

FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Structural Health Monitoring of Adhesive Joints Using Lamb Waves and Machine Learning Algorithms

Gabriel Martins Franco Ramalho



Thesis submitted for the degree of Doctor of Philosophy
in Mechanical Engineering

Supervisor: António M. Lopes

Co-supervisor: Lucas F. M. da Silva

April 15, 2024

Structural Health Monitoring of Adhesive Joints Using Lamb Waves and Machine Learning Algorithms

Gabriel Martins Franco Ramalho

Thesis submitted for the degree of Doctor of Philosophy
in Mechanical Engineering

April 15, 2024

Abstract

The search for stronger, lighter, and more efficient structures has led the industry, particularly the aeronautics sector, to use new materials with customized properties and multimaterial structures. Adhesive joints eliminate fastening holes, distribute loads over larger areas than other bonding methods, uniformize stress fields, and allow for thinner substrates, reducing weight. However, adhesive joints are sensitive to substrate surface treatment, cyclic loads, arbitrary load combinations, and environmental conditions, requiring monitoring throughout their lifecycle. Identifying critical damage should precede potential failure, ensuring structural integrity and human safety. Although adhesive joints have advantages over other bonding methods, there are obstacles to their application in aeronautics and other key industries. In fact, current safety regulations require reliable non-destructive testing (NDT) techniques for each bonded part, according to section 23.573(5)-(iii) of the Federal Aviation Regulations (FAR).

Some NDT methods have been explored for monitoring adhesive joints, such as ultrasonic, thermographic, radiographic, holographic, and based on electro-mechanical impedance spectroscopy. However, current NDT methods do not offer good solutions for monitoring the integrity of the bonded surface in primary structures. Structural health monitoring (SHM) utilizes NDT techniques for continuous in-situ monitoring with equipment permanently attached to the structure. SHM involves different technologies, such as instrumentation, signal conditioning, data processing, and damage detection, localization, and quantification. Recently, specific SHM applications have been developed in various areas, with some success, but reliable solutions for general use are not yet available, and applied research on adhesive joints is scarce.

A promising approach for SHM is based on Lamb waves (LW), excited/detected through piezoelectric actuators/sensors. LWs are a particular type of guided waves that propagate through materials and are sensitive to structural damage. LWs are difficult to process due to electromagnetic noise, environmental disturbances, and the complexity of their physical mechanisms, involving dispersive modes that overlap in both the time and frequency domains. Thus, proper processing of LW signals is crucial to extract information on structural integrity. Several data processing techniques have been proposed for LW-based SHM in various areas, but their applicability to bonded structures has still to be proven. Analysis with small-scale structures, simple geometries, and the existence of only one damage focus revealed the potential of LWs to detect damage in adhesive joints. However, LW data processing techniques need to be further developed to extract information on incipient damage, impossible to detect by other methods, as is the case with weak adhesion (a.k.a. kissing bond or zero volume void). This type of damage is characterized by a reduction in the Young's modulus of the adhesive, in the border zone with the substrate, of at least 20%. Currently, there are no NDT methods capable of conveniently detecting weak adhesion, which severely limits the use of adhesives in critical structures in multiple potential application fields. Thus, developing a method for continuous monitoring of adhesive joints throughout their lifespan is essential.

This thesis consists of an extended summary and six papers, detailing the progression of work

developed on detecting and characterizing weak adhesion in adhesive joints using LWs and machine learning (ML) algorithms. The work ranges from understanding the problem of weak adhesion and the current limitations in detecting this type of damage, to proposing a method capable of detecting, assessing intensity, and locating weak adhesion in simple lap joints (SLJs).

The first paper reviews equipment, procedures, and NDT and SHM techniques, focusing on applications in adhesive joints. The fundamentals of LWs and their application in damage detection using various signal processing methods, such as statistical indices and ML, are discussed. Issues of modeling, simulation, and manufacturing of SLJs with different values of weak adhesion are addressed. This paper lays the groundwork for subsequent research, highlighting existing research gaps and opportunities.

The second paper describes exploratory work on synthetic LWs data generation and the use of data-driven algorithms for damage detection. It compares the performance of conventional feedforward artificial neural networks (FNNs) and convolutional artificial neural networks (CNNs) for simple damage classification in aluminum plates and proposes a methodology adaptable to various types of damage and structures.

The third paper addresses a specialized feature extraction method on time series representing LWs generated in simulated SLJs subjected to weak adhesion. Followed by feature selection using the Benjamini-Hochberg procedure, supervised ML methods such as Random Forest and Naive Bayes classifiers are employed to achieve classification metrics and isolate relevant features for damage differentiation.

The fourth paper explores different ML algorithms, trained and tested with synthetic data, namely FNN and Gated Recurrent Unit (GRU) networks, showing their performance in terms of accuracy and convergence time.

The fifth paper presents an innovative approach using ML regression and LWs to determine weak adhesion in SLJs. A numerical model of SLJs is validated with real data, and an artificial neural network-based damage detection method is developed, achieving over 95% accuracy.

The sixth paper describes a methodology for detecting and characterizing weak adhesion, using transfer learning, where an extensive synthetic database is used to train CNN-based algorithms, which are then fine-tuned with some experimental data. Tests with SLJs where weak adhesion intensity could vary from 100 MPa to 500 MPa, and damage localization could change up to 125 mm within the adhesive area, showed that the developed pipeline can not only detect weak adhesion in simulated data with over 95.3% accuracy but also identify about 100% of cases with damage in experimental data. Regarding the intensity of weak adhesion, the algorithm achieves an average loss of 45 MPa for the experimental validation dataset, with an average error of 140 MPa and best cases of only 3.6 MPa. As for damage localization, the algorithm exhibits an average loss of 8 mm in the validation synthetic dataset. Importantly, the methodology is flexible enough to deal with other weak adhesion characteristics beyond existence, intensity, and localization, without requiring major alterations.

The developed work demonstrates the potential of properly processed LWs with ML algorithms to improve the quality control of adhesive bonding using NDT and improve the safety and durability of bonded structures throughout their lifespan through SHM.

Resumo

A procura por estruturas mais resistentes, leves e eficientes tem levado a indústria, nomeadamente a aeronáutica, a utilizar novos materiais, com propriedades personalizadas e estruturas multimatriciais. As juntas adesivas dispensam os furos de fixação, distribuem cargas por áreas maiores do que outros métodos de ligação, uniformizam os campos de tensão e permitem substratos mais finos, reduzindo o peso. Porém, as juntas adesivas são sensíveis ao tratamento superficial dos substratos, cargas cíclicas, combinações arbitrárias de cargas e condições ambientais, requerendo monitorização ao longo do seu ciclo de vida. A identificação de dano crítico deve preceder uma potencial falha, garantindo a integridade estrutural e a segurança humana. Embora as juntas adesivas tenham vantagens sobre outros métodos de ligação, existem entraves na sua aplicação na aeronáutica e em outras indústrias chave. De facto, os regulamentos de segurança vigentes exigem técnicas de ensaio não destrutivo (END) fiáveis em cada peça adesivada, de acordo com a secção 23.573(5)-(iii) da “Federal Aviation Regulations”. Alguns métodos END têm sido explorados para a monitorização de juntas adesivas, tais como os ultrassónicos (mais comuns), termográficos, radiográficos, holográficos, e baseados em espectroscopia de impedância eletromecânica. Porém, os atuais métodos END não oferecem boas soluções para monitorizar a integridade da superfície adesivada em estruturas primárias. A monitorização de integridade estrutural (MIE) utiliza técnicas END para monitorização contínua in-situ com equipamento permanentemente ligado à estrutura. A MIE envolve diferentes tecnologias, como a instrumentação, condicionamento de sinal, processamento de dados e deteção, localização e quantificação de dano. Recentemente, foram desenvolvidas aplicações específicas de MIE em várias áreas, com algum sucesso, mas ainda não estão disponíveis soluções fiáveis para uso geral, sendo escassa a investigação aplicada a juntas adesivas. Uma abordagem promissora para MIE baseia-se em Ondas Lamb (OL), excitadas/detetadas por meio de atuadores/sensores piezoelétricos. As OL são um tipo particular de ondas guiadas que se propagam através dos materiais e são sensíveis ao dano estrutural. As OL são difíceis de processar devido ao ruído eletromagnético, às perturbações ambientais e à complexidade dos seus mecanismos físicos, envolvendo modos dispersivos, que se sobrepõem tanto no domínio do tempo como da frequência. Assim, o processamento adequado dos sinais de OL é crucial para extrair dados sobre a integridade da estrutura. Foram propostas várias técnicas de processamento de dados para MIE baseado em OL em diversas áreas, mas a sua aplicabilidade a estruturas adesivadas requer comprovação. A análise com estruturas de pequena dimensão, geometrias simples e a existência de apenas um foco de dano revelou o potencial das OL para detetar dano em juntas adesivas. Contudo, as técnicas de processamento de dados de OL têm de ser mais desenvolvidas para se extrair informação sobre dano incipiente, impossível de detetar por outros métodos, como é o caso de “fraca adesão”. Este tipo de dano é caracterizado por uma redução do módulo de Young do adesivo, na zona de fronteira com o substrato, de pelo menos 20%. Atualmente, não existem métodos END capazes de detetar convenientemente a “fraca adesão”, o que limita profundamente o uso de adesivos em estruturas críticas em múltiplos campos de potencial aplicação. Deste modo, o desenvolvimento de um método para monitorização contínua de juntas adesivas ao longo da sua

vida útil é essencial.

A tese é composta por um resumo estendido e seis artigos de revista, detalhando o progresso do trabalho desenvolvido sobre detecção e caracterização de “fraca adesão” em juntas adesivas usando OL e algoritmos de aprendizagem máquina (ML). O trabalho vai desde a compreensão do problema da “fraca adesão” e das limitações atuais na detecção deste tipo de dano, até à proposta de um método capaz de detetar, avaliar intensidade e localizar “fraca adesão” em juntas de sobreposição simples (JSS).

O primeiro artigo revê equipamentos, procedimentos e técnicas END e MIE, com foco em aplicações em juntas adesivas. Discutem-se os fundamentos das OL e a sua aplicação na detecção de dano, usando vários métodos de processamento de sinal, como índices estatísticos e ML. Abordam-se questões de modelação, simulação e fabrico de SJLs com diferentes valores de “fraca adesão”. Este artigo lança as bases para o estudo subsequente, destacando as lacunas e as oportunidades de investigação existentes.

O segundo artigo descreve trabalho exploratório sobre geração de dados de OL sintéticos e utilização de algoritmos baseados em dados para detecção de dano. Ele compara o desempenho de redes neurais “feedforward” (FNNs) convencionais e redes neurais artificiais convolucionais (CNNs) para classificação de dano simples em placas de alumínio e propõe uma metodologia adaptável a vários tipos de dano e estruturas.

O terceiro artigo descreve a implementação de um método especializado de extração de características (“features”) em séries temporais correspondentes a OL geradas em JSS simuladas, sujeitas a “fraca adesão”. Seguido da seleção de características usando o procedimento de Benjamini-Hochberg, métodos de ML supervisionados, como classificadores “Random Forest” e “Naive Bayes” são empregues para obter métricas de classificação e isolar características relevantes para diferenciação de dano.

O quarto artigo explora distintos algoritmos de ML, treinados e testados com dados sintéticos, nomeadamente FNNs e redes de unidade recorrente controlada (GRU), mostrando a sua performance em termos de precisão e tempo de convergência.

O quinto artigo apresenta uma abordagem inovadora usando ML e OL para determinar “fraca adesão” em JSS usando modelos de regressão. Um modelo numérico de JSS é validado com dados de juntas reais, e um método de detecção de danos baseado em redes neurais artificiais é desenvolvido, obtendo-se mais de 95% de precisão.

O sexto artigo descreve uma metodologia para detecção e caracterização de “fraca adesão”, utilizando aprendizagem por transferência (“transfer learning”) onde uma extensa base de dados sintética é usada para treino de algoritmos baseados em CNNs, que depois são afinados com alguns dados experimentais. Testes com JSS, em que a “fraca adesão” podia variar de 100 MPa a 500 MPa, e a localização do dano podia mudar até 125 mm dentro da área adesiva, mostraram que o pipeline desenvolvido não só pode detetar “fraca adesão” em dados simulados com mais de 95,3% de precisão, mas também identificar cerca de 100% dos casos com dano em dados experimentais. Em relação à intensidade de “fraca adesão”, o algoritmo alcança uma perda média (“loss”) de 45 MPa para o conjunto de dados de validação experimental, com erro médio de 140 MPa e melhores casos de apenas 3,6 MPa. Quanto à localização de dano, o algoritmo apresenta uma perda média de 8 mm no conjunto de dados sintéticos de validação. É importante realçar que a metodologia é suficientemente flexível para lidar com outras características de “fraca adesão” além da intensidade e localização, sem exigir grandes alterações.

O trabalho desenvolvido mostra o potencial das OL processadas adequadamente com algoritmos de ML, para melhorar o controlo de qualidade da junta adesiva e melhorar a segurança e durabilidade das estruturas adesivadas ao longo do seu tempo de vida através de MIE.

Acknowledgments

Without the help of others this thesis would not have been possible. I am immensely grateful to all that helped in so many ways.

First, I would like to thank Professor António M. Lopes not only for the technical and academic guidance, as well as going above and beyond to help with life's challenges that might otherwise have gone unnoticed. I would also like to express my gratitude to Professor Lucas da Silva for the invaluable help throughout the entire thesis helping me with my doubts.

To Jonathan Holt that helped me simulate a metric shit ton of stuff, bogging his PC down for weeks on end and not allowing him to play PoE because "I had to finish damage size 25" or something like that. He also was there for more philosophical reasons such as helping me answer questions of life and PhD until obscene times at night.

To Matheus Di Vaio simply for being there in all moments of my life even when we are currently in different countries. One of the very very few people that I would call and accept a call of "Buy a plane ticket and be here now I need help".

To my Mother to whom I owe so much in my life and has always been there for me in any situation without batting an eye. —You are and will always be my inspiration to continue on and always persevere. This thesis will always have your mark of "Carry a stone while you rest".

In memory of my father... —To you who said almost these exact words also in your PhD thesis: "To my father... That saw how it all started, but did not have a chance to see how it ended." —I truly miss you.

To my Wife Thamiris Ramalho for being by my side for all these years helping me grow and become who I am. For accepting the countless nights and weekends I had to stay home and study and for all the hardships we passed through from a simple to fix Hangry Gabriel to a freaking Pandemic. —I could not have finished this stage of my life without you by my side.

Finally to my Grandfather João that treats not only but my mom with so much warmth, caring and love that I cannot express the joy I have to have him by my side.

Gabriel M. F. Ramalho

*“It’s the questions we can’t answer that teach us the most.
They teach us how to think.”*

Patrick Rothfuss

Contents

1	Introduction	1
1.1	Background and motivation	1
1.2	Objectives	2
1.3	Research methodology	3
1.4	Outline of the thesis	5
2	Literature Review	8
2.1	Fundamentals of LWs in SHM	8
2.2	Adhesive joints	12
2.2.1	The single lap joint	12
2.2.2	Defects in adhesive joints	12
2.2.3	Testing methods	13
2.2.4	Instrumentation	15
2.3	Statistical and ML based damage detection	18
2.3.1	Statistical based methods	19
2.3.2	Machine learning methods	20
2.4	Theoretical simulation	22
2.4.1	Modeling piezoelectric transducers	22
2.4.2	Modeling adhesive structures	23
2.4.3	Computer modeling software	24
2.5	Summary	25
3	Numerical methods	26
3.1	FEM models	26
3.1.1	Model-1	26
3.1.2	Model-2	28
3.1.3	Model-3	28
3.2	Actuator and LW simulation	29
3.3	Adhesive and weak adhesion simulation	30
3.4	Data processing	30
3.5	Summary	32
4	Experimental Setup	34
4.1	Experimental setup	34
4.1.1	Creating weak adhesion	34
4.1.2	Experimental testing	35
4.2	Experimental model validation	36
4.3	Summary	38

5	Machine Learning Algorithms	40
5.1	Feedforward neural network	40
5.2	Recurrent neural network	41
5.2.1	Long short-term memory	41
5.2.2	Gated recurrent unit	42
5.3	Convolutional neural network	43
5.4	Transfer learning	45
5.5	Summary	45
6	A ML Pipeline for Detecting and Assessing Weak Adhesion in SLJs	47
6.1	Proposed methodology	47
6.1.1	Design of the CNNs	47
6.1.2	Design of the transfer learning scheme	49
6.2	Final results	50
6.2.1	Damage detection	50
6.2.2	Damage intensity evaluation	52
6.2.3	Damage localization	54
6.3	Summary	55
7	Conclusion and Future Work	56
	References	58
A	Paper A	69
B	Paper B	92
C	Paper C	113
D	Paper D	128
E	Paper E	148
F	Paper F	166

List of Figures

1.1	Illustration of an LW-based SHM scheme applied to an aircraft.	3
1.2	Representation of the delineated work plan.	4
2.1	Example of symmetric and anti-symmetric modes in a wave phase velocity vs. frequency graph.	10
2.2	Relation between the wavelength of each mode and the frequency.	11
2.3	Example of how a sinusoidal signal is altered when multiplied by a Hann function.	11
2.4	Example of different types of defects, where A) is a void and B) is weak adhesion between the adhesive and the substrate.	13
2.5	Examples of WTB and ATB sensor/actuator placement for LWs testing.	14
2.6	Comb and interdigital transducer structure.	16
2.7	Probability of detection caused by a defect located: (left) at the center; (right) close to a border. Sensors/actuators are represented as blue circles [1].	19
2.8	Schematic example of the output of the RAPID algorithm [2].	20
2.9	Example of a NN with its input, hidden and output layers.	21
3.1	Representation of an aluminum plate, with actuator, sensors, and a hole type defect.	27
3.2	Simulation of LWs moving in the aluminum sheet.	27
3.3	Illustration of the dimensions, and actuator and sensor placement, of the first type of SLJ, used to address weak adhesion detection and intensity evaluation.	28
3.4	Illustration of the dimensions, and actuator and sensors placement, of the second type of SLJ, used to address weak adhesion detection, intensity evaluation and localization.	29
3.5	Simulated SLJs showing the region of weak adhesion.	29
3.6	Representation of the forces that approximate the behavior of the piezoelectric round actuators used in real SLJs.	30
3.7	Representation of the 3-layer approach to simulating weak adhesion.	31
3.8	Representation of the data preprocessing steps.	32
3.9	MDS representation of five weak adhesion classes.	33
4.1	Experimental setup with four samples being produced in a fabrication jig and two samples in another one.	35
4.2	Data acquisition setup of one SLJ, with actuator and sensor connected to a signal generator and an oscilloscope, respectively.	36
4.3	Stress-strain test performed with an Instron 3367 testing machine.	37
4.4	Load-displacement curves of all SLJs.	37
4.5	A SLJ after rupture.	38
4.6	Complete approach for experimental SLJ models validation.	39

5.1	Fundamental architecture of an FNN with the interaction of each component represented.	41
5.2	The architecture of an LSTM cell with the input cell circled in green, the forget cell in yellow, the cell state in red, and finally, the output gate in purple.	42
5.3	Architecture of a GRU cell with the reset gate circled in purple and the update gate in green.	44
5.4	Architecture of a CNN comprising convolutional and pooling layers with a final flattening layer. The dimensions of each layer are represented under each one. . .	44
5.5	Overall structure of a transfer learning scheme. The components within the borderline have the same weights and biases as the pre-trained model, while the rest are reset to be fine-tuned.	45
6.1	Representation of the pipeline proposed for weak adhesion detection, intensity evaluation and localization in SLJs.	48
6.2	Overall structure of the CNN used to detect damage in simulated data.	48
6.3	Overall structure of the CNN used to evaluate damage intensity in simulated data.	49
6.4	Overall structure of the CNN used for damage localization in simulated data. . .	49
6.5	Overall structure of the transfer learning scheme for damage detection. The components within the borderline have the same weights and biases as the pre-trained model, while the rest are reset to be fine-tuned.	50
6.6	Overall structure of the transfer learning scheme for evaluating the intensity of weak adhesion. The components within the borderline have the same weights and biases as the pre-trained model, while the rest are reset to be fine-tuned.	50
6.7	Loss value for each epoch for the pre-trained damage detection algorithm.	51
6.8	The accuracy for each epoch for the pre-trained damage detection algorithm. . . .	51
6.9	The loss value for each epoch for the pre-trained damage intensity evaluation algorithm.	52
6.10	The error for each value of damage intensity studied.	53
6.11	The intensity error for each value of the position of damage studied.	53
6.12	The loss value in each epoch for the damage localization algorithm.	54
6.13	The localization error for each value of damage position studied.	54
6.14	The localization error for each value of damage size studied.	55

Acronyms

ADAM	Adaptive Moment Estimation
ATB	Across The Bond
CEC	Constant Error Carousel
CNN	Convolutional Neural Network
CZM	Cohesive Zone Method
DL	Deep Learning
EMAT	Electromagnetic Acoustic Transducer
FAR	Federal Aviation Regulations
FDM	Finite Difference Method
FE	Finite Element
FEM	Finite Element Method
FNN	Feedforward Neural Network
GRU	Gated Recurrent Unit
LISA	Location Interaction Simulation Approach
LSTM	Long Short-Term Memory
LW	Lamb Wave
MAE	Mean Absolute Error
MDS	Multidimensional Scaling
MEMS	Micro Electro-Mechanical System
ML	Machine Learning
MLM	Machine Learning Method
MSE	Mean-Squared Error
NAN	Not a Number
NDT	Non-Destructive Testing
NN	Neural Network
PCoA	Principal Coordinates Analysis
PDE	Partial Differential Equation
PWAS	Piezoelectric Wafer Active Sensor
PZT	Lead Zirconate Titanate
RAPID	Reconstruction Algorithm for Probabilistic Inspection of Damage
RELU	Rectified Linear Unit
RNN	Recurrent Neural Network
SAFE	Semi-Analytical Finite Element Method
SDC	Signal Difference Coefficient
SHM	Structural Health Monitoring
SLJ	Single Lap Joint
TOFD	Time Of Flight Diffraction
WTB	Within The Bond

Chapter 1

Introduction

This chapter presents the overall background and the motivation that led to studying NDT and SHM of adhesive joints using LW and ML algorithms. The main objectives of the work are defined and the research methodology is established, yielding a sequence of steps to be followed to gradually study the problem. Finally, the outline of the thesis is presented.

1.1 Background and motivation

Adhesive joints have advantages over other joining processes, but are sensitive to surface treatment, cyclic loadings and environmental variables, among other conditions [3, 4]. This is critical in primary structures, and regulations oblige the use of NDT methods to monitor adhesive joints through their lifecycle, so that severe damage and potential failure can be detected [5]. However, state-of-the-art NDT methods cannot offer good solutions to monitor bondline integrity, specifically in what concerns weak adhesion (a.k.a. kissing bond or zero-volume void). This has been the most serious issue hindering the use of adhesive primary structures in key industries, as in the aeronautical and automotive ones. Weak adhesion is nowadays the most challenging issue in adhesive science. Thus, the emergence of an NDT method able to detect and characterize weak adhesion will constitute a revolution for adhesive bonding.

SHM appeared within intelligent structures able to perform auto-diagnostic [6, 7]. Active SHM uses NDT for continuous in-situ monitoring, with equipment permanently attached to the structure. Often lead zirconate titanate (PZT) piezoelectric elements are used [8]. Specific SHM applications in certain areas have recently been addressed, with some success, but reliable solutions are not yet available for widespread implementation. Plus, in what concerns adhesive joints, current NDT and SHM techniques do not offer good solutions and no NDT based method can deal with weak adhesion.

When comparing different SHM techniques, the approach utilizing LWs stands out as one of the most promising candidates. Typically, lightweight piezoelectric actuators and sensors are used to generate and sense a special kind of guided wave that makes the structure vibrate in a certain way, depending on its overall characteristics. Although it is possible to detect damage, LWs are

very difficult to process due to noise, environmental variables, and other intrinsic characteristics that may affect the signals received at the sensors [9].

Due to the complex nature of LWs, several data processing methods have been adopted, namely for adhesive joints. However, those techniques have been tried just in small and simple structures that have only one type of damage or simple types of damage, such as voids [10, 11]. To address large-scale parts and complex damage cases, the LW signals need to be effectively treated so that LWs data can be related with damage signatures. This is an open issue, not only when dealing with general damage (voids, porosity and cracks), but especially for weak adhesion. Existing algorithms for damage detection, characterization and localization often present incremental difficulty. Several classifications exist [12, 13, 14, 15], but they are rather vague and overlaps exist. Data-driven methods [15, 16] are currently opening new research avenues in SHM. These do not require physical models. They take observable features of the structures and, automatically, learn the relationship between inputs and health condition. Typically, this involves ML models trained with large amounts of data. These data can be from real structures or, more practically, generated by numerical models of the structures, namely by FE models [17]. Using numerical (simulation) data for training ML algorithms may lead to suboptimal performance due to discrepancies between training and target (real) data domains. Therefore, recent ML trends rely on generative and transfer learning [18, 19]. Generative models are able to generate new data samples similar to the training data they were trained on, thus performing data augmentation. Transfer learning allows models, trained with large volumes of data, to be fine-tuned, with small quantities of data from the target domain, thus transferring previous knowledge to new tasks. This is also crucial when the target domain data varies in time, as is the case of damage.

The LWs data processing approach based on ML is followed in this thesis. Weak adhesion is nowadays the most challenging issue in adhesive science. Acoustic emission [20] and electromechanical impedance spectroscopy [21] can handle the issue to some extent, but the emergence of a disruptive NDT solution that revolutionizes adhesive bonding has still to be found [21, 22].

1.2 Objectives

State-of-the-art NDT methods do not offer good solutions to monitor bondline integrity, specifically in what concerns weak adhesion. This has been the most serious issue hindering the use of bonded primary structures, as regulations demand that those structures be monitored along their lifecycle using NDT methods.

The main goal of this work is to develop an effective LW-based SHM methodology to in-situ detect and characterize weak adhesion in bonded structures. Figure 1.1 illustrates the concept applied to an aircraft. The development of such a methodology will constitute a revolution for adhesive bonding.

The specific objectives are:

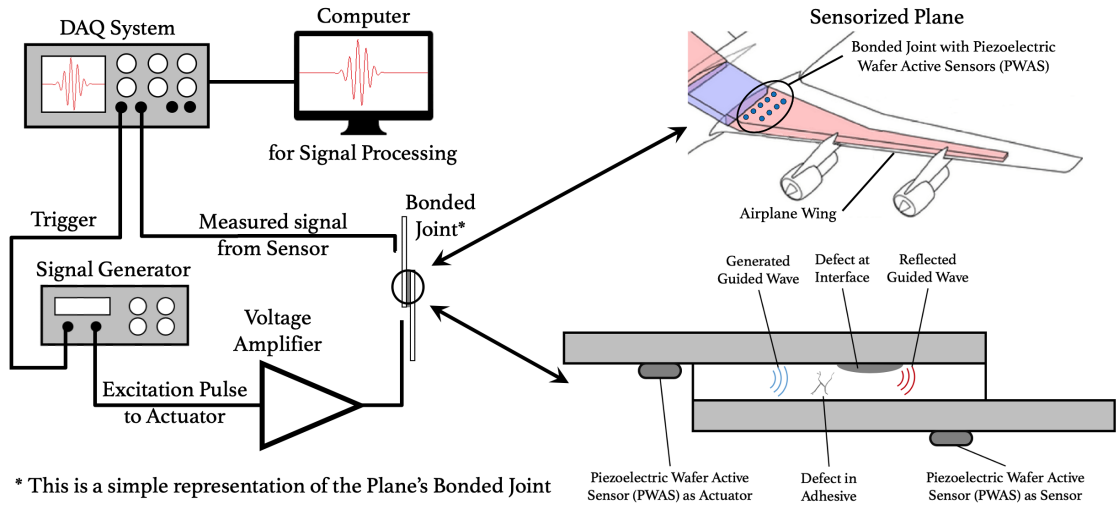


Figure 1.1: Illustration of an LW-based SHM scheme applied to an aircraft.

- To develop numerical models that are able to replicate the behavior of real SLJs subjected to weak adhesion and LWs excitation, and can rapidly generate trustful damage-dependent data;
- To establish experimental procedures for fabricating SLJs representative of the damage cases of interest, with good repeatability as will be explained in 4;
- To develop a method that validates the SLJs numerical models with real experimental data;
- To study how the LWs data can be (pre)processed to facilitate the use of ML algorithms for detecting and characterizing weak adhesion;
- To innovate on data-driven algorithms, namely ML ones, for detecting and characterizing weak adhesion, and investigate their discriminative performance;
- To create a ML pipeline able to swiftly detect the presence of weak adhesion and determine its characteristics.

1.3 Research methodology

To provide answers to the challenges faced, a methodology that combines experimental and computational research was established and materialized in a work plan comprising six interrelated steps, as illustrated in Figure 1.2 and detailed in the following.

1. Review of LW, weak adhesion, and ML applications

This step involves a comprehensive review of the literature to illuminate the road of the research. In this step, the published studies on damage detection and characterization in adhesive joints are analyzed, focusing in weak adhesion. This step also covers the existing

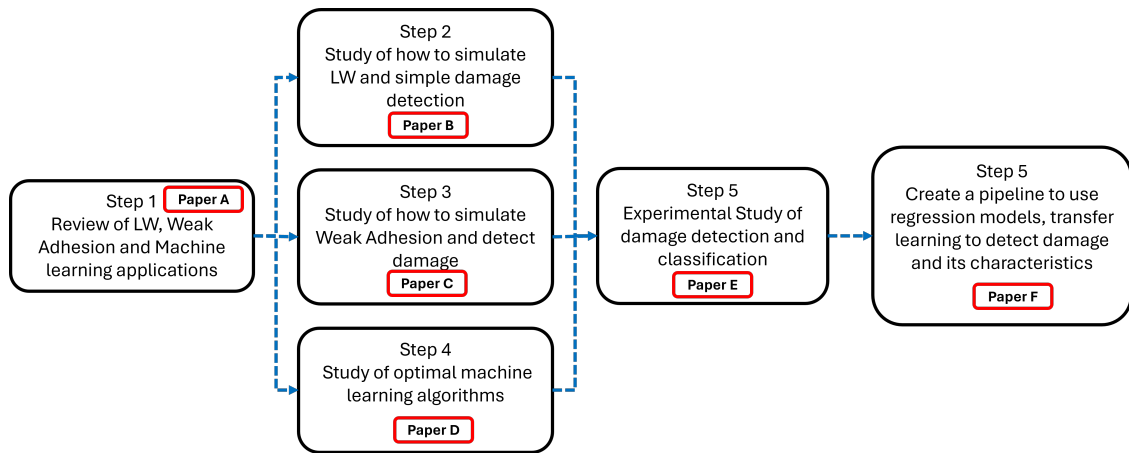


Figure 1.2: Representation of the delineated work plan.

numerical and experimental efforts for generating LW, creating weak adhesion and collecting data, as well as data processing methods and ML applications.

2. Study of how to simulate LWs, and simple damage detection

In this step, LWs in SLJs are modeled and simulated using FE software (Abaqus), and their potential to detect simple damage types, such as voids, is addressed. Simple ML algorithms are assessed to process the LWs data.

3. Study of how to simulate weak adhesion and detect damage

This step studies means for creating and simulating weak adhesion and understanding how the generated LWs data can be treated, visualized, and used. Thus, damage detection is performed, but the focus is to understand the data features and best overall metrics to be used.

4. Study of ML algorithms

Multiple ML algorithms are tested with the intent of determining the types and parameters that are best suited to the problem at hand. Simplified ML classification algorithms are considered rather than more complicated regression models.

5. Experimental study of damage detection and classification

An experimental setup is created, generating data for validating the SLJs numerical models. Weak adhesion intensity is studied using a regression ML model.

6. Create a ML pipeline to use regression models, and transfer learning to detect weak adhesion and its characteristics.

A ML pipeline is created to condense all previously studied variables into a methodology that can be applied in any scenario, to not only efficiently detect weak adhesion but also its characteristics such as damage intensity and localization.

1.4 Outline of the thesis

This thesis is based on the material reported in six peer-reviewed papers already published by the author, with the exception of the sixth paper, which is still under review. It includes an extended summary, divided into six chapters, followed by the papers mentioned above. The correspondence between papers and work plan main steps is presented in Figure 1.2. This introductory chapter contains a brief description of the problem addressed, as well as the background and motivation of this work and its objectives. Additionally, it displays a summary of each paper. Chapter 2 presents an in-depth literature review of the subjects needed for the studied. Chapter 3 addresses the overall simulation aspects in this work, including LWs and weak adhesion modeling and simulation. Chapter ?? details experimental procedures used to generate data for models validation and testing. Chapter 5 presents the adopted ML algorithms. Chapter 6 presents the overall methodology created along with the final results on weak adhesion detection and characterization. Finally, chapter 7 summarizes the conclusions and future work.

- **Paper A: Structural health monitoring of adhesive joints using Lamb waves: A review**

This paper presents a comprehensive review of equipment, testing procedures, and techniques adopted in NDT and SHM, with emphasis on applications involving SHM of adhesive joints. The fundamentals of LWs and their application to damage detection are discussed, and different signal processing, statistical, ML, and simulation methods are presented. The paper represents a basis to deepen the understanding of the problem at hand and is a thorough compilation of relevant information for future work. Although LW-based SHM methods have been heavily studied, there is a gap of few to no studies between these topics and adhesive joints, namely, for monitoring weak adhesion.

- **Paper B: Damage Classification Methodology Utilizing Lamb Waves and Artificial Neural Networks**

In this article, the performance of conventional FNNs and CNNs for simple damage classification in aluminum sheets is compared, and a novel methodology to classify damage is proposed. The ML techniques adopted require large sets of prior data, which are generated by numerical simulations utilizing FE models. The damage classification pipeline comprises (i) generating LW by one actuator, measuring the structure response using a set of sensors, (iii) extracting features from the raw signals and training the ML algorithms, and (iv) assessing the classification accuracy. The methodology has the advantage of being baseline free, easily extendable for automatic feature extraction and testing, and adaptable to different types of damage and structures, as long as the algorithms are trained with suitable data.

- **Paper C: Feature Extraction and Visualization for Damage Detection on Adhesive Joints, Utilizing Lamb Waves and Supervised Machine Learning Algorithms**

In this paper, a powerful time series specialized feature extraction method is implemented. Initially, over 75 different prominent features and their variations are extracted from each sensor's raw data. Then, by utilizing the Benjamini-Hochberg procedure some are selected as relevant for a damage classification problem. After the initial selection, the features are inserted into supervised ML methods, such as Random Forest and Naïve Bayes classifiers, where not only is it possible to achieve high classification metrics using all features, but also reveal and isolate which features allow the best differentiation of each damage class. This selection methodology accounts for robustness by utilizing different layers of selection and classification, validating the feature relevance in relation to the appropriate set of classes. As such, different damage types and ranges can be utilized in this multi-class classification pipeline.

- **Paper D: Identifying Weak Adhesion in Single-Lap Joints Using Lamb Wave Data and Artificial Intelligence Algorithms**

In this paper, NDT techniques are proposed to detect weak adhesion. These are based on LWs data and artificial intelligence algorithms. A dataset consisting of simulated LW time series extracted from SLJs subjected to multiple levels of weak adhesion was generated. The raw time series were preprocessed to avoid numerical saturation and to remove outliers. The processed data were then used as the input to different artificial intelligence algorithms, namely FNNs, long short-term memory (LSTM) networks, gated recurrent unit (GRU) networks, and CNNs, for their training and testing. The results showed that all algorithms were capable of detecting up to 20 different levels of weak adhesion in SLJs, with an overall accuracy between 97% and 99%. Regarding the training time, the FNN emerged as the most appropriate. On the other hand, the GRU showed overall faster learning, being able to converge in less than 50 epochs. Therefore, the FNN and GRU presented the best accuracy and had relatively acceptable convergence times, making them the most suitable choices. The proposed approach constitutes a new framework allowing the creation of standardized data and optimal algorithm selection for further work on NDT damage detection and localization in adhesive joints.

- **Paper E: Assessing Weak Adhesion in Single Lap Joints Using Lamb Waves and Machine Learning Methods for Structural Health Monitoring**

This paper presents a novel approach utilizing ML and LWs to determine the level of weak adhesion. Firstly, a numerical model of SLJs with different levels of weak adhesion is created and an original approach is proposed for its validation with data from real samples so that reliable LWs data can further be easily generated to train and test any other data-driven algorithm for tackling damage. Secondly, a damage detection method is proposed, based on artificial neural networks (NNs) and fed with simulated data, to determine the level of damage in SLJs, independent of their location. The results show that the simulation model can be validated with a small set of experimental data, being capable of replicating real damage in SLJs. Additionally, the use of simulated data in the training algorithm can

increase the accuracy of the simulation model up to 26% when compared to only considering experimental data. The adopted artificial NN for detecting weak adhesion emerges as a promising approach, yielding a precision of over 95%. Thus, ML and LW data can be used to improve the reliability and accuracy of adhesive bonding quality control, as well as function as a technique for SHM, which can enhance the safety and durability of bonded structures.

- **Paper F: Detecting and Assessing Weak Adhesion in Structural Single Lap Joints Using a Machine Learning Pipeline with Lamb Waves Data**

In this paper, an NDT testing technique is proposed for detecting, evaluating intensity, and locating weak adhesion in SLJs. The method utilizes LWs data in a ML pipeline. First, a large dataset of simulated LW time series for SLJs with varying levels of weak adhesion, damage locations, and sizes is generated. After preprocessing to remove outliers and discrepancies, these raw time series are fed into a pipeline consisting of CNNs, trained, and tested with synthetic data to characterize damage. Finally, the weights and biases from the CNNs are saved for use in a transfer learning algorithm, which is fine-tuned with a small amount of experimental data. The algorithm is then applied to detect the presence of weak adhesion and to assess its intensity. Tests with SLJs where weak adhesion intensity could vary from 100 MPa to 500 MPa, and damage localization could change up to 125 mm within the adhesive area, showed that the pipeline can not only detect weak adhesion in simulated data with over 95.3% accuracy but also identify about 100% of damaged cases in experimental data. Regarding the weak adhesion intensity, the algorithm achieves an average loss of 45 MPa for the experimental validation dataset, with an average error of 140 MPa and best cases of only 3.6 MPa. As for the weak adhesion localization, the algorithm exhibited an average loss of 8 mm in the validation synthetic dataset. Importantly, the methodology remains flexible enough to tackle damage characteristics beyond existence, intensity, and localization, without requiring major alterations.

Chapter 2

Literature Review

This chapter reviews fundamental concepts of LW, ML, adhesive joints, and SLJs modeling and simulation. Furthermore, the state of the art in NDT and SHM based damage detection and characterization in adhesive joints is addressed. More information and details can be found in the appended review paper, Paper A.

2.1 Fundamentals of LWs in SHM

As wear and tear occur on parts due to everyday use, the chances for the emergence of defects grow. Most times the problems occur underneath the outer layer of the material, where it is difficult to see without destructive inspection techniques. Thus, efficient monitoring methods that do not involve destroying the part are crucial. To accomplish this, NDT methods were devised for different engineering structures, including bonded parts. The most used are the visual or optical, liquid penetrant, magnetic particle, electromagnetic, radiographic, and ultrasonic testing methods.

Out of all NDT techniques, the ultrasonic, more specifically, the LW-based ultrasonic method, revealed large possibilities of application in cutting-edge industries, namely in the aeronautical field. This is largely due to the fact that airplanes contain thin and large areas and, thus, the ultrasonic waves can potentially analyze entire structures.

The concept of LW was developed by Lamb in 1917. Throughout the Second World War up to 1960, LWs were used mostly in the medical field, until Worlton used them to detect damage. A LW is a form of guided wave that can exist in isotropic, plain, and thin structures with parallel free edges [23]. In anisotropic and complex geometry structures, guided waves can propagate, which are not LWs. Nevertheless, in this work, the common practice of using the term LW in such a broader scope is followed.

LWs are nowadays seen as a prime candidate for damage detection in composite structures and adhesive joints due to: (i) their sensitivity to interference in the propagation path; (ii) their potential capability for traveling over a long distance, thus allowing for the analysis of large parts, limited by the damping characteristics of the medium and the geometric complexity of the structure; and (iii) the existence of various modes, allowing to detect damage that is internal [23, 24, 25]. LWs are

also capable of traveling inside curved walls with shallow curvatures, thus making them suitable to be used in the aeronautical field.

There are many ways to produce LWs, ranging from piezoelectric actuation to lasers, ultra-sounds, and X-rays [26, 27]. Therefore, depending on the intended application, there are pros and cons of each method. The main drawback of LWs in the context of SHM is the high complexity of the LW signals, which demands sophisticated processing algorithms and high computational power [23]. This has recently been facilitated with ML methods that allow the algorithms to learn and grow, thus simplifying the problem at hand.

Regarding the adhesive joints, there are few studies that use LWs for defect detection. Most research is for composite structures and is focused on the transmission alterations that occur when LWs traverse the adhesive section, rather than on the interactions of the LWs with defects [23, 28, 29, 30].

Although there is vast literature addressing LWs, a brief introduction to the basic theory is presented herein. In a solid medium, various elastic waves can be distinguished according to the different motions of the particles. LWs propagate in thin plates guided by their upper and lower boundaries, being actually the superposition of longitudinal and shear modes. One of the key features of LWs is that, when observed across the thickness of the material, they present a stationary wave pattern that can be divided into symmetric S_n and anti-symmetric A_n modes, where $n \in \mathbb{N}$ is the number of inflection points [31]. The LW phase velocity is dependent on the relation between the frequency and the material thickness. Thus, at any possible frequency value, there can be multiple modes that, in turn, complicate the evaluation of the measured LW signals.

To better understand the existing modes, S_n and A_n , the analytical dispersion curves are used, which may be written as [31]:

$$\frac{\tan(qh)}{\tan(ph)} + \frac{4k^2qp}{(k^2 - q^2)^2} = 0, \quad (2.1)$$

$$\frac{\tan(qh)}{\tan(ph)} + \frac{(k^2 - q^2)^2}{4k^2qp} = 0, \quad (2.2)$$

with

$$p^2 = \frac{\omega^2}{c_L^2} - k^2, \quad q^2 = \frac{\omega^2}{c_T^2} - k^2, \quad k = \frac{2\pi}{\lambda}, \quad (2.3)$$

where p and q are placeholder variables, h stands for the half thickness of the plate, c_L and c_T denote the longitudinal and shear wave velocities, respectively, k is the wavenumber, λ represents the wavelength and ω is the angular frequency.

The longitudinal and shear velocities depend on the material properties, being given by:

$$c_L = \sqrt{\frac{E(1 - \nu)}{\rho(1 + \nu)(1 - 2\nu)}}, \quad (2.4)$$

$$c_T = \sqrt{\frac{E}{2\rho(1+\nu)}}, \quad (2.5)$$

where E and ν represent the Young's modulus and Poisson's coefficient, and ρ stands for the density of the material.

Equations (2.1)-(2.2) have multiple roots, thus allowing for multiple modes. Numerical methods are used to obtain the relationships between phase velocity, wavelength, wavenumber, and frequency, $c_P = \frac{\omega}{2\pi} \lambda = \frac{\omega}{k}$. The results are often depicted using dispersion curves, which can be presented in various forms. Figure 2.1 illustrates the dispersion curves of a specimen, where each mode is represented as a phase velocity versus frequency curve in a given frequency range. The specimen is an aluminum plate with a thickness of 2 mm, density $\rho = 2500 \text{ kg/m}^3$, Poisson's ratio $\nu = 0.33$, and Young's modulus $E = 72.4 \text{ GPa}$. In Figure 2.2 it is possible to see how the wavelength of each mode varies in relation to the frequency.

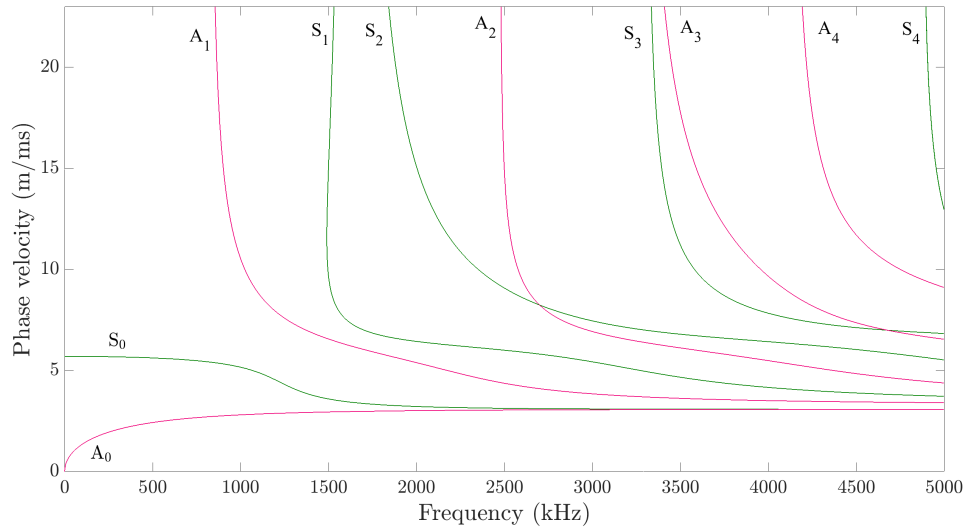


Figure 2.1: Example of symmetric and anti-symmetric modes in a wave phase velocity vs. frequency graph.

It can be verified that there is a value of frequency below which only the S_0 and A_0 modes are present, and for frequencies beyond this value multiple modes emerge. Therefore, above such a threshold value, any analysis becomes complicated.

Non-zero volume defects, such as voids, require using LWs of wavelength smaller than twice the size of the void [32]. This means that small defects can be detected as long as high-frequency signals are used. For the case of zero-volume defects, such as weak adhesion in adhesive joints, the concept of size is unclear and has to be replaced by “level of adhesion”. To the best of the author's knowledge, no studies are addressing the relation between wavelength and “level of adhesion”.

Another important aspect in the context of NDT and SHM is the type of exciting signal for generating LWs. Since LWs are dispersive, packets of waves containing different frequencies

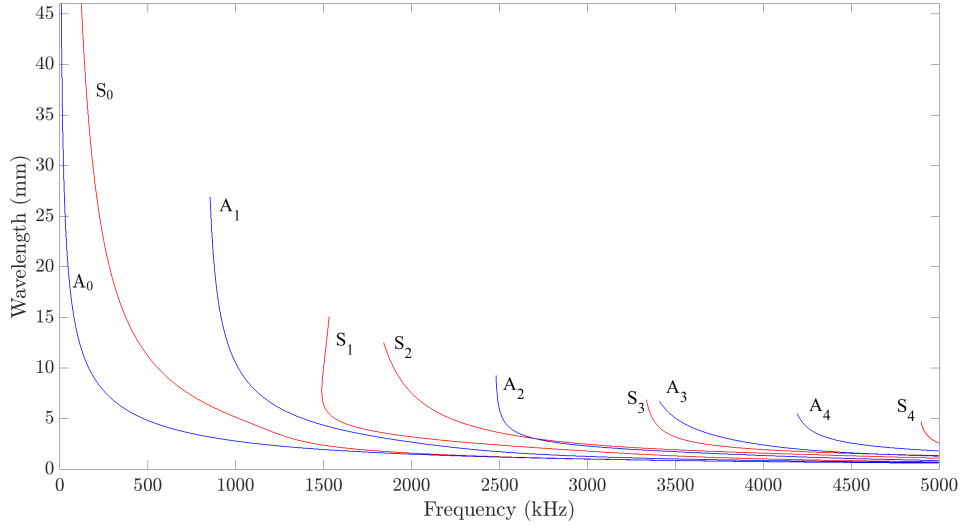


Figure 2.2: Relation between the wavelength of each mode and the frequency.

tend to spread out and distort, difficulting the separation of different modes both in the time and the frequency domains. Short time duration and narrow frequency spectrum excitation signals mitigate the problem of dispersion. The Hann-windowed tone burst possesses those characteristics and, thus, has been widely adopted to generate LWs, but other alternatives are also possible, such as the Gaussian pulse or Gaussian windowed tone burst. The effect of the window is to concentrate most energy of the input signal around a carrier frequency. When exciting LWs at points on the dispersion curves that correspond to almost constant group velocity with respect to frequency, the windowed tone bursts reduce the wave dispersion.

The Hann window is given by:

$$w(n) = 0.5 - 0.5 \cos \frac{2\pi n}{M-1}, \quad (2.6)$$

where M is the total number of data points and $n = 0, 1, \dots, M-1$. When applied to a sinusoidal signal, a burst-type waveform composed of a number of wave pulses results, as illustrated in Figure 2.3. Such signal, also called tapering function [33], has a known form and duration, leading to data easier to analyze than those obtained with other types of excitation signals.

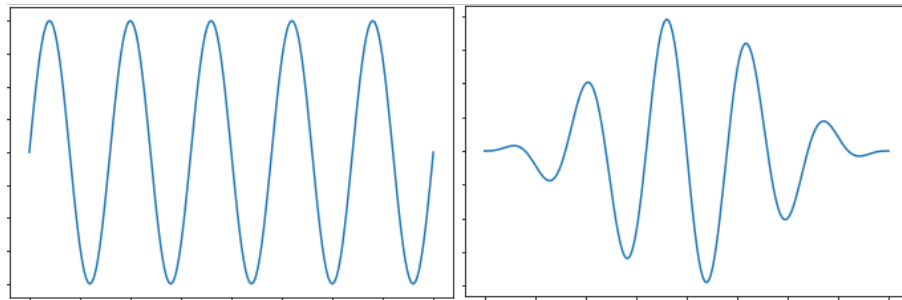


Figure 2.3: Example of how a sinusoidal signal is altered when multiplied by a Hann function.

Although there are many papers that report the use of Hann windowed tone bursts [34, 10, 35], other works use alternative exciting signals. One example is the work of Phong B. Et al [36], where cointegration is used in conjunction with a wavelet transform to determine damage in structures. Another case is reported in the works of Liang Xu Et al [37], where multiple channel guided waves were used to create damage indices that fed NNs for damage detection. More specifically to adhesive joints, the work of Puthillath, Et al [38] addressed the inspection of a titanium repair patch bonded to an aluminum aircraft skin. Referencing the works of Ren Et al [39] studied the use of modal content-based damage indicators to improve the sensitivity of guided waves to disbonds in the adhesive of composite structures. The work of Kumar Et al [40] proposed a LW based technique for detecting multiple disbonds using damage features related to mode conversion and nonlinear breathing phenomena.

2.2 Adhesive joints

There are different types of adhesive joints, but the SLJ is the most used in the industry [41]. Most research on NDT and SHM of adhesively bonded structures addresses SLJ, but all the methods and techniques developed for SLJ can be easily adapted to deal with other types of joints.

2.2.1 The single lap joint

A SLJ is composed of two adherends that overlap one another, with the adhesive in the between. Although SLJs involve simple constructive procedures due to their simple geometry, the interaction of LWs with the SLJ materials is complex. The work of Mori Et al [42] showed that the reflection and transmission coefficients of the anti-symmetric mode A_0 vary with the tangential stiffness and frequency. Furthermore, there are multiple frequencies that present maxima and minima reflection and transmission coefficients. The complex nature of the interactions of LWs with the materials composing SLJs was also investigated in the works of K. Heller Et al [43], where a combination of an ultrasonic laser technique and sophisticated signal processing methods were used to measure extreme degradation due to high temperature in specimens.

2.2.2 Defects in adhesive joints

Defects in adhesive bonds tend to occur in the adhesive layer or in the substrate, as illustrated in Figure 2.4, and may be caused by manufacturing problems (e.g., improper surface preparation, environment contamination or poor curing) or in service deterioration (e.g., water or moisture absorption, extreme temperature or loading conditions). In regards to the adherend, defects can be superficial, in multiple sizes, and internal cracking formations. Referring more specifically to the adhesive, three main defects can occur, namely poor cohesive strength of the adhesive, voids or disbonds, and weak adhesion between the adhesive and the adherend [44, 45, 46]. It is important to point out that voids can be subdivided into complete voids, where there is no adhesive between the two bonding surfaces, small voids that stay present only in the adhesive and can be due to

small air bubbles, and finally, surface voids, or delaminations that occur between the adhesive and the substrate [45]. Although kissing bond is a term commonly adopted in the literature to refer to weak adhesive bonding (e.g., slip bond, smooth bond, partial bond, zero-volume disbond, and imperfect interface), herein it will be used to designate perfect contact between two surfaces which transmits no shear stress. Conversely, the term weak adhesion will denote any intermediate level of adhesion that can range from complete adhesion to kissing bond. Out of all defects, weak adhesion between the adhesive and substrate is the hardest to detect accurately, and out of all NDT or SHM methods, the most promising results come from guided waves, more specifically LWs [44].

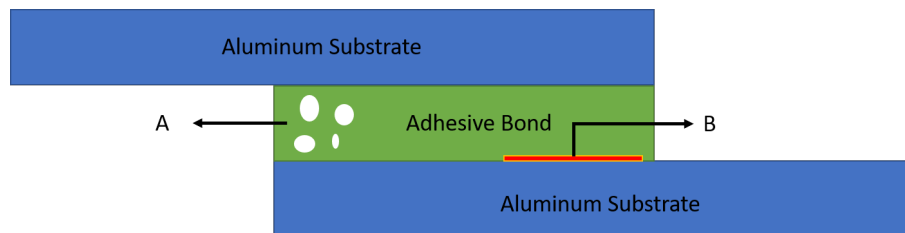


Figure 2.4: Example of different types of defects, where A) is a void and B) is weak adhesion between the adhesive and the substrate.

One unique use of LWs is the possibility of determining surface and internal damage, which is possible since each LW mode is particularly sensitive to specific types of damage. For example, cracks can be detected using symmetric modes, while surface damage affects more the anti-symmetric modes. For a given structure, if there is a defect between one actuator/sensor pair, then the signal measured at the sensor will be different from the one acquired in a pristine specimen. Increasing the number of actuator/sensor pairs will increase the accuracy of the damage detection algorithm [47]. Moreover, to determine the extension and characteristics of the damage, all aspects of the LW should be observed, both in the time and in the frequency domains. In other words, by processing multiple data features, it is possible to determine additional information about damage [43].

2.2.3 Testing methods

The most important part of a testing method suitable for LW-based SHM is the positioning of the sensors and actuators in relation to the defect. This is extremely important due to the fact that only the sensors that are in line with the defect and the actuators will measure a significant change in the signal (in comparison with the signal acquired in a pristine specimen). Out of the studies that address detection of defects in adhesive bonded structures using LWs, there are two main approaches regarding sensor/actuator placement and data collection: (i) within the bond (WTB); and (ii) across the bond (ATB), as illustrated in Figure 2.5. In the WTB approach, the LWs are generated and detected in the adhesive region. In the ATB, the LWs are generated and detected away from the bonded area, having the waves to pass the adhesive before they arrive at the sensor. In the works of Verze Et al [45] the ATB approach was adopted for the analysis of defects in

adhesive structures. On the other hand, in the work of Kundu Et al [48] the use of WTB was reported for investigating the sensitivity of normal incidence bulk waves.

Normally, the WTB is used as benchmark, as it is difficult to implement in real structures, since it requires access to the adhesive joint. However, in SHM this is not an issue, since the part is always instrumented with a sensor/actuator array. The main benefit of the WTB method is that the LW modes are more easily detected by using a suitable positioning of the transducers and specific signals. The method was adopted in the works of Puthillanth Et al [38], where guided waves were used to inspect repairs made using adhesive bonds in aluminum surfaces. The ATB implementation has the transducers placed away from the joint and can represent an easier approach to the application in real parts [49]. However, the drawback is a discontinuity that will modify that signal, since it is generated in the adherend [2].

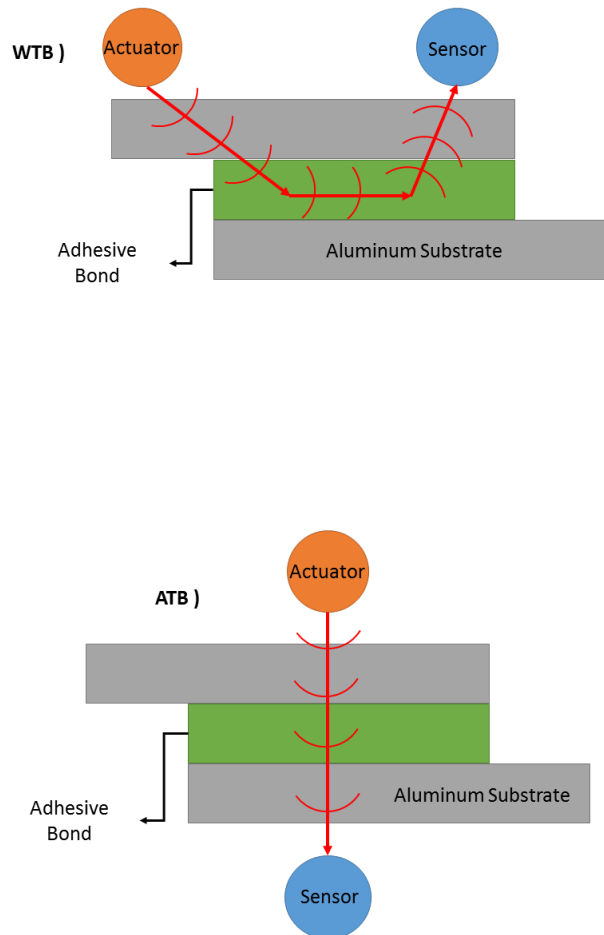


Figure 2.5: Examples of WTB and ATB sensor/actuator placement for LWs testing.

Out of many possible equipment and methods employed in NDT and SHM, just a few have already been tested in adhesive joints. In Heller Et al [43] a Nd:YAG laser (1064 nm) with a low pass filter at 10 MHz was used on an aluminum structure with dimensions $100\text{ mm} \times 100\text{ mm} \times 0.9398\text{ mm}$. The adhesive, placed on the entire surface forming a 0.25 mm thick layer, was a M3 tap product F-9473PC. Lasers were also used in other studies [50, 51] that analyzed different properties of adhesive bonds in specimens that ranged from $100\text{ mm} \times 100\text{ mm}$ to $300\text{ mm} \times 300\text{ mm}$, with adhesive layers of 0.25 mm in average. In the works of Deng Et al [28], the substrate was a composite material and the overlap was studied using lengths of 50 mm, 100 mm, and 200 mm. Referencing the work of Ren Et al [29] it is possible to see the use of transducers, but no specific mention was made to their type. In this study, plates of composite material with $300\text{ mm} \times 300\text{ mm}$ were used with a 50 mm wide epoxy stringer.

All studies have in common the use of large structures with an average size of $100\text{ mm} \times 100\text{ mm}$, and a relatively small thickness, between 1 mm and 3 mm. The adhesive layer is of around 0.25 mm [52, 50, 51]. Due to the overall values of sensor placement and specimen size, these can be used as an initial estimate for further work.

One of the main limitations of the aforementioned testing rigs is that relatively large and simple sheets are used. This allows for new studies, regarding different specimen sizes, shapes and types, and their effects on the ability to detect defects, more specifically in the case of weak adhesion.

2.2.4 Instrumentation

Although there are many ways to approach the use of LW in SHM, first, it is normally necessary to understand the designated use of the specimen to, then, determine the technology, instrumentation and testing methods that are possible and more suitable. When the intended purpose is an outdoor application, where lightweight, reliable and small size components are fundamental, certain equipment, such as laser interferometers, suited to workbench use, is inappropriate. Therefore, out of the remaining possible options, transducer-based equipment is a prime candidate for LW-based SHM applications. In a simplified way, such technology works by placing two or more transducers on the designated part, leaving the region where it is necessary to determine defects in between the transducer [27, 26].

A few prominent transducer-based solutions are presented in the following. A brief overview of the physical traits are given, followed by a simple description of how each method produces LWs.

- Electromagnetic Acoustic Transducers (EMAT)

This transducer can be regarded as a speaker composed of a coil and a permanent magnet. Its working principle is based on Lorentz's forces and magnetic coupling that cause the permanent magnet and coil to create a relative movement between them, depending on the way the coil is functioning. This movement at high speed creates vibrations and thus can excite LWs [53, 54]. These sensors were used in the works of Wilcox Et al [55] to generate

LW in a 5 mm thick aluminum plate. It was shown that the sensors' omni-directional sensitivity allows for a precise wave detection in one plane. EMATs were used with adhesive joints to assess the applicability of LWs and shear horizontal waves in the evaluation of thin plate structures in the works of Rokhlin Et al [56]. In the work of Sun Et al [57] electromagnetic pulse-induced acoustic testing was used to detect debonding in plastic composite/metal specimens.

- Comb and Interdigital Transducers

Comb and interdigital transducers are normally composed by 3 layers of material, forming a sandwich of two electrodes with a layer of piezoelectric material in the middle, as illustrated in Figure 2.6. As the name suggests, usually, the top layer electrode is shaped forming a comb like structure [58, 59].

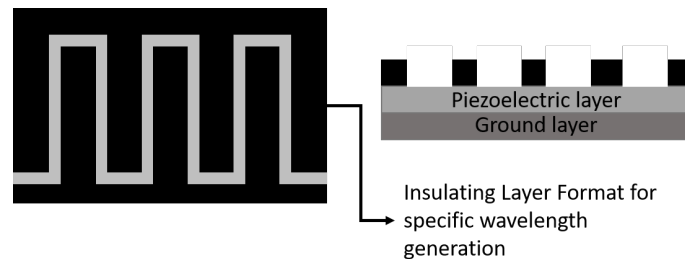


Figure 2.6: Comb and interdigital transducer structure.

The main drawback of these transducers is that the comb pattern determines the wavelength range that can be produced, which, in turn, can not be changed quickly. Although they are used in LW-based NDT of diverse materials and structures, their application with adhesive joints has been quite limited.

- Micro Electro-Mechanical Systems (MEMS)

Micro electro-mechanical systems (MEMS) can have many configurations [60]. They can normally be constructed with flexible materials coupled with coils and permanent magnets. The main difference between MEMS and EMAT is the overall configuration of the structure and how each component is placed [61, 62]. Although they have been used with LWs [62], they were adopted with parsimony, namely to monitor adhesive joints, probably due to their high price and high susceptibility to noise for in-situ applications.

- Laser Vibrometry

A laser Doppler vibrometer makes non-contact vibration measurements of a surface. The laser beam is directed to the object and the vibration amplitude and frequency are extracted from the Doppler shift of the reflected beam frequency. The output of the sensor is directly proportional to the object velocity along the direction of the laser beam. Besides velocity, displacement can also be measured with appropriate signal conditioning. Laser Doppler vibrometry allows measuring with high resolution and linearity. However, the equipment is

expensive and, although it can be useful in NDT for monitoring out-of-service components, it is not suitable for SHM, since can not be permanently fixed to the structure. Normally, pulsed Nd:YAG lasers or piezoelectric elements are used to excite the LWs whose propagation characteristics are then acquired by the vibrometer. Within the scope of NDT of adhesive joints, the technology has been used by many researchers [34, 63, 64, 65].

- Fiber Bragg Gratings

Fiber optic sensors, namely fiber Bragg gratings have proved their effectiveness as ultrasonic sensors. Their main advantages include small weight and size and immunity to electromagnetic interference, which are very interesting for SHM applications. A fiber Bragg grating sensor is a microstructure with a typical length of a few millimeters that can be inserted into the core of a standard singlemode fiber. The sensor acts as a wavelength selective mirror. Light from a broadband source is injected into the optical fiber, but just the part within a very narrow spectrum centered on the Bragg wavelength is reflected. The remaining light is not affected and continues its path through the optical fiber. The Bragg wavelength is essentially defined by the period of the microstructure and the refractive index of the nucleus. When acting as a strain sensor, the fiber is stretched or compressed, which causes a change in the period of the microstructure and in the Bragg wavelength. Fiber Bragg gratings have been used with LW-based NDT techniques [66, 67], but their application to adhesive joints has been limited [68].

- Distributed Sensors

Although sensors can be integrated individually on a structure, a practical and cost-effective alternative is to use a (pre-built) network of sensors. One example is the Acellent Technologies' SMART Layer, which consists of a network of piezoelectric elements that can be efficiently deployed on both simple and complex shaped structures [69]. The technology uses advanced electronics industry manufacturing processes, which involve printing and etching a conductor pattern onto a dielectric substrate, laminating a dielectric cover layer for electrical insulation, and mounting arrays of transducers on the circuit. The SMART Layer is treated as an extra ply by the composite layup process or can be surface mounted on structures made with a variety of materials. Acellent Technologies provides also the SMART Suitcase product to interface the SMART Layer directly, as well as software for damage diagnosis.

Another example of distributed sensors is the case of phased array probes, which are made up of multiple elements, each one pulsed automatically at specific time instants. The advantage is the possibility of scanning large areas without the need for moving the probe [70].

Applications of distributed sensors within the scope of damage detection in adhesive joints [71, 72, 73] have been limited, although they are potentially interesting in SHM.

- Piezoceramic Transducers

This type of transducer can vary in geometry, material, and size, but, generally, they are thin wafers of piezoelectric material and, thus, they are also called piezoelectric wafer active sensors (PWAS). The piezoelectric properties allow the material to alter its shape when subjected to an electrical voltage excitation. Therefore, by applying a variable signal to the wafer, it vibrates at the desired frequency, creating LWs. On the other hand, when a piezoelectric material is mechanically deformed, it generates also an electric signal, thus allowing the PWAS to work either as an actuator or as a sensor. The main benefits of this technology are its simplicity, lightweight, and low cost [74]. PWAS can be commonly seen as candidates for SHM in aeronautics, where large arrays are needed to monitor large parts [75]. An example of use was reported in [74], where it was shown that PWAS are particularly sensitive to the LW S_0 mode at around 300 kHz. Reference [75] also used PWAS to detect damage in-situ by using LWs. Specifically for adhesive joints monitoring under the framework of LW-based SHM, PWAS have been widely adopted [40, 76, 35, 77].

Since the PWAS are often bonded to the structure, their effects in the SHM monitoring system must also be considered [78]. Studies reported a shear lag effect caused by the adhesive [79, 80], more critical for lower shear modulus and thicker adhesive layers, which translated into worse shear transfer capability between the PWAS and the structure and reduced signal amplitude. Other studies showed an increase in the signal amplitude when using thicker adhesive layers [81], which was attributed to the PWAS resonant behavior under different constraints imposed by the adhesive. This effect was studied numerically [82], and the issue was addressed with the objective of generating high amplitude LWs with limited electrical energy for wave excitation [83].

2.3 Statistical and ML based damage detection

Before determining the methodology that will be used to detect a defect in a testing part, it is necessary to determine the optimal placement of the sensors/actuators. Although for adhesive joints the problem is still not solved, for overall SHM there have been many studies that can serve as a baseline. In [84], genetic algorithms were used to find the optimal location of a specified number of elements. Genetic algorithms were also adopted in [85], where the main optimization objective was maximizing the damage detection area. It is important to note that most research work seeks to determine either the optimal number of sensors/actuators or their optimal placement, while little work has been done combining both objectives [86].

A way to determine sensor/actuator placement and number is by calculating the spatial density of information that is required. This issue is illustrated in Figure 2.7. The existing sensor/actuator “overlapping paths” would allow for an accurate detection of a defect at the center of the specimen. For a defect close to a border, there is a limited number of opposing actuator/sensor pairs. In the example, the vertical axis is richer in information than the horizontal one. Thus, the horizontal coordinate of the border defect would be detected more accurately than the vertical coordinate. This is illustrated by the resulting oval area of detection.

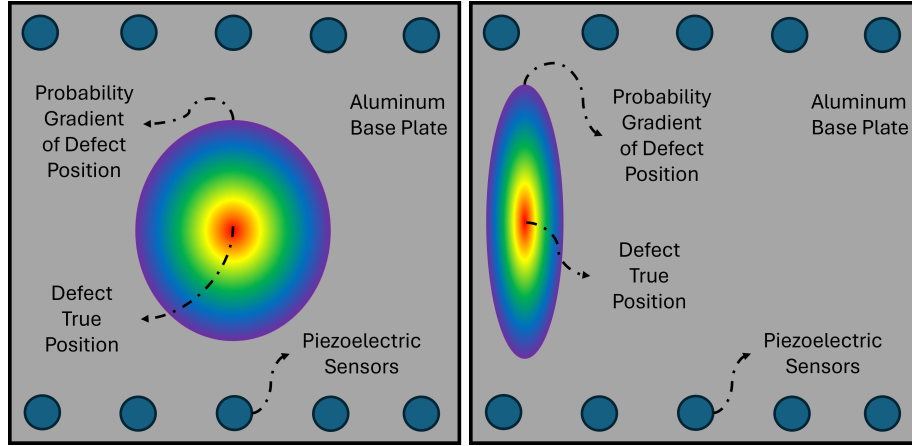


Figure 2.7: Probability of detection caused by a defect located: (left) at the center; (right) close to a border. Sensors/actuators are represented as blue circles [1].

Even using the optimal sensor/actuator positions and quantity, detecting a defect utilizing LWs is difficult when looking only at the raw data. To generate a meaningful and valid answer out of the data, it is necessary to pass the collected information through one or more suitable processing steps, either based on statistical approaches or ML algorithms.

2.3.1 Statistical based methods

Statistical based methods rely on the divergence, in frequency and/or time domains, between base-line signals and actual sensor measurements. To exemplify this, it is better to imagine that each LW, when hitting a defect, changes its direction, form and time of arrival at the sensor, in comparison with a “base test” (performed in a pristine specimen), as it has to “go around” the defect [2, 1]. Statistical methods of reconstruction have subtle differences in their algorithms and, thus, are classified in two main groups: (i) time of flight diffraction, or difference, or delay (TOFD) [47]; and (ii) signal difference coefficient (SDC) [87].

One example of SDC is the reconstruction algorithm for probabilistic inspection of damage (RAPID), where there are two main assumptions. The first is that every effect that come from all actuator/sensor pairs can be linearly summed to determine a defect probability distribution for a given inspected area. The second is that the area that an actuator/sensor pair can inspect is some subarea around the direct path between them. The mathematical formulation used for this method is [2]:

$$P(x, y) = \sum_{k=1}^N p_k(x, y) = \sum_{k=1}^N A_k \left(\frac{-1}{\beta - 1} R(x, y, x_{1k}, y_{1k}, x_{2k}, y_{2k}) + \frac{\beta}{\beta - 1} \right), \quad (2.7)$$

$$R = \frac{\sqrt{(x - x_{1k})^2 + (y - y_{1k})^2} + \sqrt{(x - x_{2k})^2 + (y - y_{2k})^2}}{\sqrt{(x_{1k} - x_{2k})^2 + (y_{1k} - y_{2k})^2}}, \quad (2.8)$$

where P is the probability of a defect at the coordinates (x, y) , k stands for a actuator/sensor pair and N is the total number of actuator/sensor pairs in the network. Finally, the total distance between the actuator and sensor is R [2].

The variations present in the time domain signals S_0 and A_0 in the presence and absence of a defect are only slight and without a careful analysis it is almost impossible to determine the characteristics of the defect.

Figure 2.8 represents the sensors acquiring the data that are used in the RAPID algorithm to create an image representing the most probable location of the defect. A defect at the central area can be detected accurately, but defects close to the borders are hard to detect, requiring a higher actuator/sensor network resolution.

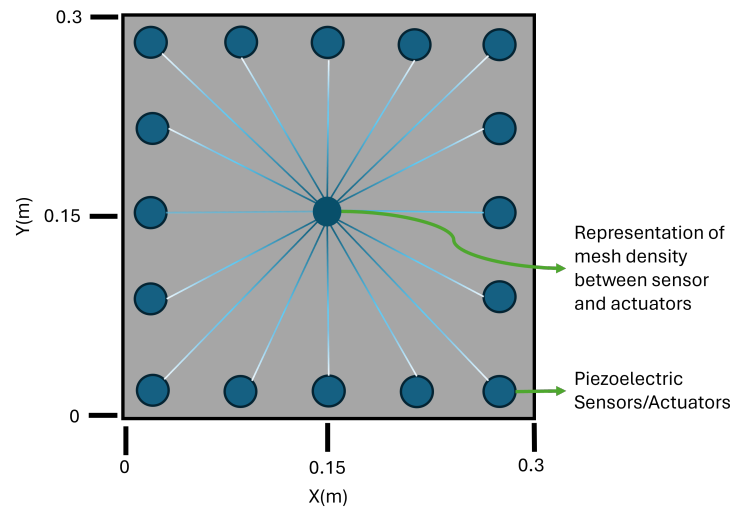


Figure 2.8: Schematic example of the output of the RAPID algorithm [2].

In [2], a statistical method was used to determine the loss of material in aircraft parts by using LWs excited/sensed by transducers embedded in the structure. In reference [87] a statistical method to determine damage in composite structures was addressed.

Out of all review done, no evidence of statistical methods applied to LW-based SHM of adhesive joints was found. This allows for novel studies in this area and, more specifically, in the use of statistical methods to detect weak adhesion between bonded materials.

2.3.2 Machine learning methods

ML methods can be divided into three main categories, namely supervised, unsupervised and reinforced learning. The first category is normally used when the objective is to classify and label objects [88]. The second is adopted as a means to divide large quantities of information (big data) into groups created by the algorithm [89, 90]. Finally, the last category is often used in the field of robotics, where the algorithm has to learn and refine its objective in various stages and “generations”, in a way similar to a genetic algorithm.

To find the categories more suited to LW-based SHM, it is necessary first to determine what is wanted. LWs are capable of detecting not only the location of a defect, but also its size and type. Therefore, the objective is to classify the information obtained in classes that are chosen by the user, which elects the supervised learning the best approach. However, other ML may also be adopted.

As stated previously, the objective of the analysis is to determine the defect position, size and type. To do this with supervised learning it is necessary to determine the type of information that is deemed acceptable. For example, the position of a defect can be represented by the indices of a cell in a rectangular grid. The type of answer required can drastically change the way the algorithm is constructed and used.

Inside the category of supervised learning, there is a vast world of subcategories that can be explored, but for the problem at hand, NN and deep learning (DL) play a key role due to their ability in categorizing images and speech patterns that, if analyzed carefully, show many similarities with damage detection problems [91].

The NN and DL are ML that rely on a matrix structure representation similar to the neural synapses in humans. Although difficult to understand at first hand, the application of NNs for analyzing LW signals follows specific steps.

First, as with the statistical methods, the data of interest must be acquired. These data, representing amplitude of vibration versus time, measured at known sensor locations, are segmented depending on the level of detail required. The resulting fragments are used as inputs to the neurons. The algorithm then uses weights, biases and a nonlinear function to create a cost function, or “hidden layer”. This cost function is compared with the wanted results in the “output layer”, which in the problem at hand could be, for example, the presence or absence of damage. Depending on the comparison result, the NN adapts the weights and biases by means of some optimization method. A schematic representation of a NN is depicted in Figure 2.9.

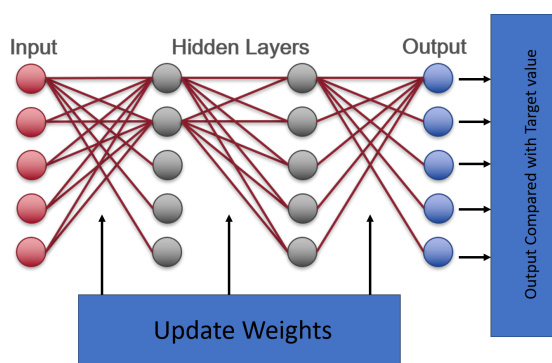


Figure 2.9: Example of a NN with its input, hidden and output layers.

As there are many papers that investigate NNs and DL to analyze LWs and defects, it is necessary to clarify the difference between the algorithms. The two terms describe the use of many intermediate “hidden layers”, where each neuron can be seen as a line that is created in a plane to separate data points. Furthermore, each layer deforms the lines received from the previous layer to

better suit the problem. This is important to understand, as each problem has an optimum number of neurons and layers and it is fundamental not to use more layers nor neurons than necessary to avoid overfitting. It should also be mentioned that inside the artificial NN category, there are many variants. For example, the implementation of memory layers can be useful in certain cases. However, the discussion of what techniques can, or should, be used is outside the scope of this work.

As stated previously, ML have been used in various studies. One can mention the work [92], where ML was adopted to diagnose damage on a specimen using a LW sensing network. Another work [91] used LWs in conjunction with CNNs to quantify and localize damage. Finally, in [93] DL to predict and determine the occurrence of delaminations in composite parts was studied. As with the statistical methods, out of all reviews done, no evidence of any type of ML being used in conjunction with LWs and adhesive joints was found. This allows for further studies in this area and, more specifically, in the use of ML for the detection of weak adhesion between materials.

2.4 Theoretical simulation

When developing the simulations it is important to not only look at the problem and find the most trustworthy solution but also find one that is less complex and allows for quicker simulation times. There is also the aspect that the more layers of complexity that are added, the more variables are used and there is more chance of errors to occur. Therefore, this section will analyze the equations and validated techniques behind each component to determine what level of detail the model will have in that aspect.

2.4.1 Modeling piezoelectric transducers

Piezoelectric transducers are regarded as prime candidates for LW-based SHM of adhesive joints, and their dynamics must be considered to obtain reliable simulation models. Often, the models are calibrated using real data from a few experimental tests.

The main constitutive equation of a linear piezoelectric element is the relation between the mechanical and electrical characteristics of the material, namely strain S_{ij} and stress T_{kl} [47]:

$$S_{ij} = s_{ijkl}^E T_{kl} + d_{kij} E_k, \quad (2.9)$$

where E_k is the electric field, s_{ijkl}^E denotes the mechanical compliance of the material in which the electric field is zero, and d_{kij} is the distance where this field is also zero. It is also important to note that the indexes i, j, k represent the three Cartesian axes. Therefore, the equation that expresses the direct piezoelectric effect is [47]:

$$D_j = d_{jkl} T_{kl} + \epsilon_{jk}^E E_k, \quad (2.10)$$

where D_j is the electrical displacement, and ϵ_{jk}^E is the dielectric permittivity of the material measured when the mechanical stress is zero.

When observing the force application and experimental setup, the piezoelectric wafer is permanently fixed on the structure. This causes the strain/displacement compatibility and stress/force equilibrium principles to apply. The interaction force will be called F_{PZT} and it is assumed to interact only with the sensors boundary [47]. In turn, this force will induce the activation forces N_a and moments M_a given by [47]:

$$N_a = F_{PZT}, \quad (2.11)$$

$$M_a = F_{PZT} \frac{h}{2}. \quad (2.12)$$

where h is the height of the sheet of material.

By studying these models it is possible to not only understand how they work but also their limitations and where they can be simplified. In the problem studied in this work, it is possible to see that there is no need for a complicated simulation as there is a linear behavior of the electrical signal with the forces applied. Thus it is better to simply consider a direct force being applied to the part and then create multiple levels of error trying to simulate the electrical displacements and properties. This will allow us to simulate the actuators and sensors in the simplest possible form without detracting from the result.

2.4.2 Modeling adhesive structures

One of the most promising applications of LWs is to detect weak adhesion in adhesive joints [28]. One way to model different levels of weak adhesion is adopting the cohesive zone method (CZM). This method is based on the use of interface elements [28, 94], where during the computer analysis the stiffness of the cohesive zone suffers a step-by-step iteration following the traction-separation law. This law presents three possible failure modes with a separation occurring in the normal direction, shear occurring in the in-plane direction and mixed mode occurring as a combination of the previous two modes. To calculate the normal and shear stresses, the following equations are used:

$$\sigma_n = K_n u_n (1 - d_n), \quad (2.13)$$

$$\tau_t = K_t u_t (1 - d_t), \quad (2.14)$$

where σ_n and τ_t are the normal and shear stresses, with K_n and K_t being the respective stiffness coefficients, u_n and u_t standing for the relative displacements of the surface, and d_n and d_t being calculated parameters that define the maximum allowable stress in each direction.

It should be mentioned that weak adhesion is different from kissing bonds since the kissing bond is represented by a contact surface that has ultimately no cohesive elements between the substrate and the adhesive [29].

2.4.3 Computer modeling software

To accomplish the computer modeling, other than the basic mechanical equations that guide how the simulation should behave, there are many methods that can be used [95]. In this section, the various techniques will be introduced and examples will be given to determine what method is more adequate to simulate LW in adhesive bonds subjected to weak adhesion.

- **Finite Elements Method** - The laws of physics can describe many space-time problems by using partial differential equations (PDE). However, these analytical methods have limitations of geometry and forces where the problem becomes too complex to solve analytically. To overcome these problems, the FEM is applied, where the material has its form discretized into small parts to create a mesh. This allows the PDE to be approximated by a numerical model and thus, arrive at a result. This method is used by most commercial programs, such as Abaqus and Ansys, and has been adopted in many studies [96, 97, 25, 98]. For example, reference [99] used the FEM to detect damage on a spectral beam using an iterative search technique. In [35] the FEM was applied within SHM of a bonded lap joint to analyze dis-bonds. The work [100] used the FEM in simulations of kissing bond defects in adhesive joints.
- **Finite Difference Method** - The basic concept behind the finite difference method (FDM) is similar to the one in FEM. However, in the FDM the PDEs are replaced with many discrete equations called finite difference equations and are mostly used for regular grid and rectangular shapes [101]. One example of the application of the FDM can be found in [101], that used the method in conjunction with wave motion for SHM of SLJs.
- **Semi-Analytical Finite Element Method** - The semi-analytical finite element method (SAFE) is often used in problems subjected to waves, as it only requires the discretization of the cross-section of the wave. Furthermore, it can utilize a pure analytical description of a wave problem [102, 103, 104]. A few examples of studies with SAFE are the work [103], where the method was implemented in a graphical interface for the simulation of guided waves, and the work [28], that used the SAFE method to study the propagation of guided waves in the adhesive layer of bonded composite structures.

All three methods can be used for simulating LWs in adhesive bonds subjected to weak adhesion defects, each one with its advantages and disadvantages. To determine the best option, it is necessary to observe secondary characteristics, such as ease of use and application of the method with multi-physics, which simulates the sensors and actuators electrical properties. This leaves the FEM as prime candidate as it has multiple commercial software implementations.

- **Local Interaction Simulation Approach** - The local interaction simulation approach (LISA) is essentially a FDM variant [105, 106]. It has received increased attention for the simulation of guided waves due to its computational reliability and efficiency. LISA uses iterative

equations to model the displacements at a given point based on those at their neighbors at past time steps. Those equations are derived from elastodynamic equilibrium. Reference [107] adopted LISA to model LWs in isotropic plates. The work [108] used LISA to model damage in both isotropic and orthotropic plate structures. In modeling adhesive joints, LISA was also used [109].

It should be emphasized that despite all modeling/simulation methods available, the high-order FEM is the most suitable for wave propagation, especially the spectral element methods. Their effectiveness with adhesive joints was addressed in [110].

2.5 Summary

In this chapter LW-based SHM was addressed, with emphasis in adhesive joints. SHM goes beyond NDT, since it permits in-situ monitoring, meaning detection, localization and characterization of damage. Despite the potential of LWs to detect incipient damage, its application to detect certain types of defects, as is the case of weak adhesion, is still too far and requires much attention. This entails a gap of studies that can be done to ensure a full overview of the use of LWs and ML to detect said damage. This chapter reviewed the work done in the last few years, with emphasis in equipment, testing procedures and techniques adopted in that field. The fundamentals of LWs and their application to damage detection were discussed, and different statistical, ML, and simulation methods were presented. The information presented constitutes a basis to deepen the understanding about the problem and points out future directions of work, where ML can be used to detect damage or weak bonds in adhesive joints by using LWs.

Chapter 3

Numerical methods

This chapter presents the multiple FE models created along with the methods used to generate LWs and weak adhesion in SLJs. After combining the models and methods, simulations were performed to generate a large database of synthetic data that served as a backbone for developing and (pre)training all adopted ML methods.

3.1 FEM models

In total three different models were developed. The first represents just a sheet of aluminum with simple damage in its central region. The objective was focusing on the generation of LWs, analyzing the interaction of LWs with simple damage, and collecting preliminary data to be further correlated with damage. The second model corresponds to a small SLJ, where the objective was to model the adhesive and weak adhesion, and analyze their effect on LWs. This model could generate data to develop ML algorithms for detecting and assessing weak adhesion intensity. Finally, the last model is for a large SLJ, where the objective was to generate data for developing ML methods for weak adhesion detection, intensity evaluation and localization. All models were implemented in Abaqus. A dynamic explicit method was used for the simulations, due to the time dependency of the problem at hand. The mesh size for all cases was chosen to be 1.5 mm with elements of the type C3D8R. This value was used in order to minimize the computational burden, while being smaller than half-size the LWs wavelength and, thus, small enough to not cause the simulations to diverge. Usually, the smaller the mesh, the better the simulations accuracy, but at the cost of a higher simulation time. To further reduce the computational complexity, the mesh outside the areas defined by the actuator/sensors were chosen uniform, while inside it was allowed to change.

3.1.1 Model-1

For the first model, the aluminum sheet is $300 \times 300 \times 2$ mm, with density $\rho = 2,500 \text{ kg/m}^3$, Poisson's ratio $\nu = 0.33$ and Young's modulus $E = 72.4 \text{ GPa}$ (identical material for all models). The

choice for aluminum was due to the fact that most primary structures of vehicles in the aeronautical industry are fabricated out of this material. The sheets are subjected to damage in the form of cylindrical holes that can be 2, 6, or 10 mm in diameter.

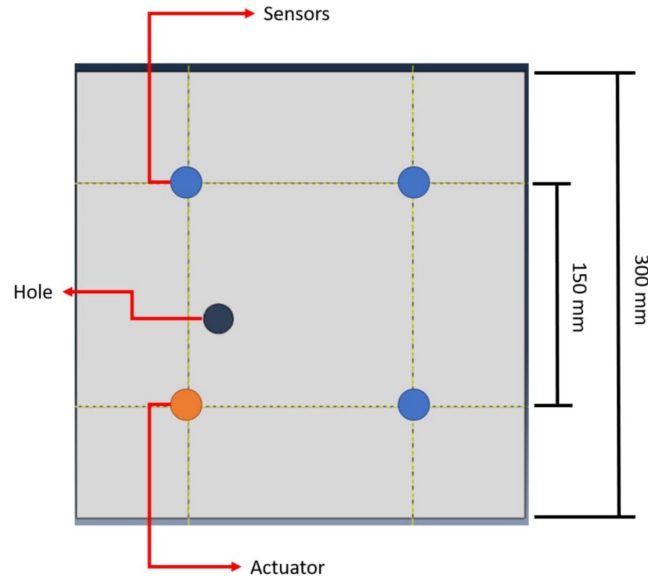


Figure 3.1: Representation of an aluminum plate, with actuator, sensors, and a hole type defect.

One actuator and three sensors were positioned in a square configuration with a 150 mm side, where the actuator is located at the bottom left corner (75,75) mm, as can be seen in Figure 3.1. The positions for the sensors were chosen to allow a large monitoring coverage, while still maintaining a low sensor count. This is especially beneficial in the applications to aircrafts, as they have large wing panels that can not have excess weight coming from complicated sensor arrays. In Figure 3.2 it is possible to see the propagation of the LWs on the plate and their interactions with the hole and plate boundaries.

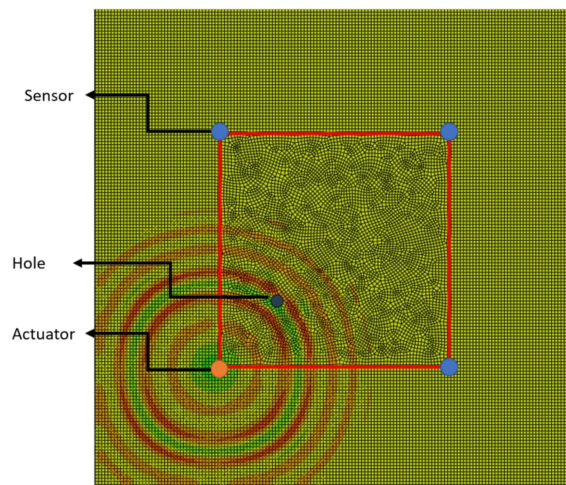


Figure 3.2: Simulation of LWs moving in the aluminum sheet.

In this model, the defects can be positioned in a random fashion inside a square with a resolution of 1 mm, and their size can be randomly generated within the values $\{2, 6, 10\}$ mm. Simulation parameters were thoroughly tested and adjusted, but their initial values were obtained from the literature [111, 112, 113].

3.1.2 Model-2

For the second model, the focus was on the simulation of the adhesive and weak adhesion, therefore a SLJ was created consisting of two aluminum substrates measuring $120 \times 25 \times 2$ mm each, along with an adhesive layer of 0.2 mm. Positioned on the upper substrate is a single actuator, situated 25 mm away from the edge. A single sensor is located on the lower substrate. Furthermore, there are 6 mm holes in the substrates used to experimentally test the SLJs for traction. These parts are schematically represented in Figure 3.3. It should be noted that the substrates dimensions of the model used in Paper C were slightly different, but were adjusted thereafter to optimize the simulations. Different levels of weak adhesion could be implemented as described in section 3.3

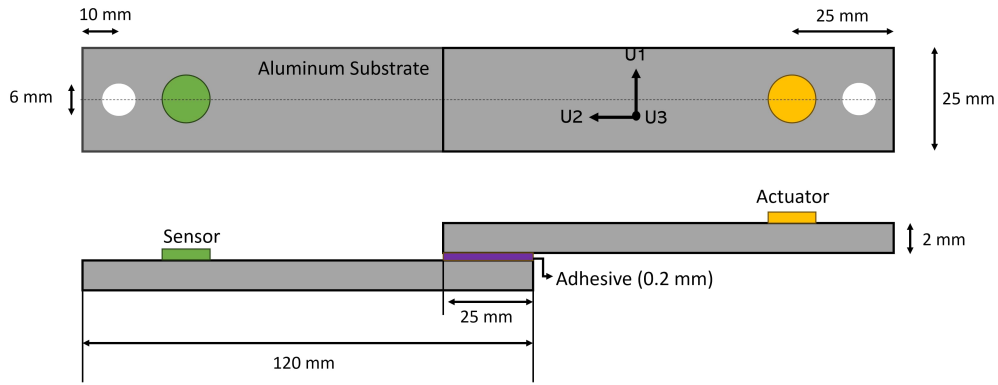


Figure 3.3: Illustration of the dimensions, and actuator and sensor placement, of the first type of SLJ, used to address weak adhesion detection and intensity evaluation.

3.1.3 Model-3

Finally, for the third model, the objective was to create an area where more characteristics could be applied, such as damage location and position. Therefore, two aluminum plates with dimensions $120 \times 350 \times 2$ mm were used, bonded with an adhesive layer of 0.2 mm, forming a SLJ. All dimensions are shown in Figure 3.4. The SLJ included one actuator and five sensors. Weak adhesion defects were simulated by creating a thin layer of adhesive where the Young's modulus was reduced in comparison to the rest of the adhesive material as will be further discussed in section 3.3.

The damaged area, spanning 25×25 mm, could be incrementally shifted across the substrates overlap area (i.e., direction U1), ensuring a minimum distance of 50 mm from the edges of the SLJ to mitigate LWs reflection effects. Furthermore, to ensure a comprehensive dataset, the dimensions of the damage width could be varied in increments of 25 mm, ranging from 25 to 100 mm, resulting

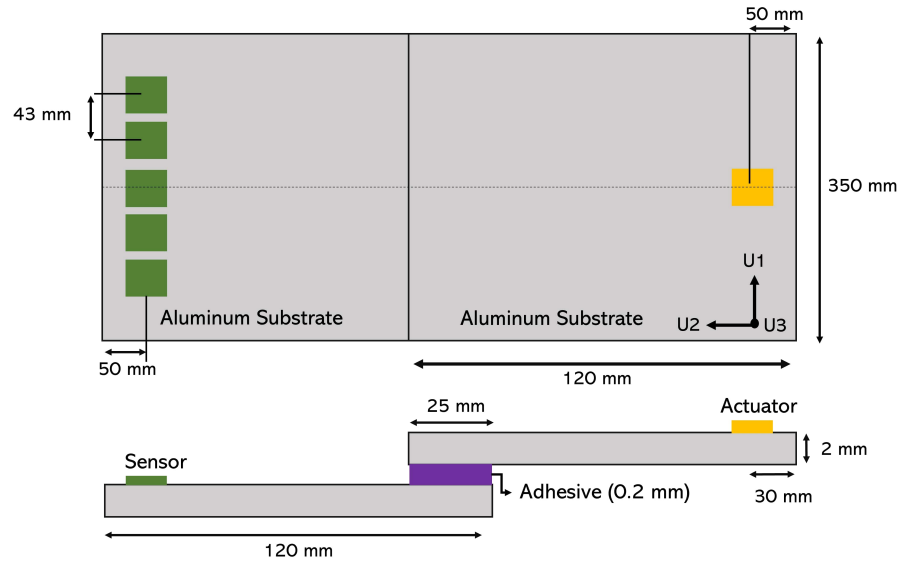


Figure 3.4: Illustration of the dimensions, and actuator and sensors placement, of the second type of SLJ, used to address weak adhesion detection, intensity evaluation and localization.

in damage sizes of 25×25 , 50×25 , 75×25 , and 100×25 mm. Figure 3.5 provides an overview of the extent, boundaries, positioning, and size of the region with weak adhesion.

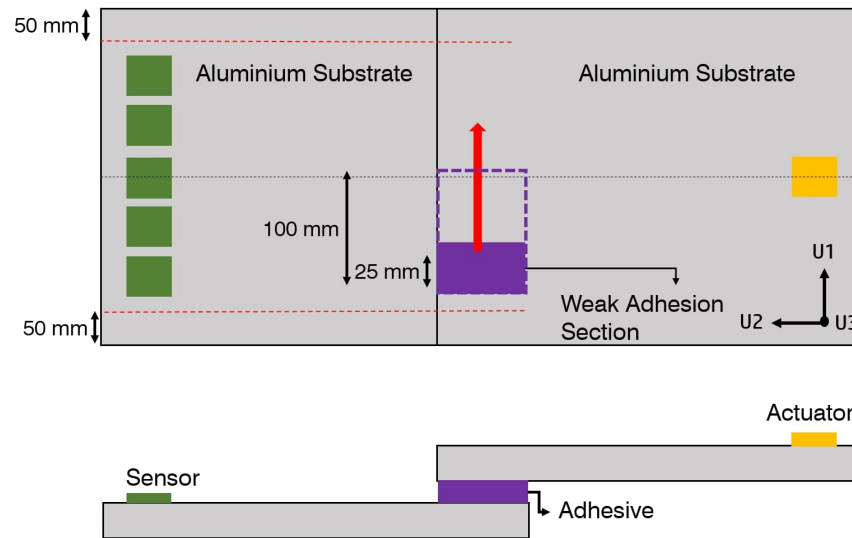


Figure 3.5: Simulated SLJs showing the region of weak adhesion.

3.2 Actuator and LW simulation

In the process of simulating LWs, it was crucial to understand the mechanism through which vibrations are generated, as this directly influences the direction in which the LWs propagate. In this study the vibrations needed to emulate motion generated by piezoelectric round actuators,

which have small radial movements. Consequently, LWs propagate parallel to the surface of the substrate and emanate in a 360° pattern from the border of the actuator. To approximate this behavior, forces are applied at the edges of a square area representing the location of the actuator, as illustrated by arrows in Figure 3.6. Previous empirical testing has confirmed that this simplification adequately mimics experimental conditions and was therefore deemed acceptable. The applied forces should vary in time according to a 5-cycle Hanning-windowed sinusoidal burst centered at 100 kHz [114].

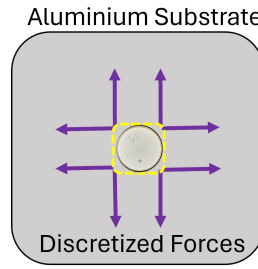


Figure 3.6: Representation of the forces that approximate the behavior of the piezoelectric round actuators used in real SLJs.

There are multiple ways of recreating and representing the effect of these forces in Abaqus. The one chosen in this work was to create a Python script that applies a variable deformation on the surface of the part, simulating the sinusoidal pattern of the Hanning-windowed signal. Furthermore, the simulation program discretizes the vibrations measured at the three primary Cartesian components U1, U2, and U3. This will be further analyzed in Chapter 4 to determine what component or combination of components is most suited and similar to the real signal.

3.3 Adhesive and weak adhesion simulation

To simulate weak adhesion it was first necessary to divide the simulated adhesive into three parts, as represented in Figure 3.7. The parts closer to the substrates are considered as layers of weak adhesion, with an overall thickness of 0.001 mm, while the center of the adhesive, with the remaining thickness, is considered without any alterations and thus has the original mechanical properties of the material.

In regards to the adhesive's properties, the overall value of stiffness of the weak adhesion layer is lowered by reducing its Young's modulus, as suggested in [115, 116] and reinforced in [117], where it is possible to see the initial validation of the weak adhesion simulation.

3.4 Data processing

All collected data sequences undergo an initial cleaning process to create an usable dataset. This involves choosing the data Cartesian component that most accurately represents the experimental data. Studies showed that averaging the values of U1 and U2 yields the best option. This is

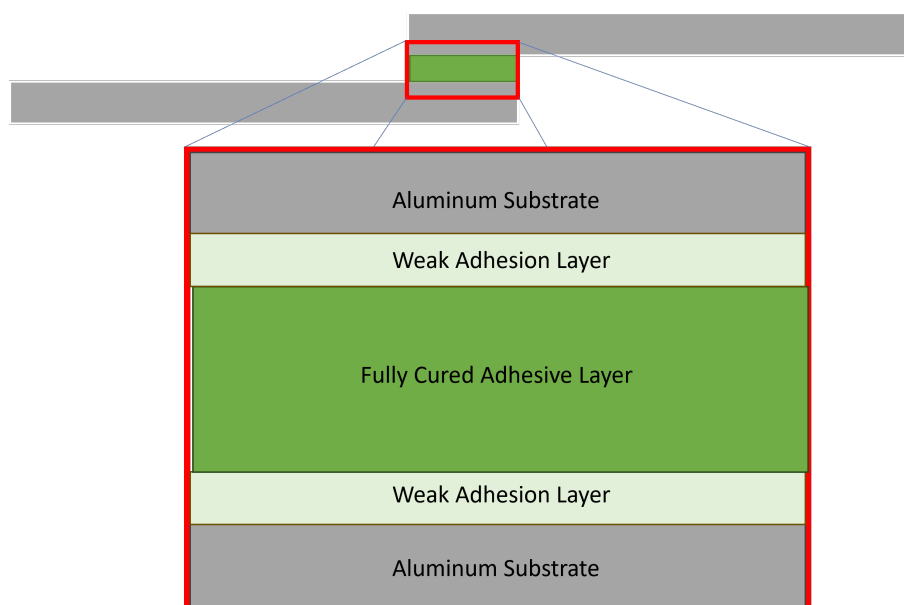


Figure 3.7: Representation of the 3-layer approach to simulating weak adhesion.

further explained in Paper E. Then, initial cleaning for eliminating missing or invalid values is performed. While this is less critical in simulated data, where the user has more control of the output, it is important to eliminate any possibilities of corrupted values in order to establish a robust methodology applicable to experimental data.

Following initial cleaning, the data need to be re-sampled. A step size of 10^{-7} s was used to ensure uniform time series and match starting and ending points. The total number of points in each time series is established balancing the acceptable noise levels generated by reflections on SLJs' boundaries and the need for a minimum number of points to accurately represent the arriving wave at the sensor. For the final study, a total of 1,200 points was utilized and was chosen based on previous work [114].

Subsequently, normalization and remapping of the values were applied to all time series. This step is crucial as the dimensions of experimental and simulated data can influence the behavior of the ML models. Figure 3.8 illustrates the data preprocessing steps.

When dealing with data from multiple sensors, these data can be organized in different ways. One is to concatenate the sensors' data and create a new larger time series. Another way is to take the average values of all sensors' time series, thus keeping the original time-series dimension. For this work, the approach was rather to consider that each sensor's data corresponds to a damage case. This approach not only assists the algorithm in learning the characteristics of damage but also makes the methodology flexible enough to accommodate any number of sensors.

Other than the general form of preprocessing described, there was a need for a specific approach regarding the case of "no damage". The presence of only one instance of "no damage" introduces data cases imbalance for the ML algorithms. To address this issue, multiple instances of "no damage" were "artificially" created by adding Gaussian white noise to the signals at varying levels of intensity. The noise has zero mean and the same standard deviation and size as

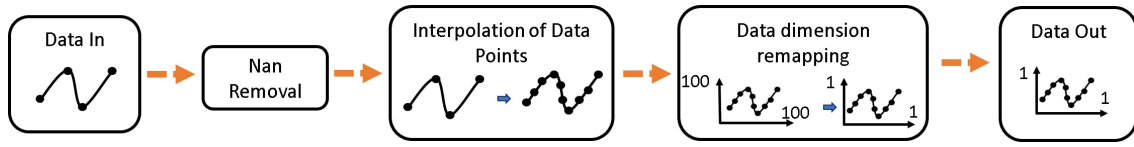


Figure 3.8: Representation of the data preprocessing steps.

the original signal. Subsequently, the noise was re-sized for being 10^{-2} times smaller than the average value of the signal. These additional instances were generated following all preceding preprocessing steps and were subsequently incorporated directly into the learning algorithms.

One way to observe the meaningful information embedded in the collected data is to apply visualization techniques. This helps the user to better understand the relationships between data points and the problem that generated the data. Data visualization regards the manipulation of sampled data for comprehensive display, conducive to a deeper understanding of the data and highlighting their underlying physical laws and properties. It is an important tool that helps the data scientist in different stages of a project, by pointing out useless, incorrect or inconsistent information that can be eliminated, and assessing the results, to expose dynamics and help to define the focus points and regions of interest.

Dimensionality reduction is applied as a procedure to create projections of the data, mapping these into a low dimensional space, in order to enable an insightful view of how data instances relate to each other, namely the appearance of structures such as high local density, interesting relations between observations and the presence of clusters. Time-oriented data visualization is a widely researched topic, and visualization techniques can be categorized in many ways, such as the structure of time itself (linear, cyclic, or branched), the frame of reference (spatial or abstract), the number of variables that are time-dependent, and the dimensionality that is to be obtained (2D or 3D, since those are intuitively understood by the human brain).

One of these techniques is multidimensional scaling (MDS). This technique is a multivariate statistical method that represents measurements of proximity/similarity among pairs of objects as distances between points in a low-dimensional space. MDS is also known as principal coordinates analysis (PCoA) or even Torgerson scaling, and can be considered as a non-supervised ML method. Anyway, in this work, MDS was used as an exploratory tool to help understanding the potential of LWs to detect damage. Indeed, if MDS fed with LWs data can cluster together similar damage cases, then LWs would be able to classify damage. In Figure 3.9 it is possible to see how five weak adhesion classes are positioned relative to one another using the MDS technique forming clear patterns.

3.5 Summary

In this chapter three different simulation models were created, each one with their specific characteristics and with their own individual objectives. The first model was developed for generating LWs, while analyzing their interaction with simple damage, and collecting preliminary data to be

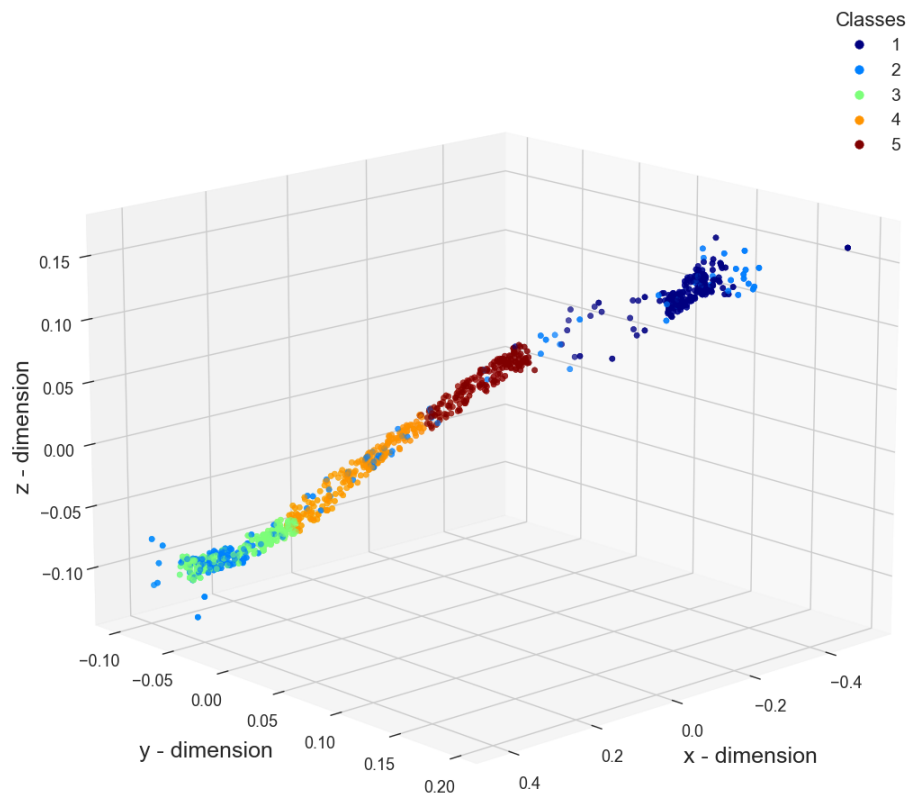


Figure 3.9: MDS representation of five weak adhesion classes.

further correlated with damage in Paper B. The second model was necessary to study weak adhesion intensity in SLJs, being used in Papers C - F. The third model was used to detect multiple weak adhesion characteristics, including localization. This model served as a basis for further studies in SLJs and weak adhesion. It was used in Papers E - F.

Chapter 4

Experimental Setup

In this chapter, an experimental setup is presented to serve as source of data for validation of simulation models and for testing ML algorithms. This is accomplished by developing a way to create multiple levels of weak adhesion in a real SLJ, followed by LWs and tensile testing.

4.1 Experimental setup

The experimental phase is divided into two stages. For SLJs manufactured with distinct levels of weak adhesion, the first stage consists of exciting the samples and capturing the relevant LWs. The second stage involves subjecting the SLJs to tensile tests in order to determine their corresponding stress-strain curves.

4.1.1 Creating weak adhesion

SLJs with overall structure and properties as presented in section 3.1.2 are produced with multiple levels of weak adhesion. Each substrate was prepared in the area where the adhesive would go. They were sand blasted to maximize adhesive interaction. After all, the parts were geometrically finalized and thoroughly cleaned with acetone to remove any particles that could alter the adhesive bonding results. After adhesive curing, piezoelectric elements were bonded on the substrates to allow LWs excitation and measurement.

To create multiple levels of weak adhesion, various quantities of release agent Loctite 770-NC Frekote were used. For this experimental setup, four overall levels were created, comprising a total of 11 SLJs. The first level corresponded to full adhesion, with no release agent applied, and 2 samples manufactured. The second and third levels, with 3 SLJs each, corresponded to intermediary levels of weak adhesion, where the parts were subjected to one layer of release agent and one layer of a mixture of 50% release agent plus 50% acetone, respectively. Finally, the fourth level, with 3 samples, was a severe weak adhesion case, where the SLJs were subjected to 2 layers of release agent. After the parts had the necessary quantity of release agent applied, they were placed in a dimensional jig and received the adhesive Plexus MA 560-1 [118] in order to create

the SLJs. The fabrication setup can be seen in Figure 4.1, where there are two samples in one jig and four samples in the other one.

It is worth emphasizing that, although the SLJs were manufactured based on controlling the quantity of release agent applied, fabrication issues may affect the production and the obtention of the desired four levels of weak adhesion. Therefore, further testing was necessary to determine the real level of weak adhesion, as will be described in the following.

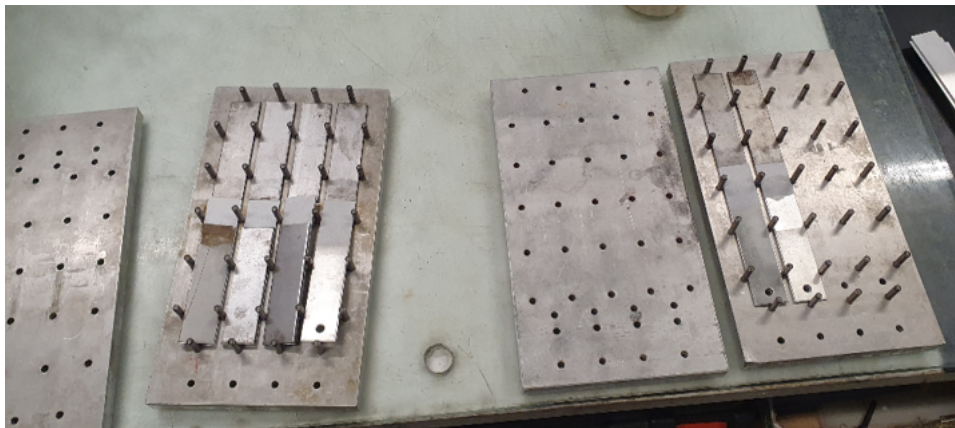


Figure 4.1: Experimental setup with four samples being produced in a fabrication jig and two samples in another one.

4.1.2 Experimental testing

As previously mentioned, the experimental phase includes two stages. The first consists on LWs testing, meaning electrical testing. The second is classical tensile testing to determine the real level of weak adhesion affecting the manufactured SLJs, so that a direct relationship between values is possible.

Regarding the first stage, each individual part was instrumented with piezoelectric elements PIC 255 piezoceramic (PRYY + 1119 model). These piezoelectric elements were chosen due to their lightweight, low cost, and versatility to serve as either actuators or sensors. This versatility will also allow for further tests to be conducted and having an array of sensors to analyze large areas. A 5-cycle Hanning-windowed voltage sinusoidal burst centered at the frequency of 100 kHz [107, 119, 120, 121] was applied to the actuator by a signal generator AIM & Thurbly Thander Instruments, model TGF4042. This type of excitation signal keeps LWs dispersion and attenuation at a minimum, while still maximizing sensitivity. The sensor was connected to a digital oscilloscope Tektronix, model TBS1000C, which samples and memorizes the signals. To facilitate input and output synchronization, the Hanning-windowed signal applied to the actuator was also collected by the oscilloscope. In Figure 4.2 the data acquisition setup can be seen.

After all LWs data were acquired from the SLJs, in a second stage, the sensors and actuators were removed and the samples were subjected to tensile tests. Each part was carefully placed on an Instron 3367 machine and stressed until rupture (Figure 4.3). It is important to analyze the

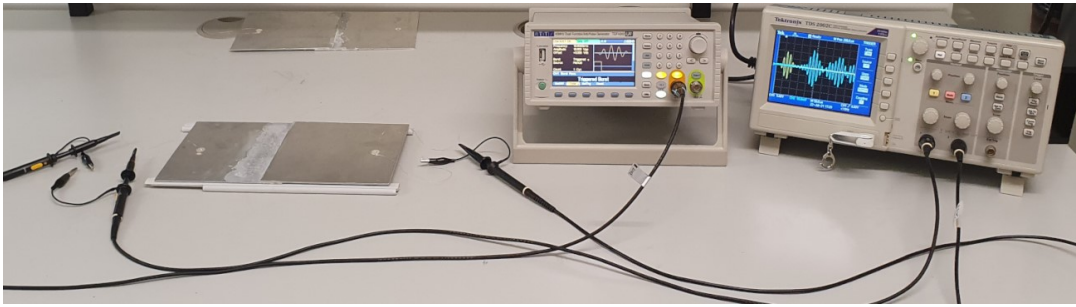


Figure 4.2: Data acquisition setup of one SLJ, with actuator and sensor connected to a signal generator and an oscilloscope, respectively.

stress–strain curves obtained, as adhesives are inherently complex, and even when fully cured in the correct manner, variations in Young’s modulus over 275 MPa can be verified. This uncertainty may be higher when dealing with artificially created SLJs with weak adhesion and might cause difficulties when trying to simulate vibration data. In Figure 4.4, the load-displacement curves of all SLJs are depicted. As expected, four groups with distinct levels of maximum load can be identified. The group produced with two layers of release agent reveals the smallest ultimate stress, while the cases without release agent correspond to the largest loads. Therefore, the method adopted for the fabrication of SLJs based on the application of a release agent to create distinct levels of weak adhesion is quite reliable. It is also interesting to observe that the two cases without the release agent presented a larger plastic deformation, which may be caused by the adhesive material deforming under loads, instead of a clean break of the adhesive on the contact surface of the substrate, as seen for the other cases. When analyzing the samples, there is a stark contrast between the adhesive of the samples that reinforces this hypothesis.

In Figure 4.5, it is possible to observe the difference between the sample that had plastic deformation and the sample where the limit layer of the adhesive failed. With the maximum loads determined, all samples can now be referenced to these values, and a linear percentile analysis of Young’s modulus is used to compare simulated and experimental data. It is important to note that Young’s modulus is being used as it is a variable that can be calculated by the tensile test and is the main variable that is altered to determine the desired level of weak adhesion present in the simulation.

When LWs data from all 11 SLJs are analyzed and compared, it is possible to verify that no clear patterns emerge. This is clear when analyzing SLJs that have almost exactly the same maximum tensile strength but possess completely different LWs vibrational patterns. This means that directly correlating LWs with specific levels of weak adhesion is unfeasible. Therefore, these collected data are used in conjunction with simulated data to validate the simulation models.

4.2 Experimental model validation

As already said, the collected experimental data served for validating simulation models, namely Model-2 presented in Chapter 3.1.2. A diagram of the complete approach can be seen in Figure

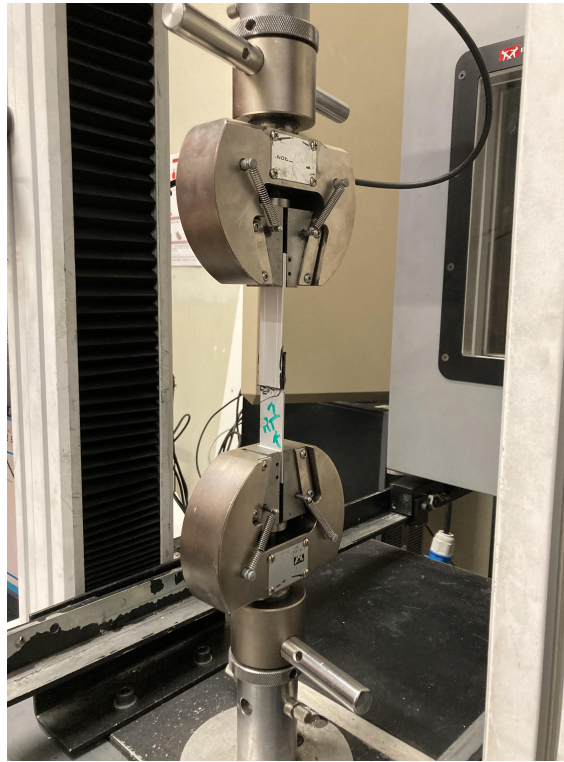


Figure 4.3: Stress-strain test performed with an Instron 3367 testing machine.

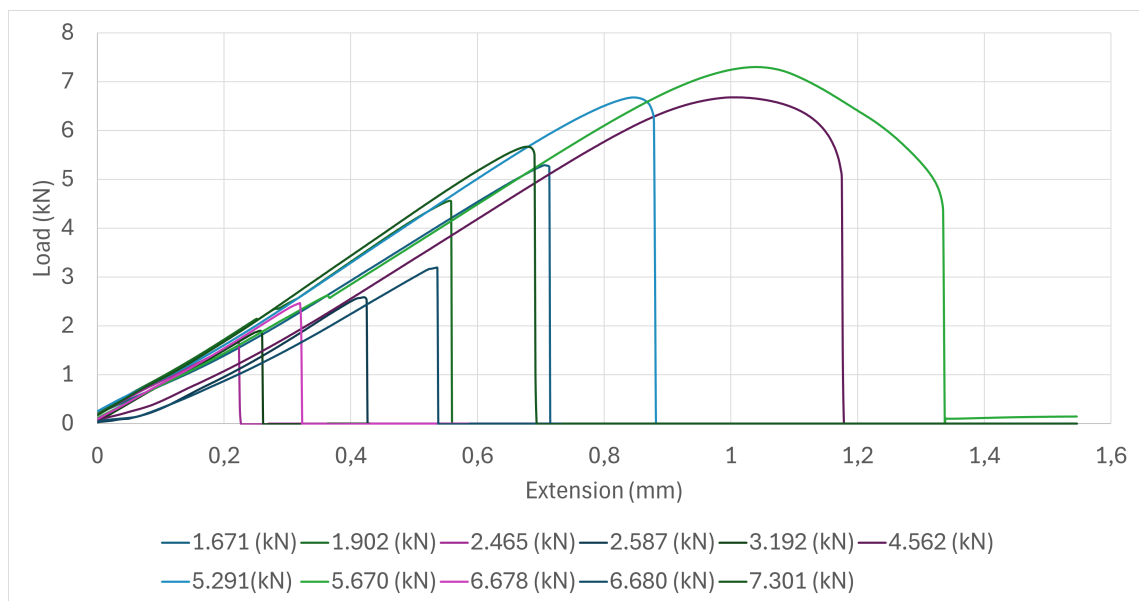


Figure 4.4: Load-displacement curves of all SLJs.

4.6. The experimental part is shown on the left-hand side, comprising SLJs fabrication, with distinct levels of weak adhesion, and LWs and strain–stress testing and data acquisition. These data are correlated to correctly match LWs to levels of weak adhesion. The FEM simulation model of the SLJs is represented on the right-hand side of the diagram. Represented at the bottom of the

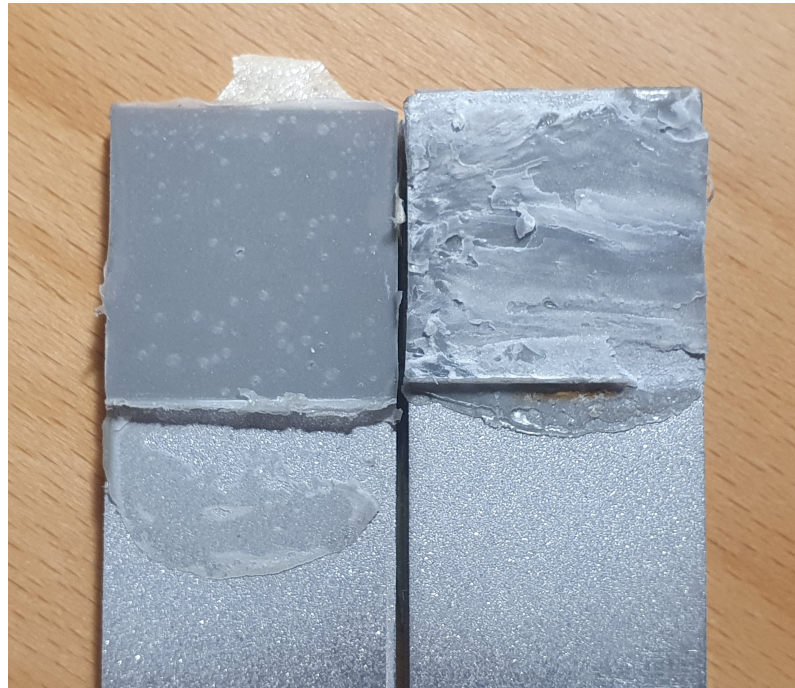


Figure 4.5: A SLJ after rupture.

diagram, a ML algorithm is used, which takes numerical and experimental data and validates the FE model by comparing experimental and simulated Young's modulus.

4.3 Summary

In this chapter an experimental setup was described. This is able to generate data for SLJ models validation and ML algorithms testing. The SLJs fabrication and testing processes were described. Experimental validation of SLJ models was illustrated. This was performed by creating a means to link a certain level of weak adhesion, determined by the tensile strength test data of a sample, to the LWs signals captured by the SLJ sensor, and compare it to the simulation data. This will be accomplished using ML.

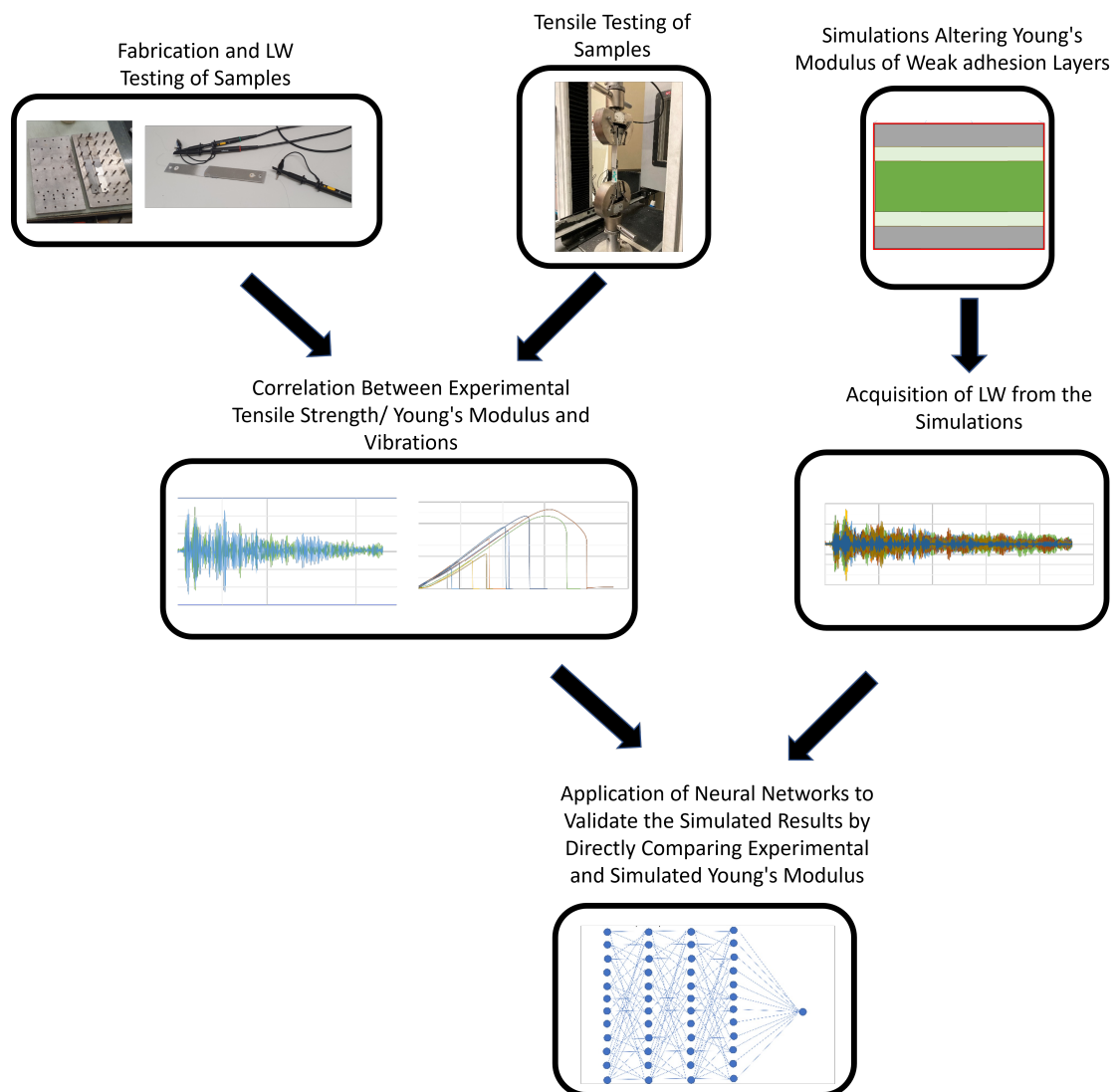


Figure 4.6: Complete approach for experimental SLJ models validation.

Chapter 5

Machine Learning Algorithms

In this chapter, the adopted ML algorithms are briefly explained starting from the simple FNN, and diving into more advanced models such as two different types of RNNs, the CNN, and transfer learning. Both the CNN and transfer learning are explained in the perspective of creating the final methodology for weak adhesion monitoring.

5.1 Feedforward neural network

The multi-layer FNN has been extensively used in multiple applications, starting with the work [122], where backpropagation algorithms were first adopted to adjust the weights in the hidden layers. In an FNN, the elements that process the data, also known as neurons, are structured in multiple successive layers that go from the input to the output, as can be seen in Figure 5.1. These layers are all interconnected in such a way that all elements in a layer have their output connected to every element in the next layer. Associated with each connection, there is a value, called the weight, which is adjusted during the learning phase [123, 124]. Each neuron of a layer applies the associated weight and utilizes a nonlinear function to transform the data that passes through it. A commonly used function is the sigmoid function [125]:

$$g(h) = \frac{1}{1 + e^{-h}}, \quad (5.1)$$

where h denotes a dimensionless variable.

The general and simplified intent behind an FNN is to reduce the error between the processed data and target values previously known. This is performed by passing the data through the neurons from the input to the output and, then, comparing the values with the training data previously saved and known. The error that is obtained is used to determine a performance function, which is continuously differentiable and correlates all the weights present from the output to the input layer. Two examples of such performance functions that can be used are the gradient-descent-based algorithms and the mean-squared error (MSE). These functions have weights as variables and are minimized by altering them [125]. The FNN has been proven to be successful in modeling complex problems in a large range of areas, from image compression to forecasting and signal

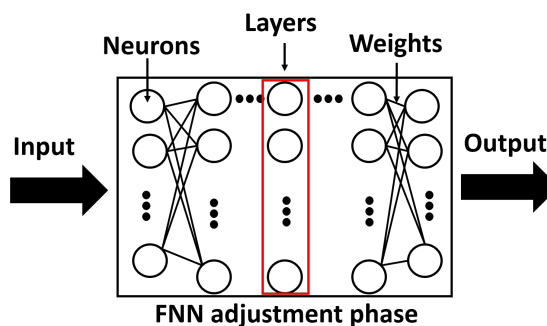


Figure 5.1: Fundamental architecture of an FNN with the interaction of each component represented.

prediction [122]. However, this model presents the disadvantage that all elements in each layer are interconnected to the next and previous layers. This requires a careful analysis of the problem when mapping the data, as well as caution relative to the number of layers and elements used. The higher the number of layers, the larger the datasets required and the more computationally intensive the process will be. Thus, it is preferable to implement an FNN with a small number of layers and elements [122].

5.2 Recurrent neural network

The RNN is a type of artificial neural network that differentiates itself by “memorizing” information that can be later used in new data. This is performed by storing the output activation from the layers and applying them together when feeding a new input to the algorithm [126]. Although RNNs are powerful and have been applied to many problems, they suffer from a reduction or “explosion” in the gradient during backpropagation. This, in turn, does not allow for the layers closer to the input to have their weights altered or altered to such a degree that they make others irrelevant and, thus, not contribute positively to the solution [127, 128]. To mitigate this problem, a few algorithms, such as long short-term memory (LSTM) and the gated recurrent unit (GRU), which contain different gating units, have been created.

5.2.1 Long short-term memory

To mitigate the vanishing gradient problem, LSTM utilizes an input gate and a forget gate, as shown in Figure 5.2 (circled in green and yellow colors, respectively), to create a constant error carousel (CEC) [129, 130]. The CEC works by enforcing a constant error flow within a special cell controlled by the gate units, which learn when to grant access (circled in red color) [131]. The various gates used in the CEC can be described as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f), \quad (5.2)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \quad (5.3)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o), \quad (5.4)$$

while the equations for the candidate state, cell state, and final output are

$$c'_t = \tanh(W_c[h_{t-1}, x_t] + b_c), \quad (5.5)$$

$$c_t = f_t c_{t-1} + i_t c'_t, \quad (5.6)$$

$$h_t = o_t \cdot \tanh(c_t). \quad (5.7)$$

In these equations, f_t is the forget gate, i_t is the input gate, o_t is the output gate, c_t is the cell state, c'_t is the candidate state, and h_t is the final output. Furthermore, W_x represents applied weights, h_{t-1} are the outputs of the previous LSTM block, x_t are the inputs at the current timestamps, and b_x are the biases for the gates. These gates can be easily visualized in Figure 5.2, where the components are in yellow, the layers are in dark blue, the line that divides represents a variable copied, and the lines combining represent concatenation. Finally, the output gate is circled in purple color and serves as the output of the cell.

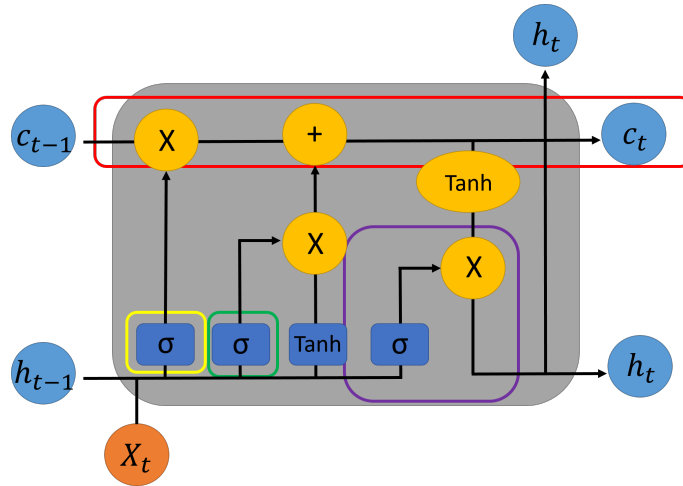


Figure 5.2: The architecture of an LSTM cell with the input cell circled in green, the forget cell in yellow, the cell state in red, and finally, the output gate in purple.

5.2.2 Gated recurrent unit

The GRU has been used in many applications but has seen more significant results in music and speech modeling, as well as natural language processing. This method was developed with the intent of allowing each recurrent unit to alter the sequence of dependencies in an adaptive manner over time. To accomplish this, the unit was built with the following four steps, where x_t is the current input, h_{t-1} is the output of the previous step, W and U are parameter matrices for the weights, and σ is the sigmoid function [132, 129]:

1. The first step is an update gate, as shown in Figure 5.3 (circled in green color), which is used to determine how much information will be updated in the unit. This gate is denoted as z_t^j and calculated by:

$$z_t^j = \sigma(W_z x_t + U_z h_{t-1})^j.$$

2. The next step is a reset gate, seen in Figure 5.3 circled in purple, denoted as r_t^j and calculated by:

$$r_t^j = \sigma(W_r x_t + U_r h_{t-1})^j.$$

This gate is used to determine how much information needs to be forgotten. When the value of this gate is close to zero, it determines that the j -th information should be forgotten in the current memory. Any value close to one means that the data will be preserved.

3. The third step is to determine the current memory. This gate is denoted as h_t^j in the following expression and, in Figure 5.3, seen as h_t .

$$h_t^j = \tanh(W_h x_t + r_t \cdot U_h h_{t-1})^j.$$

This gate also uses the Hadamard product to decide how much of the hidden state of the content should be forgotten.

4. Finally, the last step is to determine the information to be stored in the hidden layer at the current iteration that will be passed onto the next cell. This step is denoted as h_t in the following equation and, in Figure 5.3, is denoted as h_{t-1} :

$$h_t = (1 - z_t^j) h_t^j + z_t^j \tilde{h}_t^j.$$

These steps can all be easily visualized in Figure 5.3.

5.3 Convolutional neural network

Overall, the CNN can be seen as having a multi-layer feedforward structure and, normally, utilizes other types of layers as a complement to the convolutional ones. The main characteristics that define a CNN are the representation of the input layer and the way these input elements are processed in the CNN layer, which allows for significant advantages while creating a few problems. The first layer used is normally seen as a grid that can be compared to 2D images or pixels (or even a signal in the time domain arranged in an $n \times 1$ column vector), as seen in Figure 5.4.

Another characteristic that defines a CNN is a convolutional operation called the kernel, which is applied between the weights and the input CNN layer. This is performed to provide at the output of the layer a feature map [133, 134]. When evaluating the inputs and the kernels used in a

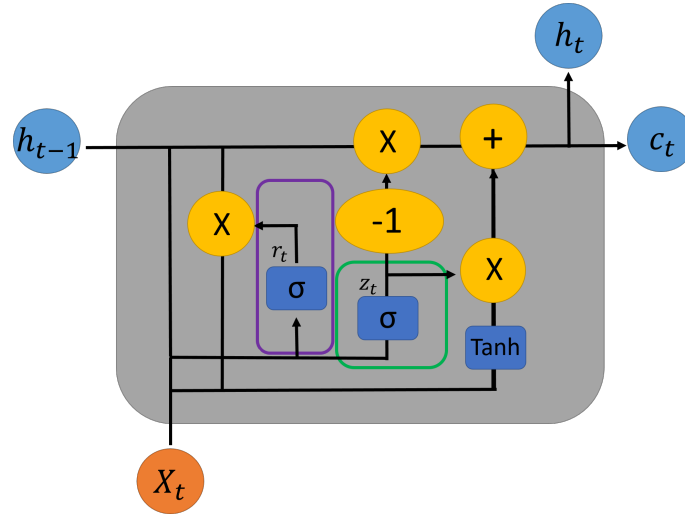


Figure 5.3: Architecture of a GRU cell with the reset gate circled in purple and the update gate in green.

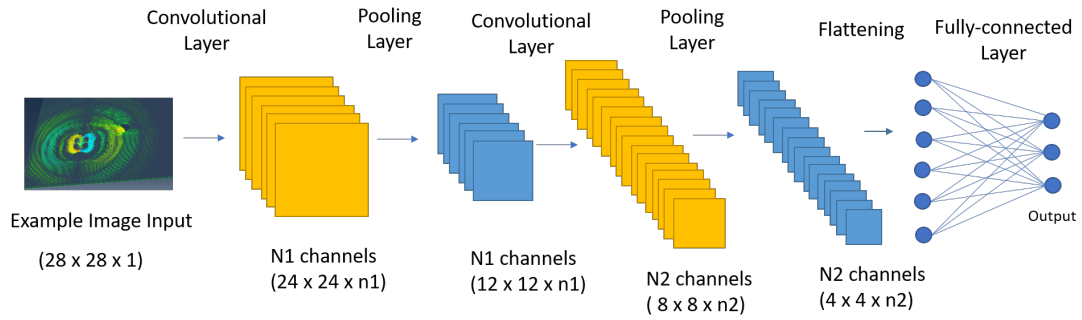


Figure 5.4: Architecture of a CNN comprising convolutional and pooling layers with a final flattening layer. The dimensions of each layer are represented under each one.

convolutional layer as square $n \times n$ arrays, the size of the output layer can be calculated using

$$n_{out} = \left\lceil \frac{n_{in} + 2p - k}{s} \right\rceil + 1, \quad (5.8)$$

where the width or height of the output and input arrays is represented by n_{out} and n_{in} , respectively. Finally, two other parameters complement these layers: the convolutional padding size is a parameter that is used when it becomes adequate to include additional information on the border arrays, while the sliding increment of the kernels over the input array is the stride parameter. These can be seen as elaborated in the following equations:

$$s(t) = \int x(a)w(t-a)da, \quad (5.9)$$

$$s(t) = (x * w)(t), \quad (5.10)$$

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a), \quad (5.11)$$

where n_{out} represents the number of output features obtained from the convolution, n_{in} is the number of input features, p is the convolutional padding size, k stands for the kernel size, and s is the stride size to be used.

One way to better visualize these kernels is to see them as filters that go through the input values, using a constant weight to identify specific features in the input data. These values are refined during the learning phase. Using a CNN instead of an FNN allows for a smaller increase in the number of variables and parameters when setting more layers, as the weights are used with all inputs. This allows for more layers and a deeper learning FNN implementation. Furthermore, it allows for a way to associate values that are near one another, which can be of interest in images, time series, or any other sequential signal. Finally, the convolutional maps are normally associated with pooling stages and processed through a nonlinear rectified linear unit (RELU) function to stabilize values in specific locations [123].

5.4 Transfer learning

Transfer learning involves utilizing a ML method wherein a model previously trained on a specific task is repurposed or adjusted to suit a similar task [135]. Rather than initiating the learning procedure anew, transfer learning uses the knowledge acquired from addressing one problem and employs it to tackle another related problem [136, 137, 138].

One such example of this is a CNN that is initially trained on a comprehensive synthetic dataset, serving as a foundational step. Subsequently, the models undergo fine-tuning using a smaller dataset comprised of experimental data. This process of using only a part of the neural network can be seen in Figure 5.5 circled in red, where the components have the same weights and biases of the pre-trained model, while the rest is reset to be fine-tuned.

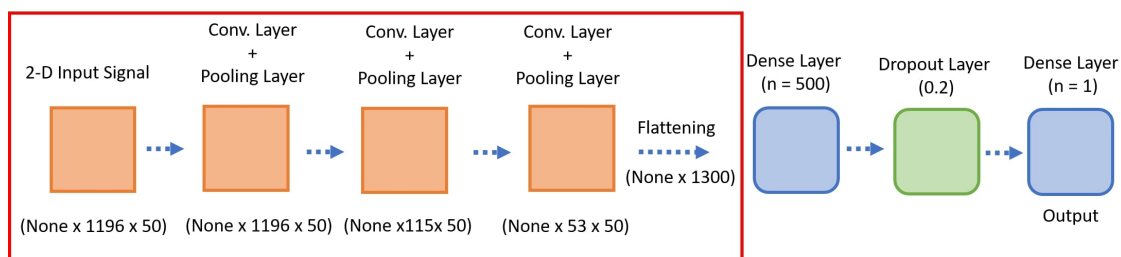


Figure 5.5: Overall structure of a transfer learning scheme. The components within the borderline have the same weights and biases as the pre-trained model, while the rest are reset to be fine-tuned.

5.5 Summary

In this chapter, the ML algorithms used in this work were explained starting from the FNN and finishing with transfer learning techniques. Transfer learning allows models, trained with large volumes of synthetic data, to be fine-tuned, with small quantities of experimental data from the target domain, thus transferring previous knowledge to new tasks. This is also crucial when the

target domain data varies in time, as is the case of damage. Transfer learning is used as the cornerstone to develop a pipeline and methodology to detect weak adhesion in-situ and determine its characteristics.

Chapter 6

A ML Pipeline for Detecting and Assessing Weak Adhesion in SLJs

In this chapter, a methodology for detecting and assessing weak adhesion in SLJs using a ML pipeline with LWs data is outlined. This method obtains both synthetic and experimental data, preprocesses the data and trains ML algorithms. The methodology is shown very effective to monitor weak adhesion in SLJ, and flexible enough to tackle damage characteristics beyond existence, intensity and localization, without requiring major alterations. Therefore, this approach holds significant potential for enhancing the safety and durability of bonded structures through SHM.

6.1 Proposed methodology

The proposed pipeline includes an initial data acquisition phase from any source, whether simulated or experimental. These data are preprocessed and prepared for subsequent phases. A specific CNN determines if damage is present in the SLJ. If damage does not exist, then there is no need for extra processing, and the pipeline stops there. If damage is detected, then the pipeline triggers additional CNNs to determine damage intensity and damage localization. The CNNs are pre-trained with synthetic data and fine-tuned and used with experimental data within a transfer learning scheme. Figure 6.1 illustrates the suggested full pipeline.

6.1.1 Design of the CNNs

In total, three CNN algorithms are employed to detect, evaluate intensity, and localize damage, respectively. The first algorithm, besides detecting the presence of damage, serves as a pre-trained model for further use in a transfer learning scheme, fine-tuned with experimental data. It utilizes a CNN with 2,800 simulated cases of SLJs, including both damaged and undamaged instances of the two types described in sections 3.1.2-3.1.3, as input. This input is followed by three hidden layer blocks consisting of a convolutional layer and a pooling layer, and finally, two hidden layers of fully connected dense layers with a dropout layer between them. Figure 6.2 illustrates this

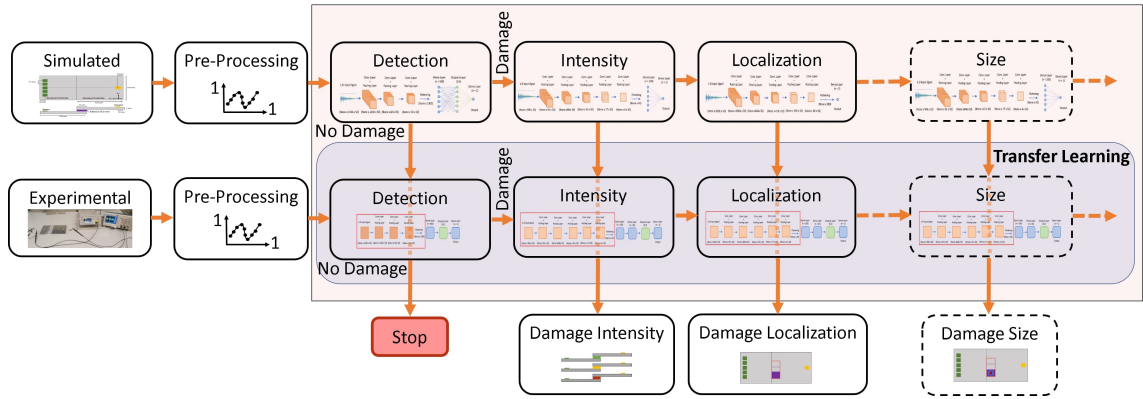


Figure 6.1: Representation of the pipeline proposed for weak adhesion detection, intensity evaluation and localization in SLJs.

algorithm. The output consists of a dense layer with one output using a RELU activation function. Binary cross-entropy was selected as the loss function, and accuracy served as the evaluation metric. A total of 600 epochs were deemed sufficient for comprehensive analysis. The batch size for this algorithm was set to 1,028, and the adaptive moment estimation (ADAM) optimization method was employed. A total of 1,200 points originated from the data interpolation preprocessing were adopted.

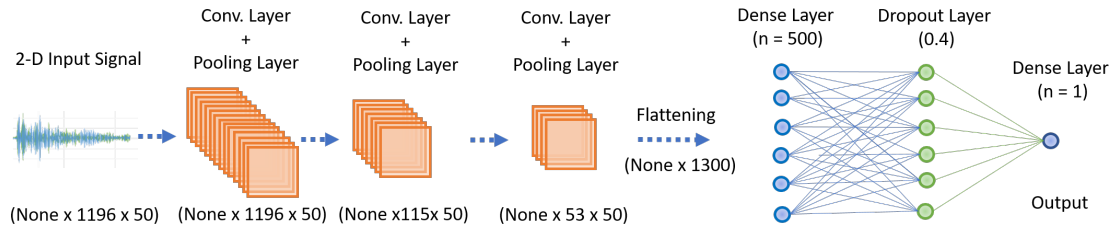


Figure 6.2: Overall structure of the CNN used to detect damage in simulated data.

The second CNN is designed to evaluate the intensity of weak adhesion. It will also be used further as a pre-trained model in a transfer learning algorithm. The overall configuration is depicted in Figure 6.3, with a total of 14 layers. The input mirrors that of the previous model, excluding the “no damage” SLJs, as all parts are now considered “with damage”. The input is followed by 5 blocks consisting of a convolutional layer and a pooling layer, a flattening layer, and 2 fully connected layers, with the last one serving as the output. In this CNN, the output data used to determine the level of damage intensity is Young’s modulus of the damaged area, as previously described, ranging from 100 MPa to 500 MPa.

Hyperparameters for all layers were empirically tested until optimal results were attained. Mean absolute error (MAE) was employed as both the loss function and evaluation metric for this algorithm. A total of 600 epochs was selected, as preliminary analysis indicated that additional iterations were unnecessary and training times remained within an acceptable range. The batch size for this algorithm was set to 512, and the ADAM optimization method was utilized. The

1,200 points originated from the data interpolation preprocessing were used.

Given that this case involves regression, the evaluation metric employed was the average and overall errors for each case. This approach enables a better understanding of limitations and their occurrence within each segment.

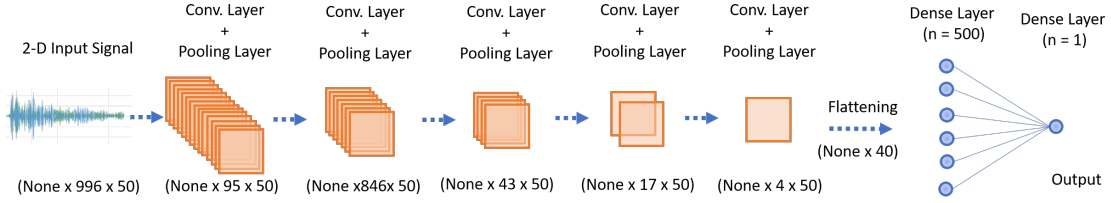


Figure 6.3: Overall structure of the CNN used to evaluate damage intensity in simulated data.

Finally, a CNN is created to determine the damage position in the SLJs of larger sizes. The overall configuration can be seen in Figure 6.4. There is a total of 14 layers again with 5 blocks composed of a convolutional and pooling layer, followed by a flattening layer and a final fully connected layer that serves as the output. For this algorithm, the output is the position of the damage along the U1 direction and the MAE is used as both the loss function and the evaluation metric. For the optimizer, ADAM was also used, and a total of 1,000 epochs was adopted with a batch size of 512 and a total of 1,200 initial points as inputs. Finally, this case also uses regression with the same evaluation method as before, adopting the average and case-to-case error values.

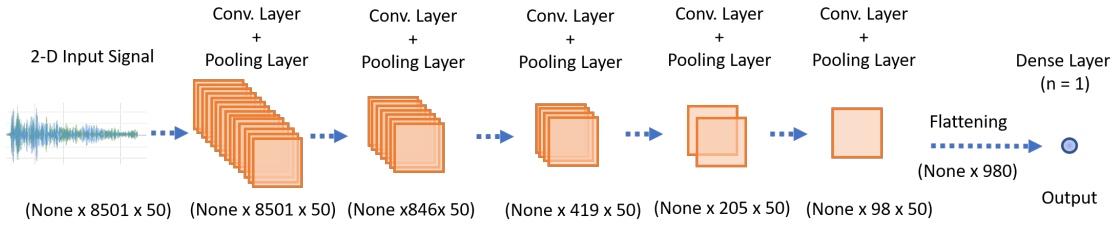


Figure 6.4: Overall structure of the CNN used for damage localization in simulated data.

6.1.2 Design of the transfer learning scheme

After the CNNs are initially trained on a comprehensive synthetic dataset, serving as a foundational step, the models undergo fine-tuning using a smaller dataset comprised of experimental data. Firstly, transfer learning is used for damage detection, as illustrated in Figure 6.5. The components within the borderline have the same weights and biases as the pre-trained model, while the rest are reset to be fine-tuned.

In Figure 6.6, the transfer learning scheme utilized for evaluating the intensity of weak adhesion is illustrated. As in the previous CNN, the components within the borderline have the same weights and biases as the pre-trained model, while the rest is reset to be fine-tuned.

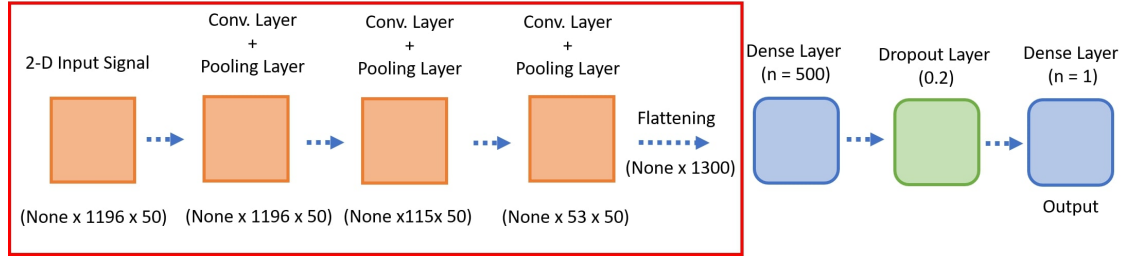


Figure 6.5: Overall structure of the transfer learning scheme for damage detection. The components within the borderline have the same weights and biases as the pre-trained model, while the rest are reset to be fine-tuned.

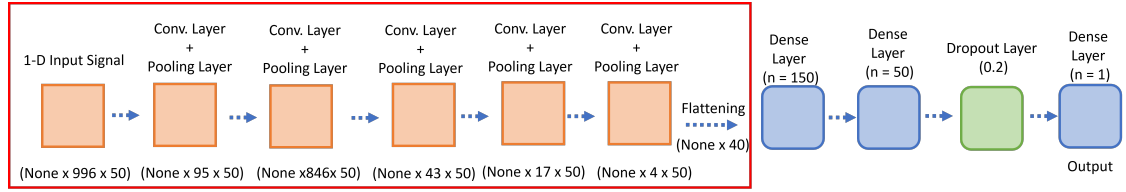


Figure 6.6: Overall structure of the transfer learning scheme for evaluating the intensity of weak adhesion. The components within the borderline have the same weights and biases as the pre-trained model, while the rest are reset to be fine-tuned.

6.2 Final results

In this section, the results obtained with transfer learning for both weak adhesion detection and intensity characterization are presented. For classification of damage locations, just results obtained with synthetic data are presented, as no experimental data are available for performing transfer learning. Following the presentation of each result, a discussion on the overall capability of the algorithms is conducted.

6.2.1 Damage detection

As mentioned in subsection 6.1.2, the initial algorithm aimed to detect damage regardless of its characteristics. The proposed pre-trained model successfully identified damage in the validation synthetic dataset with an accuracy exceeding 95.3%. Figure 6.7 illustrates the loss function for each epoch. It is evident that there is rapid convergence around the 40th epoch, followed by a further decrease in loss after 500 epochs. Due to this behavior, the maximum number of epochs was set sufficiently high to ensure attainment of the global minimum.

Figure 6.8 illustrates the algorithm's accuracy convergence for each epoch. The plot demonstrates a similar pattern to that of the loss function, with a significant convergence observed around the 40th epoch, followed by another notable convergence around the 500th epoch. Additionally, it is noticeable that approximately every 200 steps, there is a temporary decrease in accuracy and an increase in loss, which are swiftly reversed. This phenomenon occurs because the algorithm's optimization process explores alternative local minima, failing to find satisfactory values

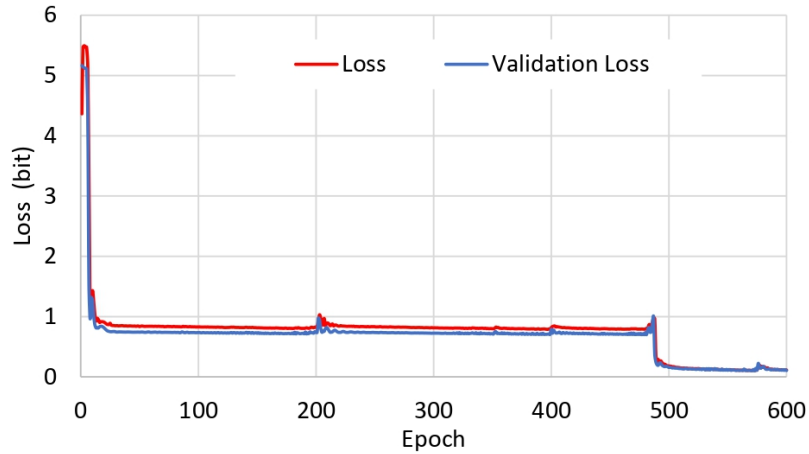


Figure 6.7: Loss value for each epoch for the pre-trained damage detection algorithm.

and consequently returning to the previous ones. It is through this exploration that the convergence observed around the 500th epoch is facilitated.

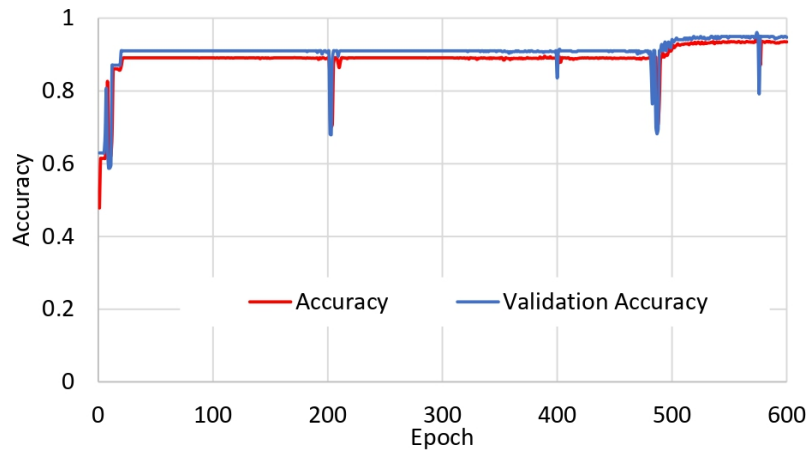


Figure 6.8: The accuracy for each epoch for the pre-trained damage detection algorithm.

Using simulated and experimental data, the algorithm successfully detected 100% of the damaged SLJs but encountered challenges in identifying non-damaged cases, achieving an approximate success rate of around 70%. Although lower than during pre-training, this success rate is highly beneficial for the algorithm, as it reveals that the algorithm ensures that all instances of true positives are detected and forwarded to any subsequent stages. A simple analogy for this scenario is akin to assessing whether an airplane wing is damaged in a real-life situation; the algorithm consistently identifies damage, and in cases where damage is not detected, further analysis can be conducted to ensure safety.

These findings are promising, indicating the algorithm's high accuracy in detecting damage, thereby allowing for a stopping point at the outset of the pipeline, which significantly reduces the computational resources required.

6.2.2 Damage intensity evaluation

In the next phase of the pipeline, a regression CNN is pre-trained on both types of simulated SLJs to evaluate the intensity of damage. Figure 6.9 illustrates the loss function for each epoch, revealing a slower convergence compared to the previous case, with the loss function converging at an error of approximately 40 MPa. Additionally, there appears to be a plateau of around 600 epochs for the validation loss, while the training loss continues to decrease. This indicates a potential tendency towards overfitting, although it is clear that the algorithm is indeed learning from the training dataset.

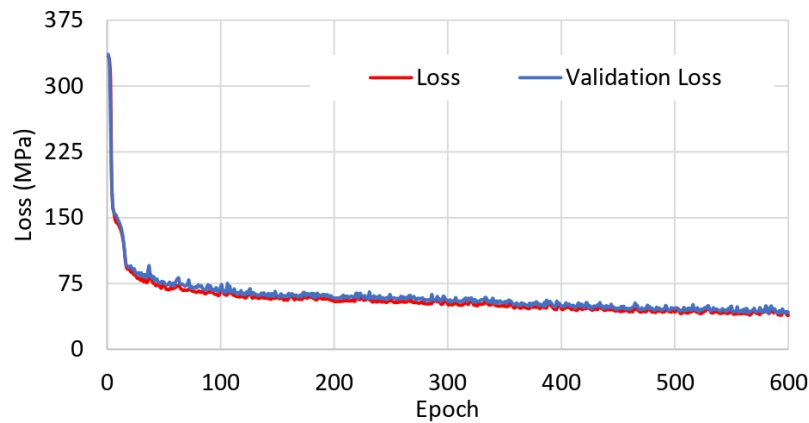


Figure 6.9: The loss value for each epoch for the pre-trained damage intensity evaluation algorithm.

While the methodology exhibits a general capability to accurately assess damage intensity, it is essential to recognize its limitations. To delineate these limitations, we can refer to the following results to identify the boundaries in each aspect. In Figure 6.10, it is evident that for most intensity values, the error is extremely low, approaching 0. However, in a few instances, the error can be quite significant, reaching up to 300 MPa. This discrepancy is attributed to the complexity of the signals received by the algorithm. In cases with low error, the algorithm utilizes small data samples where only intensity serves as a variable. Conversely, in other instances, large samples are employed, encompassing variations not only in intensity but also in the position and size of the damage. Consequently, the algorithm encounters greater difficulty in handling these variations. Nevertheless, the majority of cases exhibit errors below 100 MPa, which is a noteworthy outcome. This capability enables users not only to detect damage but also to gauge its severity independently of its location or size.

Finally, in Figure 6.11, it is evident that the largest errors occur on the sites closest to the boundaries of the SLJs. This phenomenon was previously discussed in the preceding Section. However, it is important to note that the largest errors coincide with those observed in the 25 mm damage size. This suggests that one approach to mitigate errors for smaller damage sizes is to establish a certainty field where the algorithm reliably detects larger damages closer to the edges. Alternatively, this issue can be addressed by ensuring there are no walls in proximity to the areas under analysis. An exception observed in Figure 6.11 pertains to simulated cases without any

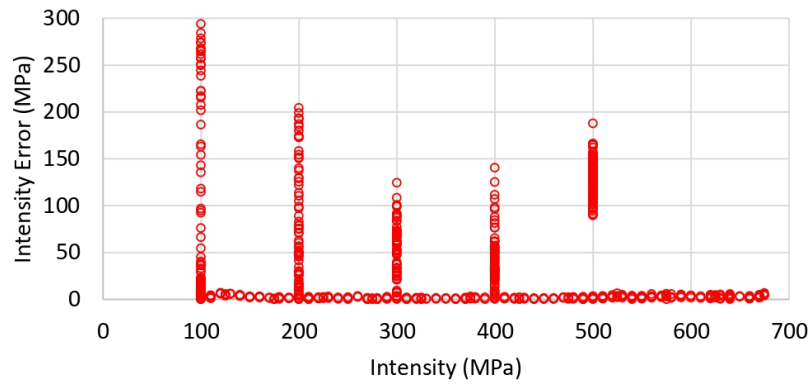


Figure 6.10: The error for each value of damage intensity studied.

positional alterations, currently grouped under position 0. For these cases, positional evaluation is irrelevant, and they exhibit no significant errors, thereby reducing their significance in the overall analysis.

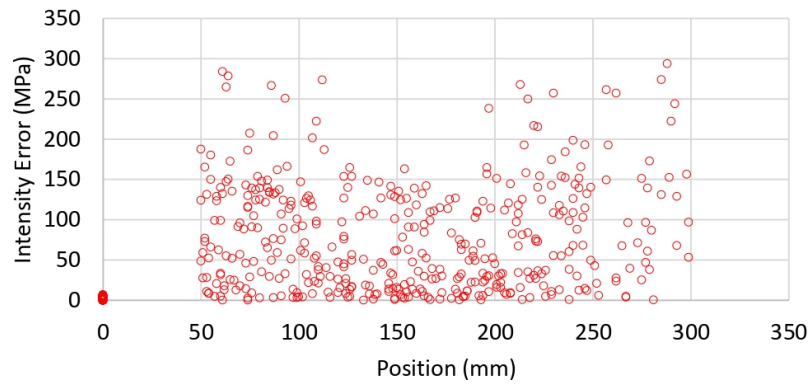


Figure 6.11: The intensity error for each value of the position of damage studied.

When observing Figures 6.10 - 6.11 together and combining the acquired results, it becomes evident that the majority of the largest intensity errors occur in cases with boundary conditions, such as the largest or smallest damage, or those located at the edges of the studied area. This indicates that the algorithm performs better with central values, and for cases with boundary conditions, a simple cutoff value is sufficient to significantly reduce errors.

When applying these pre-tests to experimental cases, similar to the previous step, certain limitations emerge. The initial analysis focused on each experimental case, encompassing only nine cases. It was observed that the average damage intensity error across all cases was 187 MPa, with the two experimental cases at the upper limit load responsible for the poorest results, showing errors ranging from 232 MPa to 406 MPa. Excluding these two cases, which could potentially be affected by fabrication or experimental errors, the average error decreases to 140 MPa. The highest error value is 250 MPa, while the lowest error originates from the case with the lowest load, measuring 3.6 MPa.

6.2.3 Damage localization

In the final phase of the pipeline, a regressive CNN is used to localize damage. Furthermore, only simulated cases are used as available experimental data and do not have a position as a variable.

Figure 6.12 illustrates the loss value in each epoch. We verify a large decrease followed by a slow decrease until the value is in a plateau at an average error of around 8 mm. As with the intensity evaluation model, the validation loss is higher than the training loss.

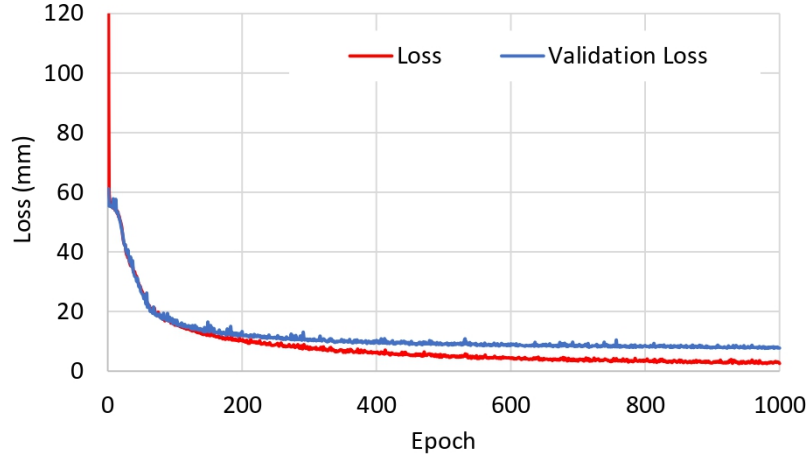


Figure 6.12: The loss value in each epoch for the damage localization algorithm.

Figure 6.13 shows the localization error for each value of the damage position. The largest errors occur more on the right of the figure but there is quite a large spread of values and positions, with most position errors concentrated below 10 mm.

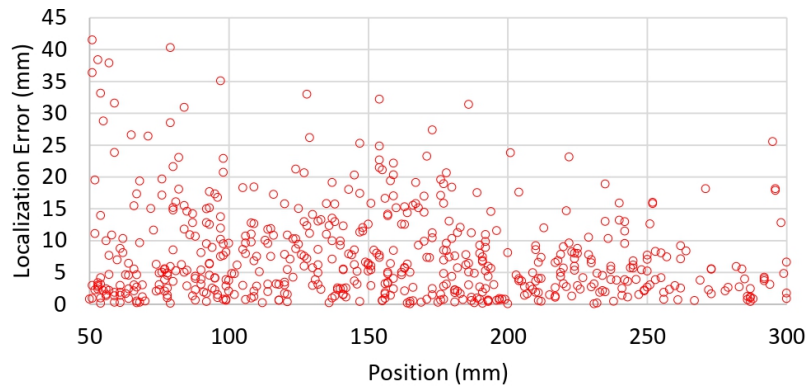


Figure 6.13: The localization error for each value of damage position studied.

In Figure 6.14 the localization error is compared for the 4 overall damage sizes that were created, with the overall cases presenting a quite uniform distribution.

Further comparisons between position and intensity yielded results similar to those previously discussed. This indicates that in the damage localization, there are no specific cases that tend to exhibit errors. All error cases are fairly evenly distributed, demonstrating that the algorithm was capable of generalizing the detection of this characteristic without encountering significant

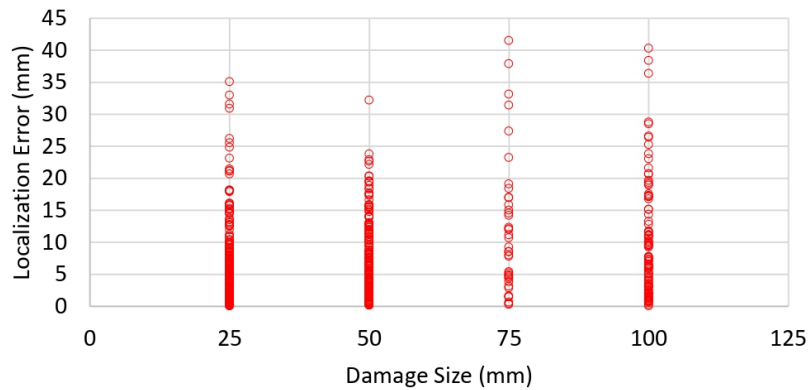


Figure 6.14: The localization error for each value of damage size studied.

issues. Moreover, the average error value of 8 mm enables precise pinpointing of the center of any damage, particularly within a range of 25 mm to 100 mm.

Additionally, a separate case study attempted to combine damage characteristics into a single ML algorithm by creating a multi-output CNN regression model. However, this approach proved to be less effective than maintaining two separate models in sequence. This disparity is likely attributed to the distinct nature of the information required to determine the position and intensity of damage within the ML algorithm. Combining both aspects did not yield any discernible benefits. An analogy that elucidates this issue is that the amplitude of the signal determines the position of the damage, while the frequency determines its intensity; thus, there are no similarities that can be exploited.

6.3 Summary

In this chapter, a methodology was outlined and used to detect and characterize damage in multiple SLJ samples both from simulated and experimental origins. Tests with SLJs where weak adhesion intensity could vary from 100 MPa to 500 MPa, and damage localization could change up to 125 mm within the adhesive area, showed that the developed pipeline, for weak adhesion detection, achieved over 95.3% accuracy in simulated scenarios and identified 100% of experimental damage cases. For weak adhesion intensity evaluation, the algorithm exhibited an average loss of 45 MPa in simulated data and 140 MPa in experimental data, with the best cases having only a 3.6 MPa error. Concerning weak adhesion localization, the algorithm demonstrated an average loss of 8 mm. The methodology is adaptable for integrating additional features, indicating promise for enhancing SHM and improving the safety and longevity of structures.

Chapter 7

Conclusion and Future Work

This thesis proposes a groundbreaking method to enhance the precision and reliability of NDT methods for detecting and characterizing weak adhesion in adhesive joints.

The method comprises an initial data acquisition phase from any source, whether simulated or experimental. These data undergo preprocessing and preparation for subsequent phases. A specific CNN determines if damage is present in the SLJ. If no damage exists, no further processing is required. If damage is detected, additional CNNs are triggered to determine damage intensity and damage localization. The CNNs are pre-trained with synthetic data, and fine-tuned and utilized with experimental data within a transfer learning scheme. This synergistic approach not only strengthens quality control but also holds potential as a robust SHM tool, ensuring the durability and reliability of adhesive joint applications across diverse industries.

The work follows a well-delineated work plan and methodology, with successive achievements reported in peer-reviewed journal papers. This thesis comprises an extended summary organized into 7 chapters, along with 6 papers presented in the appendices. Chapter 1 provides background information and outlines the sequential steps used to achieve the main goal of the work. Chapter 2 reviews previous works and identifies the challenges hindering the objective, serving as a guiding reference. Chapter 3 presents the numerical models and methods used or created to develop a comprehensive dataset of simulations for comparison with experimental data. The data obtained from these simulations were studied, and a data processing pipeline was created as the initial point for the methodology development. Chapter 4 utilizes the simulations and models to determine an experimental setup representing them, establishing a baseline for ML models. Chapter 5 explores various ML methods, with CNNs selected as the base method for implementation, along with transfer learning. Finally, chapter 6 outlines the methodology and applies it to detect, assess intensity, and determine localization of weak adhesion in both simulated and experimental samples, demonstrating significant performance.

Although significant progress has been made, and this work has extended the detection and characterization of weak adhesion in SLJ using ML and LWs data to new frontiers, there is always room for further advancement. Several limitations exist within this work, such as the small number of simulations conducted, and even when utilizing the model in section 3.1.3, the sensor placement

remains static, as does the number of sensors. Additionally, no exploration was undertaken concerning multiple damage points or moving the damage along two Cartesian axes. Bearing these limitations in mind, several avenues for future research include:

- Increasing the number of experimental samples to incorporate multiple damage characteristics;
- Detecting more than one type of damage per sample, both categorized as weak adhesion;
- Expanding the detection to encompass multiple damage types per sample;
- Generating more simulations with randomized sensor placement and varied part dimensions to create a more robust dataset;
- Integrating additional variables and characteristics into simulations, such as varying damage shapes or environmental factors like temperature and random vibrations;
- Applying the acquired knowledge to real-case scenarios, such as examining real airplane wings for weak adhesion issues.

References

- [1] Jochen Moll, Jens Kathol, Claus Peter Fritzen, Maria Moix-Bonet, Marcel Rennoch, Michael Koerdt, Axel S. Herrmann, Markus G.R. Sause, and Martin Bach. Open Guided Waves: online platform for ultrasonic guided wave measurements. *Structural Health Monitoring*, 18(5-6):1903–1914, 2019. ISSN 17413168. doi: 10.1177/1475921718817169.
- [2] T. R. Hay, R. L. Royer, Huidong Gao, Xiang Zhao, and J. L. Rose. A comparison of embedded sensor Lamb wave ultrasonic tomography approaches for material loss detection. *Smart Materials and Structures*, 15(4):946–951, 2006. ISSN 09641726. doi: 10.1088/0964-1726/15/4/007.
- [3] A. Q. Barbosa, L. F.M. Da Silva, J. Abenojar, J. C. Del Real, R. M.M. Paiva, and A. Öchsner. Kinetic analysis and characterization of an epoxy/cork adhesive. *Thermochimica Acta*, 604:52–60, 2015. ISSN 00406031. doi: 10.1016/j.tca.2015.01.025.
- [4] J. J.M. Machado, E. A.S. Marques, A. Q. Barbosa, and Lucas F.M. da Silva. Effect of hygrothermal aging on the quasi-static behaviour of CFRP joints varying the overlap length. *Composite Structures*, 214:451–462, 2019. ISSN 02638223. doi: 10.1016/j.compstruct.2019.02.035.
- [5] U.S. National Archives and Records Administration. Federal Aviation Regulations - Sec. 23.573, 2014.
- [6] Ayan Sadhu, Jack E Peplinski, Ali Mohammadkhorasani, and Fernando Moreu. A review of data management and visualization techniques for structural health monitoring using BIM and virtual or augmented reality. *Journal of Structural Engineering*, 149(1):03122006, 2023.
- [7] F Dipietrangelo, F Nicassio, and G Scarselli. Structural health monitoring for impact localisation via machine learning. *Mechanical Systems and Signal Processing*, 183:109621, 2023.
- [8] Min Ju, Zhongshang Dou, Jia-Wang Li, Xuting Qiu, Binglin Shen, Dawei Zhang, Fang-Zhou Yao, Wen Gong, and Ke Wang. Piezoelectric materials and sensors for structural health monitoring: Fundamental aspects, current status, and future perspectives. *Sensors*, 23(1):543, 2023.
- [9] Rolf Lammering, Ulrich Gabbert, Michael Sinapius, Thomas Schuster, and Peter Wierach. *Lamb-wave based structural health monitoring in polymer composites*. Springer, 2017.
- [10] Wern Hann Ong, Nik Rajic, Wing Kong Chiu, and Cedric Rosalie. Lamb wave-based detection of a controlled sisbond in a lap joint. *Structural Health Monitoring*, 17(3):668–683, 2018. doi: <https://doi.org/10.1177/1475921717715302>.

- [11] Stefano Carrino, Francesco Nicassio, and Gennaro Scarselli. An innovative method based on nonlinear Lamb waves for locating disbonds in Single-Lap joints. *2019 IEEE International Workshop on Metrology for AeroSpace, MetroAeroSpace 2019 - Proceedings*, pages 187–191, 2019. doi: 10.1109/MetroAeroSpace.2019.8869582.
- [12] A Francisco G Tenreiro, Gabriel MF Ramalho, António Mendes Lopes, and Lucas FM da Silva. Structural monitoring of adhesive joints using machine learning. In *Advances in Structural Adhesive Bonding*, pages 909–949. Elsevier, 2023.
- [13] Olivier Cherrier, Pierre Selva, Valérie Pommier-Budinger, Frederic Lachaud, and Joseph Morlier. Damage localization map using electromechanical impedance spectrums and inverse distance weighting interpolation: Experimental validation on thin composite structures. *Structural Health Monitoring*, 12(4):311–324, 2013.
- [14] Ronny Francis Ribeiro Junior and Guilherme Ferreira Gomes. On the use of machine learning for damage assessment in composite structures: A review. *Applied Composite Materials*, 31(1):1–37, 2024.
- [15] Jing Jia and Ying Li. Deep learning for structural health monitoring: Data, algorithms, applications, challenges, and trends. *Sensors*, 23(21):8824, 2023.
- [16] Qianyi Chen, Jiannong Cao, and Songye Zhu. Data-driven monitoring and predictive maintenance for engineering structures: Technologies, implementation challenges, and future directions. *IEEE Internet of Things Journal*, 2023.
- [17] Pierre Selva, Olivier Cherrier, Valérie Budinger, Frédéric Lachaud, and Joseph Morlier. Smart monitoring of aeronautical composites plates based on electromechanical impedance measurements and artificial neural networks. *Engineering Structures*, 56:794–804, 2013.
- [18] Liping Chen, Siqiang Xie, António M Lopes, and Xinyuan Bao. A vision transformer-based deep neural network for state of health estimation of lithium-ion batteries. *International Journal of Electrical Power & Energy Systems*, 152:109233, 2023.
- [19] Efstathios Branikas, Paul Murray, and Graeme West. A novel data augmentation method for improved visual crack detection using generative adversarial networks. *IEEE Access*, 11:22051–22059, 2023.
- [20] Xiao-long Ji, Yu-jiao Liang, Jia-yan Zheng, Lian-hua Ma, and Wei Zhou. Damage recognition of acoustic emission and micro-CT characterization of bi-adhesive repaired composites based on the machine learning method. *Applied Composite Materials*, pages 1–24, 2024.
- [21] A Francisco G Tenreiro, António M Lopes, and Lucas FM da Silva. A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy. *Structural Health Monitoring*, 21(2):228–249, 2022.
- [22] Gabriel MF Ramalho, António M Lopes, and Lucas FM da Silva. Structural health monitoring of adhesive joints using Lamb waves: A review. *Structural Control and Health Monitoring*, 29(1):e2849, 2022.
- [23] Zhongqing Su, Lin Ye, and Ye Lu. Guided Lamb waves for identification of damage in composite structures: A review. *Journal of Sound and Vibration*, 295(3-5):753–780, 2006. ISSN 10958568.

- [24] Andrea Melloni, Giuseppe Cusmai, and Mario Martinelli. Experimental confirmation of matched bends. *Optics Letters*, 29(5):465, 2004. ISSN 0146-9592. doi: 10.1364/ol.29.000465.
- [25] J. Sadler and R. Gr Maev. Experimental and theoretical basis of Lamb waves and their applications in material sciences. *Canadian Journal of Physics*, 85(7):707–731, 2007. ISSN 00084204. doi: 10.1139/P07-082.
- [26] W. J. Staszewski, B. C. Lee, L. Mallet, and F. Scarpa. Structural health monitoring using scanning laser vibrometry: I. Lamb wave sensing. *Smart Materials and Structures*, 13(2): 251–260, 2004. ISSN 09641726. doi: 10.1088/0964-1726/13/2/002.
- [27] L. Mallet, B. C. Lee, W. J. Staszewski, and F. Scarpa. Structural health monitoring using scanning laser vibrometry: II. Lamb waves for damage detection. *Smart Materials and Structures*, 13(2):261–269, 2004. ISSN 09641726. doi: 10.1088/0964-1726/13/2/003.
- [28] Qing Tian Deng and Zhi Chun Yang. Propagation of guided waves in bonded composite structures with tapered adhesive layer. *Applied Mathematical Modelling*, 35(11):5369–5381, 2011. ISSN 0307904X. doi: 10.1016/j.apm.2011.04.042. URL <http://dx.doi.org/10.1016/j.apm.2011.04.042>.
- [29] Baiyang Ren and Cliff J. Lissenden. Ultrasonic guided wave inspection of adhesive bonds between composite laminates. *International Journal of Adhesion and Adhesives*, 45:59–68, 2013. ISSN 01437496. doi: 10.1016/j.ijadhadh.2013.04.001.
- [30] Emmanuel Siryabe, Mathieu Renier, Anissa Meziane, and Michel Castaings. The transmission of Lamb waves across adhesively bonded lap joints to evaluate interfacial adhesive properties. *Physics Procedia*, 70(3):541–544, 2015. ISSN 18753892. doi: 10.1016/j.phpro.2015.08.012.
- [31] Joseph L Rose. *Ultrasonic guided waves in solid media*. Cambridge University Press, New York, 2014.
- [32] Kyoung-Tak Kang, Heoung-Jae Chun, Joo-Hyun Son, Jin-Ah Lee, Joon-Hyung Byun, Moon-Kwang Um, Sang-Kwan Lee, and Ju-Woong Jang. Quantitative accessibility of delamination in composite using Lamb wave by experiments and FEA. *Advanced Composite Materials*, 20(4):361–373, 2011. doi: <https://doi.org/10.1163/092430411X558503>.
- [33] Kui Fu Chen and Shu Li Mei. Composite Interpolated Fast Fourier Transform With the Hanning Window. *IEEE Transactions on Instrumentation and Measurement*, 59(6):1571–1579, 2010. doi: 10.1109/TIM.2009.2027772.
- [34] Magdalena Rucka, Erwin Wojtczak, and Jacek Lachowicz. Damage imaging in Lamb wave-based inspection of adhesive joints. *Applied Sciences*, 8(4):522, 2018. doi: <https://doi.org/10.3390/app8040522>.
- [35] F Nicassio, S Carrino, and G Scarselli. Elastic waves interference for the analysis of dis-bonds in single lap joints. *Mechanical Systems and Signal Processing*, 128:340–351, 2019. doi: <https://doi.org/10.1016/j.ymssp.2019.04.011>.
- [36] Phong B. Dao and Wieslaw J. Staszewski. Lamb wave based structural damage detection using cointegration and fractal signal processing. *Mechanical Systems and Signal Processing*, 49(1-2):285–301, 2014. ISSN 10961216. doi: 10.1016/j.ymssp.2014.04.011.

- [37] Liang Xu, Shenfang Yuan, Jian Chen, and Yuanqiang Ren. Guided wave-convolutional neural network based fatigue crack diagnosis of aircraft structures. *Sensors (Switzerland)*, 19(16), 2019. ISSN 14248220. doi: 10.3390/s19163567.
- [38] Padmakumar Puthillath and Joseph L Rose. Ultrasonic guided wave inspection of a titanium repair patch bonded to an aluminum aircraft skin. *International Journal of Adhesion and Adhesives*, 30(7):566–573, 2010. doi: <https://doi.org/10.1016/j.ijadhadh.2010.05.008>.
- [39] Baiyang Ren and Cliff J Lissenden. Modal content-based damage indicators for disbonds in adhesively bonded composite structures. *Structural Health Monitoring*, 15(5):491–504, 2016. doi: <https://doi.org/10.1177/1475921716650627>.
- [40] Sachin Kumar and Mohammed Rabiun Sunny. A novel nonlinear lamb wave based approach for detection of multiple disbonds in adhesive joints. *International Journal of Adhesion and Adhesives*, 107:102842, 2021.
- [41] Lucas F. M. da Silva, Andreas Öchsner, and Robert D. Adams, editors. *Handbook of Adhesion Technology*. Springer-Verlag Berlin Heidelberg, 2 edition, 2018.
- [42] Naoki Mori and Takayuki Kusaka. Reflection and transmission characteristics of Lamb waves at an adhesive lap joint of plates. *The Journal of the Acoustical Society of America*, 145(5):3075–3085, 2019. ISSN 0001-4966. doi: 10.1121/1.5109098. URL <http://dx.doi.org/10.1121/1.5109098>.
- [43] K. Heller, L. J. Jacobs, and J. Qu. Characterization of adhesive bond properties using Lamb waves. *NDT and E International*, 33(8):555–563, 2000. ISSN 09638695. doi: 10.1016/S0963-8695(00)00022-0.
- [44] Christopher Charles Henry Guyott, P Cawley, and RD Adams. The non-destructive testing of adhesively bonded structure: A review. *The Journal of Adhesion*, 20(2):129–159, 1986.
- [45] Mirco Verze. *Quantitative Assessment of Adhesively-bonded Joints Using Ultrasonic Guided Waves*. PhD thesis, Delft University of Technology, 2016.
- [46] Igor Kryukov and Stefan Böhm. Prospects and limitations of eddy current shearography for non-destructive testing of adhesively bonded structural joints. *The Journal of Adhesion*, 95(9):874–886, 2019.
- [47] Joana Roque Capinha. *Computational and Experimental Studies on Aircraft Structural Health Monitoring Systems Engenharia Aeroespacial*. PhD thesis, Universidade Técnica de Lisboa, 2007.
- [48] T. Kundu, A. Maji, T. Ghosh, and K. Maslov. Detection of kissing bonds by Lamb waves. *Ultrasonics*, 35(8):573–580, 1998. ISSN 0041624X. doi: 10.1016/S0041-624X(97)00095-4.
- [49] Padmakumar Puthillath. *Ultrasonic guided wave propagation across waveguide transitions applied to bonded joint inspection*. PhD thesis, Pennsylvania State University, 2010.
- [50] Robert Seifried, Laurence J. Jacobs, and Jianmin Qu. Propagation of guided waves in adhesive bonded components. *NDT & E International*, 35(5):317–328, 2002. ISSN 09638695.

- [51] Camille Gauthier, Mounsif Ech-Cherif El-Kettani, Jocelyne Galy, Mihai Predoi, Damien Leduc, and Jean Louis Izbicki. Lamb waves characterization of adhesion levels in aluminum/epoxy bi-layers with different cohesive and adhesive properties. *International Journal of Adhesion and Adhesives*, 74(December 2016):15–20, 2017. ISSN 01437496. doi: 10.1016/j.ijadhadh.2016.12.002.
- [52] Magdalena Rucka, Erwin Wojtczak, and Jacek Lachowicz. Lamb wave-based monitoring of shear failure of an adhesive lap joint. *Diagnostyka*, 19(4):51–57, 2018. ISSN 24495220. doi: 10.29354/diag/95176.
- [53] Riichi Murayama and Koichi Mizutani. Conventional electromagnetic acoustic transducer development for optimum Lamb wave modes. *Ultrasonics*, 40(1-8):491–495, 2002. doi: [https://doi.org/10.1016/S0041-624X\(02\)00164-6](https://doi.org/10.1016/S0041-624X(02)00164-6).
- [54] X. Jian, S. Dixon, R. S. Edwards, and J. Morrison. Coupling mechanism of an EMAT. *Ultrasonics*, 44(SUPPL.):653–656, 2006. ISSN 0041624X. doi: 10.1016/j.ultras.2006.05.123.
- [55] Paul D Wilcox, Michael JS Lowe, and Peter Cawley. The excitation and detection of lamb waves with planar coil electromagnetic acoustic transducers. *IEEE Transactions on ultrasonics, ferroelectrics, and frequency control*, 52(12):2370–2383, 2005. doi: 10.1109/TUFFC.2005.1563281.
- [56] F He, SI Rokhlin, and L Adler. Application of SH and Lamb wave EMAT’s for evaluation of adhesive joint in thin plate. In *Review of Progress in Quantitative Nondestructive Evaluation*, pages 911–918. Review of Progress in Quantitative Nondestructive Evaluation, 1988.
- [57] Hongjun Sun, Hiroyuki Kosukegawa, Toshiyuki Takagi, Tetsuya Uchimoto, Mitsuo Hashimoto, and Naoki Takeshita. Electromagnetic pulse-induced acoustic testing and the pulsed guided wave propagation in composite/metal adhesive bonding specimens. *Composites Science and Technology*, 201:108499, 2021. doi: <https://doi.org/10.1016/j.compscitech.2020.108499>.
- [58] RSC Monkhouse, PW Wilcox, MJS Lowe, RP Dalton, and P Cawley. The rapid monitoring of structures using interdigital Lamb wave transducers. *Smart Materials and Structures*, 9(3):304, 2000. doi: <https://doi.org/10.1088/0964-1726/9/3/309>.
- [59] Tadeusz Stepinski, Michał Mańka, and Adam Martowicz. Interdigital Lamb wave transducers for applications in structural health monitoring. *NDT & E International*, 86:199–210, 2017. doi: <https://doi.org/10.1016/j.ndteint.2016.10.007>.
- [60] Johan Bjurström, Ventsislav Yantchev, and Ilia Katardjiev. Thin film Lamb wave resonant structures—The first approach. *Solid-state Electronics*, 50(3):322–326, 2006. doi: <https://doi.org/10.1016/j.sse.2006.01.012>.
- [61] M Edward Motamedi. Micro-opto-electro-mechanical systems. *Optical Engineering*, 33(11):3505–3518, 1994. doi: 10.1117/12.181572.
- [62] Fabio Di Pietrantonio, Massimiliano Benetti, Domenico Cannatà, Romeo Beccherelli, and Enrico Verona. Guided lamb wave electroacoustic devices on micromachined AlN/Al plates. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, 57(5): 1175–1182, 2010. ISSN 08853010. doi: 10.1109/TUFFC.2010.1530.

- [63] Erwin Wojtczak and Magdalena Rucka. Wave frequency effects on damage imaging in adhesive joints using Lamb waves and RMS. *Materials*, 12(11):1842, 2019. doi: <https://doi.org/10.3390/ma12111842>.
- [64] Kuanshuang Zhang and Zhenggan Zhou. Quantitative characterization of disbonds in multilayered bonded composites using laser ultrasonic guided waves. *NDT & E International*, 97:42–50, 2018. doi: <https://doi.org/10.1016/j.ndteint.2018.03.006>.
- [65] Timotius Yonathan Sunarsa, Byeongjin Park, Peipei Liu, and H. Sohn. Noncontact debonding identification in adhesive joint using guided waves. *The 2016 Structures Congress (Structures16)*, 2016.
- [66] Zhang Haiyan, Liu Xiao, Sun Xiuli, Qi Xuerui, and Lu DongHui. Ultrasonic Lamb wave inspection using fiber Bragg gratings. In *2008 China-Japan Joint Microwave Conference*, pages 805–808. IEEE 2008 China-Japan Joint Microwave Conference, 2008.
- [67] Daniel C Betz, Graham Thursby, Brian Culshaw, and Wieslaw J Staszewski. Structural damage location with fiber Bragg grating rosettes and Lamb waves. *Structural Health Monitoring*, 6(4):299–308, 2007. doi: <https://doi.org/10.1177/1475921707081974>.
- [68] Indu Fiesler Saxena, Narciso Guzman, Kaleonui Hui, and Ajit K Mal. Disbond detection in a composite honeycomb structure of an aircraft vertical stabilizer by fiber Bragg gratings detecting guided ultrasound waves. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 231(16):3001–3010, 2017. doi: <https://doi.org/10.1177/0954406217718571>.
- [69] Mark Lin, Xinlin Qing, Amrita Kumar, and Shawn J Beard. Smart layer and smart suitcase for structural health monitoring applications. In *Smart Structures and Materials 2001: Industrial and Commercial Applications of Smart Structures Technologies*, volume 4332, pages 98–106. Smart Structures and Materials 2001: Industrial and Commercial Applications of Smart Structures Technologies, 2001.
- [70] Paul D Wilcox, MJS Lowe, and P Cawley. Mode and transducer selection for long range Lamb wave inspection. *Journal of intelligent material systems and structures*, 12(8):553–565, 2001. doi: <https://doi.org/10.1177/10453890122145348>.
- [71] YUKI Tokita, YOSHIHARU Kuze, Mitsuyoshi Uematsu, KANATA Fujii, and KOSUKE Watanabe. Evaluation of disbonds by diagnostic system using Lamb wave sensor network. In *Structural Health Monitoring, 2019: Enabling Intelligent Life-cycle Health Management for Industry Internet of Things (IIOT)*. Structural Health Monitoring, 2019: Enabling Intelligent Life-cycle Health Management for Industry Internet of Things (IIOT), 2019. doi: 10.12783/shm2019/32200.
- [72] JK Agrahari and S Kapuria. Effect of piezoelectric transducer bonding on time reversibility of Lamb waves in plates. In *Structural Health Monitoring, 2019: Enabling Intelligent Life-cycle Health Management for Industry Internet of Things (IIOT)*. Structural Health Monitoring, 2019: Enabling Intelligent Life-cycle Health Management for Industry Internet of Things (IIOT), 2019. doi: 10.12783/shm2019/32200.
- [73] Mario Kiel, Stefan Scheunemann, Maria Grotzner, Manuel Lucas, and Andreas Muck. Quality classification of adhesive bonds in composite structures by single-sided air-coupled ultrasonic testing using linear phased array probes. In *NDE of Aerospace Materials & Structures*, pages 53–58. NDE of Aerospace Materials & Structures, 2018.

- [74] Victor Giurgiutiu. Tuned Lamb wave excitation and detection with piezoelectric wafer active sensors for structural health monitoring. *Journal of Intelligent Material Systems and Structures*, 16(4):291–305, 2005. ISSN 1045389X. doi: 10.1177/1045389X05050106.
- [75] Jennifer E. Michaels and Thomas E. Michaels. Guided wave signal processing and image fusion for in situ damage localization in plates. *Wave Motion*, 44(6):482–492, 2007. ISSN 01652125. doi: 10.1016/j.wavemoti.2007.02.008.
- [76] Xinlin P Qing, Shawn J Beard, Amrita Kumar, and Robert Hannum. A real-time active smart patch system for monitoring the integrity of bonded repair on an aircraft structure. *Smart Materials and Structures*, 15(3):N66, 2006. doi: <https://doi.org/10.1088/0964-1726/15/3/N03>.
- [77] Josef Weiland, DF Hesser, W Xiong, A Schiebahn, B Markert, and U Reisgen. Structural health monitoring of an adhesively bonded CFRP aircraft fuselage by ultrasonic Lamb waves. *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, 234(13):2000–2010, 2020. doi: <https://doi.org/10.1177/0954410020950511>.
- [78] V. Giurgiutiu. *Structural health monitoring with piezoelectric active wafer sensors*. Elsevier, Oxford, 2014.
- [79] Edward F Crawley and Javier De Luis. Use of piezoelectric actuators as elements of intelligent structures. *AIAA Journal*, 25(10):1373–1385, 1987. doi: <https://doi.org/10.2514/3.9792>.
- [80] Lingyu Yu, Giola Bottai-Santoni, and Victor Giurgiutiu. Shear lag solution for tuning ultrasonic piezoelectric wafer active sensors with applications to Lamb wave array imaging. *International Journal of Engineering Science*, 48(10):848–861, 2010. doi: <https://doi.org/10.1016/j.ijengsci.2010.05.007>.
- [81] Xinlin P Qing, Hian-Leng Chan, Shawn J Beard, Teng K Ooi, and Stephen A Marotta. Effect of adhesive on the performance of piezoelectric elements used to monitor structural health. *International Journal of Adhesion and Adhesives*, 26(8):622–628, 2006. doi: <https://doi.org/10.1016/j.ijadhadh.2005.10.002>.
- [82] Sungwon Ha and Fu-Kuo Chang. Adhesive interface layer effects in PZT-induced Lamb wave propagation. *Smart Materials and Structures*, 19(2):025006, 2010. doi: <https://doi.org/10.1088/0964-1726/19/2/025006>.
- [83] Christian Willberg, Sascha Duczek, and Ulrich Gabbert. Increasing the scanning range of Lamb wave based SHM systems by optimizing the actuator–sensor design. *CEAS Aeronautical Journal*, 4(1):87–98, 2013. doi: <https://doi.org/10.1007/s13272-012-0052-x>.
- [84] Kai Zhou, Zheng Yi Wu, Xiao Hua Yi, Da Peng Zhu, Rahul Narayan, and Ji Zhao. Generic Framework of Sensor Placement Optimization for Structural Health Modeling. *Journal of Computing in Civil Engineering*, 31(4):1–14, 2017. ISSN 08873801. doi: 10.1061/(ASCE)CP.1943-5487.0000662.
- [85] Rohan Soman, Pawel Kudela, Kaleeswaran Balasubramaniam, Shishir Kumar Singh, and Pawel Malinowski. A study of sensor placement optimization problem for guided wave-based damage detection. *Sensors (Switzerland)*, 19(8), 2019. ISSN 14248220. doi: 10.3390/s19081856.

- [86] Wieslaw Ostachowicz, Rohan Soman, and Pawel Malinowski. Optimization of sensor placement for structural health monitoring: a review. *Structural Health Monitoring*, 18(3):963–988, 2019. ISSN 17413168. doi: 10.1177/1475921719825601.
- [87] Morteza Tabatabaeipour, Jan Hettler, and Steven Delrue. Reconstruction Algorithm for Probabilistic Inspection of Damage (RAPID) in Composites. In *European Conference on Non-Destructive Testing*, number Ecndt, 2014.
- [88] Sotiris B Kotsiantis, I Zaharakis, and P Pintelas. Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*, 160(1):3–24, 2007.
- [89] Alboukadel Kassambara. *Practical guide to cluster analysis in R: Unsupervised machine learning*, volume 1. Sthda, 2017.
- [90] Seth Hahne, Florian and Huber, Wolfgang and Gentleman, Robert and Falcon. *Bioconductor Case Studies*. Springer Science & Business Media, 2010. ISBN 9780387772394. doi: 10.1007/978-0-387-77240-0-7.
- [91] Chenhui Su, Mingshun Jiang, Shanshan Lv, Shizeng Lu, Lei Zhang, Faye Zhang, and Qingmei Sui. Improved damage localization and quantification of CFRP using Lamb waves and convolution neural network. *IEEE Sensors Journal*, 19(14):5784–5791, 2019. doi: 10.1109/JSEN.2019.2908838.
- [92] C. Sbarufatti, G. Manson, and K. Worden. A numerically-enhanced machine learning approach to damage diagnosis using a Lamb wave sensing network. *Journal of Sound and Vibration*, 333(19):4499–4525, 2014. ISSN 10958568. doi: 10.1016/j.jsv.2014.04.059.
- [93] Asif Khan, Dae Kwan Ko, Soo Chul Lim, and Heung Soo Kim. Structural vibration-based classification and prediction of delamination in smart composite laminates using deep learning neural network. *Composites Part B: Engineering*, 161(December 2018):586–594, 2019. ISSN 13598368. doi: 10.1016/j.compositesb.2018.12.118.
- [94] Jakub Korta, Andrzej Młyniec, Paweł Zdziebko, and Tadeusz Uhl. Finite Element Analysis of Adhesive Bonds Using the Cohesive Zone Modeling Method. *Mechanics and Control*, 33(2):51, 2014. ISSN 2083-6759. doi: 10.7494/mech.2014.33.2.51.
- [95] Christian Willberg, Sascha Duczek, Juan Miguel Vivar-Perez, and ZAB Ahmad. Simulation methods for guided wave-based structural health monitoring: A review. *Applied Mechanics Reviews*, 67(1), 2015. doi: <https://doi.org/10.1115/1.4029539>.
- [96] Ching Tai Ng. On the selection of advanced signal processing techniques for guided wave damage identification using a statistical approach. *Engineering Structures*, 67:50–60, 2014. ISSN 01410296. doi: 10.1016/j.engstruct.2014.02.019.
- [97] U Köcher. *Variational space-time methods for the elastic wave equation and the diffusion equation*. PhD thesis, Universität der Bundeswehr Hamburg, 2015.
- [98] B. C. Lee and W. J. Staszewski. Sensor location studies for damage detection with Lamb waves. *Smart Materials and Structures*, 16(2):399–408, 2007. ISSN 09641726. doi: 10.1088/0964-1726/16/2/019.

- [99] Marek Krawczuk. Application of spectral beam finite element with a crack and iterative search technique for damage detection. *Finite Elements in Analysis and Design*, 38(6): 537–548, 2002. ISSN 0168874X. doi: 10.1016/S0168-874X(01)00084-1.
- [100] C. Jeenjitkaew and F. J. Guild. The analysis of kissing bonds in adhesive joints. *International Journal of Adhesion and Adhesives*, 75(February):101–107, 2017. ISSN 01437496.
- [101] Stefano Carrino, Francesco Nicassio, Gennaro Scarselli, and Raffaele Vitolo. Finite difference model of wave motion for structural health monitoring of single lap joints. *International Journal of Solids and Structures*, 161:219–227, 2019. ISSN 00207683. doi: 10.1016/j.ijsolstr.2018.11.019.
- [102] Piotr Kijanka and Pawel Packo. Novel method for true guided waves spectral characteristics estimation using a logistic function fit and nonlinear least square algorithm. *Structural Control and Health Monitoring*, 26(9):1–13, 2019. ISSN 15452263. doi: 10.1002/stc.2388.
- [103] Paolo Bocchini, Alessandro Marzani, and Erasmo Viola. Graphical user interface for guided acoustic waves. *Journal of Computing in Civil Engineering*, 25(3):202–210, 2011. ISSN 08873801. doi: 10.1061/(ASCE)CP.1943-5487.0000081.
- [104] Joseph L Rose. *The Semi-Analytical Finite Element Method*, pages 135–154. Cambridge University Press, 2014. doi: 10.1017/CBO9781107273610.011.
- [105] PP Delsanto, RS Schechter, and RB Mignogna. Connection machine simulation of ultrasonic wave propagation in materials III: The three-dimensional case. *Wave Motion*, 26(4): 329–339, 1997. doi: [https://doi.org/10.1016/S0165-2125\(97\)00013-9](https://doi.org/10.1016/S0165-2125(97)00013-9).
- [106] P Paćko, T Bielak, AB Spencer, WJ Staszewski, T Uhl, and K Worden. Lamb wave propagation modelling and simulation using parallel processing architecture and graphical cards. *Smart Materials and Structures*, 21(7):075001, 2012. doi: <https://doi.org/10.1088/0964-1726/21/7/075001>.
- [107] BC Lee and WJ Staszewski. Modelling of Lamb waves for damage detection in metallic structures: Part I. Wave propagation. *Smart materials and structures*, 12(5):804, 2003.
- [108] Shankar Sundararaman and Douglas E Adams. Modeling guided waves for damage identification in isotropic and orthotropic plates using a local interaction simulation approach. *Journal of Vibration and Acoustics*, 130(4), 2008. doi: <https://doi.org/10.1115/1.2890389>.
- [109] PP Delsanto, Sigrun Hirsekorn, V Agostini, R Loparco, and A Koka. Modeling the propagation of ultrasonic waves in the interface region between two bonded elements. *Ultrasonics*, 40(1-8):605–610, 2002. doi: [https://doi.org/10.1016/S0041-624X\(02\)00183-X](https://doi.org/10.1016/S0041-624X(02)00183-X).
- [110] Dulip Samaratunga, Ratneshwar Jha, and S Gopalakrishnan. Wave propagation analysis in adhesively bonded composite joints using the wavelet spectral finite element method. *Composite Structures*, 122:271–283, 2015.
- [111] Vincentius Ewald, Roger M. Groves, and Rinze Benedictus. DeepSHM: a deep learning approach for structural health monitoring based on guided Lamb wave technique. page 19, 2019. ISSN 1996756X. doi: 10.1117/12.2506794.
- [112] Mario A. de Oliveira, Andre V. Monteiro, and Jozue Vieira Filho. A new structural health monitoring strategy based on PZT sensors and convolutional neural network. *Sensors*, 18(9), 2018. ISSN 14248220. doi: 10.3390/s18092955.

- [113] Chenhui Su, Mingshun Jiang, Shanshan Lv, Shizeng Lu, Lei Zhang, Faye Zhang, and Qingmei Sui. Improved Damage Localization and Quantification of CFRP Using Lamb Waves and Convolution Neural Network. *IEEE Sensors Journal*, 19(14):5784–5791, 2019. ISSN 15581748. doi: 10.1109/JSEN.2019.2908838.
- [114] Gabriel MF Ramalho, António M Lopes, and Lucas FM da Silva. Assessing weak adhesion in single lap joints using lamb waves and machine learning methods for structural health monitoring. *Applied Sciences*, 13(19):10877, 2023.
- [115] Yao Xu, Chongcong Tao, and Jinhao Qiu. Debonding detection of scarf-repaired composite laminates with laser ultrasonic lamb waves. In *Journal of Physics: Conference Series*, volume 2184, page 012041. IOP Publishing, 2022.
- [116] Yitao Zhuang, Fotis Kopsaftopoulos, Roberto Dugnani, and Fu-Kuo Chang. Integrity monitoring of adhesively bonded joints via an electromechanical impedance-based approach. *Structural Health Monitoring*, 17(5):1031–1045, 2018.
- [117] Mohammad Mehrabi, Mohammad Hossein Soorgee, Hossein Habibi, and Vassilios Kappatos. A novel application of ultrasonic lamb waves: Studying adhesive effects on the inspection of coating debonding in a three-layer waveguide. *Nondestructive Testing and Evaluation*, 36(6):616–636, 2021.
- [118] Plexus technical data sheet ma560-1. ITW Performance Polymers, 2018. https://itwperformancepolymers.com/wp-content/uploads/umb/1156/ma560-1-data-sheet_rev10.pdf.
- [119] P Packo, T Bielak, AB Spencer, WJ Staszewski, T Uhl, and K Worden. Lamb wave propagation modelling and simulation using parallel processing architecture and graphical cards. *Smart Materials and Structures*, 21(7):075001, 2012.
- [120] ZAB Ahmad and U Gabbert. Simulation of Lamb wave reflections at plate edges using the semi-analytical finite element method. *Ultrasonics*, 52(7):815–820, 2012.
- [121] Hamit Adin, Bilal Yıldız, and Mehmet Sukru Adin. Numerical investigation of fatigue behaviours of non-patched and patched aluminium pipes. *European Journal of Technique (EJT)*, 11(1):60 – 65, 2021. ISSN 2536-5010.
- [122] Jure Zupan. Introduction to artificial neural network (ANN) methods: what they are and how to use them. *Acta Chimica Slovenica*, 41:327–327, 1994.
- [123] Saad Albawi, Yasir Amer Abbas, and Yasser Almadany. Robust skin diseases detection and classification using deep neural networks. *vol*, 7:6473–6480, 2018.
- [124] AD Dongare, RR Kharde, Amit D Kachare, et al. Introduction to artificial neural network. *International Journal of Engineering and Innovative Technology (IJEIT)*, 2(1):189–194, 2012.
- [125] A Philip Plumb, Raymond C Rowe, Peter York, and Martin Brown. Optimisation of the predictive ability of artificial neural network (ANN) models: a comparison of three ANN programs and four classes of training algorithm. *European Journal of Pharmaceutical Sciences*, 25(4-5):395–405, 2005.
- [126] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

- [127] Yong Yu, Xiaosheng Si, Changhua Hu, and Jianxun Zhang. A review of recurrent neural networks: Lstm cells and network architectures. *Neural computation*, 31(7):1235–1270, 2019.
- [128] Patel Dhruv and Subham Naskar. Image classification using convolutional neural network (cnn) and recurrent neural network (rnn): a review. *Machine learning and information processing*, pages 367–381, 2020.
- [129] Shudong Yang, Xueying Yu, and Ying Zhou. LSTM and BRU neural network performance comparison study: Taking yelp review dataset as an example. In *2020 International workshop on electronic communication and artificial intelligence (IWECAI)*, pages 98–101. IEEE, 2020.
- [130] Alex Sherstinsky. Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Physica D: Nonlinear Phenomena*, 404:132306, 2020.
- [131] Ralf C Staudemeyer and Eric Rothstein Morris. Understanding LSTM—a tutorial into long short-term memory recurrent neural networks. *arXiv preprint arXiv:1909.09586*, 2019.
- [132] Zhelin Huang, Fangfang Yang, Fan Xu, Xiangbao Song, and Kwok-Leung Tsui. Convolutional gated recurrent unit–recurrent neural network for state-of-charge estimation of lithium-ion batteries. *IEEE Access*, PP:1–1, 07 2019. doi: 10.1109/ACCESS.2019.2928037.
- [133] Keiron O’Shea and Ryan Nash. An introduction to convolutional neural networks. *arXiv preprint arXiv:1511.08458*, 2015.
- [134] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.
- [135] Tala Talaie Khoei, Hadjar Ould Slimane, and Naima Kaabouch. Deep learning: Systematic review, models, challenges, and research directions. *Neural Computing and Applications*, 35(31):23103–23124, 2023.
- [136] Jianbo Yu and Yue Zhang. Challenges and opportunities of deep learning-based process fault detection and diagnosis: A review. *Neural Computing and Applications*, 35(1):211–252, 2023.
- [137] Karl Weiss, Taghi M Khoshgoftaar, and DingDing Wang. A survey of transfer learning. *Journal of Big data*, 3(1):1–40, 2016.
- [138] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2009.

Appendix A

Paper A

<https://doi.org/10.1002/stc.2849>

Structural health monitoring of adhesive joints using Lamb waves: A review

Gabriel M. F. Ramalho¹  | António M. Lopes^{1,2}  | Lucas F. M. da Silva^{1,2} 

¹Department of Mechanical Engineering, Faculty of Engineering, University of Porto, Porto, Portugal

²LAETA/INEGI, Faculty of Engineering, University of Porto, Porto, Portugal

Correspondence

António M. Lopes, Department of Mechanical Engineering, Faculty of Engineering, University of Porto, Porto, Portugal.
Email: aml@fe.up.pt

Summary

In the past decades, Lamb waves (LW) have seen encouraging results when applied to non destructive testing (NDT) and structural health monitoring (SHM), with important research done continuously through the years in both fields. This paper is a comprehensive review on equipment, testing procedures and techniques adopted in NDT and SHM, with emphasis in applications involving SHM of adhesive joints. The fundamentals of LW and their application to damage detection are discussed, and different signal processing, statistical, machine learning and simulation methods are presented. The paper represents a basis to deepen the understanding about the problem at hand and is a thorough compilation of relevant information to future work. Although LW-based SHM methods have been heavily studied, there is a gap of few to no studies between these topics and adhesive joints, namely, for monitoring weak adhesion.

KEYWORDS

adhesive joint, defect, Lamb wave, nondestructive testing, structural health monitoring

1 | INTRODUCTION

Over the past decades, materials science has created stronger and lighter materials that have revolutionized various fields. One of the most impacted is the aeronautical industry, where small weight changes can mean significant cost savings.¹ To achieve weight reductions, multi-material assemblies are used and each part combined using various types of joining techniques. One of the most promising ways is by adhesive joints that do not require fastener holes, thus distributing the stress over a large area and having limited points of stress concentration and probability of cracking. This in turn allows for thin substrates that end up reducing the overall weight.² Although adhesive joints have many advantages, they also present some drawbacks as, for example, degradation due to arbitrary load combinations, humidity, temperature, and other issues. Thus, it is necessary to constantly monitor the joint throughout its life cycle and intervene before structure failure.^{3,4}

Although disadvantages exist in adhesive joints, they are not what has limited the diffusion of adhesive joints in the aeronautics and other cutting-edge industries. The main factor is related to the existing non destructive testing (NDT) methods as, for example, ultrasonic, thermographic, radiographic, holographic, guided waves, and electromechanical impedance-based methods,^{5,6} which are not mature enough to allow for reliable and consistent monitoring, as requested by most standards, as the Federal Aviation Regulations (FAR) Section 23.573(5)—(iii).⁷

One way to go beyond NDT and achieve the required reliability is by using structural health monitoring (SHM). The SHM involves permanent and continuous analysis of the joint structure utilizing the same base techniques of NDT, but performing in-situ monitoring with all the necessary equipment permanently fixed to the structure. To accomplish

this, SHM utilizes many different technologies. The monitoring equipment obtains damage-sensitive data that are processed and structured, and then used in an algorithm that can detect if there is a defect and, if yes, where and which type and size the flaw is.

When comparing different SHM techniques, the approach utilizing Lamb waves (LW) stands out as one of the most promising candidates. This method often uses inexpensive and lightweight piezoelectric actuators and sensors to generate and sense a special kind of guided wave that makes the structure vibrate in a certain way, depending on its overall characteristics. Although it is possible to detect damage, LW are very difficult to process due to noise, environmental variables and other intrinsic characteristics that may affect the signals received at the sensors.⁸

Due to the complex nature of LW, several data processing methods have been adopted, namely for adhesive joints. However, those techniques have been implemented just in small and simple structures that have only one type of damage.⁹⁻¹⁴ To allow for large-scale and complex geometry parts inspection, there have been two main research lines. One involves utilizing data driven procedures, where the algorithm decides the best location for the sensors and actuators, according to the accuracy and resolution necessary.¹⁵ The other consists of model driven methods, where machine learning algorithms trained with data generated by simulations are compared with actual tests to determine damage.¹⁶ Furthermore, these machine learning techniques can be trained to pre-process the measured signals and to remove noise, while also creating a damage sensitive index that detects the overall characteristics of the defect.

This paper is a review on the use of LW in SHM, focusing on adhesive joints. To accomplish this, the paper is divided into eight sections. Section 2 introduces the LW fundamentals and describes how LW interact with structures and defects. Section 3 addresses adhesive joints, defects, and testing equipment. Section 4 presents and discusses several methods regarding the processing of LW signals. Section 5 demonstrates how statistical and machine learning techniques work and how they are applied to LW-based SHM of adhesive joints. Section 6 presents alternative frameworks for modeling and simulation. Section 7 summarizes the main open issues in LW-based SHM of adhesive joints. Finally, Section 8 overviews and synthesizes the main aspects of the research.

2 | FUNDAMENTALS OF LAMB WAVES IN STRUCTURAL HEALTH MONITORING

As parts are used, the chances for the emergence of defects grows. Most times the problems occur underneath the outer layer of the material, where it is difficult to see without destructive inspection techniques. Thus, efficient monitoring methods that do not involve destroying the part are crucial. To accomplish this, NDT methods were devised for different engineering structures, including bonded parts. The most used are the visual, or optical, liquid penetrant, magnetic particle, electromagnetic, radiographic, and ultrasonic testing methods.^{3,17}

Out of all NDT techniques, the ultrasonic, more specifically, the LW-based ultrasonic method, revealed large possibilities of application in cutting-edge industries, namely, in the aeronautical field. This is largely due to the fact that air-planes contain thin and large areas and, thus, the ultrasonic waves can potentially analyze entire structures.

The concept of LW was developed by Lamb in 1917. Throughout the second World War up to 1960, LW were used mostly in the medical field, until Worlton used them to detect damage.¹⁸ LW are a form of guided waves that can exist in isotropic, plain, and thin structures with parallel free edges.¹⁹ In anisotropic and complex geometry structures, guided waves can propagate, which are not LW. Nevertheless, in this work, the common practice of using the term LW in such a broader scope will be followed.

LW are nowadays seen as a prime candidate in damage detection of composite structures and adhesive joints due to (i) their sensitivity to interference in the propagation path; (ii) their potential capability for traveling over a long distance, thus allowing for the analysis of large parts, limited by the damping characteristics of the medium and the geometric complexity of the structure; and (iii) the existence of various modes, allowing to detect damage that is internal.¹⁹⁻²¹ LW are also capable of traveling inside curved walls with shallow curvatures, thus making them suitable to be used in the aeronautical field.

There are many ways to produce LW, ranging from piezoelectric actuation to lasers, ultrasounds, and X-rays.^{22,23} Therefore, depending on the intended application, there are pros and cons of each method.

The main drawback of LW in the context of SHM is the high complexity of the LW signals, which demands for sophisticated processing algorithms and high computational power.¹⁹ This has recently been facilitated with machine learning methods (MLMs) that allow the algorithms to learn and grow, thus simplifying the problem at hand.

Regarding the adhesive joints, there are few studies that use LW for defect detection. Most research is for composite structures and is focused on the transmission alterations that occur when LW pass the adhesive section, rather than on the interactions of the LW with defects.^{19,24-28}

2.1 | Dispersion curves

Although there is vast literature addressing LW, a brief introduction to the basic theory is presented here. In a solid medium, various elastic waves can be distinguished according to the different motion of the particles. LW propagate in thin plates guided by their upper and lower boundaries, being actually the superposition of longitudinal and shear modes. One of the key features of LW is that, when observed across the thickness of the material, they present a stationary wave pattern that can be divided into symmetric S_n and anti-symmetric A_n modes, where $n \in \mathbb{N}$ is the number of inflection points.²⁹ The LW phase velocity is dependent on the relation between the frequency and the material thickness. Thus, at any possible frequency value, there can be multiple modes that, in turn, complicate the evaluation of the measured LW signals.

To better understand the existing modes, S_n and A_n , the analytical dispersion curves are used, which may be written as²⁹:

$$\frac{\tan(qh)}{\tan(ph)} + \frac{4k^2qp}{(k^2 - q^2)^2} = 0, \quad (1)$$

$$\frac{\tan(qh)}{\tan(ph)} + \frac{(k^2 - q^2)^2}{4k^2qp} = 0, \quad (2)$$

with

$$p^2 = \frac{\omega^2}{c_L^2} - k^2, \quad q^2 = \frac{\omega^2}{c_T^2} - k^2, \quad k = \frac{2\pi}{\lambda}, \quad (3)$$

where p and q are placeholder variables, h stands for the half thickness of the plate, c_L and c_T denote the longitudinal and shear wave velocities, respectively, k is the wavenumber, λ represents the wavelength and ω is the angular frequency.

The longitudinal and shear velocities depend on the material properties, being given by

$$c_L = \sqrt{\frac{E(1-\nu)}{\rho(1+\nu)(1-2\nu)}}, \quad (4)$$

$$c_T = \sqrt{\frac{E}{2\rho(1+\nu)}}, \quad (5)$$

where E and ν represent the Young's modulus and Poisson's coefficient, and ρ stands for the density of the material.

Equations (1) and (2) have multiple roots, thus allowing for multiple modes. Numerical methods are used to obtain the relationships between phase velocity, wavelength, wavenumber and frequency, $c_p = \frac{\omega}{2\pi} \lambda = \frac{\omega}{k}$. The results are often depicted using dispersion curves, which can be presented in various forms. Figure 1 illustrates the dispersion curves of a specimen, where each mode is represented as a phase velocity versus frequency curve in a given frequency range. The specimen is an aluminum plate with thickness 2 mm, density $\rho = 2500 \text{ kg/m}^3$, Poisson's ratio $\nu = 0.33$ and Young's modulus $E = 72.4 \text{ GPa}$. In Figure 2 it is possible to see how the wavelength of each mode varies in relation to the frequency.

It can be verified that there is a value of frequency below which only the S_0 and A_0 modes are present, and for frequencies beyond this value multiple modes emerge. Therefore, above such threshold value, any analysis becomes complicated.

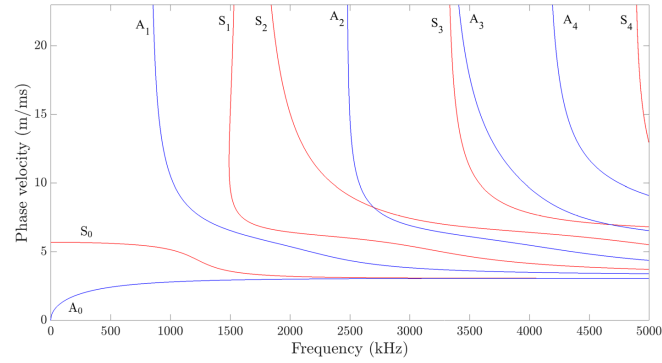


FIGURE 1 Example of symmetric and anti-symmetric modes in a wave phase velocity versus frequency graph

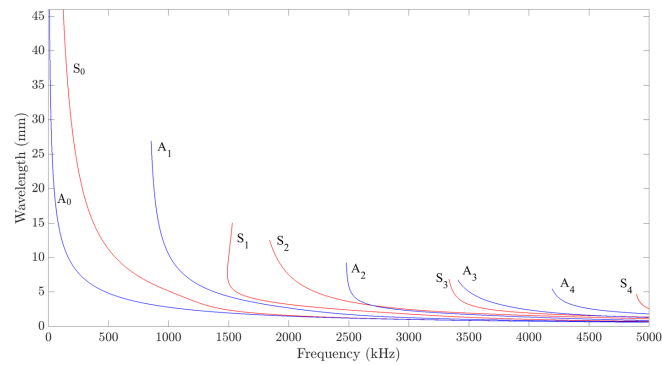


FIGURE 2 Relation between the wavelength of each mode and the frequency

Non-zero volume defects, such as voids, require using LW of wavelength smaller than twice the size of the void.³⁰ This means that small defects can be detected as long as high frequency signals are used. For the case of zero-volume defects, as weak adhesion in adhesive joints, the concept of size is unclear and has to be replaced by “level of adhesion.” To the best of the authors knowledge, there are no studies addressing the relation between wavelength and “level of adhesion.”

Another important aspect in the context of NDT and SHM is the type of exciting signal for generating LW. Since LW are dispersive, packets of waves containing different frequencies tend to spread out and distort, diffculting the separation of different modes both in the time and the frequency domains. Short time duration and narrow frequency spectrum excitation signals mitigate the problem of dispersion. The Hann-windowed tone burst possesses those characteristics and, thus, has been widely adopted to generate LW, but other alternatives are also possible, such as the Gaussian pulse or Gaussian windowed tone burst. The effect of the window is to concentrate most energy of the input signal around a carrier frequency. When exciting LW at points on the dispersion curves that correspond to almost constant group velocity with respect to frequency, the windowed tone bursts reduce the waves dispersion.

The Hann window is given by

$$w(n) = 0.5 - 0.5 \cos \frac{2\pi n}{M-1}, \quad (6)$$

where M is the total number of data points and $n = 0, 1, \dots, M - 1$. When applied to a sinusoidal signal, a burst type waveform composed of a number of wave pulses results, as illustrated in Figure 3. Such signal, also called tapering function,³¹ has a known form and duration, leading to data easier to analyze than those obtained with other types of excitation signals.

Although there are many papers that report the use of Hann windowed tone bursts,^{11,15,32} other works use alternative exciting signals. One example is the work of Dao et al.,³³ where cointegration is used in conjunction with a wavelet transform to determine damage in structures. Another case is reported by Xu et al.,³⁴ where multiple channel guided waves were used to create damage indices that fed neural networks (NN) for damage detection. More specifically to adhesive joints, Puthillath and Rose³⁵ addressed the inspection of a titanium repair patch bonded to an aluminum aircraft skin. Ren and Lissenden³⁶ studied the use of modal content-based damage indicators to improve the sensitivity of guided waves to disbands in the adhesive of composite structures. Kumar and Sunny¹⁶ proposed a LW based technique for detecting multiple disbands using damage features related to mode conversion and nonlinear breathing phenomena.

3 | ADHESIVE JOINTS

There are different types of adhesive joints, but the single lap joint (SLJ) is the most used in the industry.² Most research on NDT and SHM of adhesively bonded structures addresses SLJ, but all the methods and techniques developed for SLJ can be easily adapted to other types of joints.

3.1 | The single lap joint

A SLJ is composed of two adherends that overlap one another, with the adhesive in the between. Although SLJ involve simple constructive procedures due to their simple geometry, the interaction of LW with the SLJ materials is complex. Mori and Kusaka³⁷ showed that the reflection and transmission coefficients of the anti-symmetric mode A_0 vary with the tangential stiffness and frequency. Furthermore, there are multiple frequencies that present maxima and minima reflection and transmission coefficients. The complex nature of the interactions of LW with the materials composing SLJ was also investigated in Heller et al.,³⁸ where a combination of an ultrasonic laser technique and sophisticated signal processing methods were used to measure extreme degradation due to high temperature in specimens.

3.2 | Defects in adhesive joints

Defects in adhesive bonds tend to occur in the adhesive layer or in the substrate (Figure 4) and may be caused by manufacturing problems (e.g., improper surface preparation, environment contamination, or poor curing) or in service deterioration (e.g., water or moisture absorption, extreme temperature, or loading conditions). In regard to the adherend, defects can be superficial, in multiple sizes, and internal cracking formations. Referring more specifically to the adhesive, three main defects can occur, namely poor cohesive strength of the adhesive, voids or disbands, and weak adhesion between the adhesive and the adherend.³⁹⁻⁴¹ It is important to point out that voids can be

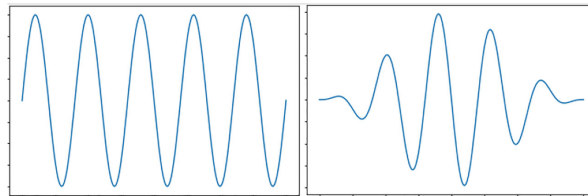


FIGURE 3 Example of how a sinusoidal signal is altered when multiplied by a Hann function

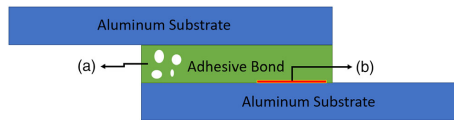


FIGURE 4 Example of different types of defects where (a) is a void and (b) is weak adhesion between the adhesive and the substrate

subdivided into complete voids, where there is no adhesive between the two bonding surfaces, small voids that stay present only in the adhesive and can be due to small air bubbles and, finally, surface voids or delaminations that occur between the adhesive and the substrate.⁴⁰ Although kissing bond is a term commonly adopted in the literature to refer weak adhesive bonding (e.g., slip bond, smooth bond, partial bond, zero-volume disbond, and imperfect interface), herein it will be used to designate perfect contact between two surfaces which transmits no shear stress. Conversely, the term weak adhesion will denote any intermediate level of adhesion that can range from complete adhesion to kissing bond.⁴² Out of all defects, weak adhesion between the adhesive and substrate is the hardest to detect accurately, and out of all NDT or SHM methods, the most promising results come from guided waves, more specifically LW.^{5,39}

One unique use of LW is the possibility of determining surface and internal damage, which is possible since each LW mode is particularly sensitive to specific types of damage. For example, cracks can be detected using symmetric modes, while surface damage affect more the anti-symmetric modes.⁴³ For a given structure, if there is a defect between one actuator/sensor pair, then the signal measured at the sensor will be different from the one acquired in a pristine specimen. Increasing the number of actuator/sensor pairs will increase the accuracy of the damage detection algorithm.⁴⁴ Moreover, to determine the extension and characteristics of the damage, all aspects of the LW should be observed, both in the time and in the frequency domains. In other words, by processing multiple data features, it is possible to determine additional information about damage.³⁸

3.3 | Instrumentation

Although there are many ways to approach the use of LW in SHM, first, it is normally necessary to understand the designated use of the specimen to, then, determine the technology, instrumentation and testing methods that are possible and more suitable. When the intended purpose is an outdoor application, where lightweight, reliable, and small size components are fundamental, certain equipment, such as laser interferometers, suited to workbench use, is inappropriate. Therefore, out of the remaining possible options, transducer-based equipment is a prime candidate for LW-based SHM applications. In a simplified way, such technology works by placing two or more transducers on the designated part, leaving the region where it is necessary to determine defects in between the transducer.^{22,23}

A few prominent transducer-based solutions are presented in the follow-up. A brief overview of the physical traits will be given, followed by a simple description of how each method produces LW.

3.3.1 | Electromagnetic Acoustic Transducers

This transducer can be regarded as a speaker composed of a coil and a permanent magnet. Its working principle is based on Lorentz's forces and magnetic coupling that cause the permanent magnet and coil to create a relative movement between them, depending on the way the coil is functioning. This movement at high speed creates vibrations and thus can excite LW.^{45,46} These sensors were used in Wilcox et al⁴⁷ to generate LW in a 5 mm thick aluminum plate. It was shown that the sensors' omni-directional sensitivity allows for a precise wave detection in one plane. Electromagnetic acoustic transducers (EMAT) were used with adhesive joints by He et al⁴⁸ to assess the applicability of LW and shear horizontal waves in the evaluation of thin plate structures. Sun et al⁴⁹ used electromagnetic pulse-induced acoustic testing to detect debonding in plastic composite/metal specimens.

3.3.2 | Comb and interdigital transducers

Comb and interdigital transducers are normally composed by three layers of material, forming a sandwich of two electrodes with a layer of piezoelectric material in the middle, as illustrated in Figure 5. As the name suggests, usually, the top layer electrode is shaped forming a comb like structure.^{50,51}

The main drawback of these transducers is that the comb pattern determines the wavelength range that can be produced, which, in turn, can not be changed quickly. Although they are used in LW-based NDT of diverse materials and structures, their application with adhesive joints has been quite limited.

3.3.3 | Micro Electro-Mechanical Systems

Micro electro-mechanical systems (MEMS) can have many configurations citepbjurstrom2006thin. They can normally be constructed with flexible materials coupled with coils and permanent magnets. The main difference between MEMS and EMAT is the overall configuration of the structure and how each component is placed.^{52,53} Although they have been used with LW, as seen, for example, in Di Pietrantonio et al,⁵³ they were adopted with parsimony, namely, to monitor adhesive joints, probably due to their high price and high sensitivity to noise for in-situ applications.

3.3.4 | Laser vibrometry

A laser Doppler vibrometer makes non-contact vibration measurements of a surface. The laser beam is directed to the object and the vibration amplitude and frequency are extracted from the Doppler shift of the reflected beam frequency. The output of the sensor is directly proportional to the object velocity along the direction of the laser beam. Besides velocity, displacement can also be measured with appropriate signal conditioning. Laser Doppler vibrometry allows measuring with high resolution and linearity. However, the equipment is expensive and, although it can be useful in NDT for monitoring out-of-service components, it is not suitable for SHM, since can not be permanently fixed to the structure. Normally, pulsed Nd:YAG lasers or piezoelectric elements are used to excite the LW whose propagation characteristics are then acquired by the vibrometer. Within the scope of NDT of adhesive joints, the technology has been used by many researchers.^{15,54-56}

3.3.5 | Fiber bragg gratings

Fiber optic sensors, namely, fiber Bragg gratings have proved their effectiveness as ultrasonic sensors. Their main advantages include small weight and size and immunity to electromagnetic interference, which are very interesting for SHM applications. A fiber Bragg grating sensor is a microstructure with a typical length of a few millimeters that can be inserted into the core of a standard singlemode fiber. The sensor acts as a wavelength selective mirror. Light from a broadband source is injected into the optical fiber, but just the part within a very narrow spectrum centered on the Bragg wavelength is reflected. The remaining light is not affected and continues its path through the optical fiber. The Bragg wavelength is essentially defined by the period of the microstructure and the refractive index of the nucleus.

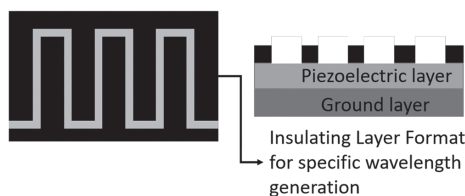


FIGURE 5 Comb and interdigital transducer structure

When acting as a strain sensor, the fiber is stretched or compressed, which causes a change in the period of the microstructure and in the Bragg wavelength. Fiber Bragg gratings have been used with LW-based NDT techniques,^{57,58} but their application to adhesive joints has been limited.⁵⁹

3.3.6 | Distributed sensors

Although sensors can be integrated individually on a structure, a practical and cost-effective alternative is to use a (pre-built) network of sensors. One example is the Acellent Technologies' SMART Layer, which consists of a network of piezoelectric elements that can be efficiently deployed on both simple and complex shaped structures.⁶⁰ The technology uses advanced electronics industry manufacturing process, which involve printing and etching a conductor pattern onto a dielectric substrate, laminating a dielectric cover layer for electrical insulation, and mounting arrays of transducers on the circuit. The SMART Layer is treated as an extra ply by the composite layup process, or can be surface mounted on structures made with a variety of materials. Acellent Technologies provides also the SMART Suitcase product to interface the SMART Layer directly, as well as software for damage diagnosis.

Another example of distributed sensors is the case of phased array probes, which are made up of multiple elements, each one pulsed automatically at specific time instants. The advantage is the possibility of scanning large areas without the need for moving the probe.⁶¹

Applications of distributed sensors within the scope of damage detection in adhesive joints⁶²⁻⁶⁴ have been limited, although they are potentially interesting in SHM.

3.3.7 | Piezoceramic transducers

This type of transducer can vary in geometry, material and size, but, generally they are thin wafers of piezoelectric material and, thus, they are also called piezoelectric wafer active sensors (PWAS). The piezoelectric properties allow the material to alter its shape when subjected to an electrical voltage excitation. Therefore, by applying a variable signal to the wafer, it vibrates at the desired frequency, creating LW. On the other hand, when a piezoelectric material is mechanically deformed, it generates also an electric signal, thus allowing the PWAS to work either as an actuator or as a sensor. The main benefits of this technology are its simplicity, lightweight and low cost.⁶⁵ PWAS can be commonly seen as candidates for SHM in aeronautics, where large arrays are needed to monitor large parts.⁶⁶ An example of use was reported in Giurgutiu,⁶⁵ where it was shown that PWAS are particularly sensitive to the LW S_0 mode at around 300 kHz. Michaels and Michaels⁶⁶ also used PWAS to detect damage in-situ by using LW. Specifically for adhesive joints monitoring under the framework of LW-based SHM, PWAS have been widely used.^{16,32,67,68}

Since the PWAS are often bonded to the structure, their effects in the SHM monitoring system must also be considered.⁶⁹ Studies reported a shear lag effect caused by the adhesive,^{70,71} more critical for lower shear modulus and thicker adhesive layers, which translated into worse shear transfer capability between the PWAS and the structure and reduced signal amplitude. Other studies showed an increase in the signal amplitude when using thicker adhesive layers,⁷² which was attributed to the PWAS resonant behavior under different constraints imposed by the adhesive. This effect was studied numerically by Ha and Chang,⁷³ while Willberg et al⁷⁴ addressed the issue with the objective of generating high amplitude LW with limited electrical energy for wave excitation.

3.4 | Testing methods

The most important part of a testing method suitable for LW-based SHM is the positioning of the sensors and actuators in relation to the defect. This is extremely important due to the fact that only the sensors that are in line with the defect and the actuators will measure a significant change in the signal (in comparison with the signal acquired in a pristine specimen). Out of the studies that address detection of defects in adhesive bonded structures using LW, there are two main approaches regarding sensor/actuator placement and data collection: (i) within the bond (WTB); and (ii) across the bond (ATB), as illustrated in Figure 6. In the WTB approach, the LW are generated and detected in the adhesive region. In the ATB, the LW are generated and detected away from the bonded area, having the waves to pass the adhesive before they arrive at the sensor. In Verze⁴⁰ the ATB approach was adopted for the analysis of defects in adhesive

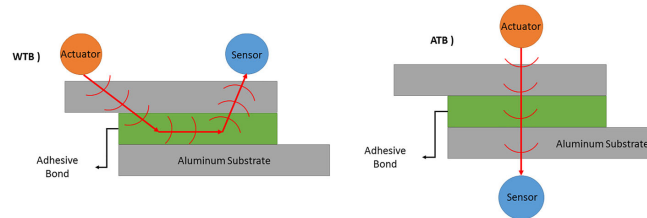


FIGURE 6 Examples of within the bond (WTB) and across the bond (ATB) sensor/actuator placement for Lamb waves (LW) testing

structures. On the other hand, in the work of Kundu et al.⁷⁵ the use of WTB was reported for investigating the sensitivity of normal incidence bulk waves.

Normally, the WTB is used as benchmark, as it is difficult to implement in real structures, since it requires access to the adhesive joint. However, in SHM this is not an issue, since the part is always instrumented with a sensor/actuator array. The main benefit of the WTB method is that the LW modes are more easily detected by using a suitable positioning of the transducers and specific signals. The method was adopted by Puthillath and Rose,³⁵ where guided waves were used to inspect repairs made using adhesive bonds in aluminum surfaces. The ATB implementation has the transducers placed away from the joint and can represent an easier approach to the application in real parts.⁷⁶ However, the drawback is a discontinuity that will modify that signal, since it is generated in the adherend.⁷⁷

Out of many possible equipment and methods employed in NDT and SHM, just a few have already been tested in adhesive joints. In Heller et al.³⁸ a Nd:YAG laser (1064 nm) with a low pass filter at 10 MHz was used on an aluminum structure with dimensions 100 mm × 100 mm × 0.9398 mm. The adhesive, placed on the entire surface forming a 0.25 mm thick layer, was a M3 tap product F-9473PC. Lasers were also used in other studies, such as those by Seifried et al.⁷⁸ and Gauthier et al.,⁷⁹ who analyzed different properties of adhesive bonds in specimens that ranged from 100 mm × 100 mm to 300 mm × 300 mm, with adhesive layers of 0.25 mm in average. In Deng and Yang,²⁵ the substrate was a composite material and the overlap was studied using lengths of 50, 100, and 200 mm. Ren and Lissenden²⁶ reported the use of transducers, but no specific mention was made to their type. In this study, plates of composite material with 300 mm × 300 mm were used with a 50-mm-wide epoxy stringer. All studies have in common the use of large structures with an average size of 100 mm × 100 mm, and a relatively small thickness, between 1 mm and 3 mm. The adhesive layer is of around 0.25 mm.⁷⁸⁻⁸⁰ Due to the overall values of sensor placement and specimen size, these can be used as an initial estimate for further work.

One of the main limitations of the aforementioned testing rigs is that relatively large and simple sheets are used. This allows for further studies, regarding different specimen sizes, shapes and types, and their effects on the ability to detect defects, more specifically for the case of weak adhesion.

4 | SIGNAL PROCESSING TECHNIQUES

During the process of SHM, the first step is data collection by the sensors. This means that the array of sensors has functioned correctly and all data have been collected on a computer. At this stage, there are two ways of obtaining results from the data. The first is to use the acquired information directly in a damage detection algorithm. The second is to pre-process the data before further treatment. This process from obtaining the data until damage localization can be seen in Figure 7. Besides experimental data, simulation data is also useful for algorithms that rely on training for learning. During an experiment in a controlled environment, such as a laboratory, there is little to no noise caused by external perturbations, such as vibrations, temperature variations, and other issues. Thus, data pre-processing is not always needed. However, this is vital when the application is in-situ and there are many disruptive variables, whose influence can not be avoided.⁶⁶

LW produced by piezoelectric transducers have, in general, multi-modal characteristics, and the structure, transducers and bandwidth are important factors. Out of the many possible options to process the LW signals, there are a few that have been tested and stand out. In the follow-up, they will be addressed briefly.

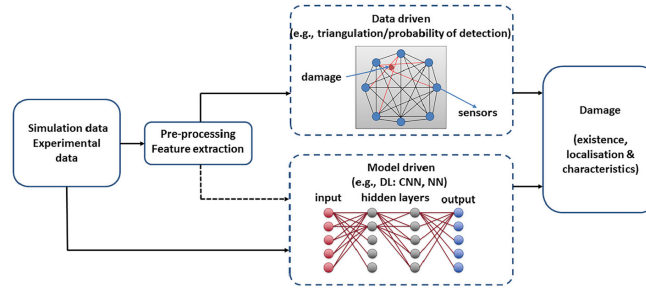


FIGURE 7 Flowchart illustrating the steps involved in processing the data collected by the sensors

4.1 | Fast fourier transform

The Fourier transform is a method that converts a time domain signal to the frequency domain. Often, using information about spectral amplitude it is possible to identify damage. The Fourier transform of a function $u(t)$ is given by

$$u(i\omega) = \int_{-\infty}^{\infty} u(t)e^{-i\omega t} dt, \quad (7)$$

where ω stands for the angular frequency and i is the imaginary unit.⁸¹⁻⁸³

When considering adhesive joints, there were a few studies that used the fast Fourier transform (FFT) signal processing method to analyze the interference of the LW with the adhesive structure. The main reasons are the simplicity and the straightforward digital implementation of the FFT.^{26,28,38,84} In Heller et al³⁸ the FFT was adopted to process LW and to determine adhesive bond properties. The results showed the effectiveness of the method, including to detect irreparable damages caused by high temperatures. Siryabe et al²⁸ used the FFT to analyze the transmission of LW across a bonded joint by signalizing the received signal. Although the method is functional in simple problems, for the analysis of multiple defects and complex joint shapes it might not be robust enough to cope with the difficulties presented.

4.2 | Hilbert transform

The Hilbert transform is given by

$$h(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{u(\tau)}{t - \tau} d\tau, \quad (8)$$

where $u(\tau)$ is a wave signal with a 90 deg phase shift in relation to $h(t)$.^{81,85}

Yu and Giurgiutiu⁸⁶ used the Hilbert transform, and other advanced signal processing techniques, to improve the performance of guided waves based methods in locating damage. Ng⁸¹ studied some effective signal processing techniques, including the Hilbert transform, applied to damage identification using guided waves and statistical methods. Willberg et al⁸⁷ adopted the Hilbert transform to extract signals' envelopes and to determine time of flights. Su et al⁸⁸ devised a method for damage localization based on the Hilbert energy spectrum and LW tomography.

4.3 | Continuous wavelet transform

The continuous wavelet transform can be used to analyze a given signal in the continuous time-frequency domain, being the signal divided into local functions. It can be defined as follows:

$$CWT(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} u(t) \psi\left(\frac{t-b}{a}\right) dt, \quad (9)$$

where a and b are constants that define the scaling and translation, and $\psi(t)$ is the main wavelet function. In LW-based SHM, the Gabor function is often used as the main wavelet, since it presents an equilibrium between frequency and time resolution and is effective in extracting local feature from signals. However, other functions can be adopted, such as the Mexican Hat, Derivative of Gaussian, and Shannon. The Gabor function can be defined as follows:

$$\psi(t) = \frac{1}{\sqrt[4]{\pi}} \sqrt{\frac{\omega_0}{\lambda}} \exp\left[\frac{(\omega_0/\lambda)^2}{2} t^2 + i\omega_0 t\right], \quad (10)$$

where λ is the shaping factor and ω_0 is the center frequency.^{81,89,90}

Like the Hilbert, the continuous wavelet transform was also used by Ng.⁸¹ Other authors such as Hameed et al.⁹¹ used it to detect damage using LW from active sensor networks. The continuous wavelet transform has been widely applied in the context of SHM for signal denoising⁹² and feature extraction.⁹³ Specifically for adhesive joints, the continuous wavelet transform was used by Rucka et al.⁸⁰ and Hong et al.,⁹⁴ just to cite a few.

4.4 | Discrete wavelet decomposition

The discrete wavelet decomposition may be written as:

$$DWT(m, d) = \int_{-\infty}^{\infty} u(t) \psi_{m,d_w}(t) dt, \quad (11)$$

where $\psi_{m,d_w}(t)$ is a orthonormal basis of functions, m and d_w are integers that represent scale and translation indices, respectively, and $u(t)$ stands for the mother wavelet function. The advantages of the DWT is that it allows the adoption of high and low pass filters that are user defined, which permits fine tuning of the method for each case.^{81,89,95,96} In Liew and Veidt⁹⁵ DWT were used in combination with NN and guided waves to find patterns in damaged specimens. The approach reported detection errors below 4%.

In Ng⁸¹ several methods were compared as advanced processing techniques for damage identification using guided waves. Out of those, the one that led to better results was the Hilbert transformation.⁸¹ However, this does not exclude the other options, as their effectiveness in a variety of possible real conditions has still to be verified. Moreover, most tests have been conducted only with statistical-based damage detection approaches and not with the application of machine learning based techniques. Other than the limited testing of signal processing methods with machine learning, there are also no studies on signal processing for determining weak adhesion.

5 | STATISTICAL AND MACHINE LEARNING BASED DAMAGE DETECTION

Before determining the methodology that will be used to detect a defect in a testing part, it is necessary to determine the optimal placement of the sensors/actuators. Although for adhesive joints the problem is still not solved, for overall SHM there have been many studies that can serve as a baseline. In Zhou et al.⁹⁷ genetic algorithms were used to find the optimal location of a specified number of elements. Genetic algorithms were also adopted in Soman et al.,⁹⁸ where the main optimization objective was maximizing the damage detection area. It is important to note that most research work seeks to determine either the optimal number of sensors/actuators or their optimal placement, while little work has been done combining both objectives.⁹⁹

A way to determine sensor/actuator placement and number is by calculating the spatial density of information that is required. This issue is illustrated in Figure 8. The existing sensor/actuator 'overlapping paths' would allow for an accurate detection of a defect at the center of the specimen. For a defect close to a border, there is a limited number of

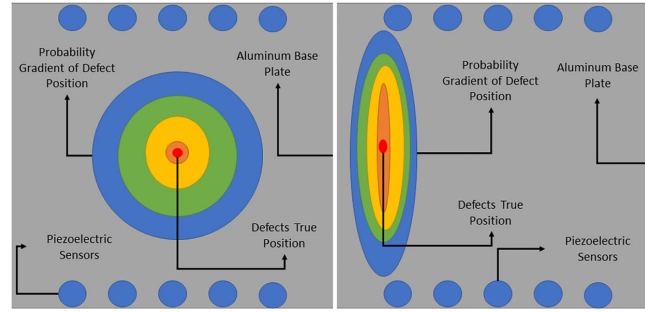


FIGURE 8 Probability of detection caused by a defect located: (left) at the center; (right) close to a border. Sensors/actuators are represented as blue circles¹⁰⁰

opposing actuator/sensor pairs. In the example, the vertical axis is richer in information than the horizontal one. Thus, the horizontal coordinate of the border defect would be detected more accurately than the vertical coordinate. This is illustrated by the resulting oval area of detection.

Even using the optimal sensor/actuator positions and quantity, detecting a defect utilizing LW is difficult when looking only at the raw data. To generate a meaningful and valid answer out of the data, it is necessary to pass the collected information through one or more suitable processing steps, either based on statistical approaches or machine learning algorithms.

5.1 | Statistical based methods

Statistical based methods rely on the divergence, in frequency and/or time domains, between baseline signals and actual sensor measurements. To exemplify this, it is better to imagine that each LW, when hitting a defect, changes its direction, form and time of arrival at the sensor, in comparison with a 'base test' (performed in a pristine specimen), as it has to 'go around' the defect.^{77,100} Statistical methods of reconstruction have subtle differences in their algorithms and, thus, are classified in two main groups: (i) time of flight diffraction, or difference, or delay (TOFD)⁴⁴; and (ii) signal difference coefficient (SDC).¹⁰¹

One example of SDC is the reconstruction algorithm for probabilistic inspection of damage (RAPID), where there are two main assumptions. The first is that every effects that come from all actuator/sensor pairs can be linearly summed to determine a defect probability distribution for a given inspected area. The second is that the area that an actuator/sensor pair can inspect is some subarea around the direct path between them. The mathematical formulation used for this method is⁷⁷

$$P(x,y) = \sum_{k=1}^N p_k(x,y) = \sum_{k=1}^N A_k \left(\frac{-1}{\beta-1} R(x,y,x_{1k},y_{1k},x_{2k},y_{2k}) + \frac{\beta}{\beta-1} \right), \quad (12)$$

$$R = \frac{\sqrt{(x-x_{1k})^2 + (y-y_{1k})^2} + \sqrt{(x-x_{2k})^2 + (y-y_{2k})^2}}{\sqrt{(x_{1k}-x_{2k})^2 + (y_{1k}-y_{2k})^2}}, \quad (13)$$

where P is the probability of a defect at the coordinates (x,y) , k stands for a actuator/sensor pair and N is the total number of actuator/sensor pairs in the network. Finally, the total distance between the actuator and sensor is R .⁷⁷

The variations present in the time domain signals S_0 and A_0 in the presence and absence of a defect are only slight and without a careful analysis it is almost impossible to determine the characteristics of the defect.

Figure 9 represents the sensors acquiring the data that are used in the RAPID algorithm to create an image representing the most probable location of the defect. A defect at the central area can be detected accurately, but defects close to the borders are hard to detect, requiring a higher actuator/sensor network resolution.

In the work of Hay et al⁷⁷ a statistical method was used to determine the loss of material in aircraft parts by using LW excited/sensed by transducers embedded in the structure. Tabatabaeipour et al¹⁰¹ addressed a statistical method to determine damage in composite structures.

Out of all review done, no evidence of statistical methods applied to LW-based SHM of adhesive joints was found. This allows for further studies in this area and, more specifically, in the use of statistical methods to detect weak adhesion between bonded materials.

5.2 | Machine learning methods

MLMs can be divided into three main categories, namely supervised, unsupervised and reinforced learning. The first category is normally used when the objective is to classify and label objects.¹⁰² The second is adopted as a means to divide large quantities of information (big data) into groups created by the algorithm.^{103,104} Finally, the last category is often used in the field of robotics, where the algorithm has to learn and refine its objective in various stages and “generations,” in a way similar to a genetic algorithm.

To find the categories more suited to LW-based SHM, it is necessary first to determine the objectives that are wanted. LW are capable of detecting not only the location of a defect but also its size and type. Therefore, the objective is to classify the information obtained in classes that are chosen by the user, which elects the supervised learning the best approach. However, other MLM may also be adopted.

As stated previously, the objective of the analysis is to determine the defect position, size, and type. To do this with supervised learning it is necessary to determine the type of information that is deemed acceptable. For example, the position of a defect can be represented by the indices of a cell in a rectangular grid. The type of answer required can drastically change the way the algorithm is constructed and used.

Inside the category of supervised learning there is a vast world of subcategories that can be explored, but for the problem at hand, NN and deep learning (DL) play a key role due to their ability in categorizing images and speech patterns that, if analyzed carefully, show many similarities with damage detection problems.⁹²

The NN and DL are MLM that rely on a matrix structure representation similar to the neural synapses in humans. Although difficult to understand at first hand, the application of NN for analyzing LW signals follows specific steps.

First, as with the statistical methods, the data of interest must be acquired. These data, representing amplitude of vibration versus time, measured at known sensor locations, are segmented depending on the level of detail required. The resulting fragments are used as inputs to the neurons. The algorithm then uses weights, biases and a nonlinear function to create a cost function, or “hidden layer.” This cost function is compared with the wanted results in the “output layer,” which in the problem at hand could be, for example, the presence or absence of damage. Depending on the comparison result, the NN adapts the weights and biases by means of some optimization method. A schematic representation of a NN is depicted in Figure 10.

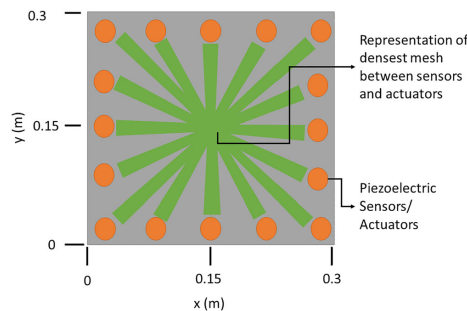


FIGURE 9 Schematic example of the output of the RAPID algorithm⁷⁷

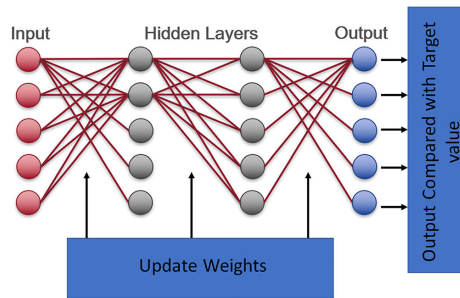


FIGURE 10 Example of a neural network (NN) with its input, hidden, and output layers

As there are many papers that investigate NN and DL to analyze LW and defects, it is necessary to clarify the difference between the algorithms. The two terms describe the use of many intermediate 'hidden layers', where each neuron can be seen as a line that is created in a plane to separate data points. Furthermore, each layer deforms the lines received from the previous layer to better suit the problem. This is important to understand, as each problem has an optimum number of neurons and layers and it is fundamental not using more layers or neurons than the necessary to avoid overfitting. It should also be mentioned that inside the artificial NN category there are many variants. For example, the implementation of memory layers can be useful in certain cases. However, the discussion of what techniques can, or should, be used are outside the scope of this paper.

As stated previously MLM have been used in various studies. One can mention the work of Sbarufatti et al,¹⁰⁵ where MLM was adopted to diagnose damage on a specimen using a LW sensing network. Another work is due to Su et al,⁹² who used LW in conjunction with convolution NN (CNN) to quantify and localize damage. Finally, the work of Khan et al¹⁰⁶ studied DL to predict and determine the occurrence of delaminations in composite parts. As with the statistical methods, out of all review done, no evidence of any type of MLM being used in conjunction with LW and adhesive joints was found. This allows for further studies in this area and, more specifically, in the use of MLM for the detection of weak adhesion between materials.

6 | MODELING AND SIMULATION OF LAMB WAVES IN STRUCTURAL HEALTH MONITORING

The use of machine learning in SHM implies the need of a large database containing information captured at multiple sensor locations, for a variety of defect sizes and types. Acquiring such volume of data by means of physically testings may be unfeasible. An alternative can rely on using simulation data for training in conjunction with real data for fine-tuning and validation of the results. From these two options, due to the long testing and high costs involved with physical testing, simulation based data play a key role.

One important aspect to consider before simulating cases to be used in MLM is to determine the optimal number of sensors and their relative position in respect to the possible damage boundaries. To accomplish this, it is possible to use optimization algorithms, as genetic algorithms, where the cost function depends on the total number of sensors and their coordinates, and other parameters related with their distribution in the desired area. This would allow minimizing the amount of tests needed to obtain worthwhile results.

6.1 | Modeling piezoelectric transducers

Piezoelectric transducers are regarded as prime candidates for LW-based SHM of adhesive joints, and their dynamics must be considered to obtain reliable simulation models. Often, the models are calibrated using real data from a few experimental tests.

The main constitutive equation of a linear piezoelectric element is the relation between the mechanical and electrical properties of the material, namely strain S_{ij} and stress T_{kl} ⁴⁴:

$$S_{ij} = s_{ijkl}^E T_{kl} + d_{kij} E_k, \quad (14)$$

where E_k is the electric field, s_{ijkl}^E denotes the mechanical compliance of the material in which the electric field is zero, and d_{kij} is the distance where this field is also zero. It is also important to note that the indexes i, j, k represent the three Cartesian axes. Therefore, the equation that expresses the direct piezoelectric effect is⁴⁴:

$$D_j = d_{jkl} T_{kl} + \epsilon_{jk}^E E_k, \quad (15)$$

where D_j is the electrical displacement, and ϵ_{jk}^E is the dielectric permittivity of the material measured when the mechanical stress is zero.

When observing the force application and experimental setup, the piezoelectric wafer is permanently fixed on the structure. This causes the strain/displacement compatibility and stress/force equilibrium principles to apply. The interaction force will be called F_{PZT} and it is assumed to interact only with the sensors boundary.⁴⁴ In turn, this force will induce the activation forces N_a and moments M_a given by⁴⁴:

$$N_a = F_{PZT}, \quad (16)$$

$$M_a = F_{PZT} \frac{h}{2}. \quad (17)$$

where h is the height of the sheet of material.

6.2 | Modeling adhesive structures

One of the most promising applications of LW is to detect weak adhesion in adhesive joints.²⁵ One way to model different levels of weak adhesion is adopting the cohesive zone method (CZM). This method is based on the use of interface elements,^{25,107} where during the computer analysis the stiffness of the cohesive zone suffers a step-by-step iteration following the traction-separation law. This law presents three possible failure modes with a separation occurring in the normal direction, shear occurring in the in-plane direction and mixed mode occurring as a combination of the previous two modes. To calculate the normal and shear stresses, the following equations are used:

$$\sigma_n = K_n u_n (1 - d_n), \quad (18)$$

$$\tau_t = K_t u_t (1 - d_t), \quad (19)$$

where σ_n and τ_t are the normal and shear stresses, with K_n and K_t being the respective stiffness coefficients, u_n and u_t standing for the relative displacements of the surface, and d_n and d_t being calculated parameters that define the maximum allowable stress in each direction.

It should be mentioned that weak adhesion is different from kissing bonds since the kissing bond is represented by a contact surface that has ultimately no cohesive elements between the substrate and the adhesive.²⁶

6.3 | Computer modeling software

To accomplish the computer modeling, other than the basic mechanical equations that guide how the simulation should behave, there are many methods that can be used.^{108,109} In this section the various techniques will be introduced

and examples will be given to determine what method is more adequate to simulate LW in adhesive bonds subjected to weak adhesion.

6.3.1 | Finite elements method

The laws of physics can describe many space-time problems by using partial differential equations (PDE). However, these analytical methods have limitations of geometry and forces where the problem becomes too complex to solve analytically. To overcome these problems, the finite elements method (FEM) is applied, where the material has its form discretized into small parts to create a mesh. This allows the PDE to be approximated by a numerical model and thus, arrive at a result. This method is used by most commercial programs, such as Abaqus and Ansys, and has been adopted in many studies.^{21,81,110,111} For example, Krawczuk⁸³ used the FEM to detect damage on a spectral beam using an iterative search technique. Nicassio et al.³² applied the FEM to SHM of a bonded lap joint to analyze disbands. Jeenjitkaew and Guild¹¹² used the FEM in simulations of kissing bond defects in adhesive joints.

6.3.2 | Finite difference method

The basic concept behind the finite difference method (FDM) is similar to the one in FEM. However, in the FDM the PDEs are replaced with many discrete equations called finite difference equations and are mostly used for regular grid and rectangular shapes.¹¹³ One example of application of the FDM can be found in Carrino et al.,¹¹³ who used the method in conjunction with wave motion for SHM of SLJ.

6.3.3 | Semi-analytical finite element method

The semi-analytical finite element method (SAFE) is often used in problems subjected to waves, as it only requires the discretization of the cross-section of the wave. Furthermore, it can utilize a pure analytical description of a wave problem.¹¹⁴⁻¹¹⁶ A few examples of studies with SAFE are the work of Bocchini et al.,¹¹⁵ where the method was implemented in a graphical interface for the simulation of guided waves, and the work of Deng and Yang,²⁵ who used the SAFE method to study the propagation of guided waves in the adhesive layer of bonded composite structures.

All three methods can be used for simulating LW in adhesive bonds subjected to weak adhesion defects, each one with its advantages and disadvantages. To determine the best option, it is necessary to observe secondary characteristics, such as ease of use and application of the method with multi-physics, which simulates the sensors and actuators electrical properties. This leaves the FEM as prime candidate as it has multiple commercial software implementations.

6.3.4 | Local interaction simulation approach

The local interaction simulation approach (LISA) is essentially a FDM variant.^{117,118} It has received increased attention for the simulation of guided waves due to its computational reliability and efficiency. LISA uses iterative equations to model the displacements at a given point based on those at their neighbors at past time steps. Those equations are derived from elastodynamic equilibrium. Lee and Staszewski¹¹⁹ adopted LISA to model LW in isotropic plates. Sundararaman and Adams¹²⁰ used LISA to model damage in both isotropic and orthotropic plate structures. In modeling adhesive joints, LISA was used by Delsanto et al.¹²¹

It should be emphasized that despite all modeling/simulation methods available, the high-order FEM are the most suitable for wave propagation, especially the spectral element methods.^{87,122,123} Their effectiveness with adhesive joints was addressed by Samarutunga et al.¹²⁴

7 | DISCUSSION

Adams and Cawley³⁹ said in their work that adhesive bonding in primary structures had been restricted by the lack of mature NDT procedures and, as such, structural reliability could not be assured. Moreover, since mechanical behavior and life cycle of an adhesive joint rely on the adhesive-substrate interface integrity, NDT were essential.⁶ These statements remain very up-to-date, since advances in this area are still needed, especially with regards to the detection of weak adhesion.

NDT emerged with great importance to evaluate adhesive joints,² and includes techniques as digital image correlation, ultrasound, holographic interferometry, thermography, radiography, electromechanical impedance spectroscopy and guided waves.⁶ However, due to lack of confidence in current NDT for bondline integrity monitoring, most standards still require traditional joining techniques within the adhesive.¹²⁵ SHM appeared in the context of smart structures able to perform auto-diagnosis. Active SHM uses NDT with sensors/actuators permanently fixed to the structure. Piezoelectric elements are widely adopted due to their ability to work as sensors or actuators, reduced cost, easy installation, and reliability. LW excited/sensed with piezoelectric elements is a promising approach to SHM.⁸ LW are sensitive to damage difficult or impossible to perceive with other methods, but the measured signals are complex, and extracting effective information about damage is still an open issue.

Some data processing methods have been used within the LW-based SHM approach for de-noising, compensating for environmental variables, and extracting damage signatures. A possible “high-level” classification arranges the damage detection, localization and quantification approaches in¹²⁶: (i) baseline-dependent; (ii) baseline-free; and (iii) instantaneous baseline methods.¹²⁷ Another possible classification distinguishes: (iv) statistical-based (image-based)¹²⁸, and (v) machine learning methods.¹²⁹ Modeling and simulation are essential to understand LW interaction with damage and loading inputs, to discern sensor-structure interaction, to find sensors/actuators optimal placement and to tune the diagnostic input parameters.¹²⁶ Recently, FEM packages have become suitable for this application, reducing the costs inherent in building and testing real prototypes.

LW-based SHM has been used with relative success to monitor various types of assemblies,¹²⁶ but its application to bonded structures is still new. Studies revealed the ability of LW for detecting small damage in both bond and interface layers, but they considered just specific conditions, as small SLJ with only one damage focus.^{13,112} Thus, they ignored the difficulties inherent to large and non-regular assemblies, as well as those posed by the increasing complexity of adhesives and materials. Therefore, the existing LW data processing techniques must be extended and new approaches investigated for attaining effective extraction of signatures of incipient damage, namely weak adhesion, which are not perceived by other methods. A common issue to any algorithm for damage detection, localization and quantification based on LW data is that they rely on effective de-noising, data reduction, mode decomposition and feature extraction, and further research is needed to cope with this. For example, tools from areas as far as economics have been used to mitigate the effect of environment variables in LW-based SHM³³ and fractional-order filtering was used with good results. Though, the interplay among areas remains to be fully explored, and the processing techniques borrowed from complex and fractional dynamics, extensively used in other areas^{130,131} have great potential herein.

The ability to tackle weak adhesion will be crucial to push the use of primary bonded structures to the next level, either in aeronautics or other fields. However, to obtain a reliable NDT method in the framework of SHM is challenging and, specifically, one must note that

- SHM can be implemented using different methods. LW excited/sensed by means of piezoelectric elements that are commonly used and found to be effective with a variety of structures in some areas. LW are sensitive to damage, but extracting damage signatures from LW raw signals is challenging;
- LW-based SHM of bonded structures is new. Research on simple adhesive joints with just one focus of damage demonstrated that LW can be used to detect incipient damage. However, current data processing methods cannot detect, localize and quantify weak adhesion effectively. As such, promising methods in other areas have to be extended to adhesively bonded structures, and novel procedures must be developed to cope with their specificities;
- Challenges posed by LW-based SHM of bonded structures involve various technologies, namely instrumentation, data acquisition, signal processing, damage detection, localization and quantification, and adhesives and adhesion. Interdisciplinary research is thus essential to address the problem.

8 | CONCLUSIONS

This paper addressed LW-based SHM, with emphasis in adhesive joints. SHM goes beyond NDT, since it permits in-situ monitoring, meaning detection, localization and characterization of damage. Up to the present day, no LW-based SHM scheme could perform all tasks effectively. This is particularly true for adhesively bonded structures, where research has been focused on simple structures and damage. Despite the potential of LW to detect incipient damage, its application to detect certain types of defects, as is the case of weak adhesion, is still too far and requires much attention. This entails a gap of studies that could be done to ensure a full overview of the use of LW and machine learning to detect said damage. This paper reviewed the work done in the last few years, with emphasis in equipment, testing procedures and techniques adopted in that field. The fundamentals of LW and their application to damage detection were discussed, and different signal processing, statistical, machine learning, and simulation methods were presented. The information presented constitutes a basis to deepen the understanding about the problem and points out future directions of work, where machine learning could be used to detect damage or weak bonds in adhesive joints by using LW.

ACKNOWLEDGEMENT

None.

AUTHOR CONTRIBUTIONS

All authors contributed equally to the work.

ORCID

Gabriel M. F. Ramalho  <https://orcid.org/0000-0002-3589-3211>

Antônio M. Lopes  <https://orcid.org/0000-0001-7359-4370>

Lucas F. M. da Silva  <https://orcid.org/0000-0003-3272-4591>

REFERENCES

- Kaufmann M, Zenkert D, Wennhage P. Integrated cost/weight optimization of aircraft structures. *Struct Multidiscip Optim*. 2019;41(2):325-334.
- da Silva LFM, Öchsner A, Adams RD. *Handbook of Adhesion Technology*. 1st ed. da Silva LFM, Öchsner A, Adams RD, eds. Berlin, Heidelberg: Springer-Verlag; 2011.
- Barbosa AQ, da Silva LFM, Abenojar J, Del Real JC, Paiva RMM, Öchsner A. Kinetic analysis and characterization of an epoxy/cork adhesive. *Thermochim Acta*. 2015;604:52-60.
- Machado JJM, Marques EAS, Barbosa AQ, da Silva LFM. Effect of hygrothermal aging on the quasi-static behaviour of CFRP joints varying the overlap length. *Compos Struct*. 2019;214:451-462.
- Adams RD, Drinkwater BW. Nondestructive testing of adhesively-bonded joints. *NDT & E Int*. 1997;30(2):93-98.
- Zhuang Y, Kopsaftopoulos F, Dugnani R, Chang FK. Integrity monitoring of adhesively bonded joints via an electromechanical impedance-based approach. *Struct Health Monit*. 2018;17(5):1031-1045.
- US National Archives and Records Administration. Federal aviation regulations—Sec. 23.573. from code of federal regulations; 2014.
- Lammering R, Gabbert U, Sinapius M, Schuster T, Wierach P. *Lamb-Wave Based Structural Health Monitoring in Polymer Composites*. Cham: Springer; 2017.
- Park B, An Y-K, Sohn H. Visualization of hidden delamination and debonding in composites through noncontact laser ultrasonic scanning. *Compos Sci Technol*. 2014;100:10-18.
- Gauthier C, El-Kettani ME-C, Galy J, Predoi M, Leduc D, Izbicki J-L. Lamb waves characterization of adhesion levels in aluminum/epoxy bi-layers with different cohesive and adhesive properties. *Int J Adhes Adhes*. 2017;74:15-20.
- Ong WH, Rajic N, Chiu WK, Rosalie C. Lamb wave-based detection of a controlled sisbond in a lap joint. *Struct Health Monit*. 2018;17(3):668-683.
- Gauthier C, El-Kettani ME-C, Galy J, Predoi M, Leduc D. Structural adhesive bonding characterization using guided Lamb waves and the vertical modes. *Int J Adhes Adhes*. 2020;98:102467.
- Carrino S, Nicassio F, Scarselli G. An innovative method based on nonlinear Lamb waves for locating disbonds in single-lap joints. In: 2019 IEEE 5th international workshop on metrology for aerospace (metroaerospace); 2019:187-191.
- Nicassio F, Carrino S, Scarselli G. Non-linear Lamb waves for locating defects in single-lap joints. *Front Built Environ*. 2020;6:45.
- Rucka M, Wojtczak E, Lachowicz J. Damage imaging in Lamb wave-based inspection of adhesive joints. *Appl Sci*. 2018;8(4):522.
- Kumar S, Sunny MR. A novel nonlinear Lamb wave based approach for detection of multiple disbonds in adhesive joints. *Int J Adhes Adhes*. 2021;107:102842.
- Tenreiro AFG, Lopes AM, da Silva LucasFM. A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy. *Struct Health Monit*. 2021;1475921721993419.

18. Worlton DC. Experimental confirmation of Lamb waves at megacycle frequencies. *J Appl Phys*. 1961;32(6):967-971.
19. Su Z, Ye L, Lu Y. Guided Lamb waves for identification of damage in composite structures: a review. *J Sound Vib*. 2006;295(3-5):753-780.
20. Melloni A, Cusmai G, Martinelli M. Experimental confirmation of matched bends. *Opt Lett*. 2004;29(5):465.
21. Sadler J, Maev RG. Experimental and theoretical basis of Lamb waves and their applications in material sciences. *Can J Phys*. 2007;85(7):707-731.
22. Staszewski WJ, Lee BC, Mallet L, Scarpa F. Structural health monitoring using scanning laser vibrometry: I. Lamb wave sensing. *Smart Mater Struct*. 2004;13(2):251-260.
23. Mallet L, Lee BC, Staszewski WJ, Scarpa F. Structural health monitoring using scanning laser vibrometry: II. Lamb waves for damage detection. *Smart Mater Struct*. 2004;13(2):261-269.
24. di Scalea FL, Bonomo M, Tuzzeo D. Ultrasonic guided wave inspection of bonded lap joints: noncontact method and photoelastic visualization. *J Res Nondestruct Eval*. 2001;13(3):153-171.
25. Deng QT, Yang ZC. Propagation of guided waves in bonded composite structures with tapered adhesive layer. *Appl Math Model*. 2011;35(11):5369-5381.
26. Ren B, Lissenden CJ. Ultrasonic guided wave inspection of adhesive bonds between composite laminates. *Int J Adhes Adhes*. 2013;45:59-68.
27. Puthillath P, Galan JM, Ren B, Lissenden CJ, Rose JL. Ultrasonic guided wave propagation across waveguide transitions: Energy transfer and mode conversion. *J Acoust Soc Am*. 2013;133(5):2624-2633.
28. Siryabe E, Renier M, Meziane A, Castaings M. The transmission of Lamb waves across adhesively bonded lap joints to evaluate interfacial adhesive properties. *Phys Procedia*. 2015;70(3):541-544.
29. Rose JL. *Ultrasonic Guided Waves in Solid Media*. New York: Cambridge University Press; 2014.
30. Kang K-T, Chun H-J, Son J-H, Lee J-A, Byun J-H, Um M-K, Lee S-K, Jang J-W. Quantitative accessibility of delamination in composite using lamb wave by experiments and FEA. *Adv Compos Mater*. 2011;20(4):361-373.
31. Chen KF, Mei SL. Composite interpolated fast fourier transform with the hanning window. *IEEE Trans Instrum Meas*. 2010;59(6):1571-1579.
32. Nicassio F, Carrino S, Scarselli G. Elastic waves interference for the analysis of disbands in single lap joints. *Mech Syst Sig Process*. 2019;128:340-351.
33. Dao PB, Staszewski WJ. Lamb wave based structural damage detection using cointegration and fractal signal processing. *Mech Syst Sig Process*. 2014;49(1-2):285-301.
34. Xu L, Yuan S, Chen J, Ren Y. Guided wave-convolutional neural network based fatigue crack diagnosis of aircraft structures. *Sensors (Switzerland)*. 2019;19(16):3567.
35. Puthillath P, Rose JL. Ultrasonic guided wave inspection of a titanium repair patch bonded to an aluminum aircraft skin. *Int J Adhes Adhes*. 2010;30(7):566-573.
36. Ren B, Lissenden CJ. Modal content-based damage indicators for disbands in adhesively bonded composite structures. *Struct Health Monit*. 2016;15(5):491-504.
37. Mori N, Kusaka T. Reflection and transmission characteristics of Lamb waves at an adhesive lap joint of plates. *J Acoust Soc Am*. 2019;145(5):3075-3085. <https://doi.org/10.1121/1.5109098>
38. Heller K, Jacobs LJ, Qu J. Characterization of adhesive bond properties using Lamb waves. *NDT and E Int*. 2000;33(8):555-563.
39. Guyott CCH, Cawley P, Adams RD. The non-destructive testing of adhesively bonded structure: a review. *J Adhes*. 1986;20(2):129-159.
40. Verze M. Quantitative assessment of adhesively-bonded joints using ultrasonic guided waves. *Master's Thesis*: Delft University of Technology; 2016.
41. Kryukov I, Böhm S. Prospects and limitations of eddy current shearography for non-destructive testing of adhesively bonded structural joints. *J Adhes*. 2019;95(9):874-886.
42. Ehrhart B, Valeske B. Quality assessment of bonded primary CFRP structures by means of laser proof testing. *Ph.D. Thesis*: Universität Bremen; 2016.
43. Duflo H, Morvan B, Izbicki J-L. Interaction of Lamb waves on bonded composite plates with defects. *Compos Struct*. 2007;79(2):229-233.
44. Capinha JR. Computational and experimental studies on aircraft structural health monitoring systems Engenharia Aeroespacial. *Master's Thesis*: Universidade Técnica de Lisboa; 2007.
45. Murayama R, Mizutani K. Conventional electromagnetic acoustic transducer development for optimum Lamb wave modes. *Ultrasonics*. 2002;40(1-8):491-495.
46. Jian X, Dixon S, Edwards RS, Morrison J. Coupling mechanism of an EMAT. *Ultrasonics*. 2006;44(SUPPL.):653-656.
47. Wilcox PD, Lowe MichaelJS, Cawley P. The excitation and detection of lamb waves with planar coil electromagnetic acoustic transducers. *IEEE Trans Ultrason, Ferroelectr, Freq Control*. 2005;52(12):2370-2383.
48. He F, Rokhlin SI, Adler L. Application of SH and Lamb wave EMAT's for evaluation of adhesive joint in thin plate. In: Review of progress in quantitative nondestructive evaluation; 1988:911-918.
49. Sun H, Kosukegawa H, Takagi T, Uchimoto T, Hashimoto M, Takeshita N. Electromagnetic pulse-induced acoustic testing and the pulsed guided wave propagation in composite/metal adhesive bonding specimens. *Compos Sci Technol*. 2021;201:108499.

50. Monkhouse RSC, Wilcox PW, Lowe MJS, Dalton RP, Cawley P. The rapid monitoring of structures using interdigital Lamb wave transducers. *Smart Mater Struct.* 2000;9(3):304.
51. Stepinski T, Mańka M, Martowicz A. Interdigital Lamb wave transducers for applications in structural health monitoring. *NDT & E Int.* 2017;86:199-210.
52. Motamedi ME. Micro-opto-electro-mechanical systems. *Opt Eng.* 1994;33(11):3505-3518.
53. Di Pietrantonio F, Benetti M, Cannatà D, Beccherelli R, Verona E. Guided Lamb wave electroacoustic devices on micromachined AlN/-Al plates. *IEEE Trans Ultrason, Ferroelectr, Freq Control.* 2010;57(5):1175-1182.
54. Wojtczak E, Rucka M. Wave frequency effects on damage imaging in adhesive joints using Lamb waves and RMS. *Materials.* 2019;12(11):1842.
55. Zhang K, Zhou Z. Quantitative characterization of disbonds in multilayered bonded composites using laser ultrasonic guided waves. *NDT & E Int.* 2018;97:42-50.
56. Sunarsa TY, Park B, Liu P, Sohn H. Noncontact debonding identification in adhesive joint using guided waves. The 2016 Structures Congress (Structures16); 2016.
57. Haiyan Z, Xiao L, Xiuli S, Xuerui Q, Donghui L. Ultrasonic Lamb wave inspection using fiber Bragg gratings. In: 2008 china-japan joint microwave conference. IEEE 2008 China-Japan Joint Microwave Conference; 2008:805-808.
58. Betz DC, Thursby G, Culshaw B, Staszewski WJ. Structural damage location with fiber Bragg grating rosettes and Lamb waves. *Struct Health Monit.* 2007;6(4):299-308.
59. Fiesler Saxena I, Guzman N, Hui K, Mal AK. Disbond detection in a composite honeycomb structure of an aircraft vertical stabilizer by fiber Bragg gratings detecting guided ultrasound waves. *Proc Inst Mech Eng, Part C: J Mech Eng Sci.* 2017;231(16):3001-3010.
60. Lin M, Qing X, Kumar A, Beard SJ. Smart layer and smart suitcase for structural health monitoring applications. In: Smart structures and materials 2001: Industrial and commercial applications of smart structures technologies, Vol. 4332; 2001:98-106.
61. Wilcox PD, Lowe MJS, Cawley P. Mode and transducer selection for long range Lamb wave inspection. *J Intell Mater Syst Struct.* 2001;12(8):553-565.
62. Tokita Y, Kuze Y, Uematsu M, Fujii K, Watanabe K. Evaluation of disbonds by diagnostic system using Lamb wave sensor network. In: Structural health monitoring, 2019: Enabling intelligent life-cycle health management for industry internet of things (iiot); 2019.
63. Agrahari JK, Kapuria S. Effect of piezoelectric transducer bonding on time reversibility of Lamb waves in plates. In: Structural health monitoring, 2019: Enabling intelligent life-cycle health management for industry internet of things (iiot); 2019.
64. Kiel M, Scheunemann S, Grotzner M, Lucas M, Muck A. Quality classification of adhesive bonds in composite structures by single-sided air-coupled ultrasonic testing using linear phased array probes. In: Nde of aerospace materials & structures; 2018:53-58.
65. Giurgiutiu V. Tuned Lamb wave excitation and detection with piezoelectric wafer active sensors for structural health monitoring. *J Intell Mater Syst Struct.* 2005;16(4):291-305.
66. Michaels JE, Michaels TE. Guided wave signal processing and image fusion for in situ damage localization in plates. *Wave Motion.* 2007;44(6):482-492.
67. Qing XP, Beard SJ, Kumar A, Hannum R. A real-time active smart patch system for monitoring the integrity of bonded repair on an aircraft structure. *Smart Mater Struct.* 2006;15(3):N66.
68. Weiland J, Hesser DF, Xiong W, Schiebahn A, Markert B, Reising U. Structural health monitoring of an adhesively bonded CFRP aircraft fuselage by ultrasonic Lamb waves. *Proc Inst Mech Eng, Part G: J Aerosp Eng.* 2020;234(13):2000-2010.
69. Giurgiutiu V. *Structural Health Monitoring With Piezoelectric Active Wafer Sensors.* Oxford: Elsevier; 2014.
70. Crawley EF, De Luis J. Use of piezoelectric actuators as elements of intelligent structures. *AIAA J.* 1987;25(10):1373-1385.
71. Yu L, Bottai-Santoni G, Giurgiutiu V. Shear lag solution for tuning ultrasonic piezoelectric wafer active sensors with applications to Lamb wave array imaging. *Int J Eng Sci.* 2010;48(10):848-861.
72. Qing XP, Chan H-L, Beard SJ, Ooi TK, Marotta SA. Effect of adhesive on the performance of piezoelectric elements used to monitor structural health. *Int J Adhes Adhes.* 2006;26(8):622-628.
73. Ha S, Chang F-K. Adhesive interface layer effects in PZT-induced Lamb wave propagation. *Smart Mater Struct.* 2010;19(2):25006.
74. Willberg C, Duczek S, Gabbert U. Increasing the scanning range of Lamb wave based SHM systems by optimizing the actuator-sensor design. *CEAS Aeronaut J.* 2013;4(1):87-98.
75. Kundu T, Maji A, Ghosh T, Maslov K. Detection of kissing bonds by Lamb waves. *Ultrasonics.* 1998;35(8):573-580.
76. Puthillath P. Ultrasonic guided wave propagation across waveguide transitions applied to bonded joint inspection. *Ph.D. Thesis:* Pennsylvania State University; 2010.
77. Hay TR, Royer RL, Gao H, Zhao X, Rose JL. A comparison of embedded sensor Lamb wave ultrasonic tomography approaches for material loss detection. *Smart Mater Struct.* 2006;15(4):946-951.
78. Seifried R, Jacobs LJ, Qu J. Propagation of guided waves in adhesive bonded components. *NDT & E Int.* 2002;35(5):317-328.
79. Gauthier C, Ech-Cherif El-Kettani M, Galy J, Predoi M, Leduc D, Izbicki JL. Lamb waves characterization of adhesion levels in aluminum/epoxy bi-layers with different cohesive and adhesive properties. *Int J Adhes Adhes.* 2017;74:15-20.
80. Rucka M, Wojtczak E, Lachowicz J. Lamb wave-based monitoring of shear failure of an adhesive lap joint. *Diagnostyka.* 2018;19(4):51-57.
81. Ng CT. On the selection of advanced signal processing techniques for guided wave damage identification using a statistical approach. *Eng Struct.* 2014;67:50-60.

82. Nag A, Mahapatra DR, Gopalakrishnan S. Identification of delamination in composite beams using spectral estimation and a genetic algorithm. *Smart Mater Struct*. 2002;11(6):899-908.
83. Krawczuk M. Application of spectral beam finite element with a crack and iterative search technique for damage detection. *Finite Elem Anal Des*. 2002;38(6):537-548.
84. Puthillath PK, Kannajosyula H, Lissenden CJ, Rose JL. Ultrasonic guided wave inspection of adhesive joints: a parametric study for a step-lap joint. *AIP Conf Proc*. 2009;1096:1127-1133.
85. Staszewski W, Boller C, Tomlinson GR. *Health Monitoring of Aerospace Structures: Smart Sensor Technologies and Signal Processing*. Chichester: John Wiley & Sons; 2004.
86. Yu L, Giurgiutiu V. Advanced signal processing for enhanced damage detection with piezoelectric wafer active sensors. *Smart Struct Syst*. 2005;1(2):185-215.
87. Willberg C, Duczek S, Perez JMVivar, Schmicker D, Gabbert U. Comparison of different higher order finite element schemes for the simulation of Lamb waves. *Comput Methods Appl Mech Eng*. 2012;241:246-261.
88. Su C, Jiang M, Liang J, Tian A, Sun L, Zhang L, Zhang F, Sui Q. Damage identification in composites based on Hilbert energy spectrum and Lamb wave tomography algorithm. *IEEE Sensors J*. 2019;19(23):11562-11572.
89. Kishimoto K, Inoue H, Hamada M, Shibuya T. Time frequency analysis of dispersive waves by means of wavelet transform. *J Appl Mech*. 1995;6:841-846.
90. Veidt M, Ng C-T. Influence of stacking sequence on scattering characteristics of the fundamental anti-symmetric Lamb wave at through holes in composite laminates. *J Acoust Soc Am*. 2011;129(3):1280-1287.
91. Hameed MS, Li Z, Chen J, Qi J. Lamb-Wave-Based Multistage Damage Detection Method Using an Active PZT Sensor Network for Large Structures. *Sensors*. 2019;19:2010.
92. Su C, Jiang M, Lv S, Lu S, Zhang L, Zhang F, Sui Q. Improved damage localization and quantification of CFRP using Lamb waves and convolution neural network. *IEEE Sensors J*. 2019;19(14):5784-5791.
93. Li F, Meng G, Kageyama K, Su Z, Ye L. Optimal mother wavelet selection for Lamb wave analyses. *J Intell Mater Syst Struct*. 2009;20(10):1147-1161.
94. Hong X, Liu Y, Lin P, Xu W. Interfacial adhesion-strength detection of structural silicone sealant for hidden frame-supported glass curtain wall based on nonlinear ultrasonic Lamb wave. *J Aerosp Eng*. 2018;31(5):04018047.
95. Liew CK, Veidt M. Pattern recognition of guided waves for damage evaluation in bars. *Pattern Recogn Lett*. 2009;30(3):321-330.
96. Staszewski WJ, Pierce SG, Worden K, Philp WR, Tomlinson GR, Culshaw B. Wavelet signal processing for enhanced Lamb-wave defect detection in composite plates using optical fiber detection. *Opt Eng*. 1997;36(7):1877-1888.
97. Zhou K, Wu ZY, Yi XH, Zhu DP, Narayan R, Zhao J. Generic framework of sensor placement optimization for structural health modeling. *J Comput Civil Eng*. 2017;31(4):1-14.
98. Soman R, Kudela P, Balasubramaniam K, Singh SK, Malinowski P. A study of sensor placement optimization problem for guided wave-based damage detection. *Sensors (Switzerland)*. 2019;19(8):1856.
99. Ostachowicz W, Soman R, Malinowski P. Optimization of sensor placement for structural health monitoring: a review. *Struct Health Monit*. 2019;18(3):963-988.
100. Moll J, Kathol J, Fritzen CP, Moix-Bonet M, Rennoch M, Koerdt M, Herrmann AS, Sause MGR, Bach M. Open guided waves: online platform for ultrasonic guided wave measurements. *Struct Health Monit*. 2019;18(5-6):1903-1914.
101. Tabatabaeipour M, Hettler J, Delrue S, Van Den Abeele K. Reconstruction algorithm for probabilistic inspection of damage (RAPID) in composites. In: Proc. 11th eur. conf. non-destructive test.(ecndt). Proceedings of the 11th European Conference on Non-Destructive Testing (ECNDT); 2014:1-8.
102. Kotsiantis SB, Zaharakis I, Pintelas P. Supervised machine learning: a review of classification techniques. *Emerg Artif Intell Appl Comput Eng*. 2007;160(1):3-24.
103. Kassambara A. *Practical Guide to Cluster analysis in R: Unsupervised Machine Learning*: STHDA; 2017.
104. Hahne F, Huber W, Gentleman R, Falcon S. *Bioconductor Case Studies*. New York: Springer Science & Business Media; 2010.
105. Sbarufatti C, Manson G, Worden K. A numerically-enhanced machine learning approach to damage diagnosis using a Lamb wave sensing network. *J Sound Vib*. 2014;333(19):4499-4525.
106. Khan A, Ko DK, Lim SC, Kim HS. Structural vibration-based classification and prediction of delamination in smart composite laminates using deep learning neural network. *Compos Part B: Eng*. 2019;161(December 2018):586-594.
107. Korta J, Mlyniec A, Zdziebko P, Uhl T. Finite element analysis of adhesive bonds using the cohesive zone modeling method. *Mech Control*. 2014;33(2):51.
108. Gopalakrishnan S, Ruzzene M, Hanagud S. *Computational Techniques for Structural Health Monitoring*. London: Springer Science & Business Media; 2011.
109. Willberg C, Duczek S, Vivar-Perez JM, Ahmad ZAB. Simulation methods for guided wave-based structural health monitoring: a review. *Appl Mech Rev*. 2015;67(1):1-20.
110. Köcher U. Variational space-time methods for the elastic wave equation and the diffusion equation. *Ph.D. Thesis*: Institut furr Werkstoffkunde; 2015.
111. Lee BC, Staszewski WJ. Sensor location studies for damage detection with Lamb waves. *Smart Mater Struct*. 2007;16(2):399-408.
112. Jeenjitkaw C, Guild FJ. The analysis of kissing bonds in adhesive joints. *Int J Adhes Adhes*. 2017;75(February):101-107.

113. Carrino S, Nicassio F, Scarselli G, Vitolo R. Finite difference model of wave motion for structural health monitoring of single lap joints. *Int J Solids Struct*. 2019;161:219-227.
114. Kijanka P, Packo P. Novel method for true guided waves spectral characteristics estimation using a logistic function fit and nonlinear least square algorithm. *Struct Control and Health Monit*. 2019;26(9):1-13.
115. Bocchini P, Marzani A, Viola E. Graphical user interface for guided acoustic waves. *J Comput Civil Eng*. 2011;25(3):202-210.
116. Rose JL. The Semi-Analytical Finite Element Method. *Ultrasonic Guided Waves in Solid Media*. Cambridge: Cambridge University Press; 2014:135-154.
117. Delsanto PP, Schechter RS, Mignogna RB. Connection machine simulation of ultrasonic wave propagation in materials III: the three-dimensional case. *Wave Motion*. 1997;26(4):329-339.
118. Paćko P, Bielak T, Spencer AB, Staszewski WJ, Uhl T, Worden K. Lamb wave propagation modelling and simulation using parallel processing architecture and graphical cards. *Smart Mater Struct*. 2012;21(7):75001.
119. Lee BC, Staszewski WJ. Modelling of Lamb waves for damage detection in metallic structures: part II. wave interactions with damage. *Smart Mater Struct*. 2003;12(5):815.
120. Sundararaman S, Adams DE. Modeling guided waves for damage identification in isotropic and orthotropic plates using a local interaction simulation approach. *J Vib Acoust*. 2008;130(4):041009.
121. Delsanto PP, Hirsekorn S, Agostini V, Loparco R, Koka A. Modeling the propagation of ultrasonic waves in the interface region between two bonded elements. *Ultrasonics*. 2002;40(1-8):605-610.
122. Ostachowicz W, Kudela P, Krawczuk M, Zak A. *Guided Waves in Structures for SHM: The Time-Domain Spectral Element Method*. Chichester: John Wiley & Sons; 2011.
123. Ha S, Chang F-K. Optimizing a spectral element for modeling PZT-induced Lamb wave propagation in thin plates. *Smart Mater Struct*. 2009;19(1):15015.
124. Samaratunga D, Jha R, Gopalakrishnan S. Wave propagation analysis in adhesively bonded composite joints using the wavelet spectral finite element method. *Compos Struct*. 2015;122:271-283.
125. Karachalios EF, Adams RD, da Silva LFM. Strength of single lap joints with artificial defects. *Int J Adhes Adhes*. 2013;45:69-76.
126. Mitra M, Gopalakrishnan S. Guided wave based structural health monitoring: a review. *Smart Mater Struct*. 2016;25(5):53001.
127. Kapuria S, Agrahari JK. Shear-lag solution for excitation, sensing, and time reversal of Lamb waves for structural health monitoring. *J Intell Mater Syst Struct*. 2018;29(4):585-599.
128. Yan F, Royer RL, Rose JL. Ultrasonic guided wave imaging techniques in structural health monitoring. *J Intell Mater Syst Struct*. 2010; 21(3):377-384.
129. de Oliveira MA, Monteiro AV, Filho JV. A new structural health monitoring strategy based on PZT sensors and convolutional neural network. *Sensors*. 2018;18(9):2955.
130. Machado JAT, Lopes AM. Fractional state space analysis of temperature time series. *Fract Calculus Appl Anal*. 2015;18(6):1518-1536.
131. Cao Labora D, Lopes AM, Machado JAT. Time-fractional dependence of the shear force in some beam type problems with negative Young modulus. *Appl Math Model*. 2020;80:668-682.

How to cite this article: Ramalho GMF, Lopes AM, da Silva LFM. Structural health monitoring of adhesive joints using Lamb waves: A review. *Struct Control Health Monit*. 2021;e2849. doi:10.1002/stc.2849

Appendix B

Paper B

<https://doi.org/10.1520/JTE20210754>



Journal of Testing and Evaluation

Gabriel M. F. Ramalho,¹ Manuel R. S. P. Barbosa,² António M. Lopes,^{2,3}
and Lucas F. M. da Silva^{2,3}

DOI: 10.1520/JTE20210754

Damage Classification
Methodology Utilizing Lamb
Waves and Artificial Neural
Networks

Gabriel M. F. Ramalho,¹ Manuel R. S. P. Barbosa,² António M. Lopes,^{2,3}
and Lucas F. M. da Silva^{2,3}

Damage Classification Methodology Utilizing Lamb Waves and Artificial Neural Networks

Reference

G. M. F. Ramalho, M. R. S. P. Barbosa, A. M. Lopes, and L. F. M. da Silva, "Damage Classification Methodology Utilizing Lamb Waves and Artificial Neural Networks," *Journal of Testing and Evaluation* <https://doi.org/10.1520/JTE20210754>

ABSTRACT

As the aerospace industry develops, there is a need for applying new materials and construction techniques, able to create lighter and more efficient aircrafts. Most advances also imply severe regulations that require novel methods suited to monitor critical components. One method that goes beyond simple nondestructive testing is structural health monitoring (SHM), more specifically Lamb waves (LW)-based SHM. Indeed, LW have shown great promise in nondestructive in-situ testing, but require computationally expensive calculations, so that precise results can be obtained. An opportunity to overcome LW drawbacks arises with the use of machine learning (ML) algorithms. In this article, the performance of conventional feedforward and convolutional artificial neural networks for damage classification in aluminum sheets is compared, and a novel methodology to classify damage is proposed. The ML techniques adopted require large sets of prior data, which are generated by numerical simulations utilizing the finite element method. The damage classification pipeline comprises (i) generating LW by one actuator, measuring the structure response using a set of sensors, (iii) extracting features from the raw signals and training the ML algorithms, and (iv) assessing the classification accuracy. The methodology has the advantage of being baseline free, easily extendable for automatic feature extraction and testing, and adaptable to different types of damage and structures, as long as the algorithms are trained with suitable data.

Keywords

lamb wave, artificial neural networks, nondestructive testing, machine learning

Manuscript received November 19, 2021; accepted for publication April 11, 2022; published online June 27, 2022.

¹ Department of Mechanical Engineering, University of Porto, Rua Dr. Roberto Frias, 4200-465 Porto, Portugal (Corresponding author), e-mail: gmframalho@gmail.com, <https://orcid.org/0000-0002-3589-3211>

² Department of Mechanical Engineering, University of Porto, Rua Dr. Roberto Frias, 4200-465 Porto, Portugal

³ LAETA/INEGI, University of Porto, Rua Dr. Roberto Frias, 4200-465 Porto, Portugal, <https://orcid.org/0000-0001-7359-4370> (A.M.L.)

Introduction

In recent years, the aeronautical industry has been urging for stronger and lighter primary structures as a way to reduce operating costs while maintaining reliability requirements.¹ This has led to an increasing interest on structural health monitoring (SHM), as a means to prematurely detect damaged areas. One promising SHM method uses a particular type of guided waves called Lamb waves (LW). The LW are sensitive to damage while also being able to discern between superficial and internal defects.^{2–4} The LW-based SHM method is especially suited for monitoring aircraft primary structures, as LW are normally used in plain and thin bodies with parallel-free edges, such as aircraft wings.²

The application of LW for damage monitoring is vast and was adopted in different areas. For instance, in Seifried, Jacobs, and Qu,⁵ LW were applied to monitor adhesive bonded aluminum plates. In Wilcox,⁶ it was reported an LW-based SHM technique, where large structures were equipped with interdigital transducers and their signals were constantly monitored and processed for damage classification. In Wilcox,⁶ two main application areas were analyzed: the first being the development of models describing the propagation of LW in curved plates, and the second being the analysis of the LW dispersion over long ranges. In Mallet,⁷ LW were used to detect damage by utilizing a single sensor. As such, laser vibrometry was adopted on two sheets of aluminum with an overall dimension of 400 by 150 by 2 mm, where one had a rectangular defect of 12 by 5 mm at the center, and the other one possessed a small circular hole with diameter 0.5 mm. The acquired LW signals showed promising results in detecting damage of distinct sizes.

The main drawbacks of LW are the high computational power and the sophisticated algorithms necessary to detect or classify damage because of the high complexity of the raw LW signals.² Although these drawbacks exist, they have been recently mitigated with the adoption of advanced machine learning (ML) techniques that enhance the capability of learning patterns embedded in the data.

The combination of both LW and ML was used in Agarwal and Mitra⁸ to automatically detect surface damages of 10 by 1 mm on a 1.6-mm-thick plate that was simulated as a two-dimensional (2D) problem without boundary conditions. Such work used LW and two types of ML algorithms, namely support-vector machine (SVM) and artificial neural networks (ANN), and presented a thorough comparison between them. In Ewald et al.,⁹ a plate of aluminum with circular defects varying from 15 to 75 mm in diameter and positioned along different angles were simulated. Afterward, these data were validated experimentally and applied to convolution neural networks (CNN), which yielded good accuracy. In Sun et al.,¹⁰ LW and least squares SVM were combined to quantify damage. Genetic algorithms were adopted to classify cracks varying from 2 to 20 mm in length, at increments of 3 mm, and from 20 to 30 mm in length, at increments 5 mm, on an aluminum sheet with dimensions 200 by 400 by 2 mm.

In this article, the performance of conventional feedforward ANN (FFNN) and CNN for damage classification in aluminum sheets is compared, and a novel methodology for damage classification is proposed. Because the algorithms adopted are a subclass of ML techniques that require large amounts of data, the required information is generated by finite element method (FEM) simulations. The damage classification pipeline comprises (i) generating LW by one actuator, (ii) measuring the structure response using a set of sensors, (iii) extracting features from the raw signals and training the ML algorithms, and (iv) assessing the classification accuracy. The methodology was able to classify the size of holes of diameter 2, 6, and 10 mm, independently of their localization. It should be mentioned that the FEM model adopted was validated using experimental data and, as such, the FEM numerical dataset is reliable. However, experimental data possess their own specificities, and the ML algorithms have to be further fine tuned and tested with data from real experiments. Nevertheless, the approach has the advantage of being baseline free, easily extendable for automatic feature extraction and testing, and adaptable to different types of damage and structures, as long as the algorithms are trained with suitable data.

The article is divided into six sections. In the section “Lamb Waves for Defect Detection and Classification,” the characteristics of LW and their suitability for damage classification is explained, along with the FEM simulations adopted. In “Conventional FFNN versus CNN,” an in-depth study on ANN and CNN is presented. In the

section “Experimental Investigation and Feature Extraction,” the damage classification approach is addressed, followed by the results obtained. Finally, the main conclusions are discussed.

Lamb Waves for Defect Detection and Classification

LW theory goes back to 1917, and their original application was in the medical field.^{3,11} In recent years, LW were applied successfully in nondestructive testing (NDT), and are nowadays seen as a prime candidate for damage detection in composite structures and adhesive joints, among other cutting-edge materials, because of their (i) sensitivity to damage along the propagation paths; (ii) capability for traveling long distance with limited attenuation; and (iii) distinct modes, allowing the detection of internal defects.^{2–4} LW are guided waves that propagate in isotropic, plain, and thin media with parallel-free boundaries.² Indeed, in anisotropic and complex geometry specimens, guided waves can propagate, but those are not LW. Nevertheless, often the term LW in such a broad scope is still adopted and will be followed in this article.

LW can be generated using several methods, namely piezoelectric actuators, lasers, X-rays and ultra-sounds.^{7,12} Every technology has pros and cons, but piezoelectric elements became attractive for in-situ monitoring because of their ability to work as both actuator and sensor, lightweight, easy installation, robustness, and cost.

A brief introduction to the theory of LW is presented in the sequel. As mentioned, LW propagate in thin plates guided by their upper and lower boundaries. They are made of the superposition of longitudinal and shear modes and, when observed across the thickness of the medium, reveal a stationary wave pattern constituted by symmetric S_n and anti-symmetric A_n modes, with $n \in \mathbb{N}$ representing the number of inflection points.¹³ The LW phase velocity is a function of the relation between frequency and material thickness, meaning that, at every frequency, there exist multiple modes, which, in turn, make harder the processing of the measured LW raw data.

To understand the wave modes, S_n and A_n , dispersion curves are often adopted, being given by the following¹³:

$$\frac{\tan(qh)}{\tan(ph)} + \frac{4k^2qp}{(k^2 - q^2)^2} = 0, \quad \frac{\tan(qh)}{\tan(ph)} + \frac{(k^2 - q^2)^2}{4k^2qp} = 0 \quad (1)$$

with

$$p^2 = \frac{\omega^2}{c_L^2} - k^2, \quad q^2 = \frac{\omega^2}{c_T^2} - k^2, \quad k = \frac{2\pi}{\lambda} \quad (2)$$

where p and q are placeholders, h represents the half thickness of the plate-like medium, c_L and c_T stand for the longitudinal and shear velocities, respectively, k corresponds to the wavenumber, λ is the wavelength, and ω denotes the angular frequency.

The longitudinal and shear wave velocities are functions of the propagation medium properties, and can be expressed as

$$c_L = \sqrt{\frac{E(1-\nu)}{\rho(1+\nu)(1-2\nu)}}, \quad c_T = \sqrt{\frac{E}{2\rho(1+\nu)}} \quad (3)$$

where E and ν stand for the modulus of Young and coefficient of Poisson, and ρ represents the material density.

Equation (1) admits different solutions, yielding for multiple wave modes. Often, to obtain the relationships between the variables phase velocity, wavelength, wavenumber, and frequency, $c_p = \frac{\omega}{2\pi} \lambda = \frac{\omega}{k}$, numerical methods are used, and the results are represented using the so-called dispersion curves.

There is a frequency threshold value below which just the modes S_0 and A_0 exist, whereas for frequencies beyond such value additional modes emerge. For the so-called non-zero volume damage, namely voids or holes,

LW with wavelength smaller than twice the ‘size’ of the void or hole are necessary for suitable detection.¹⁴ This means that, in theory, every non-zero defect can be detected, independently of its size, as long as signals of sufficiently high frequency are adopted. Another important issue when using LW-based SHM is the input applied by the actuator to generate LW. Short time and narrow frequency bandwidth excitation signals are useful to minimize dispersion and, thus, to avoid LW to spread out and distort. The Hann-windowed tone burst has been widely adopted since it possesses such characteristics. Nevertheless, alternatives are possible, such as the Gaussian windowed tone burst and the Gaussian pulse. When generating LW at points on the dispersion curves corresponding to near constant group velocity with respect to frequency, the windowed tone bursts mitigate the waves dispersion.

The Hann window is given by

$$W(n) = 0.5 - 0.5 \cos \frac{2\pi n}{M-1} \quad (4)$$

where M is the total number of points of the signal and $n = 0, 1, \dots, M-1$. When applied to a sinusoidal signal, a burst type waveform composed of a number of wave pulses is generated.¹⁵⁻¹⁸

FINITE ELEMENT SIMULATIONS

Most ML methods require large data sets to learn from. As it is costly, or not feasible, to perform large numbers of experimental tests, FEM models can be used to create an in-depth database.

Herein, an FEM model was created in the software package ABAQUS. An aluminum sheet of 300 by 300 by 2 mm was modeled, with density $\rho = 2,500 \text{ kg/m}^3$, Poisson ratio $\nu = 0.33$ and Young modulus $E = 72.4 \text{ GPa}$. The choice for aluminum was due to the fact that most primary structures of vehicles in the aeronautical industry are fabricated out of this material. The sheets are subjected to damage in the form of cylindrical holes that can have 2, 6, or 10 mm in diameter.

One actuator and three sensors were positioned in a square configuration with a 150-mm side, where the actuator is located at the bottom left corner (75,75) mm as can be seen in [figure 1](#). The positions for the sensors were chosen to allow a large monitoring coverage while still maintaining a low sensor count. This is especially

FIG. 1

Representation of an aluminum plate, with actuator, sensors, and a hole type defect.

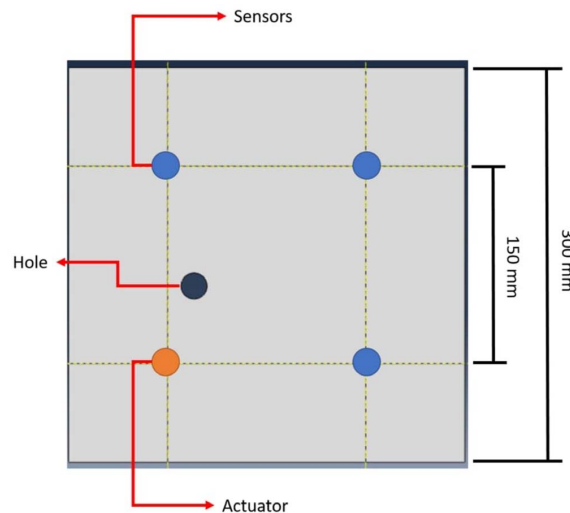
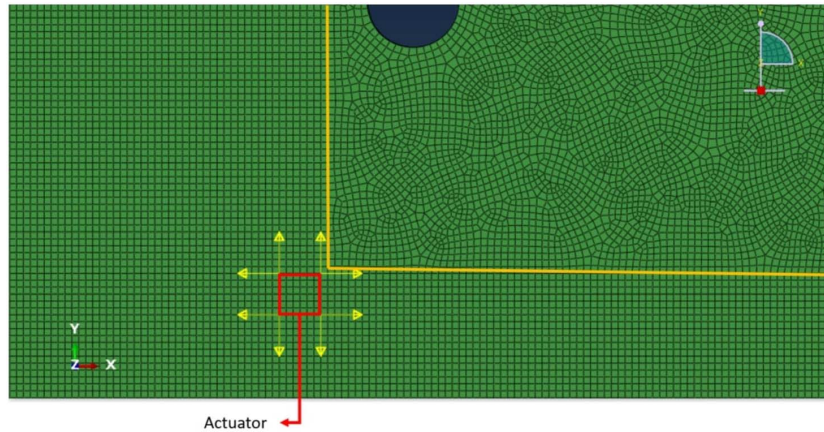


FIG. 2 Discretization and distribution of the force caused by a piezoelectric actuator (partial view of the plate and the inspection areas, delimited by the straight lines).



beneficial in the applications to aircrafts, as they have large wing panels that can not have excess weight coming from complicated sensor arrays.

An explicit dynamic analysis method was implemented in ABAQUS because of its computational efficiency, followed by a few important steps in order to ensure a correct simulation of the LW. In the first step, the total time of the simulation was fixed at 0.5 ms, as this allows the LW to interact with the damage and arrive at the sensors. The second step was the creation of a distributed force, as seen in [figure 2](#), to represent accurately the loads created by a real piezoelectric element. This is important since a piezoelectric actuator does not apply a concentrated force normal to the plate but, instead, it applies distributed tangential forces. It was determined by trial and error that applying two forces at each side of a square representing the actuator yielded good results.

After determining the forces and their configuration, the mesh size was chosen with 1.5 mm. This value was used in order to minimize the computational burden while being lesser than half-size of the wavelength and, thus, small enough to not cause the simulation to diverge. Usually, the smaller the mesh, the better the simulation accuracy, but at the cost of a higher simulation time. To further reduce the computational complexity, the mesh outside the square defined by the actuator/sensors was chosen uniform, whereas inside it was allowed to change. The established compromises led to a simulation time inferior to 20 min.

As stated previously, in the study presented in this work, the defects were positioned in a random fashion inside a square with a resolution of 1 mm, and their size was also randomly generated within the values {2,6,10} mm. We ended up with a total of 163 cases of class 2 mm, 164 cases of class 6 mm, and 194 cases of class 10 mm. Furthermore, the overall domain was populated quite uniformly by all classes.

The parameters described previously were thoroughly tested and adjusted, but their initial values were obtained from the literature.^{9,11,19}

DATA OBTAINED FROM SIMULATIONS

The simulation starts with the vibrations of the aluminum plate caused by the forces generated by the actuator. To accomplish this vibration, 5 pulse Hann-windowed 100-kHz sinusoidal force signals were used. The simulation was first validated by verifying the output vibration at the points of interest without any interference caused by reflections on the boundaries. A Python script was then developed to automatically create the database, with over 50 cases being saved at every iteration. In total, 521 cases were simulated, each yielding one time series per sensor, where these cases are individual, unique, and used in the ML algorithms either in testing or training depending

where it will randomly be allocated. In [figure 3](#), it is possible to see the propagation of the LW on the plate and their interactions with the hole and boundaries.

The signals obtained from the simulations had to be processed in order to be properly used by the ML algorithms. The first decision was to create a fixed time-step and resample all data. The chosen sampling frequency was 10^{-7} Hz as a compromise between high resolution and acceptable number of data points (5,000 in total). The resample to a fixed-step was important since the explicit dynamic simulations carried out on ABAQUS used variable-step and, thus, created simulations with a number of datapoints between 16,000 and 90,000. [Figure 4](#) illustrates the raw data obtained from a sensor in the presence of damage with three different sizes, at the same position.

After processing the signals, it was necessary to remove faulty cases. These cases may appear for two reasons: (i) the simulation does not converge because of numerical issues, or (ii) cases are repeated, that is, despite they are

FIG. 3

Simulation of LW moving in the aluminum sheet.

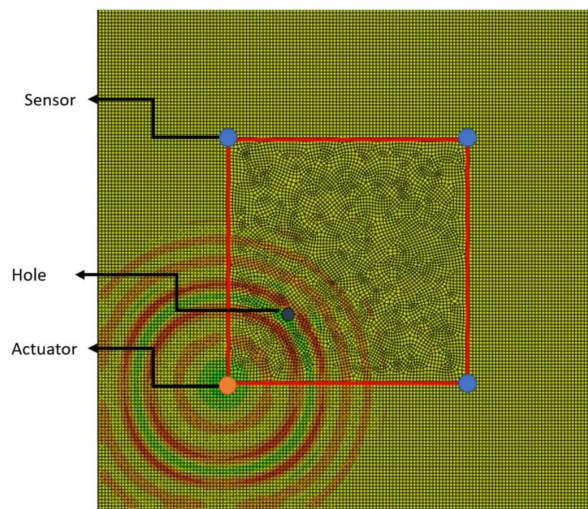
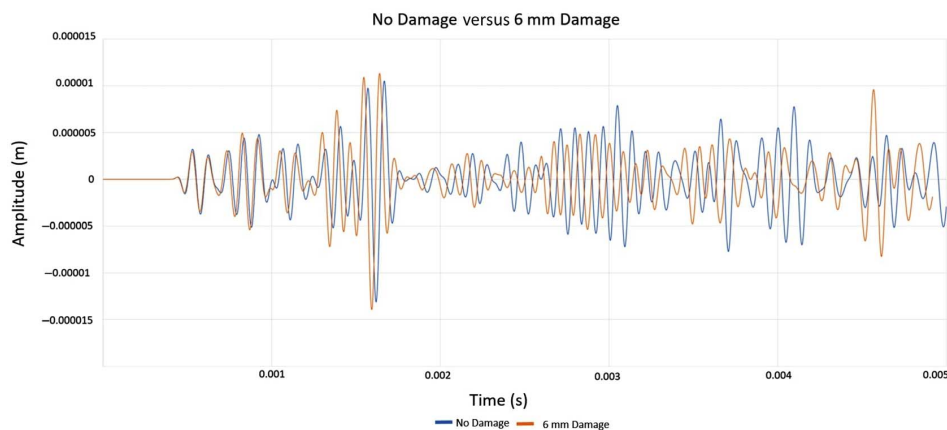


FIG. 4 Raw signals obtained from one sensor with damage of three different sizes (2, 6, and 10 mm) at the same location.



randomly generated, defects can have equal size and position. This was accomplished by automatically detecting discrepancies in the number of peaks present in each time series. Signals with less than 40 peaks were discarded along with duplicate cases created randomly. This step is very important as any faulty results could create additional problems in developing ML solutions. Thus, we began with data for 530 cases, each containing 3 time series for each of the 3 sensors. After withdrawing the faulty cases, we ended up with 521 valid ones.

It is important to note that because of the random placement of the damage, it is very difficult to visualize differences in amplitude and time position of the peaks. This is why the application of ML is beneficial for the problem at hand.

Conventional FFNN versus CNN

With the advent of technology evolution and its application across almost every field touching our day life, enormous amounts of data are available, which justify the widespread interest in exploring the capability of ML methods to deal with these data. ANN can be included in these methodologies, as they inherently require data from a specific problem to parameterize a model capable of providing a solution for that problem.²⁰

A variety of architectures, parameters, and distinguishing features have been considered in the development of ANN, but they normally involve the use of multiple, simple processor units, each implementing typically a nonlinear function. The multiple processors can be interconnected according to various structures, including feedback or recurrent connections. Within every architecture, modeling a specific problem into an ANN entails a representation phase, i.e., defining the type and encoding of the information we give to the ANN, as a set of INPUT elements, and defining the type and encoding of the information the ANN provides as a solution to the problem, i.e., a set of OUTPUT elements. Prior to being ready to provide a solution, an adjustment phase is required where the respective parameters are set, using a variety of possible methods, normally involving the minimization of a cost function, in a supervised or unsupervised mode. For this adjustment phase, i.e., learning phase, a set of data from the problem is required and determinant for the performance obtained with the ANN.²¹

The high number of parameters gives the models a high capability to represent complex problems, whether formulated as classification or function approximation problems, provided enough data are available. In spite of the diversity of architectures and learning algorithms, in general there is no definite guidelines on how to develop an ANN model for a specific problem, including the amount of data required and, less even, how to scale a given solution to a different, although related, problem.

In this work, we concentrated on comparing the applicability of two types of architectures to our damage classification problem. The first, considered as conventional multi-layer FFNN, i.e., not involving feedback or recurrent connections between elements, using mainly sigmoid type functions, back-propagation gradient descent type learning algorithms, and a reduced number of hidden elements or layers, normally designated by shallow ANN. The second architecture involves using CNN, also organized in a feedforward structure, but more often associated with deep-learning ANN and image recognition applications. In both cases, the damage classification problem is formulated as a classification type problem. The main discussion regarding these ANN approaches relates to the capability of feature recognition and generalization ability for the specific damage classification problem.²²

CONVENTIONAL MULTI-LAYER FFNN

The multi-layer feedforward structure has been used extensively, especially following the work of Zupan,²³ when the backpropagation algorithm for adjusting weights in the hidden layers was presented. In this structure, the processing elements, i.e., neurons, are arranged in successive layers, from INPUT to OUTPUT, and the output of each element of each layer is connected to every element of the next layer. Each of these connections has an associated value, i.e., weight w , which must be adjusted during the learning phase.^{22,24} Each element of a layer transforms all its inputs through a nonlinear function, typically a sigmoid function, as seen in expression 5, to its output value, which will be used as an input to the next layer of elements²⁵:

$$g(h) = \frac{1}{1 + e^{-h}} \quad (5)$$

The learning algorithm is intended to reduce the error that can be calculated when comparing the values obtained at the OUTPUT layer, once the values presented at the INPUT layer are processed (feedforward) through the hidden layers, with the known or target values for the corresponding cases. The resulting error is used to define the performance function, which must be continuously differentiable, and involves all the connection weights from the output to the input layers. A commonly used function is the mean squared error, as well as a gradient descent based algorithm (i.e., backpropagation) to find each weights' value that minimize the performance function.²⁵

This architecture has proved successful in modeling complex problems in various areas, ranging from signal prediction and forecasting to image compression.²³ However, because of the complete interconnections between elements in adjacent layers, a careful analysis is required when defining the representation of the problem in this input/output mapping, as well as the number of hidden elements. The higher the number of connection weights to be adjusted, the larger the required data set and the higher the learning computation costs will be. This characteristic makes it more viable to implement FFNN with a reduced number of layers and elements, i.e., shallow FFNN.²³

CONVOLUTIONAL NEURAL NETWORKS

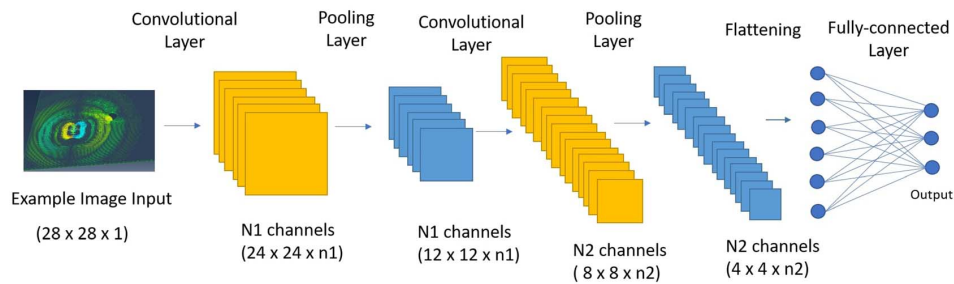
CNN can be organized as multi-layer feedforward structures and, normally, include other layers as a complement to the CNN layers. The main characteristic of the CNN relates to the representation of the input information into the network, i.e., input layer, and a specific processing of the input elements to the CNN layers, which has significant advantages in certain problems. First, the input layer is organized as a grid type layer, which makes it naturally suitable for the representation of closely related data, such as the pixels in a 2D image or the values in a sequential time signal arranged in a column vector (i.e., n by 1 grid), as seen in [figure 5](#).

The second distinct characteristic is the use of a convolution operation between sets of weights, normally referred to as kernels, and the inputs of a CNN layer, in order to provide at the output of the CNN layer a so-called feature map.^{20,26} When considering the input and kernels used in a CNN layer, as square (i.e., $n \times n$) arrays, the spatial size of the convolutional output layer volume can be obtained using

$$n_{\text{out}} = \left\lceil \frac{n_{\text{in}} + 2p - k}{s} \right\rceil + 1, \quad (6)$$

where the width (or height) of the output and input arrays are represented by n_{out} and n_{in} , respectively. The convolutional padding size p is a parameter used when it becomes adequate to include additional information

FIG. 5 Architecture of a CNN.



on the borders (limits) of the input arrays. The sliding increment of the kernels over the input array is the stride parameter.

These kernels can be seen as filters that run through all input values using the same weight values to identify specific features across the input data. These weight values are determined during the learning process. Using this approach, comparatively to a fully connected FFNN, allows for a slower increase of the number of connection parameters (i.e., weights) with an increase of the size of the FFNN, as the same set of weights is used with all inputs. As such, it leads more easily to a deep-learning ANN implementation. It also presents a way to look at associations of nearby data values, which can be of interest not only in image type data but also in time or non-natural image sequential signals. The results of the convolution maps are frequently subsequently processed through a nonlinear rectified linear unit (RELU) function and a pooling stage (i.e., max pooling) to stabilize values around specific locations.²⁴

FEATURES AND ANN REPRESENTATION

Features are important aspects of any ML algorithm; however, it does not matter how powerful the algorithm is, if the information desired is not present or retrievable in the data supplied to the ML algorithm. A feature is a characteristic or attribute of the data set, rather than all the possible information. It reduces the data being processed by the ML and should contain the most relevant data for a specific problem. When considering FFNN models, features are directly linked to the representation of the problem into a FFNN architecture. The specific encoding of the information given to the FFNN defines the number of INPUT elements of the FFNN and, therefore, directly contributes to the number of its internal parameters or links. Given the flexibility of FFNN architectures, it is conceivable to use all details for the data available in the development of an FFNN, and expect it to be capable of extracting the most relevant information for the problem when trained to give the desired solution. However, this approach can, in practice, be limited by the large number of internal parameters to be adjusted and the normally associated large number of data cases required. Alternatively, one can use the best knowledge available of the problem, or a critical analysis of the data available, to identify and select which features could be used to define the information and respective encoding to the INPUT. This approach will result in FFNN with lower internal parameters and consequently lower data requirements and faster training cycles.

Considering the use of LW signals to detect and identify damage in the problem at hand, several approaches were analyzed regarding the use of the information available in each data case. Three alternatives to treat time series were tested: (i) to work in the time domain; (ii) to convert the data to the frequency domain by applying a fast Fourier transform; and (iii) to adopt a combination of both domains using a spectrogram.

All features and data sets have their advantages and disadvantages and, in order to understand the best options, a preliminary analysis, which included using the data represented in the various domains, was performed. The frequency domain revealed low variety among distinct cases and was discarded. The spectrogram has a representation that fits well within the CNN framework, as it can directly be interpreted as an image, but it also revealed low variability, thus making classification difficult. This is illustrated in [figure 6](#), where instead of having a large range of variation in the frequency and time domains, the information is concentrated in a limited range.

The time domain representation has the advantage of being simple, since little to no processing is required, and yielded promising results that prompted further investigation. One such case was obtained with the use of maximum or/and minimum values (peaks), as illustrated in [figure 7](#). The peak values, the peaks time instants, or both, can be used as features characterizing the signals. One of the advantages of this representation is to reduce the original number of data points from 5,000 to about 100. This allows for smaller data sets and consequently lower processing times.

It should be noted that we are adopting manual feature extraction and, therefore, the question of knowing whether or not we are using the most useful features for the problem at hand remains. Indeed, ML algorithms can be fed with raw data or with a huge variety of features. Which features are the most appropriate is the research subject of Feature Engineering, which is out of the scope of this article. However, our approach can be extended to incorporate a multi-class classification pipeline that takes the raw sensor data obtained from the FEM simulations,

FIG. 6

Narrow frequency band present in the spectrogram.

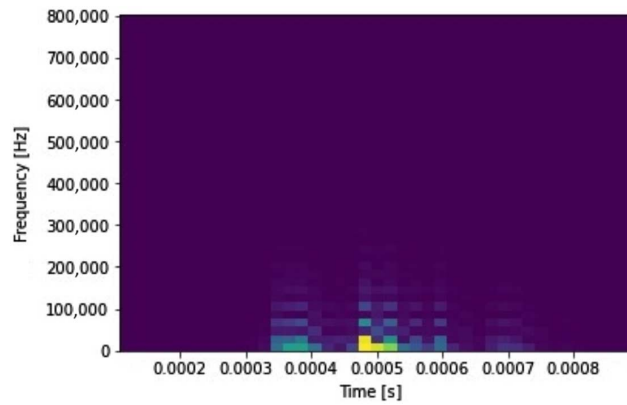
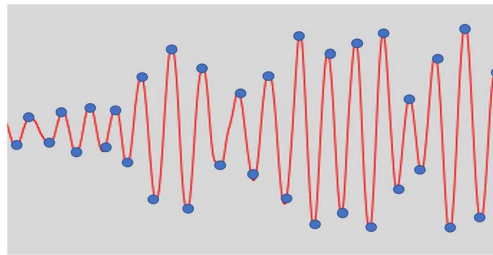
**FIG. 7**

Illustration of the peak points present in an LW signal.



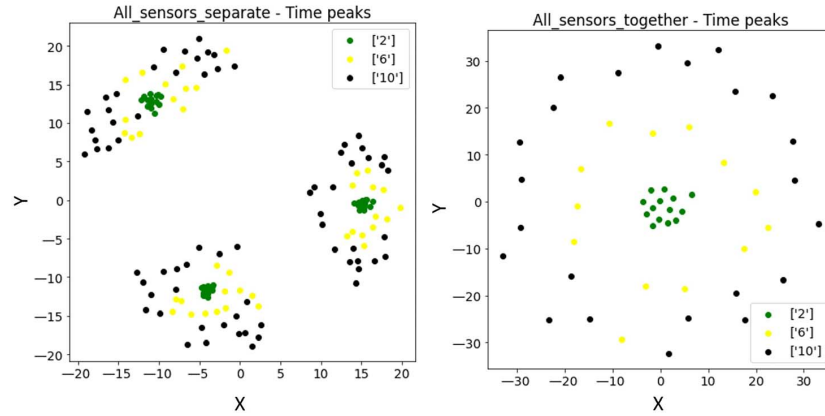
extracts features containing meaningful information regarding the data, preprocesses this information, automatically selects the features according to their significance relative to the classes, and uses them in the ML algorithms to predict the damage class for each instance of testing. Therefore, herein ML algorithms are seen as a baseline-free powerful alternative to methods based on damage indices.

As a result from this preliminary analysis, the focus of the study was on using the peak information for developing both FFNN and CNN, with the variants:

- FFNN using only peak amplitudes;
- FFNN using only peak times;
- FFNN using peak amplitudes and times;
- CNN using only peak amplitudes;
- CNN using only peak times; and
- CNN using peak amplitudes and times.

Experimental Investigation and Feature Extraction

This section describes the design approach used to develop and test FFNN and CNN, based on the preliminary feature selection performed in the section “Features and ANN Representation.” A preliminary analysis adopted multidimensional scaling (MDS)^{27–29} to clarify whether or not using information of all three sensors together can bring more discriminating capabilities relative to using the sensor signals separately. MDS is used to scale the

FIG. 8 MDS technique applied with sensor data separately and as a group.

variables to simplify its visualization in a 2D or 3D configuration. To do this, it uses Euclidean distances between the variables to represent all of them in the designated space.

By processing the data with the MDS algorithm, there was a clear distinct grouping of the cases as seen in [figure 8](#). For each sensor considered separately, there is a clustering around three points, meaning that each sensor data can be used to discriminate between cases. On the other hand, with the data of all sensors used together, there is a clear clustering of the cases, but with a larger dispersion between sizes of defect. With this information it is possible to conclude that the use of all sensors together should allow for a better classification regarding the hole size.

MODEL TRAINING AND TESTING

The methods and learning parameters that are common to the various alternative ML models, either FFNN or CNN, are described in this section. The respective INPUT varied depending on the specific representation of the selected features, as explained in the follow-up. The computing platform used to implement both FFNN and CNN structures was based on the Python programming language and the Keras/Tensorflow ML libraries. Both structures implement a classification-type ANN with three classes at the output: 2, 6, and 10-mm diameter holes defect. The same random separation of the data into a validation set (20 %) and training set (80 %) was used. After the division was done, the data in each group were standardized by using the mean and standard deviation of the training set.

Inside the ML algorithm, there are a few similarities between both cases used. The first is the need to classify the output in three categories representing the size of damage. For that, the final layer for both CNN and FFNN are a fully connected layer created by utilizing the function `model.add(tf.keras.layers.Dense(units=3, activation='softmax'))` with a dimensionality of 3 and the softmax activation function that is a normally used with multi classification models. In the case of the CNN, a flattening layer utilizing the `model.add(tf.keras.layers.Flatten())` function is used in order to compress any multidimensionality in previous layers. The learning algorithm, cost or loss function, and performance metrics used, were the same in both ANN structures: the adaptive moment estimation optimizer algorithm, the categorical cross entropy loss function and the accuracy, i.e., ratio between correct classification cases over total cases, as the performance measure. Regarding the stopping criteria, a total number of 500 epochs was used as this allowed the model to develop to a stable state.

In order to evaluate and compare the ML algorithms, a confusion matrix and two graphs containing the progression of the accuracy and loss that occurred in each epoch was used. In the confusion matrix, there are three labels that represent the three classes with '0' representing 2 mm, '1' representing 6 mm, and '2' representing 10 mm.

FFNN MODELING

Various combinations of information given to the network were tested (i.e., peak amplitudes, peaks time, and both amplitude and time peaks), which resulted in a large number of elements in the input layer and inevitably lead to larger networks. Different combinations of intermediate layers (i.e., number and size of layers) were also tested and a base structure that showed overall better results was chosen. The main objective at this stage was to concentrate on a comparison of the results when using different type of information given to the FFNN rather than optimizing each FFNN specific structure. That is why we allowed the training phase to extend over a high number of iterations in order to observe, not only the performance on accuracy but also the behavior of the loss function. The introduction of Gaussian noise layers helped on reducing overfitting.

The base structure used to implement and develop the FFNN in the Keras/tensorflow platform is represented in [figure 9](#). In addition to the input and output layers, the dense layers were included to represent the hidden layers of a classical FFNN model. Each dense layer implemented the RELU, being fully connected to the next layer. Gaussian noise layers were also used with the objective of incorporating in the data signal patterns that could be caused by noise in signals on real tests and create a more robust algorithm while also reducing the possibility of overfitting. These were implemented utilizing the Keras/tensorflow function `tf.keras.layers. GaussianNoise(0.5,inputshape=(X,))`. This function works by applying an additive zero-centered Gaussian noise, which alters the input value and mitigates the possibility of overfitting.

The first Gaussian layer used a 0.4 noise ratio followed by the fully connected layer with an input dimensionality equal to 100. After these first layers, the Gaussian noise ratio was maintained the same, but the dimensionality of the following fully connected layers decreased to 50 and 10 in order to arrive at a closer output dimension of 3. Finally a mini-batch methodology was used for the FFNN with a total size of 32.

CNN MODELING

In regards to these models, an example of a base structure used consists of three sequences of a convolution layer followed by a pooling layer ([figure 10](#)). This configuration was chosen as it can reduce large data sets quickly while still having a low computational expenditure. The convolutional layers were chosen to have a steady growing beginning at 34, 64, and finally 128, whereas the kernel size started with a (3,3) and ended with (1,1). In regards to the pooling layers, they had a constant (2,2) pooling size.

Finally a mini-batch methodology was also used for the CNN with a total size of 128.

PRELIMINARY COMPARISON TESTS

In order to evaluate and compare the results obtained from the FFNN and CNN, it is necessary to verify how the differences incorporated in the algorithm affect the individual results. To accomplish this, three tests were

FIG. 9

Simplified representation of the chosen FFNN.

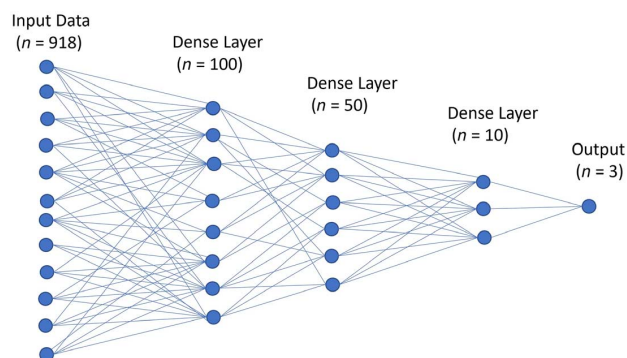
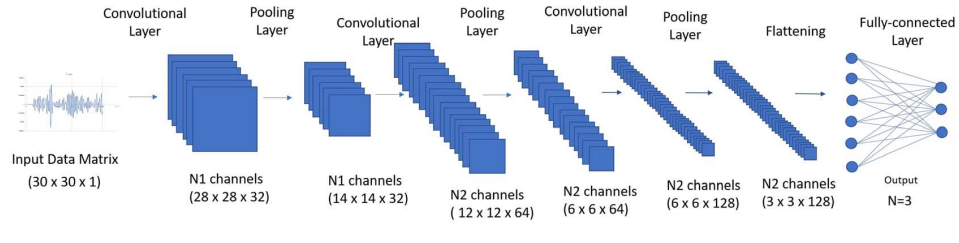


FIG. 10 Simplified representation of the chosen CNN.

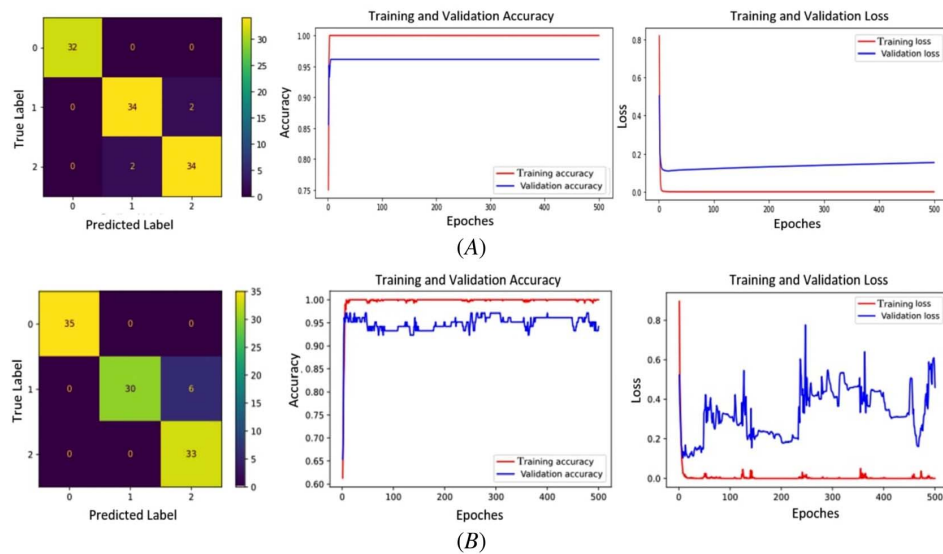
developed, with the first comparing the effect of the Gaussian noise layers on the FFNN, the second also comparing the effect of a noise layer but this time on a CNN, and finally the behavior of the CNN when reducing the number of layers to only one convolutional layer and one pooling layer. For all cases, the input data utilized are the peak amplitude and peak time data.

FFNN without Noise

For the FFNN without noise, three fully connected hidden layers were used with the input having 918 nodes, the first hidden layer with 100, and subsequently 50, 10, and finally 3 nodes at the output. All other parameters were the same as for the other FFNN.

In the FFNN without noise, it is possible to see in [figure 11A](#) the training algorithm quickly arriving at a stable maximum value in both the training and validation sets, showing little or no variations along the cost function minimization iterations.

For comparison, an FFNN with four layers and Gaussian noise with 50 % was used, and the results are depicted in [figure 11B](#). Comparing both cases, it is possible to observe that there is a growth in fluctuation

FIG. 11 Confusion matrix, accuracy and loss graph of a FFNN, when using peaks amplitude and time as input data: (A) without noise and (B) with noise.

in the accuracy and a higher growth in the loss function. The maximum accuracy remains mostly the same, which seems to suggest that including noise layers does not affect the overall results. In all results presented, the confusion matrix values correspond to the final epoch (500) learning state.

CNN with Noise

For the CNN with noise, the input was a Gaussian noise layer with (30,30,1) dimension, followed by a sequence of: convolutional, pooling, noise, convolutional, pooling, convolutional and, finally, the fully connected output layer. This was done in order to have a large number of noise layers to see their effect on the CNN learning model. [Figure 12A](#) presents the results of this case, and in [figure 12B](#), the results of the equivalent CNN model without the noise layers are shown.

Considering these preliminary tests with FFNN and CNN and the inclusion or not of noise, it seems that, overall, the major influence is on the loss function behavior with the maximum accuracy achieved being similar in overall.

CNN with Two Layers

Finally, a CNN with two layers was created with only a convolutional and a pooling layer. All other parameters were maintained the same. This was done to compare the results of the FFNN with an CNN. In both cases, no noise was applied. The CNN results are shown in [figure 13](#), which can be compared with those in [figure 11A](#). We verify that in both cases, it is possible to observe very similar behavior, with minor differences in the accuracy, loss, and even in the confusion matrix.

FFNN WITH PEAKS AMPLITUDE, TIME, AND BOTH

The peaks from all three sensors were combined into one list. Then, a hard cutoff value was chosen of 150 peaks where cases with more than 150 had the smallest peaks excluded. This allowed for a total fixed number of inputs of 459. The peak amplitude and times data sets were normalized separately with the objective of not creating a biased data set and to maintain consistency with what was done for all models developed.

FIG. 12 Confusion matrix, accuracy, and loss graph of a CNN, when using peaks amplitude and time as input data: (A) with noise and (B) without noise.

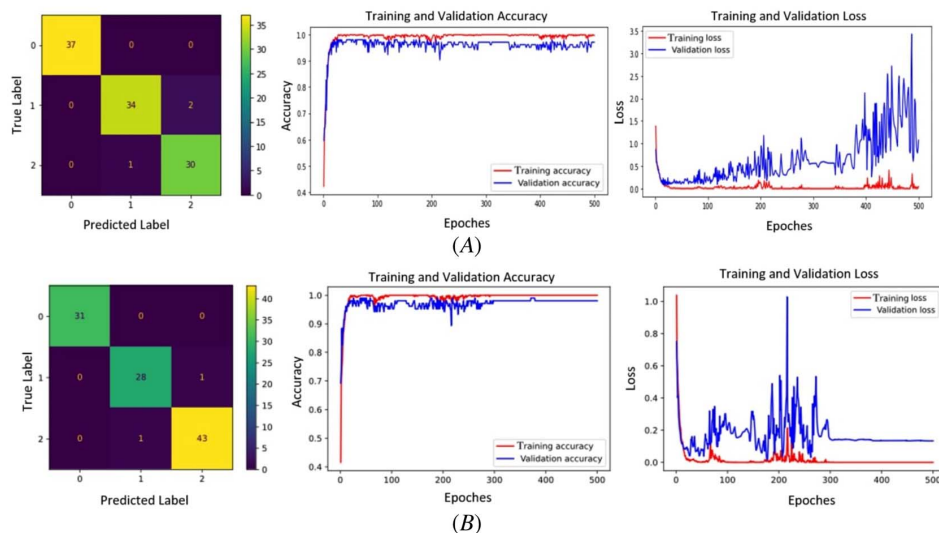
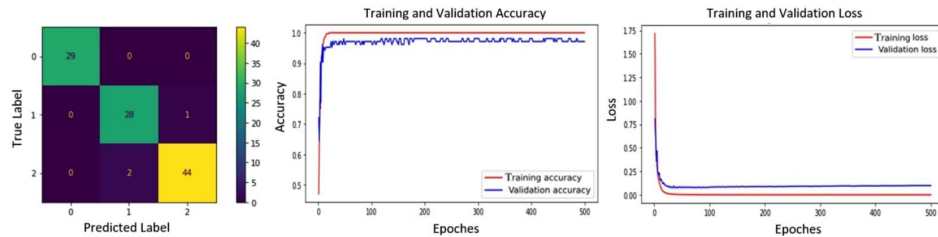


FIG. 13 Confusion matrix, accuracy, and loss graph of a CNN with two layers without noise with peaks amplitude and time as input data.



CNN WITH PEAK AMPLITUDE, TIME, AND BOTH

For the CNN cases, the initial procedure is equivalent to the FFNN with the concatenation of the peaks from the three sensors and then the creation of a cutoff value for minimum peaks to equalize the number of inputs. This is then followed by the normalization of the data just as seen previously. Finally, as a 2D CNN is used, the data have to be reshaped to a 2D matrix. Thus the number of data points has to be altered in order to have enough points to create the 2D matrix. This can be done in two ways. The first is to reduce the cutoff value of peaks in order to achieve the value and the second is to add null values at the end of the list to complete the missing values. For all CNN cases, a mixture of the two was done with the reduction of the cutoff value to the closest integer, and then null values were added if needed. It was done this way to reduce the possible influence caused by the implementation of an arbitrary number of null values. Finally, the data were divided into test/train and a new standardization was done in each one as described previously.

Results and Discussion

This section presents the best results obtained from the multiple models developed. As stated previously, in order to use the desired feature in each case the data set had to be altered accordingly. For the CNN, this meant creating a 2D array for the data, whereas for the FFNN, an input layer was created with the required number of elements and parameters according to the features used. In the following cases, a confusion matrix, the evolution of the accuracy and loss performance functions along the learning phase are used to describe the results obtained.

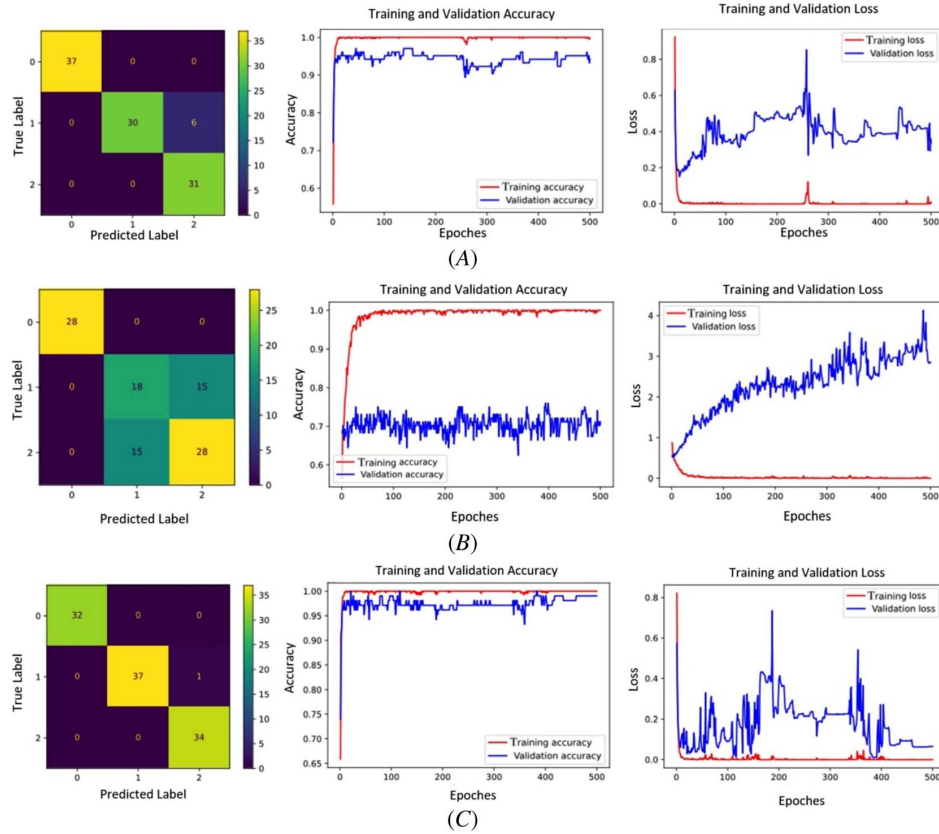
THE FFNN

In [figure 14A](#), it is possible to see the error matrix with a slightly biased error in regards to the separation of the 1 and 2 labels (6 and 10 mm holes). In spite of the matrix values represented (500 epochs) do not correspond to the minimum levels of the loss functions, this shows that the peak amplitude of both these size holes have similar behaviors and the algorithm has a harder time in determining the correct hole size. Furthermore, it can be observed that the misclassifications lie in the safe side, considering that low size holes are classified as larger holes. In the accuracy curves, there is a large growth arriving at the maximum accuracies in under 50 epochs; furthermore, the curves remain reasonably stable around the maximum levels. This trend can also be seen in the loss graph where there is a minimum value for the loss at around 30 epochs and then it grows to show that there is probable overfitting occurring.

The results obtained when using only peak times information to the FFNN models ([fig. 14B](#)) show that the accuracy on the validation sets was well below the results obtained when using peak amplitudes ([fig. 14A](#)). Moreover when observing the values in the confusion matrix, the misclassifications occur again in classes 1 and 2 and are equally distributed.

In [figure 14B](#), it is possible to see that while validation accuracy oscillates around an average value, the validation loss function shows an increasing trend, which may explain that misclassification in this data set

FIG. 14 Confusion matrix, accuracy, and loss graph of the FFNN for different input data: (A) peaks amplitude; (B) peaks time; and (C) peaks amplitude and time.



becomes easier, as well as that overfitting may be occurring. The low value in the overall testing accuracy shows that the time when a peak happens is not a good metric to evaluate the hole size when compared to the amplitudes. This is most probably because of the reduction of the wave signal when subjected to the damage being more relevant and different in each case than when the signal arrives.

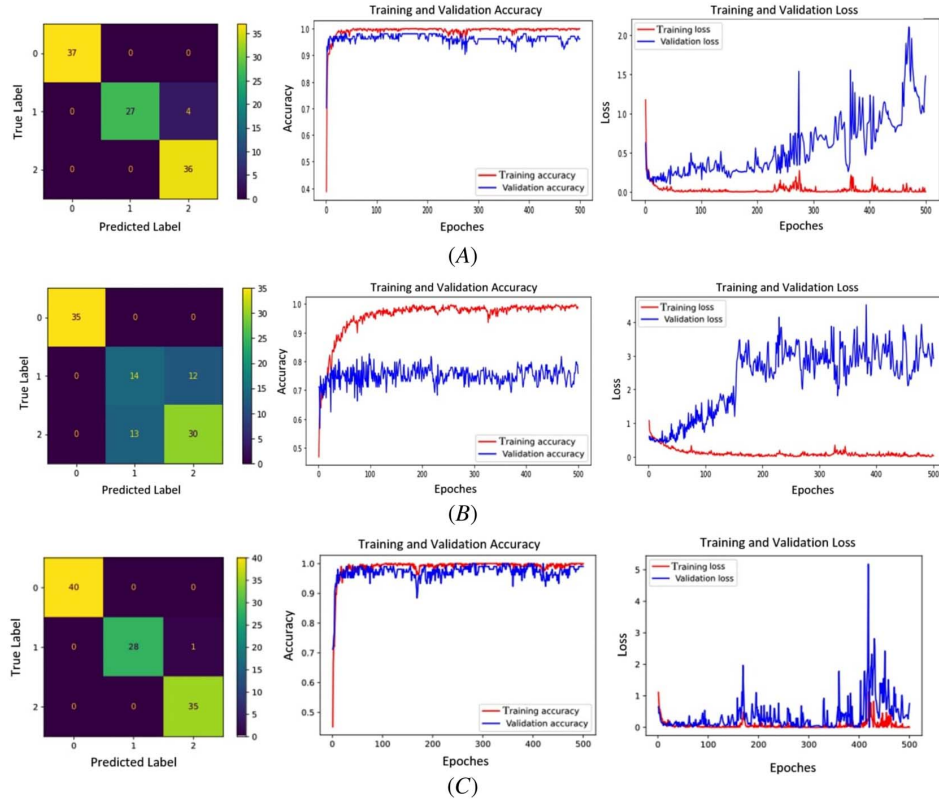
The benefits of using both amplitude and time information of the peaks extracted from the signals data can be observed in [figure 14C](#). A maximum accuracy of 99% on the validation set was achieved as well as a low value on the loss function. Overall, there still remains a misclassification in classes 1 and 2, but only with one case. Further tests showed similar results.

THE CNN

For the CNN case using only the amplitude data, it is possible to see in [figure 15A](#) the same behavior present in the FFNN case with only amplitude data, with even similar results. The largest difference is that the CNN show an increasing trend of the validation loss function along the learning iterations. It can also be observed in this case that a best overall solution in terms of accuracy and loss functions is possible (just over 100 epochs).

Also following the trend of the FFNN case, the times of the peaks present the same overall results as seen previously ([fig. 15B](#)). This demonstrates that the results are less influenced by the ML learning algorithm used

FIG. 15 Confusion matrix, accuracy, and loss graph of the CNN for different input data: (A) peaks amplitude; (B) peaks time; and (C) peaks amplitude and time.



than the features or input information used. It is also interesting to observe that the overall accuracy of this feature is very similar to the one obtained in the FFNN case demonstrating that the time of the peaks real holds less information than the amplitudes.

Finally, the peak amplitude and time are used to train a CNN model, with results that are similar, if not slightly better as they are more consistently closer to optimum values of accuracy and loss functions, than the FFNN models (fig. 15C). With these results, it is possible to say that both ANN models can provide high-quality results and that combining amplitude and time information provide the best results.

Conclusions

In this article, a thorough analysis of the effects of various features and ML methods on damage classification was successfully fulfilled. This was done by firstly creating FEM simulations of damaged aluminum sheets, exciting the specimens with LW and collecting the outputs to generate a large database of cases. Then, the database was preprocessed in order to eliminate corrupted simulations, and different features were intensively evaluated. Finally, the most promising features were chosen and used in FFNN and CNN algorithms in order to determine their overall performance to classify damage.

The main conclusions that can be drawn are as follows:

- the use of LW and ML together are promising tools for NDT and SHM;
- peaks amplitude and time data provide good results, better than those achieved with just peaks amplitude or peaks time, for all algorithms;
- FFNN and CNN have similar classification performance (around 95–98 %); and
- a small number of sensors placed correctly on the specimens can detect small damages in large areas.

Although the article gives an insight on the relationships between features and ML algorithms applied to a problem at hand, there is future work to be developed. As such, experimental data must now be used to validate the numerical results and to test the effectiveness of the overall technique proposed. Moreover, the ML algorithms should be assessed for classifying other types of damage or even different types of damage.

References

1. M. Kaufmann, D. Zenkert, and P. Wennhage, "Integrated Cost/Weight Optimization of Aircraft Structures," *Structural and Multidisciplinary Optimization* 41, no. 2 (August 2009): 325–334.
2. Z. Su, L. Ye, and Y. Lu, "Guided Lamb Waves for Identification of Damage in Composite Structures: A Review," *Journal of Sound and Vibration* 295, nos. 3–5 (August 2006): 753–780.
3. A. Melloni, G. Cusmai, and M. Martinelli, "Experimental Confirmation of Matched Bends," *Optics Letters* 29, no. 5 (March 2004): 465–467.
4. J. Sadler and R. G. Maev, "Experimental and Theoretical Basis of Lamb Waves and Their Applications in Material Sciences," *Canadian Journal of Physics* 85, no. 7 (July 2007): 707–731, <https://doi.org/10.1139/p07-082>
5. R. Seifried, L. J. Jacobs, and J. Qu, "Propagation of Guided Waves in Adhesive Bonded Components," *NDT & E International* 35, no. 5 (July 2002): 317–328.
6. P. D. Wilcox, "Lamb Wave Inspection of Large Structures Using Permanently Attached Transducers" (PhD diss., Imperial College, 1998).
7. L. Mallet, B. C. Lee, W. J. Staszewski, and F. Scarpa, "Structural Health Monitoring Using Scanning Laser Vibrometry: II. Lamb Waves for Damage Detection," *Smart Materials and Structures* 13, no. 2 (February 2004): 261–269.
8. S. Agarwal and M. Mitra, "Lamb Wave Based Automatic Damage Detection Using Matching Pursuit and Machine Learning," *Smart Materials and Structures* 23, no. 8 (July 2014): 085012, <https://doi.org/10.1088/0964-1726/23/8/085012>.
9. V. Ewald, R. M. Groves, and R. Benedictus, "Deepshim: A Deep Learning Approach for Structural Health Monitoring Based on Guided Lamb Wave Technique," in *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019*, Vol. 10970 (Bellingham, WA: International Society for Optics and Photonics, 2019).
10. F. Sun, N. Wang, J. He, X. Guan, and J. Yang, "Lamb Wave Damage Quantification Using GA-Based LS-SVM," *Materials* 10, no. 6 (June 2017): 648, <https://doi.org/10.3390/ma10060648>
11. C. Su, M. Jiang, S. Lv, S. Lu, L. Zhang, F. Zhang, and Q. Sui, "Improved Damage Localization and Quantification of CFRP Using Lamb Waves and Convolution Neural Network," *IEEE Sensors Journal* 19, no. 14 (July 2019): 5784–5791.
12. W. J. Staszewski, B. C. Lee, L. Mallet, and F. Scarpa, "Structural Health Monitoring Using Scanning Laser Vibrometry: I. Lamb Wave Sensing," *Smart Materials and Structures* 13, no. 2 (February 2004): 251–260.
13. J. L. Rose, *Ultrasonic Guided Waves in Solid Media* (Cambridge, UK: Cambridge University Press, 2014).
14. K.-T. Kang, H.-J. Chun, J.-H. Son, J.-A. Lee, J.-H. Byun, M.-K. Um, S.-K. Lee, and J.-W. Jang, "Quantitative Accessibility of Delamination in Composite Using Lamb Wave by Experiments and FEA," *Advanced Composite Materials* 20, no. 4 (2011): 361–373.
15. K. F. Chen and S. L. Mei, "Composite Interpolated Fast Fourier Transform with the Hanning Window," *IEEE Transactions on Instrumentation and Measurement* 59, no. 6 (June 2010): 1571–1579.
16. M. Rucka, E. Wojtczak, and J. Lachowicz, "Damage Imaging in Lamb Wave-Based Inspection of Adhesive Joints," *Applied Sciences* 8, no. 4 (March 2018): 522, <https://doi.org/10.3390/app8040522>
17. W. H. Ong, N. Rajic, W. K. Chiu, and C. Rosalie, "Lamb Wave-Based Detection of a Controlled Sisbond in a Lap Joint," *Structural Health Monitoring* 17, no. 3 (June 2017): 668–683, <https://doi.org/10.1177/1475921717715302>
18. F. Nicassio, S. Carrino, and G. Scarselli, "Elastic Waves Interference for the Analysis of Disbonds in Single Lap Joints," *Mechanical Systems and Signal Processing* 128 (August 2019): 340–351.
19. M. A. de Oliveira, A. V. Monteiro, and J. V. Filho, "A New Structural Health Monitoring Strategy Based on PZT Sensors and Convolutional Neural Network," *Sensors* 18, no. 9 (September 2018): 2955.
20. K. O'Shea and R. Nash, "An Introduction to Convolutional Neural Networks," *arXiv preprint arXiv: 1511.08458*, 2015, <https://doi.org/10.48550/arXiv.1511.08458>

21. S. Agatonovic-Kustrin and R. Beresford, "Basic Concepts of Artificial Neural Network (ANN) Modeling and Its Application in Pharmaceutical Research," *Journal of Pharmaceutical and Biomedical Analysis* 22, no. 5 (June 2000): 717–727, [https://doi.org/10.1016/s0731-7085\(99\)00272-1](https://doi.org/10.1016/s0731-7085(99)00272-1)
22. A. Dongare, R. Kharde, and A. D. Kachare, "Introduction to Artificial Neural Network," *International Journal of Engineering and Innovative Technology* 2, no. 1 (2012): 189–194.
23. J. Zupan, "Introduction to Artificial Neural Network (ANN) Methods: What They Are and How to Use Them," *Acta Chimica Slovenica* 41 (January 1994): 327–327.
24. S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a Convolutional Neural Network" (paper presentation, 2017 International Conference on Engineering and Technology (ICET), Antalya, Turkey, August 21–23, 2017).
25. A. P. Plumb, R. C. Rowe, P. York, and M. Brown, "Optimisation of the Predictive Ability of Artificial Neural Network (ANN) Models: A Comparison of Three ANN Programs and Four Classes of Training Algorithm," *European Journal of Pharmaceutical Sciences* 25, nos. 4–5 (July 2005): 395–405, <https://doi.org/10.1016/j.ejps.2005.04.010>
26. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning* (Cambridge, MA: MIT Press, 2016).
27. W. S. Torgerson, "Multidimensional Scaling: I. Theory and Method," *Psychometrika* 17, no. 4 (December 1952): 401–419.
28. J. T. Machado and A. M. Lopes, "Multidimensional Scaling and Visualization of Patterns in Prime Numbers," *Communications in Nonlinear Science and Numerical Simulation* 83 (April 2020): 105128.
29. J. A. Tenreiro Machado, A. M. Lopes, and A. M. Galhano, "Multidimensional Scaling Visualization Using Parametric Similarity Indices," *Entropy* 17, no. 4 (March 2015): 1775–1794.

Appendix C

Paper C

<https://doi.org/10.1177/09544062221086410>

Feature Extraction and Visualization for Damage Detection on Adhesive Joints, Utilizing Lamb Waves and Supervised Machine Learning Algorithms

Journal Title
XX(X):1-14
©The Author(s) 2021
Reprints and permission:
sagepub.co.uk/journalsPermissions.nav
DOI: 10.1177/ToBeAssigned
www.sagepub.com/

SAGE

Vasco F.F. Loreiro¹ and Gabriel M. F. Ramalho¹ and A. Francisco G. Tenreiro² and António M. Lopes^{1,2} and Lucas F. M. da Silva^{1,2}

Abstract

In recent years, the aeronautical industry has grown with new materials and fabrication methods being developed. This has caused the use of Structural Health Monitoring methods, more specifically Lamb Waves, to become more prevalent as regulations become more severe. Methods utilizing time series sensor data for damage detection have shown great promise in classifying the extent of damage present in plate structures when used in union with machine learning algorithms. Despite this success, there is still a lack of a robust method for choosing features that optimize the learning process to classify any damage.

In this paper a powerful time series specialized feature extraction method is implemented. Initially over 75 different prominent features and their variations are extracted from each sensor's raw data. Then, by utilizing the Benjamini-Hochberg procedure some are selected as relevant for a damage classification problem. After the initial selection, the features are inserted into supervised machine learning methods, such as Random Forest and Naïve Bayes classifiers, where not only is it possible to achieve high classification metrics using all features, but also reveal and isolate which features allow the best differentiation of each damage class. This selection methodology accounts for robustness by utilizing different layers of selection and classification, validating the feature relevance in relation to the appropriate set of classes. As such, different damage types and ranges can be utilized in this multi-class classification pipeline.

Keywords

Lamb Waves, Adhesive Joint, Weak Adhesion, Structural Health Monitoring, Nondestructive Testing

Introduction

Research on LW - an elastic disturbance that propagates on thin plate structures with shallow to no curvature - and their relevance to this application has been carried out throughout the last few years, in a collective effort to increase the reliability, integrity and durability of adhesive bonded structures (1), which are present and growing in popularity in different industries, such as the aeronautical and automotive industries/sectors, due to their potential for reduction of weight and cost in relation to other joining methods, such as screwed, riveted or welded connections (2). As component reliability and performance is paramount in these fields, it is necessary to be able to identify and locate defects without causing the destruction of the structure or component under test/examination/inspection, which ultimately is the aim of all NDT (3).

LW are a prime candidate for NDT, since they propagate over long distances with minimal attenuation and have the capability of interacting with various types of material discontinuities and defects (4). However, the intrinsic nature of LW propagation makes the interpretation of their characteristics more difficult, since they invariably excite more than one propagation mode at any given testing frequency (3), and interaction with defects present in the medium results in very complicated time-based response signals arising from the sensors. Hence, the opportunity to

apply Machine Learning (ML) to the time series signals should be explored, by extracting meaningful features and inputting the information into classification algorithms, in order to train them for damage detection.

The paper is divided into five parts: firstly the introduction, secondly a literature review of the subjects addressed in this paper, namely LW, adhesive joints and defects associated with them and data visualization/machine learning techniques. Then an explanation of the project's structure and development, followed by the presentation and discussion of the obtained results, ending with the conclusion.

The main objective of this paper is to present the development of a machine learning pipeline designed to take raw LW response vibration signals measured in a single-lap adhesive joint, and, through feature engineering and machine learning algorithms, predict the degree of adhesion strenght in that joint.

¹Department of Mechanical Engineering, Faculty of Engineering, University of Porto, Portugal

²LAETA/INEGI, Faculty of Engineering, University of Porto, Portugal

Corresponding author:

António M. Lopes, University of Porto, Portugal
Email: aml@fe.up.pt

Literature Review

This section is an overview of the topics covered in this paper, namely the theoretical support and definition of LW, a review on adhesion technology and considerations on the data visualization techniques and ML algorithms to be implemented, including the mathematical concepts and tools involved.

Lamb Waves

It was 1916 when Horace Lamb, published the article “On Waves in an Elastic Plate”, in which he presents his considerations on the problem of two-dimensional waves in a solid bounded by parallel planes, first approached by Lord Rayleigh in 1889 (5). In fact, both Rayleigh and Lamb mention each other on different papers on the subject of vibrations around this time (6), but in this paper in 1916, Lamb presents the equations that characterize the propagation of this type of waves, that ended up with his name.

LW techniques have proven capabilities to provide information about damage type, severity and location ever since they were first used to detect damage in 1960 by Worlton of the General Electric Company. Since then, they have been employed in a variety of fashions, from research conducted at NASA that demonstrated the possibility of using LW to detect delamination in composite beams, to different groups at Imperial College, working to optimize the generation of directional LW, among many others (7).

Assuming an infinite solid medium, elastic waves can propagate in two basic modes: pressure (P) waves and shear (S) waves. Yet, if the medium is bounded, wave reflections occur at the boundary, giving way for more complicated wave patterns. Guided Waves are particularly interesting because they remain contained in a wave guide and can travel very large distances with little amplitude attenuation. As such, they are excellent for damage detection due to the full cross-section interrogation of the material, assuring that the wave will interact with any possible defect. The sensitivity to different defects will depend on mode type and the location of the defect in the thickness of the structure. Examples of Guided Waves are LW, and others, such as Love Waves, which travel in layered materials, or Rayleigh Waves, which travel in a constrained manner the surface (8; 9). These are actually the typical seismic waves that propagate on the surface of the earth during an earthquake.

LW in specific are a form of elastic perturbation that propagates in a solid thin plate with parallel free boundaries, but can also occur on shell-like structures with shallow curvature, and they are made up of a superposition of pressure modes, whose characteristics vary with entry angle, excitation and structural geometry (10). They have two fundamental propagation modes: Symmetric (Sn) and Anti-symmetric (An).

This symmetry or anti-symmetry happens with respect to the plate's mid-plane. Considering a plate with stress-free upper and lower surface, the outline of the equations for a LW propagation, following Giurgiutiu, et al. and Su, et al., is presented (8; 10; 11). Consider the equation of motion for an isotropic elastic medium, that describes the displacement field by satisfying Navier's displacement equation:

$$\mu \nabla^2 \mathbf{u} + (\lambda + \mu) \nabla \nabla \cdot \mathbf{u} = \rho \frac{\partial^2 \mathbf{u}}{\partial t^2} \quad (1)$$

where λ and μ are the Lamé constants, which are two material-dependent quantities that arise from the study of elastic stress-strain relationships, ρ is the mass density, and $\mathbf{u}$ is the displacement vector, given by:

$$\mathbf{u} = \nabla \Phi + \nabla \times \Psi \quad (2)$$

where Φ and Ψ are the potential functions.

The wave equations can be written as a function of this potential functions, the mass density, the Lamé constants, and both the longitudinal (L) wavespeed, given by $c_L^2 = (\lambda + 2\mu)/\rho$, and the transversal (T) wavespeed, given by $c_T^2 = \mu/\rho$:

$$\begin{aligned} \frac{\partial^2 \Phi}{\partial x^2} + \frac{\partial^2 \Phi}{\partial y^2} + \frac{\omega^2}{c_L^2} \Phi &= 0 \\ \frac{\partial^2 \Psi}{\partial x^2} + \frac{\partial^2 \Psi}{\partial y^2} + \frac{\omega^2}{c_T^2} \Psi &= 0 \end{aligned} \quad (3)$$

The time dependency for these waves is assumed harmonic, in the form $e^{i\omega t}$, bringing the general solution to equation (3) as:

$$\begin{aligned} \Phi &= (A_1 \sin py + A_2 \cos py) e^{i(\xi x - \omega t)} \\ \Psi &= (B_1 \sin qy + B_2 \cos qy) e^{i(\xi x - \omega t)} \end{aligned} \quad (4)$$

where $\xi = \omega/c$ is the wavenumber and:

$$p^2 = \frac{\omega^2}{c_L^2} - \xi^2, \quad q^2 = \frac{\omega^2}{c_T^2} - \xi^2 \quad (5)$$

The four integration constants, A_1, A_2, B_1, B_2 are to be obtained from the boundary conditions. Getting the relations between the potential functions and the displacements, stresses and strains:

$$u_x = \frac{\partial \Phi}{\partial x} + \frac{\partial \Psi}{\partial y} \quad (6a)$$

$$\tau_{yx} = \mu \left(2 \frac{\partial^2 \Phi}{\partial x \partial y} - \frac{\partial^2 \Psi}{\partial x^2} + \frac{\partial^2 \Psi}{\partial y^2} \right) \quad (6b)$$

$$u_y = \frac{\partial \Phi}{\partial y} - \frac{\partial \Psi}{\partial x} \quad (6c)$$

$$\tau_{yy} = \lambda \left(\frac{\partial^2 \Phi}{\partial x^2} + \frac{\partial^2 \Phi}{\partial y^2} \right) + 2\mu \left(\frac{\partial^2 \Phi}{\partial x^2} - \frac{\partial^2 \Psi}{\partial x \partial y} \right) \quad (6d)$$

$$\epsilon_x = \frac{\partial u_x}{\partial x} \quad (6e)$$

and plugging them into the general solution equations gets:

$$u_x = [(A_2 i \xi \cos py + B_1 q \cos qy) + (A_1 i \xi \sin py - B_2 q \sin qy)] e^{i(\xi x - \omega t)} \quad (7)$$

$$u_y = [-(A_2 p \sin py + B_1 i \xi \sin qy) + (A_1 p \cos py + B_2 i \xi \cos qy)] e^{i(\xi x - \omega t)} \quad (8)$$

For free wave motion, the homogeneous solution is derived by applying the stress-free boundary conditions at the upper and lower surfaces ($y = \pm d$), where d is half of the plate thickness, obtaining the characteristic equations:

$$D_S = (\xi^2 - q^2)^2 \cos pd \sin qd + 4\xi^2 pq \sin pd \cos qd = 0 \quad (9a)$$

$$D_A = (\xi^2 - q^2)^2 \sin pd \cos qd + 4\xi^2 pq \cos pd \sin qd = 0 \quad (9b)$$

And finally, equations (9a) and (9b) can be rewritten in the more compact form as the Rayleigh-Lamb equation:

$$\frac{\tan pd}{\tan qd} = - \left[\frac{4\xi^2 pq}{(\xi^2 - q^2)^2} \right]^{\pm 1} \quad (10)$$

where the exponent +1 corresponds to symmetric (S) motion and -1 to anti-symmetric (A) motion. Equations (9a) and (9b) accept a number of eigenvalues, $\xi_0^S, \xi_1^S, \xi_2^S, \dots$, and $\xi_0^A, \xi_1^A, \xi_2^A, \dots$, respectively. Each parameter corresponds to a set of eigencoefficients (A_2, B_1) for the symmetric case and (A_1, B_2) for the anti-symmetric one, that can be plugged into equations (7) and (8) and yield the corresponding modes: $S_0, S_1, S_2, \dots, S_n$ and $A_0, A_1, A_2, \dots, A_n$.

The coefficients p and q in equations (9a) and (9b) are dependant on the angular frequency, ω , and, consequently, the eigenvalues ξ_i^S and ξ_i^A will change accordingly, and since the wavespeeds correspond to $c_i = \omega/\xi_i$, they will also change with frequency, and this change produces the so-called wave dispersion.

LW are highly dispersive, meaning that the fundamental way to concretely describe their propagation in a material is through their dispersion curves, that plot the phase and group velocities against the excitation frequency (often shown as a product with thickness), since, for each frequency-thickness product, and each solution of the Rayleigh-Lamb equation, one finds a corresponding LW mode (7; 11).

A proper LW mode for damage detection should feature non-dispersion, low attenuation, high sensitivity, easy excitability and good detectability. The best way to prevent wave dispersal is to have an input signal with a narrow bandwidth, such as a windowed toneburst which is a more frequently adopted input signal.

The generation of LW can be done through a variety of instruments, roughly grouped under five categories, ultrasonic probes, laser, interdigital transducers, optical fibre, piezoelectric elements (10). All of these methods have strengths and weaknesses. Piezoelectric, or lead zirconate titanate (PZT) elements have advantages, since they can be used for both LW generation and acquisition, delivering excellent performance, allied to their neglectable mass/volume, effortless integration, outstanding mechanical strength, wide frequency response range, low power consumption and acoustic impedance, and low cost, making them particularly suitable for SHM applications as an in-situ generator/sensor. On the other hand, some nonlinear behaviour and hysteresis under large strains/voltages, or at high temperatures should be accounted for, and their

brittleness and low fatigue life may cause concerns or limit some applications. Importantly, PZT-generated LW unavoidably excite multiple modes that generate complex response signals, requiring sophisticated signal processing to successfully utilize them for damage detection (10).

Adhesive Joints and Defects

An adhesive is formally defined as a material which, when applied to surfaces, can join them together and resist separation. Adhesive is, therefore, the general term which covers materials like glue, cement, paste, among others (12). An adhesive joint is the finished connection of two surfaces, made of similar or different materials, through the use of adhesives. The materials that are bonded by the adhesive, before bonding, are called substrates, and after bonding, they are referred to as adherends (12). The region linking the adherend and the adhesive is the interphase, whose chemical and physical characteristics critically influence the mechanical properties of the adhesive bond itself. Not to be confused with the interface also known as the boundary layer, that resides within the interphase (where various interfaces connecting different materials can exist), which is the plane defined by the contact between the surface and the two materials, where, during the formation stages of the bond, the intimate molecular contact is created (13).

Adhesive joints provide a wide variety of advantages when compared to conventional mechanical fasteners, according to (13): more uniform stress distribution along the bonded area, that leads to a good resistance to dynamic solicitation as well as load transmission and higher stiffness, as well as the reduction of the weight on the structure and consequently, the cost; The possibility of automating the adhesive application is also appealing.

However, some disadvantages should also be considered, like the need to avoid peel and cleavage stress because they create a load concentration in a small area, resulting in low strength in that area, limited resistance to extreme environmental conditions, such as high temperature and humidity, and the difficult quality control, since there is no expeditious way to assess the integrity of the bond - that could change with non-destructive testing techniques (12; 13).

Even if a certain adhesive is the perfect choice for a given application, its durability is a function of the entire bonding system, that is, adhesion defects and other problems can still arise and lead the joint to failures of different types when subjected to mechanical stress, be it because of the lack of proper surface preparation, bad chemical formulation of the adhesive, incomplete curing cycle or other environmental disturbances, such as high humidity.

Structural bonds, in particular, are expected to undergo some form of loading for a significant part of their service life, and so, an understanding of the bond failure and failure modes is critically important. It can occur in a number of places within a bonded joint or structure, as reported by (13; 14), cohesively within the adherends, interfacially between the adherend and the adhesive layer or cohesively within the adhesive. The bond might also contain "isolated phenomena" that compromises its structural integrity, such as voids, debonds, porosity or cracks within the adhesive

layer, and these should be detected as soon as possible to avoid serious damage or failure of the bond.

Data Visualization Techniques

Data visualization regards the manipulation of sampled and computed data for comprehensive display, conducive to a deeper understanding of the data and highlighting the underlying physical laws and properties. It is an important tool that helps the data scientist in different stages of a project, by pointing out useless, incorrect or inconsistent information that can be eliminated, and assessing the results, to expose dynamics and help define the focus points and regions of interest (15).

Dimensionality reduction is applied as a procedure to create projections of the data, mapping it into a low dimensional space, in order to enable an insightful view of how data instances relate to each other, namely the appearance of structures such as high local density, interesting relations between observations and the presence of clusters (16; 17).

Time-oriented data visualization is a widely researched topic, and according to Aigner, et al. (18), visualization techniques can be categorized in many ways, such as the structure of time itself (linear, cyclic or branched), the frame of reference (spatial or abstract), the number of variables that are time-dependant, and the dimensionality that is to be obtained (2D or 3D, since those are intuitively understood by the human brain).

It is a common procedure in data science to transform the raw data formats into more suitable and consistent ones before applying any further techniques, through processes like smoothing, generalization and normalization. Normalization is likely to improve accuracy and efficiency of classification algorithms, and for distance-based methods in particular, it prevents attributes with initially large value ranges from outweighing those with smaller ranges, uniforming the importance of any given testing instance, while keeping the intrinsic information intact. Among others, data normalization methods include Min-Max normalization, Z-Score normalization, l^2 normalization and normalization by decimal scaling (19; 20).

Min-Max normalization performs a linear transformation on the original data. If an attribute A has a range of values of $[a_{min}, a_{max}]$, Min-Max normalization maps a value x of A , to its counterpart x' in the new predetermined range $[a'_{min}, a'_{max}]$ by computing: (19)

$$x' = \frac{x - a_{min}}{a_{max} - a_{min}} \times (a'_{max} - a'_{min}) + a'_{min} \quad (11)$$

where, in this case, the new selected range was $[a'_{min}, a'_{max}] = [0, 1]$.

Two of the most widespread visualization techniques, Multidimensional Scaling (MDS), and t-distributed Stochastic Neighbor Embedding (t-SNE), are implemented for the projection and visualization of the time series themselves and also to visualize some features later on.

Multidimensional Scaling (MDS) MDS is a multivariate statistical method that represents measurements of proximity/similarity (or dissimilarity) among pairs of objects geometrically, as distances between points of a low-dimensional

space. Torgerson proposed the first MDS method and coined its name, Multidimensional Scaling, that can also be known as Principal Coordinates Analysis (PCoA) or even Torgerson Scaling (21).

MDS shows the correlations among instances of the data, displaying each of these as a point on a plane, so that the closer together the points are, the more correlated the respective instances are, turning the data from immense arrays of numbers to an accessible visual representation, for easy inspection and exploration (22).

The application of MDS is exploratory, so as to uncover the data elements accounting for the proximity of the data, rather than to test *a priori* hypothesis about the existence and properties of those elements (23). The vastly used family of procedures known as *Principal Components Analysis* (PCA), which should not be mistaken with PCoA, is closely related to MDS in function, but differs in some key aspects, the principal being the fact that MDS starts with a matrix of similarities between a set of individuals, while PCA starts directly with the initial data matrix (24; 25).

MDS models are defined by the similarity or dissimilarity of data - the proximity indexes p_{ij} between pairs (i, j) of objects, that construct an $n \times n$ matrix $\mathbf{C}$, being n the total number of objects - and how those proximity indexes are mapped into distances of an m -dimensional MDS space configuration: $\mathbf{X}$. In classic MDS, $\mathbf{C}$ is symmetric, with $p_{ij} > 0$ for $i \neq j$ and its main diagonal is composed of "1" (17).

The mapping is given by a representation function $f(p_{ij})$, that specifies how the proximities should be related to the distances $d_{ij}(\mathbf{X})$, seeking the configuration (in a given dimensionality m) whose distances satisfy f as closely as possible. The condition "as closely as possible" is quantified by a badness-of-fit measure, also called a *loss function* - an expression that aggregates the representation errors: $e_{ij} = f(p_{ij}) - d_{ij}(\mathbf{X})$. The most common loss function in MDS is named raw-Stress (ρ), also known as "Kruskal stress" (24). It varies between 0 and 1, with values near 0 evidently indicating a better fit (22; 26).

$$\rho = [f(p_{ij}) - d_{ij}]^2, i, j = 1, \dots, n \quad (12)$$

Shepard plots are also used to evaluate the fit of the mapping, by comparing d_{ij} versus p_{ij} for a given value of m . A narrow scatter of points, resembling a smooth straight line without sudden steps indicates a successful representation (22; 24; 26).

The m -dimensional MDS space configuration always refers to a coordinate system, customarily a set of m directed axes, perpendicular to each other and intersecting in one point, the origin. If the value for m is chosen to be 2, for example, this would define a Cartesian plane. Since the MDS interpretation is based on the emerging clusters and distances between points in the mapping, rather than on their absolute coordinates, the units of the axes are meaningless, and so, the MDS map can be rotated and translated, as the distances between points remain the same (17; 22). As for the distances' definition, the most natural and frequently used is the Euclidean distance, corresponding to the length of the straight line segment connecting i and j , computed by the formula (22):

$$d_{ij}(\mathbf{X}) = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2} \quad (13)$$

Thus, $d_{ij}(\mathbf{X})$ equals the square root of the sum of the intradimensional differences $x_{ia} - x_{ja}$, which, in plain terms, is the Pythagorean theorem for the length of the hypotenuse of a right triangle. Generalizing to the m -dimensional case, yields:

$$d_{ij}(\mathbf{X}) = \left[\sum_{a=1}^m (x_{ia} - x_{ja})^2 \right]^{1/2} \quad (14)$$

The dissimilarity matrix $\mathbf{C}$ can adopt different measures, such as the so-called Canberra and Manhattan distances, among others. It should be noted that the use of alternative measure methods within the MDS is a common procedure, often having distinct representations of the same data set, that view phenomena with different perspectives, opening up the possibility of choosing the MDS charts that yield better visualizations (26).

t-distributed Stochastic Neighbor Embedding Stochastic Neighbor Embedding (SNE), as originally presented by Hinton and Roweis (27), is a probabilistic approach to the task of placing objects, from high-dimensional vectors or by pairwise dissimilarities, in a low-dimensional space in such a way that preserves neighbor identities. It serves the same purpose as MDS, dimensionality reduction, but unlike MDS, SNE makes use of a Gaussian distribution, centered on each object of the high dimensional space, and the densities under this distribution are used to define a probability distribution over all the potential neighbors of the object (24; 27).

Briefly, it starts by converting the high-dimensional Euclidean distances between datapoints, x_j and x_i into conditional probabilities $p_{j|i}$, representing the probability that x_i would pick x_j as its neighbor, if neighbors were picked in proportion to their probability density under a Gaussian centered at x_i . This probability will be high for nearby points, and almost infinitesimal for widely separated ones.

$$p_{j|i} = \frac{\exp(-||x_i - x_j||^2 / 2\sigma_i^2)}{\sum_{k \neq i} \exp(-||x_i - x_k||^2 / 2\sigma_i^2)} \quad (15)$$

where σ_i is the variance of the Gaussian distribution centered around x_i . Now for their low-dimensional counterparts, y_i and y_j , a similar conditional probability is computed (but with a fixed variance), denoted by $q_{j|i}$. If these conditional probabilities are equal, in other words, if the distributions are matched, the model is correctly mapping the data (27; 28).

So, the aim of the embedding is to match the distributions as well as possible, which is also achieved by minimizing a cost function. A natural measure of the faithfulness with which the probabilities match is the Kullback-Leibler divergence. Therefore a cost function C is defined by a sum of the Kullback-Leibler divergences between the original ($p_{j|i}$) and the induced ($q_{j|i}$) distributions over neighbors for each object. SNE minimizes C using a gradient descent method (27; 28).

$$C = \sum_i \sum_j p_{j|i} \log \frac{p_{j|i}}{q_{j|i}} \quad (16)$$

The t-SNE is a variation of SNE, with two important differences, which aim to solve some shortcomings of the SNE method (27; 28).

Firstly, since the Kullback-Leibler divergence is not symmetric, different types of error in the pairwise distances present in the low-dimensional map are not weighted equally. For instance, there is a large cost for using widely spaced map points to represent nearby datapoints, but a small cost for using neighboring map points to represent datapoints. In t-SNE, conditions to this function are applied to ensure that it is symmetrized, eliminating that problem. It is said to be symmetric because it has the property that $p_{ij} = p_{ji}$ and $q_{ij} = q_{ji}$, $\forall i, j$, hereby named joint probabilities. The new cost function C comes:

$$C = \sum_i \sum_j p_{ij} \log \frac{p_{ij}}{q_{ij}} \quad (17)$$

and this cost function is minimized by the gradient descent method given by:

$$C y_i = 4 \sum_j (p_{ij} - q_{ij})(y_i - y_j)(1 + ||y_i - y_j||^2)^{-1} \quad (18)$$

The issue known as the "Crowding Problem", lies in the fact that if small distances are to be accurately mapped, the moderately distanced datapoints will be placed much too far away in the representation. As a solution, in t-SNE, instead of using a Gaussian distribution, it is swapped by the heavy-tailed Student t-distribution with one degree of freedom (also known as Cauchy distribution) on the low-dimensional map, q_{ij} . The mismatched tails on this distribution compensate the mismatched dimensionalities on the data.

There are various parameters that can be tinkered with in a t-SNE application to optimize the cost function gradient descent, some of which are the number of iterations, early exaggeration, learning rate and perplexity, interpreted as a smooth measure of the effective number of neighbors; so adjusting all these parameters yields different results even for the same data set (28).

Machine Learning and Features

ML is the subfield of AI that gives "computers the ability to learn without being explicitly programmed" (29). Evolved from the study of pattern recognition, ML explores the construction and optimization of algorithms that can learn from, and make predictions on data. They operate by building and improving models from sample inputs, making data-driven decisions instead of following strict program instructions. It is closely related to (and often overlaps with) computational statistics, making regular use of mathematical and statistical methods.

Even with the powerful tools that ML has to offer, it is difficult for ML algorithms to produce proper results if the input is not preprocessed. There could exist outliers that need to be discarded, missing values on tests that should be eliminated or appended with accordingly interpolated values (30). This preprocessing is fundamental, even more so if the data is obtained from real life sensors, that might contain noise and interference effects that should be minimized, or malfunctions that should be accounted for. Such is not the case in the present project, as all the data is obtained from

simulations, so the preprocessing stage has a lighter overall significance.

If a large number of observations are registered, the whole data set turns into a high-dimensional one. It is important to reduce this dimensionality in order to handle the data adequately, and use it successfully in ML algorithms. Ideally, the reduced representation should have a dimensionality that corresponds to the intrinsic dimensionality of the data, the minimum number of parameters needed to account for the observed properties (31).

However, one needs to differentiate between the number of cases (observations) in a large data set, and the number of variables available for each case - these variables comprise specific information about the data and are referred to as "features". These features are not present in the original measurements, but signal processing tools can extract these from the raw data, enabling a more efficient use of ML algorithms. This procedure can be viewed as "nontrivial extraction of implicit, previously unknown and potentially useful information from data, or the search for relationships and global patterns that exist in databases" (32).

Feature Engineering plays a vital role in ML algorithms and big data analytics, encompassing the generation, extraction, transformation, selection, analysis and evaluation of features. Indeed, little can be achieved if there is a short amount of features to represent the underlying data objects, and the quality of the results obtained in those algorithms will reflect the quality of the available features themselves (33; 34).

Feature Engineering is often data specific and application dependent, which means that different data types - text, images, streaming data, social media data - require specialized techniques (33).

It is useful to distinguish three main types of features, besides simple **Statistical Features** (which can also be significant), based on the domain their information is in, namely **Time Domain**, **Frequency Domain** and **Time-Frequency Domain**:

Statistical features are the simplest form of features, obtained directly from the signal by statistical analysis, and represent basic information about the data. Some examples are the Mean, Variance, Standard Deviation, Skewness, Kurtosis and higher order moments, and even Maximum and Minimum values (Peaks). Even though they do not result from complex analysis and advanced methods, their information can be valuable (35).

Time domain features, are typically used to predict future values for signals using time-based models like the Autoregressive (AR), Integrated (I) and Moving Average (MA) models, that can be fused together in the ARIMA model first introduced by Box and Jenkins (36). However, some orders/parameters of these models can be used as a feature in itself, as well as the Auto-Correlation dimensions of the signal (where it is compared to itself with a small delay). The Auto-Correlation coefficients produced by the vibration of a healthy structure could be different than those from a faulty one. From the ML algorithms viewpoint, these features are just arrays of organized information to be used in a specific task, with no connection to the time-based models that originated them, or their purpose;

Frequency domain features are based on the frequency domain analysis, which is arguably the most far-reaching set of mathematical tools utilized in engineering, specially signal analysis, and its cornerstone is the Fourier Transform (FT). It is based on the premise that every function - no matter how complex it looks - can be decomposed into a sum of simpler functions, a concept proposed by Joseph Fourier in 1822 (37; 38).

Taking $f(t)$ as a time-dependant input signal, that may be composed by harmonic and/or periodic elements, its Fourier Transform $F(\omega)$ is called the signal's *spectrum*, and can be viewed as the frequency response - a transformation of the time signal into a sum of basis functions (sinusoidal) of various frequencies, which the original signal contains as periodic components, where (37; 39; 40):

$$F(\omega) = \int_{t=-\infty}^{\infty} f(t)e^{-j\omega t} dt \quad (19)$$

with $j = \sqrt{-1}$ and the complex exponentials as the sinusoids: $e^{j\theta} = \cos \theta + j \sin \theta$. A Fourier Transform pair is often written $f(t) \leftrightarrow F(\omega)$. The Inverse Fourier Transform is also applicable, changing the content from the frequency to the time domain:

$$f(t) = \frac{1}{2\pi} \int_{\omega=-\infty}^{\infty} F(\omega)e^{j\omega t} d\omega \quad (20)$$

$F(\omega)$, which is written as a complex number in terms of its magnitude and phase, ultimately tells how much content the original signal has at any frequency ω ;

The necessity for **Time-Frequency domain features** arises from the fact the the Fourier Transform is of great use to transform a signal into the frequency domain, where it has great resolution, at the expense of the time domain information, as it contains none. In other words, it is known at which frequencies the signal oscillates, but not at which time these oscillations occur. So if a signal has a dynamic frequency spectrum, i.e. the frequency content changing over time or frequencies appearing abruptly for a short period of time, the Fourier Transform will not expose them. For that, the Time-Frequency domain is approached, specially through the Short-Time Fourier Transform (STFT), the Wavelet Transform or the Hilbert-Huang Transform, among others (37).

The STFT can be used as a way of quantifying the change of a non-stationary signal's frequency and phase content over time, by dividing a time-based signal into shorter segments of equal length and then computing the Fourier Transform in each of those segments separately, therefore keeping in the results of the magnitude and phase content for each point in time. The use the Fast Fourier Transform on these segments yields the discrete-time STFT, expressed as:

$$STFT_{x(k)}(m, n) = \sum_{k=0}^{L-1} x(k)g(k-m)e^{-j2\pi nk/L} \quad (21)$$

where $x(k)$ denotes the discrete time signal, that is multiplied by $g(k)$, an L -point window function with a fixed size n , that will divide the signal into chunks as it slides through the signal with m amount of shift. The FFT is then applied

to each of these chunks to compute the STFT (41; 42). The Hamming window, a smooth, “bell-shaped” curve is a popular choice for the window function employed. The STFT can also be called a Gabor transform, if the window used is a Gaussian function (43).

The STFT is utilized to construct what is called the Spectrogram, a 2-D visualization that plots, in a logarithmic scale, the normalized, squared magnitude of the STFT coefficients (41; 44).

Machine Learning pipeline

Acquisition of simulation data

LW based NDT methods can detect incipient damage, often unnoticed by other techniques, with the help of suitable electric signals applied to a PZT actuator which induces the propagation of this type of waves on the structure or specimen. Other PZT sensors, placed strategically in the specimen, measure the vibrations and output electric signals, with distinct amplitude and phase from the input, and whose characteristics will depend on the existence and type of damage in the structure.

Data processing algorithms based on ML require large volumes of data to be trained and, therefore, it would be impracticable to use experimental data in their development. The alternative is to use simulation data from numerical models, generated with finite element method (FEM) software - ABAQUS. For the purpose of this project, an adhesive joint simulated specimen was modeled.

An adhesive joint among two aluminium plates, with a single-lap joint design with varying degrees of adhesion strength on each test (ranging from 600 to 270000 kPa), with 1 PZT actuator on the top plate and 1 PZT sensor on the lower plate. The aluminium plate has a density $\rho = 2500 \text{ kg/m}^3$, Poisson ratio $\nu = 0.33$ and Young modulus $E = 72.4 \text{ GPa}$. The chosen adhesive to simulate was a 0.2 mm layer of Nagase T-836/R-810, as it has great potential for industrial applications, specifically aeronautical and automotive. The simulated adhesive joint is presented on Figure 1.

This model was run 900 times, and since it measures only one sensor's displacement as a function of time, accounts for 900 time series. All signals obtained were made uniform as a vector of equal dimension, achieved by interpolating the whole original array of values, imposing a fixed time step of 5000 to fit an array of predetermined size. The simulation ran with a fixed time of 0.5 ms, as this is enough time to have the waves interact with the defects / adhesive joint and arrive at the sensor without receiving too many reflected waves from the opposite wall. The excitation signal chosen was a 5-cycle Hanning-windowed sinusoidal tone burst with the central frequency of 100 KHz, applied to the PZT elements.

As an example, two signals from different tests are shown in Figure 2, and 3, a test with a higher adhesion strength in the joint:

In Figure 2 only the top 10 peaks were marked directly on the time series plot, but the values of all the local minima and maxima of the entire domain are saved in an array, for each of the tests - a statistical feature.

It is perceptible that the second signal comes from a stronger, firmer and more consistent medium, as the LW

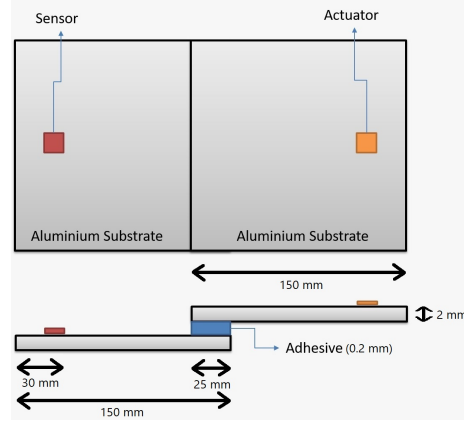


Figure 1. Model of the adhesive joint simulation setup.

propagates and arrives at the sensor more smoothly, creating a more balanced response. The average displacement measured on the sensor is higher, and all of the 10 peaks appear above the $1 \times 10^{-5} \text{ m}$ mark, while on the first test, the single highest peak falls short of that mark, being the only one that surpasses $0.75 \times 10^{-5} \text{ m}$.

Automatic Feature Extraction

Viewed as one of the general topics of feature engineering, Automatic Feature Extraction is a methodology capable of automatically generating a large number of features from a data set and subsequently selecting the most effective subset of these features to be applied in the ML algorithms. The best way to differentiate the information within the signals is to have the highest possible number of features being initially extracted from the time series, in all the domains discussed in the previous chapter, and then choosing the best, most meaningful and adequate subset to the problem at hand, so that ML algorithms can use it in the most effective way possible to detect damage (33).

The automation of the feature extraction process was key, and for that effect, **tsfresh** - Time Series Feature Extraction on basis of Scalable Hypothesis - a Python package developed by Christ et. al (45), was implemented, comprised of two main steps: the **feature extraction** and **feature selection**.

The first step is the feature extraction from the time series, resulting in a $M \times N$ matrix, where the M rows correspond to the time series, identified by their **id**, while each of the N columns correspond to the extracted features, characterized by the kind of time series (which sensor) that originated the data, followed by the feature calculator itself and lastly the key-value pairs of parameters configuring the respective feature calculator. A sample of the feature matrix is shown on Figure 4:

The second step, which can be run separately, in parallel with any other ongoing feature extraction thread, is the estimation of each feature's relevance to a given ML task, through hypothesis tests and calculation of the respective

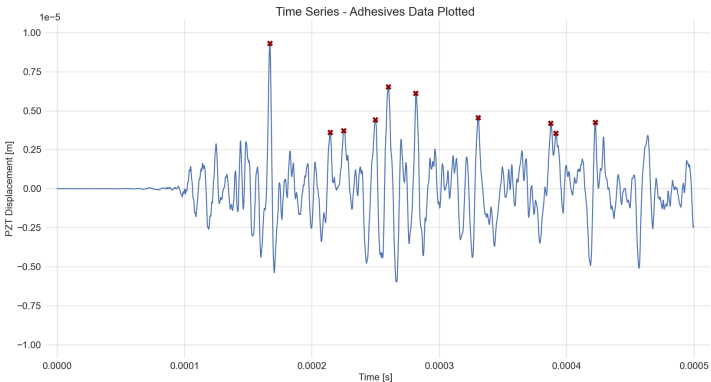


Figure 2. Representation of an adhesive joint test test, with a signal from the PZT Sensor and the top 10 peaks marked. Adhesion strength = 900 kPa.

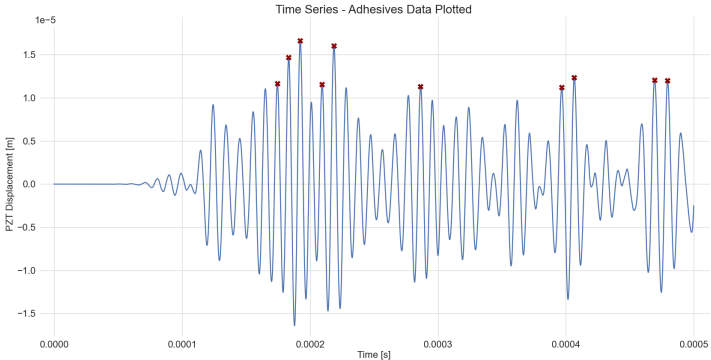


Figure 3. Representation of an adhesive joint test test, with a signal from the PZT Sensor and the top 10 peaks marked. Adhesion strength = 50100 kPa.

ID	d1_ft_coefficient_attr_angle_coeff_64	d2_change_quantiles_f_nqa_mean_nabi_tuv_gh_0.6_gf_64	d3_ft_coefficient_attr_angle_coeff_25	d4_benford_consistent
0	-165.821	5.35231e-08	162.193	0.988251
1	-166.597	6.29235e-08	-159.889	0.97646
2	-164.847	4.48842e-08	67.9614	0.965603
3	-171.661	6.10005e-08	158.88	0.969739
4	-159.386	7.38881e-08	171.275	0.962898
5	-158.972	9.23835e-08	133.348	0.912316
6	-173.121	5.3282e-08	155.487	0.975648
7	-159.821	4.74475e-08	67.5884	0.91597
8	-154.682	6.82938e-08	143.163	0.955324
9	-161.466	4.52758e-08	182.138	0.964783
10	-143.166	5.88839e-08	-152.86	0.959445
11	-69.8983	6.33425e-08	167.786	0.951394
12	-178.289	4.77189e-08	152.826	0.979217

Figure 4. tsfresh feature matrix sample.

p -values. The hypothesis tests are automatically configured depending on the type of supervised ML problem (classification/regression) and feature type (categorical/continuous). It also involves a multiple testing procedure, utilizing an instrument called *Benjamini-Hochberg Method*, which is designed to control the false discovery rate (FDR). This feature selection step is crucial, as the effectiveness of a feature is ultimately measured in terms of its performance to the ML task at hand, and whether or not it improves its metrics, in other words, whether or not the feature has relevance to the problem at hand (33).

Table 1. *tsfresh* classification-task oriented feature filtering steps results

Classes	Adhesive Joint				
	1	2	3	4	5
Extracted features	788				
Features with $p\text{-value} \leq 0.05$	681	636	599	598	590
Benjamini-Hochberg Selected features	657	559	555	571	571
Top features	244				

Through this selection method, the pool of extracted features considered relevant by the univariate hypothesis testing (those that scored p -values lower or equal to 0.05) is filtered, leaving only the so called “selected features”, which have remained relevant for the classification task of at least one class. Table 1 shows the feature filtering process results. The “Top” features are those considered relevant for all classes simultaneously. It is fair to mention that this automated feature selection module of *tsfresh* is just as appropriate and decisive as the feature extraction module itself. They work together seamlessly and elegantly, allowing for the whole direct data processing, from preprocessed time series to finely selected, ML-task oriented features.

Results and Discussion

Visualization of the data / Features

The results of the application of MDS and t-SNE is now presented, both to the signals’ original time series and the extracted/selected features.

The chart in Figure 5 represents the MDS applied to the time series themselves. The absence of legend is due to the fact that the results are not shown per class, but directly using the adhesion strength value, from the weakest adhesion being the deepest blue to the strongest adhesion in the dark red, yielding the direct realization that the LW propagation signals are as closely related as the adhesion strength itself.

Figure 6 presents the t-SNE mapping of the data. It follows the color map convention used on the MDS visualization, and the result has the same overall character, with a steady evolution of distances following the adhesion strength increase in a smoother trend than with the results obtained using MDS.

For the visualization of features, considering that the adhesion strength value varies from 600 to 270000 kPa, five classes were arbitrarily assumed, by dividing that range in five equal intervals, intended to illustrate qualitatively the data: **1** - Very Low Adhesion Force; **2** - Low Adhesion force; **3** - Medium Adhesion force; **4** - High Adhesion force; **5** - Very High Adhesion force; The target vectors are then composed by the corresponding time series id, that should be consistent with the features id, of its respective class.

In Figure 7, a feature calculated from a linear least-squares regression of the time series values, is represented in MDS mapping. The differentiation among classes is evident here, with the sole exception of class number 2 (low adhesion strength), that does not stand on its own, isolated from the others.

Supervised Machine Learning - Classification Algorithms

Naïve Bayes For each feature $\mathbf{x}$, the Naïve Bayes approach to classification is to formulate a probabilistic model that estimates the posterior probability, $P(y|\mathbf{x})$, of the different classes, y , and to predict the one with the largest posterior probability. According to Bayes’ Theorem, one has that:

$$P(y|\mathbf{x}) = \frac{P(\mathbf{x}|y)P(y)}{P(\mathbf{x})} \quad (22)$$

where $P(y)$ can be estimated by counting the proportion of class y in the training set, and $P(\mathbf{x})$ can be ignored since we are comparing different y on the same $\mathbf{x}$; thus, the only component that needs to be considered is $P(\mathbf{x}|y)$. If an accurate estimate for $P(\mathbf{x}|y)$ is obtained, that will correspond to the **Bayes optimal classifier**, with the smallest theoretical error rate. Estimating $P(\mathbf{x}|y)$ is not straightforward, given that it involves the estimation of exponential numbers of joint-probabilities of the features. That can be avoided by assuming that, in each class label, the n features are independent of each other, and so we can estimate the conditional probability by:

$$P(\mathbf{x}|y) = \prod_{i=1}^n P(x_i|y) \quad (23)$$

In the training stage, these probabilities are estimated, and then in the testing stage, a feature $\mathbf{x}$ will be predicted as label y , if y leads to the largest value of:

$$P(y|\mathbf{x}) \propto P(y) \prod_{i=1}^n P(x_i|y) \quad (24)$$

The different Naïve Bayes classifiers differ mainly in the assumptions made regarding the distribution of $P(x_i|y)$. In this case, a Normal distribution is appointed (46).

k-Nearest Neighbors In the **k-Nearest Neighbors** (KNN) classification algorithm, one relies on the simple principle that objects similar in the input space will also be similar in the output space. It is considered a *lazy learning* approach, known as *instance based* or *non-generalizing learning*, as it does not have an explicit training process nor does it attempt to construct a general internal model. It merely stores the instances of the training set. In training, the KNN model will pick out the k instances from the training set that are closer to the test instance. Then, for classification, the test instance will be classified to the majority class among the k nearest instances, with k being a value specified by the user. The basic KNN uses uniform weights: the value assigned to a query point is computed from a simple majority vote of the nearest neighbors. Under some circumstances, it is better to weigh the neighbors such that the nearer neighbors contribute more to the fit (46; 47).

Ensemble methods Ensemble methods are state-of-the-art ML approaches that train multiple learners to solve the same problem and combine their results, significantly improving the accuracy compared to a single learner model. Ensemble learning is also called *committee-based learning* or *multiple classifier systems*. They are constructed in two

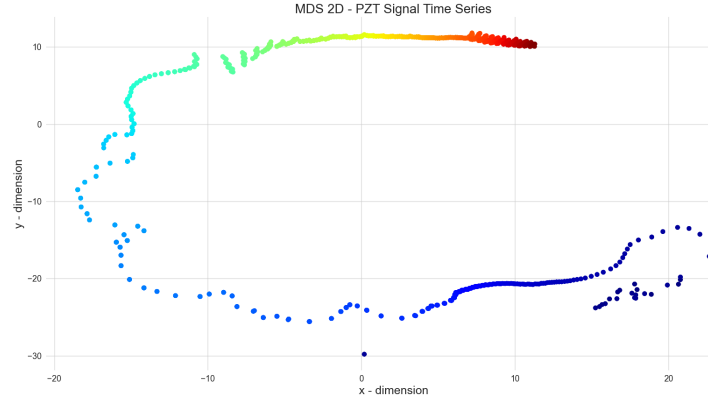


Figure 5. 2-D MDS Visualization of the adhesive joint simulation tests.

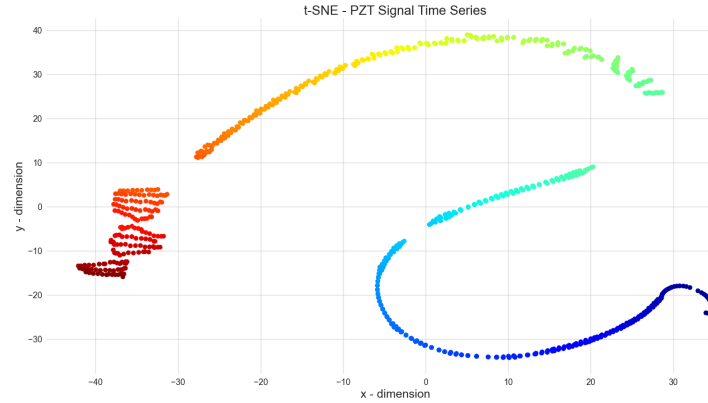


Figure 6. 2-D t-SNE Visualization of the adhesive joint simulation tests.

steps: generating the base models, that should be as accurate and diverse as possible, and then averaging their results (46).

The ensemble contains a number of learners called **base learners**, generated from the training data by a base algorithm, which can be decision trees, neural networks or other kinds of models. All of the three ensemble methods mentioned are based on the decision tree model, and by using a single base algorithm, they produce *homogenous* base learners, leading to **homogenous ensembles**. That implies that *heterogeneous* ensembles also exist, using various learning algorithms that get the name individual/component learners, instead of base learners (46). Before expanding on ensemble methods, defining the used base learner is in order.

A **Decision Tree** is a non-parametric model made up of tree-structured decision tests, working in a *divide-and-conquer* way, predicting the value of a target variable by learning simple decision rules inferred from the data features. It starts on the root node and from there each non-leaf node is associated with a feature test, also called a **split**. Data falling into the node will be split into subsets according to their

different results on the feature test, eventually landing in a leaf node, associated with a classification label to which that instance will be assigned. **Decision Tree** learning algorithms are generally recursive processes, since, in each step, a data set is given and a split is selected, then acting as the given data set for the next step. The key of the decision tree algorithm is in the selection criteria of the splits. Typical split criteria include the “information gain” or the Gini criteria (46).

A final distinction among ensemble methods is required on how the base learners are generated, which can be divided in two paradigms (46):

- **Boosting** - Refers to a family of algorithms that convert “weak learners” to “strong learners” by having the weak models working together. Characterized by being sequential ensemble methods, where the base learners are generated in succession, exploiting the dependence between them and boosting overall performance in a residual-decreasing way. Gradient Boosting is a representative of this kind;

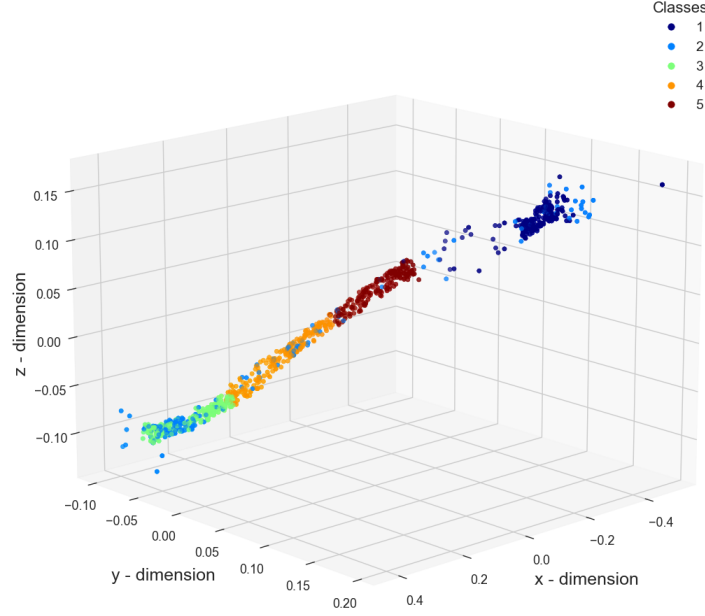


Figure 7. MDS 3-D Adhesive Joint Feature: "value_agg_linear_trend_attr_intercept_chunk_len_10_f_agg_var".

- **Bagging** - Exploits the independence between base learners by setting them up parallel to each other, reducing the error by combining them and averaging out the results. To have independent base learners, one possibility is to apply bootstrap sampling. That means training those base models with non-overlapped subsets of the training data pool. Not only does bagging improve performance, but also decreases variance and helps handling overfitting. Random Forest represents this kind.

According to Zhou (46), for many tasks, "the best off-the-shelf learning technique at present is an ensemble method such as **Random Forest**, facilitated with feature engineering which constructs/generates usually an overly large number of new features rather than simply working on the original features."

Classification Metrics and Evaluation

In ML, the algorithm's performance is presented and analysed through the results' **metrics**. Numerous metrics exist, specifically designed to evaluate certain aspects of each ML category (classification, regression, clustering, etc.), that can go from a broad assessment of the algorithms' behaviour, to very particular measurements that could be of special interest. The most mainstream and widely used classification metrics were examined, as presented by (47; 48): **Confusion Matrix**, also known as an error matrix, a confusion matrix is a square table layout that allows for the visualization of the performance of an algorithm. Each row of the matrix represents the instances in an actual class while each column

represents the instances in a predicted class. Evidently there are as many rows and columns as there are classes, and the diagonal represents the instances that were properly classified. The name stems from the fact that it makes it easy to see whether the system is confusing two classes (i.e. commonly mislabeling one as another). Figure 8 represents one of the confusion matrices obtained from the K-Nearest Neighbors algorithm, using the Top Features data subset. The accuracy is almost perfect, only missing the prediction of a few tests.

The **Accuracy Score (acc)** measures the ratio of correct predictions over the total number of instances evaluated:

$$acc = \frac{tp + tn}{tp + fp + tn + fn} \quad (25)$$

Precision Score (p) is the ratio of correctly predicted positive observations to the total number of positive observations. Intuitively, it is the ability of the classifier not to label as positive a sample that is negative:

$$p = \frac{tp}{tp + fp} \quad (26)$$

Recall Score (r) is the ratio of correctly predicted positive observations to all observations in actual class. Intuitively, it is the ability of the classifier to find all the positive samples:

$$r = \frac{tp}{tp + fn} \quad (27)$$

F1 Score (F1), also known as balanced F-score or F-measure, is a weighted average of recall and precision, that

is a parameter of great importance when having an uneven class distribution in data:

$$F1 = \frac{2 \times p \times r}{p + r} \quad (28)$$

Despite having a fairly balanced class distribution, the dataset is not perfectly balanced, so measuring the F1 score is valid.

The symbols tp , fp , tn and fn signify *true positive*, *false positive*, *true negative* and *false negative* respectively. All classification scores are calculated by averaging the results for each class.

	0	1	2	3	4
0	52	2	0	1	0
1	0	51	0	0	0
2	0	0	48	0	0
3	0	0	2	60	0
4	0	0	0	0	54

Figure 8. Confusion Matrix - KNN Classifier - Top Features data set.

Prior to the models being put into practice, the data set must be split into two parts: the **training / testing sets**. In this split, a ratio must be chosen between the data to which the model will be fitted to (trained on), and the data left aside to be used in the class prediction (tested on). In this work, the 70% training / 30% testing ratio was adopted.

While splitting, the properties of the original data set should be kept as much as possible, otherwise the results could be misleading (by chance of a really favorable or really poor split/sampling). To avoid that, a commonly used validation method is called ***k*-fold cross-validation**: the original data set is partitioned into k equal sized disjoint subsets, and then k runs of fitting/predicting are performed. For any iteration of this process, $k - 1$ subsets are randomly chosen as the training set, and testing of this fold is done with the remaining subset. The average results of the k runs' metrics are taken as results of the cross-validation (46; 49). A usual configuration is the 10-fold cross validation, which has been adopted in this work.

The adhesive joint strength classification results are shown in Table 2. The ensemble algorithms are utilizing the available features perfectly, the k -fold cross-validation shows 98-100% accuracy on all the 10 running instances, so they are as successful as one can be with this data set. Evaluating the **Gaussian Naïve Bayes** and **k-Nearest Neighbors** models, the first one shows a major excellent metrics also, although not as perfect as the **Random Forest Classifier**. As for the KNN, it shows major improvement on the top features subset, that contains 244 features. It is possible that some sort of feature number threshold was preventing the model from scoring higher.

Conclusions

A Structural Health Monitoring method, based on a Machine Learning classification pipeline, was successfully assembled, taking as inputs raw vibration signals from sensors, in a time series format. These signals originated from Finite Element

Model simulations of a Lamb Wave propagating through a solid medium - a single-lap adhesive joint (with variable adhesion strength). After preprocessing, the relation between the time series was visualized through the employment of dimensionality reduction techniques.

Those time series signals were then subject to an automated feature extraction and selection procedure, where a large pool of features - attributes that characterize the signals in various domains (time, frequency, time-frequency, statistical) - were derived from the time series, and filtered through statistical methods, according to their relevance to the classification task.

Finally, those features were used to train Supervised Machine Learning algorithms, making them capable of predicting the approximate adhesion strength of the single-lap adhesive joint with great accuracy.

The principal conclusions drawn from this project are:

- Feature selection is a crucial part of any Machine Learning project that involves feature engineering, as the best results will emerge from the algorithms when the best possible set of features is available;
- More training data generally means better performance of the algorithms, so the working data set should be as big as possible;
- Ensemble methods are the best off-the-shelf ML algorithms in terms of classification performance, specially if applied along with feature engineering.

References

- [1] M. Hong, Z. Su, Y. Lu, H. Sohn, X. Qing, Locating fatigue damage using temporal signal features of nonlinear lamb waves, *Mechanical Systems and Signal Processing* 60 (2015) 182–197.
- [2] Z. Chen, R. Adams, L. F. Da Silva, Prediction of crack initiation and propagation of adhesive lap joints using an energy failure criterion, *Engineering Fracture Mechanics* 78 (6) (2011) 990–1007.
- [3] D. N. Alleyne, The nondestructive testing of plates using ultrasound lamb waves. (1991).
- [4] M. Mańka, M. Rosiek, A. Martowicz, T. Stepinski, T. Uhl, Pzt based tunable interdigital transducer for lamb waves based ndt and shm, *Mechanical Systems and Signal Processing* 78 (2016) 71–83.
- [5] H. Lamb, On waves in an elastic plate, *Proceedings of the Royal Society of London. Series A, Containing Papers of a Mathematical and Physical Character* 93 (648) (1917) 114–128.
- [6] L. Rayleigh, On Waves Propagated along the Plane Surface of an Elastic Solid, *Proceedings of the London Mathematical Society* s1-17 (1) (1885) 4–11.
- [7] S. Kessler, S. Spearing, Structural health monitoring in composite materials using lamb wave methods (2001).
- [8] V. Giurgiutiu, A. Cuc, Embedded non-destructive evaluation for structural health monitoring, damage detection, and failure prevention, *The Shock and Vibration Digest* 37 (2005).
- [9] J. Dodson, D. Inman, Thermal sensitivity of lamb waves for structural health monitoring applications, *Ultrasonics* 53 (3) (2013) 677–685.

Table 2. Classification algorithms' metrics - Adhesion Strength prediction on Single Lap Joint - 70/30 data split.

Models		Adhesive Joint Data Set		
		Full Features	Selected Features	Top Features
Naïve Bayes	acc	0.948	0.948	0.981
	p	0.952	0.952	0.981
	r	0.945	0.945	0.982
	F1	0.948	0.948	0.982
k-Nearest Neighbors	acc	0.552	0.552	0.982
	p	0.566	0.566	0.981
	r	0.550	0.550	0.980
	F1	0.555	0.555	0.982
Gradient Boosting	acc	0.996	1.00	0.993
	p	0.997	1.00	0.993
	r	0.996	1.00	0.993
	F1	0.996	1.00	0.993
Random Forest	acc	1.00	1.00	1.00
	p	1.00	1.00	1.00
	r	1.00	1.00	1.00
	F1	1.00	1.00	1.00

- [10] Z. Su, L. Ye, Y. Lu, Guided lamb waves for identification of damage in composite structures: A review, *Journal of Sound and Vibration* 295 (3) (2006) 753–780.
- [11] V. Giurgiutiu, Tuned lamb wave excitation and detection with piezoelectric wafer active sensors for structural health monitoring, *Journal of Intelligent Material Systems and Structures* 16 (2005) 291 – 305.
- [12] R. D. Adams, R. D. Adams, J. Comyn, W. C. Wake, W. Wake, *Structural adhesive joints in engineering*, Springer Science & Business Media, 1997.
- [13] L. F. Da Silva, A. Öchsner, R. D. Adams, *Handbook of adhesion technology*, Springer Science & Business Media, 2011.
- [14] D. Packham, B. Cope, A. Kinloch, D. Aubrey, M. Pascoe, B. Kneafsey, D. Dixon, D. Brewis, G. Critchlow, D. Dillard, S. Millington, G. Curtis, *Handbook of Adhesion*, John Wiley & Sons, Ltd, 2005.
- [15] C. B. (Ed.), C. Bajaj, C. F. J. Wiley, *Data visualization techniques* (1998).
- [16] P. E. Rauber, A. X. Falcao, A. C. Telea, et al., Visualizing time-dependent data using dynamic t-sne. (2016).
- [17] J. T. Machado, A. M. Lopes, Fractional state space analysis of temperature time series, *Fractional Calculus and Applied Analysis* 18 (6) (2015) 1518–1536.
- [18] W. Aigner, S. Miksch, W. Müller, H. Schumann, C. Tominski, Visualizing time-oriented data – a systematic view, *Computers Graphics* 31 (2007) 401–409. doi:10.1016/j.cag.2007.01.030.
- [19] L. Al Shalabi, Z. Shaaban, Normalization as a preprocessing engine for data mining and the approach of preference matrix, in: 2006 International Conference on Dependability of Computer Systems, 2006, pp. 207–214. doi:10.1109/DEPCOS-RELCOMEX.2006.38.
- [20] A. Zheng, A. Casari, *Feature engineering for machine learning: principles and techniques for data scientists*, "O'Reilly Media, Inc.", 2018.
- [21] F. W. Young, D. F. Harris, *Multidimensional scaling*, LL Thurstone Psychometric Laboratory, University of North Carolina, 1983.
- [22] I. Borg, P. J. Groenen, *Modern multidimensional scaling: Theory and applications*, Springer Science & Business Media, 2005.
- [23] G. R. Hancock, R. O. Mueller, L. M. Stapleton, *The reviewer's guide to quantitative methods in the social sciences*, Routledge, 2010.
- [24] L. Wilkinson, et al., Multidimensional scaling, *Systat* 10.2 Statistics II (2002) 119–145.
- [25] S. A. Mohammadi, B. Prasanna, Analysis of genetic diversity in crop plants—salient statistical tools and considerations, *Crop science* 43 (4) (2003) 1235–1248.
- [26] J. T. Machado, A. M. Lopes, On the mathematical modeling of soccer dynamics, *Communications in Nonlinear Science and Numerical Simulation* 53 (2017) 142–153.
- [27] G. Hinton, S. T. Roweis, Stochastic neighbor embedding, in: NIPS, Vol. 15, Citeseer, 2002, pp. 833–840.
- [28] L. Van der Maaten, G. Hinton, Visualizing data using t-sne., *Journal of machine learning research* 9 (11) (2008).
- [29] P. Ongsulee, Artificial intelligence, machine learning and deep learning, in: 2017 15th International Conference on ICT and Knowledge Engineering (ICT&KE), IEEE, 2017, pp. 1–6.
- [30] A. Desarda, <https://towardsdatascience.com/getting-data-ready-for-modelling-feature-engineering-feature-selection-dimension-reduction-77f2b9fad0b>, accessed: 31-07-2021 (2018).
- [31] L. Van Der Maaten, E. Postma, J. Van den Herik, et al., Dimensionality reduction: a comparative review, *J Mach Learn Res* 10 (66-71) (2009) 13.
- [32] Y. Benjamini, M. Leshno, Statistical methods for data mining, in: *Data mining and knowledge discovery handbook*, Springer, 2005, pp. 565–587.
- [33] G. Dong, H. Liu, *Feature engineering for machine learning and data analytics*, CRC Press, 2018.
- [34] S. Ozdemir, D. Susarla, *Feature Engineering Made Easy: Identify unique features from your dataset in order to build powerful machine learning systems*, Packt Publishing Ltd,

- 2018.
- [35] E. (https://stats.stackexchange.com/users/16137/emile), <https://stats.stackexchange.com/questions/50807/features-for-time-series-classification>, accessed: 05-08-2021 (2014).
- [36] Y. Xiong, D.-Y. Yeung, Time series clustering with arma mixtures, *Pattern Recognition* 37 (8) (2004) 1675–1689.
- [37] A. Taspinar, <https://ataspinar.com/2018/04/04/machine-learning-with-signal-processing-techniques/>, accessed: 08-08-2021 (2018).
- [38] D. J. Struik, <https://www.britannica.com/biography/Joseph-Baron-Fourier>, accessed: 09-08-2021 (2021).
- [39] P. Heckbert, Fourier transforms and the fast fourier transform (fft) algorithm, *Computer Graphics - Carnegie Mellon University* 2 (1995) 15–463.
- [40] S. R. Kulkarni, Frequency domain and fourier transforms, *Lecture Notes - Introduction to Electrical Signals and Systems* (2002).
- [41] N. Kehtarnavaz, **Chapter 7 - frequency domain processing**, in: N. Kehtarnavaz (Ed.), *Digital Signal Processing System Design* (Second Edition), second edition Edition, Academic Press, Burlington, 2008, pp. 175–196. doi:<https://doi.org/10.1016/B978-0-12-374490-6.00007-6>. URL <https://www.sciencedirect.com/science/article/pii/B9780123744906000076>
- [42] B. Rajoub, **Chapter 2 - characterization of biomedical signals: Feature engineering and extraction**, in: W. Zgallai (Ed.), *Biomedical Signal Processing and Artificial Intelligence in Healthcare, Developments in Biomedical Engineering and Bioelectronics*, Academic Press, 2020, pp. 29–50. doi:<https://doi.org/10.1016/B978-0-12-818946-7.00002-0>. URL <https://www.sciencedirect.com/science/article/pii/B9780128189467000020>
- [43] M. Kiyimik, I. Guler, A. Dizibuyuk, M. Akin, Comparison of stft and wavelet transform methods in determining epileptic seizure activity in eeg signals for real-time application, *Computers in biology and medicine* 35 (2005) 603–16. doi:[10.1016/j.combiomed.2004.05.001](https://doi.org/10.1016/j.combiomed.2004.05.001).
- [44] N. Sairamya, L. Susmitha, S. Thomas George, M. Subathra, **Chapter 12 - hybrid approach for classification of electroencephalographic signals using time-frequency images with wavelets and texture features**, in: D. J. Hemanth, D. Gupta, V. Emilia Balas (Eds.), *Intelligent Data Analysis for Biomedical Applications, Intelligent Data-Centric Systems*, Academic Press, 2019, pp. 253–273. doi:<https://doi.org/10.1016/B978-0-12-815553-0.00013-6>. URL <https://www.sciencedirect.com/science/article/pii/B9780128155530000136>
- [45] M. Christ, N. Braun, J. Neuffer, A. W. Kempa-Liehr, **Time series feature extraction on basis of scalable hypothesis tests (tsfresh – a python package)**, *Neurocomputing* 307 (2018) 72–77. doi:<https://doi.org/10.1016/j.neucom.2018.03.067>. URL <https://www.sciencedirect.com/science/article/pii/S0925231218304843>
- [46] Z.-H. Zhou, *Ensemble Methods: Foundations and Algorithms*, Chapman and Hall/CRC, 2019.
- [47] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, E. Duchesnay, Scikit-learn: Machine learning in Python, *Journal of Machine Learning Research* 12 (2011) 2825–2830.
- [48] M. Hossin, M. N. Sulaiman, A review on evaluation metrics for data classification evaluations, *International journal of data mining & knowledge management process* 5 (2) (2015) 1.
- [49] G. Chandrashekar, F. Sahin, A survey on feature selection methods, *Computers & Electrical Engineering* 40 (1) (2014) 16–28.

Appendix D

Paper D

<https://doi.org/10.3390/app13042642>

Article

Identifying Weak Adhesion in Single-Lap Joints Using Lamb Wave Data and Artificial Intelligence Algorithms

Gabriel M. F. Ramalho ^{1,*} , António M. Lopes ^{1,2,*} , Ricardo J. C. Carbas ^{1,2}  and Lucas F. M. Da Silva ^{1,2} 

¹ Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal

² INEGI—Institute of Science and Innovation in Mechanical and Industrial Engineering, 4200-465 Porto, Portugal

* Correspondence: gmframalho@gmail.com (G.M.F.R.); aml@fe.up.pt (A.M.L.)

Abstract: In the last few years, the application of adhesive joints has grown significantly. Adhesive joints are often affected by a specific type of defect known as weak adhesion, which can only be effectively detected through destructive tests. In this paper, we propose nondestructive testing techniques to detect weak adhesion. These are based on Lamb wave (LW) data and artificial intelligence algorithms. A dataset consisting of simulated LW time series extracted from single-lap joints (SLJs) subjected to multiple levels of weak adhesion was generated. The raw time series were pre-processed to avoid numerical saturation and to remove outliers. The processed data were then used as the input to different artificial intelligence algorithms, namely feedforward neural networks (FNNs), long short-term memory (LSTM) networks, gated recurrent unit (GRU) networks, and convolutional neural networks (CNNs), for their training and testing. The results showed that all algorithms were capable of detecting up to 20 different levels of weak adhesion in SLJs, with an overall accuracy between 97% and 99%. Regarding the training time, the FNN emerged as the most-appropriate. On the other hand, the GRU showed overall faster learning, being able to converge in less than 50 epochs. Therefore, the FNN and GRU presented the best accuracy and had relatively acceptable convergence times, making them the most-suitable choices. The proposed approach constitutes a new framework allowing the creation of standardized data and optimal algorithm selection for further work on nondestructive damage detection and localization in adhesive joints.

Keywords: artificial intelligence; adhesive joints; machine learning; Lamb wave



Citation: Ramalho, G.M.F.; M. Lopes, A.; Carbas, R.J.C.; Da Silva, L.F.M. Identifying Weak Adhesion in Single-Lap Joints Using Lamb Wave Data and Artificial Intelligence Algorithms. *Appl. Sci.* **2023**, *13*, 2642. <https://doi.org/10.3390/app13042642>

Academic Editors: Furui Wang, Zhen Zhang and Chao Xu

Received: 30 January 2023

Revised: 11 February 2023

Accepted: 15 February 2023

Published: 18 February 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In recent years, there has been an increase in the use of adhesive joints in many industries. They are attractive due to their ability to bond different classes of materials, such as metals and composites, while uniformly distributing stress and being lighter than conventional joining methods, namely rivets [1–3]. Different types of adhesive joints can be manufactured, the single-lap joint (SLJ) being one of the most-used, with applications ranging from the automotive to the aeronautical industries [4]. Although the adoption of adhesive joints is widespread, their use in critical primary structures is still limited due to their inability to meet the needed strict certification and inspection criteria [5]. Existing standards require that, for any joining mechanism, there must exist reliable and robust nondestructive testing (NDT) methods for damage detection. Current NDT methods have strong limitations with adhesive joints, and certain types of damage cannot be effectively detected [5–7], as is the case of weak adhesion. Weak adhesion is characterized by a reduction of at least 20% of the maximum adhesive strength of the joint, without presenting any discernible voids, cracks, or other visible alterations in the structure. Weak adhesion is normally caused by contamination between the adhesive and the substrate and is commonly due to the presence of oil or dust or improper surface preparation for the desired adhesive [8].

Some NDT methods have been proposed for detecting weak adhesion. The one that has recently shown the most-promising results involves Lamb waves (LWs). LWs are a form of elastic disturbance that propagates through thin plates with shallow to no curvature and possess the capacity to travel long distances without large signal attenuation [9,10]. These properties come with the disadvantage that the raw signals are extremely complex, and depending on the frequencies and materials used, they are multimodal, which further complicates any required type of analysis [11]. This complexity can be mitigated by choosing appropriate methods to evaluate and process the LW data. One such option is the use of machine learning methods applied to the time series, as they allow a hands-off approach for detecting and classifying any damage present in the bonded structures. For using machine learning, large datasets are often needed for training and testing the algorithms. Creating large datasets experimentally is costly or even impracticable. Therefore, developing numerical models of the SLJ and, subsequently, validating them with experimental data reduce the overall burden. An added benefit is that any large volumes of data can be obtained to develop machine learning algorithms.

This paper proposes an NDT technique based on LW data and artificial intelligence algorithms for detecting weak adhesion in SLJs. Initially, a dataset was generated by simulating LWs propagating in an SLJ subjected to multiple levels of weak adhesion. This was accomplished by a finite-element model (FEM) developed in the software Abaqus (Dassault Systemes, Vélizy-Villacoublay, France), which generated over 1000 variations of weak adhesion at the SLJ. The numerical data were validated with experimental tests, for the sake of reliability, thus forming the base of the present work. The raw data were pre-processed to remove outliers and generate normalized time series. These processed data were then used in different artificial intelligence algorithms, namely feedforward neural networks (FNNs), long short-term memory (LSTM) networks, gated recurrent unit (GRU) networks, and convolutional neural networks (CNNs). These data-driven algorithms were chosen as they are widely used for time series forecasting, while still being commonly used in other non-time related datasets. The algorithms were adjusted and compared in terms of accuracy and training burden. The four methods for LW data processing allowed not only accurately detecting up to 20 different levels of weak adhesion in SLJs, but also choosing an efficient training method for the problem at hand. The proposed framework allows the correlation between the methods' parameters, accuracy, and training time and can be further used with different data and algorithms.

This paper is divided into sections as follows: Section 2 presents a literature review on the subjects addressed in the paper, namely LWs, adhesive joints, and defects. Section 3 introduces each artificial intelligence method adopted in the paper. Section 4 describes the SLJ model and the generation of the dataset. Section 5 presents the algorithms' adjustments and discusses the obtained results. Finally, Section 6 summarizes the main conclusions.

2. Preliminary Concepts

This section presents a model for LWs and introduces adhesive joints and their possible defects.

2.1. Lamb Waves

An LW is a type of elastic guided wave that moves through a solid medium, exhibiting pressure (P) and shear (S) propagation modes. When applied to a medium that has boundary conditions, reflection emerges and creates complex patterns. LWs present a particularly interesting property, which is their capacity to travel long distances and even pass through multiple materials with small attenuation [12,13]. When LWs interact with a defect in the material, they alter their wave pattern, and thus, they are sensitive enough to detect, and even discern between, the damage type, size, and location [14]. When propagating in a thin plate, an LW presents two fundamental modes, namely the symmetric (S_n) and the

anti-symmetric (An) modes. These modes occur in relation to the mid-plane of the plate. The vector of displacement of these waves can be analytically described by

$$\mu \nabla^2 \mathbf{u} + (\lambda + \mu) \nabla \nabla \cdot \mathbf{u} = \rho \frac{\partial^2 \mathbf{u}}{\partial t^2}, \quad (1)$$

where μ and λ stand for the Lamé constants, which are two material-dependent quantities that come from the elastic stress–strain relationships, ρ is the material's mass density, and the vector $\mathbf{u}$ represents the displacement, such that

$$\mathbf{u} = \nabla \Phi + \nabla \times \Psi, \quad (2)$$

with Φ and Ψ denoting potentials.

These equations can be divided into the transverse and longitudinal displacements and be written, in turn, by defining the longitudinal (L) wave speed $c_L^2 = (\lambda + 2\mu)/\rho$ and the transverse (T) wave speed $c_T^2 = \mu/\rho$, yielding:

$$\begin{aligned} \frac{\partial^2 \Phi}{\partial x^2} + \frac{\partial^2 \Phi}{\partial y^2} + \frac{\omega^2}{c_L^2} \Phi &= 0, \\ \frac{\partial^2 \Psi}{\partial x^2} + \frac{\partial^2 \Psi}{\partial y^2} + \frac{\omega^2}{c_T^2} \Psi &= 0, \end{aligned} \quad (3)$$

where ω stands for the angular frequency.

One way to visualize LWs is through their dispersion curves, where it is possible to depict the phase alteration depending on the frequency [15–18]. In the case of damage detection applications, the dispersion must be kept to a minimum, together with the attenuation, while still maximizing the sensitivity. This can be achieved by using a windowed tone burst as an excitation signal, as is the case of a Hann window. Several possible actuators can be employed, namely piezoelectric, due to their versatility, lightweight, and low cost. These elements have the advantage of being used also as sensors and possess a wide bandwidth, which can allow for multiple frequencies to be studied [14,19].

2.2. Adhesive Joints and Defects

An adhesive is a substance that has the capacity to join two materials together, independently of their (dis)similarity, giving them the ability to resist any form of separation [20]. When an adhesive connects two separate parts, an adhesive joint is formed. This concept can be further expanded by classifying the parts as substrates, before the bonding process, and adherents, after the creation of the joint [20]. Furthermore, the adhesive layer in contact with the adherents is called an interface, also known as the boundary layer [6].

When comparing adhesive joints with traditional fastening methods, their benefits include a more uniform distribution of stress along the bonded area, which yields good resistance to dynamic solicitation and excellent load transmission, as well as higher stiffness. Due to not using bulky fasteners, there is also a large reduction of the weight of the structure and, consequently, a minimization of the cost. However, these benefits also come with many disadvantages, which hinder the widespread application of bonded primary structures. Indeed, a major drawback is the absence of effective NDT techniques to detect damage [6,20]. The NDT methods need to be robust because, even if an adhesive is adequate for an application, many variables can alter the overall quality of the bonded joint and lead to premature mechanical failure. Common problems affecting adhesive joints are the lack of proper surface finishing, an incomplete or altered curing cycle, high humidity, or a degraded chemical composition caused by improper handling or storing of an adhesive [21]. These perturbations, when verified together, can cause a defective part, but there are cases when only one of these issues occurs. This can lead to damage types like those illustrated in Figure 1. These defects can occur in several places in the bond, such as cohesively within the adhesive, inter-facially between the adherend and adhesive,

or segmented throughout the bonded joint. Often, these are voids, debonds, porosity, or cracks within the adhesive layer. A few of these defects are detectable by certain NDT methods, but there is one defect in particular that still cannot be effectively detected by NDT, specifically weak adhesion. This defect consists of an inter-facial defect that reduces the maximum strength of an adhesive joint by at least 20% and is extremely hard to detect by conventional methods, as there is no gap or alteration in the structure; just a small reduction in the overall surface adhesion exists.

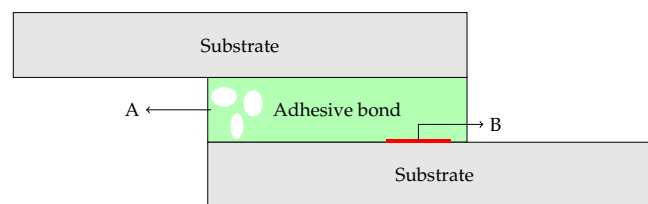


Figure 1. Representation of common defects in an SLJ, with “A” illustrating voids in the adhesive and “B” indicating weak adhesion.

3. Artificial Intelligence Algorithms

This section introduces the machine learning algorithms that were used in this paper.

3.1. Feedforward Neural Networks

The multi-layer FNN has been extensively used in multiple applications, starting with the work [22], where backpropagation algorithms were first used to adjust the weights in the hidden layers. In an FNN, the elements that process the data, also known as neurons, are structured in multiple successive layers that go from the input to the output (Figure 2). These layers are all interconnected in such a way that all elements in a layer have their output connected to every element in the next layer. Associated with each connection, there is a value, called the weight, which is adjusted during the learning phase [23,24]. Each neuron of a layer applies the associated weight and utilizes a nonlinear function to transform the data that pass through it. A commonly used function is the sigmoid function [25]:

$$g(h) = \frac{1}{1 + e^{-h}} \quad (4)$$

where h denotes a dimensionless variable.

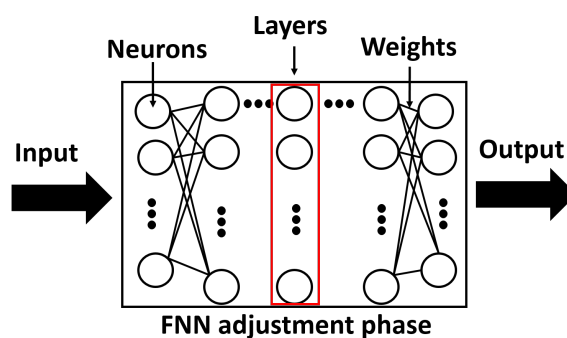


Figure 2. Fundamental architecture of an FNN with the interaction of each component represented.

The general and simplified intent behind an FNN is to reduce the error between the processed data and target values previously known. This is performed by passing the data through the neurons from the input to the output and, then, comparing the values with the training data previously saved and known. The error that is obtained is used to determine a performance function, which is continuously differentiable and correlates all the weights present from the output to the input layer. Two examples of such performance functions that can be used are the gradient-descent-based algorithms and the mean-squared error (MSE). These functions have weights as variables and are minimized by altering them [25]. The FNN model has been proven to be successful in modeling complex problems in a large range of areas, from image compression to forecasting and signal prediction [22]. However, this model presents the disadvantage that all elements in each layer are interconnected to the next and previous layers. This requires a careful analysis of the problem when mapping the data, as well as caution relative to the number of layers and elements used. The higher the number of layers, the larger the datasets required and the more computationally intensive the process will be. Thus, it is preferable to implement an FNN with a small number of layers and elements [22].

3.2. Recurrent Neural Network

The RNN is a type of artificial neural network that differentiates itself by “memorizing” information that can be later used in new data. This is performed by storing the output activation from the layers and applying them together when feeding a new input to the algorithm [26]. Although RNNs are powerful and have been applied to many problems, they suffer from a reduction or “explosion” in the gradient during backpropagation. This, in turn, does not allow for the layers closer to the input to have their weights altered or altered to such a degree that they make others irrelevant and, thus, not contribute positively to the solution [27,28]. To mitigate this problem, a few algorithms, such as LSTM and the GRU, which contain different gating units, have been created.

3.2.1. Long Short-Term Memory

To mitigate the vanishing gradient problem, LSTM utilizes an input gate and a forget gate, as shown in Figure 3 (circled in green and yellow colors, respectively), to create a constant error carousel (CEC) [29,30]. The CEC works by enforcing a constant error flow within a special cell controlled by the gate units, which learn when to grant access (circled in red color) [31]. The various gates used in the CEC can be described as

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f), \quad (5)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \quad (6)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o), \quad (7)$$

while the equations for the candidate state, cell state, and final output are

$$c'_t = \tanh(W_c[h_{t-1}, x_t] + b_c), \quad (8)$$

$$c_t = f_t c_{t-1} + i_t c'_t, \quad (9)$$

$$h_t = o_t \cdot \tanh(c_t). \quad (10)$$

In these equations, f_t is the forget gate, i_t is the input gate, o_t is the output gate, c_t is the cell state, c'_t is the candidate state, and h_t is the final output. Furthermore, W_x represents applied weights; h_{t-1} are the outputs of the previous LSTM block; x_t are the inputs at the current timestamps; b_x are the biases for the gates. These gates can be easily visualized in Figure 3, where the components are in yellow, the layers are in dark blue, the line that divides represents a variable copied, and lines combining represent concatenation. Finally, the output gate is circled in purple color and serves as the output of the cell.

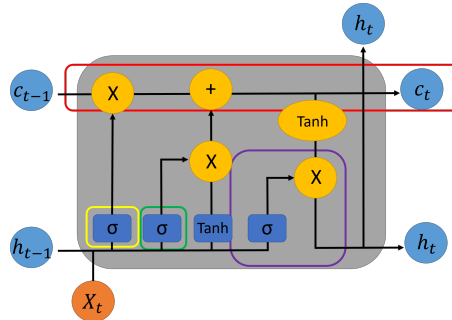


Figure 3. The architecture of an LSTM cell with the input cell circled in green, the forget cell in yellow, the cell state in red, and finally, the output gate in purple.

3.2.2. Gated Recurrent Unit

The GRU has been used in many applications, but has seen more significant results in music and speech modeling, as well as natural language processing. This method was developed with the intent of allowing each recurrent unit to alter the sequence of dependencies in an adaptive manner over time. To accomplish this, the unit was built with the following four steps, where x_t is the current input, h_{t-1} is the output of the previous step, W and U are parameter matrices for the weights, and σ is the sigmoid function [29,32]:

1. The first step is an update gate, as shown in Figure 4 (circled in green color), which is used to determine how much information will be updated in the unit. This gate is denoted as z_t^j and calculated by:

$$z_t^j = \sigma(W_z x_t + U_z h_{t-1})^j.$$

2. The next step is a reset gate, seen in Figure 4, circled in purple, denoted as r_t^j and calculated by:

$$r_t^j = \sigma(W_r x_t + U_r h_{t-1})^j.$$

This gate is used to determine how much information needs to be forgotten. When the value of this gate is close to zero, it determines that the j -th information should be forgotten in the current memory. Any value close to one means that the data will be preserved.

3. The third step is to determine the current memory. This gate is denoted as h_t^j in the following expression and, in Figure 4, seen as h_t .

$$h_t^j = \tanh(W_h x_t + r_t \cdot U_h h_{t-1})^j.$$

This gate also uses the Hadamard product to decide how much of the hidden state of the content should be forgotten.

4. Finally, the last step is to determine the information to be stored in the hidden layer at the current iteration that will be passed onto the next cell. This step is denoted as h_t in the following equation and, in Figure 4, is denoted as h_{t-1} :

$$h_t = (1 - z_t^j) h_t^j + z_t^j \tilde{h}_t^j.$$

These steps can all be easily visualized in Figure 4.

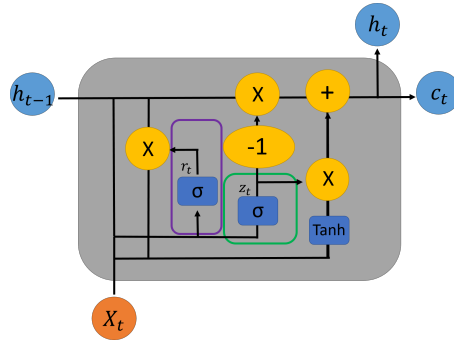


Figure 4. Architecture of a GRU cell with the reset gate circled in purple and the update gate in green.

3.3. Convolutional Neural Network

Overall, the CNN can be seen as having a multi-layer feedforward structure and, normally, utilizes other types of layers as a complement to the convolutional ones. The main characteristics that define a CNN are the representation of the input layer and the way these input elements are processed in the CNN layer, which allows for significant advantages while creating a few problems. The first layer used is normally seen as a grid that can be compared to 2D images or pixels (or even a signal in the time domain arranged in an $n \times 1$ column vector), as seen in Figure 5.

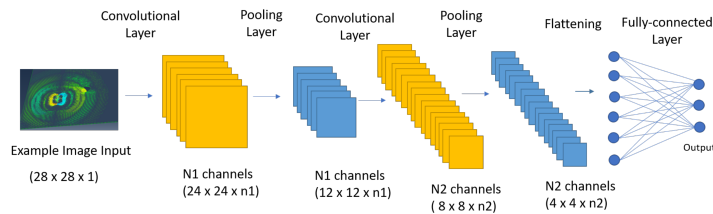


Figure 5. Architecture of a CNN comprising convolutional and pooling layers with a final flattening layer. The dimensions of each layer are represented under each one.

Another characteristic that defines a CNN is a convolutional operation called the kernel, which is applied between the weights and the input CNN layer. This is performed to provide at the output of the layer a feature map [33,34]. When evaluating the inputs and the kernels used in a convolutional layer as square $n \times n$ arrays, the size of the output layer can be calculated using

$$n_{out} = \left\lceil \frac{n_{in} + 2p - k}{s} \right\rceil + 1, \quad (11)$$

where the width or height of the output and input arrays is represented by n_{out} and n_{in} , respectively. Finally, two other parameters complement these layers: the convolutional padding size is a parameter that is used when it becomes adequate to include additional information on the border arrays, while the sliding increment of the kernels over the input array is the stride parameter. These can be seen as elaborated in the following equations:

$$s(t) = \int x(a)w(t-a)da, \quad (12)$$

$$s(t) = (x * w)(t), \quad (13)$$

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a), \quad (14)$$

where n_{out} represents the number of output features obtained from the convolution, n_{in} is the number of input features, p is the convolutional padding size, k stands for the kernel size, and s is the stride size to be used. One way to better visualize these kernels is to see them as filters that go through the input values, using a constant weight to identify specific features in the input data. These values are refined during the learning phase. Using a CNN instead of an FNN allows for a smaller increase in the number of variables and parameters when setting more layers, as the weights are used with all inputs. This allows for more layers and a deeper learning FNN implementation. Furthermore, it allows for a way to associate values that are near one another, which can be of interest in images, time series, or any other sequential signal. Finally, the convolutional maps are normally associated with pooling stages and processed through a nonlinear rectified linear unit (RELU) function to stabilize values in specific locations [23].

4. Numerical Simulated Data

To fully utilize the combination of LWs and machine learning methods, it is necessary to create a large dataset that can be used to train and test the algorithms. As there is a need for a large volume of data, creating these experimentally would be labor-intensive, costly, and difficult to obtain consistently. Therefore, the alternative of using simulation data from accurate and experimentally validated numerical models has considerable advantages. Herein, a model of an SLJ composed of two aluminum substrates bonded with the epoxy-modified Nagase T-836/R-810 was adopted. This adhesive was chosen as it has great potential for industrial applications, specifically in the aeronautical and automotive sectors. However, any other epoxy-based adhesive with similar mechanical properties can be used with the same methodology. One actuator was chosen to excite the LWs, and one sensor captured the SLJ response. The specimen dimensions and the positions of the actuator and sensor can be seen in Figure 6.

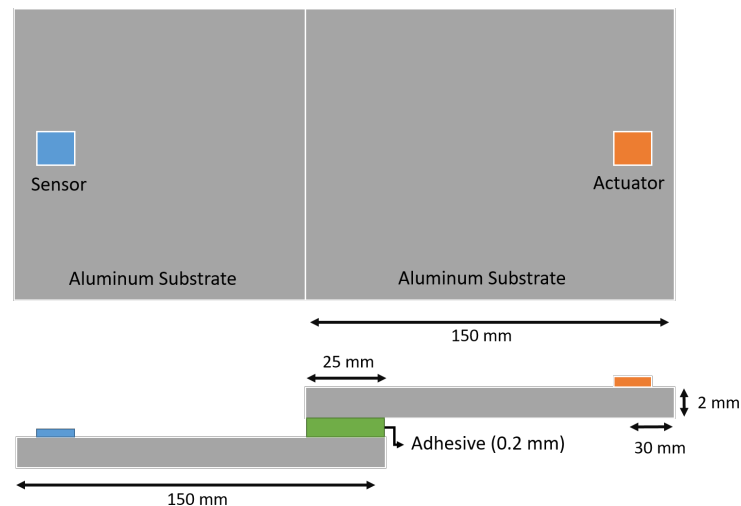


Figure 6. Top and side view of the adhesive joint simulation setup with the position of the sensor and actuator and the overall dimensions of each part.

The model was developed and simulated using the FEM in the software Abaqus. The two SLJ aluminum plates were modeled with a density $\rho = 2500 \text{ kg/m}^3$, a Poisson's ratio of $\nu = 0.33$, and a Young's modulus of $E = 72.4 \text{ GPa}$. Weak adhesion defects were simulated by creating a thin layer of adhesive where Young's modulus was reduced in comparison to the rest of the adhesive material. A total of 1000 cases were simulated with linearly distributed values between 600 and 270,000 kPa. For exciting the SLJ, a distributed discretized tangential force was applied to the substrate plane, as illustrated in Figure 7. A 5-cycle Hanning-windowed sinusoidal burst centered at the frequency of 100 kHz was adopted [35–38]. The amplitude of the force was adjusted in accordance with the experimental observations, by successive trials. The explicit dynamic analysis was adopted, due to its computational efficiency and because the excitation is impulsive and the time-dependent reaction needs to be captured. The total simulation time was limited to 0.5 ms, which corresponds to enough time for the LW to interact with the weak adhesion defects and arrive at the sensor [39,40]. Following a mesh convergence study, a mesh size of 1.5 mm with elements of the type C3D8R was utilized. This was performed to reduce the computational burden and, thus, the time necessary for each simulation, while still maintaining a small enough mesh to not cause any numerical divergence. This combination allowed a simulation time inferior to 20 min for each case.

Aluminum Substrate

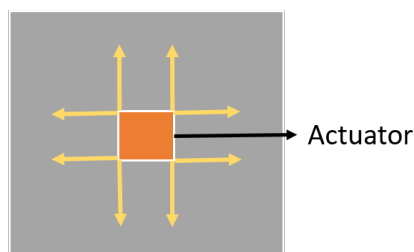


Figure 7. Representation of how the forces were simulated by discretizing and applying them to the edges of a square that has the same dimensions as the actuator.

Due to the explicit dynamic analysis carried out in Abaqus, the time series generated presented varying lengths, as each simulation was performed without a fixed time step. Thus, it was necessary to interpolate the data to have a fixed number of points. The value of 5000 points was chosen, this being enough to represent the LW signals well while keeping the amount of data limited.

It should be noted that the use of only one actuator/sensor pair on the SLJ is the minimum necessary to detect damage. However, it does not allow for damage localization. Indeed, this work focused only on determining the level of weak adhesion in an SLJ of reduced dimensions. For localizing damage in larger parts, extra sensors are needed, along with some triangulation methods for data processing.

5. Algorithm Application and Results

5.1. Evaluation of Components and Indicators

To use artificial neural networks, it is first necessary to describe the desired outcome of the model and, from there, determine how the task should be handled. Adhesive materials intrinsically have many variables that determine their overall bonding strength [41,42]. For a given adhesive and joint, damage can limit the joint strength to a specific interval, between no adhesion up to full-strength adhesion. Therefore, the problem at hand is considered as involving classification into a given number of weak adhesion classes, rather than a regression problem. A total of 20 classes were chosen, as this was a large enough

value to visualize any possible damage progression, while still small enough to allow for distinct classes.

With the basic concept chosen, various parameters can immediately be defined. Thus, the evaluation metric or loss function adopted was the categorical cross-entropy, and all final layers before the output contained the softmax activation function with a kernel equal to 20, that is the number of classes. Finally, the accuracy metric was chosen, as it is widely implemented in classification problems and is a simple metric to assess the different models that were used. To train the model, the data were divided into training and testing in the proportion 70% and 30%, respectively, as these percentages are classic values that work in most cases and give a good baseline to initiate the study. Finally, the chosen epoch size was 400, as the objective of this work was to properly understand each algorithm and not allow for an early stop, which could exclude important behaviors. This may cause overfitting of the training data, but this was not considered a concern during the analysis, as it was an expected outcome. Although there would be a constant of 100 epochs, each algorithm was also evaluated accordingly with the epoch at which the accuracy started to converge and how long this process took.

To give the best evaluation of each model for each type of dataset, it is necessary to assess several parameters and algorithm architectures. These parameters vary from algorithm to algorithm, and their optimization requires an extensive grid search to determine, inside the chosen grid, the best parameters. To minimize the total time expended in such an optimization, a broad trend search was conducted, where the total accuracy was compared to the time spent to reach the solution. This allowed the algorithm not only be efficient, but also faster when compared to other configurations, which can take days to train on a dataset. Initially, the parameters listed in Table 1 were chosen to start the optimization study on the FNN, as it is one of the fastest methods.

Table 1. Initial parameters of the FNN.

Experimental Variables to Be Tested		
Batch Size	Kernel Size	Number of Hidden Layers
32	50	1
64	100	3
128	400	7

After testing these values, it was possible to see how each variable behaved. During the tests, the time spent to test a batch with a kernel size of 400 compared to a kernel size of 50 was over 12-times greater with minimal accuracy changes. Thus, all tests using kernel sizes of 400 were discarded as being too time-consuming for minimal results. In Figure 8, it is possible to see that, for an algorithm depth of one hidden layer, the batch size had a small influence on the time per training, while there was no variation in the accuracy. Therefore, a batch size of 128 was chosen, as it was the fastest in both cases with comparable results.

The number of hidden layers was tested together with multiple values of the kernel and batch sizes, and the ones with the shortest training times and highest accuracy were chosen. To compare the influence of the number of hidden layers, three tests were conducted with a constant batch size of 128, as defined previously, and a varying kernel size between 50 and 100. In Figure 9, it is possible to verify that, while there was a linear growth in time for the kernel size of 100, there was a plateau at the kernel size of 50. Therefore, it was better to not only utilize a kernel size equal to 50, but also to use more layers. This may change if the model is tested for a larger number of hidden layers or for other algorithms, but these data served as a starting point for further evaluations.

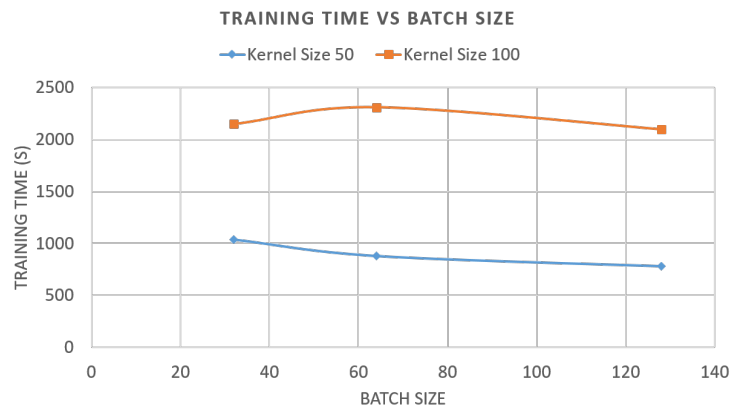


Figure 8. Comparison between the total training time and batch size for the FNN when fixing the kernel size to 50 (blue) and 100 (orange).

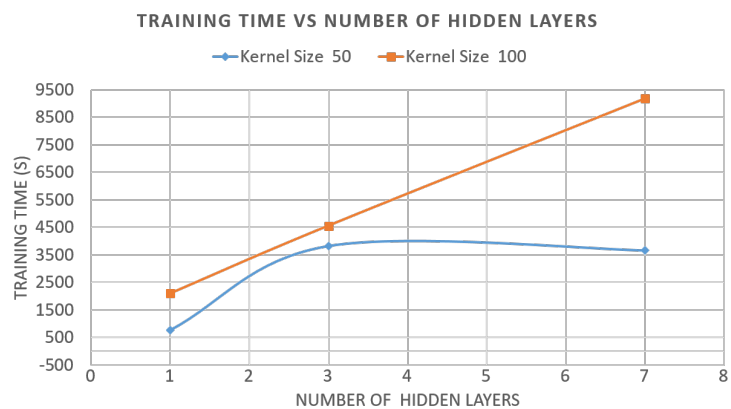


Figure 9. Comparison between the total training time and the number of hidden layers for the FNN when fixing the kernel size to 50 (blue) and 100 (orange).

When comparing the previous graphs and results, it is possible to conclude that the configuration of the parameters and algorithm architecture that brought the most-consistent and highest values of accuracy, while still taking the least time, was:

- Batch size: 128;
- Number of hidden layers: seven;
- Kernel size: 50.

Therefore, the chosen configuration for the FNN had a total of four dense layers, as shown in Figure 10.

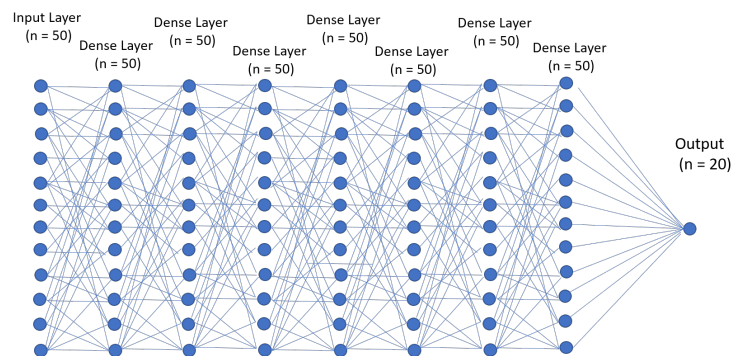


Figure 10. Graphic representation of the FNN configuration, chosen after the optimization process, with a total of 7 dense hidden layers.

Although the batch size can be defined for all algorithms, every one has specific characteristics that need to be altered individually. One example of this concerns the CNN, which not only has the kernel size, but also has filters and utilizes max pooling layers, which have their own individual parameters, namely the pool size. In these cases, the base parameters are maintained as much as possible, while each unique parameter must be individually studied.

When optimizing the two RNN algorithms, the main obstacle was related to the training time. This was not only due to a large number of inputs, but also to the very nature of the algorithms, in which each neuron had a recurring unit, which further necessitated calculations and, thus, required additional computational power. Due to these restrictions, the optimization of the RNNs was limited to creating a model that requires a training time similar to that of the FNN and CNN. This optimization led to a simple algorithm that had only two recurring layers, each one with a kernel size equal to 10. The batch size was maintained from the previous analysis at the value of 128. Therefore, the chosen configuration for the GRU had a total of two recurrent GRU layers, as shown in Figure 11, and for the LSTM, there was a total of four dense layers, as shown in Figure 12.

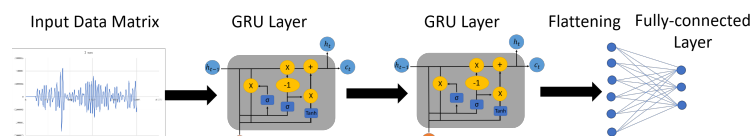


Figure 11. Graphic representation of the GRU's configuration, chosen after the optimization process, with two layers.

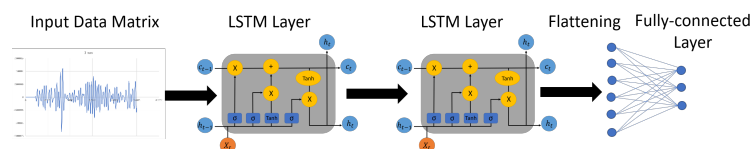


Figure 12. Graphic representation of the LSTM's configuration, chosen after the optimization process, with two layers.

In comparison to the RNNs, the CNN algorithm did not have the training time as a limiting factor, and thus, it was possible to test multiple configurations, as done with the FNN. The first analysis conducted was to determine the batch size that would be used for the CNN. It is possible to see in Figure 13 that the overall batch size did not influence the training time greatly, while the size of the kernel did. Therefore, the chosen batch size was 64, as it is an average value that could be used as a base for the next variable testing. It is important to note that, although not explicitly shown in the following figures, the first criterion when choosing the variables was the achieved overall accuracy, and only after confirming that the differences in the accuracy were small, the time criterion was used.

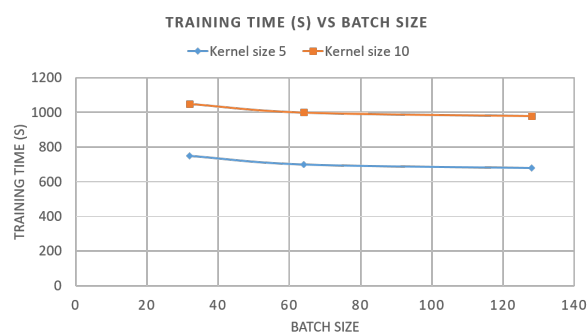


Figure 13. Comparison between the total training time and the number of hidden layers for the CNN when fixing the kernel size to 5 (blue) and 10 (orange).

With the batch size chosen, the next variable studied was the kernel size. It was already shown in Figure 13 that the kernel size played an important role in the training time, and this becomes more apparent in Figure 14, where it is possible to see that, with low pooling sizes, the training time grew significantly. Therefore, to minimize the training, the chosen kernel size was five.

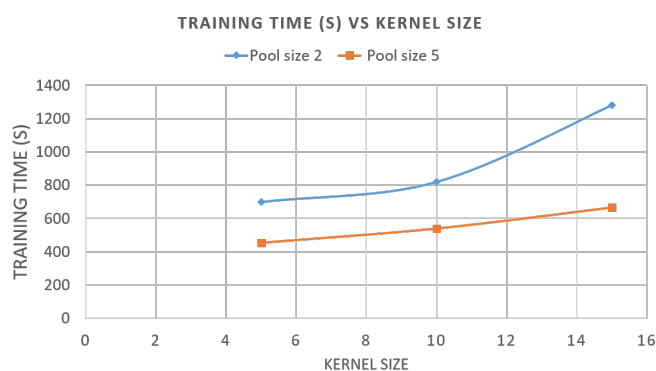


Figure 14. Comparison between the total training time and the kernel size for the CNN when fixing the pool size to 2 (blue) and 5 (orange).

Although Figure 15 shows that the fastest training cycles occurred at a pool size of 10 and a filter of 50, the chosen values for these were slightly different. To choose the pooling and filter size, the accuracy criterion was used instead of the time, as the values

obtained from a pooling size of two and a filter size of 50 were slightly larger than the other values.

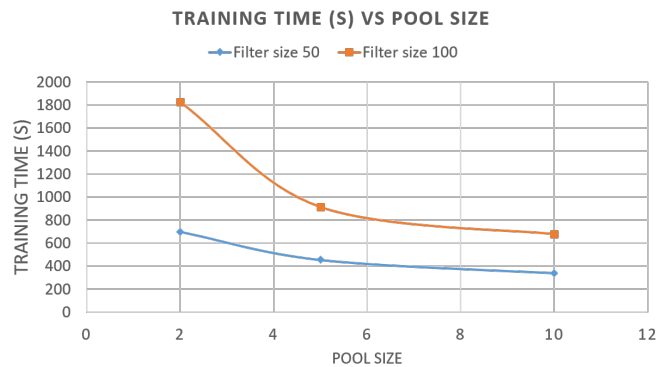


Figure 15. Comparison between the total training time and the pool size for the CNN when fixing the filter size to 50 (blue) and 100 (orange).

Therefore, the chosen configuration for the CNN had a total of two convolutional and two pooling layers, as shown in Figure 16.

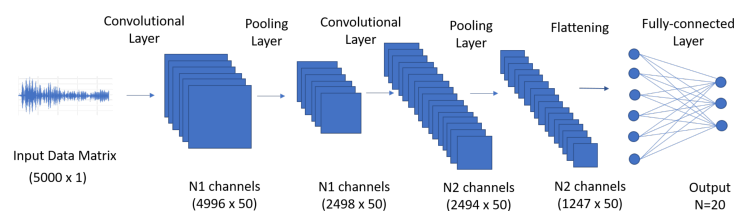


Figure 16. Chosen architecture for the CNN, with two convolutional and two pooling layers with the total size of each layer represented under the graphical representation.

5.2. Results and Discussion

With all models' architecture and parameters chosen, the algorithms were trained for 400 epochs. As stated previously, this was performed to fully understand the behavior of each algorithm. As expected, after model optimization, the algorithms quickly converged and had the lowest loss values before 100 epochs, as seen in Figures 17–20. For the FNN, at about 250 epochs, the validation loss function started to grow, indicating that the algorithm was overfitting the data. While this showed that the FNN was more prone to overfitting compared to the other algorithms, the quick convergence mitigated the problem and allowed the algorithm to be suitable for the problem at hand. For the other algorithms, no overfitting occurred, even after 400 epochs, showing that they were more robust.

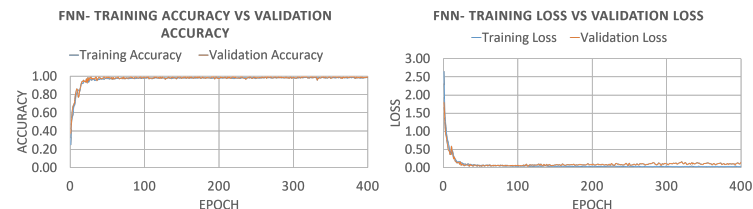


Figure 17. Comparison between the loss and accuracy for the FNN algorithm in both training and validation cycles.

Relative to the FNN, the CNN presented little variation in the graphs, with a smooth decrease in loss and a steady increase in accuracy.

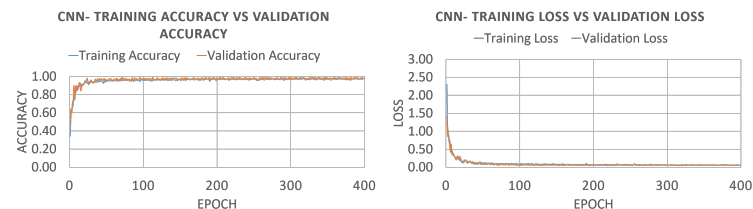


Figure 18. Comparison between the loss and accuracy for the CNN algorithm in both training and validation cycles.

Compared to the other algorithms, the GRU started with the highest value of the accuracy, around 0.60, while the others yielded about 30. Moreover, it had the lowest loss. This demonstrated the exceptional learning capacity of the algorithm for the type of problem presented. This was further confirmed by the aggressive overall growth until convergence, with around 35 epochs until the value stabilized. It is also important to point out that the maximum value was achieved in less than 20 epochs, but it took around 40 epochs until the values stabilized. Utilizing just the accuracy and loss criteria, the GRU emerged as the most-suitable algorithm of the ones studied in this work.

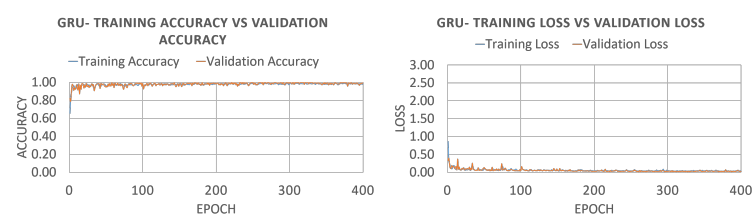


Figure 19. Comparison between the loss and accuracy for the GRU algorithm in both training and validation cycles.

The LSTM presented an initial and final accuracy similar to that of the CNN and FNN. The most-striking difference was the low learning rate that the algorithm showed, taking between 150 and 200 epochs to converge. This can be further seen with the erratic initial behavior of this algorithm, which implies that the weight values were being altered, which created an overshooting effect. When only analyzing Figure 20, it can be concluded that the LSTM algorithm was the least suitable for the problem at hand.

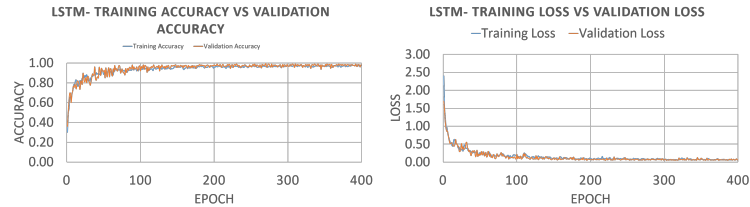


Figure 20. Comparison between the loss and accuracy for the LSTM algorithm in both training and validation cycles.

As expected, due to the low layer count of all algorithms, there was no plateau followed by large decreases in the loss. With the plots broadly observed, it is still possible to dive deeper by using the variables listed in Table 2, where a condensed version of the information obtained from the graphs can be seen. These variables are commonly used to describe the performance and represent information that could be seen in a confusion matrix or error matrix:

- The **accuracy score (acc)** is used to evaluate the ratio of correct predictions to the total number of instances. This can be calculated as

$$acc = \frac{tp + tn}{tp + fp + tn + fn}; \quad (15)$$

where tp denotes true positives, tn stands for true negatives, fp represents false positives, and finally, fn corresponds to false negatives.

- The **precision score (p)** is the ratio of correctly predicted positive observations to the total number of positive ones. From a more intuitive perspective, it is the capacity of the algorithm to not label a positive sample as a negative one. It is given by:

$$p = \frac{tp}{tp + fp}; \quad (16)$$

- The **recall score (r)** is the ratio of correctly predicted positive observations in a class, thus from an intuitive perspective, it is the capacity of the algorithm to determine all positive samples. Its value is calculated as:

$$r = \frac{tp}{tp + fn}; \quad (17)$$

- The **F1-score (F1)** is the weighted average of the recall and precision and is commonly more important when there are large imbalances of the data in the class distributions. It is given by:

$$F1 = \frac{2 \times precision \times recall}{precision + recall}. \quad (18)$$

In the case of the tested algorithms, the lowest values can be seen for the CNN, while the highest ones were observed for the FNN and GRU models. Even with these differences, the overall results showed that all algorithms could be used to determine the classes presented in this work. It is worth noting that, when evaluating an SLJ, it is more important that the algorithm does not give false negatives than it generates false positives. This remark makes the recall score more important than the other indices. Indeed, the recall score is directly dependent on the false negatives, while the other criteria use false negatives more indirectly. Using this as a basis, it is possible to see in Table 2 that both LSTM and the CNN presented lower recall values than the FNN and GRU. This makes

both LSTM and the CNN less suitable for the problem at hand and both the FNN and GRU the most-promising ones.

Table 2. Algorithms' evaluation criteria.

Algorithm	Evaluation Criteria			
	Accuracy	Precision	Recall	F1-Score
FNN	0.99	0.99	0.99	0.99
CNN	0.975	0.97	0.98	0.97
GRU	0.99	0.99	0.99	0.99
LSTM	0.98	0.98	0.98	0.98

It is important to understand that the accuracy, precision, recall, and F1-scores of Expressions (15)–(18) are relevant, but other evaluation criteria need also to be analyzed, such as the number of epochs to reach convergence and the total time taken to achieve the solutions. In Table 3, it is possible to compare the results, which give a more accurate insight into each algorithm. One surprising value is that, although the GRU took longer to calculate for each epoch compared to the CNN and FNN, the total epochs required were fewer, which allowed for the total time to be minimized. It is also possible to see that the GRU and LSTM would largely benefit from a feature extraction protocol, which could reduce the number of features to a few dozens, as large datasets tend to slow calculations and the training process.

Table 3. Performance comparison of the algorithms.

Algorithm	Epochs and Total Time		
	Epochs to Converge	Time to Converge (min)	Total Time (min)
FNN	100	7	28.0
CNN	150	4.5	12.3
GRU	35	15	177.5
LSTM	150	89	238.3

When considering the results summarized in Tables 2 and 3, it is possible to see that, out of all the algorithms, the CNN presented good results, as it was only 2% off the best accuracy and could accomplish this in almost half the time of the next fastest algorithm. At the other end of the spectrum, LSTM took quite a long time to reach the solution and presented the second-lowest value for the accuracy. Finally, the FNN and GRU presented the best accuracy and had relatively acceptable convergence times, making them overall the most-suitable choices.

6. Conclusions

This paper proposed an NDT technique based on LW data and artificial intelligence algorithms to detect weak adhesion defects in an SLJ. Four algorithms were trained and tested with simulated LW data from an FEM developed and experimentally validated. The algorithms were assessed and compared. A total of 20 different levels of weak adhesion could be detected, with overall accuracy between 97% and 99%. The results showed the effectiveness of the proposed nondestructive methods to treat the problem, which, until now, could only be solved with classical destructive mechanical testing. Furthermore, the overall training capability was studied, revealing that the training time for each algorithm could be reduced by almost 60% by altering the algorithm's parameters. The LSTM emerged as the least-suitable, taking over 200 epochs to converge, and the GRU the most-applicable, converging in less than 50 epochs. Regarding the training time, the FNN proved to be more appropriate. Therefore, the FNN and GRU presented the best accuracy and showed

relatively acceptable convergence times, making them the most-suitable choices. Further work will expand the technique to increase the resolution for detecting weak adhesion, as well as to localize defects in adhesive joints with a larger and more complex geometry.

Author Contributions: Conceptualization, G.M.F.R., L.F.M.D.S. and A.M.L.; methodology, G.M.F.R. and A.M.L.; software, G.M.F.R.; validation, G.M.F.R., L.F.M.D.S., A.M.L. and R.J.C.C.; formal analysis, G.M.F.R., L.F.M.D.S., A.M.L. and R.J.C.C.; investigation, G.M.F.R. and A.M.L.; writing—original draft preparation, G.M.F.R.; writing—review and editing, G.M.F.R., L.F.M.D.S., A.M.L. and R.J.C.C.; supervision, L.F.M.D.S. and A.M.L.; project administration, L.F.M.D.S. and A.M.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Chen, Z.; Adams, R.; Da Silva, L.F. Prediction of crack initiation and propagation of adhesive lap joints using an energy failure criterion. *Eng. Fract. Mech.* **2011**, *78*, 990–1007. [\[CrossRef\]](#)
- da Silva, L.F.M.; Öchsner, A.; Adams, R.D. *Handbook of Adhesion Technology*, 2nd ed.; Springer: Berlin/Heidelberg, Germany, 2018. [\[CrossRef\]](#)
- Adin, M.S.; Killickap, E. Strength of double-reinforced adhesive joints. *Mater. Test.* **2021**, *63*, 176–181. [\[CrossRef\]](#)
- Ramvalho, G.M.; Lopes, A.M.; da Silva, L.F. Structural health monitoring of adhesive joints using Lamb waves: A review. *Struct. Control. Health Monit.* **2021**, *29*, e2849. [\[CrossRef\]](#)
- U.S. National Archives and Records Administration. *Federal Aviation Regulations—Sec. 23.573*; U.S. National Archives and Records Administration: Washington, DC, USA, 2014.
- Guyott, C.C.H.; Cawley, P.; Adams, R. The non-destructive testing of adhesively bonded structure: A review. *J. Adhes.* **1986**, *20*, 129–159. [\[CrossRef\]](#)
- Adin, H.; Adin, M.S. Effect of particles on tensile and bending properties of jute epoxy composites. *Mater. Test.* **2022**, *64*, 401–411. [\[CrossRef\]](#)
- Jeenjikaew, C.; Guild, F.J. The analysis of kissing bonds in adhesive joints. *Int. J. Adhes. Adhes.* **2017**, *75*, 101–107. [\[CrossRef\]](#)
- Mańka, M.; Rosiek, M.; Martowicz, A.; Stepinski, T.; Uhl, T. PZT based tunable Interdigital Transducer for Lamb waves based NDT and SHM. *Mech. Syst. Signal Process.* **2016**, *78*, 71–83. [\[CrossRef\]](#)
- Adin, H.; Saglam, Z.; Adin, M.S. Numerical Investigation of Fatigue Behavior of Non-patched and Patched Aluminum/Composite Plates. *Eur. Mech. Sci.* **2021**, *5*, 168–176. [\[CrossRef\]](#)
- Alleyne, D.N. The Nondestructive Testing of Plates Using Ultrasound Lamb Waves. Ph.D. Thesis, Imperial College London (University of London), London, UK, 1991.
- Giurgiutiu, V.; Cuc, A. Embedded Non-Destructive Evaluation for Structural Health Monitoring, Damage Detection, and Failure Prevention. *Shock Vib. Dig.* **2005**, *37*, 83–105. [\[CrossRef\]](#)
- Dodson, J.; Inman, D. Thermal sensitivity of Lamb waves for structural health monitoring applications. *Ultrasonics* **2013**, *53*, 677–685. [\[CrossRef\]](#)
- Su, Z.; Ye, L.; Lu, Y. Guided Lamb waves for identification of damage in composite structures: A review. *J. Sound Vib.* **2006**, *295*, 753–780. [\[CrossRef\]](#)
- Kessler, S.; Spearing, S.; Soutis, C. Structural Health Monitoring in Composite Materials Using Lamb Wave Methods. *Smart Mater. Struct.* **2002**, *11*, 269–278. [\[CrossRef\]](#)
- Giurgiutiu, V. Tuned Lamb Wave Excitation and Detection with Piezoelectric Wafer Active Sensors for Structural Health Monitoring. *J. Intell. Mater. Syst. Struct.* **2005**, *16*, 291–305. [\[CrossRef\]](#)
- De Luca, A.; Perfetto, D.; Petrone, G.; De Fenza, A.; Caputo, F. Guided-waves in a low velocity impacted composite winglet. In *Key Engineering Materials*; Trans Tech Publications Ltd.: Sevilla, Spain, 2018; Volume 774, pp. 343–348.
- Petrone, G. Dispersion curves for a natural fibre composite panel: Experimental and numerical investigation. *Aerosp. Sci. Technol.* **2018**, *82*, 304–311. [\[CrossRef\]](#)
- Kumar, S.; Sunny, M.R. A novel nonlinear Lamb wave based approach for detection of multiple disbonds in adhesive joints. *Int. J. Adhes. Adhes.* **2021**, *107*, 102842. [\[CrossRef\]](#)
- Adams, R.D.; Adams, R.D.; Comyn, J.; Wake, W.C.; Wake, W. *Structural Adhesive Joints in Engineering*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 1997.
- Wojtczak, E.; Rucka, M. Monitoring the curing process of epoxy adhesive using ultrasound and Lamb wave dispersion curves. *Mech. Syst. Signal Process.* **2021**, *151*, 107397. [\[CrossRef\]](#)

22. Zupan, J.; Novič, M.; Li, X.; Gasteiger, J. Classification of multicomponent analytical data of olive oils using different neural networks. *Anal. Chim. Acta* **1994**, *292*, 219–234. [\[CrossRef\]](#)
23. Albawi, S.; Abbas, Y.A.; Almadany, Y. Robust skin diseases detection and classification using deep neural networks. *Int. J. Eng. Technol.* **2018**, *7*, 6473–6480.
24. Dongare, A.; Kharde, R.; Kachare, A.D. Introduction to artificial neural network. *Int. J. Eng. Innov. Technol. (IJEIT)* **2012**, *2*, 189–194.
25. Plumb, A.P.; Rowe, R.C.; York, P.; Brown, M. Optimisation of the predictive ability of artificial neural network (ANN) models: A comparison of three ANN programs and four classes of training algorithm. *Eur. J. Pharm. Sci.* **2005**, *25*, 395–405. [\[CrossRef\]](#)
26. Hochreiter, S.; Schmidhuber, J. Long short-term memory. *Neural Comput.* **1997**, *9*, 1735–1780. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Yu, Y.; Si, X.; Hu, C.; Zhang, J. A review of recurrent neural networks: LSTM cells and network architectures. *Neural Comput.* **2019**, *31*, 1235–1270. [\[CrossRef\]](#) [\[PubMed\]](#)
28. Dhruv, P.; Naskar, S. Image classification using convolutional neural network (CNN) and recurrent neural network (RNN): A review. In *Machine Learning and Information Processing*; Springer: Singapore, 2020; pp. 367–381.
29. Yang, S.; Yu, X.; Zhou, Y. LSTM and BRU neural network performance comparison study: Taking yelp review dataset as an example. In Proceedings of the 2020 International workshop on Electronic Communication and Artificial Intelligence (IWECAI), Shanghai, China, 12–14 June 2020; pp. 98–101.
30. Sherstinsky, A. Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Phys. D Nonlinear Phenom.* **2020**, *404*, 132306. [\[CrossRef\]](#)
31. Staudemeyer, R.C.; Morris, E.R. Understanding LSTM—a tutorial into long short-term memory recurrent neural networks. *arXiv* **2019**, arXiv:1909.09586.
32. Huang, Z.; Yang, F.; Xu, F.; Song, X.; Tsui, K.L. Convolutional Gated Recurrent Unit–Recurrent Neural Network for State-of-Charge Estimation of Lithium-Ion Batteries. *IEEE Access* **2019**, *7*, 93139–93149. [\[CrossRef\]](#)
33. O’Shea, K.; Nash, R. An introduction to convolutional neural networks. *arXiv* **2015**, arXiv:1511.08458.
34. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016.
35. Lee, B.; Staszewski, W. Modelling of Lamb waves for damage detection in metallic structures: Part I. Wave propagation. *Smart Mater. Struct.* **2003**, *12*, 804. [\[CrossRef\]](#)
36. Packo, P.; Bielak, T.; Spencer, A.; Staszewski, W.; Uhl, T.; Worden, K. Lamb wave propagation modelling and simulation using parallel processing architecture and graphical cards. *Smart Mater. Struct.* **2012**, *21*, 075001. [\[CrossRef\]](#)
37. Ahmad, Z.; Gabbert, U. Simulation of Lamb wave reflections at plate edges using the semi-analytical finite element method. *Ultrasonics* **2012**, *52*, 815–820. [\[CrossRef\]](#)
38. Adin, H.; Yıldız, B.; Adin, M.S. Numerical investigation of fatigue behaviours of non-patched and patched aluminium pipes. *Eur. J. Tech. (EJT)* **2021**, *11*, 60–65. [\[CrossRef\]](#)
39. Loreiro, V.; Ramalho, G.; Tenreiro, A.; Lopes, A.M.; da Silva, L. Feature extraction and visualization for damage detection on adhesive joints, utilizing Lamb waves and supervised machine learning algorithms. *Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci.* **2022**, *236*, 8842–8855. [\[CrossRef\]](#)
40. Ramalho, G.M.; Barbosa, M.R.; Lopes, A.M.; da Silva, L.F. Damage Classification Methodology Utilizing Lamb Waves and Artificial Neural Networks. *J. Test. Eval.* **2022**, *50*, 19. [\[CrossRef\]](#)
41. Poudel, A.; Chu, T.P. Assessment of Composite Aluminum Adhesive Joints Using Digital Image Correlation. *Mater. Eval.* **2022**, *80*. [\[CrossRef\]](#)
42. Cantrell, D.R. Onset of Kissing Bond Formation for Varying Levels of Bondline Contamination in CFRP. Ph.D. Thesis, Georgia Institute of Technology, Atlanta, GA, USA, 2022.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

Appendix E

Paper E

<https://doi.org/10.3390/app131910877>

Article

Assessing Weak Adhesion in Single Lap Joints Using Lamb Waves and Machine Learning Methods for Structural Health Monitoring

Gabriel M. F. Ramalho ^{1,*} , António M. Lopes ^{1,2,*}  and Lucas F. M. da Silva ^{1,2} 

¹ Department of Mechanical Engineering, Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal; lucas@fe.up.pt

² INEGI—Institute of Science and Innovation in Mechanical and Industrial Engineering, 4200-465 Porto, Portugal

* Correspondence: gmframalho@gmail.com (G.M.F.R.); aml@fe.up.pt (A.M.L.)

Abstract: The use of adhesive joints has become increasingly popular in various industries due to their many benefits, such as low weight and good mechanical performance. However, adhesive joints can suffer from defects, one of them being weak adhesion. This defect poses a significant risk to structural integrity and can lead to premature failure, but is hard to detect using existing nondestructive testing methods. Therefore, there is a need for an effective technique that can detect weak adhesion in single-lap joints (SLJ) to prevent failure and assist in maintenance, namely in the framework of structural health monitoring. This paper presents a novel approach utilizing machine learning and Lamb Waves (LW) to determine the level of weak adhesion. Firstly, a numerical model of SLJs with different levels of weak adhesion is created and an original approach is proposed for its validation with data from real samples so that reliable LW data can further be easily generated to train and test any other data-driven algorithm for tackling damage. Secondly, a damage detection method is proposed, based on artificial neural networks and fed with simulated data, to determine the level of damage in SLJs, independent of their location. The results show that the simulation model can be validated with a small set of experimental data, being capable of replicating real damage in SLJs. Additionally, the use of simulated data in the training algorithm can increase the accuracy of the simulation model up to 26% when compared to only considering experimental data. The adopted artificial neural network for detecting weak adhesion emerges as a promising approach, yielding a precision of over 95%. Thus, machine learning and LW data can be used to improve the reliability and accuracy of adhesive bonding quality control, as well function as a technique for structural health monitoring, which can enhance the safety and durability of bonded structures.

Keywords: artificial intelligence; adhesive joint; machine learning; lamb wave



Citation: Ramalho, G.M.F.; Lopes, A.M.; da Silva, L.F.M. Assessing Weak Adhesion in Single Lap Joints Using Lamb Waves and Machine Learning Methods for Structural Health Monitoring. *Appl. Sci.* **2023**, *13*, 10877. <https://doi.org/10.3390/app131910877>

Academic Editor: Chenyin Ni

Received: 18 September 2023

Revised: 26 September 2023

Accepted: 28 September 2023

Published: 30 September 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In the last few years, the utilization of adhesive joints has seen an increase in various industries. This is attributed to their ability to connect different materials while providing uniform stress distributions around the joining areas, as well as to create structures that are lighter than those obtained with traditional joining methods [1–3]. Examples of industries that have benefited from the use of adhesives are the automotive manufacturing industry, with adhesive bonds in body panels, interior components, and even in joining chassis parts, allowing for cars to be built in fewer parts and thus making them lighter and cheaper [1], and the healthcare industry, with delicate applications for securing catheters to human skin, or even for attaching orthopedics to bones [4]. Other industries that can be mentioned are the renewable energy sector, with the fabrication of efficient and easier-to-install solar panels, the marine industry, with the fabrication of lightweight hulls and deck components,

and the packaging industry, where adhesive tapes have been heavily relied upon to secure and protect packages [5–7].

The single lap joint (SLJ) is one of the most used types of adhesive assemblies, with applications in different industries, ranging from the automotive to the aeronautical sectors [8]. However, the use of adhesive structural joints in cutting-edge industries has been restricted due to the high certification and inspection requirements posed by industry standards, as is the case for the Federal Aviation Regulations (FAR) Section 23.573(5)-(iii) [9]. Indeed, these standards demand reliable and robust non-destructive testing methods (NDT) to detect damage in joined parts, but existing testing methods for adhesive joints have great limitations and are inadequate in detecting some types of damage [9,10].

One of the primary types of damage that affects adhesive joints, for which there is a lack of suitable NDT methods, is weak adhesion. This defect is present when the maximum adhesive strength of the joint decreases more than 20% without showing any noticeable voids, cracks, or other visible changes. Usually, this happens when, during the manufacturing process, there is contamination between the adhesive and the substrates, which is often caused by oils, dust, or a poorly prepared surface that does not allow the adhesive to adhere properly [11].

To detect weak adhesion, several methods have been proposed, one of the most promising being based on the use of Lamb wave (LWs) data. LWs are a kind of guided wave that have the ability to travel over long distances and to sensitively interact with structural defects, meaning that their characteristic parameters change in the presence of defects, even in parts with complex geometries, making them a powerful tool in the realm of NDT [8]. The major drawback to their application is the complexity of the signals produced, which poses challenges to correlating LW with damage. To counter this problem, the implementation of robust methods, such as those based on machine learning, is needed.

While traditional signal-processing approaches may struggle when dealing with low signal-to-noise ratios or sparse data acquisition points, machine learning algorithms can effectively process complex information and still yield valuable insights. As more data are collected from different structures and inspection scenarios, the algorithms can continually refine their understanding of complex LW data, enabling them to better discriminate between normal wave patterns and those associated with defects.

When using machine learning, large datasets are often needed to train and test the algorithms. Creating large datasets experimentally is costly or even impracticable. Therefore, developing reliable numerical models of the SLJs, validated with experimental data from real parts, can reduce the overall burden [12]. An added benefit is that any large volumes of data can be obtained to develop machine learning algorithms.

In recent years there have been a few attempts to develop weak adhesion detection in SLJ. Initial studies were conducted with simulated data to determine features and find the best visualization methods to detect this form of damage in Loreiro et al. [13]. Further studies were conducted with simulated data and limited experimental validation such as in Ramalho et al. [14], where machine learning was used together with LWs to detect damage using a limited number of classes, but no direct correlation to experimental data was used to increase accuracy nor was the damage limited to a small area of the SLJ and intensity found independent of its position.

This paper proposes a new framework for the detection and classification of weak adhesion within SLJs through a fusion of LW data and machine learning techniques. The main contributions are as follows:

- A finite element method (FEM)-based model of SLJs for properly modeling weak adhesion is developed.
- An approach to validate the numerical model of SLJs subjected to weak adhesion using a small set of experimental data and machine learning algorithms is derived.
- A machine learning algorithm for classifying weak adhesion based on simulated LWs data and neural networks is proposed, exhibiting remarkable potential in precisely

predicting the extent of weak adhesion, and being robust even when the defect's location within the joint is altered.

This paper is divided into sections. In Section 2, a numerical method is developed, able to generate LW data characterizing SLJs with different levels of weak adhesion. The numerical model is tuned and validated by comparing, via machine learning, the LW signals with those obtained from a real experimental setup. The validated model, being reliable, constitutes the basis upon which further algorithms are trained and tested for weak adhesion classification. In Section 3, large volumes of model-simulated data for multiple cases of weak adhesion are generated, and a suitable machine learning algorithm is developed, which is robust enough to detect the level of weak adhesion independent of where it is located within the SLJs. The results are reviewed and discussed. Finally, in Section 4, the main conclusions are drawn.

2. Numerical Model Development and Experimental Validation

In this section, a numerical model for generating LW data from SLJs subjected to weak adhesion is developed. The model is validated, using machine learning techniques, by comparing the simulation results with those from experimental tests with real SLJs. A diagram of the approach can be seen in Figure 1. The experimental part is shown on the left-hand side, comprising SLJ fabrication, with distinct levels of weak adhesion, and LWs and strain–stress data acquisition. These data are correlated to correctly match LWs to levels of weak adhesion. The FEM simulation model of the SLJs is represented on the right-hand side of the diagram. At the bottom of the chart, a machine learning algorithm is used, which takes numerical and experimental data and validates the FEM model.

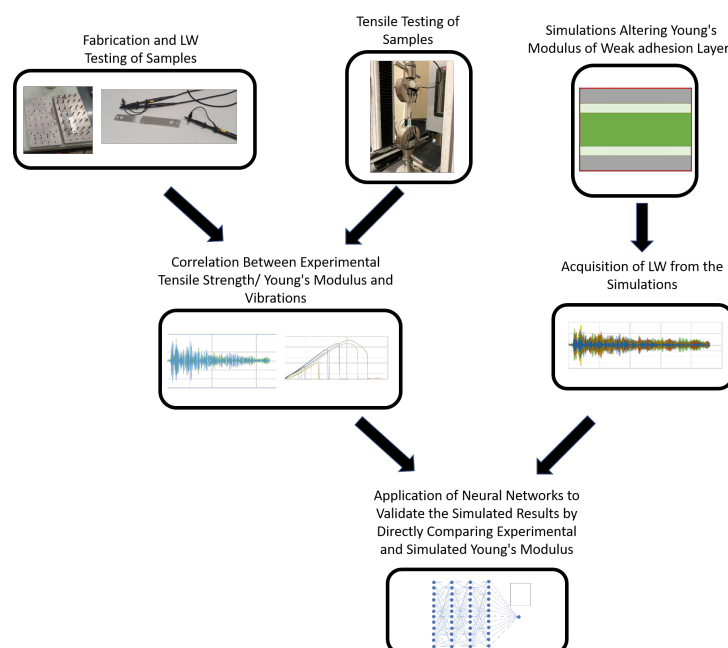


Figure 1. Diagram of the proposed approach for FEM model development and validation.

2.1. Experimental Setup

The experimental setup is divided into two stages. For SLJs manufactured with distinct levels of weak adhesion, the first stage consists of exciting the samples and capturing the relevant LWs. The second stage involves subjecting the SLJs to tensile tests in order to determine their corresponding stress–strain curves.

2.1.1. Creating Weak Adhesion

Before any experimental tests, samples were produced with multiple levels of weak adhesion. This was done by initially cutting aluminum 6061 bars into $120 \times 25 \times 2$ mm parts to have the upper and lower substrates of the SLJs. Each part was then drilled with a 6 mm hole at 10 mm from one of its ends to allow it to be held at the tension testing machine, as will be described in the follow-up. The other end of each substrate, where the adhesive would go, was sand blasted to maximize adhesive interaction. Next, the parts were geometrically finalized and thoroughly cleaned with acetone to remove any particles that could alter the adhesive bonding results. After adhesive curing, piezoelectric elements were bonded on the substrates to allow LW excitation and measurement. In Figure 2, a diagram of a final part can be seen, along with the overall measurements and the Cartesian coordinates that are used during simulation. The piezoelectric elements' dimensions and their placement are also represented.

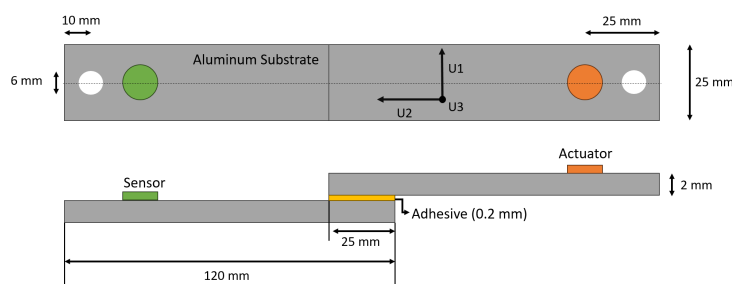


Figure 2. Representation and dimensions of a SLJ along with the Cartesian axis description that is used during simulations.

To create multiple levels of weak adhesion, various quantities of release agent Loctite 770-NC Frekote were used. For the study at hand, four overall levels were created, comprising a total of 11 SLJs. The first level corresponded to full adhesion, with no release agent applied, and two samples were manufactured. The second and third levels, with three SLJs each, corresponded to intermediary levels of weak adhesion, where the parts were subjected to one layer of release agent and one layer of a mixture of 50% release agent plus 50% acetone, respectively. Finally, the fourth level, with three samples, was a severe weak adhesion case, where the SLJs were subjected to two layers of release agent. After the parts had the necessary quantity of release agent applied, they were placed in a dimensional jig and received the adhesive Plexus MA 560-1 [15] in order to create the SLJs.

It is worth emphasizing that, although the SLJs were manufactured based on controlling the quantity of release agent applied, fabrication issues may affect the production and the obtention of the desired four levels of weak adhesion. Therefore, further testing is necessary to determine the real level of weak adhesion, as will be described in the follow-up.

2.1.2. Experimental Testing

As previously described, there were two stages in the experimental setup, with the first being used to determine the effect of weak adhesion on LW parameters, and the second

one to determine the real level of weak adhesion affecting the manufactured SLJs, so that a direct relationship between values is possible.

Regarding the first stage, each individual part was instrumented with two piezoelectric elements PIC 255 piezoceramic (PRYY + 1119 model), with one serving as sensor and the other working as an actuator, as illustrated in Figure 2. These piezoelectric elements were chosen due to their light weight, low cost, and versatility to serve as either actuators or sensor. This versatility will also allow for further tests to be conducted and will allow for having an array of sensors to analyze large areas. A five-cycle Hanning-windowed sinusoidal burst centered at a frequency of 100 kHz [16–19] was applied to the actuator by a signal generator AIM & Thurbly Thander Instruments, model TGF4042. This type of excitation signal keeps LW dispersion and attenuation at a minimum, while still maximizing sensitivity. The sensor was connected to a digital oscilloscope Tektronix, model TBS1000C, which samples and memorizes the signals. To facilitate input and output synchronization, the Hanning window signal applied to the actuator was also collected by the oscilloscope. In Figure 3 the data acquisition setup can be seen.

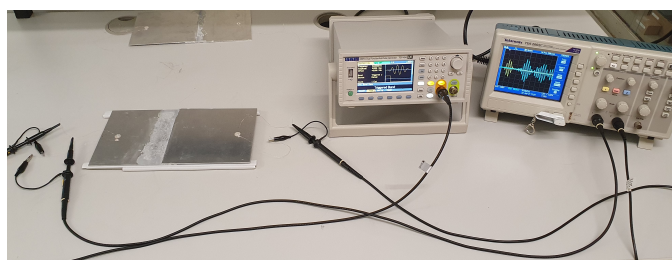


Figure 3. Data acquisition setup of one SLJ, with actuator and sensor connected to a signal generator and an oscilloscope, respectively.

After all LW data were acquired from the SLJs, in a second stage, the sensors and actuators were removed and the samples were subjected to tensile tests. Each part was carefully placed on an Instron 3367 machine and stressed until rupture.

It is important to analyze the stress–strain curves obtained, as adhesives are inherently complex, and even when fully cured in the correct manner, variations in Young modulus over 275 Mpa can be verified [15]. This uncertainty may be higher when dealing with artificially created SLJs with weak adhesion and might cause difficulties when trying to simulate vibration data.

In Figure 4, the load–displacement curves of all SLJs are depicted. As expected, four groups with distinct levels of maximum load can be identified. The group produced with two layers of release agent reveals the smallest ultimate stress, while the cases without release agent correspond to the largest loads. Therefore, the method adopted for the fabrication of SLJs based on the application of a release agent to create distinct levels of weak adhesion is quite reliable. It is also interesting to observe that the two cases without the release agent presented a larger plastic deformation, which may be caused by the adhesive material deforming under loads, instead of a clean break of the adhesive on the contact surface of the substrate, as seen for the other cases. When analyzing the samples, there is a stark contrast between the adhesive of the samples that reinforces this theory. In Figure 5, it is possible to observe the difference between the sample that had plastic deformation and the sample where the limit layer of the adhesive failed.

With the maximum loads determined, all samples can now be referenced to these values, and a linear percentile analysis of Young’s modulus is used to compare simulated and experimental data. It is important to note that Young’s modulus is being used as it is a variable that can be calculated by the tensile test and is the main variable that is altered to determine the desired level of weak adhesion present in the simulation.

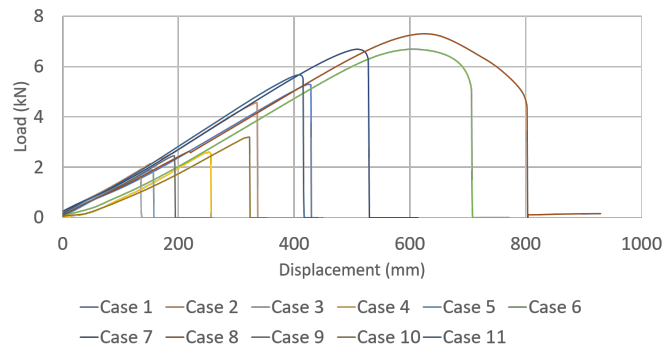


Figure 4. Load-displacement curves for all 11 experimental SLJs. Each case represents a sample fabricated with a different level of weak adhesion, adding up to four different fabrication groups.

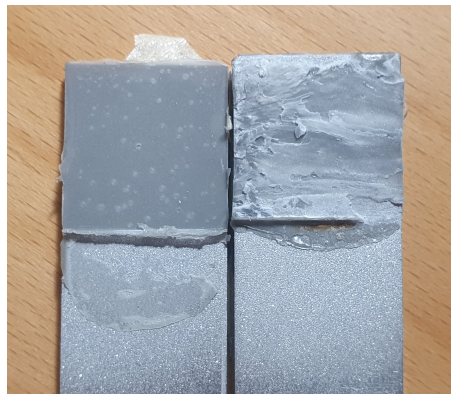


Figure 5. Comparison between a sample that had no plastic deformation (**left**) and one that had intense plastic deformation (**right**).

When LW data from all 11 SLJs are analyzed and compared, it is possible to verify that no clear patterns emerge. This is more evident when analyzing two tests that have almost exactly the same maximum tensile strength but possess completely different vibrational patterns, as can be seen in Figure 6. This means that directly correlating LWs with specific levels of weak adhesion is unfeasible. Thus, it is preferable to have the machine learning algorithm compare the acquired data directly than to forcefully try to distill any type of results from these signals.

As can be seen, the process of obtaining experimental data from SLJ is very labor-intensive and complex, which results in a very high overall cost to create a large number of cases. In any real-world cases, this could not be reliably used. Therefore, these collected data will be used in conjunction with simulated data to validate the simulated methodology.

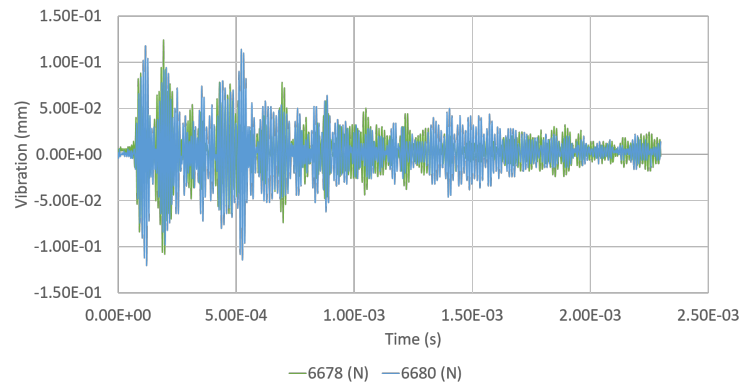


Figure 6. The LW of two samples 6678 N and 6680 N, obtained during the tensile test, shows that even very similar tensile strengths generate completely different signals.

2.2. Numerical Model

A FEM model of SLJ was developed and simulated using the software Abaqus (Dassault Systemes, Vélizy-Villacoublay, France). To create the simulation model, the values of most parameters were chosen based on the existing literature. The mesh size of 1.5 mm was selected, as this is the largest allowable value still below half the LW wavelength, as suggested by the works of Jeenjitkaew et al. [11]. Along the thickness of the substrates, another approach was taken, with the mesh size being governed by the number of layers rather than by the overall size of each element. The value chosen was four layers in each part thickness in order to have enough elements on the thickness to allow the wave to transverse it while still maintaining a reasonable simulation time, which on average corresponded to 1 h per case. A dynamic explicit simulation was chosen due to the temporal flow intrinsic to the problem at hand, while the element type chosen was C3D8R.

2.2.1. Lamb Waves Simulation

To simulate LWs, it was first necessary to observe how the vibrations are induced on the real SLJs. In this work, piezoelectric actuators were used. Thus, the overall excitation occurs on the surface of the substrate, radially from the actuator. To approximate this behavior, the forces were discretized and placed on the edges of the actuator, represented in yellow in Figure 7. Through empirical testing, it was seen that this discretization was enough to mimic experimental tests and, thus, was deemed accepted.

Aluminium Substrate

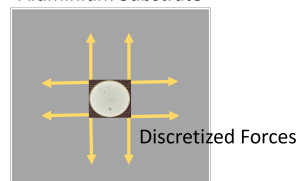


Figure 7. Illustration of a piezoelectric sensor with the forces being discretized at the tips of the square that encompasses the sensor.

The LWs were generated with Hanning window pulse forces with the same characteristics as in the experiment setup. There are multiple ways of creating and representing these

waves in Abaqus, the one chosen in this work was to create a Python script that would apply a variable deformation on the surface of the part simulating the sinusoidal pattern of the Hanning window. Furthermore, the simulation program Abaqus discretizes the vibrations received into the three primary Cartesian components, U1, U2, and U3, as shown in Figure 2. This will be further analyzed in Section 2.3.2 to determine what component or combination of components is most suited and similar to the real signal.

2.2.2. Weak Adhesion Simulation

To simulate weak adhesion, it was first necessary to divide the simulated adhesive into three parts, as represented in Figure 8. The outside edges were considered a layer of weak adhesion with an overall thickness of 0.001 mm, while the center of the adhesive, with the remaining height, was considered not to have been subjected to any physical alterations and thus had the total mechanical properties of the material.

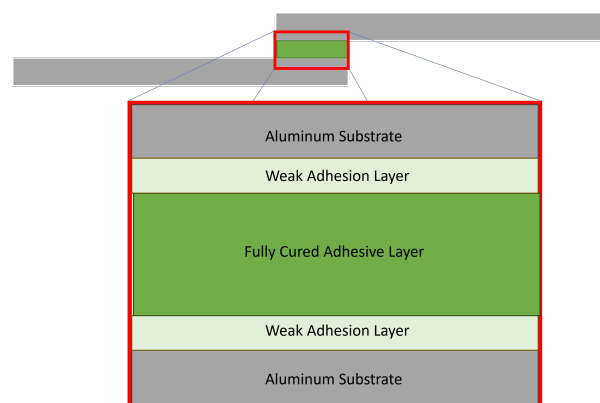


Figure 8. Representation of the three-layer approach to simulating weak adhesion.

In regards to the materials' properties, the overall value of stiffness of the weak adhesion layer was lowered by reducing its Young's modulus, as suggested in [20,21] and reinforced in [22], where it is possible to see the initial validation of the weak adhesion simulation.

Utilizing the previously described techniques, a total of 72 unique cases were generated, each one with a different level of weak adhesion varying from 100 to 700 MPa. These simulations presented time-series that had an overall close visual aspect to the experimental ones, but no conclusions or validation could be made based only on this due to the discrepancies of data previously commented on and seen in Figure 6.

2.3. Numerical Model Validation

2.3.1. Data Processing

Before any analysis of the experimental and simulated data, the collected LW time-series were subjected to interpolation with a step size of 10^{-7} , so that their overall size and start and finishing points were the same. Then, all data were normalized in amplitude to the interval $[-1, 1]$. Furthermore, due to the small size of the experimental dataset, it was necessary to do a cross-validation where each of the 11 experimental time-series was used as a validation set. To do this, the 11 experimental time-series were divided into three categories, with one case being used as a validation set, two used for testing, and the other eight used for training. Once the validation dataset was classified, a new validation dataset was chosen, and this was repeated until all 11 were chosen. This was done so that the results were not subjected to any bias that could arise from the low number of experimental cases and possible inconsistencies of the experimental setup.

As stated previously, during the simulations, a total of 72 were created, thus there was a large discrepancy between the 11 experimental datasets we had and the 72 that came from the simulation. Therefore it was necessary to implement a data augmentation method to increase the number of experimental points. The chosen method was the application of a Gaussian white noise filter that was 5% of the average size of the overall signal. This allows for multiple cases that directly correlate to an experimental setup where multiple data acquisitions are taken of the same sample and the only difference is the noise caused by small environmental variations. After all data were treated and augmented, it was combined and normalized in order to have the same dimensionality.

2.3.2. Machine Learning

The objective of this machine learning algorithm is to analyze the correlation between the experimental and simulated data and determine if the simulations can be used as stand-ins for experimental tests and what are their limitations.

With all the data correctly organized and divided, the machine learning method of choice was a Feed Forward Neural Network (FFNN) due to its simplicity and ease of use. It was also chosen due to its suitability as a regression model, thus the damage can be detected more precisely without the need for classes. The chosen batch size was 16 and the number of data points/input data used was 500 from the total 1700 obtained during the interpolation process of the time-series previously acquired. On the other hand, the output data used were, for the simulated data, Young's modulus of the damaged area, and for the experimental, an approximation of Young's modulus obtained from the tensile test was used. This small number of 500 points out of 1700 from the time-series was used as they possessed a portion of the initial vibration without a large influence of the reflections. This shows that the simulation is lacking in the reflections when compared to the experimental cases and thus there is a fine-tuning between too few data points and where the reflections start to heavily influence the data. The mean absolute error (MAE) was chosen both as a loss function and as an evaluation metric, while for the optimization the ADAM method was used. Finally, a total of 100 epochs was selected as previous analysis showed that there was no need for more iterations and the overall training times were in the accepted range.

The overall structure of the FFNN can be seen in Figure 9, with a total of five layers, one input, three hidden, and one output layer. The input consisted of the 500 data points of one signal and the subsequent layers had several nodes that were tested empirically until the best results were achieved.

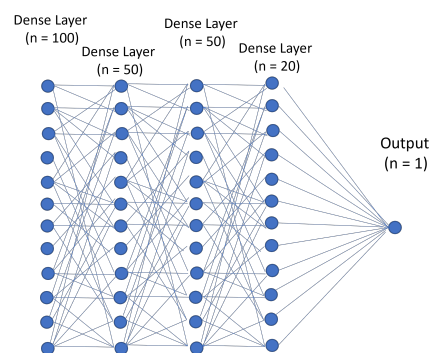


Figure 9. Overall structure of the chosen FFNN with five layers, each one with a different kernel size.

The first test conducted was to determine what signal direction from the simulation should be used. To do this, five tests for each direction were conducted, whose results are listed in Table 1.

Table 1. Average error for each validation case for the three Cartesian Axes plus two others that represent an average of the results in order to represent other intermediate directions. All data are represented in MPa.

	U1	U2	U3	U1 + U2	U1 + U2 + U3
Case 1671 N	464.5	227.1	406.4	406.2	461.8
Case 1902 N	169.8	166.2	166.5	169.0	161.4
Case 2465 N	147.7	161.2	130.7	159.4	130.1
Case 2587 N	137.0	173.4	144.7	163.2	195.7
Case 3192 N	225.3	199.7	163.6	194.4	156.1
Case 4562 N	205.9	221.8	140.1	201.3	197.9
Case 5291 N	327.6	286.0	332.8	280.4	279.6
Case 5670 N	250.2	308.3	299.5	245.0	246.6
Case 6678 N	415.1	331.9	349.7	413.7	415.7
Case 6680 N	347.4	303.1	317.6	379.2	324.9
Case 7301 N	224.3	267.5	439.4	325.5	220.8
Average	265.0	240.6	262.8	267.0	253.7

The average of the five combinations of directions was taken for each case. Finally, the average of these results was obtained. It is possible to see that the direction U2 has the lowest average value, with a total of 240 MPa of average error. Finally, when analyzing the complete dataset obtained from the five cases, U2 was the only case where there was no complete error case and where the algorithm obtained the wrong result by at least the maximum analysis range. The use of U2 also makes sense when analyzing the simulated specimen, as U2 is the direction in which the sensor is from the actuator, thus it is the shortest path and has fewer cases of reflections when compared with the other Cartesian directions.

With the chosen vibrational direction, it is possible to determine the influence of the simulated data when combined with the experimental. This was done following the previous test but instead of the vibrational direction, the number of experimental cases was altered in comparison to the simulated. For each case, a total of five tests were conducted and the average can be seen in Table 2.

In Table 2, the previously mentioned results can be seen and it is possible to conclude two things:

- A few experimental cases constantly have bad results. This is probably because the tests had some form of inconsistency during the experimental setup and thus can be considered faulty.
- The average values are always lower when simulated values are used, showing their reliability as a form of simple data augmentation.
- The validation cases cannot be correctly determined when testing and training are done only with simulated values, showing that there is still a need for a few experimental cases to create a correlation between the experimental and simulated data.

It is also important to note that the experimental cases shown in this validation had a very narrow shape and thus were subjected to many reflections, this shows the robustness of the method as it was capable of detecting damage and even detecting a few of the samples to extremely close values. This test demonstrates that the use of experimental and simulated data in conjunction allows for the correct identification of damage and thus validates the use of the simulated parameters.

Table 2. Multiple tests conducted with different levels of simulated data and noise with the chosen Cartesian direction. All values are represented in MPa.

	77 Exp, 15% Noise		22 Exp, 15% Noise		22 Exp, 5% Noise		49 Exp, 5% Noise	
	Simu + Exp	Exp	Sim + Exp	Exp	Sim + Exp	Exp	Sim + Exp	Exp
Case 1671 N	288.5	465.2	470.0	462.8	415.6	450.9	470.3	468.5
Case 1902 N	205.4	144.3	235.2	288.7	272.9	306.8	228.6	169.9
Case 2465 N	42.3	134.2	94.3	256.3	100.4	259.0	82.0	140.7
Case 2587 N	215.2	154.7	177.6	288.9	214.5	276.5	224.7	200.4
Case 3192 N	24.9	146.6	134.7	283.9	76.6	266.2	136.7	241.1
Case 4562 N	197.7	211.8	176.2	31.3	209.7	127.5	185.0	141.1
Case 5291 N	350.8	161.0	299.5	187.1	279.3	195.9	232.1	162.6
Case 5670 N	253.8	253.1	163.3	99.1	65.0	292.5	163.1	247.9
Case 6678 N	427.0	420.2	321.3	188.9	312.7	184.3	373.9	427.9
Case 6680 N	195.4	417.3	203.0	188.5	181.8	284.6	185.2	355.8
Case 7301 N	313.6	328.4	500.2	326.1	163.0	333.2	355.9	357.9
Average	228.6	257.9	252.3	236.5	208.3	270.7	239.8	264.9

3. Weak Adhesion Detection and Classification

With the simulation model validated, the necessary volumes of data for training and testing machine learning algorithms can be reliably generated, and weak adhesion detection can be performed without the need for experimental data.

In this section, the basic parameters for the simulations are maintained as previously performed, as well as the methods to simulate LWs and to create weak adhesion, while only the size of the samples and the positioning of the sensors/actuators were changed. Larger parts have fewer LW reflections captured by the sensors, which had already been seen as detrimental. Furthermore, weak adhesion detection is conducted in SLJs considering a wide enough damaged areas to have damage detection independent of position.

3.1. Simulation Data

The experimental setup is composed of two substrates with dimensions $120 \times 350 \times 2$ mm and the same adhesive structure previously described in Section 2.2. There is also one actuator located on the top substrate at a distance of 50 mm from the edge. On the lower substrate, there are five sensors equally positioned, as can be seen in Figure 10.

As the objective is to detect damage without any dependence on its location, the damaged section with a width of 25 mm was moved in increments of 1 mm in the adhesive area, always keeping a minimum distance of 50 mm from the edges to reduce the effect of the reflections on the acquired data. In Figure 11, it is possible to see the overall size, limits, and positioning of the weak adhesion region.

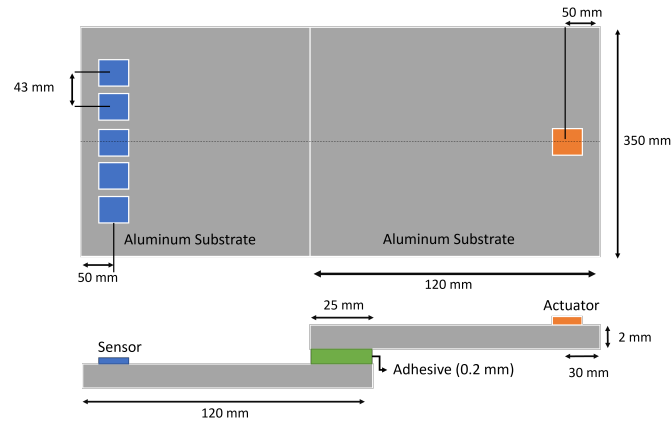


Figure 10. Simulated parts dimensions and positioning of the actuator and sensor components.

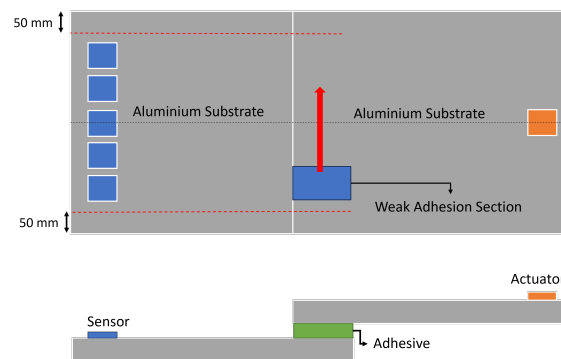


Figure 11. Simulated parts showing the region of weak adhesion.

3.2. Machine Learning Application

As a simple FFNN has been shown to detect damage without any significant problems, it will also be used to detect the damage in this case. The overall structure of the FFNN has only been slightly altered to six layers after a few empirical tests were conducted to maximize the results obtained and the final configuration can be seen in Figure 12.

To iterate on the used parameters and data, a total of 1255 cases were used, divided into 225 different positions for five different levels of damage ranging from 100 to 500 MPa. Each case had five sensors receiving the signal from one actuator and all these data were combined into one continuous time-series. Therefore, the input used was a time-series composed of a total of 2500 data points, concatenated from 500 points from each of the five sensors. For the machine learning algorithm, 500 epochs were chosen to better guarantee conversion, with a batch size of 64, and the maximum absolute error (MAE) was used for both loss function and metrics.

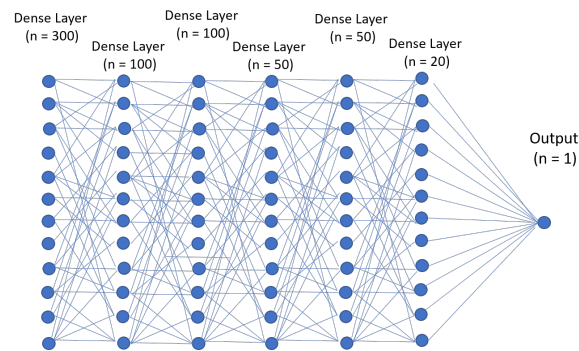


Figure 12. Graphic representation of a FFNN used in the final study with six dense layers.

4. Results and Discussion

From the machine learning setup, it was possible to accomplish the required simulations and in Figure 13 it is possible to see the loss function for both the training and validation cycles. In this figure, there is a gradual decrease in loss from both cases, with the training loss always lower than the validation. It is possible to see that, after around 500 epochs, there is a stabilization of the value of the validation loss, followed by an increase at around 800 epochs. For the training loss, there is a slow decrease after 500 epochs, thus showing signs of overfitting. The option for 1500 epochs was for allowing to visualize the behavior of the loss curve and have the guarantee of its convergence.

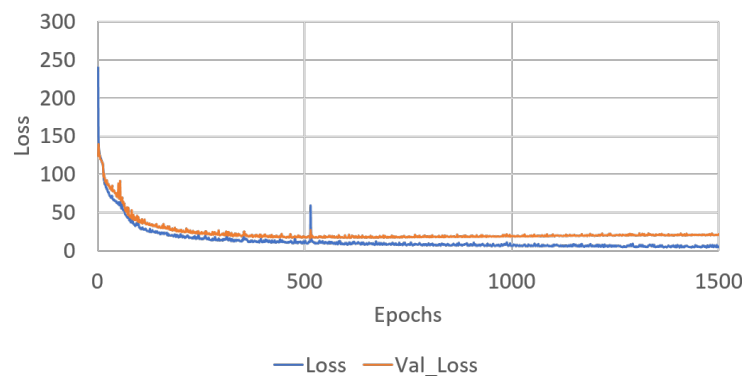


Figure 13. Plot of the loss function for both the training and the validation sets per epoch.

In Figure 14, the predicted values obtained from the validation dataset were compared to the original values and the error was plotted from smallest to largest. In the figure, the difference between them is plotted, showing that there are more cases with less than 50 MPa of error, with a few cases above 150 MPa of error. These values by themselves do not hold a large significance but, when compared with the values of Young's modules from weak adhesion, it is possible to see that most of the error represents, on average, less than 5% of the damage. This means that this method can detect the level of damage with a 95% accuracy without needing to know where the damage is located. Furthermore, the figure shows that only a few occurrences have an error over 25%, which may be acceptable. However, due to the possible future practical applications of this method, it is

important to better understand when these errors occur, to allow for further investigation and increase robustness.

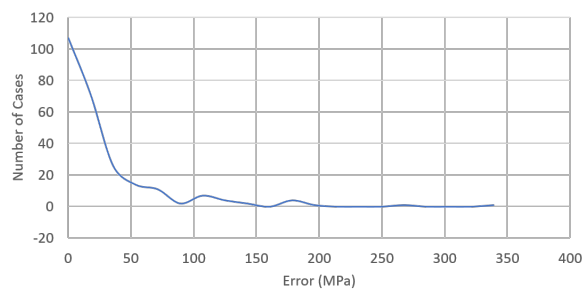


Figure 14. Plot of the number of cases in each error class showing that most errors are below 50 MPa.

To analyze the data even further, the cases were separated between their real value, and in Figure 15 it is possible to see how the error is spread out for each case. It can be seen that the case with the most and largest errors is when the weak adhesion has a Young's modulus of 100 MPa, while all other cases present few errors with a value over 100 MPa. This shows that there is a more pronounced difference between the simulations in the lower range tested and thus, to create a more robust method, a minimum threshold should be adopted, where any values lower than 200 MPa are indicative of damage and no further evaluation should be taken.

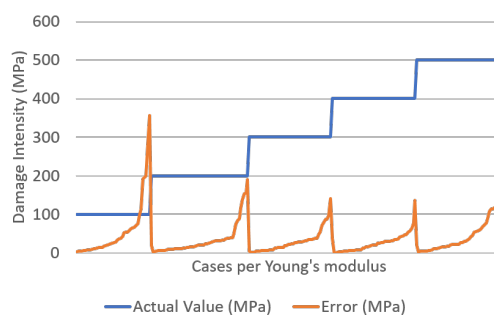


Figure 15. Comparison between the error for each real value of damage.

Following the previous analysis, the data were divided into not only the error but also the overall position of the error for each different case of real value. This division can be seen in Figure 16, where each of the circles corresponds to a different level of real value and the overall dimension of the circles represents the size of the panels. In this Figure, it is possible to see that the larger errors occur on the edges of the panels where there is less information being captured by the sensors and the information that does get captured can be subjected to reflections on the walls. This shows not only where the errors are occurring but also reinforces that the previous study of comparing the simulated and experimental data was done in sub-optimal conditions and still generated significant positive results.

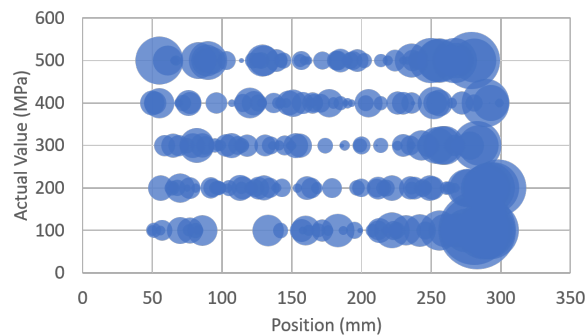


Figure 16. Comparison between the error for each real value of damage in their x coordinate location. The size of the circles represents the dimension of the error.

5. Conclusions

This paper delves into a comprehensive investigation of weak adhesion detection within SLJ through a fusion of LW simulations and advanced machine learning techniques.

Adhesive joints have gained considerable popularity in diverse industries, yet weak adhesion remains a formidable challenge due to its difficult detection before triggering premature structural failure. The utilization of Law, acknowledged for its sensitivity to these types of defects, coupled with machine learning algorithms, presents a novel and promising avenue for addressing this critical issue.

The study methodology encompasses the generation of validated simulated weak adhesion scenarios, closely aligned with experimental ones. Leveraging the intrinsic capabilities of LWs, combined with the sophisticated capabilities of machine learning, enables accurate determination of weak adhesion damage levels. The simulations are compared with realistic cases, leading to LW signals that are subsequently harnessed by machine learning models for robust damage quantification with an over 26% increase in capacity. The validation process serves to underscore the efficacy of amalgamating simulated data with a more limited experimental dataset to train the machine learning models, as these augmentations of the experimental dataset result in tangible improvements in terms of detection accuracy. It also allows for further studies to be conducted only with simulated data. The proposed machine learning framework, manifested as a FFNN, exhibits remarkable potential in precisely predicting the extent of weak adhesion damage, holding true even when the defect's location within the joint is altered, with an overall damage quantification of 95%.

In essence, this study advances the notion that the integration of LW simulations and machine learning techniques offers a pioneering solution that enhances both the precision and dependability of weak adhesion defect detection in adhesive joints. The resultant synergy between these two methodologies holds the key to elevating the quality control of adhesive bonding processes, providing an unparalleled degree of accuracy in damage assessment. This promising approach not only bolsters quality control but also offers the prospect of serving as a potent structural health monitoring tool, thereby fortifying the integrity and longevity of adhesive joint applications across an array of industries.

Using the methods outlined in this paper along with more simulations will allow to determine not only the intensity of the damage but also its location, shape, and dimension. It can also be used to determine whether the damage is a void, weak adhesion, adhesive cracks, or any other type of damage. Furthermore, there is a large area of practical research where the effects of temperature, humidity, and noise need to be studied and determined. Finally, in order to widen the scope and practicality of this study, it should include highly

flexible adhesives, as is the case of silicone, and those with a broad band of characteristics, such as epoxies.

Author Contributions: Conceptualization, G.M.F.R., L.F.M.d.S. and A.M.L.; methodology, G.M.F.R. and A.M.L.; software, G.M.F.R.; validation, G.M.F.R., L.F.M.d.S. and A.M.L.; formal analysis, G.M.F.R., L.F.M.d.S. and A.M.L.; investigation, G.M.F.R. and A.M.L.; writing—original draft preparation, G.M.F.R.; writing—review and editing, G.M.F.R., L.F.M.d.S. and A.M.L.; supervision, L.F.M.d.S. and A.M.L.; project administration, L.F.M.d.S. and A.M.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data available on request to the authors.

Conflicts of Interest: The authors declare no conflict of interest.

References

- da Silva, L.F.M.; Öchsner, A.; Adams, R.D. *Handbook of Adhesion Technology*, 2nd ed.; Springer: Berlin/Heidelberg, Germany, 2018.
- Higgins, A. Adhesive bonding of aircraft structures. *Int. J. Adhes. Adhes.* **2000**, *20*, 367–376. [\[CrossRef\]](#)
- Binhasan, M.; Al-Habeeb, K.M.; Almuqbil, A.S.; Alhaidary, T.A.; Alfawaz, Y.F.; Farooq, I.; Vohra, F.; Abduljabbar, T. Assessment of the physical properties of an experimental adhesive dentin bonding agent with carbon nanoparticles. *Crystals* **2022**, *12*, 1441. [\[CrossRef\]](#)
- Shah, N.V.; Meislin, R. Current state and use of biological adhesives in orthopedic surgery. *Orthopedics* **2013**, *36*, 945–956. [\[CrossRef\]](#) [\[PubMed\]](#)
- Mehdi, G.; Ali, N.; Hussain, S.; Zaidi, A.A.; Shah, A.H.; Azeem, M.M. Design and fabrication of automatic single axis solar tracker for solar panel. In Proceedings of the 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), Sukkur, Pakistan, 30–31 January 2019; IEEE: Piscataway Township, NJ, USA, 2019; pp. 1–4.
- Mahmud, K.; Morsalin, S.; Khan, M.I. Design and fabrication of an automated solar boat. *Int. J. Adv. Sci. Technol.* **2014**, *64*, 31–42. [\[CrossRef\]](#)
- Ciccotti, M.; Giorgini, B.; Vallet, D.; Barquins, M. Complex dynamics in the peeling of an adhesive tape. *Int. J. Adhes. Adhes.* **2004**, *24*, 143–151. [\[CrossRef\]](#)
- Ramalho, G.M.; Lopes, A.M.; da Silva, L.F. Structural health monitoring of adhesive joints using Lamb waves: A review. *Struct. Control Health Monit.* **2021**, *29*, e2849. [\[CrossRef\]](#)
- Archives, U.N.; Administration, R. *Federal Aviation Regulations-Section 23.573*; U.S. Government Printing Office: Washington, DC, USA, 2014.
- Guyott, C.C.H.; Cawley, P.; Adams, R. The non-destructive testing of adhesively bonded structure: A review. *J. Adhes.* **1986**, *20*, 129–159. [\[CrossRef\]](#)
- Jeenjitkaew, C.; Guild, F.J. The analysis of kissing bonds in adhesive joints. *Int. J. Adhes. Adhes.* **2017**, *75*, 101–107. [\[CrossRef\]](#)
- Teixeira de Freitas, S.; Zarouchas, D.; Poulis, J. The use of acoustic emission and composite peel tests to detect weak adhesion in composite structures. *J. Adhes.* **2018**, *94*, 743–766. [\[CrossRef\]](#)
- Loreiro, V.; Ramalho, G.; Tenreiro, A.; Lopes, A.M.; da Silva, L. Feature extraction and visualization for damage detection on adhesive joints, utilizing Lamb waves and supervised machine learning algorithms. *Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci.* **2022**, *236*, 09544062221086410. [\[CrossRef\]](#)
- Ramalho, G.M.; Lopes, A.M.; Carbas, R.J.; Da Silva, L.F. Identifying Weak Adhesion in Single-Lap Joints Using Lamb Wave Data and Artificial Intelligence Algorithms. *Appl. Sci.* **2023**, *13*, 2642. [\[CrossRef\]](#)
- Plexus Technical Data Sheet MA560-1. *ITW Performance Polymers*. Available online: <https://itwperformancepolymers.com/> (accessed on 29 April 2023).
- Lee, B.; Staszewski, W. Modelling of Lamb waves for damage detection in metallic structures: Part I. Wave propagation. *Smart Mater. Struct.* **2003**, *12*, 804. [\[CrossRef\]](#)
- Packo, P.; Bielak, T.; Spencer, A.; Staszewski, W.; Uhl, T.; Worden, K. Lamb wave propagation modelling and simulation using parallel processing architecture and graphical cards. *Smart Mater. Struct.* **2012**, *21*, 075001. [\[CrossRef\]](#)
- Ahmad, Z.; Gabbert, U. Simulation of Lamb wave reflections at plate edges using the semi-analytical finite element method. *Ultrasonics* **2012**, *52*, 815–820. [\[CrossRef\]](#) [\[PubMed\]](#)
- Adin, H.; Yildiz, B.; Adin, M.S. Numerical investigation of fatigue behaviours of non-patched and patched aluminium pipes. *Eur. J. Tech. (EJT)* **2021**, *11*, 60–65. [\[CrossRef\]](#)
- Xu, Y.; Tao, C.; Qiu, J. Debonding detection of scarf-repaired composite laminates with laser ultrasonic Lamb waves. *Proc. J. Phy. Conf. Ser.* **2022**, *2184*, 012041. [\[CrossRef\]](#)

21. Zhuang, Y.; Kopsaftopoulos, F.; Dugnani, R.; Chang, F.K. Integrity monitoring of adhesively bonded joints via an electromechanical impedance-based approach. *Struct. Health Monit.* **2018**, *17*, 1031–1045. [[CrossRef](#)]
22. Mehrabi, M.; Soorgee, M.H.; Habibi, H.; Kappatos, V. A novel application of ultrasonic Lamb waves: Studying adhesive effects on the inspection of coating debonding in a three-layer waveguide. *Nondestruct. Test. Eval.* **2021**, *36*, 616–636. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

Appendix F

Paper F

Neural Computing and Applications

Detecting and Assessing Weak Adhesion in Structural Single Lap Joints Using a Machine Learning Pipeline with Lamb Waves Data

--Manuscript Draft--

Manuscript Number:	NCAA-D-24-01740
Full Title:	Detecting and Assessing Weak Adhesion in Structural Single Lap Joints Using a Machine Learning Pipeline with Lamb Waves Data
Article Type:	Original Article
Keywords:	Weak adhesion; Lamb wave; Convolutional neural network; Transfer Learning
Corresponding Author:	Gabriel Martins Franco Ramalho FEUP: Universidade do Porto Faculdade de Engenharia Porto, PORTUGAL
Corresponding Author Secondary Information:	
Corresponding Author's Institution:	FEUP: Universidade do Porto Faculdade de Engenharia
Corresponding Author's Secondary Institution:	
First Author:	Gabriel Martins Franco Ramalho
First Author Secondary Information:	
Order of Authors:	Gabriel Martins Franco Ramalho António Lopes Lucas Silva
Order of Authors Secondary Information:	
Funding Information:	
Abstract:	Adhesive joints are widely used in various industries due to their low weight and good mechanical performance. However, they are affected by defects and damage along their life cycle, with weak adhesion being the most significant issue affecting structural integrity. Currently, weak adhesion can only be effectively detected by destructive testing techniques, posing a serious obstacle to the widespread use of adhesives in the manufacture of primary structures, which are crucial in key industries such as aerospace and automotive sectors. In this paper, we propose a nondestructive testing technique for detecting, evaluating intensity and locating weak adhesion in single lap joints (SLJs). The method utilizes Lamb waves (LWs) data in a machine learning pipeline. First, we generate a large dataset of simulated LW time-series for SLJs with varying levels of weak adhesion, damage locations and sizes. After pre-processing to remove outliers and discrepancies, these raw time-series are fed into a pipeline consisting of convolutional neural networks (CNNs), trained and tested with synthetic data to characterize damage. Finally, the weights and biases from the CNNs are saved for use in a transfer learning algorithm, which is fine-tuned with a small amount of experimental data. The algorithm is then applied to detect the presence of damage and to assess its intensity. The results demonstrate that the pipeline can not only detect damage in simulated data with over 95.3% accuracy but also identify about 100% of damaged cases in experimental data. Regarding the weak adhesion intensity, the algorithm achieves an average loss of 45 MPa for the experimental validation dataset, with average error of 140 MPa and best cases of only 3.6 MPa. As for the weak adhesion localization, the algorithm exhibited an average loss of 8 mm in the validation synthetic dataset. Importantly, the methodology remains flexible enough to tackle damage characteristics beyond existence, intensity and localization, without requiring major alterations. Therefore, this approach holds significant potential for enhancing the safety and durability of bonded structures through structural health monitoring.

Detecting and Assessing Weak Adhesion in Structural Single Lap Joints Using a Machine Learning Pipeline with Lamb Waves Data

Gabriel M.F. Ramalho^{1*†}, António M. Lopes^{1,2†} and Lucas F.M. da Silva^{1,2†}

¹Department of Mechanical Engineering, Faculty of Engineering, University of Porto, Rua Dr. Roberto Frias, Porto, 4200-465, Portugal.

²INEGI, Institute of Science and Innovation in Mechanical and Industrial Engineering, Campus da FEUP, Rua Dr. Roberto Frias 400, Porto, 4200-465, Portugal.

*Corresponding author(s). E-mail(s): up201911767@edu.fe.up.pt;

Contributing authors: aml@fe.up.pt; lucas@fe.up.pt;

[†]These authors contributed equally to this work.

Abstract

Adhesive joints are widely used in various industries due to their low weight and good mechanical performance. However, they are affected by defects and damage along their life cycle, with weak adhesion being the most significant issue affecting structural integrity. Currently, weak adhesion can only be effectively detected by destructive testing techniques, posing a serious obstacle to the widespread use of adhesives in the manufacture of primary structures, which are crucial in key industries such as aerospace and automotive sectors. In this paper, we propose a nondestructive testing technique for detecting, evaluating intensity and locating weak adhesion in single lap joints (SLJs). The method utilizes Lamb waves (LWs) data in a machine learning pipeline. First, we generate a large dataset of simulated LW time-series for SLJs with varying levels of weak adhesion, damage locations and sizes. After pre-processing to remove outliers and discrepancies, these raw time-series are fed into a pipeline consisting of convolutional neural networks (CNNs), trained and tested with synthetic data to characterize damage. Finally, the weights and biases from the CNNs are saved for use in a transfer learning algorithm, which is fine-tuned with a small amount of experimental data. The algorithm is then applied to detect the presence of damage and to assess its intensity.

The results demonstrate that the pipeline can not only detect damage in simulated data with over 95.3% accuracy but also identify about 100% of damaged cases in experimental data. Regarding the weak adhesion intensity, the algorithm achieves an average loss of 45 MPa for the experimental validation dataset, with average error of 140 MPa and best cases of only 3.6 MPa. As for the weak adhesion localization, the algorithm exhibited an average loss of 8 mm in the validation synthetic dataset. Importantly, the methodology remains flexible enough to tackle damage characteristics beyond existence, intensity and localization, without requiring major alterations. Therefore, this approach holds significant potential for enhancing the safety and durability of bonded structures through structural health monitoring.

Keywords: Adhesive joint; Weak adhesion; Lamb wave; Convolutional neural network; Transfer learning.

1 Introduction

Over recent years, there has been a rise in the use of adhesive joints across diverse industries. This increase is due to the capability of adhesives to join different materials, ensure uniform stress distribution, and allow structures that are lighter than those created using conventional jointing methods (Chen et al, 2011; da Silva et al, 2018; Borges et al, 2023). Among the different types of joints, the single lap joint (SLJ) stands out as one of the most frequently employed, finding application in industries, namely the vehicle sector (Ramalho et al, 2021). However, the utilization of adhesive joints in certain industries, such as aeronautics, still faces limitations due to strict inspection and certification requirements imposed by industry standards, such as the Federal Aviation Regulations (FAR) Section 23.573(5)-(iii) (Archives and Administration, 2014). One of the main requirements is the need for reliable non-destructive testing methods (NDTs) to identify damage. Unfortunately, existing NDT methods for adhesive joints exhibit constraints and are inadequate for detecting certain types of damage (Ramalho et al, 2021; Guyott et al, 1986; Heilmann and Hoffmann, 2023; Akaike and Akiyama, 2023), namely weak adhesion (a.k.a. kissing bond or zero volume void).

Weak adhesion corresponds to a reduction in maximum adhesive strength by at least 20%, without the joint displaying any noticeable voids, cracks, or any other observable evidences. This typically occurs when contamination (e.g., with oils or dust) or inadequate surface preparation interfere with the proper adhesion of the adhesive to the substrates (Jeenjitkaew and Guild, 2017). Various NDT methods have been proposed to detect weak adhesion, with the most promising being based on Lamb waves (LWs).

LWs are guided waves that propagate through a solid medium, having both a pressure and shear propagation modes. When encountering boundary conditions within the medium, they undergo reflection, giving rise to intricate patterns. One of the advantages of LWs is their capability to traverse long distances without much attenuation, even in complex geometries. They are very sensitive to incipient damage, making them

1 suitable as an NDT method (Ramalho et al, 2022; Giurgiutiu and Cuc, 2005; Dod-
2 son and Inman, 2013). However, a major drawback lies in the complex signals they
3 produce, and relating their patterns with damage signatures is challenging. To fully
4 explore the potential of LW as an NDT method, the implementation of robust data
5 processing algorithms becomes imperative (Ramalho et al, 2021; Tenreiro et al, 2022).

6 There are two primary approaches to relate LW data with damage: statistical
7 methods and machine learning methods. Statistical-based methods rely on identifying
8 discrepancies, either in time or frequency domains, between baseline signals and actual
9 data. There are subtle variations in the used algorithms, which are broadly categorized
10 into two groups: (i) time of flight diffraction (TOFD) (Capinha, 2007; Hay et al, 2006);
11 and (ii) signal difference coefficient (SDC) (Tabatabaeipour et al, 2014). In the study
12 by Hay et al (2006), LWs generated and detected with transducers integrated into an
13 aircraft structure were used in a statistical method to assess material loss in aircraft
14 components. Similarly, Tabatabaeipour et al (2014) utilized a statistical method to
15 identify damage in composite structures, achieving varying degrees of success.

16 Various studies have explored the application of machine learning methods in
17 detecting defects, including some involving LWs data, but not specifically dealing
18 with adhesive joints. One such study was conducted by Sbarufatti et al (2014), where
19 machine learning techniques were employed to diagnose damage in a specimen using
20 an LW sensing network. Similarly, Su et al (2019) utilized LWs in combination with
21 convolutional neural networks (CNNs) to quantify and localize damage. Additionally,
22 Khan et al (2019) investigated the use of deep learning (DL) (Kovvilpillai and Jayan-
23 thy, 2023) to predict and identify delaminations in composite parts. Ramalho et al
24 (2023) addressed weak adhesion using simulated data from an experimentally vali-
25 dated model and characterized SLJs' damage in terms of the Young's modulus of the
26 adhesive at its interface with the substrates. The machine learning-based approaches
27 parallel the methodologies observed in statistical methods. Unlike more standard
28 signal-processing approaches, which reveal difficulties with low signal-to-noise ratios or
29 sparse data, machine learning models can effectively process information and extract
30 valuable insights. As more data is gathered from diverse structures and conditions, the
31 algorithms continually enhance their knowledge of complex LWs data, enabling them
32 to better distinguish between normal wave patterns and those related to damage.

33 In this paper, a novel NDT technique is proposed to characterize weak adhesion
34 in SLJs. The method utilizes LWs data in a machine learning pipeline. First, a large
35 synthetic dataset for SLJs with varying levels of weak adhesion, damage locations,
36 and sizes is generated. Then, the dataset undergoes pre-processing to remove outliers
37 and discrepancies before being fed into a pipeline of CNNs. These CNNs are trained
38 and tested with the synthetic data for detecting, evaluating the intensity, and locat-
39 ing damage. Subsequently, the (pre)trained CNNs are utilized in a transfer learning
40 scheme, thus they are fine-tuned with small amounts of experimental data and then
41 applied to detect the presence of damage and assess its intensity. Furthermore, the
42 size of the damage is varied, introducing a new variable and broadening the level of
43 complexity that the ML algorithm has to handle. The main novelties of the paper
44 include:
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

- Creation of finite element (FE) models able to describe weak adhesion damage, and LWs generation and propagation in SLJs;
- Development of a machine learning pipeline based on CNNs trained with synthetic data to detect, evaluate, and locate weak adhesion in simulated SLJs;
- Use of transfer learning to fine-tune the (pre)trained CNNs with experimental data to detect and evaluate weak adhesion in real SLJs.

The paper is divided into 6 sections. Section 2 presents the FE modeling and simulation of SLJs. Section 3 details the experimental setup used to acquire SLJs experimental data. Section 4 presents the machine learning algorithms along with the methodology developed to characterize weak adhesion damage. Section 5 presents and discusses the main results. Section 6 summarizes the conclusions.

2 SLJs Modeling and Simulation

FE models of SLJs were implemented and LWs were simulated using the software package ABAQUS. To generate the synthetic dataset, several important variables' values were selected based on prior literature (Ramalho et al, 2023), serving as an initial foundation for all simulated SLJs. A frequency of 100 kHz was adopted for LWs because it falls below the range where multiple modes occur, yet it remains sufficiently high to detect damage. The mesh size was set equal to 1.5 mm, which is the largest value that remains below half the wavelength of the LWs (Jeenjitkaew and Guild, 2017), except in the direction of the SLJ's materials thicknesses. In this case, the mesh size was determined by a fixed number of layers rather than the overall size of each element. Specifically, 4 layers were selected in each part thickness to ensure sufficient layers for an apparent wave traversal while still maintaining a reasonable simulation time, averaging 1 hour per simulated SLJ. A dynamic explicit simulation was chosen due to the intrinsic temporal flow of the problem at hand, and the element type selected was C3D8R.

Two types of SLJs were modeled with experimental setups in mind, which will be briefly explained in Section 3. The first type was used to treat weak adhesion detection and intensity evaluation. Thus, the SLJs consist of two substrates measuring $120 \times 25 \times 2$ mm each, along with an adhesive layer of 0.2 mm, as further detailed in Section 2.2. Positioned on the upper substrate is a single actuator, situated 25 mm away from the edge. A single sensor is located on the lower substrate. Furthermore, there are 6 mm holes in the substrates used to experimentally test the SLJs for traction. These parts are schematically represented in Figure 1.

The second type was used to address damage localization. Thus, the SLJs are wider than the previous ones, consisting of two substrates measuring $120 \times 350 \times 2$ mm each, also with an adhesive thickness of 0.2 mm. Positioned on the upper substrate is a single actuator, situated 50 mm away from the edge, while on the lower substrate a total of five sensors are placed evenly distributed, as depicted in Figure 2. It is important to note that all other variables, except those stated herein, were maintained as for the first type of SLJ.

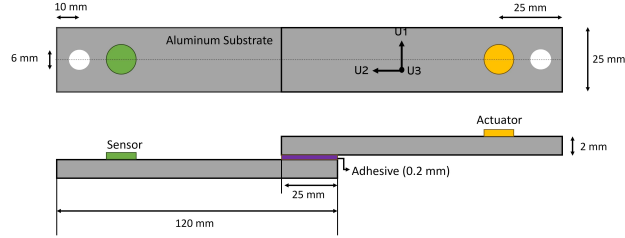


Fig. 1 Illustration of the dimensions, and actuator and sensor placement, of the first type of SLJ, used to address weak adhesion detection and intensity evaluation.

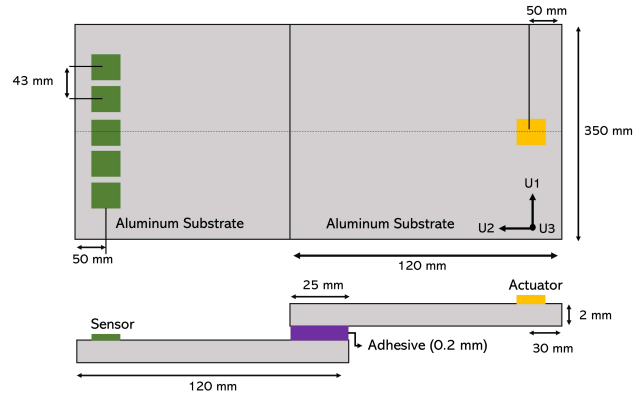


Fig. 2 Illustration of the dimensions, and actuator and sensor placement, of the second type of SLJ, used to address weak adhesion localization.

2.1 Lamb Waves Simulation

In the process of simulating LWs, it was crucial to understand the mechanism through which vibrations are generated, as this directly influences the direction in which the LWs propagate. In this study, the vibrations needed to emulate motion generated by piezoelectric round actuators, which have small radial movements. Consequently, LWs propagate parallel to the surface of the substrate and emanate in a 360° pattern from the edges and on the plane of the simulated actuator. To approximate this behavior, forces are applied at the edges of a square area representing the location of the actuator, as illustrated by arrows in Figure 3. Previous empirical testing has confirmed that this discretization adequately mimics experimental conditions and was

therefore deemed acceptable. The applied forces vary in time according to a 5-cycle Hanning-windowed sinusoidal burst centered at 100 kHz (Ramalho et al, 2023).

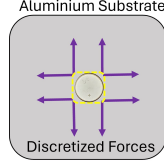


Fig. 3 Representation of the forces that approximate the behavior of the piezoelectric round actuators used in real SLJs.

When propagating within a thin plate away from boundary conditions, LWs exhibit two fundamental modes: the symmetric (Sn) and the anti-symmetric (An), which are relative to the plate's mid-plane. The displacement vector $\mathbf{u}$ is analytically described by:

$$\mu \nabla^2 \mathbf{u} + (\lambda + \mu) \nabla (\nabla \cdot \mathbf{u}) = \rho \frac{\partial^2 \mathbf{u}}{\partial t^2}, \quad (1)$$

where μ and λ denote the Lamé constants, which are material-specific parameters arising from elastic stress-strain relationships, and ρ represents the material mass density. Thus, we have:

$$\mathbf{u} = \nabla \Phi + \nabla \times \Psi, \quad (2)$$

with Φ and Ψ representing potentials.

As ABAQUS cannot directly generate guided waves as needed, a Python script was implemented to apply the necessary forces, discretized into a number of points. These discretized values were then transmitted to ABAQUS and assigned to the desired Cartesian components, which, in the context of this work, correspond to the plane of the actuator.

2.2 Weak Adhesion Simulation

To simulate weak adhesion, we partition the adhesive layer into three parts, as illustrated in Figure 4. The faces that were in direct contact with the aluminum substrates were designated as a layer of weak adhesion with a total thickness of 0.001 mm, while the center of the adhesive, comprising the remaining height of 0.198 mm, was considered unaffected and retained the material's original mechanical properties.

Regarding material properties, the stiffness of the weak adhesion layer was reduced by adjusting its Young's modulus, in line with previous research (Xu et al, 2022; Zhuang et al, 2018; Mehrabi et al, 2021; Ramalho et al, 2023).

To generate the synthetic datasets, two approaches were employed depending on the type of SLJ. For the first type, focused on detecting the presence and assessing the intensity of weak adhesion, the damaged area's intensity was incrementally altered in 2

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

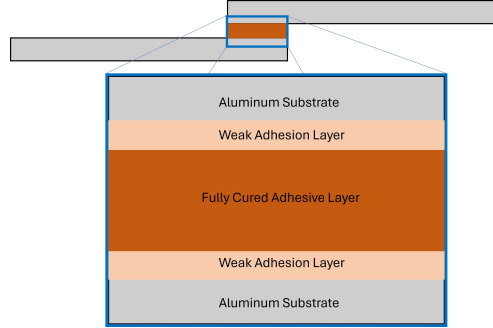


Fig. 4 Representation of the adhesive 3-layer partition to simulate weak adhesion.

MPa increments, ranging from 100 MPa to 500 MPa, compatible with the experimental results in Section 3, while maintaining a constant size of 25 mm. For the second type, focused on damage localization, the damaged area, spanning 25×25 mm, was systematically shifted in 1 mm increments across the substrates overlap area (i.e., direction U1), ensuring a minimum distance of 50 mm from the edges of the SLJs to mitigate LWs reflection effects. Furthermore, to ensure a comprehensive dataset, the dimensions of the damage width were also varied in increments of 25 mm, ranging from 25 to 100 mm, resulting in damage sizes of 25×25 , 50×25 , 75×25 , and 100×25 mm. By combining all cases, over 14,000 simulations were generated, each featuring distinct levels of weak adhesion, damage positions, and sizes. It should be noted that the synthetic dataset can be easily enlarged with the inclusion of further intricacies into the simulations, establishing a protocol and methodology to enhance the simulation's resemblance to real-world scenarios. Figure 5 provides an overview of the extent, boundaries, and positioning of the region with weak adhesion.

3 Experimental SLJs' Testing

The experimental dataset was obtained using the first type of SLJ depicted in Figure 1. Piezoelectric elements PIC 255 piezoceramic (PRYY + 1119 model) were used as sensors and actuators. These elements were selected due to their light weight, low cost, and versatility. Their versatility will also facilitate conducting further tests and enable the use of sensor arrays to analyze large SLJ areas. The substrates are made of aluminum 6061 with holes drilled to allow the parts to be held in a tension testing machine. The adhesive used was Plexus MA 560-1. Multiple levels of weak adhesion were created by applying different quantities of release agent Loctite 770-NC Frekote, resulting in a total of 11 SLJs.

The experimental test was divided into two parts. The first part aimed to capture the LWs at the sensor. The second part was used to determine the overall maximum

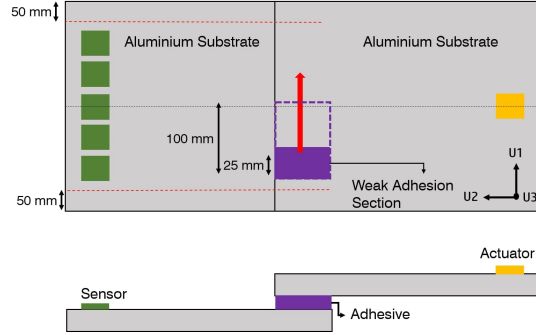


Fig. 5 Simulated SLJs showing the region of weak adhesion.

load capability of the joint. Consistent with the simulated setup, a five-cycle Hanning-windowed sinusoidal burst centered at a frequency of 100 kHz was applied to the actuator by a signal generator AIM & Thurbly Thander Instruments, model TGF4042. This approach mitigates the dispersion effects of the LWs while maintaining good sensitivity. To simplify input and output synchronization, the excitation signal was also collected by a data acquisition system Tektronix, model TBS1000C.

Once all the experimental data were acquired, the sensor and actuator were removed, and the parts were subjected to a tensile test using an Instron 3367 machine until rupture occurred. Figure 6 depicts the load-displacement curves of all SLJs, from which the Young's modulus can be determined.

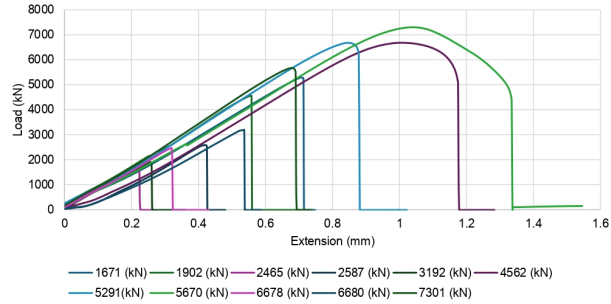


Fig. 6 Load-displacement curves for the 11 experimental SLJs. Each case represents a sample fabricated with a different level of weak adhesion.

4 Machine Learning Pipeline

This Section presents an overview of the entire pipeline proposed to characterize weak adhesion in SLJs. It is composed of an initial data acquisition phase from any source, whether simulated or experimental. These data are pre-processed and prepared for subsequent phases. A specific CNN determines if damage is present in the SLJ. If damage does not exist, then there is no need for extra processing, and the pipeline stops there. If damage is detected, then the pipeline triggers additional CNNs to determine damage intensity and damage localization. The CNNs are pre-trained with synthetic data and fine-tuned and used with experimental data within a transfer learning scheme. Figure 7 illustrates the suggested full pipeline.

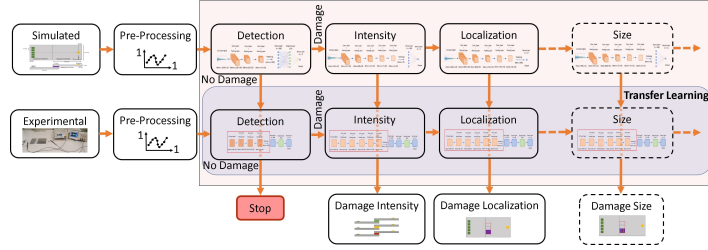


Fig. 7 Representation of the pipeline proposed for locating and evaluating weak adhesion in SLJs.

4.1 Data Pre-processing

The simulations generate LWs with components along the three Cartesian axes U1, U2, and U3 of the SLJs. The average values between U1 and U2 represent the closest match to experimental data and are thus utilized for further processing (Ramalho et al, 2023). All data sequences undergo an initial cleaning process to create a usable dataset. While this is less critical in simulated data, where the user has more control of the output, it is important to eliminate any possibilities of corrupt values in order to establish a robust methodology applicable to experimental data.

Following initial cleaning, the data was re-sampled with a step size of 10^{-7} s to ensure uniform time-series and match starting and ending points. The total number of points in each time-series is fixed balancing the acceptable noise levels generated by reflections on SLJs' boundaries and the need for a minimum number of points to accurately represent the arriving wave at the sensor. For this study, a total of 1,200 points was utilized, based on previous work (Ramalho et al, 2023).

Subsequently, normalization and remapping of the values were applied to all time-series. This step is crucial as the dimensions of experimental and simulated data can influence the behavior of the CNNs. Figure 8 illustrates the pre-processing steps.

When dealing with data from multiple sensors, these data can be organized in different ways. One is to concatenate the sensors' data and create a new larger time-series. Another way is to take the average values of all sensors' time-series, thus keeping the original time-series dimension. For this paper, the approach was rather to consider that each sensor's data corresponds to a damage case. This approach not only assists the algorithm in learning the characteristics of damage but also makes the methodology flexible enough to accommodate any number of sensors.

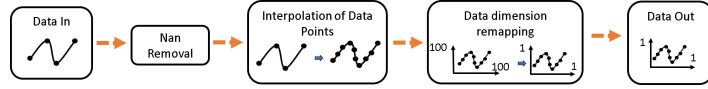


Fig. 8 Representation of the data pre-processing sequence.

Other than the general form of pre-processing described, there was a need for a specific approach regarding the case of 'no damage'. The presence of only one instance of 'no damage' introduces data cases imbalance for the machine learning algorithms. To address this imbalance, multiple instances of 'no damage' were 'artificially' created by adding Gaussian white noise to the signals at varying levels of intensity. The noise has zero mean and the same standard deviation and size as the original signal. Subsequently, the noise was re-sized to be 10^{-2} times smaller than the average value of the signal. These additional instances were generated following all preceding pre-processing steps and were subsequently incorporated directly into the learning algorithms.

4.2 Design of the Convolutional Neural Network

With all data correctly organized, the chosen machine learning method was a CNN, selected for its simplicity, ease of use, and suitability as a regression model. Additionally, this algorithm reduces its overall size at each pooling level, making it more efficient and faster to calculate than others, which is crucial, particularly if more variables are incorporated into the simulations or for in-situ real-time applications.

In total, three CNN algorithms were employed to detect, evaluate intensity, and localize damage, respectively. The first algorithm, besides detecting the presence of damage, serves as a pre-trained model for further use in a transfer learning scheme, fine-tuned with experimental data. It utilizes a CNN with 2,800 simulated cases of SLJs, including both damaged and undamaged instances of the two types described in Section 2, as input. This input is followed by three hidden layer blocks consisting of a convolutional layer and a pooling layer, and finally, two hidden layers of fully connected dense layers with a dropout layer between them. Figure 9 illustrates this algorithm. The output consists of a dense layer with one output using a RELU activation function. Binary cross-entropy was selected as the loss function, and accuracy served as the evaluation metric. A total of 600 epochs were deemed sufficient for comprehensive analysis. The batch size for this algorithm was set to 1,028, and the ADAM

optimization method was employed. A total of 1,200 points originated from the data interpolation pre-processing were adopted.

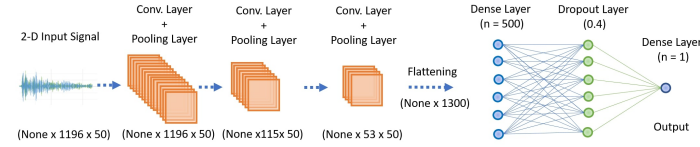


Fig. 9 Overall structure of the CNN used to detect damage in simulated data.

The second CNN was designed to evaluate the intensity of weak adhesion. It will also be used further as a pre-trained model in a transfer learning algorithm. The overall configuration is depicted in Figure 10, with a total of 14 layers. The input mirrors that of the previous model, excluding the ‘no damage’ SLJs, as all parts are now considered ‘with damage’. The input is followed by 5 blocks consisting of a convolutional layer and a pooling layer, a flattening layer, and 2 fully connected layers, with the last one serving as the output. In this CNN, the output data used to determine the level of damage intensity is the Young’s modulus of the damaged area, as previously described, ranging from 100 MPa to 500 MPa.

Hyperparameters for all layers were empirically tested until optimal results were attained. Mean absolute error (MAE) was employed as both the loss function and evaluation metric for this algorithm. A total of 600 epochs was selected, as preliminary analysis indicated that additional iterations were unnecessary and training times remained within an acceptable range. The batch size for this algorithm was set to 512, and the ADAM optimization method was utilized. The 1,200 points originated from the data interpolation pre-processing were used.

Given that this case involves regression, the evaluation metric employed was the average and overall errors for each case. This approach enables a better understanding of limitations and their occurrence within each segment.

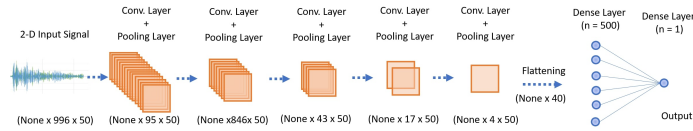


Fig. 10 Overall structure of the CNN used to evaluate damage intensity in simulated data.

Finally, a CNN was created to determine the damage position in the SLJs of larger sizes. The overall configuration can be seen in Figure 11. There is a total of 14 layers

again with 5 blocks composed of a convolutional and pooling layer, followed by a flattening layer and a final fully connected layer that serves as the output. For this algorithm the output is the position of the damage along U1 direction and the MAE is used as both the loss function and the evaluation metric. For the optimizer, ADAM was also used, and a total of 1,000 epochs was adopted with a batch size of 512 and a total of 1,200 initial points as inputs. Finally, this case also uses regression with the same evaluation method as before, adopting the average and case-to-case error values.

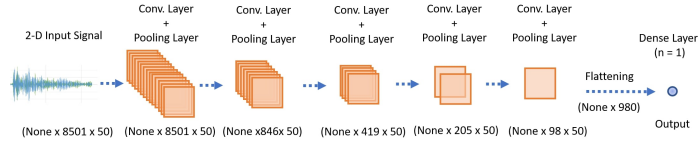


Fig. 11 Overall structure of the CNN used for damage localization in simulated data.

4.3 Transfer Learning

Transfer learning involves utilizing a machine learning method wherein a model previously trained on a specific task is repurposed or adjusted to suit a similar task (Talaie Khoei et al, 2023). Rather than initiating the learning procedure anew, transfer learning uses the knowledge acquired from addressing one problem and employs it to tackle another related problem (Yu and Zhang, 2023; Weiss et al, 2016; Pan and Yang, 2009).

In this study, the CNNs are initially trained on a comprehensive synthetic dataset, serving as a foundational step. Subsequently, the models undergo fine-tuning using a smaller dataset comprised of experimental data. This methodology proves particularly advantageous in the context of the problem at hand, given the relatively low complexity associated with generating a large simulated dataset compared to the practical implementation of an experimental setup to collect data.

Firstly, transfer learning is used for damage detection, as illustrated in Figure 12. The components within the border line have the same weights and biases of the pre-trained model, while the rest is reset to be fine-tuned.

In Figure 13, transfer learning scheme utilized for evaluating the intensity of weak adhesion is illustrated. As in the previous CNN, the components within the border line have the same weights and biases of the pre-trained model, while the rest is reset to be fine-tuned.

5 Results and Discussion

In this Section, the results obtained with transfer learning for both weak adhesion detection and intensity characterization are presented. For damage position classification, just results obtained with synthetic data are presented, as no experimental

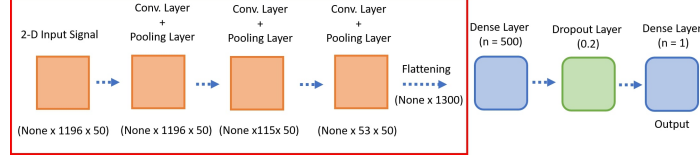


Fig. 12 Overall structure of the transfer learning scheme for damage detection. The components within the border line have the same weights and biases of the pre-trained model, while the rest is reset to be fine-tuned.

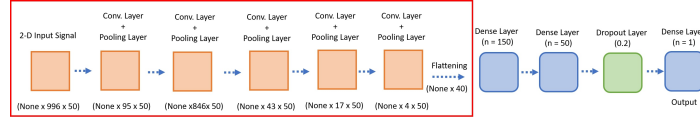


Fig. 13 Overall structure of the transfer learning scheme for evaluating the intensity of weak adhesion. The components within the border line have the same weights and biases of the pre-trained model, while the rest is reset to be fine-tuned.

data are available for performing transfer learning. Following the presentation of each result, a discussion on the overall capability of the algorithms is conducted.

5.1 Damage Detection

As mentioned in Subsection 4.3, the initial algorithm aimed to detect damage regardless of its characteristics. The proposed pre-trained model successfully identified damage in the validation synthetic dataset with an accuracy exceeding 95.3%. Figure 14 illustrates the loss function for each epoch. It is evident that there is rapid convergence around the 40th epoch, followed by a further decrease in loss after 500 epochs. Due to this behavior, the maximum number of epochs was set sufficiently high to ensure attainment of the global minimum.

Figure 15 illustrates the algorithm's accuracy convergence for each epoch. The plot demonstrates a similar pattern to that of the loss function, with a significant convergence observed around the 40th epoch, followed by another notable convergence around the 500th epoch. Additionally, it is noticeable that approximately every 200 steps, there is a temporary decrease in accuracy and an increase in loss, which are swiftly reversed. This phenomenon occurs because the algorithm's optimization process explores alternative local minima, failing to find satisfactory values and consequently returning to the previous ones. It is through this exploration that the convergence observed around the 500th epoch is facilitated.

Using simulated and experimental data, the algorithm successfully detected 100% of the damaged SLJs but encountered challenges in identifying non-damaged cases, achieving an approximate success rate of around 70%. Although lower than during

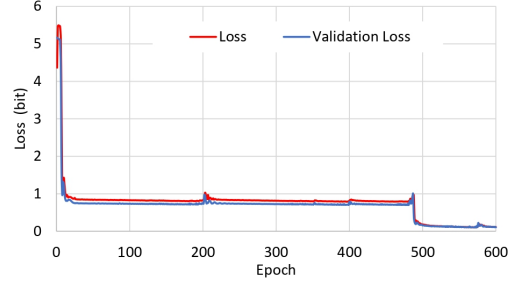


Fig. 14 Loss value for each epoch for the pre-trained damage detection algorithm.

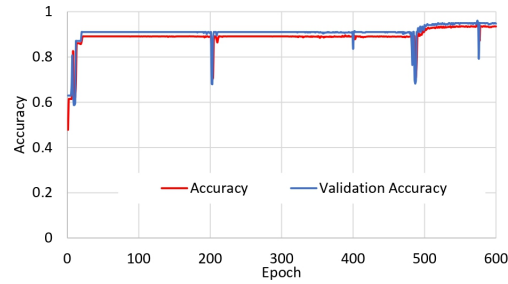


Fig. 15 The accuracy for each epoch for the pre-trained damage detection algorithm.

pre-training, this success rate is highly beneficial for the algorithm, as it reveals that the algorithm ensures that all instances of true positives are detected and forwarded to any subsequent stages. An apt analogy for this scenario is akin to assessing whether an airplane wing is damaged in a real-life situation; the algorithm consistently identifies damage, and in cases where damage is not detected, further analysis can be conducted to ensure safety.

These findings are promising, indicating the algorithm's high accuracy in detecting damage, thereby allowing for a stopping point at the outset of the pipeline, which significantly reduces the computational resources required.

5.2 Damage Intensity

In the next phase of the pipeline, a regression CNN is pre-trained on both types of simulated SLJs to evaluate the intensity of damage. Figure 16 illustrates the loss function for each epoch, revealing a slower convergence compared to the previous case, with the loss function converging at an error of approximately 40 MPa. Additionally, there

appears to be a plateau around 600 epochs for the validation loss, while the training loss continues to decrease. This indicates a potential tendency towards overfitting, although it is clear that the algorithm is indeed learning from the training dataset.

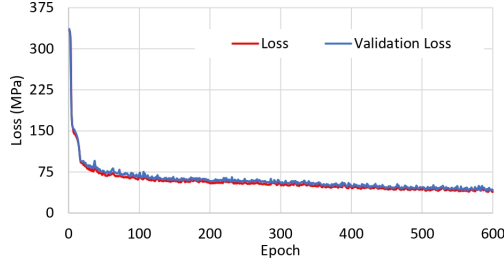


Fig. 16 The loss value for each epoch for the pre-trained damage intensity evaluation algorithm.

While the methodology exhibits a general capability to accurately assess damage intensity, it is essential to recognize its limitations. To delineate these limitations, we can refer to the following results to identify the boundaries in each aspect. In Figure 17, it is evident that for most intensity values, the error is extremely low, approaching 0. However, in a few instances, the error can be quite significant, reaching up to 300 MPa. This discrepancy is attributed to the complexity of the signals received by the algorithm. In cases with low error, the algorithm utilizes small data samples where only intensity serves as a variable. Conversely, in other instances, large samples are employed, encompassing variations not only in intensity but also in the position and size of the damage. Consequently, the algorithm encounters greater difficulty in handling these variations. Nevertheless, the majority of cases exhibit errors below 100 MPa, which is a noteworthy outcome. This capability enables users not only to detect damage but also to gauge its severity independently of its location or size.

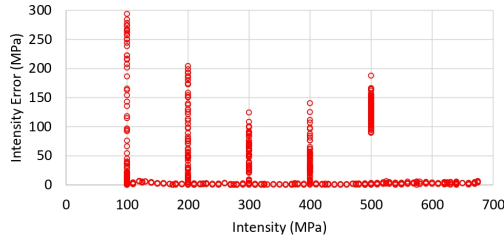


Fig. 17 The error for each value of damage intensity studied.

Finally, in Figure 18, it is evident that the largest errors occur on the sites closest to the boundaries of the SLJs. This phenomenon was previously discussed in the preceding Section. However, it is important to note that the largest errors coincide with those observed in the 25 mm damage size. This suggests that one approach to mitigate errors for smaller damage sizes is to establish a certainty field where the algorithm reliably detects larger damages closer to the edges. Alternatively, this issue can be addressed by ensuring there are no walls in proximity to the areas under analysis. An exception observed in Figure 18 pertains to simulated cases without any positional alterations, currently grouped under position 0. For these cases, positional evaluation is irrelevant, and they exhibit no significant errors, thereby reducing their significance in the overall analysis.

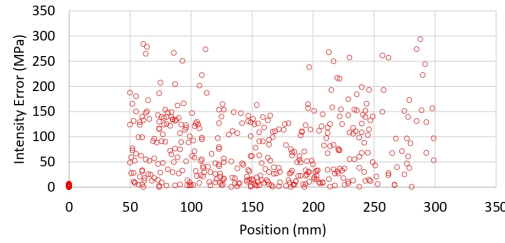


Fig. 18 The intensity error for each value of position of damage studied.

When observing Figures 17 - 18 together and combining the acquired results, it becomes evident that the majority of the largest intensity errors occur in cases with boundary conditions, such as the largest or smallest damage, or those located at the edges of the studied area. This indicates that the algorithm performs better with central values, and for cases with boundary conditions, a simple cutoff value is sufficient to significantly reduce errors.

When applying these pre-tests to experimental cases, similar to the previous step, certain limitations emerge. The initial analysis focused on each individual experimental case, encompassing only nine cases. It was observed that the average damage intensity error across all cases was 187 MPa, with the two experimental cases at the upper limit load responsible for the poorest results, showing errors ranging from 232 MPa to 406 MPa. Excluding these two cases, which could potentially be affected by fabrication or experimental errors, the average error decreases to 140 MPa. The highest error value is 250 MPa, while the lowest error originates from the case with the lowest load, measuring 3.6 MPa.

5.3 Damage Localization

In the final phase of the pipeline, a regressive CNN is used to localize damage. Furthermore, only simulated cases are used as available experimental data do not have a position as a variable.

Figure 19 illustrates the loss value in each epoch. We verify a large decrease followed by a slow decrease until the value is in a plateau at an average error of around 8 mm. As with the intensity evaluation model, the validation loss is higher than the training loss.

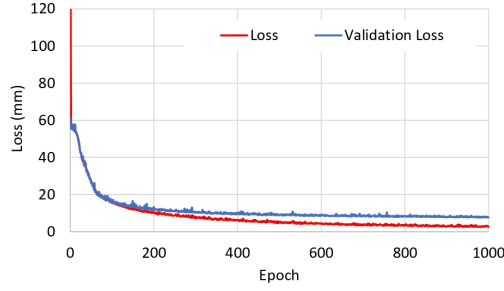


Fig. 19 The loss value in each epoch for the damage localization algorithm.

Figure 20 shows the localization error for each value of damage position. The largest errors occur more on the right of the figure but there is quite a large spread of values and positions, with most position errors concentrated below 10 mm.

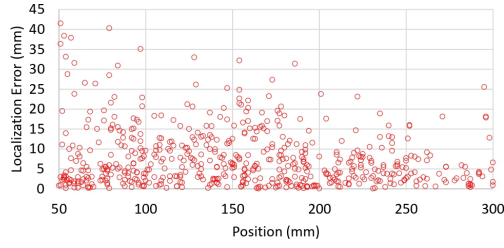


Fig. 20 The localization error for each value of damage position studied.

In Figure 21 the localization error is compared for the 4 overall damage sizes that were created, with the overall cases presenting a quite uniform distribution.

Further comparisons between position and intensity yielded results similar to those previously discussed. This indicates that in the damage localization, there are no specific cases that tend to exhibit errors. All error cases are fairly evenly distributed, demonstrating that the algorithm was capable of generalizing the detection of this characteristic without encountering significant issues. Moreover, the average error

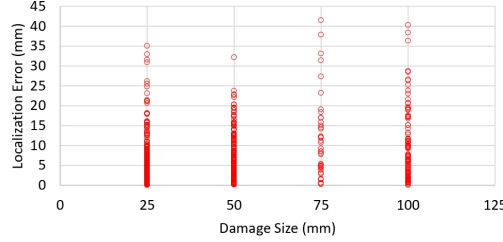


Fig. 21 The localization error for each value of damage size studied.

value of 8 mm enables precise pinpointing of the center of any damage, particularly within a range of 25 mm to 100 mm.

Additionally, a separate case study attempted to combine damage characteristics into a single machine learning algorithm by creating a multi-output CNN regression model. However, this approach proved to be less effective than maintaining two separate models in sequence. This disparity is likely attributed to the distinct nature of the information required to determine the position and intensity of damage within the machine learning algorithm. Combining both aspects did not yield any discernible benefits. An analogy that elucidates this issue is that the amplitude of the signal determines the position of the damage, while the frequency determines its intensity; thus, there are no similarities that can be exploited.

6 Conclusions

The primary focus of this paper was to comprehensively explore the development of a robust methodology for characterizing weak adhesion in structural SLJs. The methodology relies on LWs data processed by a machine learning pipeline made of CNNs pre-trained on synthetic data and fine-tuned on experimental data in a transfer learning scheme that successively detects, assesses intensity and localizes damage, establishing a general framework that can accommodate additional damage types and their characteristics.

The proposed machine learning pipeline demonstrated efficacy in weak adhesion detection, achieving over 95.3% accuracy in simulated scenarios and identifying 100% of experimental damage cases. For weak adhesion intensity evaluation, the algorithm exhibited an average loss of 45 MPa in simulated data and 140 MPa in experimental data, with the best cases having only a 3.6 MPa error. Concerning weak adhesion localization, the algorithm demonstrated an average loss of 8 mm. The methodology is adaptable for integrating additional features, indicating promise for enhancing structural health monitoring and improving the safety and longevity of structures.

In conclusion, the proposed methodology constitutes a groundbreaking solution to enhance the precision and reliability of NDT methods for detecting and characterizing weak adhesion in adhesive joints. This synergistic approach not only bolsters quality control but also holds potential as a robust structural health monitoring tool, thereby

ensuring the durability and reliability of adhesive joint applications across diverse industries.

Further research will investigate alternative machine learning models. Subsequently, complex real-world structures will be considered. Finally, the study will incorporate environmental variables relevant in real-case scenarios, such as humidity, temperature, or random vibrations, to broaden the scope of cases and enhance fidelity.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

Available upon reasonable request.

References

- Akaike K, Akiyama H (2023) Direct observation of oil-surface adhesion via sum frequency generation spectroscopy. *The Journal of Adhesion* pp 1–14
- Archives UN, Administration R (2014) Federal Aviation Regulations - Sec. 23.573
- Borges CS, Akhavan-Safar A, Tsokanas P, et al (2023) From fundamental concepts to recent developments in the adhesive bonding technology: A general view. *Discover Mechanical Engineering* 2(1):8
- Capinha JR (2007) Computational and Experimental Studies on Aircraft Structural Health Monitoring Systems Engenharia Aeroespacial. PhD thesis, Universidade Técnica de Lisboa
- Chen Z, Adams R, Da Silva LF (2011) Prediction of crack initiation and propagation of adhesive lap joints using an energy failure criterion. *Engineering Fracture Mechanics* 78(6):990–1007
- Dodson J, Inman D (2013) Thermal sensitivity of Lamb waves for structural health monitoring applications. *Ultrasonics* 53(3):677–685
- Giurgiutiu V, Cuc A (2005) Embedded Non-Destructive Evaluation for Structural Health Monitoring, Damage Detection, and Failure Prevention. *The Shock and Vibration Digest* 37:83–105
- Guyott CCH, Cawley P, Adams R (1986) The non-destructive testing of adhesively bonded structure: A review. *The Journal of Adhesion* 20(2):129–159
- Hay TR, Royer RL, Gao H, et al (2006) A comparison of embedded sensor Lamb wave ultrasonic tomography approaches for material loss detection. *Smart Materials and Structures* 15(4):946–951. <https://doi.org/10.1088/0964-1726/15/4/007>

- Heilmann L, Hoffmann M (2023) On the sensitivity of bondline control specimens with respect to the detection of adhesion defects. *The Journal of Adhesion* 99(6):988–1015
- Jeenjitkaew C, Guild FJ (2017) The analysis of kissing bonds in adhesive joints. *International Journal of Adhesion and Adhesives* 75(February):101–107
- Khan A, Ko DK, Lim SC, et al (2019) Structural vibration-based classification and prediction of delamination in smart composite laminates using deep learning neural network. *Composites Part B: Engineering* 161(December 2018):586–594. <https://doi.org/10.1016/j.compositesb.2018.12.118>
- Kovilpillai JJA, Jayanthi S (2023) An optimized deep learning approach to detect and classify defective tiles in production line for efficient industrial quality control. *Neural Computing and Applications* pp 1–20
- Mehrabi M, Soorgee MH, Habibi H, et al (2021) A novel application of ultrasonic lamb waves: Studying adhesive effects on the inspection of coating debonding in a three-layer waveguide. *Nondestructive Testing and Evaluation* 36(6):616–636
- Pan SJ, Yang Q (2009) A survey on transfer learning. *IEEE Transactions on knowledge and data engineering* 22(10):1345–1359
- Ramvalho GM, Lopes AM, da Silva LF (2021) Structural health monitoring of adhesive joints using Lamb waves: A review. *Structural Control and Health Monitoring* p e2849
- Ramvalho GM, Barbosa MR, Lopes AM, et al (2022) Damage classification methodology utilizing Lamb waves and artificial neural networks. *Journal of Testing and Evaluation* 50(5)
- Ramvalho GM, Lopes AM, da Silva LF (2023) Assessing weak adhesion in single lap joints using lamb waves and machine learning methods for structural health monitoring. *Applied Sciences* 13(19):10877
- Sbarufatti C, Manson G, Worden K (2014) A numerically-enhanced machine learning approach to damage diagnosis using a Lamb wave sensing network. *Journal of Sound and Vibration* 333(19):4499–4525. <https://doi.org/10.1016/j.jsv.2014.04.059>
- da Silva LFM, Öchsner A, Adams RD (2018) *Handbook of Adhesion Technology*, 2nd edn. Springer-Verlag Berlin Heidelberg
- Su C, Jiang M, Lv S, et al (2019) Improved Damage Localization and Quantification of CFRP Using Lamb Waves and Convolution Neural Network. *IEEE Sensors Journal* 19(14):5784–5791. <https://doi.org/10.1109/JSEN.2019.2908838>
- Tabatabaeipour M, Hettler J, Delrue S (2014) Reconstruction Algorithm for Probabilistic Inspection of Damage (RAPID) in Composites. In: *European Conference on*

Non-Destructive Testing, Ecndt

- Talaei Khoei T, Ould Slimane H, Kaabouch N (2023) Deep learning: Systematic review, models, challenges, and research directions. *Neural Computing and Applications* 35(31):23103–23124
- Tenreiro AFG, Lopes AM, da Silva LF (2022) A review of structural health monitoring of bonded structures using electromechanical impedance spectroscopy. *Structural Health Monitoring* 21(2):228–249
- Weiss K, Khoshgoftaar TM, Wang D (2016) A survey of transfer learning. *Journal of Big data* 3(1):1–40
- Xu Y, Tao C, Qiu J (2022) Debonding detection of scarf-repaired composite laminates with laser ultrasonic lamb waves. In: *Journal of Physics: Conference Series*, IOP Publishing, p 012041
- Yu J, Zhang Y (2023) Challenges and opportunities of deep learning-based process fault detection and diagnosis: A review. *Neural Computing and Applications* 35(1):211–252
- Zhuang Y, Kopsaftopoulos F, Dugnani R, et al (2018) Integrity monitoring of adhesively bonded joints via an electromechanical impedance-based approach. *Structural Health Monitoring* 17(5):1031–1045

Supplementary Material



Click here to access/download
Supplementary Material
paper.pdf

