itself as a reliable metric for better damage detection. While a similar thing can be said for the results of the *RMSD* for this spectral case, one sees that, in relative terms, the gap between the maximum value from an undamaged joint and the minimum value from a damaged joint was comparatively smaller than the respective gap of the *ACD* metric.

4.1.5. Combination of the Three Measured Spectra from $f_i = 1$ kHz to $f_f = 1$ MHz

Figure 14 shows the average and standard deviation of the damage metrics computed by joining the three originally measured impedance spectra, thus obtaining a resultant spectrum of a frequency range of $f \in [1, 1000]$ kHz, with a total of 2389 sampled points.

With this case, one hopes that more sampled points will enable a better understanding of the integrity of the SLJ specimens.

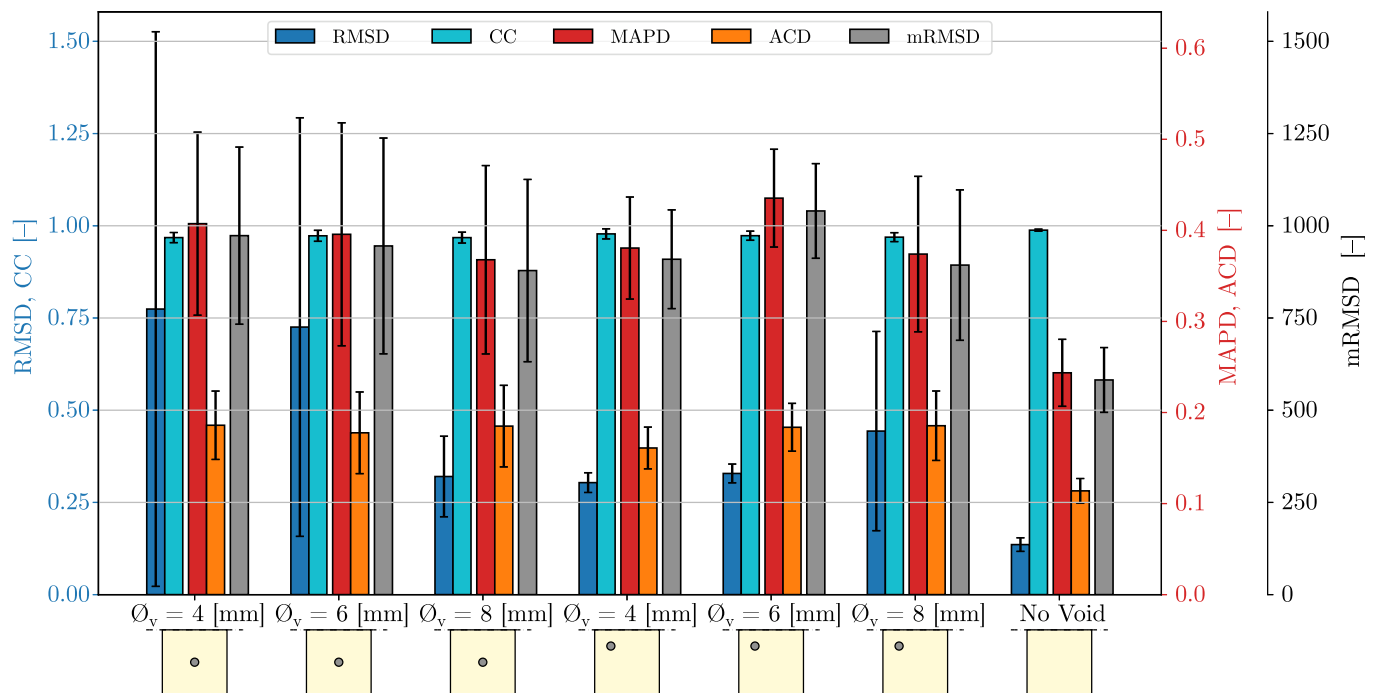


Figure 14. Plot comparing the average and standard deviation of the obtained damage metrics, computed using the real component of the measured impedance from $f_i = 1$ kHz to $f_f = 1$ MHz (2389 spaced points).

As with the previous impedance spectral case, a quick overview of the CC showed that the impedance spectra from the undamaged joints were similar, thus having index values closer to the unit value, when compared to the CC values from the damaged joints. However, when comparing to both the values obtained for the directly measured linearly and logarithmically sampled spectra, these results were much closer to the ones obtained in the logarithmically sampled spectra. This can be stated since the average $\overline{CC}$ values calculated from the linearly spaced spectra (frequency range $f \in [1, 1000]$ kHz with 801 sampled frequencies) had a wider dispersion, $\overline{CC} \in [0.77, 0.93]$, while for the logarithmically spaced spectra (frequency range $f \in [1, 1000]$ kHz with 801 sampled frequencies), a smaller dispersion was observed, $\overline{CC} \in [0.986, 0.995]$. For comparison, this combination of the three spectra yielded average CC values varying between 0.967 and 0.988.

Unsurprisingly and in the same fashion as in previous spectral case studies, there was a considerable overlap between the CC metric values from the undamaged and damaged cases, which were mostly present when using the impedance spectra of the reference specimen SLJ₀ 2, which can be attributed to the lack of significant spectral differences, as shown in Figure 6a.

Regarding the four distance-based metrics, *RMSD*, *mRMSD*, *MAPD*, and *ACD*, one sees that there was a clearer distinction between the damaged and undamaged cases. When analyzing the results obtained for the *mRMSD*, *MAPD*, and *ACD* damage metrics, one sees that all metric averages for all six damaged cases were 1.5- to 2-times higher than the average values for undamaged joints, as shown in Figure 15. However, upon closer examination, one sees that there was a slight overlap in the values between the undamaged and damaged joints when using the *mRMSD* and *MAPD* metrics. For instance, the computed *MAPD* index for the SLJ 2 specimen with a void in the middle of the adhesive layer ($\varnothing_v = 8$ mm) was 0.2591 when the maximum *MAPD* value obtained for an undamaged joint was of

0.2604. Likewise, for the same artificially damaged joint, a $mRMSD$ value of 619 was obtained, when the maximum metric value from an undamaged joint was 622. This small overlap (or near overlap) does not occur with the $RMSD$ index, which yielded average values 2-times or higher for the damaged cases, when compared with the baseline undamaged case. This is also illustrated in Figure 15.

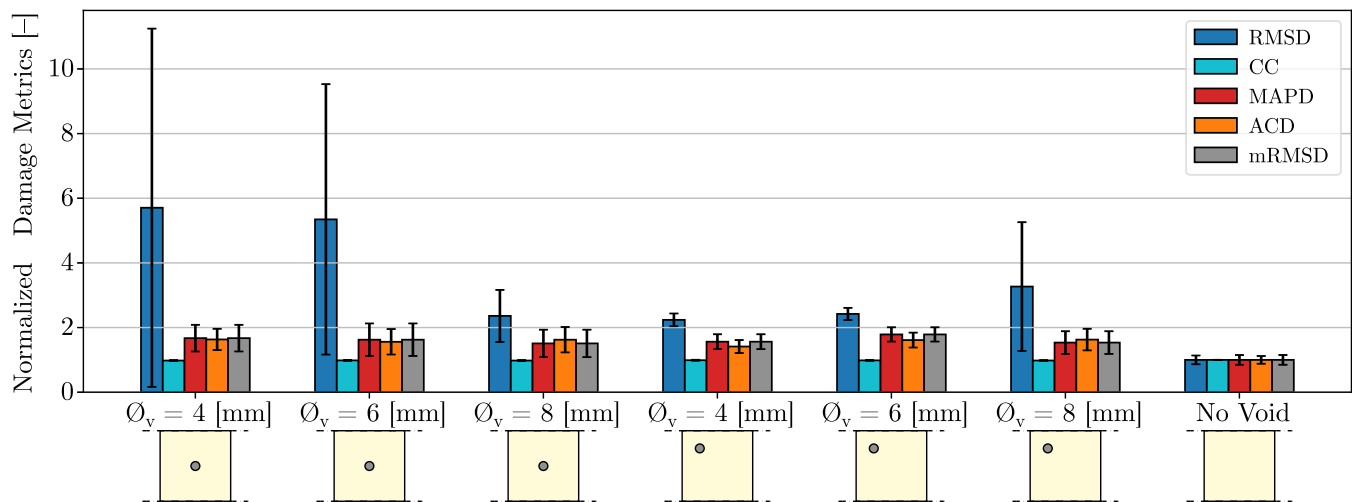


Figure 15. Bar plot comparing the normalized average and standard deviation of the obtained damage metrics, computed using the real component of the measured impedance from $f_i = 1$ kHz to $f_f = 1$ MHz (2389 spaced points).

When comparing this spectral case with both the originally measured linearly and logarithmically spaced spectra results, one sees that the $mRMSD$, $MAPD$, and ACD attained similar values to the ones obtained with the metrics from the linearly sampled frequency spectra. However, the $RMSD$ metric can take advantage of the added spectral information by combining all three directly measured spectra, thus obtaining values that range between the ones yielded in the linearly sampled spectra and the ones from the logarithmically spaced spectra.

4.2. Metrics Using the Complex Active Impedance

4.2.1. Linearly Spaced Spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz

Figure 16a,b present the average and standard deviation of the proposed $cRMSD$, cCC , and $NCED$ metrics, which were compared to their equivalent metrics that use exclusively the real component, $\text{Re}(Z_e|_m)$. Note that, in Figure 16a, two different $cRMSD$ metrics are presented, one using the measured impedance, $Z_e|_m$, and a second one using the active impedance, $Z_e|_A$, as specified in Equation (3b).

From Figure 16a, one sees that there was virtually no difference between the traditional $RMSD$ metric and the $cRMSD$ that was computed using the measured impedance. This was the case since the imaginary component of the impedance was mainly composed by the passive impedance, as described in Equation (3a) [14]. Therefore, performing the difference operation between the imaginary components of the reference impedance, $\text{Im}(Z_e^0|_m)$, and of the electrical impedance of the joint being inspected, $\text{Im}(Z_e|_m)$, will yield an almost null result, resulting in similar values to the ones obtained with the $RMSD$ index.

Conversely, removing the passive component of the impedance, as per Equation (3a), should yield better results, as shown in Figure 16a, where the average $cRMSD$ values for all six damaged cases, and for the pristine case, are twice those of the values obtained for the $RMSD$ index. In this manner, despite the fact that there was a wide dispersion of $cRMSD$ values for the damaged cases, there was a wide gap when compared to the values obtained for the undamaged SLJs.

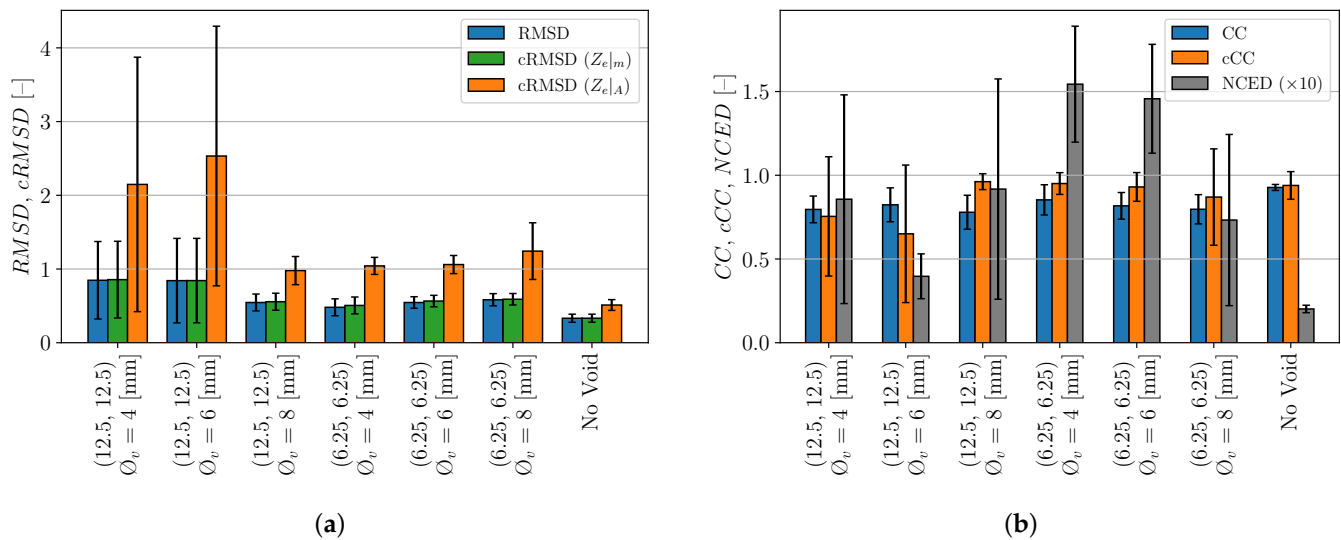


Figure 16. Bar plot comparing the proposed complex damage metrics with their original ones from the impedance spectra from $f_i = 1$ kHz to $f_f = 1$ MHz (801 spaced points). (a) Comparison between the $RMSD$ and $cRMSD$ (with both measured and active impedances, $Z_e|_m$ and $Z_e|_A$, respectively). (b) Comparison between the CC and cCC (with active impedance, $Z_e|_A$).

The $NCED$ metric, which can be viewed as loosely inspired by the proposed $cRMSD$ metric, presented a completely different behavior, as shown in Figure 16b. Note that the obtained values were one order of magnitude smaller than as actually represented here. As with most metrics presented so far, the metric values obtained for the *no void* case were concentrated, having an average value of $\overline{NCED}(\text{no void}) = 2.017 \times 10^{-2}$ and a small standard deviation of $\sigma_{NCED}(\text{no void}) = 2.230 \times 10^{-3}$. Conversely, the damaged adhesive joints tended to have higher damage metric values. Note that a couple of outlier values existed with this metric or, in other words, some $NCED$ values from the damaged joints were in the same range of values as the $NCED$ values from the undamaged joints.

However, unlike with other damage metrics, one sees that the maximum $NCED$ damage metric values did not occur in the SLJs with voids of diameter $\varnothing_v \in \{4, 6\}$ mm in the middle of the overlap, but occurred in the SLJs with voids of diameter $\varnothing_v \in \{4, 6\}$ mm in the corner of the overlap. The only other metrics that followed a similar pattern were the $mRMSD$ and $MAPD$ metrics, but to a lesser degree.

Furthermore, from Figure 16b, one sees a comparison between the obtained CC values, which were calculated with the real component of the measured electrical impedance, $\text{Re}(Z_e|_m)$, and the complex Correlation Coefficient values, cCC , which made use of both the real and imaginary components of the active impedance, $\text{Re}(Z_e|_A)$ and $\text{Im}(Z_e|_A)$, respectively. While the CC metric was able to differentiate between damaged and undamaged adhesive joints, the cCC index was unable to achieve this, since there was a large overlap of cCC between the damaged and undamaged specimens. One must point out that the only reason why the average cCC values were lower for the damage classes, $(x, y) = (12.5, 12.5)$ mm, $\varnothing_v \in \{4, 6\}$ mm, was that some extremely lower values existed for these cases. In this manner, while cCC can indeed help in the task of damage detection, this was not the trend observed for this case.

Figure 17 plots the measured and active electrical impedances, $Z_e|_m$ and $Z_e|_A$, respectively. One sees that the active impedance was significantly different in three regards. Firstly, the imaginary component had a significant change in behavior, having positive values throughout the frequency range in the analysis. Consequently, one can say that the capacitive behavior present in the passive component of the measured impedance was removed and that the resultant active impedance had an inductive behavior.

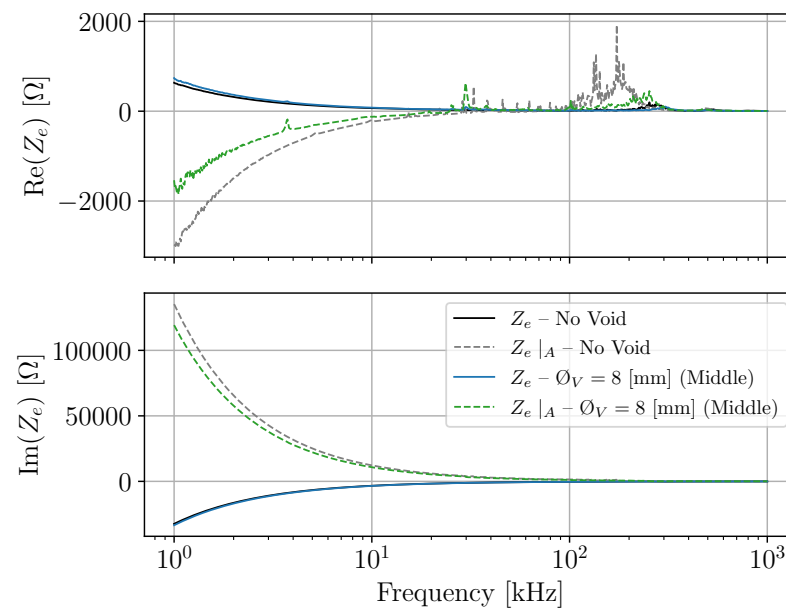


Figure 17. Plot comparing the measured and active impedances, $Z_{e|m}$ and $Z_{e|A}$, respectively, from an undamaged and a damaged adhesive joint specimen, for the frequency range of $f \in [1, 1000]$ kHz.

Secondly, the peaks observed in the real component of the active impedance, $\text{Re}(Z_{e|A})$, had increased amplitudes. This was because, while removing the passive impedance, as described in Equation (3a), the added influence of the dielectric loss factor, δ , was also removed. In this manner, a passive resistive component was also removed from the measured impedance, enabling better damage detection.

However, thirdly, and more importantly, in the beginning of the frequency range in the analysis, one sees that negative resistive values were observed in the active impedance. At first glance, this result seems physically impossible, since negative resistance values are physically impossible to obtain, unless special electronic circuits are employed that receive energy from outside the electrical system in question [43]. However, the piezoceramic material used in this piezoelectric element was a modified lead zirconate titanate material, thus meaning that the added chemical elements into the ceramic may significantly influence the material properties. Although the authors do not know the chemical composition of the PIC 255 piezoceramic material, research has shown that modified lead zirconate titanate materials may have dielectric constant values varying with the excitation frequency [44].

Given this, the dielectric constant value given by the sensor manufacturer may only be applicable in a portion of the frequency range in question. As such, when considering the active impedance for damage detection, this paper only tackled the linearly spaced active impedance spectra from $f_i = 100$ kHz to $f_f = 1$ MHz and the logarithmically spaced active impedance spectra from $f_i = 10$ kHz to $f_f = 200$ kHz, given that these ranges did not appear to have negative values of $\text{Re}(Z_{e|A})$ or the influence of such values may be comparatively smaller in damage detection.

4.2.2. Linearly Spaced Spectrum from $f_i = 100$ kHz to $f_f = 1$ MHz

Figure 18a,b present the average and standard deviation of the proposed $cRMSD$, cCC , and $NCED$ metrics, which were compared to their equivalents that use exclusively the real component, $\text{Re}(Z_{e|m})$. Note that, in Figure 18a, the $cRMSD$ metric was computed using the active impedance, $Z_{e|A}$, as specified in Equation (3b), since, as previously shown, the imaginary component of the measured impedance did not contribute to the damage detection.

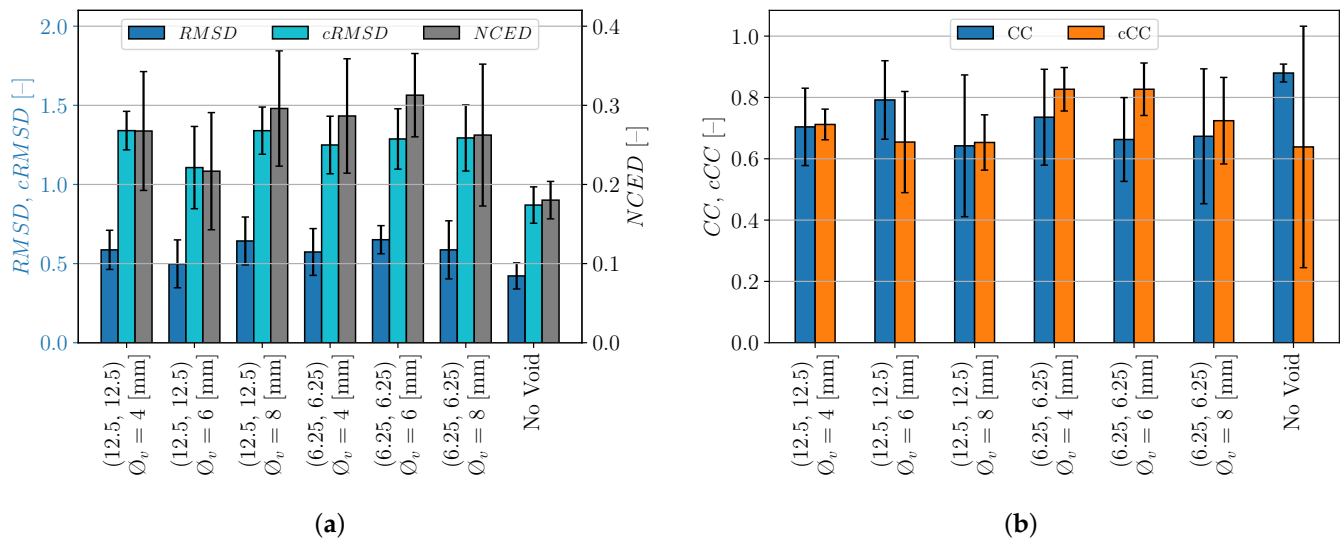


Figure 18. Bar plot comparing the proposed complex damage metrics with their original ones from the impedance spectra from $f_i = 100$ kHz to $f_f = 1$ MHz (801 spaced points). (a) Comparison between the $RMSD$, $cRMSD$, and $NCED$. (b) Comparison between the CC and cCC .

From the analysis of Figure 18a, one sees that the $cRMSD$ index, which was computed using the active impedance, $Z_e|_A$, yielded higher values overall, when compared with the $RMSD$, which was computed with only the real component of the measured impedance, $\text{Re}(Z_e|_m)$. Furthermore, when compared with the $RMSD$ damage index, there was considerably less overlap of the damage metric values between the results of the classes of the SLJs with a void and the undamaged adhesive joints when using the $cRMSD$. This can be seen by the fact that there was a significant overlap of the standard distribution between the damaged and undamaged cases, when viewing the $RMSD$ metric, while, conversely, this overlap only occurred between the *no void* and $(x, y) = (12.5, 12.5)$ mm, $\varnothing_v = 6$ mm, cases, when viewing the $cRMSD$ metric results. Furthermore, this overlap reduction was achieved despite the fact that the average values of $cRMSD$ and $RMSD$ for the damaged cases tended to be approximately 1.5-times those of the average value for the *no void* case.

This increased accuracy of the $cRMSD$ occurred in a spectral region where significant overlap occurred, as seen in the previous subsection. However, a comparison between the measured impedance, $Z_e|_m$, and the active impedance, $Z_e|_A$, as presented in Figure 19 revealed that the removal of the passive component of the impedance yielded a spectral region that appeared more sensitive to the mechanical integrity of the adhesive joint. This was the case both for the real and imaginary components, $\text{Re}(Z_e|_A)$ and $\text{Im}(Z_e|_A)$, respectively, and was especially pronounced at the beginning of the frequency range under study (below 300 kHz).

However, this increased performance was only observed for the $cRMSD$ and was not verified for the proposed $NCED$ metric, which had a significant overlap in metric values between the damaged and undamaged cases. Indeed, a comparison between the average values of the $cRMSD$ and $NCED$ metrics showed that there was a smaller gap (in absolute and relative terms) between the average $NCED$ value of the *no void* case and the average for the same metric for the $(x, y) = (12.5, 12.5)$ mm, $\varnothing_v = 6$ mm case, when compared to the $cRMSD$ metric.

This difference in performance can be attributed to two distinct causes. Firstly, most cases of the damage metric values of the damaged joints overlapping with the values from the *no void* case corresponded to the cases where the reference undamaged joint was SLJ₀ 2. In this manner, the issue first pointed out with the help of Figure 6 persisted if proper damage metrics were not chosen. However, it is also noted that the $NCED$ metric yielded

comparatively smaller values overall, thus making the damage detection comparatively harder than with the $cRMSD$ metric.

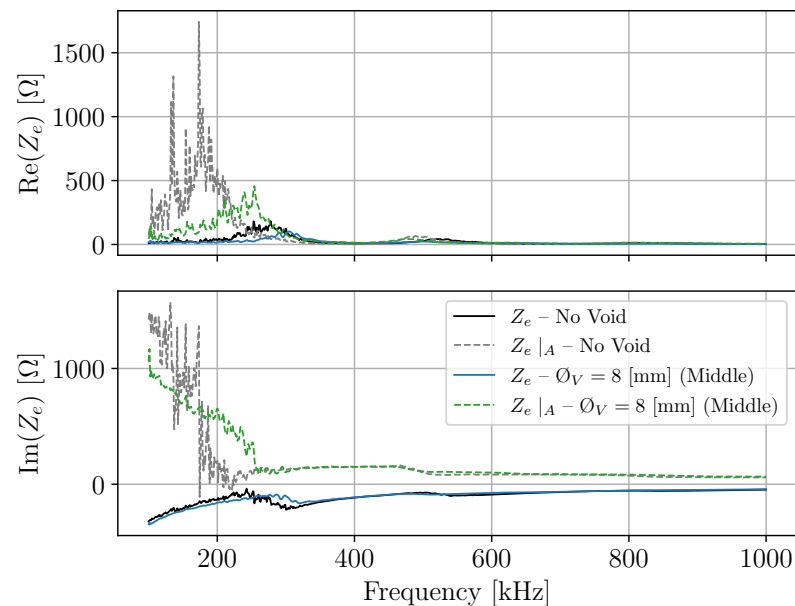


Figure 19. Plot comparing the measured and active impedances, $Z_e|_m$ and $Z_e|_A$, respectively, from an undamaged and a damaged adhesive joint specimen, for the frequency range of $f \in [100, 1000]$ kHz.

Finally, with the analysis of Figure 18b, one sees that the complex Correlation Coefficient, cCC , had a terrible performance in the damage detection, even when compared with the traditional CC metric or when compared with the cCC results obtained in the previous spectral case study. Indeed, it appeared that the imaginary component, $\text{Im}(Z_e|_A)$, may have significant changes in values between the damaged and undamaged cases, as shown in Figure 19, and no clear trend can be seen with this specific metric since the active impedance can have significant changes.

4.2.3. Logarithmically Spaced Spectrum from $f_i = 10$ kHz to $f_f = 200$ kHz

Figure 20a,b display the average and standard deviation of the proposed $cRMSD$, cCC , and $NCED$ metrics, which were compared to their equivalents that use exclusively the real component, $\text{Re}(Z_e)$. Note that this impedance spectrum was obtained by cropping the measured logarithmically spaced impedance spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz, obtaining a sub-spectrum with 347 sampled points.

From Figure 20a, one sees, once again, that the $cRMSD$ metric values, which were computed with both the real and imaginary components of the active impedance, $\text{Re}(Z_e|_A)$ and $\text{Im}(Z_e|_A)$, respectively, were overall comparatively higher than what was obtained with the $RMSD$ index, which was computed with only the real component of the measured impedance, $\text{Re}(Z_e|_m)$. However, unlike with the $RMSD$ index, where no overlap of the metric values between the damaged and undamaged joints existed, in the case of the $cRMSD$ metric, some overlap existed. In this case, the outlier value may be present in the *no void* class, since the $cRMSD$ value comparing the spectra of the undamaged SLJ 3 with the reference SLJ 0 2 was approximately 0.9140, which was approximately equal to the sum between the average value for the specific class and twice the standard deviation or, in other words,

$$0.913962 \approx \overline{cRMSD}(\text{No Void}) + 2 \cdot \sigma_{cRMSD}(\text{No Void}).$$

Therefore, and once again, the issue first pointed out with the help of Figure 6 may persist. However, despite this, overall, the $cRMSD$ metric was helpful in the damage detection,

as seen by the fact that all average values for the six different cases of voids were twice that of the *no void* case.

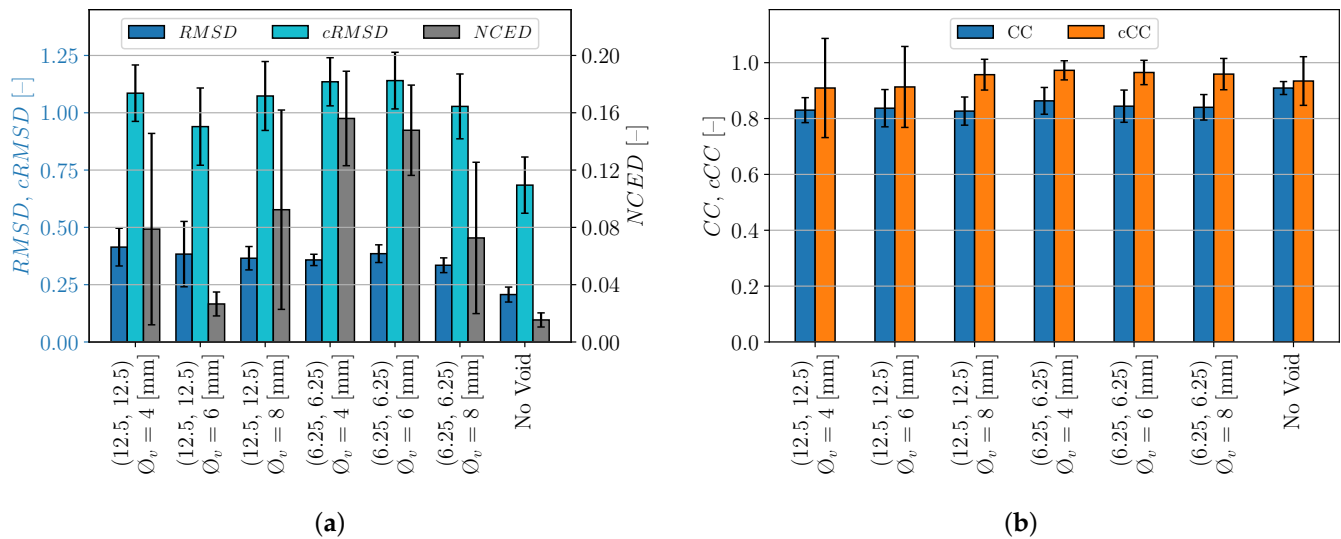


Figure 20. Bar plot comparing the proposed complex damage metrics with their original ones from the impedance spectra from $f_i = 10$ kHz to $f_f = 200$ MHz (347 logarithmically spaced points). (a) Comparison between the $RMSD$, $cRMSD$, and $NCED$. (b) Comparison between the CC and cCC .

Conversely, there was little overlap between the values of the $NCED$ for the undamaged and damaged joints. Furthermore, the overlap only occurred for the damaged case of voids in the $(x, y) = (12.5, 12.5)$ mm, $\varnothing_v = 6$ mm case. This was also the class of the adhesive joints with voids, with the lowest average value of the $cRMSD$ metric. However, for this case, the average value still was considerably higher than for undamaged joints. In this manner, this may indeed have occurred due to the fact that the active impedance spectra were less pronounced for the specimens of this specific case. However, to the best of the authors' knowledge, there was no specific explanation for this, since, for instance, the $RMSD$ metric was able to better detect damages in this class.

Finally, the complex Correlation Coefficient, cCC , was once again unable to effectively differentiate between the damaged and undamaged adhesive joints. This may be due to the fact that the real component of the active impedance was more sensitive to the damage than the actual real component of the measured impedance, but no real change in the shape of the overall impedance spectra occurred, as seen in Figure 21.

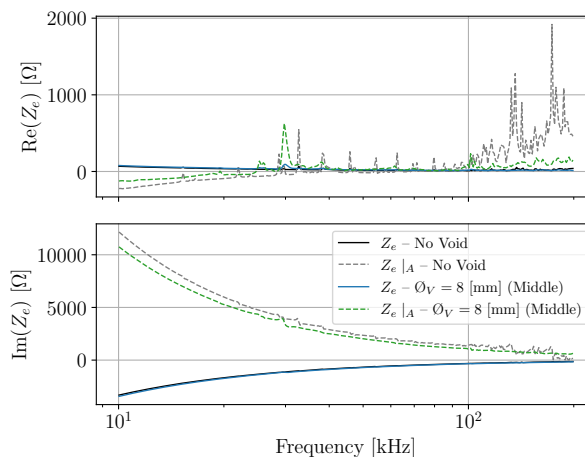


Figure 21. Plot comparing the measured and active impedances, $Z_e|_m$ and $Z_e|_A$, respectively, from an undamaged and a damaged adhesive joint specimen, for the frequency range of $f \in [10, 200]$ kHz.

5. Conclusions

This paper studied the feasibility of using EMIS-based damage metrics for void detection in adhesive SLJ specimens with the help of experimentally obtained electric impedance spectra. Four traditional damage metrics were tested in this research—the Root-Mean-Squared Deviation, *RMSD*, the Mean Absolute Percentage Deviation, *MAPD*, the Correlation Coefficient, *CC*, and the modified Root-Mean-Squared Deviation, *mRMSD*—which make use of the real component of the measured electrical impedance. Likewise, a new metric was proposed that makes use of this component, which is the Averaged Canberra Distance, *ACD*. Furthermore, three new damage metrics were also proposed that can use the real and imaginary components of the active impedance, which were more sensitive to damage. These were the complex Root-Mean-Squared Deviation index, *cRMSD*, the Normalized Complex Euclidean Distance, *NCED*, and the complex Correlation Coefficient, *cCC*.

From this study, one can conclude that, overall, the Root-Mean-Squared Deviation, *RMSD*, was able to better differentiate between damaged and undamaged joints, especially when studying the whole frequency range in question, which was $f \in [1, 1000]$ kHz. In this manner, the *RMSD* values from the damaged joints tended to be double the metric values from the undamaged joints, with some extreme values being over ten-times higher. Conversely, the Averaged Canberra Distance, *ACD*, which is based on the Canberra Distance, could perform better in the damage detection when other metrics showed a large overlap between the damaged and undamaged cases. While the Correlation Coefficient, *CC*, could also help in a significant manner in the task of void detection, the obtained results were also strongly dependent on the spectral frequency conditions. The Mean Absolute Percentage Deviation, *MAPD*, and the modified Root-Mean-Squared Deviation, *mRMSD*, permitted the damage detection, but were overall less exact in distinguishing between the damaged and pristine SLJs. The only exception to this occurred with the logarithmically sampled spectral measurement of $f \in [10, 200]$ kHz.

Damage metrics that make use of the active impedance were also able to detect the damage in the adhesive joints. The complex Root-Mean-Squared Deviation index, *cRMSD*, allowed for better damage detection, when compared to the traditional *RMSD* index. Meanwhile, the Normalized Complex Euclidean Distance, *NCED*, showed itself to be sensitive to the damage present in the corner of the overlap, while most other metrics were more sensitive to the damage in the middle of the overlap. Despite these interesting results, the complex Correlation Coefficient, *cCC*, appeared to be the most-ill-suited metric for damage detection, since, despite the fact that the active impedance was more sensitive to the mechanical changes in the structure, these changes were more pronounced in the peaks, rather than the changes in the overall spectra.

Author Contributions: Conceptualization, A.F.G.T., A.M.L. and L.F.M.d.S.; investigation, A.F.G.T.; methodology A.F.G.T. and A.M.L.; formal analysis A.F.G.T.; resources, A.M.L. and L.F.M.d.S.; data curation A.F.G.T.; supervision, A.M.L. and L.F.M.d.S.; writing—original draft, A.F.G.T.; writing—review and editing, A.M.L. and L.F.M.d.S. All authors have read and agreed to the published version of the manuscript.

Funding: The authors gratefully acknowledge the funding of Grant 2021.07689.BD, which was provided by Fundação para a Ciência e Tecnologia (FCT).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Metrics

Appendix A.1. Metrics Using the Real Component of the Impedance

Appendix A.1.1. Linearly Spaced Spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz

This subsection will present all of the obtained metrics for damage detection using the linearly spaced measured impedance spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz.

Table A1. RMSD damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.881747	0.847592	0.620563	0.541951	0.615546	0.631591	0.314935
σ	0.531134	0.612240	0.094997	0.144474	0.049026	0.049174	0.065269
SLJ 1	0.508978	1.554390	0.600701	0.377542	0.559442	0.583762	nan
SLJ 2	1.489896	0.481300	0.723921	0.648654	0.650143	0.682007	0.361087
SLJ 3	0.646365	0.507087	0.537067	0.599656	0.637053	0.629004	0.268783
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.802185	0.847246	0.440877	0.408856	0.454990	0.516274	0.383830
σ	0.707944	0.732888	0.091309	0.045811	0.017794	0.110137	0.040763
SLJ 1	0.336837	1.687976	0.470309	0.376610	0.463022	0.438675	0.412654
SLJ 2	1.616902	0.510577	0.513840	0.461294	0.467351	0.467816	nan
SLJ 3	0.452817	0.343185	0.338481	0.388664	0.434596	0.642331	0.355007
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.858162	0.832527	0.576104	0.491676	0.566757	0.601925	0.297836
σ	0.562824	0.633286	0.093154	0.127461	0.040423	0.046103	0.030430
SLJ 1	0.468224	1.563525	0.563547	0.347402	0.524166	0.548896	0.276318
SLJ 2	1.503389	0.450235	0.674900	0.589012	0.604591	0.632492	0.319353
SLJ 3	0.602873	0.483820	0.489866	0.538615	0.571515	0.624387	nan
Overall Damage Metric Data							
Mean	0.847365	0.842455	0.545848	0.480828	0.545764	0.583263	0.332200
σ	0.525611	0.572983	0.114362	0.114857	0.078549	0.082811	0.055022

Table A2. mRMSD damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	331.06	294.04	338.63	333.68	368.98	326.92	199.01
σ	72.06	84.17	64.91	19.17	15.50	82.78	19.71
SLJ 1	259.67	377.44	376.68	325.68	361.15	378.91	nan
SLJ 2	329.75	209.13	375.53	319.82	386.84	370.40	212.94
SLJ 3	403.76	295.55	263.68	355.56	358.96	231.46	185.07
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	229.78	264.24	227.36	256.24	315.38	242.75	260.31
σ	46.75	60.57	83.93	38.30	32.69	73.54	32.15
SLJ 1	216.96	327.65	312.52	297.75	285.44	322.51	237.57
SLJ 2	190.78	206.98	224.85	248.71	350.26	228.13	nan
SLJ 3	281.61	258.10	144.71	222.27	310.44	177.62	283.05
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	373.34	370.78	372.65	367.46	425.29	370.32	217.46
σ	84.22	93.09	82.76	31.05	37.04	124.60	34.30
SLJ 1	306.20	461.75	438.30	384.21	396.95	473.29	193.20
SLJ 2	345.97	275.71	399.97	331.63	467.20	405.84	241.72
SLJ 3	467.84	374.88	279.69	386.55	411.72	231.82	nan
Overall Damage Metric Data							
Mean	311.39	309.69	312.88	319.13	369.88	313.33	225.59
σ	87.75	84.38	94.12	56.02	54.18	100.51	36.21

Table A3. MAPD damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.413307	0.367095	0.422759	0.416585	0.460652	0.408145	0.248447
σ	0.089958	0.105075	0.081034	0.023931	0.019352	0.103350	0.024605
SLJ 1	0.324176	0.471213	0.470262	0.406586	0.450877	0.473046	nan
SLJ 2	0.411675	0.261088	0.468822	0.399275	0.482942	0.462423	0.265845
SLJ 3	0.504069	0.368982	0.329192	0.443894	0.448138	0.288964	0.231049
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.286868	0.329890	0.283845	0.319902	0.393731	0.303061	0.324982
σ	0.058370	0.075621	0.104784	0.047818	0.040814	0.091812	0.040142
SLJ 1	0.270860	0.409055	0.390161	0.371724	0.356351	0.402630	0.296597
SLJ 2	0.238173	0.258398	0.280711	0.310496	0.437277	0.284804	nan
SLJ 3	0.351572	0.322219	0.180664	0.277486	0.387564	0.221749	0.353366
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.466087	0.462891	0.465237	0.458756	0.530950	0.462320	0.271486
σ	0.105149	0.116214	0.103318	0.038766	0.046239	0.155551	0.042828
SLJ 1	0.382272	0.576461	0.547197	0.479664	0.495571	0.590879	0.241202
SLJ 2	0.431917	0.344202	0.499334	0.414025	0.583270	0.506670	0.301769
SLJ 3	0.584071	0.468010	0.349180	0.482579	0.514010	0.289410	nan
Overall Damage Metric Data							
Mean	0.388754	0.386625	0.390614	0.398414	0.461778	0.391175	0.281638
σ	0.109546	0.105345	0.117498	0.069938	0.067644	0.125476	0.045206

Table A4. CC damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.739077	0.784894	0.712721	0.796544	0.752017	0.742571	0.927577
σ	0.063712	0.120879	0.102763	0.106013	0.060672	0.097335	0.028361
SLJ 1	0.811437	0.652629	0.752830	0.918415	0.821075	0.737922	nan
SLJ 2	0.691395	0.889643	0.595952	0.725643	0.707276	0.647644	0.907522
SLJ 3	0.714400	0.812409	0.789381	0.745573	0.727700	0.842146	0.947631
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.873875	0.872934	0.868886	0.924405	0.903613	0.871404	0.917079
σ	0.057451	0.087767	0.053948	0.032939	0.028585	0.033853	0.013515
SLJ 1	0.923146	0.772023	0.872726	0.961476	0.931589	0.856564	0.907522
SLJ 2	0.810770	0.931495	0.813121	0.898500	0.874456	0.847505	nan
SLJ 3	0.887708	0.915284	0.920811	0.913240	0.904795	0.910143	0.926635
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.775366	0.813026	0.755923	0.838629	0.796687	0.777016	0.937133
σ	0.059034	0.112013	0.090588	0.086733	0.051527	0.080468	0.014847
SLJ 1	0.841546	0.694385	0.787170	0.938277	0.852763	0.768172	0.947631
SLJ 2	0.728127	0.916958	0.653848	0.780127	0.751425	0.701336	0.926635
SLJ 3	0.756424	0.827736	0.826751	0.797484	0.785874	0.861541	nan
Overall Damage Metric Data							
Mean	0.796106	0.823618	0.779177	0.853193	0.817439	0.796997	0.927263
σ	0.079750	0.101153	0.101469	0.090257	0.079621	0.087238	0.017944

Table A5. ACD damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.199087	0.176478	0.216578	0.172232	0.193134	0.207812	0.121839
σ	0.024083	0.043029	0.037334	0.017802	0.024094	0.047329	0.011662
SLJ 1	0.171598	0.213994	0.218008	0.158128	0.176144	0.217648	nan
SLJ 2	0.209190	0.129508	0.253176	0.166333	0.220708	0.249450	0.130085
SLJ 3	0.216473	0.185931	0.178549	0.192234	0.182549	0.156338	0.113593
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.138748	0.149336	0.144150	0.135678	0.167471	0.153320	0.140878
σ	0.019474	0.030223	0.040807	0.012950	0.024146	0.035980	0.015264
SLJ 1	0.134801	0.175769	0.170352	0.148633	0.146410	0.183983	0.130085
SLJ 2	0.121550	0.116387	0.164966	0.135666	0.193824	0.162266	nan
SLJ 3	0.159894	0.155854	0.097133	0.122734	0.162178	0.113711	0.151672
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.217853	0.211173	0.235850	0.192907	0.217909	0.228564	0.132632
σ	0.027058	0.045375	0.041883	0.012986	0.034048	0.061819	0.026926
SLJ 1	0.192805	0.249831	0.247225	0.193571	0.189610	0.257388	0.113593
SLJ 2	0.214203	0.161217	0.270870	0.179602	0.255694	0.270707	0.151672
SLJ 3	0.246550	0.222470	0.189454	0.205548	0.208424	0.157596	nan
Overall Damage Metric Data							
Mean	0.185229	0.178996	0.198859	0.166939	0.192838	0.196565	0.131783
σ	0.041281	0.043891	0.054374	0.028163	0.032523	0.054514	0.017080

Appendix A.1.2. Logarithmically Spaced Spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz

This subsection will present all of the obtained metrics for damage detection using the logarithmically spaced measured impedance spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz.

Table A6. RMSD damage metric results for logarithmically spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.754661	0.716674	0.257899	0.258360	0.276146	0.394470	0.067530
σ	0.930806	0.701788	0.157617	0.037594	0.033325	0.368588	0.012561
SLJ 1	0.202885	1.495496	0.438806	0.298382	0.305568	0.215461	nan
SLJ 2	1.829335	0.521131	0.150194	0.252911	0.239956	0.149573	0.076413
SLJ 3	0.231763	0.133395	0.184695	0.223788	0.282913	0.818376	0.058648
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.773826	0.737301	0.247847	0.266245	0.282722	0.394143	0.072821
σ	0.963189	0.730361	0.185275	0.049889	0.040746	0.399604	0.007618
SLJ 1	0.205004	1.543603	0.457289	0.320886	0.320673	0.216495	0.078208
SLJ 2	1.885924	0.548240	0.105344	0.254724	0.239663	0.114166	nan
SLJ 3	0.230551	0.120058	0.180909	0.223125	0.287831	0.851768	0.067434
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.755157	0.717311	0.253401	0.256808	0.274928	0.391449	0.062505
σ	0.935426	0.705344	0.162628	0.040437	0.034716	0.373832	0.005138
SLJ 1	0.200788	1.499863	0.439603	0.300294	0.306591	0.213582	0.058872
SLJ 2	1.835167	0.521535	0.139217	0.249793	0.237806	0.139761	0.066138
SLJ 3	0.229516	0.130536	0.181383	0.220338	0.280389	0.821004	nan
Overall Damage Metric Data							
Mean	0.761215	0.723762	0.253049	0.260471	0.277932	0.393354	0.067619
σ	0.816933	0.617223	0.146368	0.037464	0.031736	0.329886	0.008351

Table A7. *mRMSD* damage metric results for logarithmically spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	356.74	323.07	250.73	272.21	295.22	257.15	110.72
σ	179.92	191.42	71.76	15.92	8.76	51.92	14.63
SLJ 1	209.76	543.52	333.59	258.01	287.16	248.74	nan
SLJ 2	557.38	226.87	210.32	269.20	293.95	209.95	121.06
SLJ 3	303.07	198.83	208.28	289.42	304.55	312.77	100.37
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	333.86	325.49	225.35	254.34	279.72	244.65	136.25
σ	176.06	187.82	87.49	8.27	9.82	73.08	0.63
SLJ 1	201.23	539.08	325.88	259.78	270.55	247.22	136.70
SLJ 2	533.61	251.27	166.47	244.82	278.52	170.31	nan
SLJ 3	266.73	186.12	183.70	258.41	290.08	316.41	135.81
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	381.32	357.19	271.33	294.04	323.58	281.32	112.61
σ	177.90	196.11	83.49	16.46	12.91	50.65	8.67
SLJ 1	233.52	582.96	367.71	284.75	309.38	290.12	106.48
SLJ 2	578.77	259.55	221.24	284.34	326.76	226.85	118.74
SLJ 3	331.68	229.07	225.04	313.05	334.61	327.00	nan
Overall Damage Metric Data							
Mean	357.31	335.25	249.13	273.53	299.51	261.04	119.86
σ	155.49	166.93	73.09	21.09	21.36	53.96	14.83

Table A8. *MAPD* damage metric results for logarithmically spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.445365	0.403336	0.313020	0.339841	0.368563	0.321040	0.138221
σ	0.224614	0.238981	0.089593	0.019874	0.010937	0.064820	0.018269
SLJ 1	0.261874	0.678546	0.416463	0.322116	0.358505	0.310532	nan
SLJ 2	0.695855	0.283236	0.262572	0.336081	0.366977	0.262116	0.151140
SLJ 3	0.378366	0.248226	0.260025	0.361326	0.380207	0.390472	0.125303
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.416799	0.406353	0.281331	0.317527	0.349210	0.305425	0.170106
σ	0.219804	0.234480	0.109221	0.010325	0.012262	0.091240	0.000783
SLJ 1	0.251219	0.673004	0.406836	0.324324	0.337765	0.308636	0.170660
SLJ 2	0.666176	0.313694	0.207824	0.305646	0.347712	0.212622	nan
SLJ 3	0.333001	0.232360	0.229333	0.322610	0.362152	0.395017	0.169552
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.476059	0.445932	0.338736	0.367097	0.403972	0.351214	0.140584
σ	0.222097	0.244835	0.104232	0.020550	0.016115	0.063235	0.010821
SLJ 1	0.291533	0.727788	0.459062	0.355491	0.386245	0.362203	0.132932
SLJ 2	0.722560	0.324029	0.276203	0.354975	0.407935	0.283205	0.148235
SLJ 3	0.414084	0.285978	0.280944	0.390824	0.417737	0.408235	nan
Overall Damage Metric Data							
Mean	0.446074	0.418540	0.311029	0.341488	0.373915	0.325893	0.149637
σ	0.194118	0.208406	0.091243	0.026329	0.026662	0.067362	0.018515

Table A9. CC damage metric results for logarithmically spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.984010	0.986183	0.986347	0.989893	0.988144	0.986067	0.995341
σ	0.007379	0.007496	0.003706	0.004261	0.002607	0.001758	0.001051
SLJ 1	0.989829	0.977565	0.988048	0.994808	0.991090	0.987016	nan
SLJ 2	0.975711	0.991197	0.982095	0.987244	0.986133	0.984038	0.994598
SLJ 3	0.986490	0.989786	0.988897	0.987628	0.987210	0.987146	0.996085
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.990416	0.991065	0.993544	0.995702	0.994904	0.992346	0.995102
σ	0.007442	0.006154	0.001783	0.001326	0.001210	0.000885	0.000713
SLJ 1	0.995308	0.983975	0.993995	0.997231	0.996117	0.993009	0.994598
SLJ 2	0.981852	0.994190	0.991579	0.994873	0.993697	0.992688	nan
SLJ 3	0.994087	0.995028	0.995058	0.995001	0.994897	0.991342	0.995606
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.986226	0.988390	0.988262	0.991647	0.989918	0.987990	0.995845
σ	0.006226	0.006484	0.003241	0.003538	0.002241	0.001534	0.000338
SLJ 1	0.991190	0.981078	0.989832	0.995730	0.992333	0.988408	0.996085
SLJ 2	0.979241	0.993436	0.984536	0.989478	0.987904	0.986291	0.995606
SLJ 3	0.988248	0.990658	0.990420	0.989734	0.989516	0.989271	nan
Overall Damage Metric Data							
Mean	0.986884	0.988546	0.989384	0.992414	0.990988	0.988801	0.995430
σ	0.006714	0.006205	0.004156	0.003842	0.003540	0.003053	0.000679

Table A10. ACD damage metric results for logarithmically spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.186704	0.169451	0.152429	0.146724	0.159973	0.155045	0.068149
σ	0.066003	0.072190	0.030705	0.008539	0.008094	0.016774	0.008864
SLJ 1	0.132395	0.252802	0.187494	0.138734	0.151772	0.152015	nan
SLJ 2	0.260164	0.128666	0.139439	0.145716	0.167955	0.139993	0.074417
SLJ 3	0.167552	0.126885	0.130353	0.155722	0.160191	0.173128	0.061881
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.167593	0.162040	0.131412	0.135880	0.149909	0.141345	0.074243
σ	0.060471	0.068122	0.036702	0.002270	0.006109	0.026538	0.000246
SLJ 1	0.119533	0.239733	0.173720	0.136852	0.142975	0.145140	0.074417
SLJ 2	0.235491	0.133842	0.112385	0.133286	0.154501	0.113114	nan
SLJ 3	0.147754	0.112544	0.108130	0.137503	0.152250	0.165781	0.074069
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.196937	0.183557	0.162383	0.158290	0.172696	0.165807	0.067975
σ	0.063263	0.073801	0.034301	0.007051	0.010871	0.015294	0.008618
SLJ 1	0.143473	0.268769	0.201731	0.152874	0.160919	0.169303	0.061881
SLJ 2	0.266779	0.141860	0.146619	0.155733	0.182345	0.149069	0.074069
SLJ 3	0.180560	0.140043	0.138797	0.166263	0.174825	0.179051	nan
Overall Damage Metric Data							
Mean	0.183745	0.171683	0.148741	0.146965	0.160859	0.154066	0.070122
σ	0.056305	0.062564	0.032467	0.011231	0.012372	0.020436	0.006386

Appendix A.1.3. Linearly Spaced Spectrum from $f_i = 100$ kHz to $f_f = 1$ MHz

This subsection will present all of the obtained metrics for damage detection using the linearly spaced measured impedance spectrum from $f_i = 100$ kHz to $f_f = 1$ MHz.

Table A11. *RMSD* damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.669123	0.552689	0.725040	0.635695	0.724630	0.647266	0.384474
σ	0.090364	0.185429	0.136827	0.192643	0.064645	0.215598	0.078856
SLJ 1	0.598398	0.701757	0.651203	0.415521	0.650918	0.702932	nan
SLJ 2	0.638047	0.345046	0.882925	0.773237	0.771678	0.829573	0.440233
SLJ 3	0.770924	0.611264	0.640993	0.718327	0.751294	0.409294	0.328714
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.460313	0.434451	0.521912	0.501687	0.553089	0.494587	0.510496
σ	0.089950	0.080553	0.140258	0.070704	0.029375	0.168660	0.051677
SLJ 1	0.402936	0.510434	0.469443	0.440081	0.561432	0.566185	0.547037
SLJ 2	0.414022	0.349997	0.680841	0.578886	0.577389	0.615637	nan
SLJ 3	0.563981	0.442922	0.415453	0.486095	0.520445	0.301939	0.473955
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.631016	0.508455	0.682001	0.582717	0.675490	0.618528	0.371504
σ	0.088761	0.200071	0.137168	0.177919	0.055680	0.200313	0.038993
SLJ 1	0.560072	0.650485	0.611527	0.380110	0.617324	0.673732	0.343932
SLJ 2	0.602426	0.279646	0.840080	0.713482	0.728297	0.785451	0.399077
SLJ 3	0.730548	0.595235	0.594397	0.654559	0.680848	0.396402	nan
Overall Damage Metric Data							
Mean	0.586817	0.498532	0.642985	0.573366	0.651069	0.586794	0.422158
σ	0.123725	0.151334	0.151311	0.147843	0.088817	0.183578	0.082448

Table A12. *mRMSD* damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	334.26	292.63	352.75	340.07	378.49	341.05	212.38
σ	74.98	68.79	71.09	19.50	16.35	96.55	19.87
SLJ 1	264.95	352.68	386.19	337.24	374.70	397.90	nan
SLJ 2	323.99	217.57	400.97	322.13	396.41	395.68	226.43
SLJ 3	413.85	307.63	271.11	360.82	364.38	229.57	198.33
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	221.21	256.16	227.23	254.91	318.39	246.20	277.82
σ	54.24	38.96	87.29	47.48	33.07	82.65	36.10
SLJ 1	217.72	289.99	312.54	306.27	290.97	333.88	252.29
SLJ 2	168.79	213.57	231.06	245.85	355.12	235.01	nan
SLJ 3	277.11	264.92	138.10	212.63	309.09	169.72	303.34
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	377.48	372.19	387.13	373.45	435.80	387.00	231.90
σ	89.28	77.42	89.08	36.44	38.89	141.72	36.43
SLJ 1	315.05	437.97	450.63	398.06	409.01	500.31	206.14
SLJ 2	337.64	286.87	425.47	331.59	480.40	432.61	257.66
SLJ 3	479.74	391.73	285.30	390.70	417.97	228.09	nan
Overall Damage Metric Data							
Mean	310.98	306.99	322.37	322.81	377.56	324.75	240.70
σ	94.96	75.51	102.30	61.58	57.47	113.69	38.83

Table A13. MAPD damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.417305	0.365326	0.440393	0.424552	0.472527	0.425780	0.265148
σ	0.093605	0.085884	0.088752	0.024344	0.020410	0.120542	0.024807
SLJ 1	0.330775	0.440301	0.482129	0.421028	0.467786	0.496755	nan
SLJ 2	0.404477	0.271624	0.500583	0.402162	0.494890	0.493987	0.282690
SLJ 3	0.516663	0.384054	0.338466	0.450466	0.454905	0.286599	0.247607
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.276163	0.319799	0.283689	0.318245	0.397496	0.307371	0.346838
σ	0.067721	0.048634	0.108971	0.059272	0.041290	0.103183	0.045066
SLJ 1	0.271807	0.362032	0.390192	0.382361	0.363257	0.416832	0.314972
SLJ 2	0.210725	0.266627	0.288466	0.306926	0.443349	0.293391	nan
SLJ 3	0.345957	0.330736	0.172408	0.265450	0.385882	0.211891	0.378704
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.471257	0.464656	0.483313	0.466229	0.544064	0.483150	0.289518
σ	0.111459	0.096658	0.111215	0.045493	0.048550	0.176934	0.045483
SLJ 1	0.393323	0.546783	0.562590	0.496955	0.510629	0.624602	0.257357
SLJ 2	0.421523	0.358139	0.531168	0.413966	0.599751	0.540093	0.321679
SLJ 3	0.598924	0.489046	0.356181	0.487765	0.521811	0.284756	nan
Overall Damage Metric Data							
Mean	0.388242	0.383260	0.402465	0.403009	0.471362	0.405434	0.300501
σ	0.118552	0.094268	0.127715	0.076883	0.071752	0.141940	0.048477

Table A14. CC damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.622266	0.742590	0.542318	0.651393	0.563916	0.607346	0.883698
σ	0.113564	0.170569	0.265791	0.191181	0.117978	0.292615	0.044959
SLJ 1	0.714153	0.579105	0.709128	0.871533	0.697941	0.591624	nan
SLJ 2	0.657344	0.919454	0.235808	0.527045	0.475768	0.322909	0.851907
SLJ 3	0.495302	0.729211	0.682017	0.555601	0.518039	0.907506	0.915489
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.831398	0.861182	0.789575	0.846404	0.800863	0.778199	0.861729
σ	0.056031	0.038335	0.177828	0.067021	0.065122	0.136262	0.013890
SLJ 1	0.867427	0.824443	0.892223	0.922288	0.864737	0.749211	0.851907
SLJ 2	0.859923	0.900935	0.584237	0.795308	0.734562	0.658764	nan
SLJ 3	0.766844	0.858167	0.892267	0.821615	0.803290	0.926622	0.871551
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.658409	0.771616	0.594816	0.708907	0.623920	0.634469	0.893520
σ	0.100674	0.153188	0.246282	0.162876	0.104856	0.253035	0.031069
SLJ 1	0.741878	0.651234	0.744664	0.896303	0.737627	0.610501	0.915489
SLJ 2	0.686746	0.944047	0.310574	0.601410	0.531043	0.394271	0.871551
SLJ 3	0.546603	0.719566	0.729210	0.629007	0.603089	0.898635	nan
Overall Damage Metric Data							
Mean	0.704024	0.791796	0.642236	0.735568	0.662900	0.673338	0.879649
σ	0.126150	0.127959	0.231211	0.156278	0.136639	0.219949	0.029118

Table A15. ACD damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.204761	0.181074	0.227880	0.175610	0.198835	0.218562	0.129717
σ	0.023605	0.040918	0.042809	0.018139	0.026114	0.055057	0.011748
SLJ 1	0.178200	0.213107	0.225318	0.162587	0.181495	0.228937	nan
SLJ 2	0.212743	0.134980	0.271912	0.167915	0.228870	0.267694	0.138025
SLJ 3	0.223340	0.195137	0.186409	0.196328	0.186140	0.159056	0.121410
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.138104	0.149447	0.147124	0.135832	0.170606	0.158065	0.149907
σ	0.022389	0.025627	0.044083	0.016497	0.025853	0.041014	0.016804
SLJ 1	0.138145	0.166545	0.172213	0.152566	0.149088	0.191689	0.138025
SLJ 2	0.115694	0.119982	0.172937	0.135346	0.199284	0.170136	nan
SLJ 3	0.160472	0.161814	0.096223	0.119583	0.163445	0.112371	0.161790
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.224262	0.217380	0.247941	0.196777	0.224021	0.240922	0.141600
σ	0.027340	0.043669	0.047148	0.014294	0.037156	0.070561	0.028553
SLJ 1	0.201433	0.250115	0.256180	0.199977	0.193812	0.272391	0.121410
SLJ 2	0.216794	0.167797	0.290427	0.181154	0.265510	0.290275	0.161790
SLJ 3	0.254560	0.234228	0.197217	0.209199	0.212741	0.160102	nan
Overall Damage Metric Data							
Mean	0.189042	0.182634	0.207648	0.169406	0.197821	0.205850	0.140408
σ	0.044523	0.043888	0.060297	0.030322	0.034904	0.061654	0.018152

Appendix A.1.4. Logarithmically Spaced Spectrum from $f_i = 10$ kHz to $f_f = 200$ kHz

This subsection will present all of the obtained metrics for damage detection using the logarithmically spaced measured impedance spectrum from $f_i = 10$ kHz to $f_f = 200$ kHz. Note that this impedance spectrum was obtained by cropping the measured logarithmically spaced impedance spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz, obtaining a sub-spectrum with 347 sampled points.

Table A16. RMSD damage metric results for logarithmically spaced impedance spectra (347 points), from $f_i = 10$ kHz to $f_f = 200$ kHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.415146	0.385332	0.375259	0.355423	0.380993	0.348802	0.207618
σ	0.079543	0.145637	0.039697	0.027965	0.042388	0.015298	0.041910
SLJ 1	0.357120	0.548640	0.420312	0.332916	0.332564	0.350533	nan
SLJ 2	0.505818	0.268920	0.360047	0.346624	0.399067	0.332713	0.237253
SLJ 3	0.382501	0.338436	0.345417	0.386730	0.411347	0.363160	0.177983
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.410031	0.379741	0.353050	0.358586	0.386809	0.317204	0.225708
σ	0.105721	0.176132	0.072339	0.029854	0.043957	0.045060	0.045935
SLJ 1	0.322527	0.582962	0.435277	0.344429	0.339190	0.328040	0.258189
SLJ 2	0.527501	0.271160	0.299215	0.338444	0.395402	0.267715	nan
SLJ 3	0.380066	0.285102	0.324657	0.392884	0.425835	0.355858	0.193228
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.416436	0.385075	0.367908	0.360042	0.388020	0.338190	0.187373
σ	0.097533	0.170430	0.056628	0.027311	0.046871	0.033308	0.000316
SLJ 1	0.340822	0.579836	0.433198	0.340980	0.335025	0.347559	0.187597
SLJ 2	0.526524	0.263250	0.332166	0.347816	0.405000	0.301201	0.187150
SLJ 3	0.381963	0.312140	0.338361	0.391331	0.424033	0.365810	nan
Overall Damage Metric Data							
Mean	0.413871	0.383383	0.365406	0.358017	0.385274	0.334732	0.206900
σ	0.082236	0.142574	0.050989	0.024678	0.038627	0.032208	0.032673

Table A17. *mRMSD* damage metric results for logarithmically spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	123.475	115.641	107.670	117.004	121.076	98.788	50.091
σ	24.661	56.030	24.050	14.709	12.830	11.587	7.635
SLJ 1	97.296	179.208	135.005	102.608	106.262	101.706	nan
SLJ 2	146.269	73.427	89.763	116.394	128.684	86.020	55.489
SLJ 3	126.861	94.287	98.241	132.008	128.281	108.637	44.692
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	125.916	123.305	110.541	123.026	127.896	101.027	65.379
σ	26.701	49.498	29.764	15.621	12.410	15.264	11.248
SLJ 1	97.657	180.394	144.161	109.910	114.100	106.486	73.332
SLJ 2	150.723	97.137	87.554	118.861	131.442	83.784	nan
SLJ 3	129.367	92.384	99.908	140.308	138.148	112.811	57.425
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	131.017	123.727	113.315	125.803	130.621	105.090	50.311
σ	25.423	54.102	27.038	15.475	15.543	13.625	2.943
SLJ 1	103.820	185.774	143.794	110.741	112.826	110.807	52.392
SLJ 2	154.186	86.406	92.218	125.007	137.498	89.538	48.229
SLJ 3	135.043	99.001	103.932	141.660	141.540	114.924	nan
Overall Damage Metric Data							
Mean	126.802	120.891	110.508	121.944	126.531	101.635	55.260
σ	22.427	46.310	23.554	13.789	12.577	12.078	10.007

Table A18. *MAPD* damage metric results for logarithmically spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.355836	0.333259	0.310287	0.337186	0.348922	0.284691	0.144353
σ	0.071070	0.161471	0.069307	0.042389	0.036975	0.033393	0.022003
SLJ 1	0.280392	0.516450	0.389063	0.295702	0.306232	0.293100	nan
SLJ 2	0.421524	0.211605	0.258683	0.335430	0.370846	0.247897	0.159912
SLJ 3	0.365593	0.271721	0.283114	0.380426	0.369687	0.313074	0.128794
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.362869	0.355345	0.318563	0.354543	0.368578	0.291144	0.188411
σ	0.076947	0.142644	0.085774	0.045018	0.035763	0.043989	0.032414
SLJ 1	0.281432	0.519867	0.415449	0.316743	0.328818	0.306876	0.211332
SLJ 2	0.434359	0.279932	0.252318	0.342540	0.378794	0.241452	nan
SLJ 3	0.372816	0.266236	0.287921	0.404346	0.398120	0.325104	0.165491
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.377570	0.356562	0.326555	0.362544	0.376430	0.302852	0.144987
σ	0.073266	0.155913	0.077920	0.044597	0.044792	0.039265	0.008482
SLJ 1	0.299194	0.535372	0.414393	0.319137	0.325148	0.319330	0.150985
SLJ 2	0.444341	0.249009	0.265757	0.360252	0.396248	0.258033	0.138989
SLJ 3	0.389173	0.285306	0.299516	0.408243	0.407895	0.331194	nan
Overall Damage Metric Data							
Mean	0.365425	0.348389	0.318468	0.351424	0.364643	0.292896	0.159251
σ	0.064631	0.133459	0.067880	0.039738	0.036245	0.034807	0.028838

Table A19. CC damage metric results for logarithmically spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.779139	0.791750	0.776139	0.816884	0.798089	0.791415	0.903565
σ	0.013037	0.070195	0.033619	0.036364	0.049424	0.022141	0.033967
SLJ 1	0.765372	0.733458	0.805168	0.851781	0.855123	0.791693	nan
SLJ 2	0.791298	0.869669	0.739304	0.819658	0.767826	0.769135	0.879547
SLJ 3	0.780745	0.772122	0.783946	0.779211	0.771318	0.813415	0.927583
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.879327	0.881751	0.876999	0.908565	0.889885	0.890197	0.899993
σ	0.012560	0.047695	0.023078	0.024953	0.042768	0.014207	0.028914
SLJ 1	0.867038	0.833013	0.900264	0.926850	0.938931	0.886173	0.879547
SLJ 2	0.892142	0.928331	0.854112	0.918708	0.870362	0.878437	nan
SLJ 3	0.878800	0.883909	0.876622	0.880138	0.860361	0.905982	0.920438
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.831819	0.837640	0.826890	0.864610	0.844764	0.839143	0.924011
σ	0.012242	0.067342	0.029658	0.030707	0.052193	0.017783	0.005053
SLJ 1	0.818479	0.774049	0.855358	0.893333	0.905031	0.833393	0.927583
SLJ 2	0.842537	0.908192	0.796171	0.868253	0.814577	0.824946	0.920438
SLJ 3	0.834442	0.830678	0.829141	0.832244	0.814685	0.859089	nan
Overall Damage Metric Data							
Mean	0.830095	0.837047	0.826676	0.863353	0.844246	0.840252	0.909189
σ	0.044756	0.066733	0.050428	0.047947	0.057698	0.045633	0.023182

Table A20. ACD damage metric results for logarithmically spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.165298	0.147486	0.148882	0.151185	0.156804	0.142783	0.076247
σ	0.026043	0.050035	0.023230	0.013098	0.013286	0.008259	0.013780
SLJ 1	0.139077	0.201318	0.175683	0.137056	0.141972	0.145293	nan
SLJ 2	0.191159	0.102400	0.136435	0.153579	0.167614	0.133560	0.085991
SLJ 3	0.165658	0.138741	0.134528	0.162921	0.160826	0.149495	0.066502
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.152394	0.142662	0.137395	0.146083	0.151235	0.131255	0.079065
σ	0.027173	0.040053	0.028497	0.013037	0.010581	0.013858	0.009795
SLJ 1	0.124935	0.188883	0.170245	0.134045	0.139168	0.137758	0.085991
SLJ 2	0.179272	0.118139	0.119311	0.144275	0.155613	0.115341	nan
SLJ 3	0.152975	0.120965	0.122631	0.159931	0.158925	0.140665	0.072139
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.168557	0.151494	0.149991	0.155612	0.162190	0.145316	0.069321
σ	0.025733	0.047312	0.025642	0.013120	0.015554	0.010626	0.003986
SLJ 1	0.142140	0.203847	0.179596	0.141319	0.144241	0.151640	0.066502
SLJ 2	0.193547	0.111798	0.134786	0.158409	0.171706	0.133047	0.072139
SLJ 3	0.169984	0.138837	0.135591	0.167108	0.170623	0.151260	nan
Overall Damage Metric Data							
Mean	0.162083	0.147214	0.145423	0.150960	0.156743	0.139784	0.074878
σ	0.023969	0.040015	0.023212	0.012061	0.012454	0.011637	0.008970

Appendix A.1.5. Combination of the Three Measured Spectra from $f_i = 1$ kHz to $f_f = 1$ MHz

This subsection will present all of the obtained metrics for damage detection using a combination of all three measured impedance spectrum, obtaining final spectra from $f_i = 1$ kHz to $f_f = 1$ MHz, with a total of 2389 sampled points (all repeated sampled frequencies are removed).

Table A21. *RMSD* damage metric results for the combined impedance spectra (2389 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.779328	0.723491	0.344277	0.318448	0.345664	0.458659	0.134231
σ	0.838973	0.634069	0.104747	0.017085	0.014077	0.284345	0.027017
SLJ 1	0.266822	1.437669	0.462720	0.310932	0.352819	0.297412	nan
SLJ 2	1.747535	0.506064	0.306279	0.338002	0.329447	0.291591	0.153335
SLJ 3	0.323627	0.226740	0.263833	0.306410	0.354726	0.786975	0.115127
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.770306	0.731426	0.288385	0.288580	0.308771	0.423924	0.148274
σ	0.910178	0.687603	0.146699	0.040176	0.033044	0.348401	0.015688
SLJ 1	0.223730	1.495576	0.457771	0.329370	0.341714	0.254377	0.159368
SLJ 2	1.821003	0.536045	0.202328	0.287324	0.275628	0.192749	nan
SLJ 3	0.266186	0.162659	0.205057	0.249047	0.308972	0.824647	0.137181
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.773061	0.721221	0.328129	0.303958	0.331189	0.447645	0.124533
σ	0.853529	0.642525	0.112847	0.016662	0.016291	0.297678	0.012017
SLJ 1	0.253332	1.444184	0.456897	0.307986	0.345060	0.284549	0.116036
SLJ 2	1.758131	0.504073	0.281018	0.318236	0.313249	0.267158	0.133030
SLJ 3	0.307720	0.215405	0.246471	0.285651	0.335260	0.791227	nan
Overall Damage Metric Data							
Mean	0.774232	0.725379	0.320264	0.303662	0.328541	0.443410	0.135680
σ	0.751810	0.567399	0.109212	0.026706	0.025456	0.270089	0.018387

Table A22. *mRMSD* damage metric results for the combined impedance spectra (2389 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	1014.45	903.45	935.06	939.10	1035.95	918.50	517.74
σ	251.13	320.68	179.60	51.97	29.70	132.45	52.86
SLJ 1	729.13	1263.93	1088.32	913.97	1016.48	1018.78	nan
SLJ 2	1201.97	649.90	979.41	904.47	1070.14	968.35	555.12
SLJ 3	1112.25	796.51	737.43	998.86	1021.23	768.36	480.37
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	780.34	839.54	676.23	760.55	908.10	729.21	670.13
σ	133.41	267.28	245.63	86.30	66.74	147.47	67.85
SLJ 1	631.24	1147.39	945.44	856.78	843.37	898.57	622.15
SLJ 2	888.45	666.61	618.95	734.90	976.67	629.22	nan
SLJ 3	821.33	704.63	464.30	689.99	904.26	659.82	718.11
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	1124.95	1093.01	1024.34	1028.13	1176.52	1032.58	558.08
σ	238.44	340.36	231.48	76.26	80.21	237.96	79.01
SLJ 1	849.78	1473.35	1247.81	1058.74	1108.42	1257.00	502.21
SLJ 2	1254.36	817.11	1039.60	941.32	1264.94	1057.67	613.95
SLJ 3	1270.70	988.56	785.61	1084.33	1156.20	783.06	nan
Overall Damage Metric Data							
Mean	973.25	945.33	878.54	909.26	1040.19	893.43	581.99
σ	240.11	292.51	247.11	133.85	128.30	203.93	87.84

Table A23. MAPD damage metric results for the combined impedance spectra (2389 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.424634	0.378171	0.391401	0.393094	0.433632	0.384469	0.216720
σ	0.105120	0.134230	0.075178	0.021756	0.012434	0.055441	0.022125
SLJ 1	0.305205	0.529062	0.455555	0.382574	0.425483	0.426447	nan
SLJ 2	0.503129	0.272040	0.409968	0.378597	0.447943	0.405339	0.232364
SLJ 3	0.465570	0.333409	0.308678	0.418110	0.427470	0.321623	0.201075
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.326639	0.351421	0.283059	0.318357	0.380117	0.305234	0.280508
σ	0.055844	0.111881	0.102816	0.036124	0.027934	0.061730	0.028402
SLJ 1	0.264230	0.480282	0.395745	0.358633	0.353022	0.376130	0.260424
SLJ 2	0.371891	0.279033	0.259083	0.307617	0.408821	0.263384	nan
SLJ 3	0.343796	0.294947	0.194350	0.288821	0.378508	0.276190	0.300591
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.470886	0.457516	0.428774	0.430361	0.492474	0.432222	0.233604
σ	0.099809	0.142469	0.096893	0.031922	0.033576	0.099608	0.033072
SLJ 1	0.355704	0.616722	0.522316	0.443173	0.463968	0.526160	0.210218
SLJ 2	0.525056	0.342029	0.435162	0.394023	0.529484	0.442727	0.256989
SLJ 3	0.531896	0.413798	0.328845	0.453886	0.483970	0.327778	nan
Overall Damage Metric Data							
Mean	0.407386	0.395703	0.367745	0.380604	0.435408	0.373975	0.243610
σ	0.100505	0.122440	0.103435	0.056029	0.053706	0.085364	0.036767

Table A24. CC damage metric results for the combined impedance spectra (2389 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.958053	0.965331	0.956908	0.968576	0.962361	0.959597	0.987918
σ	0.011511	0.017337	0.013531	0.015296	0.008471	0.010950	0.004279
SLJ 1	0.970148	0.946147	0.962304	0.986153	0.971986	0.959809	nan
SLJ 2	0.947232	0.979881	0.941511	0.958285	0.956041	0.948543	0.984893
SLJ 3	0.956778	0.969964	0.966907	0.961292	0.959056	0.970440	0.990944
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.980700	0.981733	0.982354	0.989616	0.986975	0.981522	0.986722
σ	0.010958	0.011867	0.006286	0.004370	0.003593	0.002297	0.002587
SLJ 1	0.989072	0.968051	0.982815	0.994555	0.990454	0.980434	0.984893
SLJ 2	0.968298	0.989232	0.975850	0.986251	0.983278	0.979970	nan
SLJ 3	0.984731	0.987915	0.988397	0.988043	0.987192	0.984161	0.988552
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.965152	0.971413	0.964486	0.975806	0.970016	0.966282	0.989748
σ	0.010123	0.015400	0.011581	0.012288	0.007050	0.008975	0.001691
SLJ 1	0.975682	0.954994	0.968739	0.989922	0.977657	0.965651	0.990944
SLJ 2	0.955492	0.985536	0.951380	0.967511	0.963763	0.957640	0.988552
SLJ 3	0.964281	0.973711	0.973340	0.969983	0.968628	0.975557	nan
Overall Damage Metric Data							
Mean	0.967968	0.972826	0.967916	0.977999	0.973117	0.969134	0.988129
σ	0.013762	0.014873	0.014738	0.013665	0.012353	0.012089	0.002726

Table A25. ACD damage metric results for the combined impedance spectra (2389 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.196741	0.175650	0.198843	0.164764	0.183971	0.193700	0.106372
σ	0.033674	0.047980	0.029906	0.014741	0.019212	0.028529	0.010673
SLJ 1	0.160608	0.226486	0.210218	0.153135	0.169736	0.199537	nan
SLJ 2	0.227247	0.131156	0.221391	0.159814	0.205824	0.218859	0.113919
SLJ 3	0.202369	0.169309	0.164919	0.181343	0.176353	0.162703	0.098825
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.148238	0.153445	0.140971	0.135758	0.162683	0.150901	0.121529
σ	0.015217	0.036375	0.036671	0.009538	0.018255	0.021641	0.010762
SLJ 1	0.130692	0.193801	0.172181	0.145748	0.146366	0.173664	0.113919
SLJ 2	0.157828	0.123181	0.150150	0.134778	0.182399	0.148450	nan
SLJ 3	0.156193	0.143354	0.100582	0.126747	0.159285	0.130590	0.129139
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.213045	0.204030	0.215357	0.182605	0.204711	0.211854	0.113982
σ	0.029337	0.049915	0.034763	0.010869	0.027041	0.039930	0.021435
SLJ 1	0.179318	0.256376	0.234936	0.181953	0.181302	0.233200	0.098825
SLJ 2	0.232657	0.156965	0.235914	0.172076	0.234311	0.236575	0.129139
SLJ 3	0.227159	0.198750	0.175220	0.193784	0.198519	0.165788	nan
Overall Damage Metric Data							
Mean	0.186008	0.177709	0.185057	0.161042	0.183788	0.185485	0.113961
σ	0.037534	0.044848	0.044791	0.022932	0.026260	0.038128	0.013557

Appendix A.2. Metrics Using the Complex Active Impedance

Appendix A.2.1. Linearly Spaced Spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz

This subsection will present all of the obtained metrics for damage detection using the linearly spaced active impedance spectrum (real and imaginary components) from $f_i = 1$ kHz to $f_f = 1$ MHz.

Table A26. $cRMSD(Z_e|_m)$ damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.888306	0.848320	0.628944	0.561299	0.630622	0.636770	0.315463
σ	0.526871	0.611719	0.094587	0.146750	0.054990	0.043063	0.064873
SLJ 1	0.509676	1.554531	0.622987	0.393100	0.567391	0.597981	nan
SLJ 2	1.490020	0.482967	0.726369	0.663213	0.667270	0.683109	0.361335
SLJ 3	0.665221	0.507463	0.537477	0.627585	0.657205	0.629222	0.269591
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.812173	0.847828	0.452502	0.436961	0.477515	0.523814	0.384130
σ	0.700657	0.732478	0.098571	0.044701	0.013855	0.103032	0.040650
SLJ 1	0.338086	1.688044	0.500707	0.394135	0.473814	0.459235	0.412874
SLJ 2	1.616976	0.511703	0.517694	0.483326	0.492844	0.469571	nan
SLJ 3	0.481456	0.343738	0.339106	0.433421	0.465886	0.642635	0.355386
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.867605	0.833170	0.588123	0.519537	0.588478	0.609823	0.298460
σ	0.556526	0.632924	0.094270	0.129571	0.047056	0.035447	0.030158
SLJ 1	0.470233	1.563741	0.593844	0.371140	0.536663	0.569274	0.277135
SLJ 2	1.503662	0.450773	0.679402	0.610239	0.628554	0.634927	0.319785
SLJ 3	0.628920	0.484996	0.491122	0.577231	0.600216	0.625267	nan
Overall Damage Metric Data							
Mean	0.856028	0.843106	0.556523	0.505932	0.565538	0.590136	0.332684
σ	0.520308	0.572613	0.115266	0.114383	0.077775	0.077730	0.054771

Table A27. $cRMSD(Z_e|_{act})$ damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	2.150494	2.572109	0.954573	1.020838	1.036755	1.225825	0.482553
σ	2.033942	2.061741	0.210635	0.104482	0.119432	0.457442	0.077328
SLJ 1	0.833835	4.812211	1.174676	0.910822	0.899625	1.066591	nan
SLJ 2	4.493081	2.150077	0.934150	1.032964	1.117989	0.869281	0.427874
SLJ 3	1.124564	0.754038	0.754894	1.118728	1.092652	1.741604	0.537232
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	2.191113	2.633881	0.926825	0.974558	1.002551	1.224560	0.535051
σ	2.157269	2.186830	0.226465	0.122683	0.137629	0.494005	0.127505
SLJ 1	0.797651	5.010481	1.160811	0.845859	0.844738	1.054552	0.444892
SLJ 2	4.676002	2.184535	0.910948	0.987641	1.097669	0.838010	nan
SLJ 3	1.099687	0.706625	0.708716	1.090175	1.065248	1.781119	0.625211
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	2.101113	2.392290	1.054661	1.131452	1.142372	1.277951	0.516859
σ	1.765284	1.823692	0.192192	0.089802	0.107212	0.367658	0.041283
SLJ 1	0.951229	4.417474	1.254071	1.037822	1.019102	1.167650	0.487668
SLJ 2	4.133640	1.879520	1.039304	1.139674	1.213890	0.978070	0.546050
SLJ 3	1.218470	0.879876	0.870608	1.216860	1.194124	1.688134	nan
Overall Damage Metric Data							
Mean	2.147573	2.532760	0.978686	1.042283	1.060560	1.242779	0.511488
σ	1.725764	1.761115	0.191152	0.115681	0.123123	0.384464	0.073190

Table A28. cCC damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.731113	0.691183	0.989086	0.980003	0.973896	0.963964	0.985472
σ	0.431745	0.442396	0.005323	0.010848	0.012074	0.042513	0.018707
SLJ 1	0.983409	0.182498	0.994039	0.968247	0.976695	0.993276	nan
SLJ 2	0.232589	0.904987	0.983458	0.982136	0.960668	0.983410	0.972244
SLJ 3	0.977341	0.986066	0.989761	0.989626	0.984324	0.915206	0.998700
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.927047	0.912900	0.995970	0.992485	0.991875	0.991281	0.998705
σ	0.114515	0.127400	0.002144	0.004130	0.002062	0.007508	0.000012
SLJ 1	0.995011	0.766152	0.997603	0.988071	0.991761	0.997122	0.998714
SLJ 2	0.794834	0.977365	0.993542	0.993128	0.989873	0.993909	nan
SLJ 3	0.991297	0.995184	0.996766	0.996255	0.993991	0.982812	0.998696
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.605243	0.347038	0.900431	0.879389	0.825213	0.654478	0.833412
σ	0.478175	0.467435	0.021357	0.072320	0.064932	0.473700	0.008178
SLJ 1	0.884426	0.044831	0.898863	0.802021	0.815447	0.960850	0.827630
SLJ 2	0.053106	0.110845	0.922529	0.890855	0.765717	0.893712	0.839195
SLJ 3	0.878196	0.885438	0.879901	0.945292	0.894475	0.108871	nan
Overall Damage Metric Data							
Mean	0.754468	0.650374	0.961829	0.950626	0.930328	0.869908	0.939196
σ	0.356042	0.410590	0.047451	0.064999	0.085833	0.287766	0.082659

Table A29. NCED damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 1$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.081119	0.041578	0.086009	0.145352	0.136958	0.067527	0.020333
σ	0.067994	0.015058	0.071872	0.038278	0.035559	0.055721	0.003323
SLJ 1	0.031578	0.055789	0.166252	0.110154	0.096403	0.131000	nan
SLJ 2	0.053140	0.043149	0.064229	0.139799	0.151676	0.044912	0.017983
SLJ 3	0.158639	0.025795	0.027548	0.186104	0.162795	0.026670	0.022683
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.081506	0.036902	0.086639	0.151201	0.142224	0.068831	0.018765
σ	0.072117	0.014895	0.077081	0.038090	0.035786	0.059046	0.000941
SLJ 1	0.030654	0.051711	0.172283	0.116695	0.101419	0.136420	0.018099
SLJ 2	0.049823	0.037072	0.064800	0.144834	0.156985	0.042795	nan
SLJ 3	0.164041	0.021922	0.022833	0.192073	0.168268	0.027278	0.019431
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.094481	0.040535	0.102619	0.166634	0.157860	0.083431	0.021398
σ	0.074380	0.015844	0.077001	0.038944	0.036371	0.060200	0.002434
SLJ 1	0.046068	0.057740	0.188075	0.131032	0.116372	0.151951	0.023119
SLJ 2	0.057249	0.026543	0.081152	0.160645	0.172958	0.059314	0.019677
SLJ 3	0.180125	0.037322	0.038630	0.208226	0.184251	0.039029	nan
Overall Damage Metric Data							
Mean	0.085702	0.039671	0.091756	0.154396	0.145681	0.073263	0.020165
σ	0.062310	0.013395	0.065769	0.034624	0.032490	0.051110	0.002230

Appendix A.2.2. Linearly Spaced Spectrum from $f_i = 100$ kHz to $f_f = 1$ MHz

This subsection will present all of the obtained metrics for damage detection using the linearly spaced active impedance spectrum (real and imaginary components) from $f_i = 100$ kHz to $f_f = 1$ MHz.

Table A30. $cRMSD(Z_e|_{act})$ damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	1.352921	1.132051	1.351402	1.252441	1.286597	1.305977	0.829478
σ	0.079012	0.273625	0.133630	0.162613	0.181572	0.197616	0.069397
SLJ 1	1.286721	1.256988	1.385234	1.071973	1.082785	1.415119	nan
SLJ 2	1.331652	0.818258	1.464865	1.297771	1.431092	1.424952	0.780407
SLJ 3	1.440391	1.320906	1.204108	1.387580	1.345913	1.077861	0.878549
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	1.227120	0.986807	1.241473	1.124923	1.178139	1.173564	0.939293
σ	0.119271	0.255472	0.182134	0.214342	0.235502	0.277852	0.191089
SLJ 1	1.137591	1.107732	1.322740	0.890196	0.912197	1.361026	0.804173
SLJ 2	1.181255	0.693323	1.368827	1.174314	1.360276	1.305322	nan
SLJ 3	1.362515	1.159365	1.032852	1.310258	1.261944	0.854344	1.074414
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	1.440811	1.201361	1.427066	1.371119	1.397872	1.402469	0.841000
σ	0.064966	0.306678	0.108534	0.119576	0.144531	0.138134	0.101430
SLJ 1	1.394348	1.355709	1.471450	1.239507	1.235214	1.490105	0.769278
SLJ 2	1.413038	0.848173	1.506374	1.400768	1.511544	1.474067	0.912722
SLJ 3	1.515047	1.400200	1.303375	1.473081	1.446858	1.243235	nan
Overall Damage Metric Data							
Mean	1.340284	1.106739	1.339981	1.249494	1.287536	1.294003	0.869924
σ	0.121754	0.259882	0.149111	0.181771	0.190744	0.209138	0.115055

Table A31. *cCC* damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.722710	0.731421	0.680192	0.829257	0.791979	0.719665	0.968920
σ	0.031882	0.027068	0.110570	0.092818	0.096103	0.187356	0.000089
SLJ 1	0.737295	0.700589	0.789763	0.936282	0.888211	0.677677	nan
SLJ 2	0.744691	0.742397	0.568650	0.780696	0.696005	0.556866	0.968983
SLJ 3	0.686144	0.751277	0.682163	0.770793	0.791722	0.924452	0.968857
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.709602	0.520881	0.625924	0.821473	0.898904	0.737817	0.161579
σ	0.090016	0.256267	0.094427	0.051212	0.024148	0.121098	0.012631
SLJ 1	0.628221	0.574617	0.719152	0.777628	0.909149	0.830162	0.170511
SLJ 2	0.694295	0.242007	0.628279	0.809033	0.871323	0.600711	nan
SLJ 3	0.806290	0.746019	0.530342	0.877759	0.916240	0.782577	0.152648
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.703371	0.711123	0.653377	0.829389	0.789369	0.715122	0.785326
σ	0.024669	0.044926	0.095550	0.093919	0.088076	0.171675	0.242382
SLJ 1	0.704281	0.659716	0.749927	0.937473	0.871854	0.664645	0.613936
SLJ 2	0.727572	0.742850	0.558860	0.783038	0.696603	0.574344	0.956715
SLJ 3	0.678259	0.730805	0.651344	0.767657	0.799651	0.906377	nan
Overall Damage Metric Data							
Mean	0.711894	0.654475	0.653164	0.826707	0.826751	0.724201	0.638608
σ	0.050051	0.164992	0.090112	0.070923	0.085579	0.141131	0.393773

Table A32. *NCED* damage metric results for linearly spaced impedance spectra (801 points), from $f_i = 100$ kHz to $f_f = 1$ MHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.313210	0.252926	0.341746	0.317485	0.351828	0.299703	0.176887
σ	0.055542	0.083690	0.056381	0.090318	0.036653	0.100506	0.035029
SLJ 1	0.272498	0.321031	0.330758	0.213262	0.309546	0.336047	nan
SLJ 2	0.290650	0.159500	0.402811	0.372840	0.374586	0.376981	0.201657
SLJ 3	0.376483	0.278246	0.291668	0.366352	0.371353	0.186081	0.152118
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.194296	0.168821	0.224089	0.240606	0.252418	0.201958	0.196560
σ	0.060355	0.032630	0.055009	0.034021	0.014498	0.071372	0.020750
SLJ 1	0.157311	0.200062	0.244871	0.201323	0.236698	0.248510	0.211233
SLJ 2	0.161634	0.134960	0.265679	0.260066	0.265263	0.237578	nan
SLJ 3	0.263943	0.171441	0.161716	0.260431	0.255292	0.119787	0.181888
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.295184	0.228644	0.322227	0.301584	0.334264	0.285578	0.167184
σ	0.059195	0.090719	0.055728	0.081505	0.033011	0.092609	0.015622
SLJ 1	0.251990	0.294050	0.321222	0.207479	0.296829	0.325402	0.156138
SLJ 2	0.270904	0.125079	0.378451	0.349686	0.359205	0.351614	0.178230
SLJ 3	0.362659	0.266803	0.267008	0.347588	0.346757	0.179719	nan
Overall Damage Metric Data							
Mean	0.267564	0.216797	0.296020	0.286559	0.312837	0.262413	0.180211
σ	0.075089	0.074026	0.072866	0.072282	0.052651	0.089645	0.023655

Appendix A.2.3. Logarithmically Spaced Spectrum from $f_i = 10$ kHz to $f_f = 200$ kHz

This subsection will present all of the obtained metrics for damage detection using the logarithmically spaced active impedance spectrum (real and imaginary components) from $f_i = 10$ kHz to $f_f = 200$ kHz. Note that this impedance spectrum was obtained by cropping the measured logarithmically spaced impedance spectrum from $f_i = 1$ kHz to $f_f = 1$ MHz, obtaining a sub-spectrum with 347 sampled points.

Table A33. $cRMSD(Z_e|_{act})$ damage metric results for logarithmically spaced impedance spectra (347 points), from $f_i = 10$ kHz to $f_f = 200$ kHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	1.066446	0.923113	1.062975	1.131531	1.132624	1.013796	0.635077
σ	0.138231	0.173680	0.167036	0.101225	0.124459	0.156911	0.064526
SLJ 1	0.929624	1.108537	1.234420	1.024744	0.988999	1.184887	nan
SLJ 2	1.063668	0.764234	1.053776	1.143770	1.208801	0.979891	0.589450
SLJ 3	1.206045	0.896569	0.900728	1.226080	1.200073	0.876608	0.680703
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	1.065565	0.962622	1.028297	1.071120	1.084544	0.981617	0.804972
σ	0.142647	0.190595	0.169613	0.114080	0.149372	0.156754	0.154135
SLJ 1	0.902280	1.182589	1.207728	0.952952	0.912100	1.157804	0.695982
SLJ 2	1.128456	0.858756	1.006567	1.079792	1.173814	0.929445	nan
SLJ 3	1.165960	0.846522	0.870596	1.180616	1.167717	0.857600	0.913962
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	1.124266	0.933012	1.128306	1.202823	1.203786	1.087888	0.612888
σ	0.133223	0.213990	0.161258	0.088382	0.111603	0.148069	0.055788
SLJ 1	1.004546	1.130444	1.296110	1.110359	1.074988	1.251285	0.573440
SLJ 2	1.100468	0.705622	1.114300	1.211649	1.271854	1.049784	0.652336
SLJ 3	1.267784	0.962970	0.974507	1.286461	1.264516	0.962594	nan
Overall Damage Metric Data							
Mean	1.085426	0.939582	1.073193	1.135158	1.140318	1.027767	0.684312
σ	0.123085	0.168486	0.150341	0.105013	0.123546	0.141445	0.122639

Table A34. cCC damage metric results for logarithmically spaced impedance spectra (347 points), from $f_i = 10$ kHz to $f_f = 200$ kHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.985319	0.974518	0.986788	0.992460	0.990152	0.987684	0.983142
σ	0.004655	0.013577	0.003081	0.000595	0.001351	0.005771	0.019618
SLJ 1	0.985945	0.960153	0.990303	0.992446	0.991479	0.992096	nan
SLJ 2	0.980383	0.976260	0.985507	0.993061	0.990201	0.989803	0.997014
SLJ 3	0.989629	0.987140	0.984555	0.991871	0.988778	0.981153	0.969270
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.749143	0.774388	0.890915	0.929909	0.909734	0.895834	0.822756
σ	0.261286	0.200810	0.047342	0.024166	0.026993	0.059042	0.005897
SLJ 1	0.856708	0.543410	0.937685	0.903224	0.878601	0.941616	0.826926
SLJ 2	0.451244	0.907526	0.892039	0.936185	0.926598	0.916692	nan
SLJ 3	0.939477	0.872228	0.843021	0.950317	0.924003	0.829195	0.818586
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.993498	0.990492	0.993517	0.995475	0.994814	0.993777	0.997061
σ	0.000738	0.004122	0.000781	0.000234	0.000916	0.002066	0.000007
SLJ 1	0.993516	0.985922	0.994418	0.995402	0.995781	0.995314	0.997066
SLJ 2	0.992752	0.991628	0.993040	0.995736	0.994702	0.994587	0.997056
SLJ 3	0.994227	0.993928	0.993093	0.995285	0.993958	0.991429	nan
Overall Damage Metric Data							
Mean	0.909320	0.913133	0.957073	0.972614	0.964900	0.959098	0.934320
σ	0.177532	0.144940	0.055076	0.034259	0.043575	0.056028	0.087124

Table A35. NCED damage metric results for logarithmically spaced impedance spectra (347 points), from $f_i = 10$ kHz to $f_f = 200$ kHz (damage location and diameter in mm).

Case	(12.5, 12.5) $\varnothing_v = 4$	(12.5, 12.5) $\varnothing_v = 6$	(12.5, 12.5) $\varnothing_v = 8$	(6.25, 6.25) $\varnothing_v = 4$	(6.25, 6.25) $\varnothing_v = 6$	(6.25, 6.25) $\varnothing_v = 8$	No Void
Reference SLJ for Damage Metric Calculation: SLJ ₀ 1							
Mean	0.070861	0.024927	0.084062	0.146669	0.138525	0.064544	0.014976
σ	0.075120	0.006817	0.078396	0.035918	0.034188	0.059096	0.007633
SLJ 1	0.028121	0.024461	0.172495	0.115090	0.099542	0.132405	nan
SLJ 2	0.026864	0.031965	0.056596	0.139173	0.152624	0.036821	0.009579
SLJ 3	0.157599	0.018354	0.023094	0.185744	0.163408	0.024406	0.020373
Reference SLJ for Damage Metric Calculation: SLJ ₀ 2							
Mean	0.074994	0.024756	0.088489	0.152232	0.144017	0.068832	0.012744
σ	0.076379	0.003736	0.079586	0.036095	0.034370	0.060058	0.004408
SLJ 1	0.031688	0.026930	0.178170	0.120519	0.104832	0.137788	0.009627
SLJ 2	0.030110	0.026897	0.061022	0.144666	0.158158	0.040736	nan
SLJ 3	0.163184	0.020442	0.026274	0.191510	0.169060	0.027973	0.015861
Reference SLJ for Damage Metric Calculation: SLJ ₀ 3							
Mean	0.090496	0.029917	0.104444	0.169163	0.160835	0.084510	0.018434
σ	0.077780	0.013877	0.080856	0.036646	0.034902	0.061055	0.003311
SLJ 1	0.046698	0.040506	0.195507	0.136946	0.121039	0.154589	0.020775
SLJ 2	0.044491	0.014208	0.076754	0.161514	0.175224	0.056138	0.016093
SLJ 3	0.180299	0.035038	0.041070	0.209030	0.186243	0.042803	nan
Overall Damage Metric Data							
Mean	0.078784	0.026533	0.092331	0.156021	0.147792	0.072629	0.015385
σ	0.066798	0.008348	0.069574	0.032969	0.031518	0.052817	0.004930

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Appendix E

Paper E

Pattern recognition in electromechanical impedance spectroscopy damage detection of adhesive joints using multidimensional scaling

Pattern recognition in electromechanical impedance spectroscopy damage detection of adhesive joints using multidimensional scaling

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Structural Health Monitoring
1–20

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DOI: 10.1177/14759217241258666

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Abstract

Adhesive joints are prone to various types of damage sources, which may not be identifiable with current non-destructive tests (NDTs). Structural health monitoring techniques, such as those based on electromechanical impedance spectroscopy (EMIS), aim to outperform NDTs in damage detection, by continuously monitoring structures. Although the EMIS-based algorithmic performance of damage detection has been evaluated on metallic and composite components, integrity monitoring of adhesive joints is yet to be fully determined. Therefore, this article investigates the use of multidimensional scaling (MDS) to cluster and visualize experimental impedance measurements of bonded joints in a three dimensional space. With these results, an Euclidean distance *damage metric* is used to try and classify the type of damage. The results show that damage detection is easily performed with the MDS algorithm, but effectiveness is dependent on the spectral measurement conditions. Furthermore, reduced dimensional spaces can yield information regarding the size and location of the damage in the adhesive layer, yielding increased knowledge on the integrity of structural adhesive joints.

Keywords

Structural health monitoring, electromechanical impedance spectroscopy, adhesive joints, multidimensional scaling, machine learning, distances, damage identification

Introduction

Structural health monitoring (SHM) is the field of technology where one sensor, or a network of sensors, examines a given structure for damage in a continuous and automatic manner. In this manner, said sensors measure physical variables that are influenced by structural material properties. As such, if damage is present, the measured variables will alter. The obtained measurements are then sent to a computer and are analyzed algorithmically, in order to detect and quantify structural damage.^{1,2} SHM is gaining prominence in both academic and industrial environments, since it may reduce the number and duration of costly maintenance operations. These maintenance operations require non-destructive tests (NDTs) that are unreliable in damage characterization in adhesive joints.^{2,3} Furthermore, the field of SHM is enabling engineers and scientists to

better understand new materials and complex structures.^{4–6}

One such SHM method is the electromechanical impedance spectroscopy (EMIS) method, which makes use of electromechanical coupling that occurs in piezo-electric wafer active sensors (PWAS). In EMIS, an AC voltage signal of varying excitation frequency, ω , is fed to the PWAS. For each excitation frequency, ω_i , the

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piezoelectric element converts the electrical voltage, $V(\omega_i)$, into a mechanical vibration, with a corresponding load, $F(\omega_i)$, and particle velocity, $\dot{x}(\omega_i)$. These are correlated by the mechanical impedance of the structure, $Z_{m,s}(\omega_i)$, such that $Z_{m,s}(\omega_i) = F(\omega_i)/\dot{x}(\omega_i)$. Note that this mechanical impedance can be stated as a function of the structural mass, m_s , damping, c_s , and stiffness, k_s . Concurrently, the mechanical vibration will influence the electrical current passing through the PWAS, $I(\omega_i)$. Therefore, given this coupling, the PWAS behaves simultaneously as an actuator and a sensor. However, measuring the mechanical impedance directly is impossible, and, as such, an impedance analyzer computes the electrical impedance of the PWAS, $Z_e(\omega_i)$, such that $Z_e(\omega_i) = V(\omega_i)/I(\omega_i)$, thus indirectly examining the integrity of the structure.^{1,3,7}

Many have proposed mathematical models that relate the mechanical impedance, $Z_{m,s}$, with the electrical impedance, $Z_e(\omega_i)$. Liang et al.⁸ were the first to develop such a model to correlate the electrical impedance with the mechanical impedance of a one-dimensional structure, yielding:

$$Z_e(j\omega) = \left[j\omega \frac{w_p l_p}{h_p} \left(\frac{1}{\epsilon_{33}^T} - \frac{Z_{m,s}(j\omega)}{Z_{m,s}(j\omega) + Z_{m,p}(j\omega)} d_{31} \overline{Y_{11}^E} \right) \right]^{-1}, \quad (1)$$

where the width, length and thickness of the piezoelectric element are represented by w_p , l_p , and h_p , respectively. Variables j and d_{31} correspond to the imaginary unit, $j = \sqrt{-1}$, and the piezoelectric induced strain coefficient, respectively, whereas $Z_{m,p}(j\omega)$ is the mechanical impedance of the PWAS. The complex Young's modulus of the PWAS material, determined under null electric field conditions ($E=0$), $\overline{Y_{11}^E}$, is defined as $\overline{Y_{11}^E} = |Y_{11}^E|(1+j\eta)$, with η being the mechanical loss factor. Furthermore, the dielectric constant at zero stress ($T=0$), ϵ_{33}^T , is calculated by, where δ stands for the dielectric loss factor.

In these mathematical models, structural damping and stiffness are defined as constants throughout the frequency range, which may not be always true, as shown by Tenreiro et al.⁴ Therefore, the mechanical properties defining the structural impedance, $Z_{m,s}(j\omega)$ change with the excitation frequency, ω . Furthermore, it is assumed that the dielectric constant, ϵ_{33}^T , is a fixed value in the frequency range in question, which may be an incorrect assumption, as hypothesized by Tenreiro et al.⁹ and shown by Kumari et al.¹⁰

Although mathematical modeling of the phenomenon is of relevance to EMIS, most research has been focused on algorithms for damage detection and localization.⁷ In SHM, machine learning algorithms are of

great interest to study structural damage.^{11,12} However, in the specific case of EMIS, most of the research has been focused on the use of different types of artificial neural networks (ANNs).⁷

Giurgiutiu and Kropas-Hughes¹³ trained and validated a probabilistic neural network (PNN) to detect how far a crack is from the centrally placed PWAS, in a circular aluminum plate of 100 mm diameter. For this study, two frequency bands were analyzed, one from 10 to 40 kHz, and a second one from 10 to 150 kHz. Measurements were extracted from pristine plates, and from plates where cracks were present at 40, 25, 10, and 3 mm from the PWAS. Resonant peak frequencies were extracted and inputted to the PNN. For the first frequency range in question, the four most pronounced frequency features were insufficient for damage localization, but the network model was able to accurately classify the damage distance, when using six and eleven resonant peak frequencies. For the broader frequency range of 10–150 kHz, 22 frequencies were needed to classify the crack distance.

Selva et al.¹⁴ also trained a PNN algorithm for damage localization on a carbon fiber-reinforced polymer with three piezoelectric elements. Finite element simulations were used, with damage modeled in different locations. These damage foci replicated the damage caused by an impact of a drop-weight impact machine, with an impact mass of 2 kg and impact energy of 20 J. Various inputs were considered, based on both the real and imaginary components of the electrical impedance, $\text{Re}(Z_e)$ and $\text{Im}(Z_e)$, respectively. Afterwards, the network model was tested with experimental data, to evaluate the training procedure. The PNN was able to locate damage with an area of 600 mm², placing correctly three of five damages. However, the localization performance with damage areas of 225 mm² was unsatisfactory. Experimental data shows that a damage was present and not detected for localized areas of inspection.

Other types of ANN models have also been deployed for damage evaluation. De Oliveira et al.¹⁵ trained a convolutional neural network model to detect the presence of one of three possible damage foci in an aluminum plate, obtaining a 100% accuracy in the testing phase, with three epochs of training. He et al.¹⁶ trained a feed-forward neural network (FFNN) to detect, localize, and quantify damage in a truss structure, where damage was caused by the unscrewing of the bolts. Root mean square deviation (RMSD) values were calculated for portions of the measured spectrum, and were then inputted to the FFNN, which would, in turn, indicate the damage location and severity. The RMSD is defined as:

$$\text{RMSD} = \sqrt{\frac{\sum_{j=1}^n (\text{Re}(Z_e) - \text{Re}(Z_e^0))^2}{\sum_{f=1}^n \text{Re}(Z_e^0)^2}} \quad (2)$$

where $\text{Re}(Z_e)$ and $\text{Re}(Z_e^0)$ are the real electrical impedance components of the signal under evaluation, and of a reference/pristine measurement, respectively.

Despite the focus on using ANN for EMIS-based structural monitoring, other algorithms have been used. For instance, Park et al.¹⁷ proposed an unsupervised learning auto-regressive model, with exogenous frequency domain inputs, for damage identification in structures. Given the non-Gaussian nature of the extracted features, extreme value distributions are employed for robust damage classification. Rabiei et al.¹⁸ input impedance spectra from an array of PWAS, which were placed on an aluminum mobile bridge structure, on a mixture of Gaussian kernels, thus creating maps of damage location. Gonzalez et al.¹⁹ made an analysis of variance (ANOVA) study with Tukey's multiple comparison tests to locate loosening of one or multiple bolts in an aluminum aeronautical panel. Although the ANOVA approach was able to accurately locate the source of stiffness loss, this required an initial step of determining the optimal impedance frequency bandwidth for damage location.

Defect detection in adhesively bonded structures is considerably harder, since many different sources of damage may occur, either during the manufacture or during the joint's useful life.^{6,20} Furthermore, durability of structural adhesives is an issue, where fatigue cracks may appear, or where hygrothermal aging may occur.^{21–23} NDT methods are unreliable in defect detection, as shown in various studies.^{24–26} Conversely, various SHM methods appear to be more robust in damage detection,^{2,3,27} such as EMIS.²⁸ However, most research on the application of EMIS to monitor structural adhesive joints relies on the use of common damage metrics, namely the RMSD.^{29,30} Recently, Tenreiro et al.⁹ compared different damage metrics, and made use of the active impedance,³¹ which is more sensitive to structural changes, for void detection in single lap joints (SLJs).

To the best of the author's knowledge, Rautela and Bijudas³² performed the only work where FFNNs were developed to detect damage in structural adhesives. In their work, two FFNNs were developed, one with data from numerical simulations, and another from experimentally obtained measurements. In both simulations and experiments, the adhesive joints either have a void in the structural adhesive layer or in the adhesive that bonds the PWAS to the upper substrate. The neural

networks were able to estimate with accuracy the void size in the sensor adhesive layer, but more data were required to obtain a good accuracy in determining the void size of the structural adhesive.

This article presents the use of multidimensional scaling (MDS), as an unsupervised machine learning model, to tackle damage detection and classification/localization in modified epoxy adhesive SLJs, with and without artificially created voids. The MDS model is a dimensionality reduction algorithm, where the distances between all instances, observed in the higher dimensionality space, are maintained in the reduced space. This is done using EMIS measurements from SLJs, which were performed and studied in Tenreiro et al.²⁸ Three different spectral measuring conditions, and various distances were used in this study for the dimensionality reduction scheme. Results from the MDS models are also used to tackle damage classification, that is, estimate the size and position of the void.

Given this, section “Algorithmic approach” describes the MDS algorithm, and the distance-based quantification method that determines the size and placement of the artificial void. Afterwards, section “Experimental details” presents the SLJ specimens manufacturing and instrumentation procedures, whereas section “Data analysis and visualization” discusses the obtained algorithmic results. Finally, section “Conclusion” details the concluding remarks of this investigation.

Algorithmic approach

Multidimensional scaling

High-dimensionality datasets are difficult to comprehend. Although two or three-dimensional (2D or 3D) plots can show the inherent data structure, higher dimension plots are less intuitive. To help in the data structure visualization, the dataset dimension should be reduced in some manner. One approach is to use Manifold Learning as a tool for nonlinear dimensionality reduction, where algorithms are based on the fact that the high dimensionality of a given dataset is only artificial. One such Manifold Learning method is MDS, which seeks to compute a low-dimensional representation of a dataset that is originally of high dimension, and where the final distances between instances respect, as best as possible, the distances in the original high-dimensional space.^{33–36}

The MDS algorithm starts by computing the initial dissimilarities between all pairs of N data instances. Therefore, for instances i and j , one obtains the dissimilarity δ_{ij} , in the initial m -dimensional space, where $m > 3$, and where each axis of this higher dimension space corresponds to a feature axis. These

dissimilarities are then inserted to the matrix of dissimilarities, $\Delta = [\delta_{ij}]$, such that it has $N \times N$ dimensions.

In the classical metric MDS approach, three properties are observed. First, the dissimilarity of instance i with itself is null, $\delta_{ii} = 0$. Second, for any data instances i and j , their dissimilarity must either be zero or positive, $\delta_{ij} \geq 0$. Third, the dissimilarity between instances i and j , and the dissimilarity between instances j and i are identical, $\delta_{ij} = \delta_{ji}$. This means that matrix Δ is symmetric with a principal diagonal of zeros.

After computing the dissimilarities, the metric MDS model assigns each instance in the $\mathbb{R}^m$ space and tries to estimate its coordinates in a new $\mathbb{R}^d$ space ($d < m$), such that the final distances between instance i and all other instances are as close as possible to the ones observed in the initial $\mathbb{R}^m$ space. In other words, the MDS model tries to approximate the initial and final dissimilarities.

In order to obtain a final $\mathbb{R}^d$ space similar to the $\mathbb{R}^m$ space, MDS uses an iterative algorithm that evaluates the configuration obtained in $\mathbb{R}^d$, by minimizing a loss function. Usually this loss function is the raw stress, σ_r , which is defined as:

$$\sigma_r = \sum_{i,j=1}^N [d_{ij} - f(\delta_{ij})]^2 \quad (3)$$

where d_{ij} and δ_{ij} are the reproduced and observed distances in the $\mathbb{R}^d$ and $\mathbb{R}^m$ spaces, respectively, whereas function f represents a monotonic transformation function. However, if one wishes to compare the performance of each distance on the MDS model, one needs to normalize σ_r . To achieve this, one may compute the Stress-1, σ_1 , which is defined as:

$$\sigma_1 = \sqrt{\frac{\sigma_r}{\sum_{i,j=1}^N d_{ij}^2}} = \sqrt{\frac{\sum_{i,j=1}^N [d_{ij} - f(\delta_{ij})]^2}{\sum_{i,j=1}^N d_{ij}^2}} \quad (4)$$

Note that usually, $d=2$ or $d=3$, meaning that the final d -dimensional domain is a 2D or 3D space, where one can visualize the final results in a *map* or plot. Given that MDS performs a comparison between the data instances, one can rotate, translate or zoom the final *map*, while maintaining the distances between data points.

One can evaluate the final performance of the MDS model with the help of stress or Shepard plots. The stress plot shows the obtained raw stress, or Stress-1, with the number of d dimensions, and should decrease with the increase of dimensionality. The Shepard plot compares d_{ij} and δ_{ij} for a given dimension d . In this manner, if one observes a narrow scatter of points near

the 45° line, then a good fit between d_{ij} and δ_{ij} is obtained.

Distance functions

For the dimensionality reduction, four sets of distances, $\{\delta_A, \delta_C, \delta_E, \delta_M\}$, are adopted to measure the dissimilarity between two different instances of measurements. These distances are computed for each pair of measurements i and k , $\mathbf{M}_i$ and $\mathbf{M}_k$, such that

$$\mathbf{M}_i = [\text{Re}(Z_{e,i}(j\omega_1)), \text{Re}(Z_{e,i}(j\omega_2)), \dots, \text{Re}(Z_{e,i}(j\omega_f)), \dots, \text{Re}(Z_{e,i}(j\omega_n))]^T \quad (5)$$

$$\mathbf{M}_k = [\text{Re}(Z_{e,k}(j\omega_1)), \text{Re}(Z_{e,k}(j\omega_2)), \dots, \text{Re}(Z_{e,k}(j\omega_f)), \dots, \text{Re}(Z_{e,k}(j\omega_n))]^T \quad (6)$$

where $\text{Re}(Z_{e,i}(j\omega_f))$ and $\text{Re}(Z_{e,k}(j\omega_f))$ are the real component of the measured electrical impedance from measurements i and k at the sampled frequency ω_f . Finally, one obtains a matrix of distances, or dissimilarities, Δ , as indicated in the previous section, which is a $N \times N$ dimensional matrix. Please remember from the previous subsection that N is the number of measurements, and, consequently, the number of points in both higher-dimensionality and reduced-dimensionality spaces.

The aforementioned distances are the Arccosine distance, δ_A , the Canberra distance, δ_C , the Euclidean distance, δ_E , and the Manhattan distance, δ_M , and are defined by:

$$\begin{aligned} \delta_A &= \arccos \left(\frac{\mathbf{M}_i \cdot \mathbf{M}_k^T}{\|\mathbf{M}_i\| \cdot \|\mathbf{M}_k\|} \right) \\ &= \arccos \left(\frac{\sum_{f=1}^n \text{Re}(Z_{e,i}(j\omega_f)) \text{Re}(Z_{e,k}(j\omega_f))}{\sqrt{\sum_{f=1}^n \text{Re}(Z_{e,i}(j\omega_f))^2} \sqrt{\sum_{f=1}^n \text{Re}(Z_{e,k}(j\omega_f))^2}} \right) \end{aligned} \quad (7)$$

$$\delta_C = \sum_{f=1}^n \frac{|\text{Re}(Z_{e,i}(j\omega_f)) - \text{Re}(Z_{e,k}(j\omega_f))|}{|\text{Re}(Z_{e,i}(j\omega_f))| + |\text{Re}(Z_{e,k}(j\omega_f))|} \quad (8)$$

$$\delta_E = \sum_{f=1}^n [\text{Re}(Z_{e,i}(j\omega_f)) - \text{Re}(Z_{e,k}(j\omega_f))]^2 \quad (9)$$

$$\delta_M = \sum_{f=1}^n |\text{Re}(Z_{e,i}(j\omega_f)) - \text{Re}(Z_{e,k}(j\omega_f))| \quad (10)$$

The authors note that, although these have been tested for this research, only the main results are presented here, to avoid redundant results. One must also point out that these four distances are just a small

Table 1. Properties of the adhesives and adherend used in SLJ manufacturing.⁴

	E [GPa]	ν [—]	ρ [kg m ⁻³]	η [—]
Aluminum Al 6082	70.0	0.33	2710	5.0×10^{-4}
Nagase T-836/R-810	2.55	0.41	1200	0.10

subset of various distances that can be used. The choice of the best distances for a given MDS problem is not explicitly known *a priori* and can only be known with experimentation.

Distance-based damage classification in reduced space

Traditional damage detection techniques in SHM methods, such as the EMIS technique, include the use of damage metrics, such as the RMSD, in which one compares the spectrum from a structure under evaluation with a spectrum from a reference structure.

Conversely, by using the MDS dimensionality reduction algorithm, one is inherently comparing all spectra at the same time. This occurs since the algorithm tries to transpose the original dissimilarities onto the reduced space. Therefore, the final co-domain space can also yield results regarding the detection and classification of damage. Therefore, an algorithm based on the distances between measurement instances is proposed.

Initially, the MDS algorithm, presented in subsection, performs the task of dimensionality reduction from an initial space that contains the electrical impedance measurements as points, and the dissimilarities are computed by one of the four distances proposed in subsection.

After obtaining the reduced dimensionality *map*, a reference needs to be used for comparison. In this manner, the centroid of the cluster containing all instances from undamaged SLJs is calculated. To compute this centroid, one just needs to calculate the average coordinates of all points from the class of measurements from undamaged joints.

Afterwards, the distances between the obtained centroid reference and all points in the initial input dataset are calculated. Given that humans can better understand the concept of Euclidean distances for dimensional spaces of low dimensions (i.e., 2D or 3D spaces), the Euclidean distance, δ_E , as defined in Equation (9), is used for this calculation. In this manner, this distance should be used as a *damage metric* to identify if there is damage, and to classify the type of damage. The defined classes for this task will be presented in Figure 4.

Experimental details

Materials, manufacture, and instrumentation

SLJ specimens were fabricated with 2 mm thickness 6082 aluminum alloy adherends, which were joined using the Nagase T-836/R-810 adhesive. This is a one-part modified epoxy adhesive, manufactured by Nagase ChemteX[®] (Osaka, Japan), that was formulated specifically for both automotive and aeronautical structure joining. The cure cycle of this adhesive is of 3 h at a temperature of 160°C. Table 1 presents the properties of both materials.

The aluminum substrates were abraded with 400 grit alumina oxide sandpaper, and phosphoric acid anodized procedure in accordance with industry standard ASTM D 3933-98.³⁷ The substrates were immersed in a chemical solution consisting of 10% phosphoric acid and 90% distilled water (m/m), and an electrical current, generated by a voltage source of 16 V, passed through the substrates, for a time period of 25 min. Finally, the substrates were removed from the chemical solution and rinsed with distilled water and acetone.

Artificial voids were created by placing polytetrafluoroethylene (PTFE) infills in the overlap region, before applying the modified epoxy adhesive. These infills have a diameter, $\varnothing_v$, of 4, 6 or 8 mm, and were positioned in the middle, or in the corner of the overlap, according to Figure 1. The PTFE insets were held in place with a cyanoacrylate adhesive resistant to high temperatures ($T_{\text{service}} = 200^\circ\text{C}$). Afterwards, the manufacturing mold, containing the SLJs, was placed in a hot press, which was parametrized to perform the aforementioned adhesive curing cycle.

It is noted that, after the manufacturing procedure, a second unintentional source of damage was observed, as described by Tenreiro et al.²⁸ This second source of damage consisted on a burned area surrounding the artificial void. The *de facto* void present in the adhesive layer is somewhat larger due to the added effect of this secondary damage, which the authors believe was caused by an unwanted chemical reaction between the modified epoxy adhesive and the cyanoacrylate adhesive. Despite this, the main damage to be detected should be the circular void, given that it is the biggest contributor to the defective area of the adhesive layer.

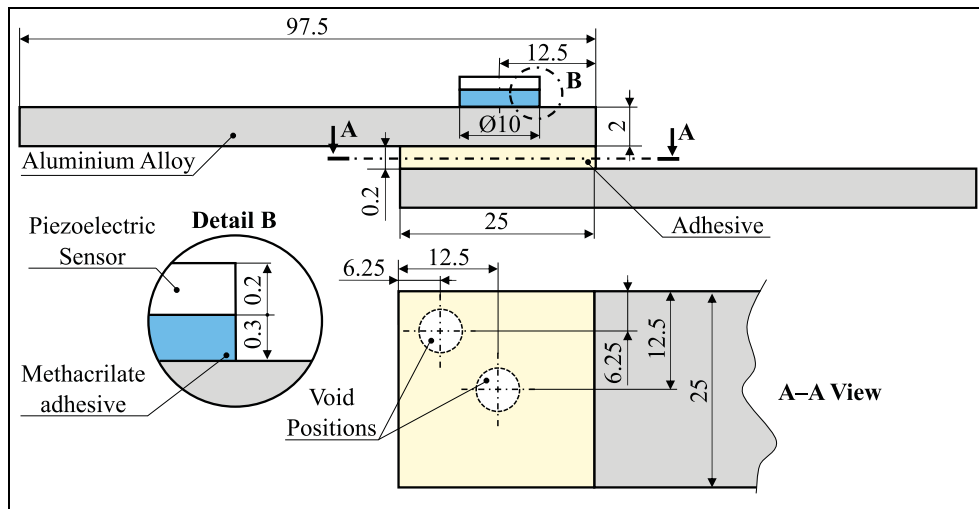


Figure 1. Schematic representation of a SLJ specimen (with dimensions in mm).
SLJ: single lap joint.

Table 2. Properties of the soft piezoceramic material PIC 255.

ρ [g cm^{-3}]	Elastic compliance coefficient		Coupling factor		$\frac{\epsilon_{33}^T}{\epsilon_0}$ [—]
	s_{11}^E [$\text{m}^2 \text{N}^{-1}$]	s_{33}^E [$\text{m}^2 \text{N}^{-1}$]	k_p	k_t	
7.80	16.1×10^{-12}	20.7×10^{-12}	0.62	0.47	1750

Table 3. Properties of the adhesive used in SLJ instrumentation.⁴

	E [GPa]	ν [—]	ρ [kg m^{-3}]	η [—]
Plexus MA 422	0.994	0.31	960	0.45

SLJ: single lap joint.

With the manufacture of the SLJs finished, PRYY + 1119 piezoelectric sensors, fabricated by PI Ceramics (Lederhose, Germany), were utilized to instrument these specimens. These PWAS, whose dimensions are detailed in Figure 1, are made of PIC 255 piezoceramic, which is a modified Lead Zirconate-Lead Titanate material with a high Curie temperature ($T_c = 350^\circ\text{C}$), and whose material properties are presented in Table 2. Here, ρ and $\epsilon_{33}^T/\epsilon_0$ stand for the mass density of the piezoceramic material and for the relative permittivity in the polarization direction, respectively. The PWAS was fixed on the upper substrate, in the center of the overlap, with the help of a manually mixed methacrylate adhesive Plexus MA 422, manufactured by ITW Performance Polymers (Chicago, IL, USA), with a cure cycle of 24 h at room temperature, and whose mechanical properties are indicated in Table 3. Before this curing procedure, a spiral copper

wire, of approximately the same diameter as the PWAS, was placed under the piezoelectric sensor, and afterwards, a second wire was soldered on the top surface of said sensor. The spiral copper wire also helps to guarantee parallelism between the lower surface of the sensor and the upper surface of the upper substrate.

Measurement procedures

The electrical impedance of the instrumented SLJs was measured with a Hioki IM 3570 impedance analyzer (Ueda, Japan), with the adhesive joints being fixed on both free ends with clamps. This was done to guarantee similar boundary conditions during the measurement procedures. Figure 2 presents the experimental setup, with its equivalent electrical circuit. For each specimen, impedance measurements were performed under three spectral conditions: (i) $f \in \{1, 1000\}$ [kHz],

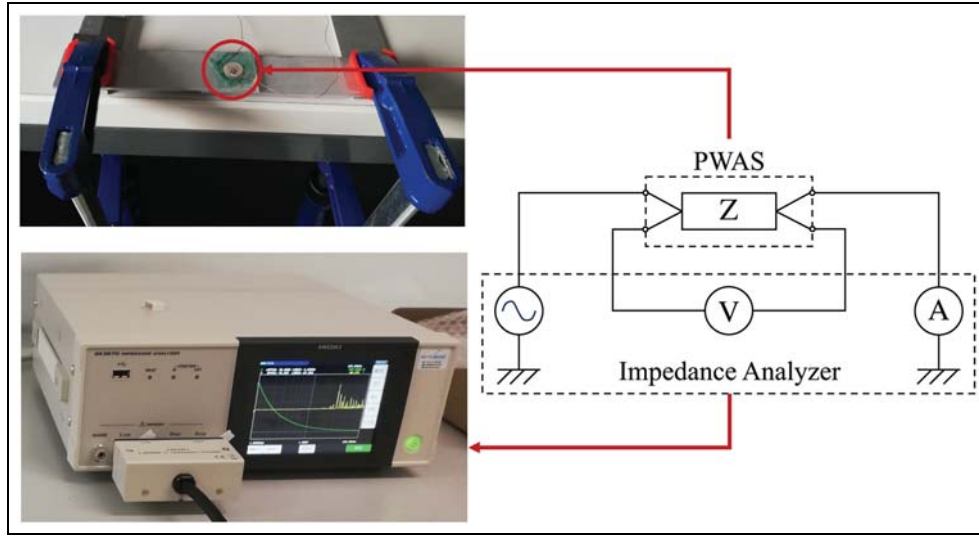


Figure 2. Experimental setup with equivalent electrical circuit.
SLJ: single lap joint.

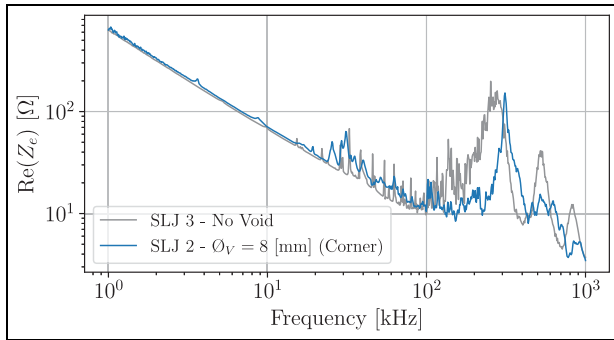


Figure 3. Plot showing the measured electrical impedance from an undamaged and a damaged SLJ, with 801 logarithmically spaced points, from $f_i = 1$ kHz to $f_f = 1$ MHz.
SLJ: single lap joint.

with linearly spaced sampled frequencies, (ii) $f \in \{1, 1000\}$ [kHz], with logarithmic spaced frequencies, and (iii) $f \in \{100, 1000\}$ [kHz], with linearly spaced sampled frequencies. Each measurement yielded 801 frequency points. Figure 3 presents some examples of the obtained measurements.

The measured electrical impedance values were initially stored with polar coordinate values—impedance modulus, $|Z_e|$, and phase of the impedance, $\arg(Z_e)$. However, these were converted to real and imaginary components, $\text{Re}(Z_e)$ and $\text{Im}(Z_e)$, respectively. Afterwards, the real electrical impedance component, $\text{Re}(Z_e)$, was inputted to the MDS models. The imaginary component of the electrical impedance, $\text{Im}(Z_e)$, was not used in this work, since it is predominantly

defined by the permittivity of the piezoceramic material, ϵ_{33}^T , and therefore, it is virtually insensitive to any structural alteration.^{3,9,31} Furthermore, damage metrics, such as the RMSD, could also be computed and then fed to the MDS algorithm. However, this approach was not chosen, since the computation of each metric can be viewed as a dimensionality reduction and, consequently, information loss may occur.

To help with the visualization of the instance point distribution in the reduced-dimensionality space, the measurements were divided into four classes, as identified in Figure 4. In this manner, the class of measurements from SLJs with *No Void*, contains three instances, whereas all other classes—*Small Voids (Corner)*, *Small Voids (Middle)*, and *Large Voids*—have six measurements each. Note that the class *Large Voids* was not separated according to the void placement, since the size is comparatively larger, that there is a large overlap of damaged cross-section, when comparing both sources of damage.

Data analysis and visualization

This section presents results regarding damage detection, as well as patterns revealed with the data reduction model. It is noted that this unsupervised machine learning algorithm has been implemented individually for all measurement sets with the same spectral conditions. As such, each of the first three subsections present, respectively, the results for measurements:

- With linearly spaced points, in the frequency range $f \in \{1, 1000\}$ [kHz]

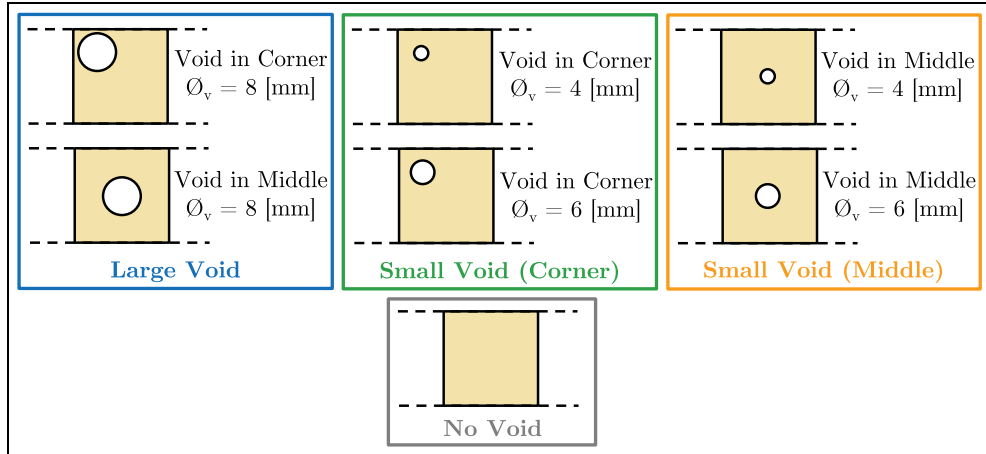


Figure 4. Dataset class definition for MDS visualization.
MDS: multidimensional scaling.

- With logarithmically spaced points, in the frequency range $f \in \{1, 1000\}$ [kHz]
- With linearly spaced points, in the frequency range $f \in \{100, 1000\}$ [kHz]

Note that different spectral conditions were used in this work because each type of measurement may contain more (or less) information in certain frequency ranges. However, all measurements contain 801 sampled points in their respective frequency range. In all cases, a 3D plot will be shown, as well as a planar projection of the 3D space.

Finally, subsection “Distance-based damage classification” presents the damage classifications results from the algorithmic approach defined in subsection “Distance-based damage classification in reduced space.”

Linearly sampled measurements in $f \in \{1, 1000\}$ [kHz]

MDS using the Euclidean distance for linearly sampled measurements in $f \in \{1, 1000\}$ [kHz]. Figure 5(a) plots the 3D reduced space with the measurements, linearly sampled from 1 kHz to 1 MHz, where the initial dissimilarities, in the higher dimensional space, were computed using the Euclidean distance, δ_E . Figure 5(b) plots the yz projection of the aforementioned reduced 3D space.

From this reduction, one observes the existence of two main cluster. One initial cluster contains the real component of the three electrical impedance measurements from undamaged joints, whereas a larger cluster of measurement instances of adhesive joints with voids is present, and is clearly separated from the points of pristine SLJs. This trend is also shown in previous

work,⁹ where damage metrics, such as the RMSD or the Mean Absolute Percentage Deviation (MAPD), which are based on the real component of the measured impedance, $\text{Re}(Z_e)$, were computed. However, unlike in this previous work, there is no superposition of the numeric results between damaged and undamaged joints.

The authors believe this overlap of values occurs with damage metrics and does not occur with the MDS data reduction algorithm for two reasons. First, damage indices yield a numerical value, thus condensing a *multidimensional* point, whereas the MDS model conceptually performs a similar task; however, in this instance, the data are presented in a 3D space. Therefore, one may guarantee a higher level of class differentiation with more dimensions. Second, damage metrics perform a spectral comparison between an adhesive joint without damage, and an adhesive joint that is under inspection. Conversely, in MDS, all measurements are compared simultaneously with the dissimilarity matrix, Δ .

Observing the cluster containing most instances of damaged joints, which are present at around $z=0$, a pattern emerges regarding the position and size of voids present in the SLJs, as seen in both Figure 5(a) and (b). From these figures, one sees that measurements from joints with small voids in the corner of the overlap are present in a small region of the reduced *map* space, defined by positive y values. Conversely, joints with voids of 8 mm diameter are on the opposite side of the cluster, where y values are below zero. Most impedance measurements from SLJs with small voids in the middle of the overlap are present in this cluster, bridging these two previously mentioned extremities.

Incidentally, two measurement instances, corresponding to SLJs with small voids in the middle of the

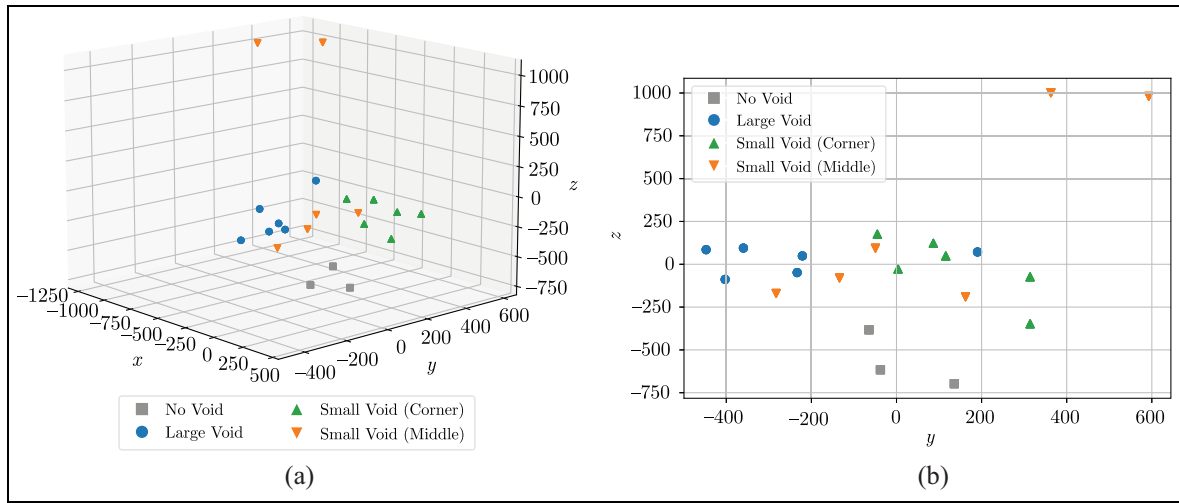


Figure 5. Reduced 3D MDS space, obtained with the Euclidean distance, of the impedance measurements: (a) 3D space and (b) yz plane projection of the 3D space. MDS: multidimensional scaling.

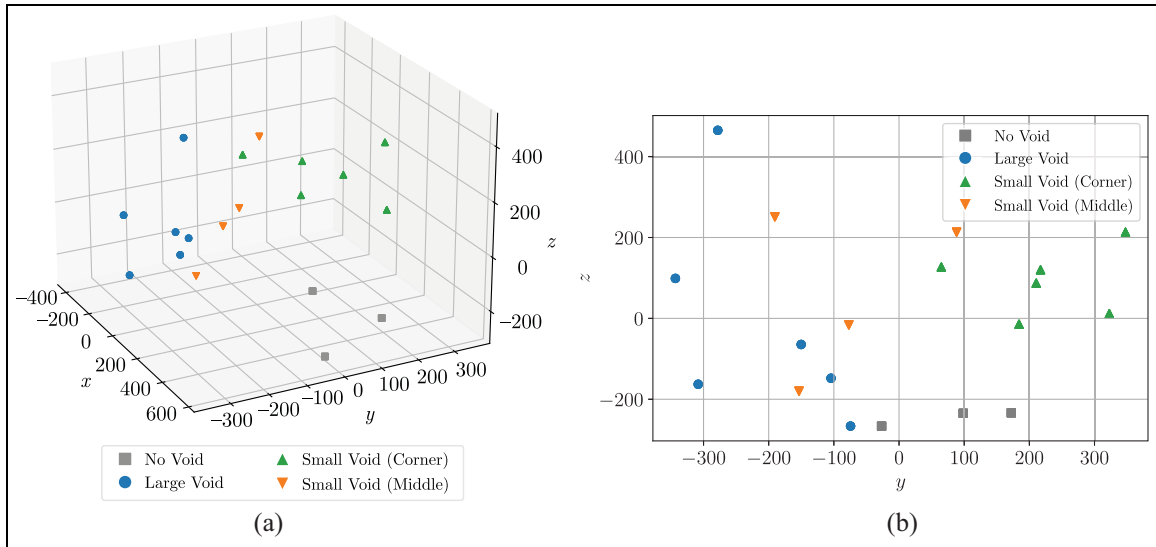


Figure 6. Reduced 3D MDS space, obtained with the Euclidean distance, of the impedance measurements (previous outlier instances were removed): (a) 3D space and (b) yz plane projection of the 3D space. MDS: multidimensional scaling.

overlap, are separated from the main cluster of damaged measurement instances. Note that the distance between either of these points and all other measurement points is considerably greater than between the main cluster of damaged instances and the cluster corresponding to undamaged adhesive joints. This was verified in previous work,⁹ where the RMSD metric differentiates these two adhesive joints from the remaining joints with artificial voids. However, this phenomenon was only observed for this metric, and with

measurements in the frequency range of $f \in \{1, 1000\}$ kHz. In this regard, the authors believe that these outliers exist because the Euclidean distance enables better outlier differentiation at lower frequencies, when compared to other metrics.

If one reruns the MDS model for the same dataset, minus the outlier instances, where the initial disparities are computed using the Euclidean distance, one obtains the 3D map shown in Figure 6(a), whereas Figure 6(b) presents the yz projection of the reduced space.

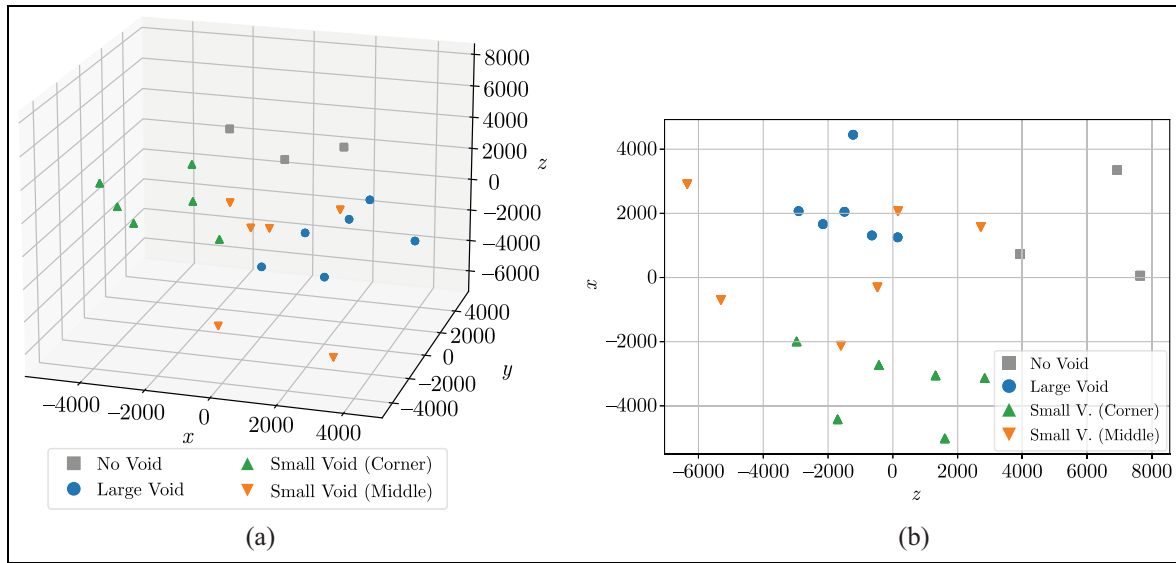


Figure 7. Reduced 3D MDS space, obtained with the Manhattan distance, of the impedance measurements: (a) 3D space and (b) zx plane projection of the 3D space.
MDS: multidimensional scaling.

With the removal of the two outliers present in Figure 5, all other measurement instances are better spread out in the $\mathbb{R}^3$ co-domain. Much like in the previous case, the three undamaged points are clearly separated from the remaining points of joints with voids. Furthermore, instances that originate from SLJs with large voids are present in one side of the main cluster of measurements, where $y < 0$. Conversely, cases of adhesive joints with small voids in the corner of the overlap are located in the other side of the main cluster, where $x > 0$. The remaining instances of joints with small voids centrally placed stand as bridging elements between both extremes. The results are consistent with results from previous studies.⁹

MDS using the Manhattan distance for linearly sampled measurements in $f \in \{1, 1000\}$ [kHz]. Figure 7(a) plots the 3D reduced space with the linearly sampled measurements from 1 kHz to 1 MHz, where the initial dissimilarities in the higher dimensional space, were computed using the Manhattan distance, δ_M . Figure 7(b) displays the zx projection of the aforementioned reduced 3D space.

The MDS model results obtained when using the Manhattan distance to compute the initial dissimilarities are similar to the ones obtained in the previous case. First, the three data instances originating from undamaged joints are well separated from the main cluster of measurements containing damaged instances, as one can see from Figure 7(a). Furthermore, a similar

trend is observed, where the instances classified as being from the *Large Void* class are placed on one side of the co-domain, whereas instances from *Small Void (Corner)* class are located in the opposite direction ($x < 0$).

The first main difference is the scale of the axes in the reduced 3D space. This is to be expected, since the initial distances were computed according to Equation (10), which yield larger distances than the Euclidean distance, δ_E .

Furthermore, instances from the *Small Void (Middle)* class act as bridging elements in the main cluster, connecting instances of the *Small Void (Corner)* and *Large Void* classes. This was also observed in the last case where the Euclidean distance was used. However, unlike in the MDS results using the Euclidean distance, no outliers are observed here. This trend is only observed when using the Euclidean distance, δ_E , to compute the initial dissimilarities. Similarly, in Teiatinreiro et al.,⁹ this trend was only observed for the RMSD metric.

It is noted that the data distribution of the 3D space, as observed in Figure 7, also occurs when using the Canberra and Arccosine distances, δ_C and δ_A , respectively. Therefore, these results are not shown here for brevity.

Performance of dimensionality reduction with the linearly sampled measurements in $f \in \{1, 1000\}$ [kHz]. The results presented in Figures 5, 6, and 7 appear to be a good map of the higher dimension space, as demonstrated

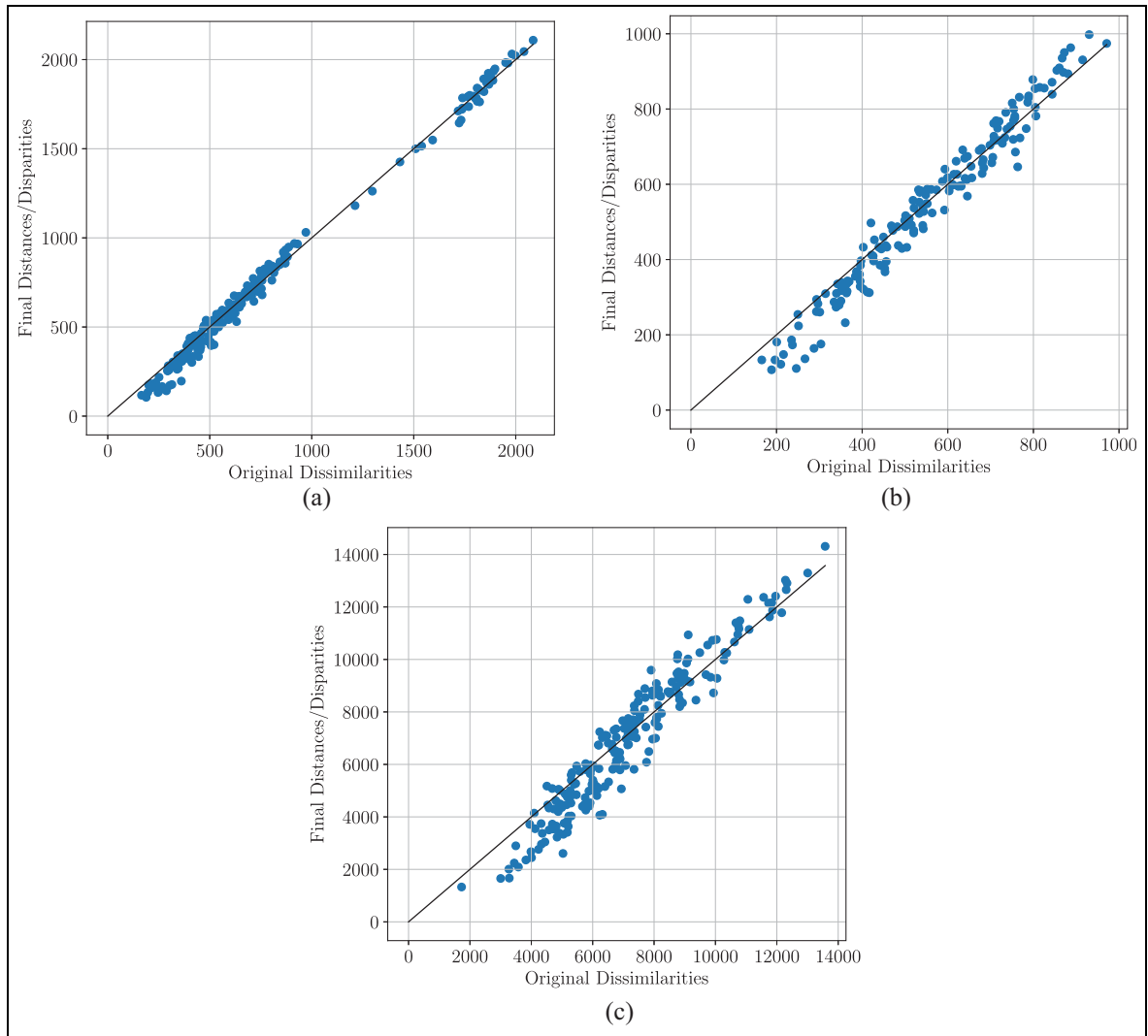


Figure 8. Shepard plots for reduced *map* space, when using linearly spaced measurements from $f_i = 1$ kHz to $f_f = 1$ MHz: (a) Euclidean distance (with outliers), (b) Euclidean distance (without outliers), and (c) Manhattan distances (with outliers).

by Figures 8(a) to (c), respectively, which show the Shepard plot comparing the initial dissimilarities of the $\mathbb{R}^{801}$ space and final distances of the 3D space. As previously stated, a good 3D reduced space is one where the final distances in this reduced space are close to the ones in the original space.

As one can see, all dissimilarities are placed near the $x = y$ line, which means that the error in transposing the Euclidean distances between both dimensionality spaces is relatively small. However, by removing the outlier values from the input dataset, the highest value dissimilarities of the initial space (i.e., Euclidean distance in the 801-dimensional space) no longer exists. Therefore, the highest distance between different points is approximately 1000, when the two outlier values are removed,

which is approximately half of the maximum dissimilarity when using the entire dataset (with outliers).

The Shepard plot of Figure 8(c) shows that the dimensionality reduction was performed as best as possible, guaranteeing a good approximation between the Manhattan distance-based original dissimilarities and the final disparities of the reduced space. However, unlike with the plot of Figure 8, the disparities appear to be more uniformly distributed in this plot, thus reflecting that the outliers are not as pronounced in the reduced space of Figure 7.

Figure 9 presents the Stress-1 plot comparing the performance of the four distances presented in Equations (7) to (10) in the dimensionality reduction algorithm. For all analyzed dimensions, the Euclidean

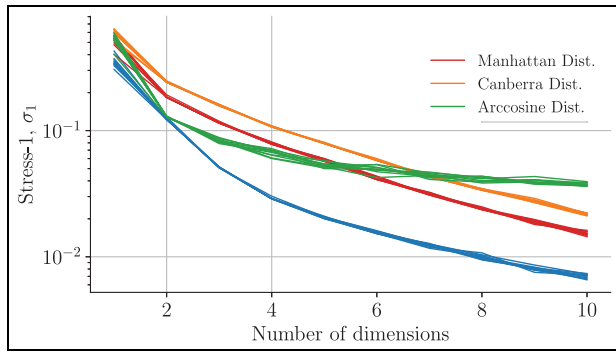


Figure 9. Stress-I plot comparing the performance of the Arccosine, Canberra, Euclidean, and Manhattan distances, $\{\delta_A, \delta_C, \delta_E, \delta_M\}$ for various number of dimensions of the reduced map.

distance has the best performance, yielding a better fitness performance in the dimensionality reduction task. Afterwards, the Arccosine distance has the second best performance at lower dimensions but is overtaken by the Canberra and Manhattan distances in higher dimensions.

Logarithmically sampled measurements in $f \in \{1, 1000\}$ [kHz]

MDS using the Euclidean distance for logarithmically sampled measurements in $f \in \{1, 1000\}$ [kHz]. Figure 10(a) plots

the obtained reduced space, where each point originally corresponds to an experimentally obtained impedance spectrum. In these measurements, the impedance was sampled between 1 kHz and 1 MHz, yielding 801 logarithmically sampled impedance points. Note that the MDS algorithms made use of the original space dissimilarities that were computed using the Euclidean distance. Figure 10(b) displays the zx projection of the aforementioned reduced 3D space.

When using logarithmically spaced impedance measurements in such a wide frequency range, each frequency order of magnitude is equally represented in the measurements. In other words, each order of magnitude has the same number of sampled points. This means that there are more measurements at lower frequencies when compared to the previous case, translating into more information on the subpeaks of the real component of the impedance, $\text{Re}(Z_e)$.

In this manner, a higher distribution of impedance points below 100 kHz in the measured spectra has enabled a better differentiation between damaged and undamaged adhesive joints. This can be stated, given the fact that there is a bigger distance between the instances from the *No Void* class and the closest instances of damaged joints when compared to the results shown in Figure 5.

However, damage differentiation is comparatively harder when using the logarithmically spaced measurements. In this case, the various damage classes are closer to each other, when compared to the relative

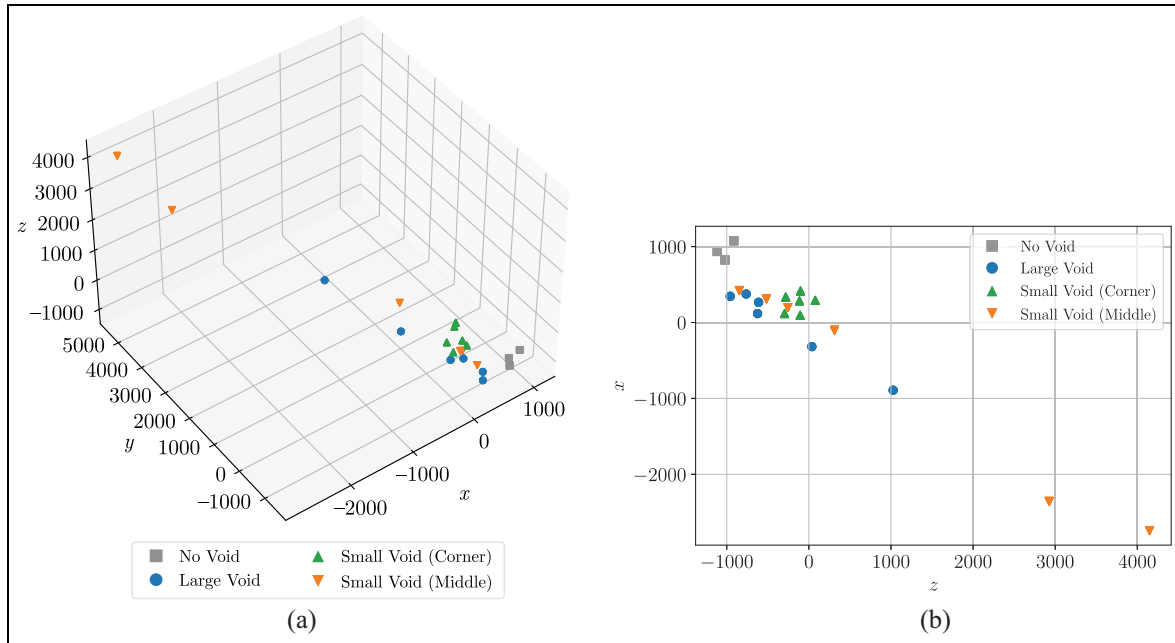


Figure 10. Reduced 3D MDS space, obtained with the Euclidean distance, of the impedance measurements: (a) 3D space and (b) zx plane projection of the 3D space.
MDS: multidimensional scaling.

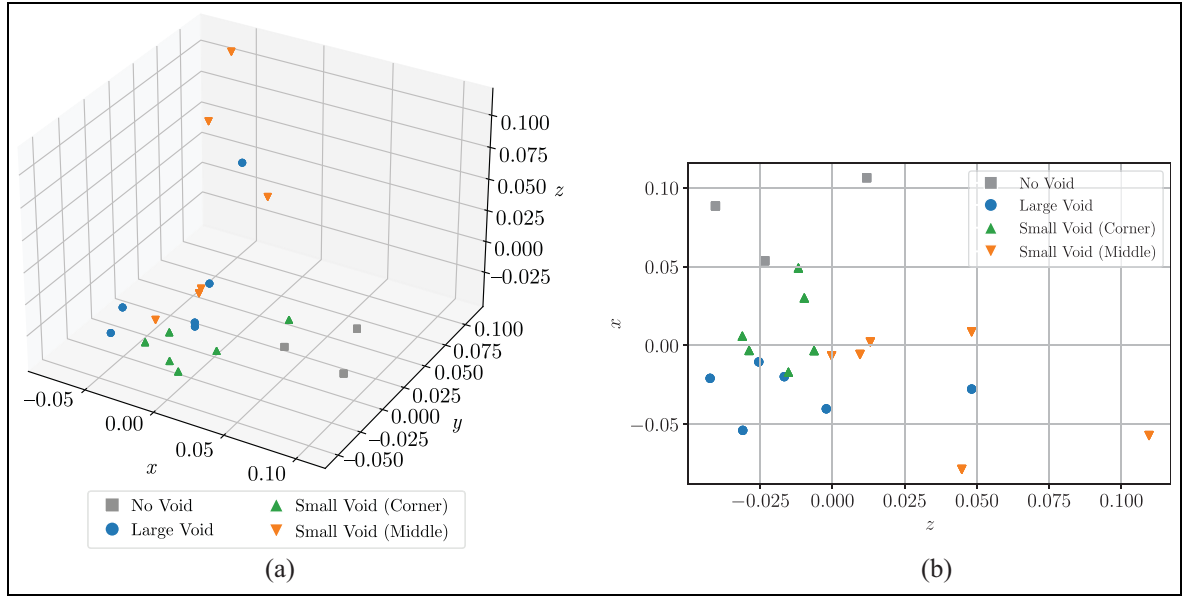


Figure 11. Reduced 3D MDS space, obtained with the Arccosine distance, of the impedance measurements: (a) 3D space and (b) zx plane projection of the 3D space.
MDS: multidimensional scaling.

difference between the main cluster of damaged instances and the undamaged measurements. This statement is also true, when considering also the overall co-domain of the reduced 3D map, which is much larger than in the previous cases. Despite this, instances from joints with small voids in the corner of the overlap, that is, $\emptyset_v \in \{4, 6\}$ [mm], are very close together, thus reflecting that the subpeaks of $\text{Re}(Z_e)$ and the overall spectra, observed at lower frequencies, are very similar for all instances of this class.

The same cannot be said for all measurement instances of the classes *Small Void (Middle)* and *Large Void*, which present a large dispersion. As shown in Figures 5 and 6, this is to be expected with two points of the class *Small Void (Middle)*, given that two outliers are present here. Furthermore, this also occurs for two instances of damaged joints belonging to the class of *Large Voids*.

Unlike the case of linearly sampled frequencies, both the original outliers and the two new instances from the *Large Voids* are farther away from the main cluster of damaged instances, which seems to indicate that the cause of this difference resides in the subpeaks of the real component of the electrical impedance occurring below 100 kHz. This is corroborated by the results shown in Tenreiro et al.,⁹ which show a similar phenomenon for the RMSD metric, which is based on the Euclidean distance.

It is noted that the obtained reduced space, when using the Manhattan distance, δ_M , to compute the

initial dissimilarities, is similar to the one shown in Figure 10.

MDS using the Arccosine distance for logarithmically sampled measurements in $f \in \{1, 1000\}$ [kHz]. Figure 11(a) displays the 3D reduced space with the measurements, logarithmically sampled from 1 kHz to 1 MHz, where the initial dissimilarities were calculated using the Arccosine distance, δ_A . Figure 11(b) displays the zx projection of the aforementioned reduced 3D space.

Unlike with the plotted reduced space in Figure 10, this space presents a more uniform distribution of the instances. This occurs since the Arccosine distance, does not measure a linear distance, like the Euclidean or Manhattan distances, but measures an angular distance. Therefore, a comparison between both types of distances is ill-advised.

The obtained distribution of the instances, in this reduced space, is similar to the ones shown in Figure 7, where the initial dissimilarities of the linearly space frequency measurements ($f \in \{1, 1000\}$ [kHz]) were computed with the Manhattan distance. In this manner, and as previously stated, the obtained distances are not comparable.

Despite this, there is a clear separation between the instances originated from undamaged joints, and the various instances from SLJs with voids. The *No Void* instances have a x coordinate superior to 0.05, as shown in Figure 11(b). Furthermore, the instances from class *Small Void (Corner)* are placed nearer to

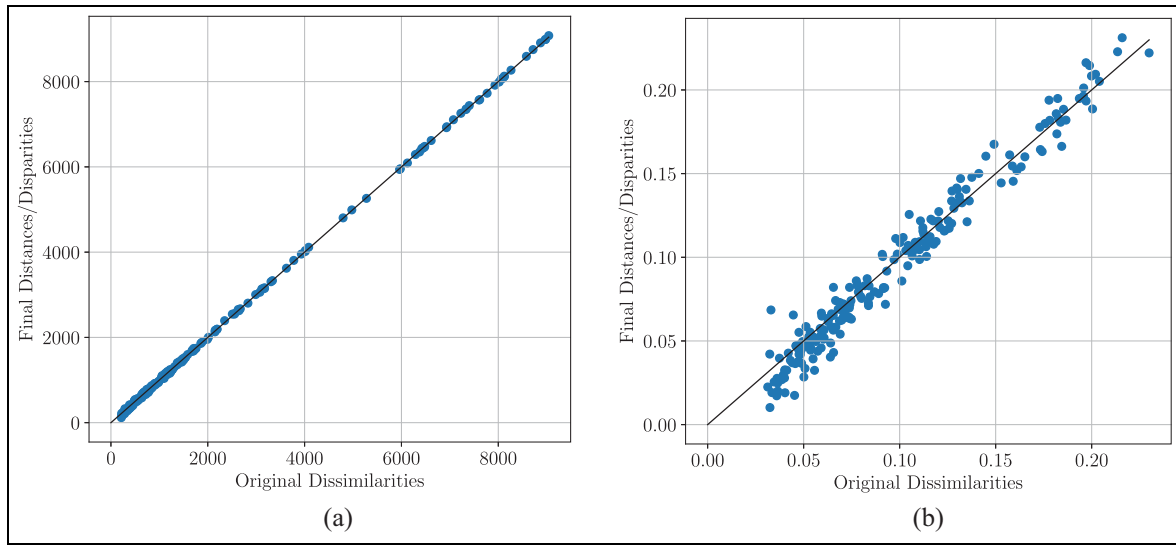


Figure 12. Shepard plots for reduced map space, when using logarithmically spaced measurements from $f_i = 1$ kHz to $f_f = 1$ MHz: (a) Euclidean distance and (b) Arccosine distance.

the instances from the *No Void* class, whereas the points from joints with large voids are placed farther away from the cases of undamaged joints. This reflects the effect that size and position have on the impedance measurements.

It is also observed that much like the results from Figure 10, most instances from class *Small Void (Middle)* are located between the other two classes of damaged joints. However, two instances from this class are farther away from the points of the *No Void* class. These are the outliers seen in the previous case, where the linearly sampled impedance spectra from 1 kHz to 1 MHz were used.

Given the pattern described herein, this condition was used to try and classify the type of joint, according to the spatial distances in the reduced space. The obtained results are presented and discussed in subsection entitled “Distance-based damage classification.”

Performance of dimensionality reduction with the logarithmically sampled measurements in $f \in \{1, 1000\}$ [kHz]. The Shepard plots presented in Figure 12(a) and (b) demonstrate the fitness of the obtained reduced space map, which were plotted in Figures 10 and 11, when compared to the initial dissimilarities of the initial higher-dimensional space.

Much like in the cases shown in subsection entitled “Linearly sampled measurements in $f \in \{1, 1000\}$ [kHz],” Figure 12(a) reveals that all distance between instances are near equal in both spaces, thus being placed near the $x=y$ line. In other words, the error in transposing the Euclidean distances between both dimensionality spaces is relatively small. Although a similar statement may be said when using

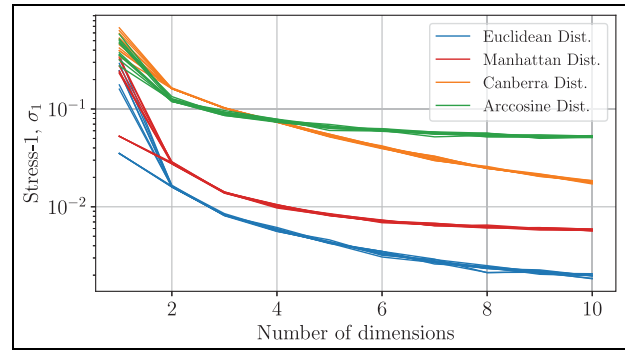


Figure 13. Stress-I plot comparing the performance of the Arccosine, Canberra, Euclidean, and Manhattan distances, $\{\delta_A, \delta_C, \delta_E, \delta_M\}$ for various number of dimensions of the reduced map.

the Arccosine distance, as shown by Figure 12(b), one may also observe that there is a wider dispersion of the disparities.

However, this is false, since the influence of the outliers is significantly more pronounced in Figure 10(a), where the Euclidean distance is used, and the observed distance is very large, when compared with the case of Figures 5 and 8(a). Conversely, by using the Arccosine distance, one is actually limiting the overall domain of the disparities to $0 \leq \delta_A \leq \pi$. Furthermore, given that most sampled impedance points should yield similar resistive values and no negative resistive value was recorded, the observed dissimilarity values are very close to one another. This aforementioned restriction in co-domain is only observed for this distance, and, as

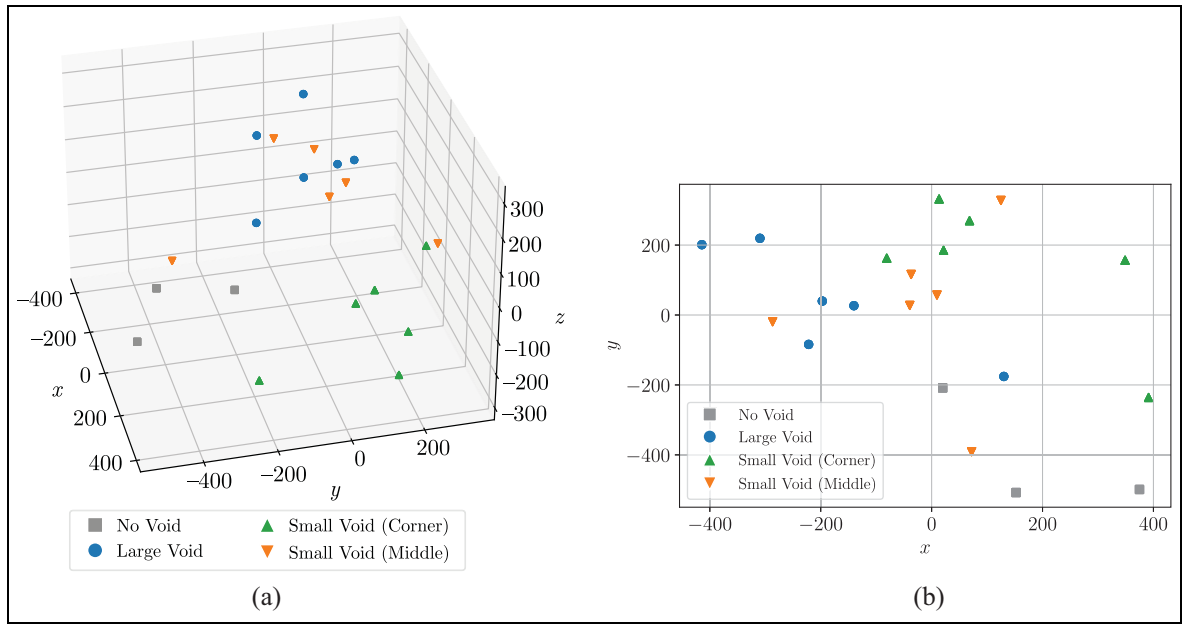


Figure 14. Reduced 3D MDS space, obtained with the Euclidean distance, of the impedance measurements: (a) 3D space and (b) xy plane projection of the 3D space.

MDS: multidimensional scaling.

such, the *closeness* of the data instances is unique to this space.

Figure 13 presents the Stress-1 plot comparing the performance of the four distances, presented in Equations (7) to (10), in the MDS algorithm. For all analyzed dimensions, the Euclidean distance has the best performance, yielding a better fitness performance in the dimensionality reduction task. Next, the Manhattan distance has the second best performance. Furthermore, these two distances behave similarly in $\mathbb{R}^1$, where the obtained Stress-1 values, σ_1 , may be significantly lower for different *maps* depending on the initialization. Finally, the Canberra and Arccosine distance present the highest values of σ_1 , but for spaces of four-dimensions or above the normalized stress values barely decrease when using the Arccosine distance. Conversely, the normalized stress values increase when using the Canberra distance.

Linearly sampled measurements in $f \in \{100, 1000\}$ [kHz]

MDS using the Euclidean distance for linearly sampled measurements in $f \in \{100, 1000\}$ [kHz]. Figure 14(a) plots the 3D space obtained after using the MDS algorithm, where each point corresponds to an experimentally obtained impedance spectrum, with 801 linearly sampled points between 100 kHz and 1 MHz. In this case, the original space dissimilarities were computed

using the Euclidean distance. Figure 14(b) presents the xy projection of the obtained 3D space.

Unlike in previous cases, where the reduced 3D space enabled a good differentiation between the spectra from damaged and undamaged joints, the MDS space, for linearly sampled impedance measurements in the frequency range $f \in \{100, 1000\}$ [kHz], did not enable good separation of the *No Void* class. At least one instance of each class identifying a possible damage scenario are placed near the cluster of three instances of measurements from the pristine adhesive joints.

These results are corroborated by the findings published in a previous work of Tenreiro et al.,⁹ where there is a significant correlation between similar portions of the measured spectra of various classes, as exemplified in Figure 15. This falls in line with previous findings by stating that higher frequencies may not be as suited in damage detection. Even if one compares these measurements with the ones used in subsection entitled “Linearly sampled measurements in $f \in \{1, 1000\}$ [kHz],” where this superposition of the impedance spectra is present in a relatively wide range of the sampled frequencies, this effect is neglectful, since all damaged instances and the three points from the *No Void* class are well separated, as shown in Figure 5. This difference can be attributed by the presence of the subpeaks of $\text{Re}(Z_e)$ that occur below 100 kHz, as studied in Tenreiro et al.^{9,28}

One may also see from Figure 14 that there is some separation between the classes of damaged adhesive

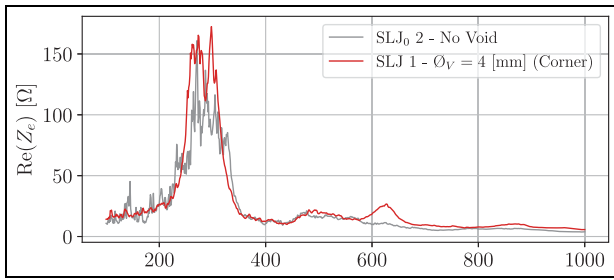


Figure 15. Plot comparing the real component of the electrical impedance of an undamaged SLJ, and the electrical impedance of the SLJ with damage in the corner of the overlap. Note that this measurement corresponds to the instance of class *Small Void (Corner)* near the cluster of instances from class *No Void*. SLJ: single lap joint.

joints *Large Void* and *Small Void (Corner)*. However, unlike in the previous spectral conditions, this distinction is less noticeable, since there is no clear geometric separation and there is a big dispersion of all classes in the 3D space. This dispersion is most noticeable for all instances of the *Small Void (Middle)* class. This shows that although one can still extract knowledge of the detected damage, this spectral range is not ideal.

MDS using the Arccosine distance for linearly sampled measurements in $f \in \{100, 1000\}$ [kHz]. Figure 16(a) plots the 3D measurement *map*, containing instances of linearly sampled impedance measurements from 100 kHz to 1 MHz, where the initial dissimilarities were calculated with the Arccosine distance, δ_A . Figure 16(b) plots the *yz* projection of the aforementioned reduced 3D space.

Much like in the previous case presented in Figure 14, there is a significant overlap between the various classes. An angular distance is neither ideal in separating the damaged and undamaged cases, nor this distance is effective in separating all instances of the three different classes of void damage.

However, unlike in the previous case where the Euclidean distance was used to compute the initial dissimilarities, in this reduced space one can see some clear borders between certain types of damages, as visualized in the *yz* projection of Figure 16(b). These hard borders are noticeable as they separate most instances of all three classes of damaged SLJs. However, these borders do not guarantee that there is a clear separation of all damage sources of certain types, as shown by the fact that some cases of damage joints are located in the middle of instances of the *No Void* class.

Performance of dimensionality reduction with the linearly sampled measurements in $f \in \{100, 1000\}$ [kHz]. The Shepard plots presented in Figure 17(a) and (b) demonstrate the fitness of the obtained reduced space *map*, which were plotted in Figures 14 and 16, when

compared to the initial dissimilarities of the initial higher-dimensional space.

The Shepard plots show that all distance between instances are near equal in both spaces, almost the ideal $x=y$ line. However, unlike in the cases of Figure 8(a) and 12(a), one can see a somewhat larger dispersion between the disparities and the $x=y$ line, in the plot of Figure 17(a). This occurs because, in the reduced space of Figure 14, there is no presence of outlier instances, unlike what occurs in the previous cases of this work. This phenomenon was also observed when the Arccosine distance was used in the MDS model, as in subsection entitled “Logarithmically sampled measurements in $f \in \{1, 1000\}$ [kHz].”

One may also deduce from these Shepard plots that the point distribution presented in the *maps* of Figures 14 and 16 is near identical to the one in the initial 801-dimensional space. This concludes that the measurements in the frequency range of $f \in \{100, 1000\}$ [kHz] are not ideal in damage detection and damage classification, which was also found in Tenreiro et al.⁹

Figure 18 plots the Stress-1 as a function of the number of dimensions in the *map* obtained with the MDS algorithm, and as a function of the distance used to calculate the initial disparities in the higher-dimensional space. Much like in subsection entitled “Logarithmically sampled measurements in $f \in \{1, 1000\}$ [kHz],” the Euclidean distance yields a better fitness performance in the dimensionality reduction task. At lower dimensions, the Canberra distance has the worst performance, with higher σ_1 values when compared to the lower values of the Manhattan and Arccosine distances, which present similar performance to each other. However, above four and six dimensions, the Manhattan and Canberra distances, respectively, outperform the Arccosine distance. Consequently, angular distances such as the Arccosine distance are not able to accurately evaluate the original impedance space for all dimensions.

Distance-based damage classification

Given the results obtained so far, it seems that in most cases, this Manifold Learning algorithm can cluster the various instances into subregions of the 3D *map*. Therefore, one may be able to use the Euclidean distance, δ_E , as defined in Equation (9), to try and quantify the difference between the various classes of damage. To achieve this, a simple algorithmic approach was performed, as described in subsection entitled “Logarithmically sampled measurements in $f \in \{1, 1000\}$ [kHz].” Figure 19 shows the obtained results for the 3D *map* presented in Figure 11.

The results shown in Figure 19 quantitatively corroborate the observations stated in subsection. First, one

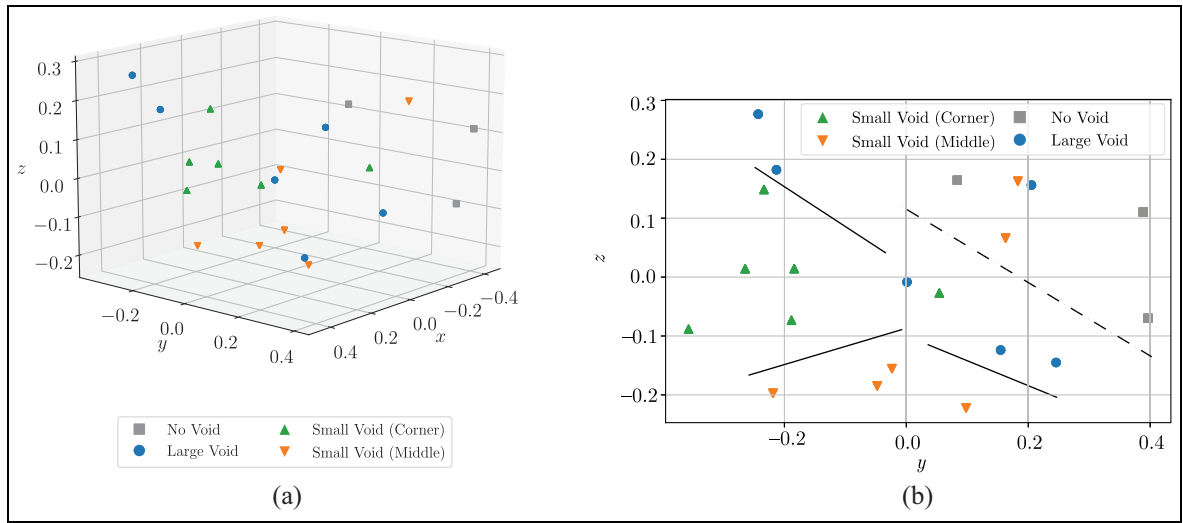


Figure 16. Reduced 3D MDS space, obtained with the Arccosine distance, of the impedance measurements: (a) 3D space and (b) yz plane projection of the 3D space. MDS: multidimensional scaling.

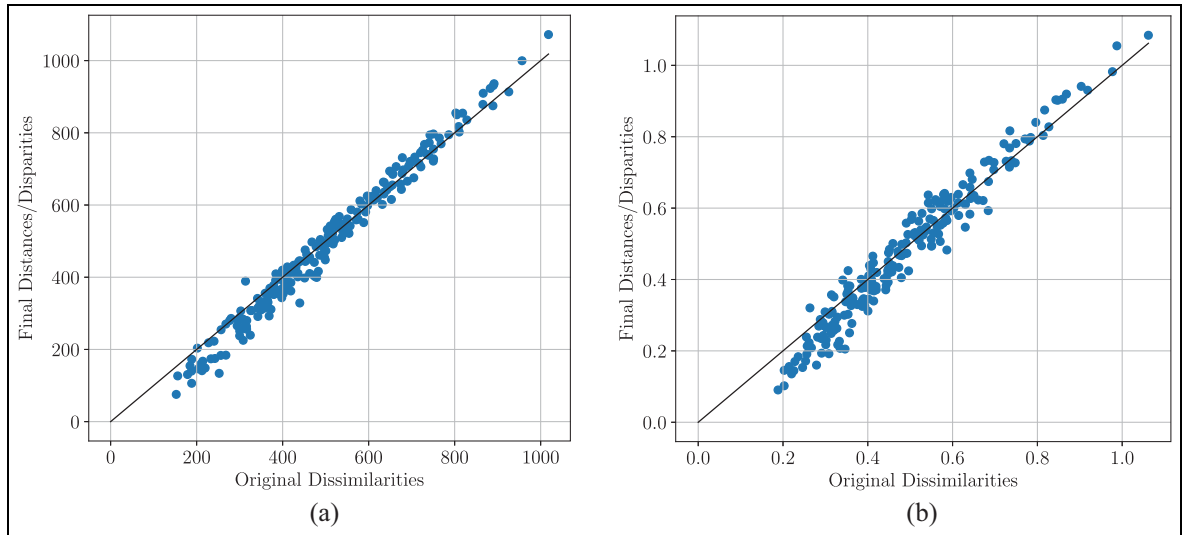


Figure 17. Shepard plots for reduced *map* space, when using linearly spaced measurements from $f_i = 100$ kHz to $f_f = 1$ MHz: (a) Euclidean distance and (b) Arccosine distance.

observes that the nearest instances of this dataset are the three instances points of the *No Void* class, which is to be expected given the method of calculating the centroid coordinates. Afterwards, it seems that all instances of *Small Void (Corner)* class and most instances of the *Small Void (Middle)* class, which tend to be at a distance of up to 0.10 from the centroid. A bit further away, one can find all instances of the *Large Void* class, which have an Euclidean distance varying between 0.10 and 0.15. Finally, the two outliers

of class *Small Void (Middle)*, with a distance slightly above 0.20, are the farthest away.

The plots in Figure 20(a) and (b) demonstrate a comparison between the obtained Euclidean distance and the values obtained with the RMSD damage metric, which was used in Tenreiro et al.⁹ Note that Figure 20(b) presents the same information, but the outlier values were removed from both the Euclidean distance dataset and the RMSD set of values.

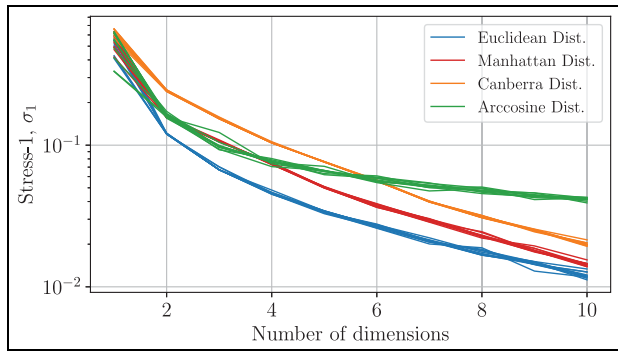


Figure 18. Stress-I plot comparing the performance of the Arccosine, Canberra, Euclidean, and Manhattan distances, $\{\delta_A, \delta_C, \delta_E, \delta_M\}$ for various number of dimensions of the reduced *map*.

In these plots, the obtained Euclidean distance from the centroid shows a clear separation between all instances originating from damaged joints and the three instances of the *No Void* class, corroborating the initial observations. This separation was also possible with use of the RMSD index, but the difference in values was less stark. Furthermore, there is also a clear separation between the distances of instances from the *Small Void (Corner)* and the *Large Void* classes, even though these have a somewhat large standard deviation. This was not possible with the use of the RMSD index, where all metrics values for the various sizes and locations of the voids were similar.

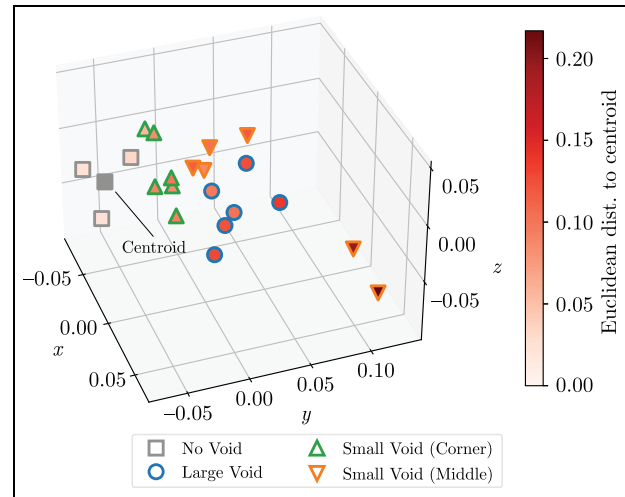


Figure 19. Reduced 3D MDS space, obtained with the Arccosine distance, of the logarithmically sampled impedance measurements, with the distance between each point and the reference centroid.
MDS: multidimensional scaling.

The only exception to this are the values obtained for the class *Small Void (Middle)*, which has a large standard deviation, when viewing both the RMSD and the Euclidean distance to the centroid. As previously stated, this is due to the presence of outliers in the dataset, and if these are removed, both standard deviation values diminish for this specific class. However, the overlap in observed values for the centroid distance is

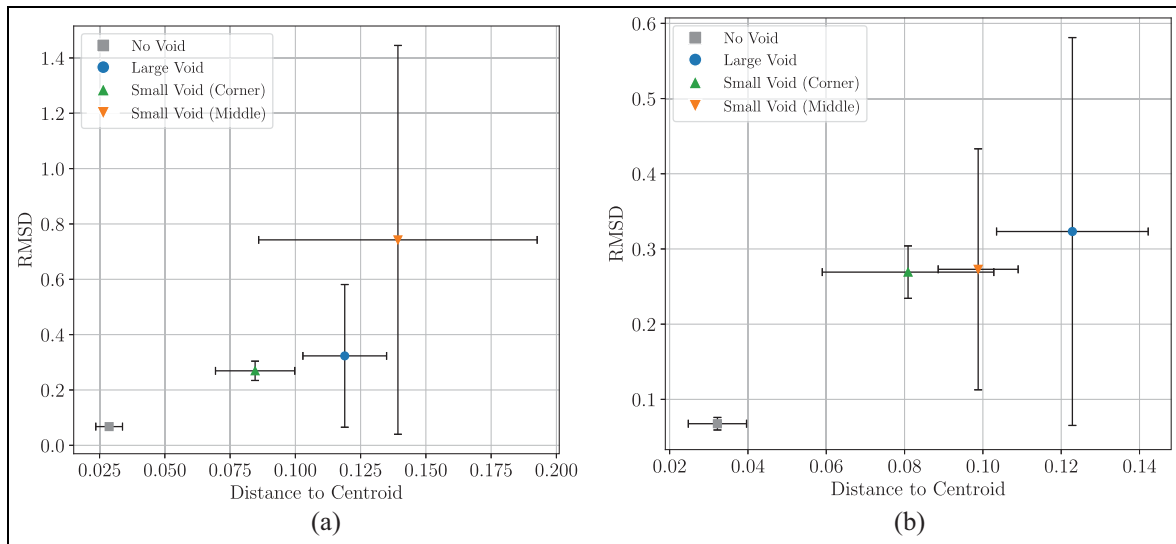


Figure 20. Average and standard deviations of the RMSD for all classes, as well as the average and standard deviations of the Euclidean distances between the centroid and all points of the four different classes: (a) average and standard deviation with outliers, and (b) average and standard deviation without outliers.
RMSD: root mean square deviation.

very small, which is not the case when analyzing the RMSD values.

Finally, a trend in these results indicates that the small voids in the corner of the overlap have a minor influence on the obtained experimental impedance measurements. This is because the distances of these instances are closer to the centroid. This is understandable given that damage is farther away from the piezoelectric element. Conversely, large voids in the adhesive layer have such an influence on the impedance measurements that these are placed farther away from the centroid of the *No Void* class.

Conclusion

This article presented a study on the use of MDS as an algorithmic tool to analyze experimentally obtained impedance measurements from adhesive joints with and without artificial voids in the adhesive layer. The Arccosine, Canberra, Euclidean, and Manhattan distances were used to perform the dimensionality reduction. This task was performed on measurements with different spectral conditions: linearly spaced measurements from 1 kHz to 1 (801 frequency points), logarithmically spaced measurements from 1 kHz to 1 MHz (801 frequency points) and linearly spaced measurements from 100 kHz to 1 MHz (801 frequency points).

From this analysis, damage detection and classification was successfully performed with measurements from 1 kHz to 1 MHz (with either linear or logarithmic sampling). However, with the Euclidean distance, outliers from the *Small Void (Middle)* damage class are detected, which occur because of information of the real component of the impedance, $\text{Re}(Z_e)$, at lower frequencies. Conversely, this is not noticed in the linearly sampled measurements from 100 kHz to 1 MHz. In this third spectral condition, there is considerable overlap between all four classes, including the *No Void* class, even though there is still an ability to detect and differentiate damage. Conversely, all other spectral conditions only reveal a small intersection between the regions where *Small Void (Corner)* and *Small Void (Middle)* instances are placed, and, likewise, where *Large Void* and *Small Void (Middle)* instances are placed. Therefore, this last spectral condition may not be ideal for SHM of adhesively bonded joints.

Finally, with the MDS results from the logarithmically spaced measurements from 1 kHz to 1 MHz, with dissimilarities computed using the Arccosine distance, damage can be analyzed both qualitatively and quantitatively. This was done by calculating the Euclidean distance between each instance and the centroid of all undamaged instances. This distance can be used not only to detect damage, but also to try and classify the type of void being detected.

Although these are very interesting and relevant results in regards to EMIS-based integrity monitoring, damage localization and classification in adhesive joints is only in its early stages. First, other sources of damage exist such as cracks, porosities, or weak adhesion, to name a few. Second, real-world bonded structures are bigger in dimensions, requiring a network of PWAS for damage detection, localization, or classification. Third, damage extension can be considered either in damage localization and classification, meaning that these steps also require clear methodology definition. Finally, given these aforementioned issues, MDS (or any other algorithm) needs to be validated for such conditions.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The authors gratefully acknowledge the funding of grant 2021.07689.BD, which is provided by Fundação para a Ciência e Tecnologia (FCT).

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Appendix F

Paper F

Frequency-based k -Nearest Neighbors algorithm for electromechanical impedance based detection of damage in adhesive joints

Frequency-based k -Nearest Neighbors algorithm for electromechanical impedance based detection of damage in adhesive joints

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Abstract: Structural adhesive joints are susceptible to many forms of damage that may not be detectable with currently deployed Non-Destructive Tests (NDT). The Electromechanical Impedance Spectroscopy (EMIS) based Structural Health Monitoring (SHM) methodology constitutes an alternative, where a given structure is continuously monitored for damage, thus outperforming NDT. While much has been done in the applicability of EMIS in metallic and composite structures, only preliminary research has been done on the EMIS-based integrity monitoring of adhesive joints. In this paper, two different k -Nearest Neighbor (k NN) approaches are used for both damage detection and damage quantification. Initially, peaks are extracted from the real component of the measured impedance of instrumented adhesive joint specimens, which are then inputted to either a conventional k NN or a novel parallel k NN model, where each individual model is fed with its respective peak information. For void detection, the parallel classifier approach presents a moderately better performance, with an average accuracy of 98% under optimal conditions, but, for damage quantification, a significant improvement in classification is observed. In all cases, the use of the Canberra distance allows for a significant increase in classification accuracy.

Keywords: Structural Health Monitoring, Electromechanical Impedance Spectroscopy, adhesive joints, k -Nearest Neighbors, Machine Learning, classification, distances, damage identification

1 Introduction

In the field of Structural Health Monitoring (SHM), transducers monitor the integrity of structures in a repetitive and automatic manner. With this, a transducer will measure a physical variable that may be affected by the material's properties, or, in other words, by any defect in the structure. The measurement signals from the transducer are then sent to a computer that will process the signals, so that one can detect and obtain information on a given structural damage [1, 2, 3]. In this manner, SHM aims to diminish costly and time-consuming maintenance operations, where legally mandatory Non-Destructive Tests (NDT) are required. Despite this, NDT results are not reliable in detecting all types of damage [2, 4], especially given the complex nature of new materials and real-world structures [5, 6, 7, 8].

Various SHM methods exist, such as the Electromechanical Impedance Spectroscopy (EMIS), where an AC voltage signal of varying excitation frequency is fed to a Piezoelectric Wafer Active Sensor (PWAS). For each frequency, ω_i , the PWAS will convert the electrical voltage, $V(\omega_i)$, into a vibration of a given load and particle velocity, $F(\omega_i)$ and $\dot{x}(\omega_i)$, respectively. One can correlate these mechanical variables with the mechanical impedance of the structure, $Z_{m,s}(\omega_i)$, which is defined as $Z_{m,s}(\omega_i) = F(\omega_i)/\dot{x}(\omega_i)$, and can be defined as a function of the local mass, m_s , damping, c_s , and stiffness, k_s , of the structure. Concurrently to the excitation of the piezoelectric element, the aforementioned vibration influences the electrical current, $I(\omega_i)$, passing through the piezoelectric transducer. Given the described electromechanical coupling of the piezoelectric elements, by measuring the electrical impedance of the PWAS, $Z_e(\omega_i)$, which is defined as $Z_e(\omega_i) = V(\omega_i)/I(\omega_i)$, one is indirectly measuring the mechanical impedance of the structure, thus relating its mechanical properties to the presence of damage [1, 4, 9].

Mathematical models have been proposed [9, 10, 11], that relate the mechanical impedance, $Z_{m,s}$, with the electrical impedance, Z_e . An initial model was proposed by Liang et al. [12], which was applied to an one-dimensional structure. As such, the electrical impedance is mathematically defined as

$$Z_e(j\omega) = \left[j\omega \frac{w_P l_P}{h_P} \left(\frac{1}{\varepsilon_{33}^T} - \frac{Z_{m,s}(j\omega)}{Z_{m,s}(j\omega) + Z_{m,P}(j\omega)} d_{31} \overline{Y_{11}^E} \right) \right]^{-1}, \quad (1)$$

where w_P , l_P and h_P are, respectively, the width, length and thickness of the PWAS, while j and d_{31} correspond to the imaginary unit, $j = \sqrt{-1}$, and the piezoelectric induced strain coefficient, respectively.

Furthermore, variable $Z_{m,P}(j\omega)$ corresponds to the mechanical impedance of the PWAS. The complex Young's Modulus of the piezoceramic material at null electric field conditions ($E = 0$), $\overline{Y_{11}^E}$, is defined as $\overline{Y_{11}^E} = |Y_{11}^E|(1 + j\eta)$, where η is the mechanical loss factor. Finally, the dielectric constant at zero stress ($T = 0$), $\overline{\varepsilon_{33}^T}$, is computed by $\overline{\varepsilon_{33}^T} = |\varepsilon_{33}^T|(1 - j\delta)$, with δ being the dielectric loss factor.

In these models, structural damping and stiffness are assumed to be constant throughout the frequency range, which is not guaranteed, even for low frequencies [5, 13]. These models also assume that the dielectric constant, $\overline{\varepsilon_{33}^T}$, is fixed with frequency, which may not be true, as hypothesized in [14], and shown in [15]. Therefore, while EMIS modeling has presented itself relevant, most research focuses on the development and use of algorithms for damage detection and information retrieval of said damage [9], such as the deployment of machine learning algorithms [16, 17].

One approach is to use Probabilistic Neural Network (PNN) models. For instance, Giurgiutiu and Kropas-Hughes [18] developed a PNN to detect the distance between a crack and a centrally placed PWAS in a circular aluminium plate. Measurements from 10 to 40 kHz and from 10 to 150 kHz were extracted, from plates with cracks present between 3 and 40 mm distance from the PWAS, and from undamaged plates. With the four most pronounced frequency features from spectra between 10 and 40 kHz, damage classification was successfully performed, but damage localization was unsuccessful, requiring more peaks. For the second frequency range, 22 frequencies were needed to determine the crack distance.

Selva et al. [19] also developed a damage localization PNN from spectra of a finite element modeled Carbon Fiber-Reinforced Polymer (CFRP), with three piezoelectric sensors. For each model, a damage foci replicated an impact damage typical from a drop-weight apparatus, with a mass of 2 kg and kinetic energy of 20 J. Inputs based on both the real and imaginary components of the electrical impedance, $\text{Re}(Z_e)$ and $\text{Im}(Z_e)$, respectively, were considered. The trained PNN could accurately locate a 600 mm² damage, but could not do the same for damage with 225 mm² of area, since the damaged surfaces had a larger area.

Another type of Neural Network being used is the Convolutional Neural Network (CNN), such as in the case of Oliveira et al. [20], who trained a CNN to detect one of three different damage foci in an aluminium plate. The developed CNN yielded a 100 % accuracy in the testing phase after three epochs of training. More recently, Li et al. [21] used CNN models to both determine the presence of damage in a concrete block, and determine the temperature at which the measurements were performed. Given the task at hand, an orthogonal matching pursuit method was used to have a high amount of input with a comparatively low set of measurements. The developed models had better accuracy in predicting the temperature at which the measurements were done, but a good accuracy was also obtained in the task of damage detection. Nguyen et al. [22] developed various CNN models to tackle damage detection in reinforced concrete girder, with various levels of pre-stress, showing excellent performance, when compared to conventional damage metrics. Zhu and Wang [23] also propose a CNN model approach to determine shrinkage of concrete beams, which shows better results when compared to damage metrics, despite the fact that a huge dataset is required, which is impractical in aerospace, civil and mechanical engineering applications. Sapidis et al. [24] also proposed a one-dimensional CNN model to monitor concrete components under compressive loads.

Traditional Feed-Forward Neural Networks (FFNN) are also employed in EMIS damage monitoring. For instance, He et al. [25] trained a FFNN model for damage detection, localization and quantification in a truss structure, where loosened bolts corresponded to a sort of stiffness loss damage. Computed Root Mean Square Deviation values, $RMSD$, for various subspectra, were used as input, while the model output would indicate the damage location and severity. Note that the $RMSD$ is defined as

$$RMSD = \sqrt{\frac{\sum_{j=1}^n (\text{Re}(Z_e) - \text{Re}(Z_e^0))^2}{\sum_{f=1}^n \text{Re}(Z_e^0)^2}} \quad (2)$$

where $\text{Re}(Z_e)$ and $\text{Re}(Z_e^0)$ correspond, respectively, to the real electrical impedance components of the signal under evaluation, and of a reference/pristine measurement. Ai et al. [26] initially performed measurements from concrete cubes with and without cracks of specific depths. The impedance measurements were then passed to a Principal Component Analysis (PCA) model, and the eight first components were then used to train a FFNN model for crack detection. Min et al. [27] performed multi-damage detection in both metallic structures, as well as in a bridge, with FFNN models, where data from specific frequency sub-ranges was performed. This approach enabled not only damage detection, but also damage size.

While much focus exists on the use of different types of Neural Networks for EMIS-based structural monitoring, other algorithms have been used. An early example is the auto-regressive machine learning model proposed by Park et al. [28], with exogenous frequency domain inputs, for damage identification in

structures. Rabiei et al. [29] inputted spectra from various piezoelectric elements, that were placed on an aluminium bridge, onto Gaussian kernels, enabling the creation of damage maps for location of damage. With an Analysis Of Variance (ANOVA) study based on Tukey’s multiple comparison tests, Gonzalez et al. [30] were able to locate loosened bolts in an aluminium aeronautical panel, despite the fact that the researchers first needed to determine the best impedance frequency bandwidth. More recently, Parida et al. [31] performed a preliminary regression-based study, where various ensemble models, e.g., XGBoost, Decision Tree, SVM, etc., were used to predict impedance measurements from steel bars.

Damage detection in adhesively bonded structures is noteworthy complex, given the various types of possible damage in the adhesive layer [7, 32, 33]. Durability of structural adhesives may incur in the creation of damage, such as fatigue cracks, or loss of stiffness due to hygrothermal aging [34, 35, 36]. Industrially adopted NDT methods are ineffective in adhesive defect detection [37, 38, 39], while SHM methods, such as the EMIS method [40], are conversely more robust in this same task [2, 4, 41]. Most research dedicated to the EMIS-based integrity monitor of structural adhesives makes use of damage metrics, such as the *RMSD* [42, 43]. For instance, Tenreiro et al. [14] compared various commonly used damage metrics, and developed new ones which made use of the active impedance [44], known to be more sensitive to changes in material properties, for void detection in adhesive Single Lap Joints (SLJ).

Very few works are published on the use of machine learning algorithms for EMIS-based damage detection in structural adhesives. Rautela and Bijudas [45] trained FFNNs to detect damage in structural adhesives. Two FFNNs were developed, one using data from numerical simulations, and another using measurement results. In both cases, adhesive joints either had a void in the adhesive layer or in the adhesive bonding the PWAS to the upper substrate. The neural networks accurately estimated the void size in the sensor adhesive layer, but more data was required to determine the void size of the structural adhesive.

This paper presents the development of two different k -Nearest Neighbors (k NN) classification approaches. The first approach is the conventional classification method, where peaks from the resistive impedance component are extracted and are inputted to a classifier for damage detection or damage quantification. A second approach is also studied here, where, initially, several peaks are extracted from the real component of the impedance spectra, $\text{Re}(Z_e)$. Afterwards, each set of peaks are given to the k NN classifiers for damage detection or damage quantification. To the best of the authors knowledge, this second approach, which is referred to as parallel k NN, ensemble k NN, or k NN per peak, has yet to be put forth in the SHM field. These two approaches were tested for two different tasks: (i) damage detection, i.e., determining if the peaks originate from adhesive joints without damage or with artificial voids, and (ii) damage quantification, i.e., determining the size and placement of the void.

In this manner, Section 2 describes the SLJ manufacturing, instrumentation and measurement procedures, while Section 3 describes the feature selection and the algorithmic approach based on the k NN classifier. Afterwards, Section 4 discusses the obtained algorithmic results and Section 5 details the conclusions of this research.

2 Experimental Details

2.1 Materials, Manufacture & Instrumentation

The SLJ specimina consist of 6082 aluminium alloy adherends, with a thickness of 2 mm, which were joined with the Nagase T-836/R-810 crash-resistant adhesive. Chemically, this is a one-part modified epoxy adhesive, which is manufactured by Nagase ChemteX® (Osaka, Japan) specifically for structural component joining in both automotive and aeronautical applications. The curing cycle of this crash-resistant adhesive is of 3 hours at a set temperature of 160°C. Table 1 presents the relevant elastic and damping properties of both materials, where E , ν , ρ and η are the Elasticity Modulus, Poisson’s Coefficient, mass density and loss factor of the materials.

Table 1: Properties of the adhesives and adherend used in SLJ manufacturing [5].

	E [GPa]	ν [-]	ρ [kg m ⁻³]	η [-]
Aluminium Al 6082	70.0	0.33	2710	$5.0 \cdot 10^{-4}$
Nagase T-836/R-810	2.55	0.41	1200	0.10
Plexus MA 422	0.994	0.31	960	0.45

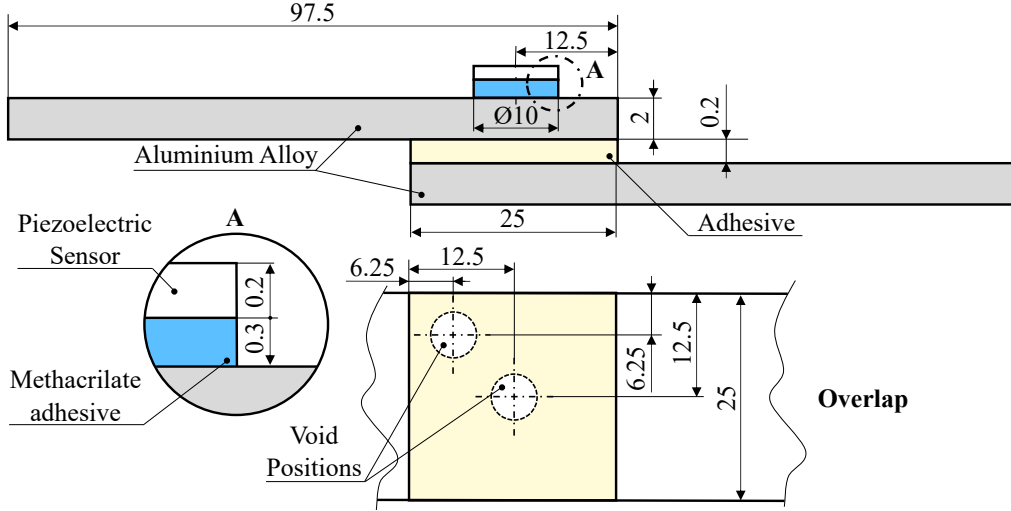


Figure 1: Schematic representation of a SLJ specimen (with dimensions in mm).

Initially, the substrates were gritted with sandpaper, and anodized as per the Phosphoric Acid Anodization procedure of standard ASTM D 3933-98 [46]. As such, the aluminium substrates were immersed in a chemical solution of 10 % phosphoric acid and 90 % distilled water (m/m), and an electrical current, generated by a voltage source of 16 V, passed through these substrates, for 25 minutes. Afterwards, the substrates were removed from the chemical solution and rinsed with distilled water and acetone.

Before adhesive deposition, artificial voids were created by placing Polytetrafluoroethylene (PTFE) infills in the overlap region, which have a diameter, $\varnothing_v$, of 4, 6 or 8 mm, and were positioned either in the middle, or in the corner of the overlap, as per Figure 1, with the help of a cyanoacrilate adhesive resistant to high temperatures ($T_{\text{service}} = 200^\circ\text{C}$). After this, the manufacturing mold, with the SLJs, was placed in a hot press, in order to perform the aforementioned curing cycle.

After the manufacture, a second undesired source of damage was observed, as described in [40]. Therefore, the real void present in the adhesive layer may be somewhat larger because of the added effect of this second source of damage, which the authors believe was due to an unwanted reaction between the modified epoxy adhesive and the cyanoacrilate adhesive. However, the damaged area of the adhesive should be fundamentally created by the circular void.

Table 2: Properties of the soft piezoceramic material PIC 255.

ρ [g cm ⁻³]	Elastic compliance coefficient		Coupling factor		$\frac{\varepsilon_{33}^T}{\varepsilon_0}$ [-]
	s_{11}^E [m ² N ⁻¹]	s_{33}^E [m ² N ⁻¹]	k_p	k_t	
7.80	$16.1 \cdot 10^{-12}$	$20.7 \cdot 10^{-12}$	0.62	0.47	1750

In the next stage, PRYY + 1119 piezoelectric sensors, of dimensions indicated in Figure 1, and fabricated by PI Ceramics (Lederhose, Germany), were used to instrument the SLJs. These PWAS are made of the PIC 255 piezoceramic, which is a modified Lead Zirconate-Lead Titanate material that has a high Curie temperature ($T_c = 350^\circ\text{C}$), and whose material properties are listed in Table 2. Here, ρ and $\frac{\varepsilon_{33}^T}{\varepsilon_0}$ correspond to the mass density and the relative permittivity in the polarization direction, respectively. Variables k_p and k_t represent the coupling factor for the planar radial oscillation and of the thickness oscillation of a round disk, respectively. The PWAS was fixed on the upper adherend, in the center of the overlap, with the help of Plexus MA 422, a methacrylate adhesive manufactured by ITW Performance Polymers (Chicago, Illinois, United States), which was manually mixed, with a curing cycle of 24 hours at room temperature, and whose mechanical properties are indicated in Table 1. Before this second curing procedure, a spiral copper wire, with approximately the same diameter as the PWAS, was placed under said sensor. This spiral copper wire also helps to guarantee parallelism between the sensor and the upper substrate. After the cure of the methacrilate adhesive, a second wire was soldered on the top surface of said sensor.

2.2 Measurement Procedures

The electrical impedance of the PWAS instrumented specimina was measured with a Hioki IM 3570 impedance analyzer (Ueda, Japan), with clamps fixing both extremities of the SLJs, thus guaranteeing similar boundary conditions for the measurements. These impedance measurements were performed for three frequency ranges: (i) $f \in \{1, 1000\}$ [kHz], with linearly spaced sampled frequencies, (ii) $f \in \{1, 1000\}$ [kHz], with logarithmic spaced frequencies, and (iii) $f \in \{100, 1000\}$ [kHz], with linearly spaced sampled frequencies. Each measurement yielded 801 frequency points.

The measured impedance values were initially expressed with polar coordinate values, i.e., impedance modulus, $|Z_e|$, and phase, $\arg(Z_e)$. These values were converted to real and imaginary components, $\text{Re}(Z_e)$ and $\text{Im}(Z_e)$, respectively, and the real electrical impedance component, $\text{Re}(Z_e)$, was used as input for the models used herein. The imaginary component, $\text{Im}(Z_e)$, was not used in this work, given that it is predominantly defined by the permittivity of the piezoceramic material, ϵ_{33}^T , thus being virtually insensitive to any mechanical alteration [4, 14, 44].

The impedance measurements were analyzed in references [14] and [40] as to evaluate and understand the influence that voids, in the adhesive layer, have on EMIS-based impedance measurements, and consequently, on the feasibility of detecting and acquiring knowledge of the detected damage.

3 Algorithmic Approach

In this section, the feature selection process is described and the algorithmic approach, based on the k -Nearest Neighbors (k NN) classification model, is presented, in order to perform damage detection and localization.

3.1 Feature Selection

An approach in the development of Machine Learning models is to use *raw* data - in this case, impedance measurements - for the training and testing of models. While this may be a viable approach for some cases, it will most likely hinder the effective development of models, due to the *Curse of Dimensionality* [47]. In this case, since the measurements have high dimensionality, the required database for model development should contain a high amount of measurements, i.e., high amount of instrumented specimina. Furthermore, complex models are needed to extract patterns from the measurements, which, in turn, requires high computational power, which may not be practically feasible in an SHM-based methodology.

In this sense, feature selection is required, and, is separated in two steps: (i) measurement uniformization in a frequency range, and, (ii) peak extraction from the real component of the impedance measurements, $\text{Re}(Z_e)$.

For the first step, all of the experimentally obtained measurements were read by a Python 3 script, and were processed so that one can obtain spectra from 1 kHz to 1 MHz. In this manner, the following experimental measurements can be used in the aforementioned methodology: (i) $f \in \{1, 1000\}$ [kHz], with 801 linearly spaced sampled frequencies, and (ii) $f \in \{1, 1000\}$ [kHz], with 801 logarithmic spaced frequencies.

These two sets of measurements contribute with 42 effective instances, and more information can be presented in the third impedance measurement, as described in subsection 2.2. Therefore, various combinations of the three experimental spectra were done for each SLJ, such as (iii) the combination of the linearly spaced impedance measurements in the range of $f \in \{1, 1000\}$ [kHz], and the logarithmically spaced impedance measurements in the same frequency range, (iv) the combination of the linearly spaced impedance measurements in the range of $f \in \{1, 1000\}$ [kHz], with the linearly spaced impedance measurements in the range of $f \in \{100, 1000\}$ [kHz], (v) the combination of the logarithmically spaced impedance measurements in the range of $f \in \{1, 1000\}$ [kHz], with the linearly spaced impedance measurements in the range of $f \in \{100, 1000\}$ [kHz], and (vi) the combination of all three experimentally obtained impedance spectra. With this, a total of 126 instances are obtained.

With this, the peak extraction process began with an iterative process of extracting the peak information. In this manner, a SciPy module function [48] initially extracted the peaks of $\text{Re}(Z_e)$ with a height of 10Ω , a minimum width of 2 sampled points, and a prominence of 0Ω , and then the height and prominence values were iteratively incremented, until reaching the desired number of peaks. Note that height is the vertical distance between the peak value and the reference value of no resistance, i.e., $\text{Re}(Z_e) = 0 \Omega$, while the prominence is the vertical distance between that same peak and the lowest

contour line, i.e., the local minimum between the peak being extracted, and the higher peaks on both sides. If the list of extracted resistive peaks has a smaller number of peaks than the manually inputted value, the width criterion becomes lax, and the peak extraction routine reruns in order to find all peaks with a minimum width of 1 sampled point. Afterwards, with this initially obtained list of peaks, the minimum required height and prominence values are iteratively incremented, until reaching the desired number of peaks, as defined by the user.

Given that the direct measurements have 801 sampled frequencies, and that the combination of measurements have more sampled frequencies, the authors decided to perform a range of computational experiments, thus extracting between 3 and 25 resistive peaks, and their respective frequencies. Note that, for damage detection, no more than 20 peaks were extracted, since more peaks did not lead to any change in classification performance.

Figure 2a presents an example of the aforementioned feature selection process, where ten peaks are to be extracted from a linearly sampled impedance measurement from a SLJ with an 8 mm diameter void in the corner of the overlap. Figure 2b presents two plots of the same measurement, comparing the initially extracted resistive peaks and the final set of impedance peaks to be used in the k NN models.

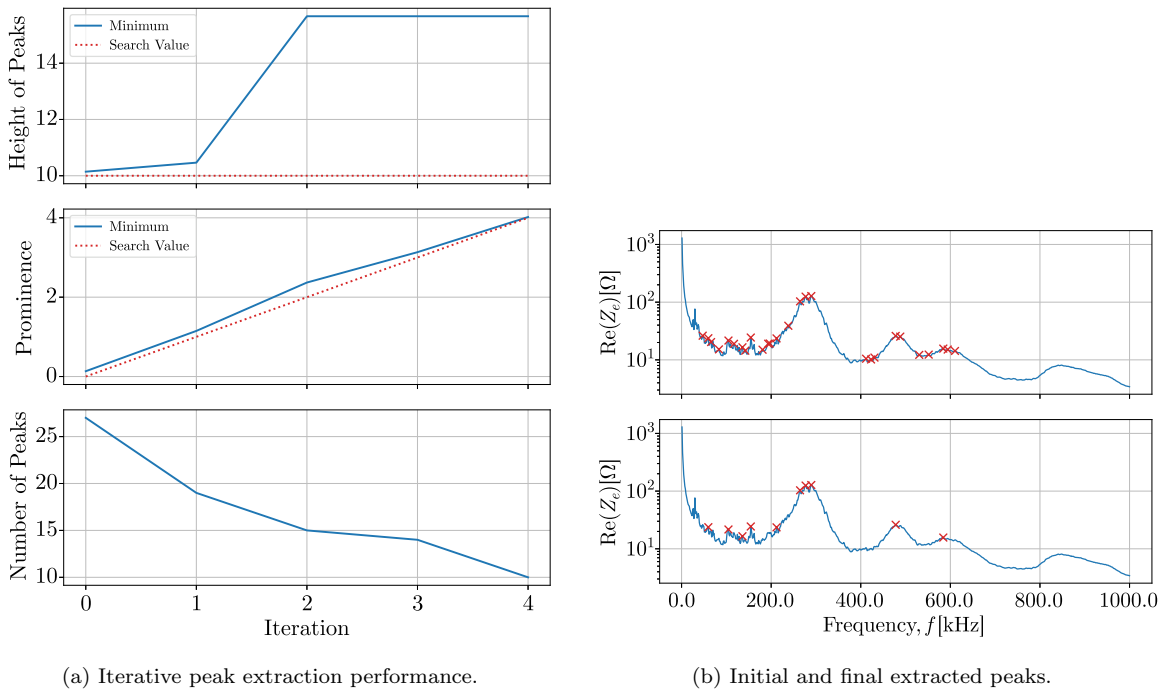


Figure 2: Plot comparing the number of extracted resistive peaks, the minimum height and prominence values of the extracted peaks, and the set height and prominence values, as a function of the iteration.

3.2 k -Nearest Neighbors Models

In this paper, the k NN classification algorithm is used to perform two different classification tasks. Firstly, it is used to perform the damage detection task, and therefore, this model separates all instances into two different classes, which are the *No Void*, and the *Void* classes, which correspond to measurements from joints without damage, and with a void in the overlap, respectively.

In the second approach, the k NN model performs the task of damage differentiation, i.e., the task of classifying the type of void being detected. Here, three different classes exist, where the classes *Small Voids (Corner)* and *Small Voids (Middle)* contain impedance readings from joints with voids of diameter of 4.0 or 6.0 mm, either in the corner or in the middle of the overlap. The class *Large Voids* contains measurements from SLJs with an 8.0 mm diameter void that is placed either in the middle, or in the corner of the overlap. Note that the instances from the *No Void* class are disregarded for this task. However, similar results are obtained if these are considered for a fourth class. Figure 3 schematically presents the various classes for both problems at hand.

These classes of damage instances were defined since previous results show that there is more difference between damage position for small voids, i.e., $\emptyset_v$, of 4 and 6 mm, respectively. Conversely, SLJs with voids

of 8 mm diameter occupy a comparatively bigger area of the overlap, since there is some area overlap if one considers the area of each specific damage in the overlap of the adhesive joint. This possible intersection of damaged areas, for this class of void, may ease on the proportion of damage, but not on its location. In this manner, the first classification task may perform the first level of damage characterization as per the hierarchical approach to damage knowledge first proposed by Rytter [49, 50], which is damage detection. However, this second task, labeled as damage differentiation, blurs information from the second SHM level of knowledge, which is damage localization, with the third level, which is damage extent. This can be well correlated with the fact that damage in the corner of the overlap hinders significantly more the mechanical performance of the adhesive, possibly leading to premature failure [51].

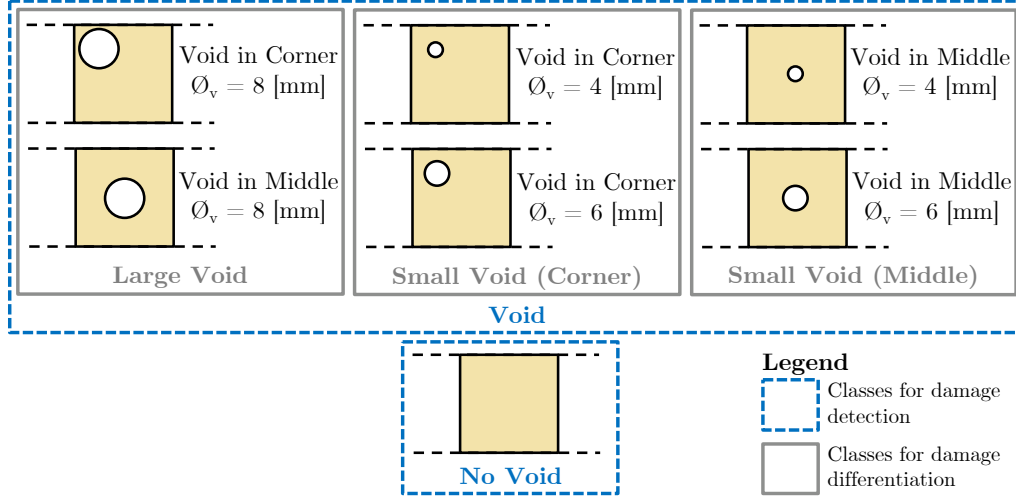


Figure 3: Dataset class definition for k NN classification.

With both the feature selection and class definition process achieved, two different algorithmic methodologies were adopted. The first k NN-based methodology involved the conventional use of the k NN model. In this manner, the n extracted peaks are joined to create an array of peaks, $\mathbf{V}_m$, for a specific measurement instance m , such that

$$\mathbf{V}_m = [\text{Re}(Z_{e,m})_1, f_{m,1}, \text{Re}(Z_{e,m})_2, f_{m,2}, \dots, \text{Re}(Z_{e,m})_i, f_{m,i}, \dots, \text{Re}(Z_{e,m})_n, f_{m,n}],$$

where $\text{Re}(Z_{e,m})_i$ and $f_{m,i}$ correspond, respectively, to the i -th extracted resistive peak of the impedance measurement, and to its respective frequency. Note that n is the number of extracted peaks, such that $n \in \{3, 25\}$, as previously mentioned, and i is one of the n extracted peaks, such that $i \in \{3, n\}$.

With this, the dataset was divided into a training subset, which contains 75% of the original dataset, while the testing subset contains the remaining instances. Note that this dataset separation was stratified, i.e., the dataset splitting into training and testing subsets was done so that the relative proportion of classes was maintained, given the large unbalance between the various classes. From this, the training subset is inputted to the k NN model, which is stored for posterior classification. Afterwards, each element of the testing subset is inputted to the k NN model, which will try to find the k nearest neighbor instances from the training subset. With this, the testing instance will be classified according to a majority vote, i.e., according to the highest presence of a given class. If a tie occurs, the nearest neighbor defines the class of the testing instance [47]. Figure 4a schematically presents the aforementioned algorithmic method.

The second developed k NN-based algorithmic approach starts in the definition of the features instances. Indeed, the same n peaks and their respective frequencies are extracted from the real component of the impedance spectra. However, the extracted information is stored in a list of sub-arrays, where each sub-array contains the information of peak i , or, in mathematical terms,

$$\mathbf{V}_m = [(\text{Re}(Z_{e,m})_1, f_{m,1}), (\text{Re}(Z_{e,m})_2, f_{m,2}), \dots, (\text{Re}(Z_{e,m})_i, f_{m,i}), \dots, (\text{Re}(Z_{e,m})_n, f_{m,n})],$$

where $n \in \{3, 25\}$, $i \in \{3, n\}$, and where $\text{Re}(Z_{e,m})_i$ and $f_{m,i}$ are the i -th resistive peak and to its respective frequency, respectively. Similarly to the previous case, 75% of the original dataset becomes the training subset, while the remainder is stored in the testing subset.

Afterwards, the k NN model is initialized for classification. However, unlike in the previous case, where only one model is instantiated, n models are instantiated, one for each extracted resistive peak.

In this manner, the first k NN model is initialized with the array of extracted peaks from all instances of the training subset, and then, each sub-array of the testing subset is given to said k NN algorithm for classification. Afterwards, the same procedure is done for the second set of sub-arrays, corresponding to the second extracted peak, and so on, until reaching the n -th peak, and respective set of sub-arrays. Figure 4b presents this second algorithmic method. Note than, when there is a tie in the ensemble classification, the closest peak is extracted from all individual k NN models, and a second ensemble-based classification is determined according to the classes of said instances.

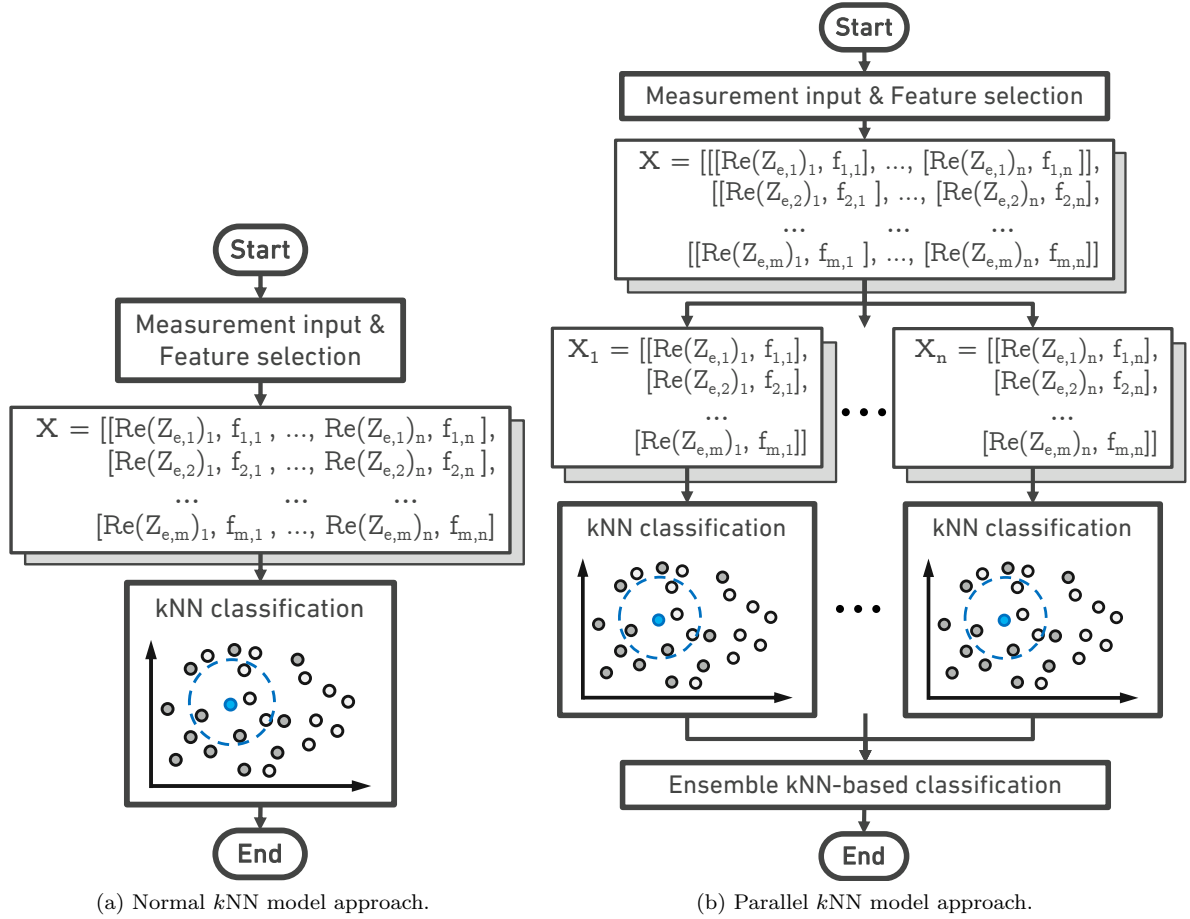


Figure 4: Schematic representation of the different k NN-based algorithmic approaches.

3.3 Distance Functions

In order to determine the k nearest neighbors of new data instances, to enable classification, one needs to compute the distance between each pair of instance points. For this, three different distances, $\{\delta_C, \delta_E, \delta_M\}$, were adopted to evaluate the proximity between each pair of instances. These are the Canberra distance, δ_C , the Euclidean distance, δ_E , and the Manhattan distance, δ_M , and are defined by

$$\delta_C = \sum_{f=1}^n \frac{|\text{Re}(Z_{e,i}(j\omega_f)) - \text{Re}(Z_{e,k}(j\omega_f))|}{|\text{Re}(Z_{e,i}(j\omega_f))| + |\text{Re}(Z_{e,k}(j\omega_f))|}, \quad (3)$$

$$\delta_E = \sum_{f=1}^n [\text{Re}(Z_{e,i}(j\omega_f)) - \text{Re}(Z_{e,k}(j\omega_f))]^2, \quad (4)$$

$$\delta_M = \sum_{f=1}^n |\text{Re}(Z_{e,i}(j\omega_f)) - \text{Re}(Z_{e,k}(j\omega_f))|, \quad (5)$$

The authors would like to point out that, while these distances were studied for this work, only the main results are presented, in order to avoid redundancy. Furthermore, these three distances are

just a small subset of various distances that can be used, and could only be chosen with the help of experimentation [52].

3.4 Classification Metrics

In order to evaluate the performance of a classification algorithm, one needs to compute evaluation metrics. The most common metric for such a task is the accuracy, Acc , which is defined as

$$Acc = \frac{\sum_{j=1}^c tp_j}{M}, \quad (6)$$

where M is the number of instances, or, in other words, the number of measurements (both direct and combined), while tp_j are the number of true positives of class j , where $j \in \{1, 2, \dots, c\}$, respectively. This corresponds to the number of instances being correctly classified as being of class j .

This metric can be visualized with the help of a confusion matrix, which is exemplified in Figure 5. In it, one sees that the main diagonal contains the number of true positives, tp , and true negatives, tn , of class *No Void*, or, in other words, all of the correctly predicted elements. Furthermore, the false positive counts, fp , of class *No Void* are the number of instances being incorrectly predicted as belonging to that class, which in this case, are 3, while the number of false negative instances, fn , of the *No Void* label, i.e., the number of incorrect predictions for this class, is 1.

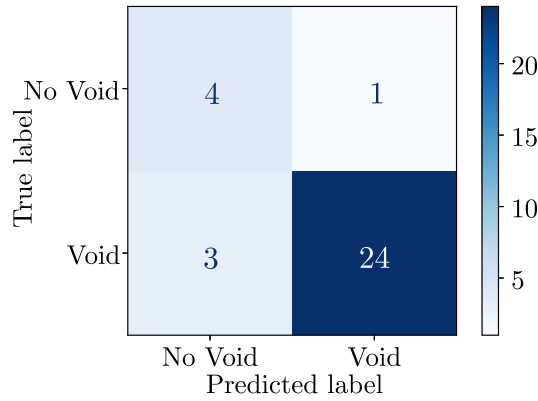


Figure 5: Example of Confusion Matrix.

These definitions are very important to define other statistics and metrics that enable a better evaluation of a given machine learning classification model, such as the F_1 -Score of class j , which is defined as

$$F_{1,j} = \frac{tp_j}{tp_j + \frac{(fn_j + fp_j)}{2}} = 2 \frac{Pr_j Re_j}{Pr_j + Re_j}, \quad (7)$$

where Pr_j and Re_j stand, respectively, for the Precision and Recall metrics of class j . The Precision metric is the fraction of instances being labeled to j class and that actually belong to that class, i.e., $Pr_j = \frac{tp_j}{tp_j + fp_j}$. Concurrently, the Recall is the fraction of j class instances that are actually classified as such, or, in mathematical terms, $Re_j = \frac{tp_j}{tp_j + fn_j}$.

Precision and Recall offer a trade-off, since a high Precision means that the classifier becomes increasingly restrictive in classifying instances of j class, having then a low count of false positives, fp_j . This however, may force the classifier model to impose such restrictions that some of the j class instances may be misclassified, increasing the false negative counts, fn_j , and the Recall. Therefore, the F_1 -Score can correlate this phenomenon, and, by maximizing it, one is maximizing both Precision and Recall [47].

4 Classification Results

This section presents the results obtained for the two different classifier models described in subsection 3.2, for both the damage detection task and damage differentiation task, presented in Figure 3. In this manner, subsection 4.1 presents the damage detection classification results when using the conventional

k NN algorithm, while subsection 4.2 discusses the obtained results when using the parallel (or ensemble) k NN classifier approach. Finally, section 4.3 presents the performance of both conventional and parallel k NN models in classifying the type of detected damage. For this last section, only the most representative cases are shown for brevity.

4.1 Damage Detection with Conventional k NN Model

This subsection presents the results of the damage detection task with the use of conventional k NN classifiers, as presented in Figure 4a. This subsection is divided into three different parts, where each will present the classification results and performance (i.e., damage detection), for each of the three different distances mentioned in subsection 3.3.

4.1.1 k NN using the Euclidean distance

Figure 6a presents the average accuracy for each combination of number of extracted resistive peaks, n , and number of k -instances for classification, while Figure 6b presents the average F_1 -Score for the *No Void* class. Note that, for each case, 25 different k NN models were instantiated, where each model has a different splitting of the dataset into label stratified training and testing subsets. These plots are complemented with topographical curves that help understand the color gradient.

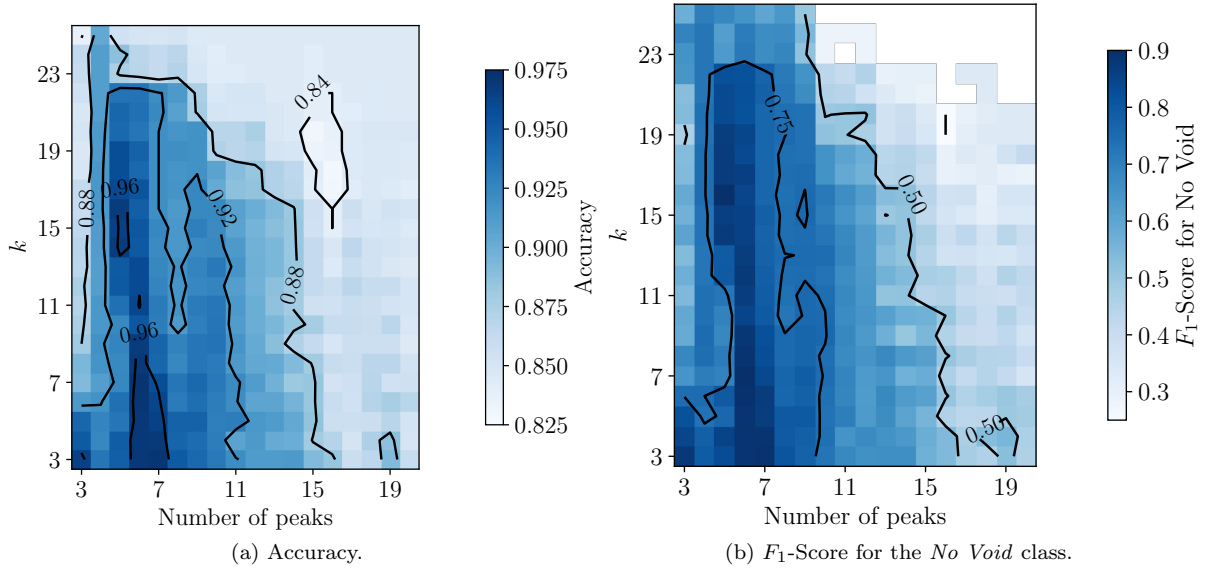


Figure 6: Average performance of the normal k NN models for damage detection, when using the Euclidean distance to determine the k -Nearest Neighbors.

Analyzing the plot of Figure 6a, one sees that, initially, with the increase of the number of peaks, and, consequently, with the increase of the number of features, one has an increase of the model accuracy, reaching a maximum mean accuracy of more than 0.96, either for 6 or 7 extracted peaks and a small number of k -instances ($n = 6 \wedge 3 \leq k \leq 11$, $n = 7 \wedge 3 \leq k \leq 7$), or for input arrays with information from 5 peaks, and where the k NN model uses 14 to 16 instances for classification ($n = 5 \wedge 14 \leq k \leq 16$). However, afterwards, with the increase of extracted peaks, n , the accuracy decreases. For instance, when $n > 11$, the mean accuracy is always below 0.92, and when $n > 15$, the average accuracy is below 0.88, except for a small pocket of instances, where $k < 5$ and $n = 19$.

Note also that Figure 6a demonstrates that, for a high number of k instances for classification, the accuracy decreases. For a low number of peaks, i.e., $n < 8$, there is a sharp decrease of the classifier accuracy when using a large number of neighbors, $k \geq 22$. However, in a mid-range of extracted peaks, or, mathematically speaking, $8 \leq n \leq 15$, one sees that the accuracy *border* of 0.88 no longer remains static for high number of k -neighbors, as seen in the contour line of Figure 6a.

The mean F_1 -Score for the *No void* class, visualized in Figure 6b, presents a similar pattern, where, for most of the k values, the F_1 -Score increases until reaching a maximum of approximately 0.9, when extracting 6 to 7 peaks, and then this metric decreases, reaching a value of 0.3 to 0.4, when extracting peak information at $n \in \{18, 20\}$. Also, similarly to the accuracy, the F_1 -Score decrease with the increase

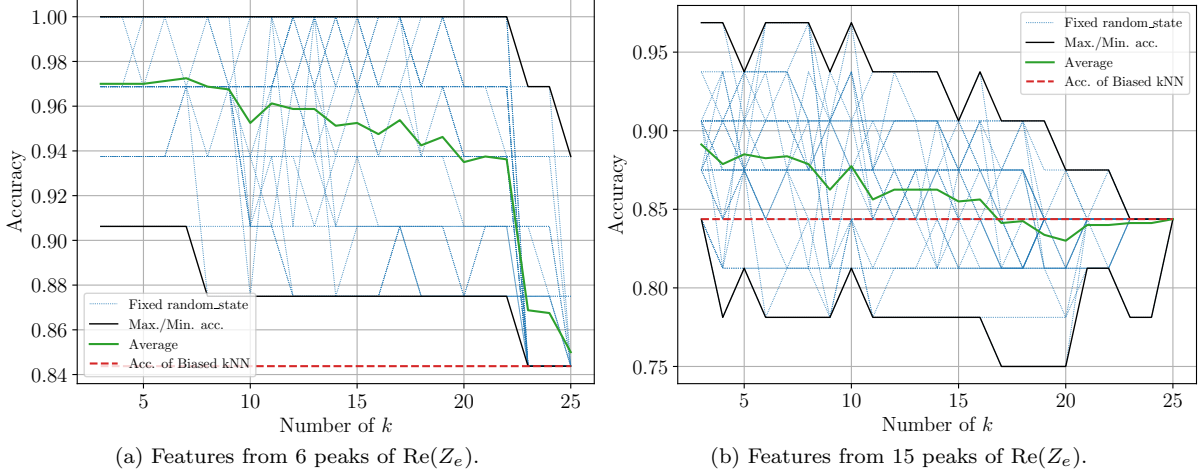


Figure 7: Accuracy performance of the k NN classifiers as a function of the k -Nearest Neighbors models that use the Euclidean distance.

of the number of nearest neighbors used for classification. However, this decrease is, comparatively speaking, not as sharp as for the accuracy.

Figures 7a and 7b plot the k NN classifier accuracy of all 25 models, as well as the obtained maximum, minimum and average values, as a function of the k neighbors, when extracting information from 6 and 15 peaks, respectively. Note that, in these plots, the dashed red line corresponds to the accuracy a given model may have, if all instances of the *No Void* class are missclassified as being part of the *Void* class. Furthermore, Figures 8a and 8b show the progression of the F_1 -Score of the *No Void* class with k , when using features from 6 and 15 peaks, respectively.

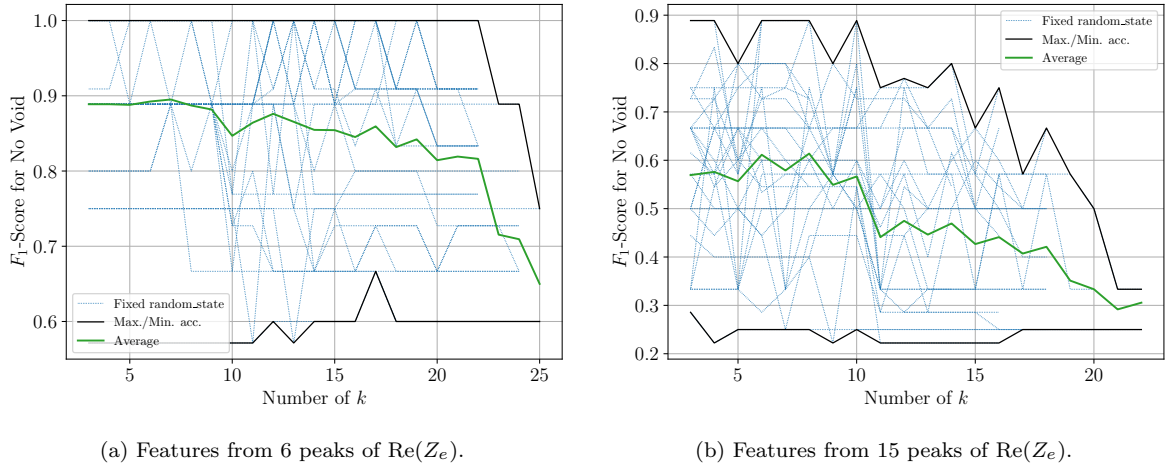


Figure 8: F_1 -Score performance for the *No Void* class of k NN classifiers as a function of the k -Nearest Neighbors models that use the Euclidean distance.

One sees from Figures 7a and 8a, when using information from 6 resistive peaks, the mean accuracy and F_1 -Score remains constant until $n = 10$. Afterwards, the average values start to decrease slightly, due to the fact that the performance of some of the classifiers starts to decrease. However, for $n > 22$, both the mean and maximum values of the accuracy and the F_1 -Score decrease drastically. This occurrence coincides with the fact that some models no longer have F_1 -Scores. In essence, this means that all instances of the *No Void* class are being labeled as *Void*, and thus, one only has false negative instances of the *No Void* class, $fn_{No Void}$.

When observing the plots of Figures 7b and 8b, that represent the performance of the conventional k NN algorithm when extracting 15 resistive peaks, one sees that this trend also occurs. In fact, the F_1 -Score is no longer calculable for some classifiers at $k = 16$, and, for all k NN classifiers, the F_1 -Score

for the undamaged joint instances becomes incalculable, for this specific reason. In this manner, it is reasonable to observe that the average accuracy of the k NN models are approximately 0.84375, which corresponds to the dashed red line of Figure 7b.

Also, from the analysis of Figures 6a and 7b, when $17 \leq k \leq 24$, the mean accuracy of the models reaches values below the aforementioned threshold value of 0.84375, where all instances of the *No Void* class are misclassified. Therefore, this means that some models are misclassifying most, or all instances of the *No Void*, while also labeling some instances of the *Void* class as being instances of undamaged SLJs. Indeed, this is more pronounced when using a large number of neighbors for classification, but occurs in the entire range of k values.

4.1.2 k NN using the Manhattan distance

Figure 9a plots the mean accuracy as a function of the extracted peaks of $\text{Re}(Z_e)$, n , and number of k -neighbors for classification, while Figure 9b presents the mean F_1 -Score for the *No Void* class, as a function of the same parameters. Note that, for each combination of k and n values, 25 different k NN models were instantiated, each model having a different dataset splitting into training and testing subsets. These two plots are complemented with topographical curves to understand the color gradient.

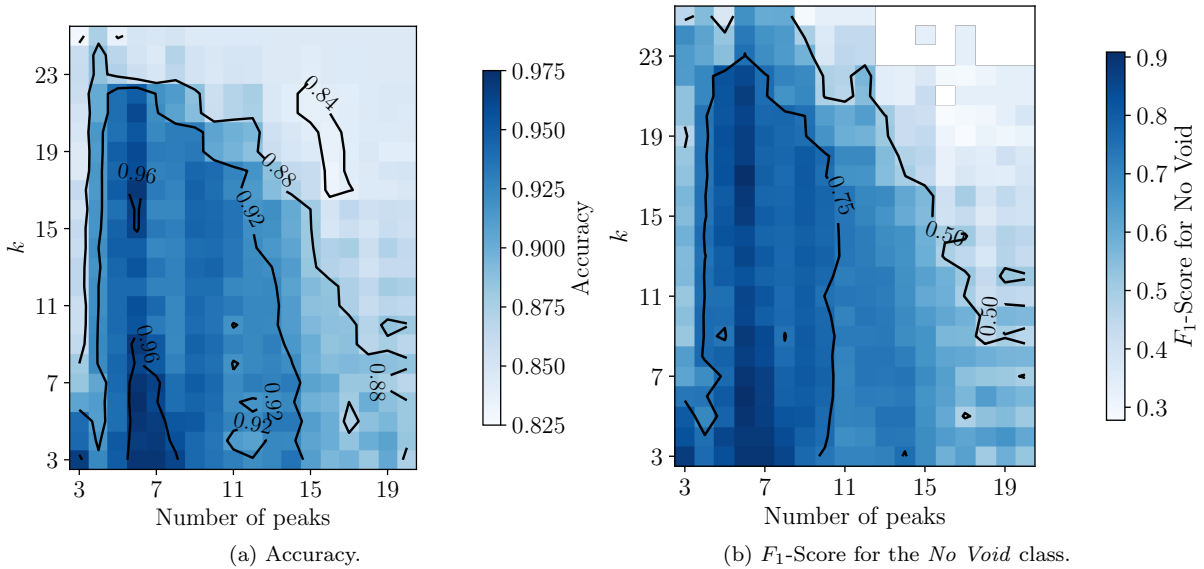


Figure 9: Average performance of the normal k NN models for damage detection, when using the Manhattan distance to determine the k -Nearest Neighbors.

Similarly to the previous case, where the conventional k NN approach with the Euclidean distance was used, one can observe that the accuracy, plotted in Figure 9a, increases with the increase of the extracted information, i.e., with more extracted $\text{Re}(Z_e)$ peaks, until reaching a maximum at around 6 to 7 peaks. Afterwards, as the number of extracted resistive peaks increase, the accuracy of the model slowly starts to decrease. However, unlike in the previous case, this decrease is not as pronounced. Indeed, when feature selection occurs for $n \geq 15$, the average k NN model has an accuracy below 0.88 for all number of k -nearest neighbors (except for $(n, k) = \{(16, 3), (19, 3), (19, 4)\}$). However, this average increases when using the Manhattan distance, to the point that, overall, the average does not decrease below 0.88 when using a low number of k -nearest neighbors. Conversely, for a high number of classification neighbors, k , and for a high number of extracted peaks, n , one still has low accuracy, and, in a sub-region of the hyperparameter domain being studied, the average accuracy is below that of the hypothetical case where all instances of the *No Void* class are being misclassified.

The plot of Figure 9b reveals a similar trend. Indeed, the average F_1 -Score for the *No Void* class, for k NN models using the Manhattan distance, increases with the increase of peaks used for feature extraction, n , reaching a maximum value of approximately 0.9 when $n \in \{6, 7\}$. Furthermore, overall, the F_1 -Score appears to be above 0.75 for a bigger sub-region of the (n, k) hyperparameter domain, when compared with the results from Figure 6b. In this case, one sees that, overall, $F_{1, \text{No Void}}$ is bigger than 0.75, when 5 to 10 peaks are used for feature extraction and selection, except only if a high number of k neighbors is used for damage detection, i.e., $k \geq 24$, for $n = 7$, or $k \geq 19$, for $n = 10$.

One must also consider that, while the decrease of the average F_1 -Score occurs for k NN models when $n > 7$, both with the Euclidean and Manhattan distances, this decrease is less pronounced when using the Manhattan distance. Indeed, for the maximum studied number of peaks, $n = 20$, inputted to the k NN model with the Euclidean distance, the F_1 -Score is below 0.5 for all of the studied k -values. However, when using the Manhattan distance, the average F_1 -Score is consistently below 0.5, when $k > 13$.

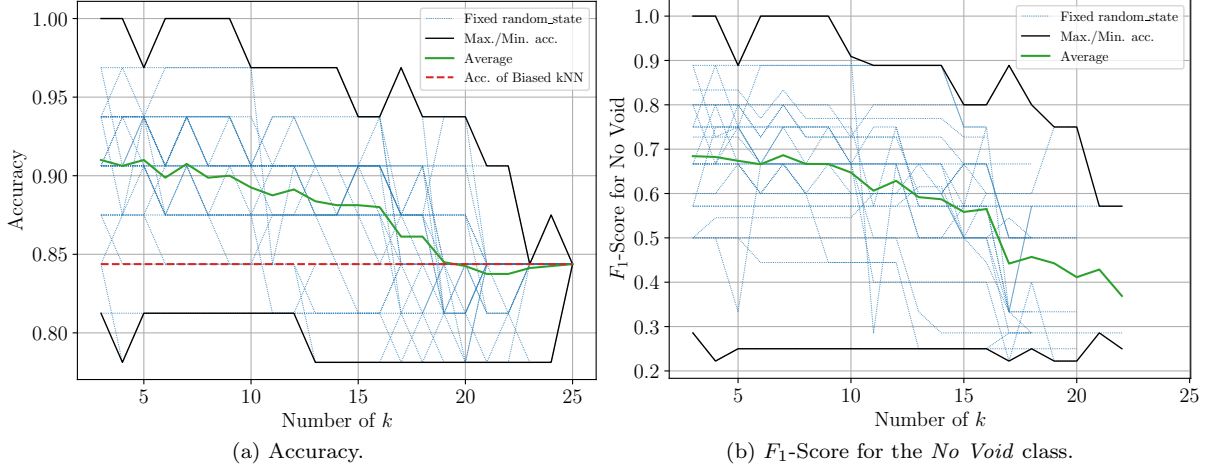


Figure 10: Classification performance of the k NN classifiers, with the Manhattan distance, as a function of the k -Nearest Neighbors, when extracting 15 peaks ($n = 15$).

Figures 10a and 10b plot the Accuracy and the F_1 -Score of the k NN classifier models with the Manhattan distance, when using information from 15 resistive peaks. Indeed, some of the previously mentioned observations for the results of Euclidean distance-based k NN classification, presented in Figures 7b and 8b, are similar. Firstly, the average accuracy gradually decreases, until reaching the threshold value 0.84375, when $k = 19$. Furthermore, some models have an even lower accuracy, no matter the value of k . However, most classifiers have a better accuracy than in the previous case where the Euclidean distance is used to determine the k neighbors. Indeed, for low values of k , i.e., $k < 10$, some models have an accuracy of 1.00, and most models have an accuracy well above the aforementioned threshold value defined in the dashed red line of Figure 10a. This was not the case, when using the Euclidean distance. The F_1 -Score shows a similar trend, since, for small k -values, most k NN models have a better performance values, and, in some cases, $F_{1, \text{No Void}} = 1.0$, and since there is a noticeable increase of the average value. Finally, one must comment that, like in Figure 8b, the F_1 -Score is no longer mathematically calculable for higher number of k -neighbors used for classification. Indeed, no F_1 value can be calculated when 23 peaks or more are used for feature selection, thus reflecting on the fact that the Precision of the undamaged joint instances, i.e., $Pr_{\text{No Void}}$ is indeterminable.

This improvement in performance is noticeable since, with the use of the Manhattan distance, the distance metric enables a better differentiation of what is nearer to the instance being classified, as well as what is further away. This change in apparent distance may occur when the Manhattan distance and the Euclidean distances differ the most, which should occur when the distance between the *as the crow flies* path, and the horizontal path make an angle of approximately 45° .

4.1.3 k NN using the Canberra distance

Figures 11a and 11b display the mean accuracy and F_1 -Score as a function of the extracted peaks, n , and number of k -neighbors for classification. Just like in previous cases, for each set of k and n values, 25 different k NN models were instantiated, each having a different splitting of the dataset into training and testing subsets. These plots are complemented with topographical curves, to improve the visualization.

When using the Canberra distance, a significant increase of the accuracy is observed. Indeed, the aforementioned patterns do occur where the maximum average classification accuracy values occur, either for low values of k and n , i.e., $k \leq 6$ and $n \leq 7$, or for large values of k , when information from 6 resistive peaks are extracted. Furthermore, the average accuracy tends to increase from $n = 3$ to $n = 6$, and then this average value decrease as the number of peaks, used for classification, increases. However, despite this, these increases and decreases are less stark, when compared to the two previously used distances.

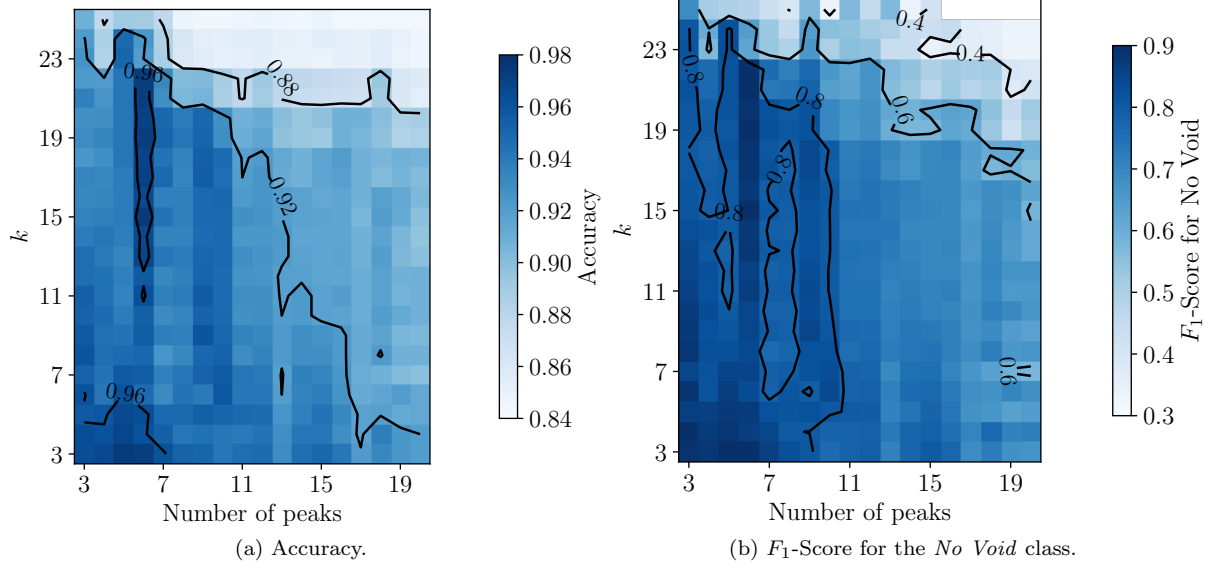


Figure 11: Average performance of the normal k NN models for damage detection, when using the Canberra distance to determine the k -Nearest Neighbors.

This means that, overall, there is less of a difference in classifier performance, between the classifiers near the optimal hyperparameter values, and most of the classifier models instantiated in this case. Indeed, the average performance of k NN classifiers only decreases significantly when a huge number of k instances is used for classification. The average accuracy seems to be below 0.88 when $k > 20$ and $n > 7$.

A similar pattern is also observed for the F_1 -Score that evaluates the classification of *No Void* instances, as seen in Figure 11b. Indeed the maximum values of F_1 appear to occur when 6 peaks are extracted from the impedance measurements, and when a large number of k neighbors is used for classification. While this is similar to the cases where the k NN made use of either the Euclidean or the Manhattan distances, it appears that, for this case, there is some difference between these values and the average accuracy, when k and n are small. Furthermore, it appears that, overall, the F_1 -Score never reaches values above 0.8, when a large number of peaks is used to create and select features, i.e., $n > 10$. Much like with the accuracy, the F_1 -Score has values below 0.6, when a high number of k -neighbors is use for classification. But, conversely to what occurs with the accuracy, this limit does change with the number of peaks, n . For instance, F_1 drops below the 0.6 line for $n = 11$ and $k > 23$, and but, for $n = 20$, it decreases for $k > 17$.

Figures 12a and 12b plot the classifier accuracy of all 25 models, and the maximum, minimum and average values, as a function of the k neighbors, when extracting 6 and 15 peaks, respectively. Note that the dashed red line corresponds to the accuracy of a model that missclassifies all instances of the *No Void* class as being part of the *Void* class. Furthermore, Figures 13a and 13b plot the F_1 -Score of the *No Void* class as a function of k , when using features from 6 and 15 peaks, respectively.

Regarding the accuracy registered in Figure 12a, when $n = 6$, the obtained average accuracy is approximately 0.97 when $k = 3$, but this accuracy decreases as the number of neighbor instances used for classification, k , increases. This occurs since, even though the maximum registered accuracy remains at 1.00, which is the maximum possible, the minimum registered accuracy decreases in the range of $k \in \{3, 10\}$. However, when $k \in \{10, 22\}$, the registered mean accuracy increases to approximately the initial beforementioned value, which coincides with the increase of the minimum registered model accuracy for the respective k . Only after $k = 22$ can one observe that the accuracy of all models starts to decrease drastically towards the limit case where all instances are labeled by the classifier as being part of the *Void* class, but not reaching this value for most models. Indeed this accuracy limit is reached sporadically in this case.

A similar trend is observed for the F_1 -Score, as shown in the plot of Figure 13a. Indeed, a small decrease of the average value occurs in the sub-range $k \in \{3, 10\}$, and then increases gradually from there up to $k = 22$. Afterwards, just like in the case of the mean accuracy shown in Figure 12a, a sharp decrease of $F_{1, \text{No Void}}$ is observed when the k NN classifier makes use of more than 22 instances for classification ($k > 22$). Despite this, the minimum registered F_1 -Score remains constant throughout the whole range

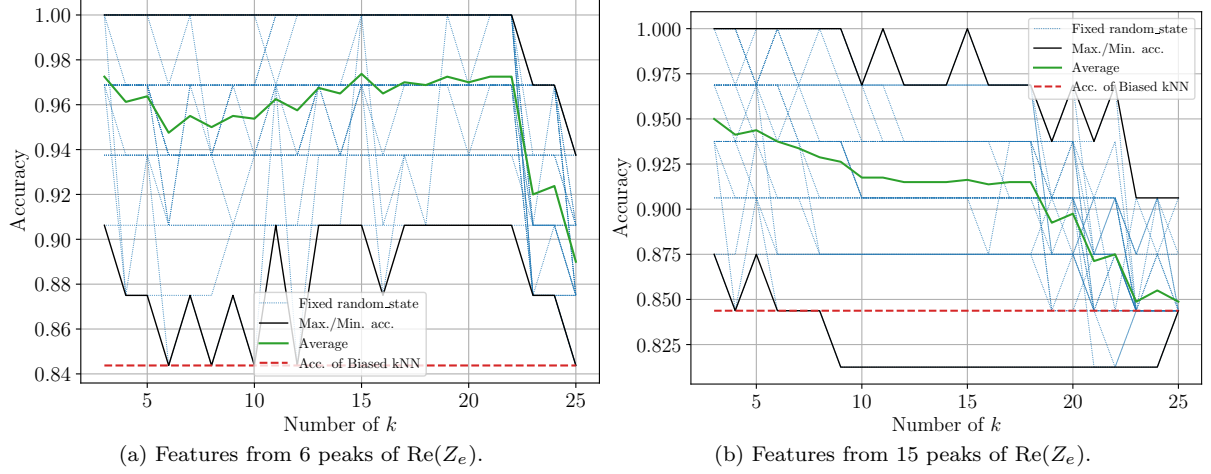


Figure 12: Accuracy performance of the k NN classifiers as a function of the k -Nearest Neighbors models that use the Canberra distance.

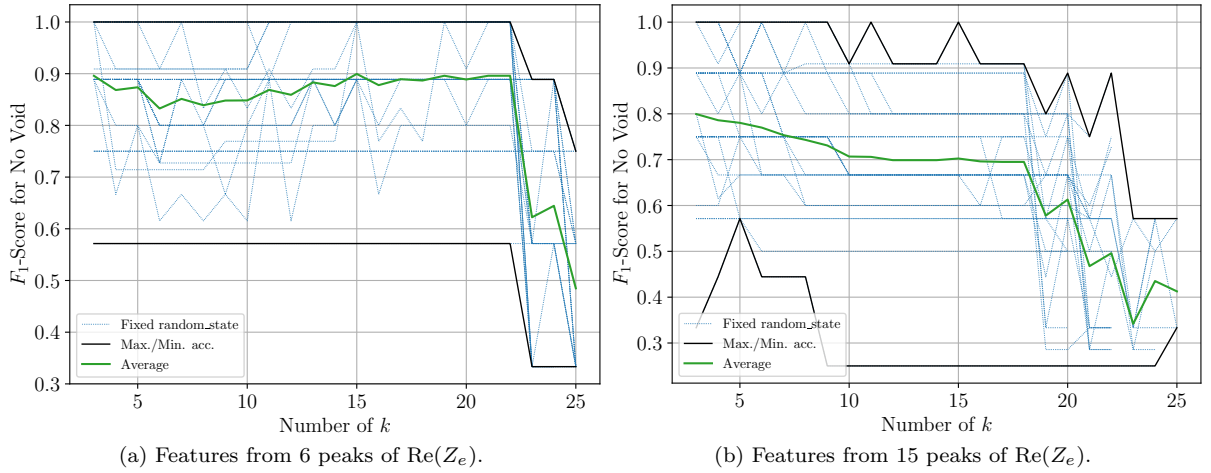


Figure 13: F_1 -Score performance for the *No Void* class of k NN classifiers as a function of the k -Nearest Neighbors models that use the Canberra distance.

of possible k values, except when $k > 22$, where all classifiers start to have a worse performance.

With an increase of the number of peaks used for damage detection, a reduction of the accuracy is noticed, as in the case of Figure 12b, where 15 peaks are extracted from the measurements for classification. In this case, while the average accuracy remains comparatively high, it is still nonetheless lower than the mean accuracy when $n = 6$. Initially, the average accuracy decreases from 0.95 to 0.92, from $k = 3$ to $k = 10$, respectively. This decrease occurs despite the fact that the maximum and minimum registered accuracy in this sub-range remains almost constant. Afterwards, most model accuracies remain almost unaltered between the range of $k \in \{10, 18\}$, and, therefore, the mean value is virtually constant. Only after $k > 18$, does one observe a significant decrease of the mean value, given that the models overall do have a lower performance as the number of neighbors used for classification, k , increase. These observations can be easily transposed to the F_1 -Score plotted in Figure 13b.

Overall, one can check that, when the Canberra distance is used to determine the k -nearest data instances for classification, a significant improvement in classification occurs. Given that the Canberra distance is a normalization of the Manhattan distance, it was to be expected that these k NN models would have a better accuracy in the task of damage detection, when compared to the k NN classifiers that make use of the Euclidean distance. However, a very well known behaviour of the Canberra distance is that it is sensitive to differences near zero [14, 52]. Therefore, it is more than expected that this distance enables the classifiers to differentiate instances of different classes.

4.2 Damage Detection with Parallel k NN Models

This subsection presents the classification results for damage detection with the parallel (or ensemble) k NN classifiers, which are schematically described in Figure 4b. This subsection is divided in two parts. The first part presents the classification performance when the k NN models use the Euclidean distance, and the second part displays the results for the parallel k NN models that use the Canberra distance. The results obtained with the Manhattan distance are not shown here for brevity, since they are similar to the k NN results for the Euclidean distance.

4.2.1 k NN using the Euclidean distance

Figure 14a plots the average accuracy for each combination of the n extracted peaks of the real component of the impedance, $\text{Re}(Z_e)$, and number of k -neighbors used for classification, while Figure 14b presents the average F_1 -Score for the *No Void* class. Like in the previous cases, 25 different k NN models were instantiated for each pair of hyperparameters, (n, k) , where each model used label stratified training and testing subsets. Both plots are complemented with topographical curves, to help visualize the color gradient.

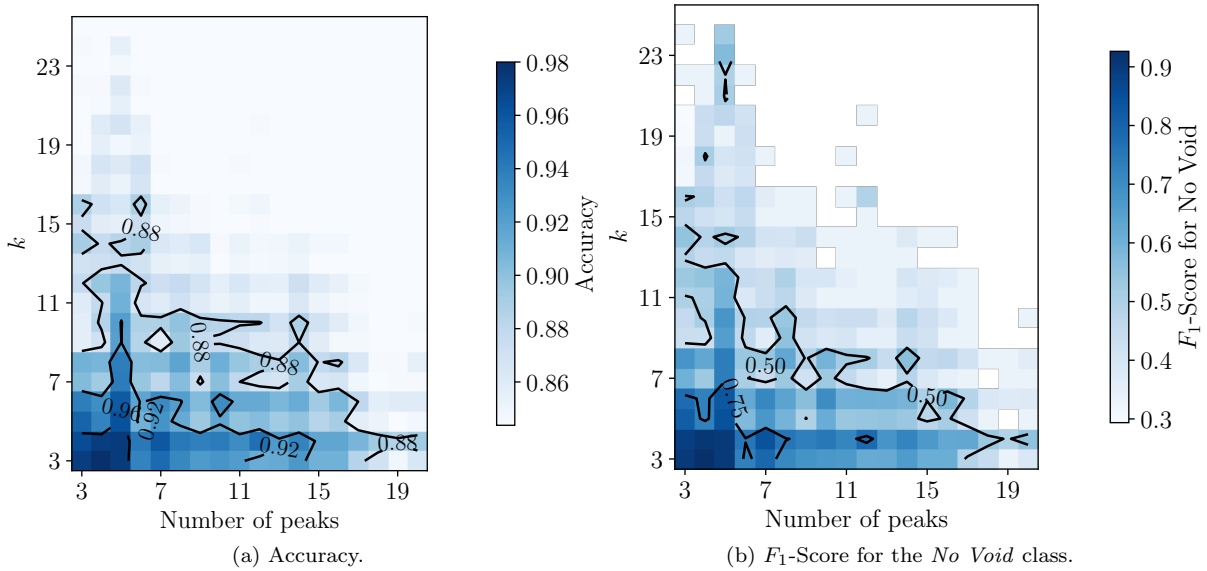


Figure 14: Average performance of the parallel k NN models for damage detection, when using the Euclidean distance to determine the k -Nearest Neighbors.

From the plot of Figure 14a, one sees that, for low number of k -instances and for a low number of n extracted peaks, i.e., $k \in \{3, 4\}$ and $n \in \{3, 5\}$, the ensemble k NN algorithm presents a near unitary mean accuracy. For low number of neighbor instances, k , used in the classification, the classifier models gradually lose accuracy with the increase of $\text{Re}(Z_e)$ peaks. Indeed, if one compares the mean and limit accuracy values for both k NN approaches, one sees that this classifier per peak approach still enables better overall accuracy when compared to the normal k NN model. Figure 15a compares the accuracy of both approaches where the maximum accuracy was obtained, meaning that, for the conventional k NN approach, 6 neighbors were used, $k = 6$, and for the ensemble approach, 4 neighbors were used, $k = 4$. These results reveal that, except in the case where 16 peaks were extracted, no ensemble k NN classifier had a worse performance than the fully biased model that classifies all instances as belonging to damaged SLJs, which is represented by the dashed red line.

A similar trend is observed for the F_1 -Score, as plotted in Figure 14b, where, for small number of peaks, n , and for small number of neighbors, k , the ensemble classifiers have a better performance in classifying all *No Void* instances. This optimal region occurs approximately at $k \in \{3, 5\}$ and $n \in \{3, 5\}$, which coincides with the optimal mean accuracy results in Figure 14a. However, much like for the accuracy, for any given number of extracted peaks, n , a steep decrease in the F_1 -Score occurs as more k instances are used for classification. Concurrently, for low values of k , a more gradual decrease of the F_1 metric is observed, as one increases the number of extracted peaks, n . Figure 15b exemplifies this, where the mean and limit F_1 -Score values are plotted for the conventional and parallel k NN approaches, with

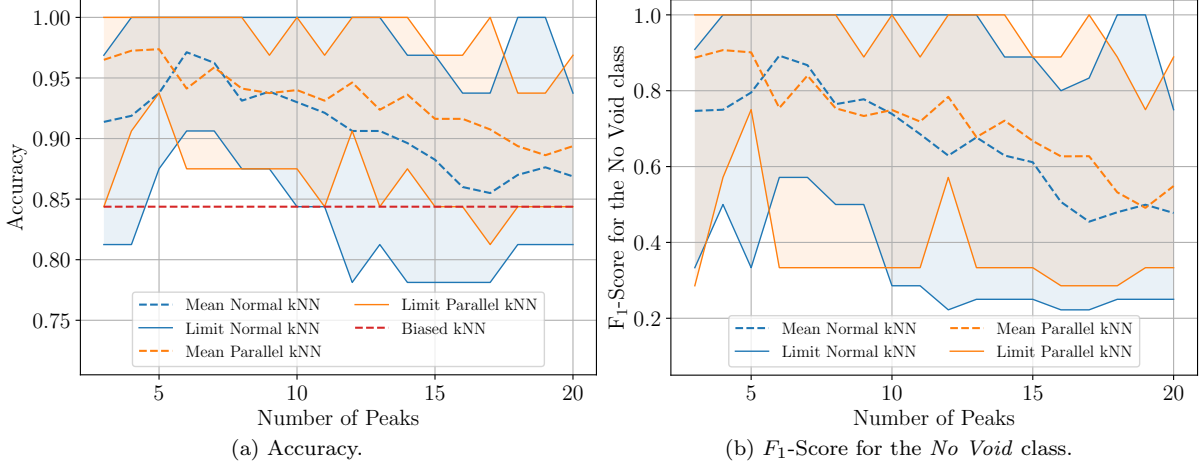


Figure 15: Comparison between the best conventional k NN classifiers, where 6 neighbors were used, $k = 6$, and the parallel k NN approach, where 4 neighbors were used, $k = 4$.

$k = 4$ and $k = 6$ respectively. These results reveal that this ensemble k NN approach does enable a better classification of the *No Void* instances, even if only moderately.

4.2.2 k NN using the Canberra distance

Figure 16a displays the mean accuracy for each combination of the n extracted peaks, and the number of k -nearest instances used for classification, while Figure 16b plots the average F_1 -Score for the *No Void* class. For each pair of hyperparameters, (n, k) , 25 different k NN models were instantiated, where each classifier used label stratified training and testing subsets. Both plots contain topographical curves, to help visualize the color gradient.

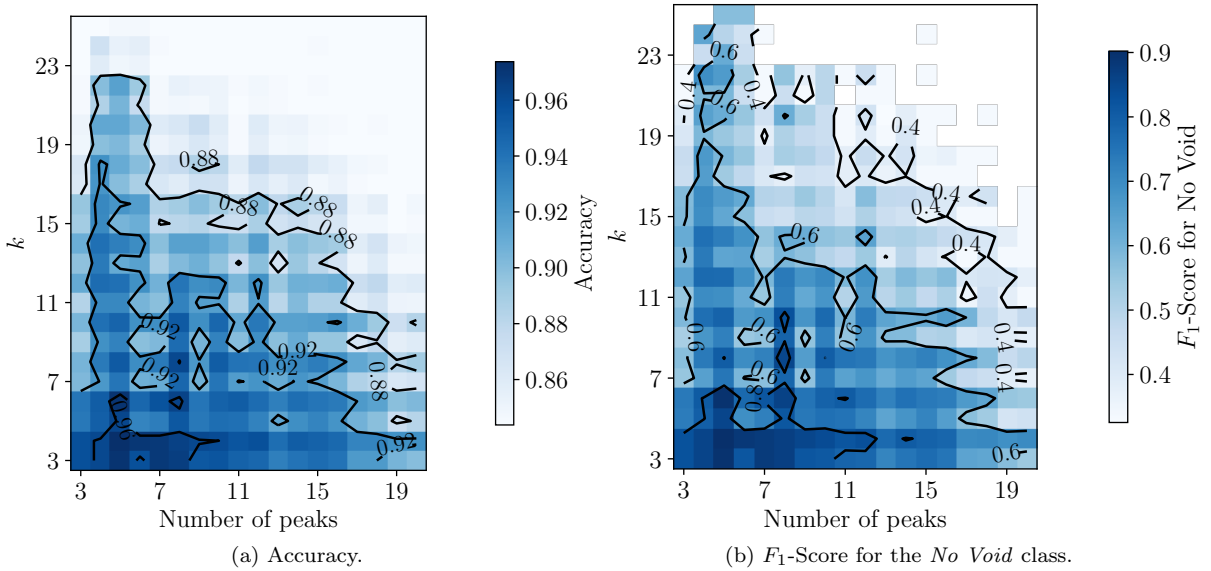


Figure 16: Average performance of the parallel k NN models for damage detection, when using the Canberra distance to determine the k -Nearest Neighbors.

Both accuracy and F_1 -Score plots reveal that the use of the Canberra distance improves the algorithm's performance in detecting damage. Indeed, similarly to the parallel k NN models that made use of the Euclidean distance, these classifiers have greater accuracy for low number of neighbors, k , and for a low number of peaks, n , i.e., for $n \in \{4, 8\}$ and for $k \in \{3, 4\}$. However, unlike in the previous case, for a given value of n , the decrease in both accuracy and F_1 -Score is comparatively more gradual, as the number of neighbors, k , increases. Furthermore, for low number of neighbor instances, k , an even less

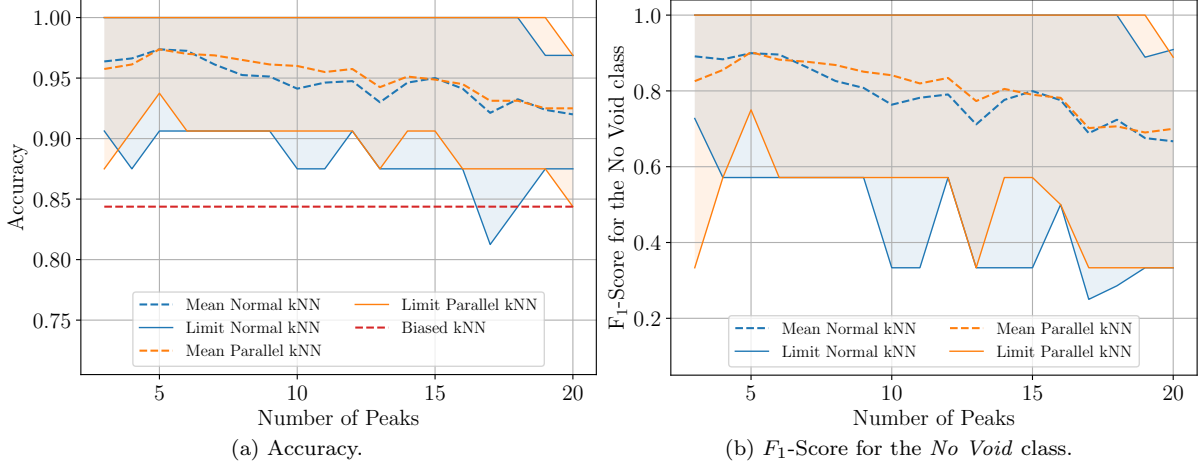


Figure 17: Comparison between the best conventional k NN classifiers, where 3 neighbors were used, $k = 3$, and the parallel k NN approach, where 4 neighbors were used, $k = 4$.

541 steep decrease of both accuracy and F_1 -Score for the *No Void* class occurs. Therefore, for this type of
 542 algorithms, an increase of the number of k -neighbors does hinder the overall accuracy of the ensemble
 543 classifier approach, irregardless of the distance used to determine which are the k nearest peaks.

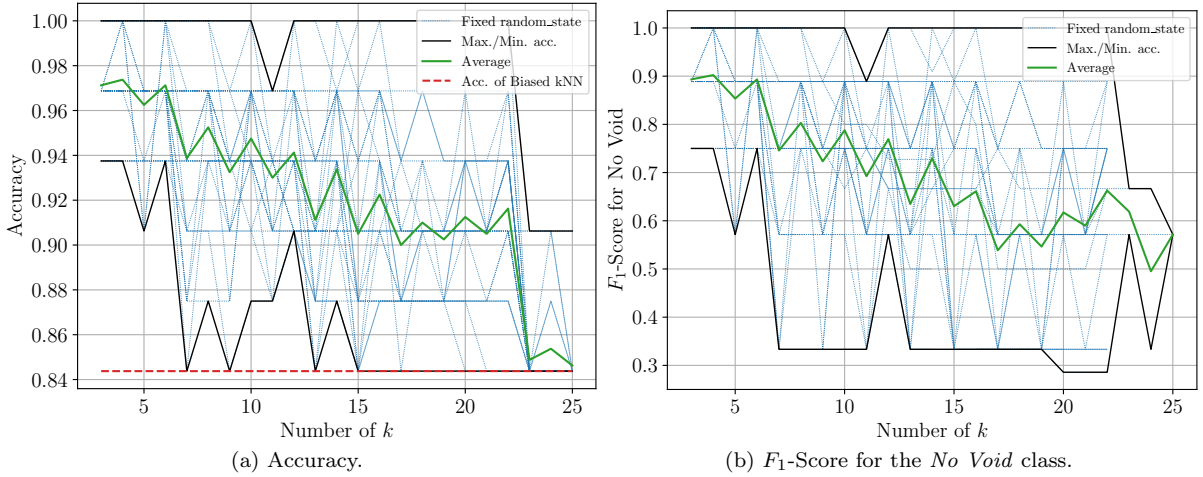


Figure 18: Classification performance of the ensemble k NN classifiers, with the Canberra distance, as a function of the k -Nearest Neighbors, when extracting 5 peaks ($n = 5$).

544 Figures 17a and 17b compare the accuracy and the F_1 -Score for the *No Void* class for both the
 545 Canberra distance-based normal and parallel k NN models with $k = 3$ and $k = 4$, respectively. These
 546 values of nearest neighbors, k correspond to the values where the best accuracy and F_1 -Score mean values
 547 occurred for both types of algorithms. Here, one sees that the maximum obtained accuracy and F_1 -Score
 548 values are almost constant and unitary throughout the studied range, and the minimum obtained values
 549 do tend to be very near each other, only reaching the accuracy of a fully biased model when extracting over
 550 15 resistive peaks. Therefore, it is understandable that the average values for both types of algorithms
 551 are near identical.

552 Figures 18a and 18b display the accuracy and F_1 -Score for the ensemble k NN method when 5 resistive
 553 peaks are used as features, and when the Canberra distance is used for classification. Here, one can
 554 better understand the decrease in classification performance, as the number of classification neighbors, k ,
 555 increases. Indeed both parameters gradually decrease as the k -instances increase. However, for $k = 23$,
 556 a sharp decrease of the mean accuracy is observed, reaching the accuracy value of the biased classifier,
 557 which is plotted as the dashed red line of Figure 18a. While this decrease does not occur for the F_1 -Score
 558 of the *No Void* class, one does see in Figure 18b that this metric becomes incalculable for most ensemble

k NN classifiers.

From these figures, one sees that both metric average values have an oscillatory trend, increasing when k is an even number, and decreasing when k is an odd number. This occurs, since the tie-breaking classification is based on the class of the nearest peak for each k NN per peak model, which normally tends to be a peak from another impedance measurement from an identical SLJ, or a similar joint with the same damage.

4.3 Damage Quantification

This subsection presents the results of the damage quantification. In this sense, the aim of these k NN classifiers is to determine what type of damage is detected, as per Figure 3. Note that, for this case, the accuracy is the only metric used to evaluate the performance of the algorithm, since all of the classes have an identical number of instances. Note also that, unlike in the previous case, a maximum of 25 resistive peaks were extracted for damage quantification. This was done, since, overall, the instantiated classifiers for damage detection yielded exactly the same accuracy value of 0.84375, when $n \geq 20$. This meant that all instances were being classified as being of the *Void* class. However, for this second task, this phenomenon was not verified and, consequently, a broader range of number of peaks was studied, $n \in \{3, 25\}$.

For brevity, this subsection will present the classification performance of the normal k NN algorithm in performing the damage quantification task when the Euclidean and Canberra distances are used. The results obtained for the Manhattan distance are very similar to the ones obtained when the k NN classifiers used the Euclidean distance, only showing a relatively minor improvement in accuracy. Conversely, only results from the ensemble k NN approach that made use of the Canberra distance will be presented here. While this algorithmic approach enables better classification results overall, when compared to the conventional method, the results appear to have similar trends, irregardless of the distance used. In this manner, only the results of the ensemble k NN with the Canberra distance are discussed here, since this is the best distance used for classification.

4.3.1 Conventional k NN using the Euclidean distance

Figure 19a plots the obtained mean accuracy for each combination of the number of extracted resistive peaks, n , and the number of nearest instances, k , used for classification, and contains topographical curves, to help correlate the color gradient with the accuracy values. Furthermore, Figures 19b, 19c and 19d display the accuracy of this k NN method when, respectively, 4, 6 and 20 resistive peaks are used as features. Note that, for each case of (n, k) hyperparameters, 25 different classifiers were instantiated, in order to obtain representative mean values of the algorithm's performance.

From Figure 19a, one observes an identical trend to all of the previous cases, where the mean accuracy of the classifiers decreases with the increase of the number of nearest instances for classification, k . However, unlike with the cases of damage detection, this decrease is not uniform throughout the range of n peaks being studied. Indeed, for an extremely low number of extracted peaks, i.e., $n \in \{3, 5\}$, the accuracy values gradually decrease from an average value of above 0.6, when $3 \leq k \leq 4$, to a value of below 0.4, when $18 \leq k \leq 25$. Indeed, Figure 19b also demonstrates this, and shows that all trained models with information from 4 extracted peaks have a similar trend, with the maximum and minimum accuracy reach a plateau of approximately 0.5 and 0.2, respectively, when using a high number of neighbors, k .

When 6 or 7 peaks are extracted, $n \in \{6, 7\}$, one observes a decrease of the mean accuracy with the increase of the number of neighbors used for classification. However, for higher values of k , an increase of the average classification accuracy is noticed. This is clearly seen in Figure 19c, where the mean, maximum and minimum observed accuracy decreases as the number of neighbors, k , increases. However, when $k \geq 14$, these aforementioned values start to increase. This is only noticed for this specific number of extracted peaks. Conversely, when more peaks are extracted from the impedance measurements, i.e., $n \in \{8, 18\}$, a similar trend in accuracy is observed to what was seen for the cases of $n \in \{3, 5\}$.

Interestingly, if one increases even further the number of peaks used for classification to the range of $n \in \{19, 25\}$, one sees an overall increase in accuracy. Indeed, while the typical decrease of accuracy is observed with the increase of number of neighbors used for classification, k , all average values for this range of extracted resistive peaks, n , are above an accuracy of 0.5. A good example of this is plotted in Figure 19d, which shows the accuracy of all 25 classifier models when $n = 20$, where, for the range of k , neighbors under analysis, very few models have an accuracy below 0.5. Despite this, the minimum observed accuracy for this specific number of extracted peaks is always below 0.5, and appears to correspond to an extreme case of low accuracy, when compared to the trend of most classifiers.

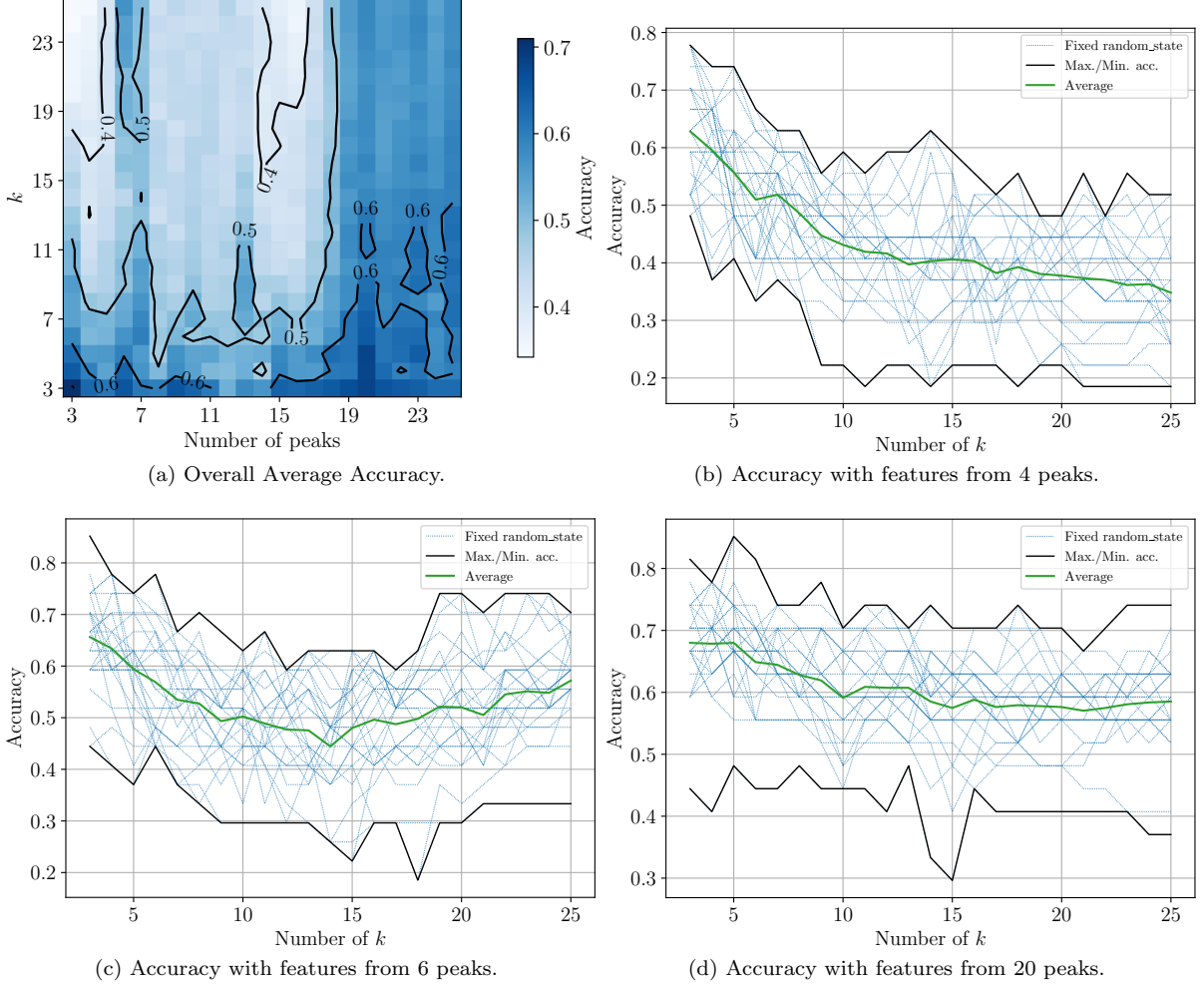


Figure 19: Accuracy of the conventional k NN models for damage quantification, when using the Euclidean distance to determine the k -Nearest Neighbors.

4.3.2 Conventional k NN using the Canberra distance

Figure 20a displays the average accuracy for each combination of extracted resistive peaks, n , and nearest instances, k , used for classification, and contains topographical curves, to ease the correlation of the color gradient with the accuracy values. Note that, for each combination of n and k , 25 different k NN models were instantiated. Figures 20b and 20c present the k NN accuracy when 7 and 20 resistive peaks are, respectively, extracted from the impedance spectra and are used as features.

The plot of Figure 20a reveals once again a similar pattern where the model accuracy decreases with the increase of the number of k elements used for classification, no matter the number of impedance peaks used for classification. Furthermore, much like in the case where the Euclidean distance was used, this decrease in accuracy is more pronounced for certain cases. For instance, this decrease is better viewed for the sub-domain of $n \in \{3, 5\}$ and for $n \in \{9, 16\}$. Conversely, in the range of $n \in \{6, 8\}$, one observes an initial decrease of the mean accuracy as the number of neighbors for classification, k , increases, but reaches a plateau when $k \in \{10, 19\}$, and then starts to decrease when $k \geq 20$. This is noticeable in Figure 20b, where the mean, maximum and minimum accuracy values do follow the aforementioned trend, which bears some resemblance with the aforementioned case where the Euclidean distance was used.

The sub-domain of $n \in \{17, 23\}$ presents a distinct behaviour. While it is clear from both Figures 20a and 20c, which show that, even though the mean average decreases as the number of classification neighbors, k , increases, these values are, overall, higher than what occurs in the remaining range of possible number of extracted peaks, n . For instance, for $n = 11$, the mean accuracy reaches a value of approximately 0.45 when $k = 13$, but, when 20 peaks are extracted, $n = 20$, this average is only reached when $k = 24$. One also sees in this sub-domain some of the highest values of mean accuracy. Indeed, for the case of $k = 20$, shown in Figure 20c, the mean accuracy almost reaches a value of 0.8 for $k = 3$, and

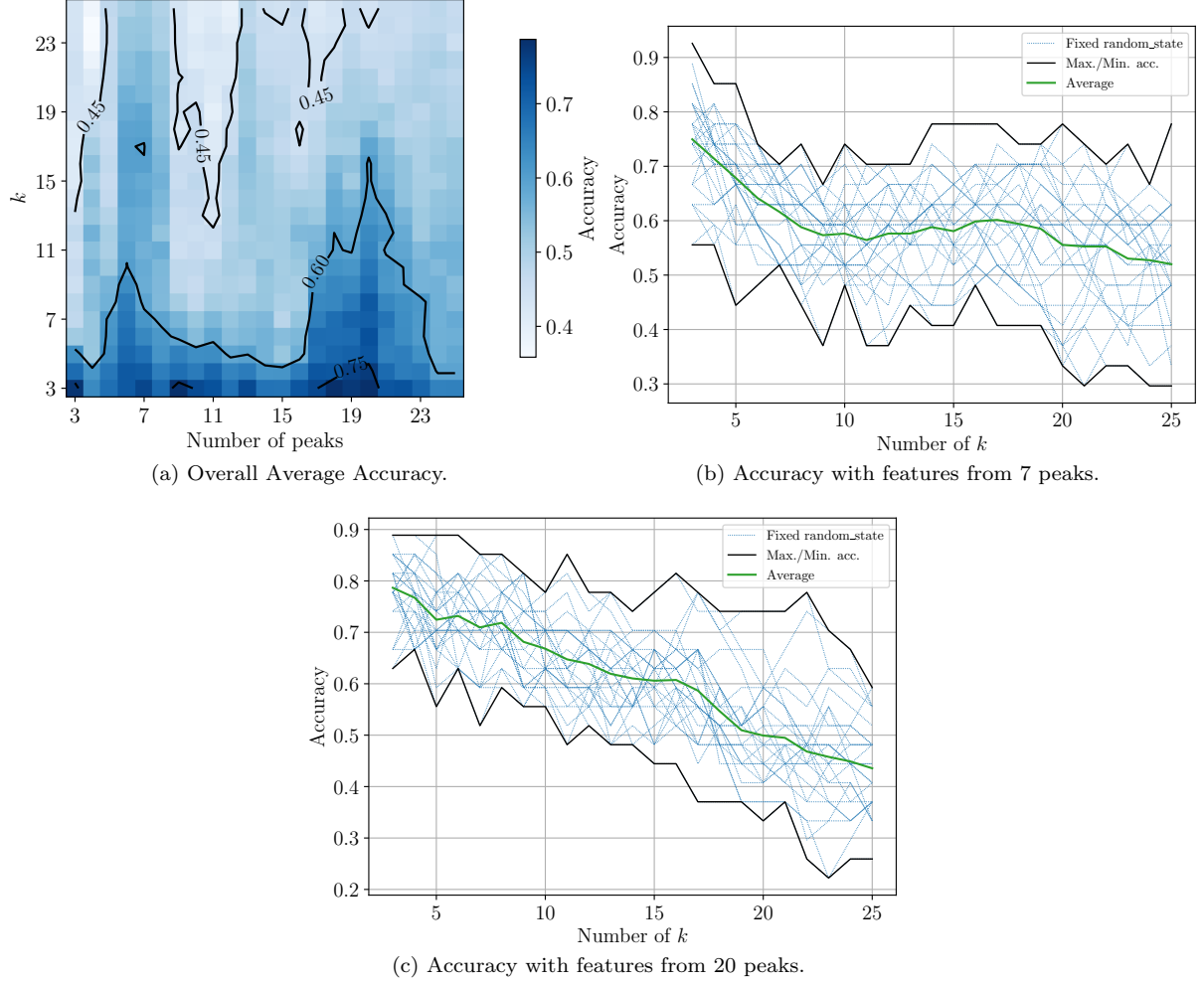


Figure 20: Accuracy of the conventional k NN models for damage quantification, when using the Canberra distance to determine the k -Nearest Neighbors.

where the maximum observed accuracy almost reaches a value of 0.9.

Figures 20b and 20c show that, with the increase of k , a dispersion in classifier performance is noted. For instance, in Figure 20c, the accuracy of the classifier is between 0.75 and 0.9 for $k \in \{3, 4\}$, but for $k = 22$, this range widens to its maximum between 0.25 and 0.75. Therefore, this decrease in accurate classification is also a function of the stratification of the database being used.

4.3.3 Parallel k NN using the Canberra distance

Figure 21a plots the mean accuracy for each combination of extracted resistive peaks and nearest instances used for classification, which are hyperparameters (n, k) . For each combination of hyperparameters, 25 different ensemble k NN classifiers, which are schematically described in Figure 4b, were instantiated. This plot contains topographical curves, to better understand the color gradient associated with the accuracy values. Furthermore, Figure 21b presents the performance of the ensemble k NN model for damage quantification, when 6 resistive peaks were extracted from the impedance measurements.

The ensemble k NN approach presents a similar pattern regarding the average accuracy, when compared to the conventional k NN approach. Overall, the mean accuracy decreases as the number of k neighbors for classification increases. However, unlike in the previous case, here the mean accuracy for low number of neighbors, i.e., $k \in \{3, 5\}$ is almost always above 0.75. Furthermore, the minimum recorded average accuracy, for most cases of n , almost never decreases below 0.45, thus appearing to be a significant improvement, when compared to the conventional k NN model results shown in Figure 20a. Indeed, Figure 22 appears to present precisely this phenomenon for the case of $n = 3$, both for the conventional and parallel k NN approaches for damage quantification, and both using the Canberra distance. In this specific case, the improvement is noticeable for a low number of of extracted peaks, while, for a high

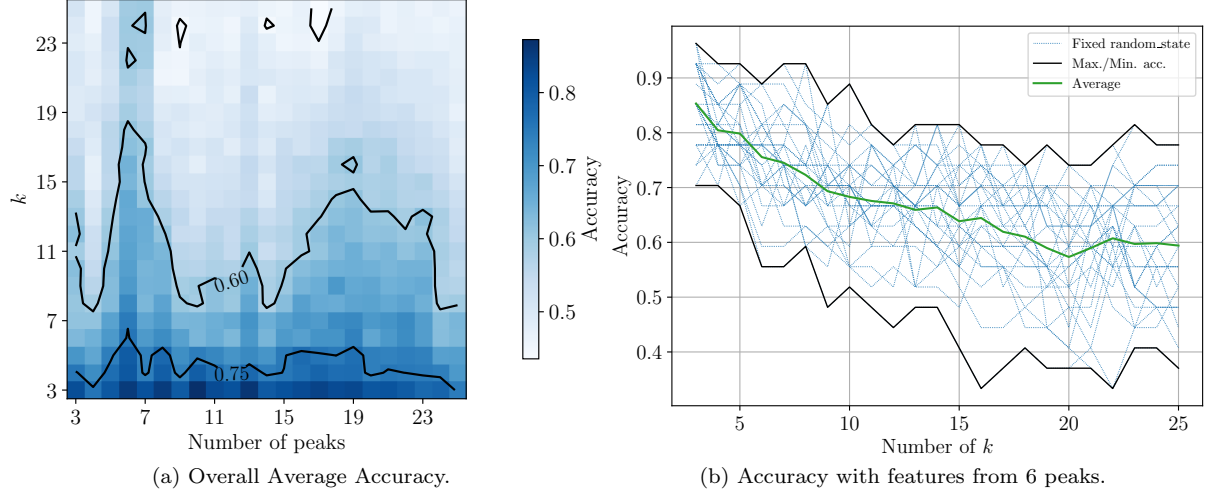


Figure 21: Accuracy of the parallel k NN models for damage quantification, when using the Canberra distance to determine the k -Nearest Neighbors.

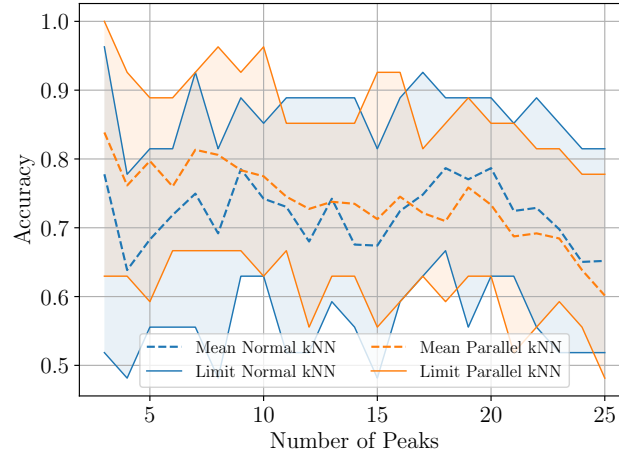


Figure 22: Comparison between the best conventional k NN classifiers when using the Canberra distance, where 3 neighbors were used for both cases, $k = 3$.

number of peaks used for classification, both the conventional and parallel approaches have the same performance, irregardless of the comparison metric (mean, maximum or minimum accuracy values).

Figure 21b also corroborates the previous findings, but for the specific case of the classifiers that try to classify the type of detected void when using information from 6 peaks, $n = 6$. Also, similarly to the conventional case, one sees that the accuracy of the instantiated models disperses as the number of neighbors used for classification increases. For instance, for $k = 3$, any given classifier has an accuracy ranging between 0.7 and 0.95, while for $k \in \{22, 25\}$, this range is between 0.35 and 0.8. Therefore, it is clear that these models have a better performance for a low number of classification neighbors.

5 Conclusion

This paper studied the use of two different k NN algorithmic approaches to tackle both damage detection and damage quantification, i.e., damage localization and size in bonded joints. The first k NN approach was the well known conventional classification model that made use of peaks from the real component of the measured impedance from SLJ specimina with and without artificially created voids. The second classification approach was to instantiate n k NN models, one for each of the n extracted peaks. With the classification results from each individual model, working in parallel in relation to each other, a *majority vote* classification was performed, much like in ensemble supervised learning methods.

For both approaches, a study of the classification performance was done based on the model hyperparameters, which were the k neighbor instances used for classification, and the number of extracted peaks, n , as features for classification. Furthermore, a comparison of the Euclidean, Manhattan and Canberra distances was done to evaluate the classification accuracy.

When performing damage detection, both algorithmic approaches have an almost unitary mean accuracy when using a low number of peaks, n , and a low number of neighbors, k . This is remarkable, given that a large portion of the instantiated models have a 100% accuracy and F_1 -Score, and given the fact that the experimentally obtained dataset has significantly more instances of damaged joints. For the conventional k NN models, the accuracy decreases moderately as either the number of neighbors, k , or the number of peaks, n , increase, only reaching the accuracy of a biased model for high numbers of neighbors and peaks, k and n respectively. Conversely, while the accuracy of the parallel k NN classifiers also decreases slightly with the increase of peaks used, for low number of k , the accuracy decreases sharply with the increase of neighbors for classification. Despite this, comparing the optimal conditions of both algorithms reveals that the ensemble k NN model performs better in the task of damage detection. Note that, for both approaches, the Canberra distance enables a better distinction between damaged and undamaged instances.

Regarding damage quantification, both methods appear to follow a similar trend where the accuracy decreases with the increase of neighbor instances for classification, k . However, for both methods, this decrease may be somewhat more pronounced for a given sub-region of possible extracted peaks, n . Despite this difference, the ensemble approach allows for a higher accuracy, when compared to the conventional approach. Furthermore, once again, the Canberra distance enables a better distinction between various types of damage. While these results are promising for the applicability of EMIS as a SHM method in void detection and quantification in adhesive joints, further study is needed to guarantee a 100 % accuracy, especially given that differences between certain types of voids may be more pronounced than other types of damage. Furthermore, this type of research should be extended to other types of damage.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors gratefully acknowledge the funding of grant 2021.07689.BD, which is provided by Fundação para a Ciência e Tecnologia (FCT).

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