

Passive Sensing of Low Velocity Impact Damage on
Composite Panels in Simulated Environmental and
Operational Conditions

By

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Declaration of Originality

I hereby declare that the work presented in this thesis is the result of my own original work and any reference to the work of others has been appropriately cited.

Aldyandra Hami Seno,

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Abstract

During its lifetime, an aircraft structure is subjected to impacts from a wide range of sources (e.g. bird strike, tool drop, hail). For composite structures, low velocity impacts may generate Barely Visual Impact Damage (BVID) that is difficult to assess without complex inspection techniques and may significantly reduce the strength of the structure. To reduce the need for costly inspection techniques, there is interest in developing integrated Structural Health Monitoring (SHM) systems to monitor the occurrence of impacts and provide location and severity estimations to allow the operators to make maintenance decisions (e.g. repairs). Many methods have been developed to achieve this using information encoded in impact induced strain waves recorded by sensors attached to the structure. However, these so-called passive methods have mostly been developed in laboratory conditions and do not consider operational and environmental in-service conditions which may significantly influence the accuracy and feasibility of these estimates. The research reported in this thesis was conducted to address some of the main challenges associated of with passive SHM application for in-service conditions, specifically accuracy, robustness, reliability and feasibility. A data driven approach was taken as it allows flexibility in scaling up from simple coupons to complex structures. Novel signal processing and reference database methods were proposed for accurate and robust impact location and maximum impact force estimation which only requires data from a single reference impact case, making it feasible for the variable conditions in service. A novel kriging based extension to these methods was developed to allow uncertainty quantification that provides more reliable information to the operator. A multifidelity approach to constructing the reference database for the data driven approach was also developed to significantly reduce the requirement of experimental sampling with alternative data sources and increase feasibility. Lastly, the developed methods were tested on prototype data acquisition units to demonstrate applicability on in-service hardware. The results of this thesis have provided novel improvements to the data driven passive SHM approach which significantly increases its applicability for aircraft structures.

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Chapter 1.

Introduction

1.1 Background

Fibre reinforced polymer composites have seen a significant increase in current application for aircraft structures due to their superior strength and stiffness to weight ratios compared to more conventional metallic structures [1,2]. The increased performance allows lighter structures, which in turn saves operational cost [1]. The superior properties come from the combination of structurally unstable high tensile strength fibres with a stiff (but brittle) polymer matrix, resulting in a material that has better performance than the constituting materials. The fibre adds anisotropic strength and stiffness whilst the matrix stabilizes the fibres such that it can take loading in more than just tension [1].

Modern polymer matrix composites commonly come in the form of partially cured pre-impregnated fibre-matrix sheets (called prepreg sheets), which can be stacked and cured under heat and pressure (usually from an autoclave) to form layered thin aircraft structures [3]. Here the orientation of the anisotropic fibre reinforcement can be varied in each layer to tailor the materials properties to fit the application [1]. However, curing large structures (e.g. an aircraft fuselage) requires an even larger autoclave, which is not always feasible [3]. Additionally, newly developed 3D reinforced composites (with transverse fibres or stitching to increase out of plane delamination resistance) cannot be formed in sheets or stacked individually [3]. Thus, recent developments of composite manufacturing have focused on alternative “out of autoclave” methods to combine resin and fibre as well as how to cure it (e.g. resin transfer moulding, vacuum bagging, etc.) [3].

The distinct layered composite microstructure that gives it such high performance also results in a particular weakness towards low velocity impact damage [2]. When an impact occurs in thin structures, local strain shockwaves propagate from the impact point before the global motion of the plate is established [2]. Damage that occurs after the global plate motion is established is

classified as low velocity impact damage [2]. On the other hand, if the damage is formed before the global plate motion is established (and is caused by the transient local shockwaves), it is classified as high velocity impact [2].

Unlike high velocity impacts which tend to cause some degree of visible localised penetration damage (similar to that in other materials), low velocity impacts cause barely visual damage unique to laminated composites which occurs in the form of delamination at the interface between layers of differing orientation (Figure 1. 1) [2]. Impact is essentially a bending load case, and for thin laminates (as used in aircraft structures) damage initiates at the lower layers as tension matrix cracks (Figure 1. 1) [2]. These cracks then propagate upwards through thickness as the load increases, until it is stopped when it reaches the interface between layers (the differently oriented fibres in the adjacent layer arrest further crack growth, Figure 1. 1) [2]. As crack growth cannot continue onwards through thickness, it progresses in-plane instead following the high interlaminar shear stress gradients between layers (caused by the sudden stiffness changes due to differing fibre orientation, Figure 1. 2) [2]. Once the crack plane orientation matches the orientation of the adjacent layer, through thickness crack growth continues (Figure 1. 2) [2]. This succession of through thickness and in-plane crack growth results in the characteristic layered delamination profile observed in composites laminates [2].

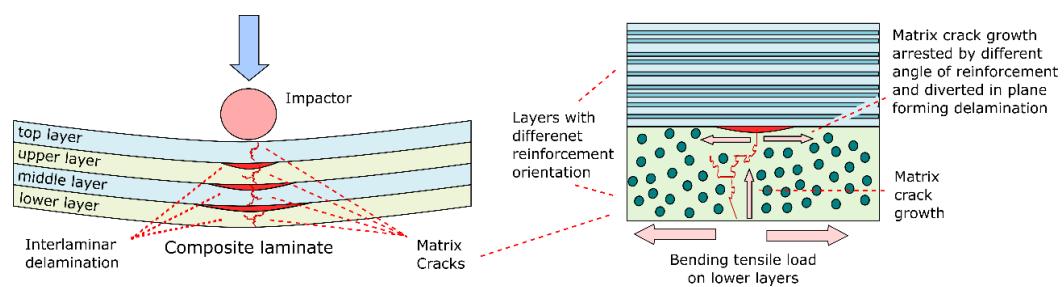


Figure 1. 1 Through thickness matrix crack and delamination due to impact in composite laminates.

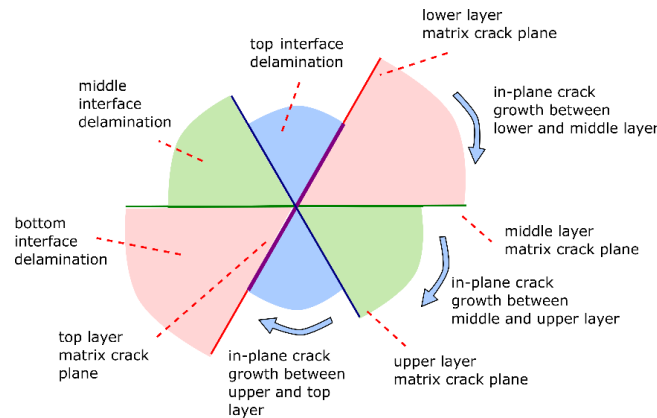


Figure 1. 2 Delamination formation due to impact in composite laminates.

During its lifetime, an aircraft is subjected to multiple impact events from various sources (such as tool drop, bird strikes, debris, hail, etc.) under various scenarios (impact velocity, angle, mass, energy, material, etc.) and conditions (temperature, vibration, etc.) [2,4,5]. Some of which may lead to impact damage which may significantly reduce the load carrying capacity of the structure [2]. To fulfil damage tolerance requirements (e.g. EASA AMC 20-29 regulations [6]), impact damage must be reliably assessable during scheduled inspections such that critical damage growth can be identified and repairs conducted before catastrophic failure occurs (structure must retain limit load capacity between inspection periods). However, unlike metallic structures that form relatively visible dents from impacts, the impact damage in composite materials can be very difficult to see visually (classified as Barely Visual Impact Damage or BVID) when the bulk of the damage occurs within the interface between layers (Figure 1. 1, Figure 1. 2) in cases of low velocity impacts [2]. Thus, more complex inspection methods (ultrasound scans, etc.) are required to detect and assess impact damage in composites (Figure 1. 3), increasing the cost of operation [1]. If reliable detection and assessment of BVID impact damage is not possible, regulation (e.g. EASA AMC 20-29 [6]) requires the structure to retain ultimate load (limit load x safety margin) capacity until it reaches a level (e.g. through damage growth) where it is detectable, leading to increased safety margins, weight, fuel efficiency and finally cost [1,7]. Both scenarios take away from the cost savings of composites structures compared to conventional metallic structures.

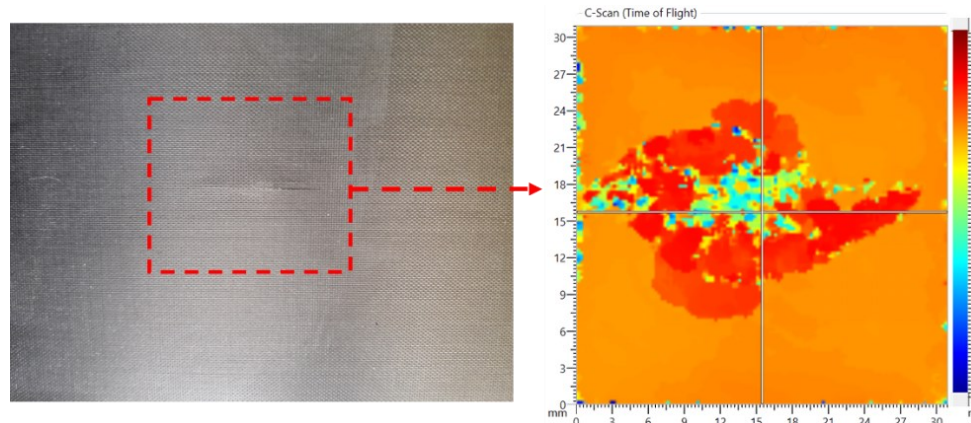


Figure 1. 3 Barely visual surface damage (matrix crack) on impacted composite lower face (left) and the actual internal damage assessed with an ultrasound scan (right).

Thus, there is interest in developing Structural Health Monitoring (SHM) systems which can automatically and reliably inform operators of the occurrence [8–15] and location of impact damage, especially BVID [16–27]. The goal is to allow condition-based maintenance for potential cost saving through reduced inspection [1,7,28–31] and structural damage tolerance design requirements [1,6]. Additionally, having such systems may allow for lighter structures, which are essential for the current drive in development to reduce aircraft emissions and make large scale electric aviation feasible [32]. Increased interest in using carbon reinforced structures as electrical energy storage to increase weight efficiency means that in the future structural integrity may not only affect safety but also propulsive efficiency, thus putting more emphasis on the need for structural health monitoring systems.

This is achieved through integration of sensors (such as optical fibres, accelerometers or PZT sensors) to the monitored structure at discrete locations, and using the information recorded (such as strain waves, modal responses etc.) to infer the occurrence and location of impact damage [1,7,33]. Many SHM approaches have been developed over the years, some prominent examples being modal analysis, acoustic emission monitoring and Lamb wave based approaches [7]. For application in aircraft structures, Lamb wave based SHM has seen large interest in recent years due to their ability to propagate as guided strain waves along thin aircraft structures, providing larger area coverage than similar through

thickness methods (such as ultrasound scans) whilst also having good sensitivity to damage [7].

An added advantage with Lamb wave methods is that it can work in 2 different sensing modes, passive and active depending on the source of the Lamb wave [1,7,33]. Active sensing uses an actuator to generate a controlled Lamb wave that propagates through the structure, interacts with any damage, and is then recorded by a sensor [1,7,33]. Any interaction with damage changes the features of the wave, which can then be used to infer the presence and location of the damage [1,7,33]. In this sense, active sensing is similar to ultrasound scans that are done periodically to inspect the structure for damage [1,7,33]. The passive approach utilizes Lamb waves generated by external events such as impacts (Figure 1. 4), which propagate from the event point across the structure and are recorded by the sensors [1,7,19,33]. As the Lamb waves are generated by the event, they contain information regarding the characteristics (such as location and severity) of the event encoded in their features (such as time of arrival or amplitude) [8,12,16–19,22,34,35]. This information can be extracted and then used to inversely estimate the location [16–19,22,34] or severity [8,12,35,36] of the event. In this sense, the passive approach is more suitable for continuous event driven monitoring [29,37,38]. Although the passive method requires continuous monitoring (vs on demand scans in active mode), it tends to be more accurate in detecting small damage as it obtains information directly from the event wave, compared to the active method which relies in damage large enough to alter the response of the structure from its expected behaviour (e.g. through a baseline) [7].

Using PZT sensors that may act as both actuator and sensor [1,7,33], it is possible to use the Lamb wave approach to provide SHM coverage in terms of passive continuous monitoring as an early warning system which is then further verified using an active scan [33]. This results in better coverage than other methods that may be limited to 1 mode of sensing only [1,7,33] (e.g. modal analysis is limited to active [39,40], whilst acoustic emission is limited to passive [20,23,41,42]). Additionally, PZT sensors produce voltage from strain directly, which saves significant energy when used in continuous passive mode as they do not need to be powered [7].

Although many methods have been developed to estimate the severity [8–10,12,13,35,36] and location [16,17,19–21,23,27,34,43,44] of impacts from information encoded in the features of impact induced Lamb waves, there remains a few challenges that need to be solved in order for passive monitoring to be acceptable for ensuring the safety of real life structures. Real life factors such as the wide range of possible impact parameters (e.g., impactor material/stiffness, mass, angle), operational conditions (e.g., vibration noise, temperature), and geometrical complexity of the structure (e.g., stiffeners, cut outs) may influence the features of the induced Lamb wave (time) and severely compromise the accuracy and reliability of these methods [18,22,27,34,35,45–47]. Lab based studies have looked into how some of these aspects affect Lamb waves (such as temperature [46,48,49], mass [18,22,27,36], impactor material [35,50], vibration [48] and geometry [27,36,51–53]) and how to incorporate them into SHM methods for impact location and severity estimation. However, in real life these factors occur simultaneously, and a combined parametric study is needed to create a passive SHM method that can account for all of these factors at once.

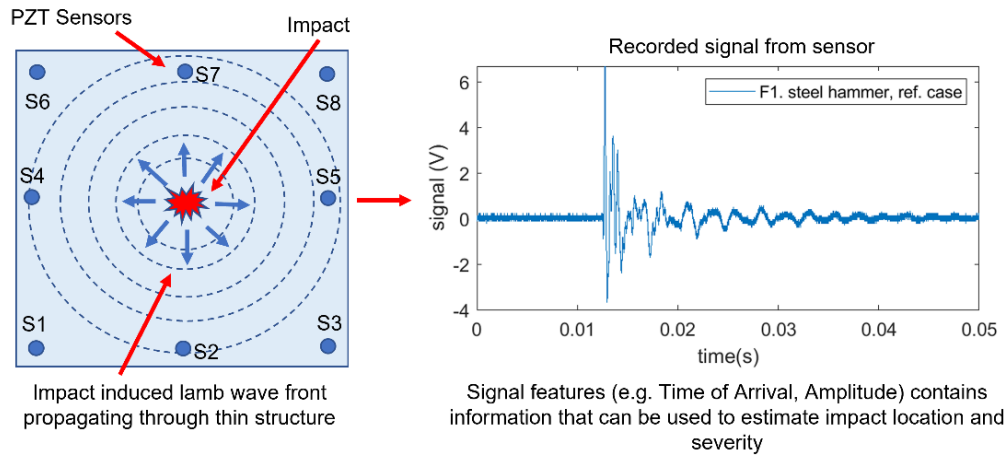


Figure 1. 4 Impact induced lamb propagation and recording in passive sensing approach.

The highly variable nature of impact events coupled with measurement and SHM estimation errors results in the need for uncertainty quantification in passive SHM methods [13,18,54,55]. A deterministic estimate of an impact location or severity with an unknown level of uncertainty may lead to incorrect structural assessment and erroneous maintenance decisions. Any passive SHM method

developed must not only give estimates that are robust towards the variability of real life impacts but must also provide the uncertainty of the estimates to provide the operator with enough information to make correct maintenance choices [13,18,54,55]. The Monte Carlo approach is commonly employed as it allows the propagation of known uncertainties (e.g. measurement uncertainties) through various SHM algorithms for location and severity [13,56,57] estimations. However, this approach relies on simulating multiple possible outcomes to produce a stochastic estimate, which may be computationally expensive depending on the SHM algorithm employed [54,55]. This may be acceptable in lab conditions with a limited number of impacts, but may not be feasible in real life operational conditions with potentially hundreds or thousands of impacts that have to be assessed within a specific time interval (e.g. between flights) [54,55]. Thus, development of a less computationally expensive uncertainty quantification method is of interest.

Most SHM approaches require some degree of initial information from the structure being monitored, be it wave propagation velocities, transfer functions, time of arrival samples and so on [13,18,19,36,46,47,50,53,58]. As a real aircraft structure is much larger and complex than most lab specimens, the of the amount of initial data required for the SHM algorithm to function accurately becomes a serious feasibility issue [47,58]. This is especially true for data driven approaches such as neural networks or database methods which will be discussed in more detail in later chapters [22,47,58]. Taking initial impact measurements for every panel on an aircraft is highly unfeasible and thus development of data fusion methods (such as multifidelity approaches) is of interest to combine/share data from various sources (e.g. sister aircraft, similar shaped panels or components, numerical simulations) that are less “expensive” than direct data sampling [59].

The final challenge relates to the limitations of the Data Acquisition (DAQ) systems that can be integrated into an aircraft structure. As mentioned previously, the goal of the SHM system is to reduce cost through reduction of weight or maintenance requirements [28,29,37,38,60,61]. This limits the weight and complexity of the systems that can be installed in order to maintain this cost reduction [28,29,37,38,60,61]. Because of this, the performance of integrated

DAQ systems tends to be much more limited performance wise (e.g. sampling rates, memory capacity for signal recording) compared to the lab based equipment (e.g. bench oscilloscopes) commonly used in studies to develop SHM methods [18,22,29,37,38,43,61]. This often rules out more complex SHM methodologies as the current state of the art in miniaturized DAQ systems cannot provide sufficient data [28,29,31,37,38]. It is thus of interest to test the performance and feasibility of developed SHM methods on miniaturized DAQ systems designed for aircraft structures.

1.2 Objectives

Based on the challenges currently present in applying passive SHM impact monitoring methods for robust monitoring of barely visual damage (BVID) caused by low velocity impact in real life composite structures, the work in this thesis aims to :

- a) Develop passive Lamb wave based low velocity impact location and severity estimation methods that are robust and accurate regardless of real life factors.
The scope of the factors taken into account in this thesis include :
 - i. Different impact parameters (impactor mass, energy, angle, material/stiffness).
 - ii. Different environmental and operational conditions (varying temperature, vibration noise).
 - iii. Different structural configurations (flat simple structures, curved structures, stiffened structures) for quasi-isotropic prepreg carbon reinforced composites.
- b) Develop uncertainty quantification methods that are reliable for impact location and severity estimates under the aforementioned real life factors.
- c) Develop methods to minimize initial data required for passive SHM methods to function and multifidelity methods to augment initial data requirements using alternative sources of data to experimental sampling (Finite Element simulations).
- d) Test developed passive SHM methods using miniaturized prototype DAQ systems designed for integration in aircraft structures.

1.3 Thesis Outline

To fulfil the objectives outlined above, the work in this thesis has been structured as can be seen below. Each research chapter is presented in the form of semi-independent articles on the research activity on certain components of the overall passive SHM method developed in this thesis.

- a) **Chapter 1.** Introduction to the problem of barely visual impact damage in composite structures and the motivation for developing SHM methods to automatically assess the location and severity of impacts.
- b) **Chapter 2.** Introduction to the basics of Lamb wave based passive SHM methods. This includes the basic characteristics and features of impact induced Lamb waves, physics based and metamodel approaches for estimating impact location and severity from Lamb wave features.
- c) **Chapter 3.** Is divided into 2 parts :
 - i. **Chapter 3.1.** Research chapter on the development of a novel, robust method for Lamb wave feature extraction and impact localisation under simulated environmental and operational conditions (as mentioned in the objectives, excluding different impactor materials) using a neural network approach.
 - ii. **Chapter 3.2.** Research chapter on the development improvements for the Lamb wave feature extraction and impact localisation methods developed in Chapter 3.1 to using a database approach to allow localisation of impacts from different stiffness impactors.
- d) **Chapter 4.** Research chapter on the development of a novel, robust method for maximum impact force estimation (as an indicator of impact severity) under simulated environmental and operational conditions (as mentioned in the objectives) using a database approach.
- e) **Chapter 5.** Research chapter on the development of a novel and reliable uncertainty quantification method as an added modification to the impact location and severity estimation methods developed in chapters 3 and 4.
- f) **Chapter 6.** Research chapter on the development of multifidelity methods to reduce the need for initial experimental data sampling for the impact location

and severity estimation methods developed in chapters 3 - 5. The approach allows substituting data from “expensive” experimental sampling with alternative “cheaper” sources of data (Finite Element simulations).

- g) **Chapter 7.** Research chapter on testing the passive SHM methods developed in previous chapters for impact induced Lamb wave measurements obtained from a miniaturised DAQ prototype system. Includes real time demonstration via included video (link and/or physical video provided).
- h) **Chapter 8.** Conclusion of work done in this thesis and how it satisfies the objective to develop passive SHM methods for monitoring impact damage in composite structures that are robust towards real life environmental and operational conditions.

1.4 Contributions

The work conducted in this thesis has so far produced the following contribution to the literature on passive SHM methods for impact monitoring. All of the figures and content in this thesis that are part of the following publications either do not require permission or have been given appropriate attribution.

a) Chapter 3.1

- i. Seno AH, Sharif Khodaei Z, Aliabadi FM. An Effective Impact Detection Method for Composite Curved Panel. In Key Engineering Materials 2018 (Vol. 774, pp. 529-534). Trans Tech Publications Ltd.
- ii. Seno AH, Khodaei ZS, Aliabadi MF. Passive sensing method for impact localisation in composite plates under simulated environmental and operational conditions. Mechanical Systems and Signal Processing. 2019 Aug 15;129:20-36.
- iii. Seno AH, Aliabadi FM. A comparative study of impact localisation in composite structures using neural networks under environmental and operational variations. In Key Engineering Materials 2020 (Vol. 827, pp. 410-415). Trans Tech Publications Ltd.

b) Chapter 3.2

- i. Seno AH, Aliabadi MH. Impact localisation in composite plates of different stiffness impactors under simulated environmental and operational conditions. *Sensors*. 2019 Jan;19(17):3659.

c) Chapter 4

- i. Seno AH, Aliabadi MF. A novel method for impact force estimation in composite plates under simulated environmental and operational conditions. *Smart Materials and Structures*. 2020 Oct 1;29(11):115029.

d) Chapter 5

- i. Seno AH, Aliabadi MF. Uncertainty quantification for impact location and force estimation in composite structures. *Structural Health Monitoring*. 2021 Jun 17:14759217211020255.

e) Chapter 6

- i. Seno AH, Aliabadi MF. Multifidelity Data Augmentation for Data Driven Passive Impact Location and Force Estimation in Composite Structures under Simulated Environmental and Operational Conditions. In prep.

f) Chapter 7

- i. Seno AH, Sharif Khodaei Z, Aliabadi FM. Real-time Impact Location Estimation with Uncertainty Quantification using an Event Driven Miniaturized Passive Sensing Data Acquisition Unit. In prep.

Chapter 2.

Fundamentals of Lamb Wave Based Passive Monitoring of Impacts in Thin Structures

This chapter provides a basic introduction to the general concepts in passive structural health monitoring of impacts in thin structures. The purpose is to provide a general introduction to the concepts and methodologies that will be further developed in more detail in subsequent chapters.

2.1 Lamb Wave Based Passive Approach for Monitoring of Impacts

When an impact event occurs, it generates strain waves that propagate throughout the structure [1,7,19,33,44]. In thin structures (such as seen in aircraft), these waves are known as Lamb waves and they propagate following the boundaries (the top and bottom surface) of the structure, hence classified as guided waves [1,7,33]. These waves propagate in a combination of 2 modes : symmetric (displacement direction parallel to wave propagation direction) and asymmetric (displacement direction transverse to propagation direction) as shown in Figure 2. 1 [1,7,33].

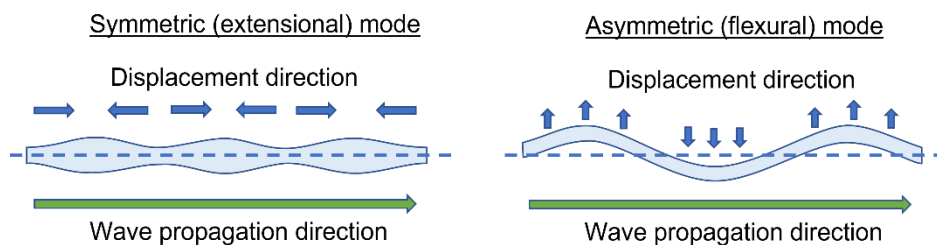


Figure 2. 1 Symmetric and asymmetric modes of Lamb wave propagation

Lamb waves can be recorded by sensors attached to the structure and can be used as an indicator of the occurrence of impacts as well as to estimate the

properties of the event [1,7,27,33,36,44,50,56,62]. For Structural Health Monitoring (SHM) purposes, the impact event properties of interest are the location and severity, which informs operators of the existence and location of damage for further assessment or repairs [1,7,27,33,36,44,50,56,62]. The use of Lamb waves generated by the event itself, rather than controlled actuated waves from a transducer (e.g. such as ultrasonic scans), is why the approach is termed as a “passive” approach [1,7,33].

In this passive approach, the Lamb waves are the only source of information available and the impact event itself is completely unknown [1,7,27,33,36,44,50,56,62]. Thus, it is an inverse problem to estimate the properties of the excitation event from the structure’s response [1,7,27,33,36,44,50,56,62]. For this purpose, the main goal is to establish a relation between features of the recorded Lamb wave (e.g. signal waveform, time of arrival, amplitude etc.) and the properties of the impact event (e.g. location, impact energy, impact force). Thus, it is very important to understand the main characteristics of impact induced Lamb waves to see which features contain relevant information [1,7,27,33,36,44,50,56,62].

2.2 Characteristics of Impact Induced Lamb Waves

Unlike active methods where actuators are used to excite Lamb waves with a controlled profile (controlled range, phase and magnitude of frequency components, such as tone burst and chirp profiles) [7,8,50], the excitation force from impacts (and subsequent induced Lamb wave) depend on the impactor – structure interaction and often has a complex profile that varies with differing impact parameters [8,50]. Figure 2. 2 shows an example of a typical impact force profile and the induced Lamb wave response on a composite panel. The resulting impact force profile has a continuous wideband frequency range which results in the induced Lamb wave having a similar frequency profile (Figure 2. 2) [8,50]. The magnitude and phase of the frequency components are non-uniform which results in a complex waveform when all the frequency components combine together [8,50].

At the beginning of the Lamb wave signal, the initial pulse has a frequency range that is continuous and wideband just like the excitation force profile (Figure 2. 2). However, after no more force is applied, the Lamb wave signal continues for certain frequency bands which indicate the natural frequency modes of the structure in free vibration and also reflections from the structure boundaries (Figure 2. 2) [8,27]. This continues until the vibration energy is dissipated by the structure through damping (such as friction etc.) [8,27].

It is known that the excitation profile from impacts and the subsequent profile of the induced Lamb wave depend on certain factors such as impactor mass, energy, and material [2,8,12,35,36,50,63]. The impact kinetic energy (which is affected by the impactor mass and velocity) is known to be positively correlated with the amplitude of the excitation force as well as the induced Lamb wave [12,35,36,50]. Different masses and materials are known to change the profile of the excitation and the waveform of the induced Lamb wave [18,22,27,36]. Other environmental factors (such as temperature) may affect the response of the structure and the resulting Lamb wave [46,48].

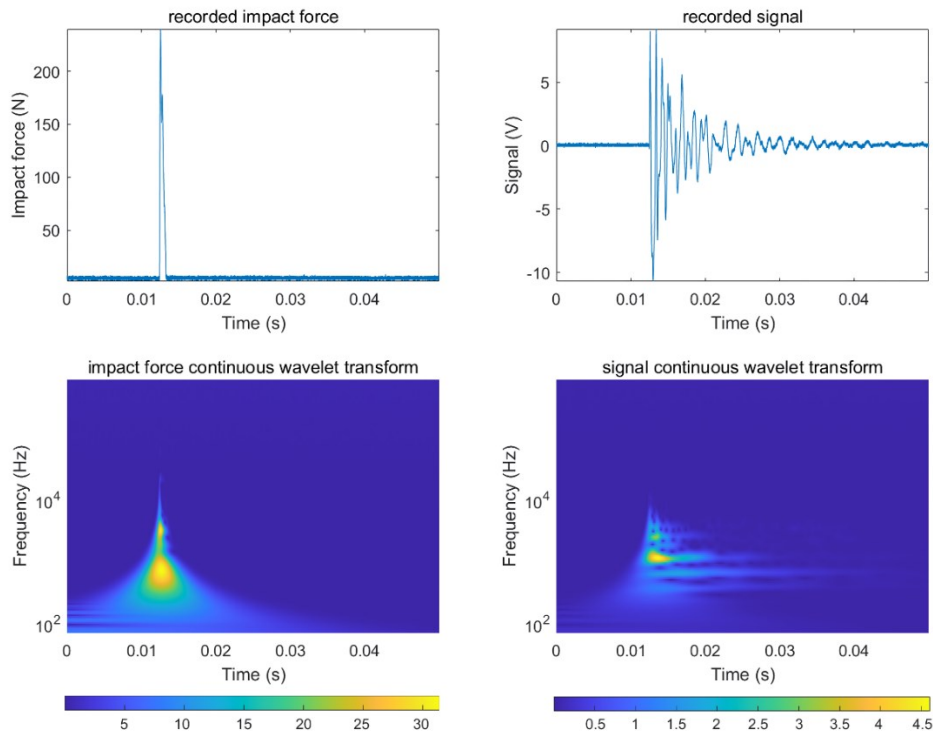


Figure 2. 2 Example of impact force profile and induced Lamb wave signal (top) and their respective frequency profiles (bottom, obtained through continuous wavelet transform)

Spatially, the Lamb wave pulse from an impact propagates outwards from the event point in all directions (Figure 2. 3) [7,23,64]. In isotropic materials, the propagation velocity of the pulse is uniform in all directions (Figure 2. 3) and the magnitude is dependent on the properties of the propagation medium (stiffness, thickness, etc.) [1,7,19,23]. However, in anisotropic materials (such as composites) the material properties are not the same in every direction, which causes a non-uniform propagation profile (Figure 2. 3) [1,7,19,23].

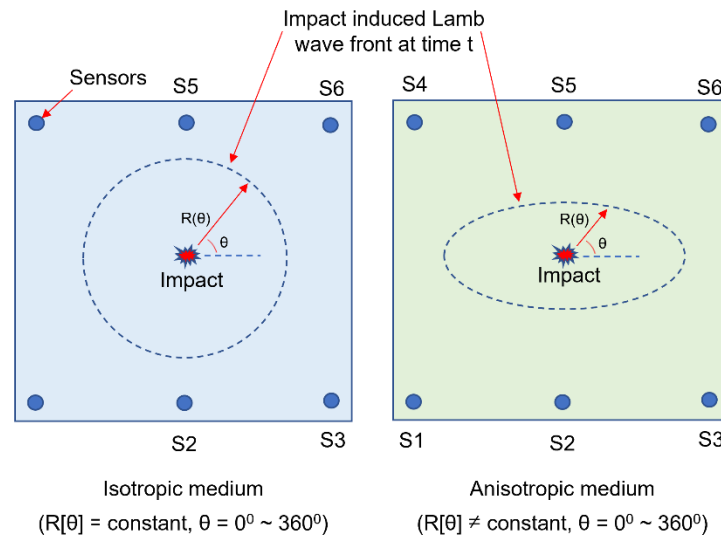


Figure 2. 3 Example of Lamb wave propagation profile difference between isotropic and anisotropic mediums

Whilst propagating throughout the structure, the Lamb wave pulse may interact with a variety of features (such as boundaries, cutouts, stiffeners or even damage) which may alter the propagation path of the Lamb wave rays emitted from the impact point (Figure 2. 4) [7,44,64,65]. Figure 2. 4 illustrates the various interaction scenarios commonly found in aircraft structures. The most common interaction that can occur is the reflection of the Lamb wave ray due to boundaries at the edge (Figure 2. 4 [a]) or within the structure (due to features such as cutouts, Figure 2. 4 [b]) [1,7,27,53]. As the Lamb wave ray cannot propagate through these boundaries, it is reflected at a mirrored angle to the original incoming direction (Figure 2. 4 [a]) [64].

Reflection may also occur when the propagation medium changes significantly (causing a mismatch in the acoustic impedance between the 2 mediums [1,7,44]) due to structural features such as a change in thickness (e.g doublers), stiffeners or change in material (Figure 2. 4 [c]) [1,7,44]. However, unlike wave interaction at the boundaries, some portion of the Lamb wave ray can still pass through between the 2 mediums [44]. This component of the Lamb wave ray may undergo a deviation in direction of propagation (also known as refraction) due to the sudden change in propagation velocities between the 2 mediums (Figure 2. 4 [c]) [44].

When a Lamb wave ray interacts with a small discontinuity (e.g. damage), it is scattered instead of being reflected (Figure 2. 4 [d]) [7,65]. The scattering spreads the ray in all directions, with the discontinuity as the focal point [7,65]. The discontinuity thus acts as if it were a new Lamb wave source [7,65].

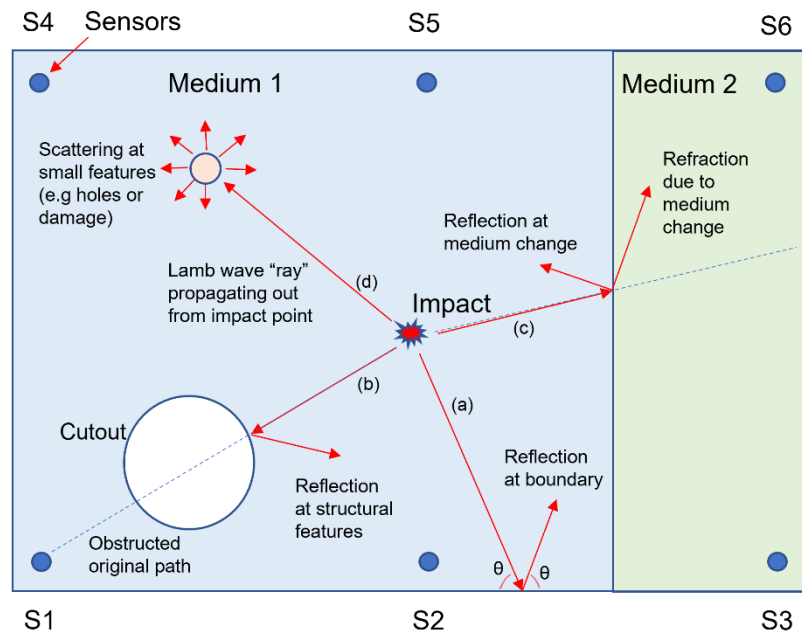


Figure 2. 4 Lamb wave interaction with various features of a structure : (a) structure boundaries, (b) structure features (e.g. cutouts), (c) change in propagation medium/properties (e.g. change in thickness or material), (d) small discontinuities (e.g. damage)

Certain features of the Lamb wave change as the wave propagates away from the original impact point [1,7,27,33]. Figure 2. 5 shows the difference between impact induced Lamb waves recorded at 2 different locations away from the

original impact point. As the distance from the original impact point increases, the Lamb wave will arrive at the sensor later as it has to propagate a longer distance (Figure 2. 5) [1,7,27,33]. The time it takes from the start of the impact force excitation to the time the signal arrives at the sensor is called the Time of Arrival (ToA) of a Lamb wave and is often used to estimate the distance between a sensor and the original impact point [1,7,27,33]. However, in the passive approach the time of excitation is unknown and thus the ToA of a Lamb wave cannot be measured directly [1,7,18,19,27,33]. Instead, it is often expressed as the difference between the ToA of Lamb waves at different sensors (where the sensor with the fastest arriving Lamb wave acts as the reference with a ToA difference of 0) [1,7,18,19,27,33]. This way, the ToA difference provides a measure of the distance of a sensor towards the original impact point relative to the other sensors [1,7,18,19,27,33].

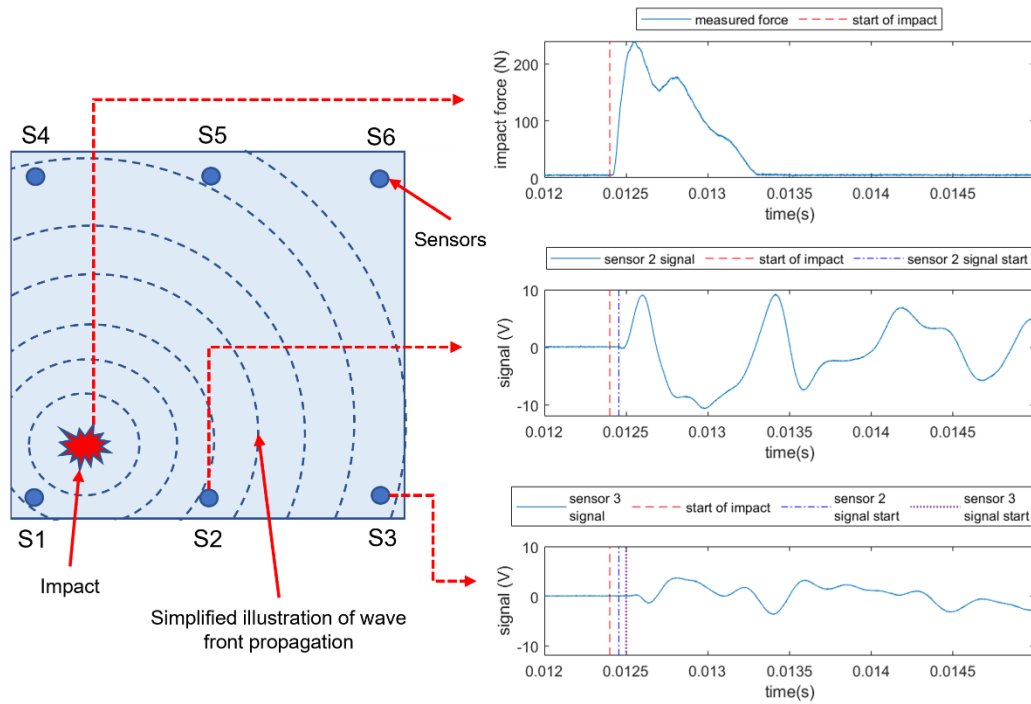


Figure 2. 5 Change in Lamb wave features as it propagates away from original impact point

As shown in Figure 2. 5, the profile of the Lamb wave also changes as it propagates away from the original impact point. The amplitude of the recorded Lamb wave decreases further away from the original impact point as the energy of

the wave is dissipated by the structure [7,27]. As mentioned previously, the main pulse of the Lamb wave is comprised of a wide range of frequency components (Figure 2. 2) [50]. Each frequency component has a different propagation velocity (called the phase velocity) which causes the frequency components to shift (a phenomena called dispersion) and distort the waveform as it propagates along the structure (Figure 2. 5) [1,7,33,42]. The Lamb wave pulse itself (which is a combination of these frequency components) propagates along the structure following the group velocity, which is an aggregate of the different phase velocities of the frequency components [1,7,33,42].

2.3 Physics Based Methods for Impact Location and Severity Estimation

Using the knowledge of how impact induced Lamb waves behave, many methods have been developed to solve the inverse problem of estimating the location and severity of impact events using Lamb wave features [1,7,13,15,18,19,22,27,33,35,44,50,62,66]. Based on how the relation between the Lamb wave features and the properties of the impact event is established, these methods can be separated into 2 main groups : physics based methods [1,7,15,19,33,44,62,66] and data driven metamodels [1,7,13,18,22,27,33,35,50]. This section will focus on the physics based approach, whilst the data driven alternative will be elaborated in section 2.4.

Physics based methods relate the Lamb wave features to the properties of the impact event through the knowledge of the physical behaviour and relation between the impact and the induced Lamb wave [1,7,15,19,33,44,62,66]. This can be in the form of analytical or numerical models that describe the response of the structure (specifically the Lamb wave response) when given an impact load [1,7,15,19,33,44,62,66]. The model is then solved inversely (for simple models) or iteratively (for more complex models) to obtain the excitation properties that would produce a response that is similar to the recorded Lamb wave response of the structure [1,7,15,19,33,44,62,66].

2.3.1 Physics Based Methods for Impact Location Estimation

One of the earliest works for estimating the location of an impact was done using the triangulation approach [19,42,67,68]. Here, the basis is the relation between the ToA of the Lamb wave with the propagation velocity ($V[\theta_i]$, may be group or phase velocity depending on wave component used) and the distance travelled (D_i) for each sensor ($i = 1, 2, \dots, n$) as shown in Figure 2. 6 [19,42]. This relation exists for each sensor and forms a system of linear equations (D_i , $i = 1, 2, \dots, n$) [19,42]. As the ToA is unknown and what is available is the ToA difference ($d\text{ToA}_i$), the unknowns for each path are the impact coordinates (X_{Im} , Y_{Im}), the direction (θ_i), the propagation velocity ($V[\theta_i]$) and the reference ToA to the closest sensor (ToA_{ref}) [19,42].

If the propagation velocity (V) is known (e.g. through experimental testing of the medium [19,42]) and the medium is isotropic (V is constant), the unknowns are reduced to the impact coordinates (X_{Im} , Y_{Im}) and the reference ToA (ToA_{ref}) [19,42]. Thus, if there are more than 3 sensors (and thus more than 3 equations) the system of linear equations is directly solvable [19,42]. However, as composites have anisotropic properties, the direction of impact (θ) cannot be ignored [19,42]. Assuming the propagation velocity profile at each direction ($V[\theta]$) is known, the problem can be solved iteratively (e.g. using genetic algorithms) to find the impact coordinates (X_{Im} , Y_{Im}), direction (θ_i) and reference ToA (ToA_{ref}) that satisfy the system of linear equations [19,42]. Another approach is to use specific placement of sensors, where some sensors are positioned closely such that the impact direction (θ) between them can be assumed the same [68]. This reduces the number of unknowns in the system of linear equations such that it is solvable with a finite number of sensors and even without the need to know the propagation velocity (V) profile [68].

Following the approach of strategic positioning of sensors, some studies have developed sensor cluster formations (Figure 2. 7) where the positioning of the sensors relative to each other allows the system of linear equations to be significantly simplified [20,67]. The result is that the distance (d) as well as the ToA difference ($d\text{ToA}$) between each sensor can be directly related to the direction of impact (θ) with relation to the cluster (Figure 2. 7) [20,67]. With at

least 2 clusters, it is then possible to obtain the location of the impact from the crossing point of the estimated directions (Figure 2. 7) [20,67].

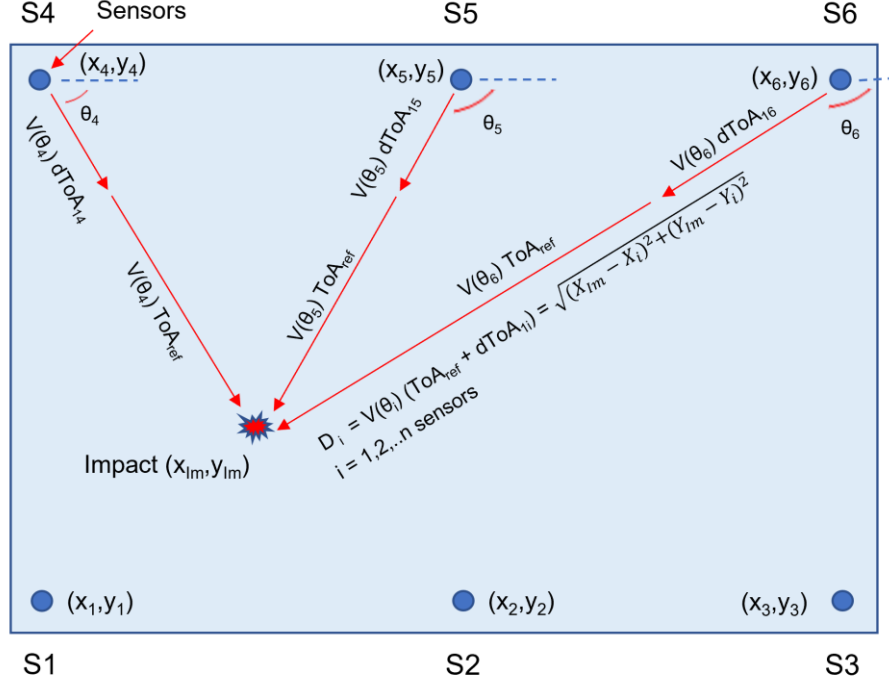


Figure 2. 6 Diagram of Lamb wave propagation paths from impact point to sensors and the relation between distance (D), propagation velocity (V) and time of arrival (ToA) used in triangulation

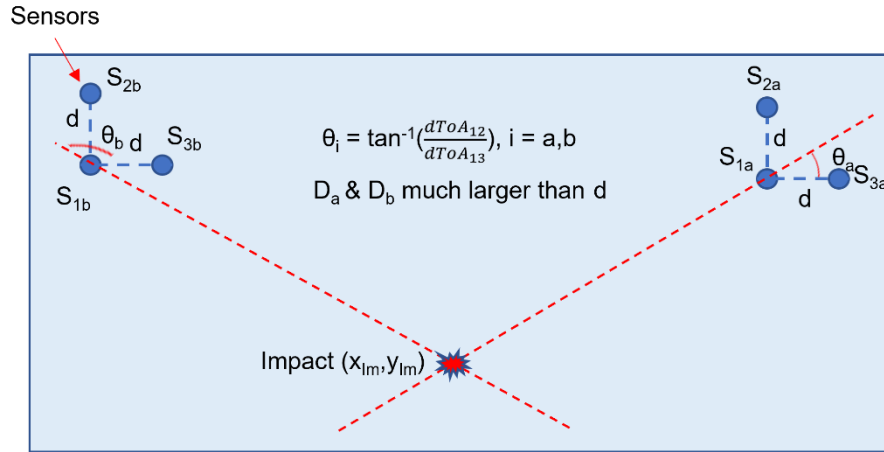


Figure 2. 7 Example of strategic sensor positioning in clusters to reduce number of unknowns in triangulation and simplify the relation between sensors

However, these triangulation based approaches rely on the assumption that there are no features in the structure that may alter the propagation of the Lamb

wave rays [19,20,42,67,68]. As shown in Figure 2. 4, the direction of propagation of the Lamb wave ray may be deviated or even obstructed by certain structural features [7,27,44,64,65]. Kundu et al. have developed novel wavefront approaches to track the refraction of propagation in heterogenous media and provide corrected location estimations [23,44]. Ebrahimkhanlou et al. [64] have developed Monte Carlo based ray tracking algorithms that track multiple propagation paths (similar to what is shown in Figure 2. 4) from different locations to find which produces the most similar response to what is recorded from the impact in question (which may potentially be useful for complex structures but has only been tested on simple plates). For very complex structures (e.g. curved stiffened panels), numerical modelling provides a general method to evaluate a structure's response to impacts (including Lamb waves) at various locations, which can be used iteratively to search for the impact location that produces the most similar response to that of the impact in question [69]. However, it can be said that as the structure has more features and the behaviour becomes more complex, the methods for estimating the location become increasingly more complex and time consuming as well to accommodate the behaviour of the structure [42,44,64,67,68]. Additionally, differing environmental and operational conditions (e.g. temperature, noise, etc.) will undoubtedly generate increased complexity in these physics based approaches (although studies on this are still very rare).

2.3.2 Physics Based Methods for Impact Severity Estimation

There are 2 main parameters that are commonly used to define the severity of impacts : the impact/kinetic energy and the impact force [2,8,13,35,36,50,70]. Equation (2. 1) shows the definition of impact energy :

$$E = \frac{1}{2} m v^2 = m g h, \quad (2. 1)$$

where E is the impact energy for an impactor with mass m and velocity v , including the case where it is a drop impact from height h and gravitational acceleration g [2]. Impact energy provides information regarding the amount of

energy contained by an impactor which is imparted into the structure (although some loss is present, e.g. from friction) and can be used as a threshold for the occurrence of damage [2,35]. However, the occurrence of impact damage is not only dependent on the impactor's state (m, v or h), but also depends on the interaction of the impactor with the structure [2,36,50]. As such, impact energy may not be a suitable indicator of severity when the impactor and structure combination vary [35]. For example, assume there are 2 impactors with the same energy, mass and geometry, but 1 being made from a soft material and the other hard (e.g. a rubber and steel ball). The impactor made from a soft material will produce an impact that is less severe towards the structure, as more energy will be absorbed by the impactor and less transferred to the structure [35]. On the other hand, the velocity and strain rate of the impact may also alter the contact behaviour of the materials (e.g. a soft material may behave like a stiffer material) [71]. This means a large mass low velocity impact and a small mass high velocity impact may have the same energy and material but behave differently depending on the material behaviour (for both impactor and structure) under different strain rates [72]. As impacts experienced by aircraft structures come from a wide range of impactors (hail, debris, tools etc.) and velocities [5], impact energy may not provide consistent measures of severity.

Impact force is also commonly used as an indicator for the severity of impacts [2,13,14,36,50]. It is a result of the impactor – structure interaction as kinetic energy is transferred from the impactor to the structure [2]. The Hertzian contact law [2,27] in equation (2. 2) describes this interaction behaviour between 2 isotropic circular bodies [2] :

$$P = k \alpha^{\frac{3}{2}}, \quad k = \frac{4}{3} E_{12} R_{12}^{\frac{1}{2}}, \quad (2. 2)$$

$$\frac{1}{R_{12}} = \frac{1}{R_1} + \frac{1}{R_2}, \quad \frac{1}{E_{12}} = \frac{1-v_1^2}{E_1} + \frac{1-v_2^2}{E_2}.$$

The law provides the relation between the contact force (P) and the resulting indentation (α) for a given contact stiffness between the 2 bodies (k) [2]. The contact stiffness itself depends on the material properties (stiffness E and Poisson's ratio ν) as well as the geometry (radius R) of both bodies (1 and 2) [2].

Thus, unlike impact energy, the impact force includes the influence of both impactor and structure [2]. Using the previous example, although a hard and a soft impactor may have exactly the same impact energy, the impact force generated will be lower due to the lower stiffness of the impactor thus giving a more consistent measure of severity than impact energy.

Using a simplified 2D model, Davies et al. (1997) [73] derived the critical threshold force for delamination to initiate in a 2D isotropic (and approximately quasi-isotropic, as the composites used in this thesis) plate under point load (such as impacts) with an existing circular delamination/damage of radius (a). Using the difference in work required to deflect the plate under damaged and undamaged conditions (signifying the transition due to delamination growth to radius a), they derived the critical force threshold required to supply enough energy to grow the initial delamination/damage as shown in equation (2. 3) [73] :

$$P_c^2 = \frac{8\pi^2 E(2h)^3}{9(1-\nu^2)} G_{IIc}. \quad (2. 3)$$

Here P_c is the critical threshold force required to supply enough energy to fulfil the mode II (shear) critical fracture toughness (G_{IIc}) and initiate damage/delamination growth in a plate with isotropic (or quasi-isotropic) stiffness E , Poisson's ratio ν and thickness h . It is interesting to note that although their original derivation started with an initial delamination of radius a , the end critical force threshold (P_c) is independent of the damage size (a). Thus, here P_c acts more as a threshold for when there is enough energy to initiate delamination, even when there is no initial damage ($a = 0$), making it an indicator for delamination initiation [73] (and has since been a good analytical base or benchmark for further experimental studies and development of more complex fracture mechanics based approaches [63,74–76]).

Further experimental observations have corroborated that the onset of delamination in composite structures occurs after a specific threshold force, which is dependent only on the quasi-static properties of the structure provided it is a low velocity impact producing BVID delamination (as studied in this thesis) [63,75,76]. Thus, the delamination threshold force for BVID is independent of the

impactor's properties (material, energy, angle, etc.) and can be evaluated for a given structure as an indicator of BVID delamination initiation [63,73,75]. This makes impact force not only more consistent compared to impact energy, but also more useful as it also provides an estimation on whether damage has occurred.

To estimate the impact force from an impact at a certain location through the physics based approach, it is necessary to obtain the relation between the applied load at the impact point with the Lamb wave strain recorded at the sensors (as shown in Figure 2. 2) [62,69]. This relation (h) is commonly written as in equation (2. 4) :

$$f(y_{im}, y_{im}) = h s(x_{sen}, y_{sen}), \quad (2. 4)$$

where f and s are the impact force profile and strain wave vs time at the sensor [62,69]. To be solvable, the impact location (x_{im}, y_{im}) must either be known first (such that location estimation must be done beforehand), or h must not have spatial dependence [14,62,69]. For simple structures (e.g. simple plates), h may be obtained from the differential equations of motion, and the estimated impact force profile (f) obtained through integration methods (e.g. piecewise integration) [62,69]. However, the differential equations of h may be prone to instability with many studies focusing on regularization methods to stabilize the solution [77,78].

The strain Lamb wave can also be considered as a convolution of the impact force profile with the impulse response as shown in equation (2. 5) :

$$s = \int_0^t f(T) g(t - T) dT, \quad F = HS, \quad H = G^{-1}, \quad (2. 5)$$

where s is the strain Lamb wave, f is the impact force profile and g is the impulse response. When transformed to the frequency domain, the relation becomes a simple linear equation where F , S , and G are the spectral form of f , s and g as shown in equation (2. 5). With H as the inverse of G , it is possible to obtain F from S [21,50,62,79], and the final impact force estimate can then be obtained from the inverse Fourier transform of F . H is commonly called the transfer function between the impact force (F) and strain (S), which for simple structures

can also be obtained through the equations of motion [62,79]. The advantage of working in the frequency domain for physics based approaches is that H tends to have a simpler form to solve than h which usually are in the form of differential equations [21,50,62,69,79]. Once the transfer function is obtained, it is possible to reconstruct the impact force profile from any type of impactor (as they only change the frequency profile of the excitation) provided the structural behaviour (transfer function) remains the same [50,62,79].

The basis of the physics based approach for impact force estimation is the determination of the relation between impact force and Lamb wave strain using the equations of motion of the structure in question [62,69]. This is feasible for simple structures (e.g. plates), but not for complex (e.g. stiffened structures or cutouts) or multiple structures with large variation (e.g. aircraft panels with different configurations) [21,62,69,79]. Variation in environmental and operational conditions (temperature, impactor properties, etc) may also add a layer of complexity, but has unfortunately received very little attention.

Additionally, for the purpose of assessing damage, it may not be necessary to obtain the full impact force profile as the maximum value is enough to assess whether the damage initiation threshold given has been passed [2,35,70]. As such, the approach of obtaining the full impact force profile may not be computationally efficient, especially since aircraft structures may experience very large number of impacts.

2.4 Data Driven Metamodels for Impact Location and Severity Estimation

An alternative approach to physics based methods for impact location and severity estimation is the data driven approach [13,18,27,33,36,43,47,51,53,70] as shown in Figure 2. 8. With this approach, the relation between the properties of the impact event (location, severity, etc.) and the features of the recorded Lamb waves (dToA, amplitude, waveform, etc.) are established without explicitly using any knowledge of the structure's behaviour in the mapping function [33,43,47,53]. Instead, it is established through mapping the relation between a set of known input (Lamb wave features, S) and output (impact event properties, F) pairs into a metamodel (H) that captures the behaviour of these data points [33,43,47,53].

Once the metamodel (H) is established, it can be used to estimate the properties of any incoming impact (F_{in}) using the features of the induced Lamb waves (S_{in}) [33,43,47,53].

Rather than explicitly establishing the behaviour of the structure in the mapping function (H), it is implicitly encoded within the chosen initial data points (F and S). This significantly simplifies the relation between impact properties and Lamb wave features compared to the physics based approach [18,22,27,36,70]. As the mapping function does not include the behaviour of the structure, this allows the function to have the same form (e.g. number of nodes in Neural Networks) regardless of the structural complexity provided a large enough initial dataset (of known inputs and outputs, F and S) is available to map the metamodel (H) to the structure [18,22,27,36,43,53,70]. As such, from the aspect of structural complexity the data driven approach is more readily scalable to real life structures than physics based approaches [27,36,53,70].

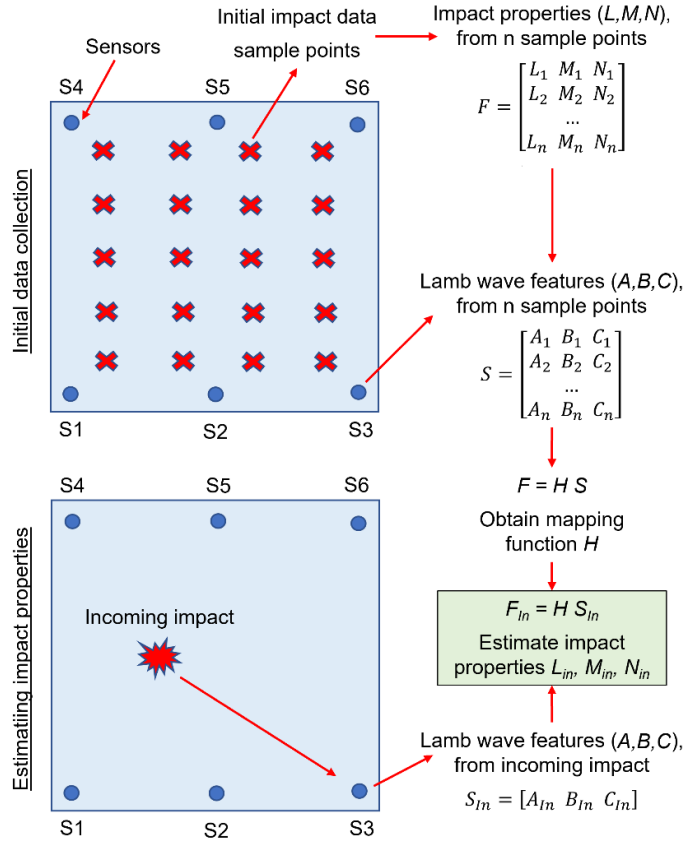


Figure 2. 8 Diagram of the data driven approach : initial data training, obtaining mapping function and estimating properties of incoming impacts

However, as the structure's behaviour is encoded solely in the initial data points (F and S) used for establishing the mapping function (H), this makes the data driven approach highly sensitive to what information is encoded in the initial data set (F and S) and what Lamb wave features are chosen for mapping [18,22,34]. The Lamb wave features chosen (e.g. dToA, amplitude, waveform etc.) must have a good correlation with the structure's behaviour and impact properties (location and severity) [27]. If not, then the relation will be poor between the chosen features and impact properties of interest, causing inaccurate estimation [27]. Thus, although it is not used explicitly in the metamodel, the knowledge of the Lamb wave propagation behaviour and how it relates to the impact excitation becomes important [27].

The initial data set needs to encompass all the possible dimensions that may affect the relation between impact properties and the Lamb wave response [18,22,27,34]. If not, there will be physical behaviour that would not be captured by the metamodel [18,22,27,34]. For the purpose of impact location and severity estimation, this means the data set must encompass the area of detection (to capture spatial behaviour, as illustrated in Figure 2. 8) as well as all probable impact cases (to capture behaviour changes due to impact parameters or environmental and operational conditions) [18,22,27,34]. Because of these factors and their combinations, the required initial data set may become impossibly large. Thus, minimising the initial data set is one of the main challenges for data driven models to be applicable in real life structures.

2.4.1 Common Types of Data Driven Metamodels

The most common form of data driven models include Artificial Neural Networks (ANNs) [13,18,22,27,36] and pattern matching algorithms [24,43,80]. Pattern matching algorithms are also known as reference database methods, as the initial data set of Lamb wave features (S , Figure 2. 8) is used as a reference for comparing against the features from the incoming Lamb wave (S_{in}) [24,43,80]. The estimated properties for the incoming impact (F_{in}) will be similar to the impact properties of the database point (F_n) that has the least difference in features

(S_n) with the incoming Lamb wave (S_m). As shown in Figure 2. 8, the reference database will be comprised of discrete sampling points [24,43,80]. Thus, to estimate the impact properties in regions between the sampled points, interpolation functions (e.g. weighted averaging) are used to interpolate the estimated impact properties from nearby sampled points [24,43,80].

Another type of data driven metamodel that is commonly used for impact location and severity estimation are ANNs [13,18,22,27,36]. ANNs are comprised of a network of nodes that are connected via weighted connections that link an input vector to an output vector via a hidden layer of nodes (as shown in Figure 2. 9) [13,18,22,27,36]. Each node represents a mathematical function that can range from a simple multiplication up to a convolution operation [13,18,22,27,36]. The structure of the network (e.g. number of layers, inputs, type of nodes) can vary significantly depending on the task and currently no fixed optimisation method exists for this structure [13,18,22,27,36].

To function, an ANN needs to be trained using an initial dataset of known input and output (F and S , Figure 2. 8). The training is an optimisation task that sets the weights to capture the behaviour of the initial dataset used for training (e.g. minimising the difference between ANN estimate and known output) [13,18,22,27,36]. The connections with more relevance will have higher weighting, whilst paths that are less relevant will have less weighting [13,18,22,27,36]. The structure of the ANN allows versatile mapping of nonlinear data that may not be achievable with other regression methods [13,18,22,27,36].

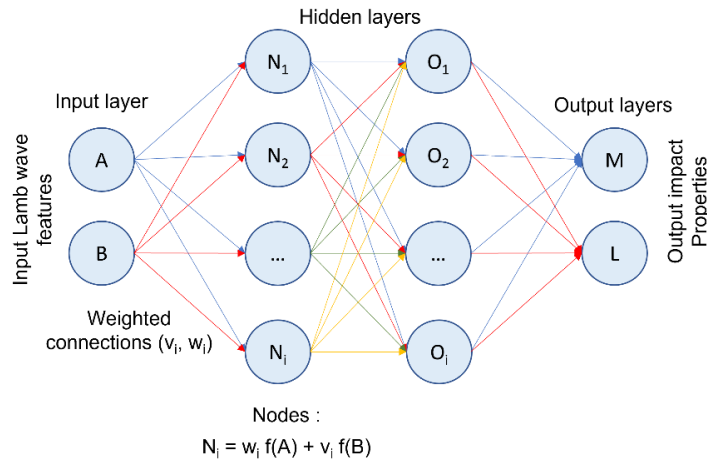


Figure 2. 9 Example diagram of an Artificial Neural Network (ANN)

2.4.2 Data Driven Approach for Impact Location Estimation

As mentioned in section 2.2, the dToA and amplitude of a Lamb wave change as the propagation distance from the impact source to the sensor changes [7,27]. By using this correlation, previous studies have successfully used ANNs [18,22,27] and also reference database approaches [24,43,80] to estimate the location of impacts using Lamb wave dToA and amplitude profiles from a set of sensors. Out of the 2 features however, dToA appears to have better correlation and is the most commonly used Lamb wave feature across studies [27].

Unlike the physics based approach, the data driven methods have been shown to be applicable from simple structures (e.g. flat plates) [18,22] up to large scale stiffened panels [24,27,43,80] and even structures with many cutouts [52,53]. Although there has been no fixed method of optimizing these methods (e.g. number of network nodes, size of initial database, etc.), they mostly remain unchanged (features used, size of networks, number of initial sample points, etc.) when scaling up from simple to complex structures [18,22,27]. There also does not seem to be any significant difference in performance between reference database [24,43,52,53,80] and ANN [13,18,22,27] approaches in terms of accuracy.

However, some studies have identified the sensitivity of these approaches (especially ANNs) towards the scope of the initial data set used for obtaining the mapping between input and output [18,22,34]. It has been found that when these methods are tested with impact cases that are outside of the initial database scope (e.g. different impactor mass [18,22,34]), the accuracy of the location estimate is significantly reduced [34]. Thus, the challenge is to either produce an initial dataset that can encompass all possible impact scenarios or develop a method that is robust towards environmental and operational variations.

2.4.3 Data Driven Approach for Impact Severity Estimation

Numerous studies have used data driven approaches for reconstructing the impact force profile as a measure of impact severity [13,14,36,50]. Equation (2. 5) presents the transfer function (H) as a way to relate the recorded Lamb wave

signal (S) with the impact force profile (F) [14,50]. This expression allows a data driven interpretation of determining the transfer function. Rather than obtaining the transfer function through derivation of the structure's equations of motion, it is obtained by taking initial data samples of F and S at various locations and simply dividing the spectral components of the impact force (F) with the spectral components of the Lamb wave signal (S) such that $H(x, y) = \frac{F(x, y)}{S(x, y)}$ [14,50]. By doing so it is possible to have the transfer function for various locations across the sensing area, allowing impact force reconstruction provided the location of impact (x, y) is known (usually by conducting location estimation first) [14]. This way, the structure's behaviour can be obtained without explicitly using the equations of motion and is applicable for simple and complex structures [14,50]. However, this method is limited to linear conditions (e.g. small deflections) [36] and is also prone to instability as some spectral components of F or S may be very small (mostly past the bandwidth of the signal where there is only noise) which may cause vary large scaling values in the transfer function and noisy results [79].

Other studies [13,51] have been able to reconstruct the impact force profile using ANNs with accurate results. Due to the structure of ANNs, they can also accommodate nonlinear structural behaviour [13,51]. However, unlike transfer functions that hold true regardless of the impactor property (thus making it robust towards different kinds of impactors) [21,50], ANNs may not be able to accommodate impact force profiles from impact scenarios that are not included in their initial training data set.

As mentioned in section 2.3.2, for structural health monitoring purposes, reconstructing the full impact force profile may not be necessary as the maximum value provides enough information for determining the onset of damage [2]. Because of that, some studies have sought to use ANNs to directly correlate the signal amplitude or energy (defined as the integration of the signal amplitude with time) with the maximum impact force or energy [36,70]. Although the results are good for impact cases that are within the scope of the initial training set, it is still inaccurate for novel impact scenarios [36].

Other studies have sought to establish a more direct and simple relation between the Lamb wave signal features and the impact severity [12,35]. It has

been found that for a single location, the Lamb wave signal energy scales linearly with the impact energy [35], whilst the amplitude of the signal scales linearly with the maximum impact force [12]. These relations allow for very simple linear regression to be used to estimate the severity (P) of impacts for a single location (x,y) using the chosen Lamb wave feature (O) provided that the linear gradient is known (K), such that $P(x,y) = K(x,y) O$ [12]. Similar to the transfer function approach, the linear gradient ($k(x,y)$) may be obtained from initial data samples (known $P(x,y)$ and O) from various locations (x,y) to provide coverage of the whole sensing area (as shown in Figure 2. 8).

However, these studies [12,35] also find that the linear relation (specifically the gradient) may change depending on the impactor properties such as material and geometry as well as potentially other environmental and operational factors. Because of this, the challenge is to find a more robust relation that is constant for most environmental and operational factors.

2.5 Conclusion

From the literature it has been observed that there are 2 main approaches to passive monitoring of impacts : physics based and data driven based. It was found that physics based methods increase in complexity when transitioning from simple to complex structures whilst data driven methods do not. Because of this, it was concluded that data driven methods are more readily suitable for the main goal of this thesis to bring passive SHM methods to real life structures under operational and environmental conditions. The goal is then to develop methods to minimise initial data sampling requirements to make it feasible for large structures as well as developing data driven methods that are more robust towards novel impact scenarios. The following chapters will detail the development of data driven methods for impact location and severity (specifically impact force) estimation.

Chapter 3 : Part 1

Passive Sensing Method for Impact Localisation in Composite Plates under Simulated Environmental and Operational Conditions¹

As mentioned in Chapter 2., the focus of development in this thesis is on data driven methods for impact location and severity estimation. This chapter will present the development of a data driven approach for impact location estimation that is robust towards simulated environmental and operational conditions.

3.1.1 Introduction

Most studies concerning Artificial Neural Networks (ANNs) for impact location estimation only focus on cases where the impact conditions are the same for both training and testing [25,27,81,82]. In real application, an aircraft structure is subjected to variable impact conditions (varying temperature, mass, angle, energy) which can introduce significant variation in wave features (amplitude, frequency, noise level) compared to the training conditions [4,18,22,48,81,83–85]. This can cause significant reduction of accuracy of an ANN (and any other data driven method in general) impact location prediction when the input data are gathered under different conditions than the original training set [22,80,81,86]. Inclusion of various impact conditions into the training set of an ANN is impractical due to the large range of possible operational conditions, which would require a very large training data set.

Recording impact induced waves under operational conditions of an aircraft, will include operational noise in the form of vibration[48,83]. If the operational

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vibration profile can be identified, an appropriate filter can be designed and applied to remove the vibration noise in the data [48] since impacts tend to generate wideband frequency responses [9,87]. Therefore, the choice of features extracted from the recorded data, to be used as input to the ANN, must consider the viability of removing noise from it. Additionally, most of the reported ANN based research have been carried out on flat composite plates [22,25,27,81]. Therefore, there remains shortcoming in investigating the influence of the plate curvature on the accuracy of ANN based localization.

The aim of this chapter is to propose an impact localization methodology based on ANN which is applicable for composite structures under operational and environmental conditions without the need for an impossibly large training data set. The influence of environmental and operational conditions on recorded impact signals on sensorized flat and curved composite plates will be investigated. A novel feature extraction methodology is then proposed which can minimize the variance of extracted features whilst also removing the effects of vibration noise. The validity of the proposed methodology is tested by training ANNs using data from only one impact scenario which is then tested using impacts of different conditions than the original training scenario. A comparison is done between ANNs trained with features extracted with current methods and ANNs trained with features extracted with the proposed method to see the improvement in accuracy.

3.1.2 Experimental Setup

Experimental tests were conducted with the aim to investigate the influence of variation in impact condition (mass, energy, angle, temperature and vibration) on the recorded response of sensorized composite structures with different geometries (flat and curved). To achieve this, a multi-parameter impact test rig was designed as shown in Figure 3.1. 1 and Figure 3.1. 2 to simulate different impact conditions and vibration noise. The setup consists of 2 quasi-isotropic $[0/+45/-45/90/0/+45/-45/90]_s$ layup) carbon fibre (M21 T800s) composite plates with differing geometries (flat and curved) and a rail guided impactor. The sensor, vibration motor and impact location layout can be seen in Figure 3.1. 2 for the flat

and curved plates. The flat plate (200 mm x 290 mm) had 8 PZT sensors bonded to the top side of the plate (impact side) whilst the curved plate (290 mm x 285 mm) had 6 PZT sensors bonded to the bottom side of the plate to simulate possible sensor installation on the inside of a curved aircraft structure. The flat plate had a silicone heating mat and temperature sensor bonded to the bottom side for testing the plate at high temperature under impact. To generate vibration noise, 8 vibration motors (consisting of 3V coin motors attached to LM8UU linear bearings) were bonded on the top side of both flat and curved plates generating noise. The frequency range was 0 – 2 kHz with the main frequency component being around 250 – 300 Hz with a maximum recorded amplitude of 200mV and 250 mV for the curved and flat plates respectively.

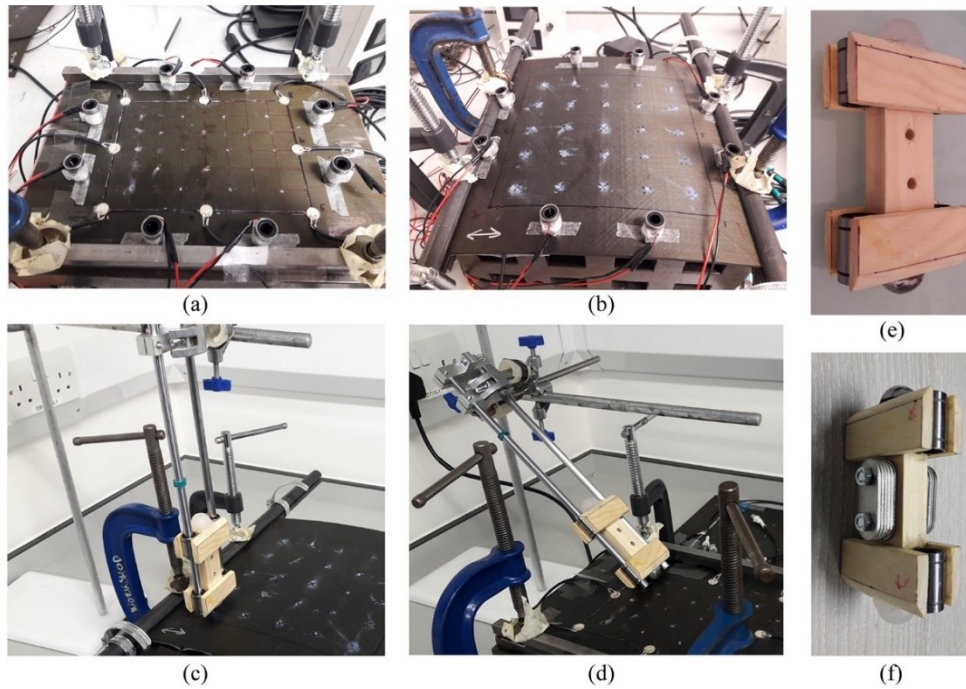


Figure 3.1. 1 Experimental impact setup : flat plate (a), curved plate (b), rail guided impactor at 900 angle (c) and 450 angle (d), impactor without added mass (e) and with added mass (f)

Impacts were generated by dropping the impactor shown in Figure 3.1. 1(c). Angled impacts were generated by tilting the guiding rails (tilt directions marked in Figure 3.1. 2) and impact energy was controlled by the vertical height from which the impactor was dropped (Figure 3.1. 2). The impactor head used was a 20 mm diameter round steel head and the impactor mass used was 100 gr (original)

and 200 gr (increased by adding extra weight attachments to the impactor). For cases with vibration noise, since the generated noise amplitude was small a PCB Piezotronics impact hammer (086C03) with a steel tip was used instead of the impactor to have impacts of smaller amplitude or “taps” to maintain a reasonable signal to noise ratio (noise level > 5% signal amplitude). Additionally, the hammer adds randomness in terms of energy and angle of impact.

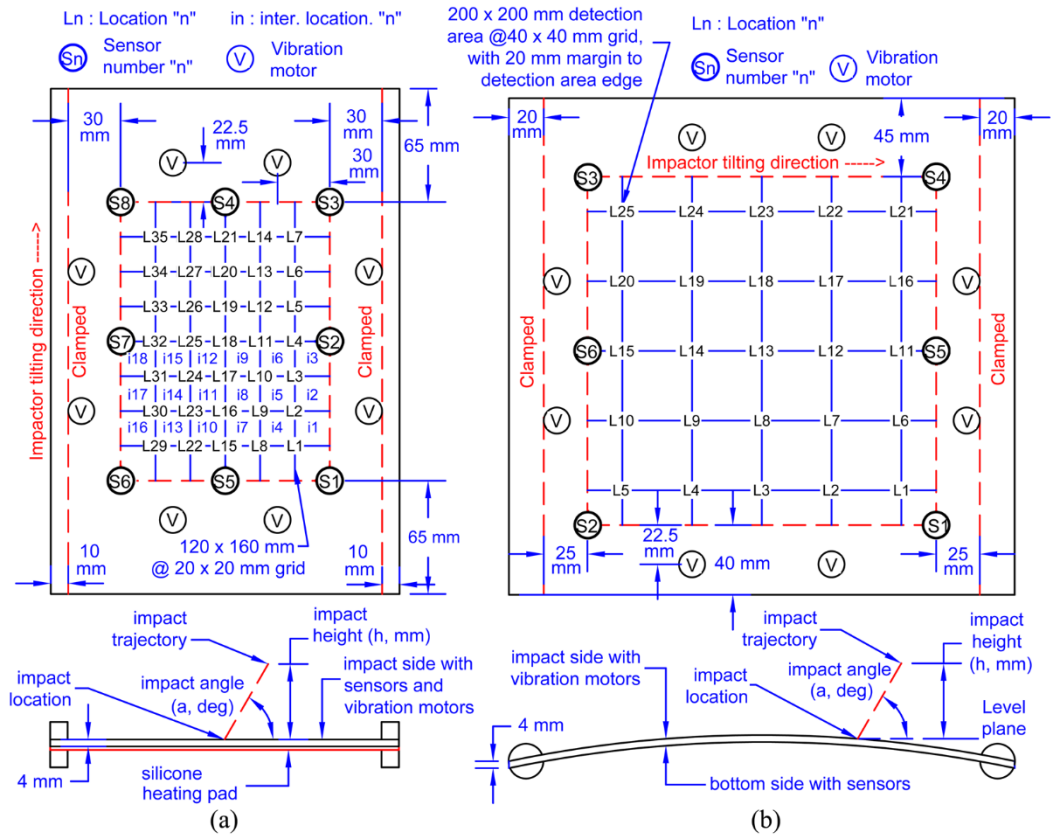


Figure 3.1. 2 Layout for flat (a) and curved (b) plates

Data acquisition was carried out using an NI PXI-5105 8 channel oscilloscope and NI SignalExpress software. Each PZT sensor was connected to the oscilloscope via 10x attenuation oscilloscope probes (except for vibration cases where the attenuation was set to 1x). For each impact, the impact signals were recorded for all sensors at 2 M samples/second with 100,000 sample points length and were repeated 4 times for consistency. A total of 1,332 impacts were collected from the flat plate (Table 3.1. 1) and 384 were collected from the curved plate (Table 3.1. 2). For each plate there is a baseline case (F1 and C1) where every

other case is a parametric deviation from the defined baseline (increased mass, temperature, etc.).

Table 3.1. 1 Impact cases (F1 – F11) conducted for the flat plate

Case	Parameters	Number of samples
F1. baseline case	h=50, a=90, m=100, T=25	140 (loc. 1-35 x 4 rep.)
F2. baseline at inter. locations (inside baseline scope)	h=50, a=90, m=100, T=25	48 (loc. (inter.) 4-15 x 4 rep.)
F3. baseline at inter. locations (outside baseline scope)	h=50, a=90, m=100, T=25	24 (loc. (inter.) 1-3 & 16-18 x 4 rep.)
F4. increased temperature	h=50, a=90, m=100, T=70	140 (loc. 1-35 x 4 rep.)
F5. angled impact	h=50, a=45, m=100, T=25	140 (loc. 1-35 x 4 rep.)
F6. increased mass	h=50, a=90, m=200, T=25	140 (loc. 1-35 x 4 rep.)
F7. increased height	h=100, a=90, m=100, T=25	140 (loc. 1-35 x 4 rep.)
F8. increased height & temperature	h=100, a=90, m=100, T=70	140 (loc. 1-35 x 4 rep.)
F9. increased height & angled impact	h=100, a=45, m=100, T=25	140 (loc. 1-35 x 4 rep.)
F10. increased height & mass	h=100, a=90, m=200, T=25	140 (loc. 1-35 x 4 rep.)
F11. hammer + vibration	h, a = random, T=25	140 (loc. 1-35 x 4 rep.)

*note : h = height, mm; a = angle, degrees; m = mass, gr; T = temperature, °C

Table 3.1. 2 Impact cases (C1 – C5) conducted for the curved plate

Case	Parameters	Number of samples
C1. baseline case	h=50, a=90, m=100, T=25	100 (loc. 1-25 x 4 rep.)
C2. angled impact	h=50, a=60, m=100, T=25	84 (loc. 1-25 except 5,10,20,25 due to clamping geometry x 4 rep.)
C3. increased mass	h=50, a=90, m=200, T=25	100 (loc. 1-25 x 4 rep.)
C4. increased height	h=100, a=90, m=100, T=25	100 (loc. 1-25 x 4 rep.)
C5. hammer + vibration	h, a = random, T=25	100 (loc. 1-25 x 4 rep.)

*note : h = height, mm; a = angle, degrees; m = mass, gr; T = temperature, °C

3.1.3 Effect of Impact Condition Variation on Structural Response

From the gathered experimental data, it was observed that variation in impact condition (mass, angle, energy, temperature) has a significant effect on impact response signals. Table 3.1. 1 and Table 3.1. 2 summarize all the impact cases conducted on the flat and the curved composite plates respectively. Analysing the data gathered on the flat plate, Figure 3.1. 3 shows the absolute value of impact signals recorded by sensor 4 for impacts under various conditions (F1, F4 - F7) at location 18. All of the recorded signals in this chapter are presented as absolute values for better observation of changes in signal features (signal start, amplitude, etc.) and to aid feature extraction later on.

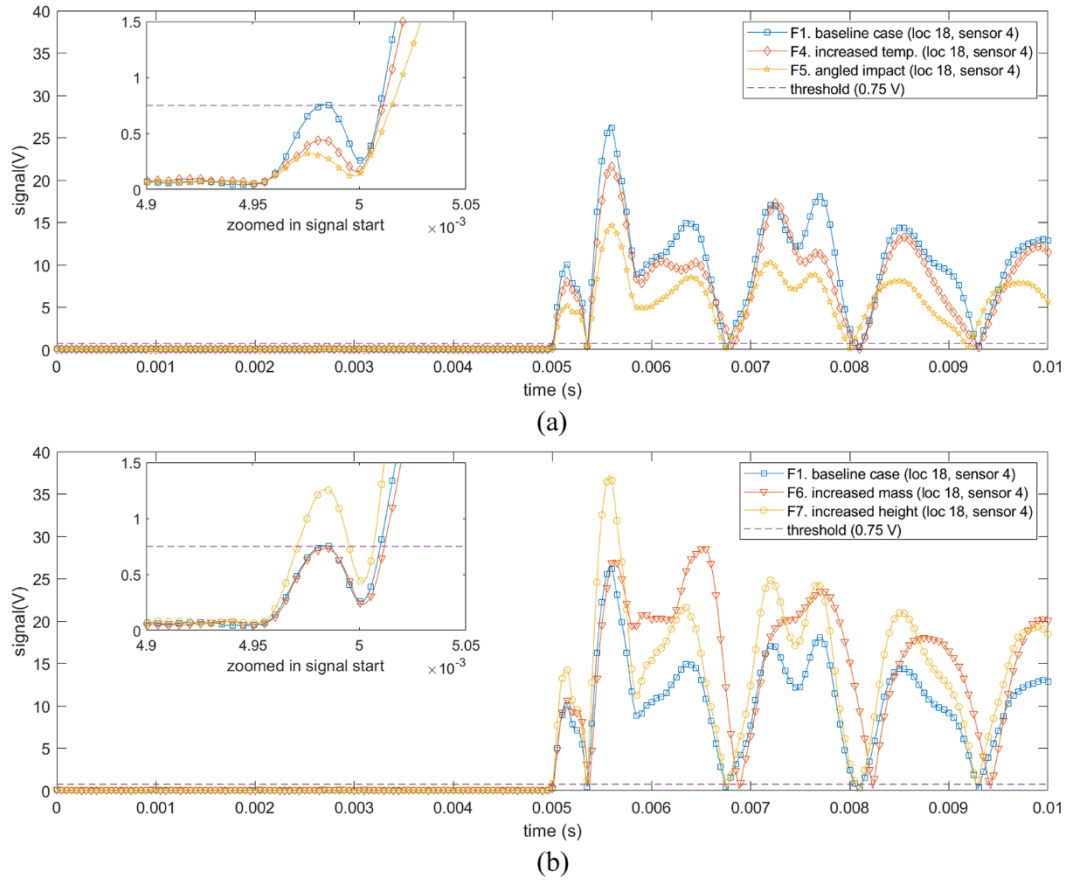


Figure 3.1. 3 Absolute value of impact signals recorded at sensor 4 for various impact cases (F1, F4, F5 [a] and F1, F6, F7 [b]) at location 18 of flat plate

From Figure 3.1. 3 it can be seen that for all cases, the waveform is similar up to the second peak which is the main peak for all cases except the increased mass (F6). Increased height (F7) gives higher kinetic energy and causes the amplitude of the signal to increase relative to the baseline case (F1) while the waveform does not change [80,84]. For increased temperature (F4), the general amplitude of the wave decreases with slight shift in the phase of wave components. This is consistent to previous findings [7,48,81,85] and may be caused by change in material properties caused by temperature in both the plate and PZT. Angled impact (F5) also lowers the general amplitude and introduces slight phase shift in the later parts of the wave without much alteration to the waveform. The reduced amplitude is caused by the reduction in transverse velocity component to the plate surface whilst the phase shift may be caused by the friction caused by the parallel velocity component [2]. Increased mass (F6) changes the waveform significantly

after the second peak (main peak for F1, F4, F5 and F7) which is caused by the change in excited frequency components as found in previous studies [18,81].

As mentioned previously, it has been found that signal TOA is a good and commonly used feature for impact localisation with ANNs [27] and thus the start of the signal is of interest. It can be observed in the enlarged portion of the signal in Figure 3.1. 3 that all the signals start at the same time and have similar waveform near the start. However, due to differences in signal amplitude determination of signal TOA using common methods such as thresholding [18,22,27,81,82] may give different results depending on the threshold value chosen [27]. This may cause inconsistencies in TOA associated to impacts in the same location but with different impact conditions.

Figure 3.1. 4 shows the comparison between the baseline case (F1) where the impact signal (generated by hammer impact (F11)) was recorded with and without vibration. It can be seen that the presence of vibration masks the signal arrival, which is of interest. In general, the probable impacts on aircraft parts, excite a wide band frequency response (above 10 kHz [9,87]) which is usually higher than operational vibration levels (under 2 kHz as stated by RCTA DO-160C [48]). Therefore it is possible to denoise the signal with high pass filters (prior to absolute value conversion) [48] to obtain the high frequency impact signal components which may still be used to obtain signal TOA as shown in Figure 3.1.

4.

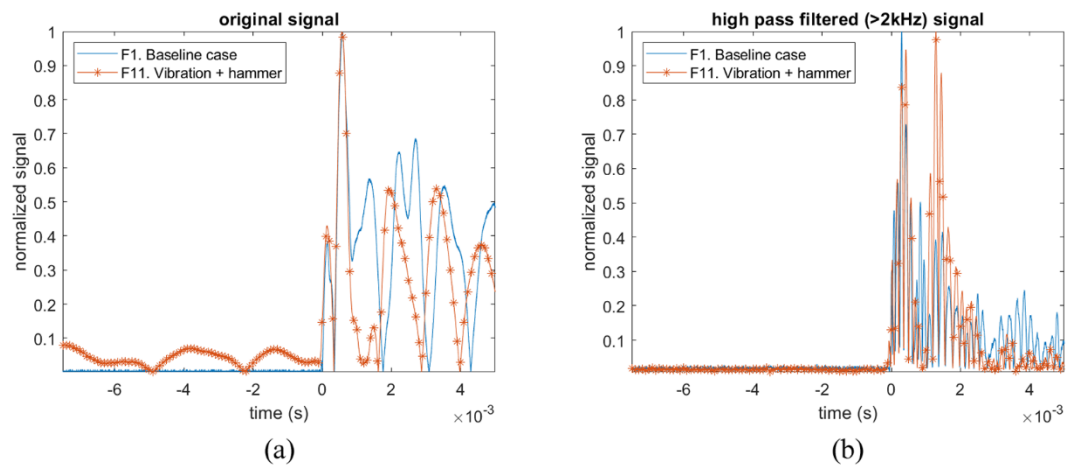


Figure 3.1. 4 (a) Effect of vibration noise on impact signal and (b) denoising via high pass filtering (< 2 kHz Butterworth IIR filter)

3.1.4 Impact Localisation Algorithm

3.1.4.1 Artificial Neural Networks (ANNs)

As mentioned earlier, the interest of this chapter is to realize the use of ANN for impact localization in real operational conditions. ANN is a meta-model that maps a given input to an output via a network of neurons separated into layers as shown in the simple example diagram in Figure 3.1. 5. The inputs (X,Y) are connected to the hidden layer via a set of weighted (W_{ij} , $i = x,y$, $j = 1,2$) connections [81,86]. In the hidden layer, the weighted inputs go through mathematical operations (functions f and g) and are then connected to the output layer via another set of weighted (V_{ij} , $i = x,y$, $j = 1,2$) connections [81,86]. The values from the hidden layer connections to the output layer are then summed to produce an output (A, B). During training, a known set of inputs and outputs are fed to the network whilst the weights are adjusted via backpropagation algorithms to produce a network that best fits the training data [86]. Once trained, the ANN can predict an output for a given input accurately if the input is in the scope of the training data (similar to regression).

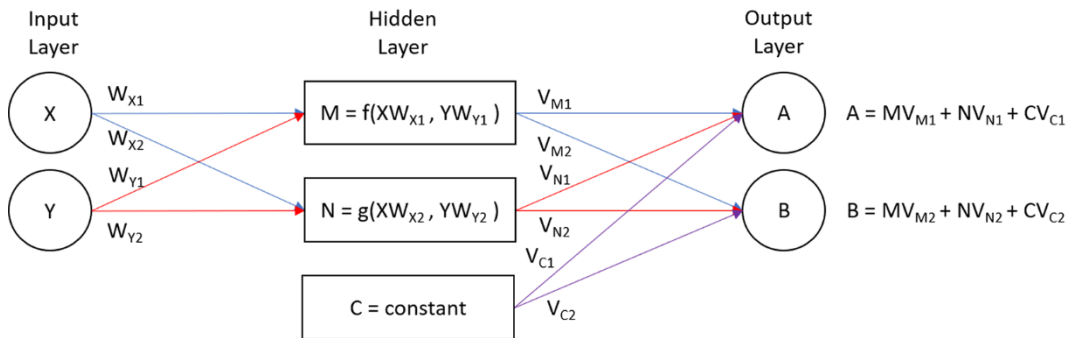


Figure 3.1. 5 Diagram of simple feed forward neural network

Since ANN training only fits a network to map a given input to a given output (from the training set), any inconsistent association between input and output (differing from the training set) will result in an inaccurate prediction of output for a given input [86]. Here, inconsistencies of the signal features (arising from feature extraction methods or differing impact conditions) used as inputs will reduce the accuracy of the predicted output which is the impact location [81].

Therefore, to maintain the accuracy of impact localisation using ANNs regardless of the impact conditions, the feature extraction method must give consistent results for a given location for all possible impact conditions.

3.1.4.2 ANN Input Feature Selection and Extraction

From previous observations (section 3.1.3 and Figure 3.1. 3) it was found that the amplitude of the signal varies with varying impact conditions and that the time of maximum amplitude changes with increased mass impacts (F6). This poses a risk of introducing inconsistencies for features relying on maximum signal amplitude. On the other hand, the start of the signal prior to the second peak shows potential consistency of waveform (even though amplitude variance exists). Coupled by the fact that previous studies have concluded that TOA is the best input for impact localisation ANN [27], it was therefore selected as the input feature used for ANN impact localisation.

For the purpose of TOA extraction, the commonly used threshold method [18,22,27,81,82] (signal “arrives” when a set threshold is passed) was used as a starting point for TOA extraction. Figure 3.1. 3 shows that variation in impact condition generates differences in the impact signal amplitude, especially at the small initial peaks at the signal start, which may affect TOA determination consistency.

Since the waveform of the initial portion before the peak is similar, normalizing the signal amplitude (dividing signal amplitude with the maximum absolute amplitude value out of all the signal from a sensor network) can reduce the variation that causes inconsistencies in the TOA extraction based on a set threshold [18,80,84]. This method of TOA extraction is referred to here as the Normalized Threshold (NT) method and was chosen as the benchmark method for comparison with the proposed TOA extraction method later on. Figure 3.1. 6 shows the normalized signals from Figure 3.1. 3 where it can be seen that the variation in amplitude at the start of the signal has been reduced significantly. However, this may not be enough to ensure localisation accuracy [18] since the problem of varying initial peaks not only occurs due to differing impact cases but also between different sensors. Figure 3.1. 7 shows the normalized (relative to the

maximum absolute amplitude of all the signals from a set of sensors) absolute value signals from sensors 1, 2 and 4 due to the baseline impact case at location 18 of the flat plate. It can be seen that the same problem arises due to differences between the amplitude of initial peaks of each sensor signal.

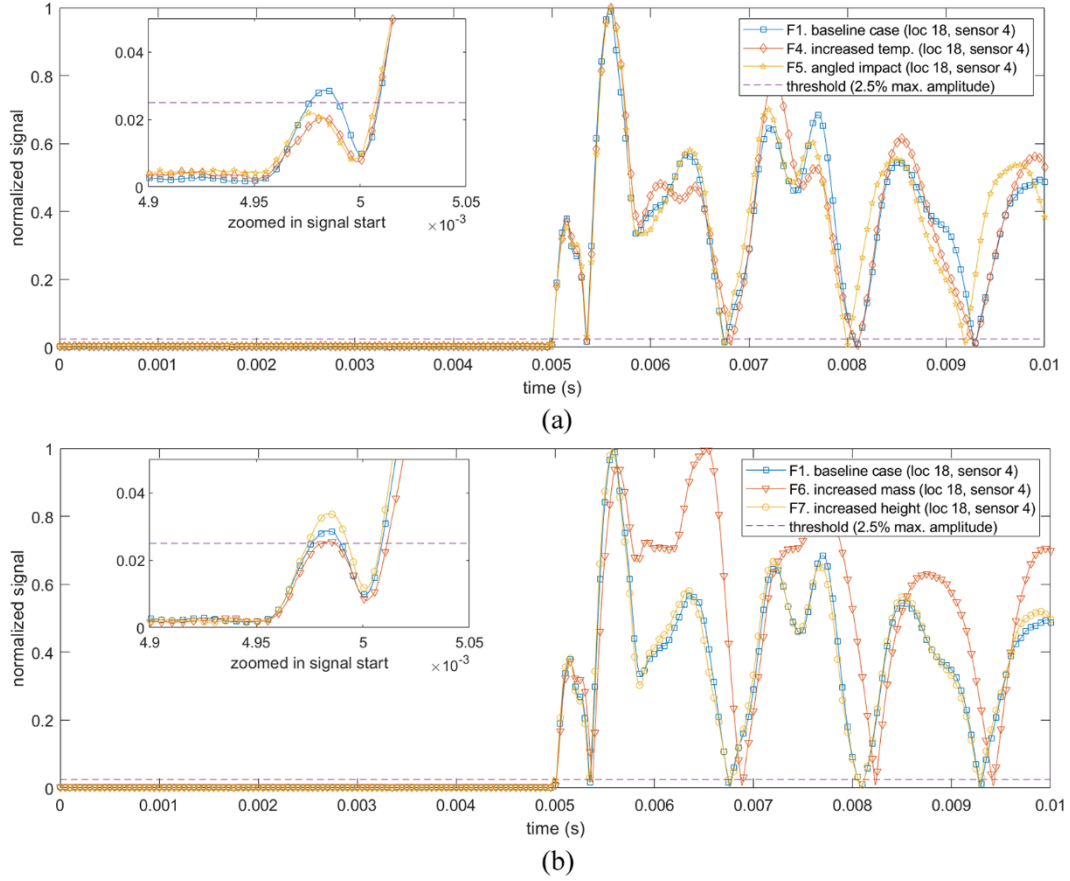


Figure 3.1. 6 Normalized absolute value impact signals recorded at sensor 4 for various impact cases (F1, F4, F5 [a] and F1, F6, F7 [b]) at location 18 of flat plate

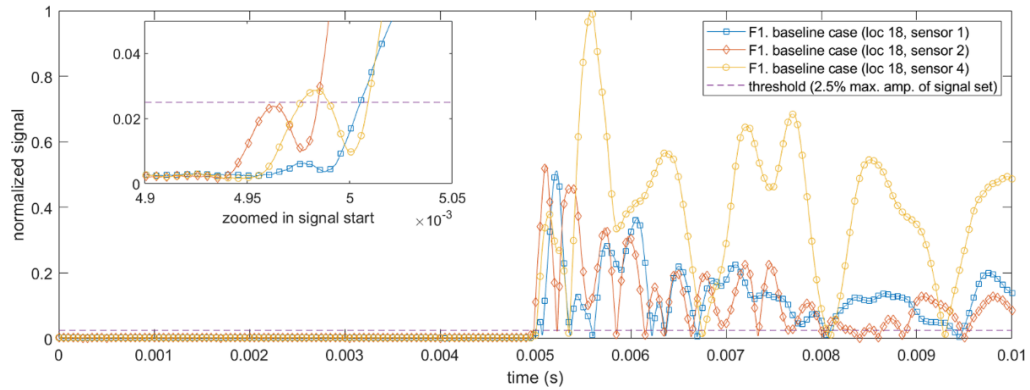


Figure 3.1. 7 Normalized (relative to max. amplitude in set) absolute value impact signals recorded at sensors 1, 2 and 4 for the baseline case (F1) at location 18 of flat plate

Since the main problem occurs due to the small initial peaks at the start of the signals, it is proposed to smooth the signals to remove the peaks. Since the signal is expressed as the absolute value, low pass filtering will yield a smoothed envelope of the signal. Figure 3.1. 9 and Figure 3.1. 8 show the envelopes of the signals shown in Figure 3.1. 6 and Figure 3.1. 7 respectively obtained by low pass filtering (< 2 kHz, Butterworth IIR filter) prior to normalization. It can be seen that the signal envelopes have a much smoother signal rising edge for both different impact cases and different sensors thus giving a much more consistent results for a wider range of threshold levels. This TOA extraction method is referred to here as the Normalized Smooth Envelope Threshold (NSET) method.

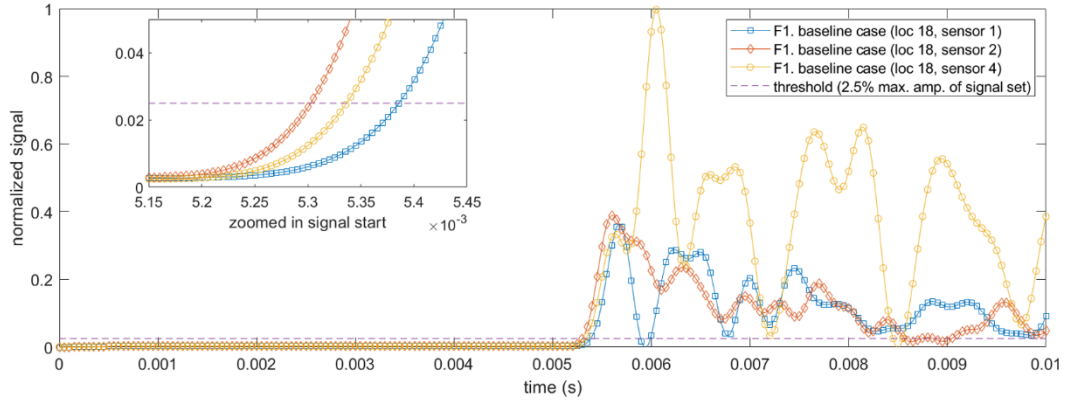


Figure 3.1. 8 Normalized (relative to max. amplitude in set) impact signal envelopes (< 2 kHz) for signals recorded at sensors 1, 2 and 4 for the baseline case (F1) at location 18 of flat plate

For vibration noise, denoising via high pass filtering (Butterworth IIR filter > 2 kHz, above vibration motor noise frequency bandwidth) was performed prior to absolute value conversion and TOA extraction to unmask the initial part of the signal. In reality an acquisition system would have a fixed filter, thus all cases were high pass filtered (training and test cases regardless of whether there was vibration noise or not).

As mentioned previously in section 3.1.1, since in operational conditions the actual time of impact is unknown (thus real TOA is unknown) the TOA inputs for the ANN are in terms of TOA differences for each sensor relative to the earliest arrival time (set as 0). TOA differences extracted with the NSET method were

compared to TOA differences extracted with the NT method as a benchmark to assess its performance as the input for localisation ANN. Extraction threshold level was set to 2.5% of maximum absolute amplitude of the signals (from all sensors in the network) for ANNs without vibration filtering and 5% for ANNs with vibration filtering (due to lower signal amplitude relative to acquisition system noise after filtering).

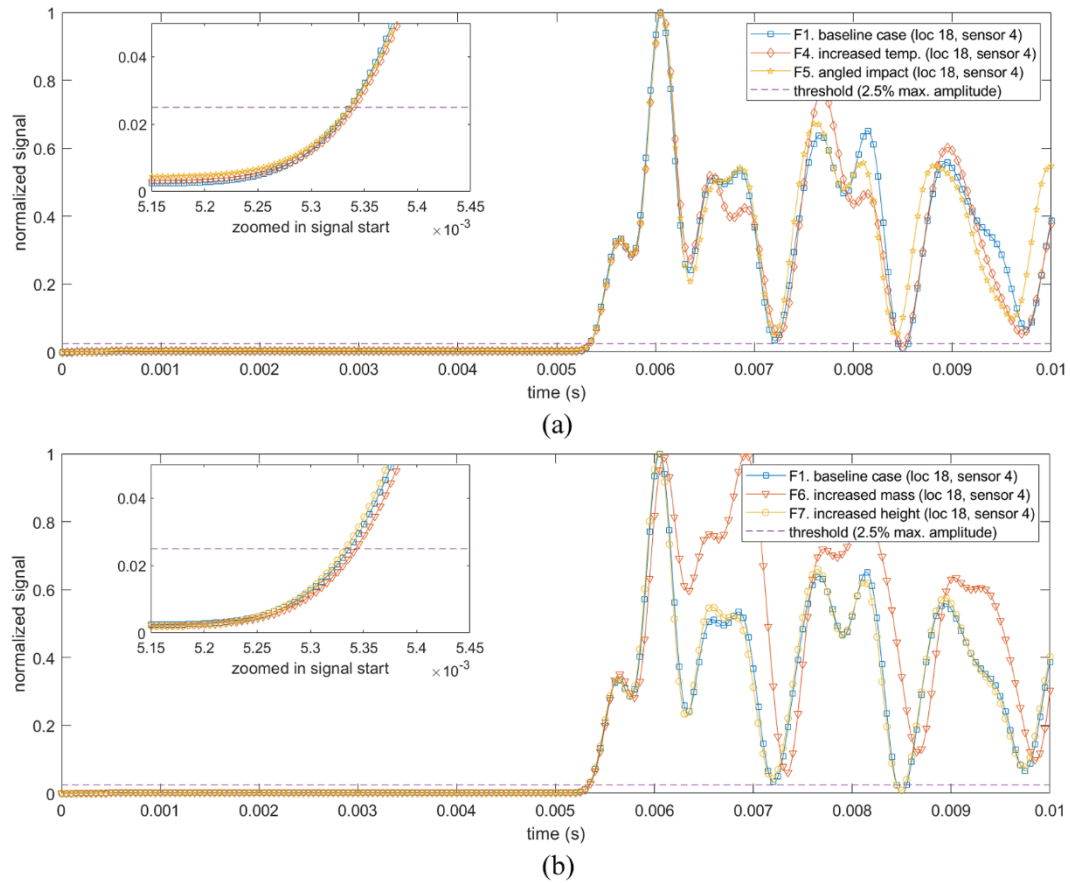


Figure 3.1. 9 Normalized impact signal envelopes (< 2 kHz) for signals recorded at sensor 4 for various impact cases (F1, F4, F5 [a] and F1, F6, F7 [b]) at location 18 of flat plate

3.1.4.3 Neural Network Training and Testing

Here 8 individual ANNs were trained and compared for impact localisation as shown in Table 3.1. 3. These ANNs were compared to see the differences in localisation performance for different geometries (flat and curved), TOA extraction methods (NSET and NT methods) and the effect of vibration noise (effect of high pass filtering prior to TOA extraction). ANN construction and

training was conducted using the “nftool” function available in MathWorks MATLAB R2018a software.

Table 3.1. 3 List of ANNs trained and used

ANN	Plate	Training Set	Vibration Noise	Test Input Sets	High Pass Filter (Training & Test sets)	TOA Extraction
ANN (F NV NSET)	Flat	F1	No	F2 – F10	No	NSET
ANN (F NV NT)	Flat	F1	No	F2 – F10	No	NT
ANN (F V NSET)	Flat	F1	Yes	F2 – F11	>2kHz	NSET
ANN (F V NT)	Flat	F1	Yes	F2 – F11	>2kHz	NT
ANN (C NV NSET)	Curved	C1	No	C2 – C4	No	NSET
ANN (C NV NT)	Curved	C1	No	C2 – C4	No	NT
ANN (C V NSET)	Curved	C1	Yes	C2 – C5	>2kHz	NSET
ANN (C V NT)	Curved	C1	Yes	C2 – C5	>2kHz	NT

Note : ANN nomenclature in parentheses: plate: Flat or Curved (F/C); vibration filtering: Vibration or No Vibration (V/NV); TOA extraction method: Normalised Smoothed Envelope Threshold or Normalized Threshold (NSET/NT).

Each ANN had an input of TOA differences for each sensor (8 for flat and 6 for curved) followed by a single hidden layer containing 10 neurons (with tansig activation function) which is then connected to the output layer (with purelin activation function) consisting of 2 neurons for the X and Y coordinates of the impact location. For each ANN, training was conducted using the Levenberg – Marquardt backpropagation algorithm [86] with Root Mean Square Error (RMSE) of the impact location coordinates (Root Square Error of single location : $RSE = [X_{\text{predicted}} - X_{\text{reference}}]^2 + [Y_{\text{predicted}} - Y_{\text{reference}}]^2$) of the training set as the performance indicator. This training was repeated 500 times to account for random initial weights for each ANN and the resulting network with lowest value of RMSE + RSE standard deviation (to minimise mean error and also error spread) for the training set is chosen. The baseline case for each plate (F1 and C1) is chosen as the training set for each ANN such that the test sets represent cases that deviate from the original training sets (F2 – F11 and C2 – C5) to test the generalisation of the trained ANN.

Testing was conducted by giving the features extracted for the derivative cases (F2 – F11 and C2 – C5) as input to the previously trained ANNs to assess the accuracy of the ANNs for cases outside of the original training case. Cases F2 and F3 were selected to test the ANNs interpolation capability in locations between

the known impact locations (intermediate locations, Figure 3.1. 2) of the training set to see if overfitting occurs. Data from case F3 was collected outside the initial training data range to see the accuracy of the ANNs for extrapolating outside of the original training data range.

Accuracy was quantified by the Cumulative Distribution Functions (CDFs) of the RSEs for each set (fitted with a lognormal distribution [18,27,88,89]). The values of RSE were translated into detection range, which represents the area around the real impact location within which an impact will be detected with a certain level of probability (smaller values mean higher accuracy). It is important to note that here that POD refers to an actual physical area around the impact point where the actual estimated impact location is, and not the more common use of POD as the probability of detecting damage. A comparison of detection range at 90% Probability of Detection [27] (POD) based on the obtained CDFs is given for all cases for ease of comparison.

3.1.5 Impact Localisation Results

Figure 3.1. 10 and Figure 3.1. 11 give the impact localisation results in terms of CDFs and detection range (90% POD) for the flat and curved plate with no filtering for vibration denoising (ANN [F NV NT], ANN [F NV NSET], ANN [C NV NT], ANN [C NV NSET]). It can be seen that in both the curved and the flat panel, both NT and NSET extraction methods allow for very good localisation of the training set (F1 and C1). For the flat plate, interpolation for intermediate location (Figure 3.1. 2) detection is still relatively accurate (detection range : 5.71 mm for NT and 4.97 mm for NSET) if the locations are still inside the training data range (F2). When outside the training data range (F3) the accuracy drops considerably (15.03 mm for NT and 9.18 mm for NSET) as expected from the limitations of ANNs [86]. Therefore, F3 is generally excluded when comparing accuracy between ANNs since it does not reflect on the generalisation capability of the trained networks.

For test cases with differing impact conditions (F2 – F10 and C2 – C4), in general the accuracy drops (Figure 3.1. 10 and Figure 3.1. 11) compared to the accuracy of localisation for the training set (F1 and C1) which confirms the results

from previous studies [22,81]. However, for ANNs using NSET extracted features (ANN [F NV NSET] and ANN [C NV NSET]), the drop in accuracy is always smaller compared to ANNs using NT extracted features (ANN [F NV NT] and ANN [C NV NT]). For the flat plate, the maximum detection range (excluding F3) is 7.78 mm (F6) for the NT ANN versus 4.97 mm (F2) for the NSET ANN (a 36.12% improvement). For the curved plate, the comparison is 40.88 mm (C3) for the NT ANN versus 8.84 mm (C3) for the NSET ANN (a 78.38% improvement).

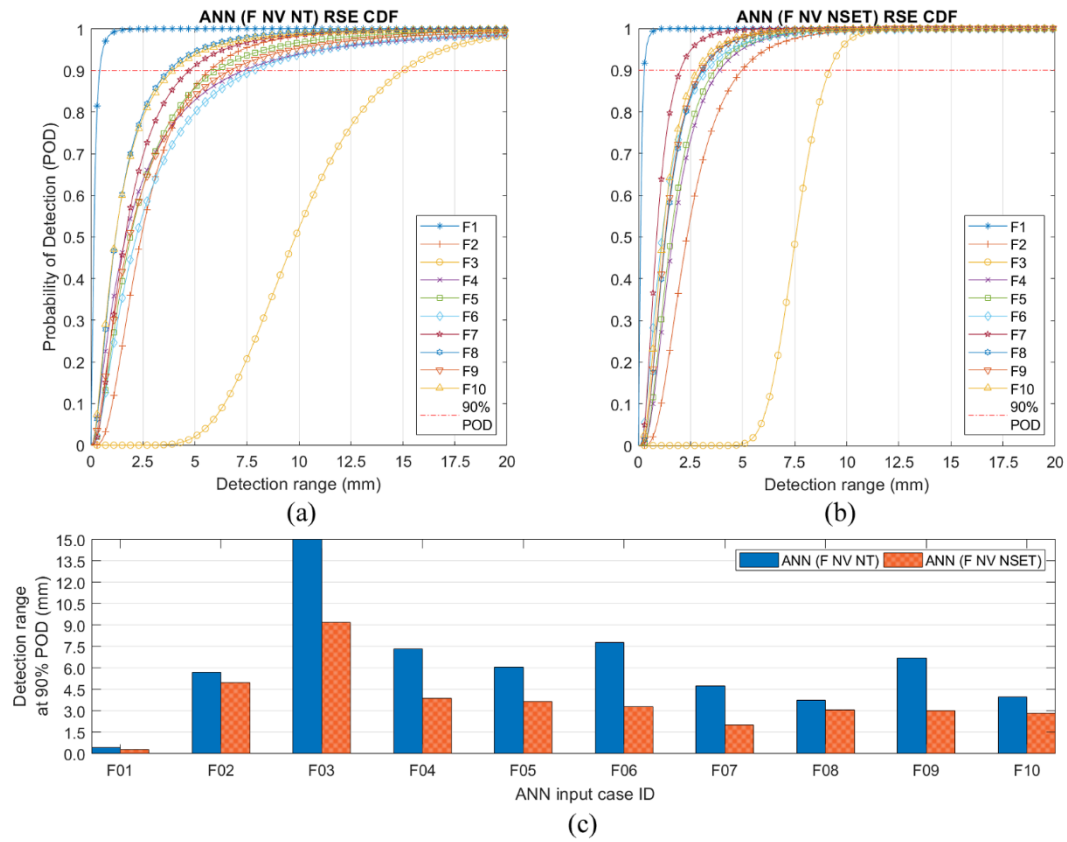


Figure 3.1. 10 Flat plate ANN localisation (without vibration filtering) CDFs for NT (a) versus NSET (b) extraction methods and detection range comparison at 90% POD (c)

Due to differences between the sensing region geometry of both plates (Figure 3.1. 2), the detection area (circular area encompassed by detection range radius) was calculated such that the accuracy of impact localisation could be compared in terms of the percentage of sensing area. For the NT ANNs, the change in curvature seems to affect the accuracy significantly (maximum detection area 0.99 % for the flat plate versus 13.13 % for the curved plate). However, for the

NSET ANNs the change in geometry seem to only slightly affect its accuracy (maximum detection area 0.40 % for the flat plate versus 0.61 % for the curved plate).

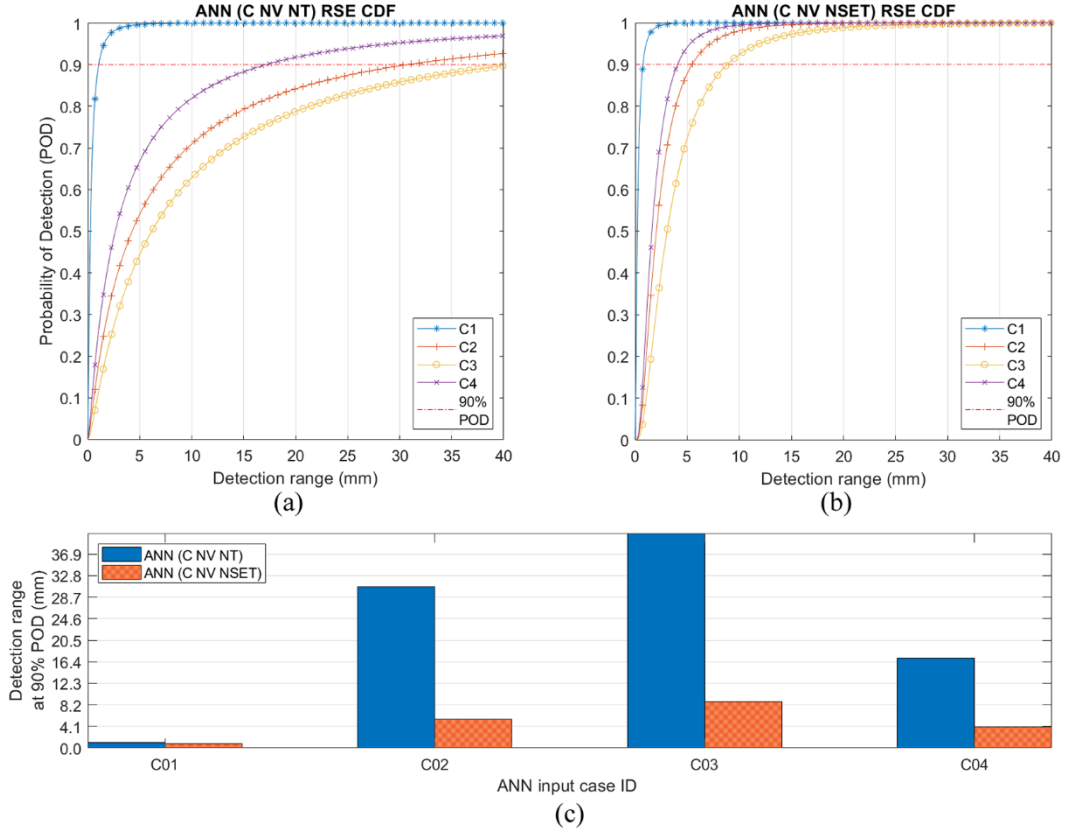


Figure 3.1. 11 Curved plate ANN localisation (without vibration filtering) CDFs for NT (a) versus NSET (b) extraction methods and detection range comparison at 90% POD (c)

For both plates, the largest accuracy drop mostly came from increasing impact mass (F6 and C3). Figure 3.1. 12 and Figure 3.1. 13 show the localisation results for cases F6 and C3 where it can be seen that for the NT ANNs a portion of the impact points are localized with acceptable accuracy. However, the rest show very large deviations from the actual impact points (indicated by the maximum RSE value) as shown in location 13 (centre of plate) of the curved plate (Figure 3.1. 13). Investigation into the extracted TOA values from both NT and NSET methods for location 13 (Figure 3.1. 13) show that the NSET method yields much more repeatable TOA profiles for repeating impacts (C3 repetitions 1 to 4) and also compared to the baseline case (C1) as shown in Figure 3.1. 14. This means

that the NSET method can effectively generalise the TOA profile of case C3 to match that of the baseline case (C1) such that accurate localisation is possible with only the baseline case (C1) used as the training data. Since C3 showed the lowest accuracy, it is assumed that for other cases the generalisation is better.

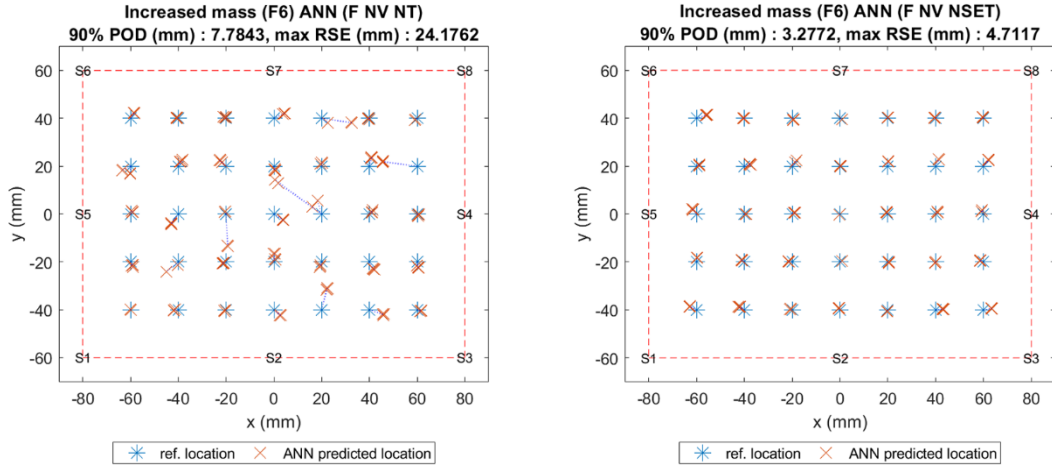


Figure 3.1. 12 Flat plate impact localisation results comparison between NT and NSET ANNs for impact case F6 (increased mass)

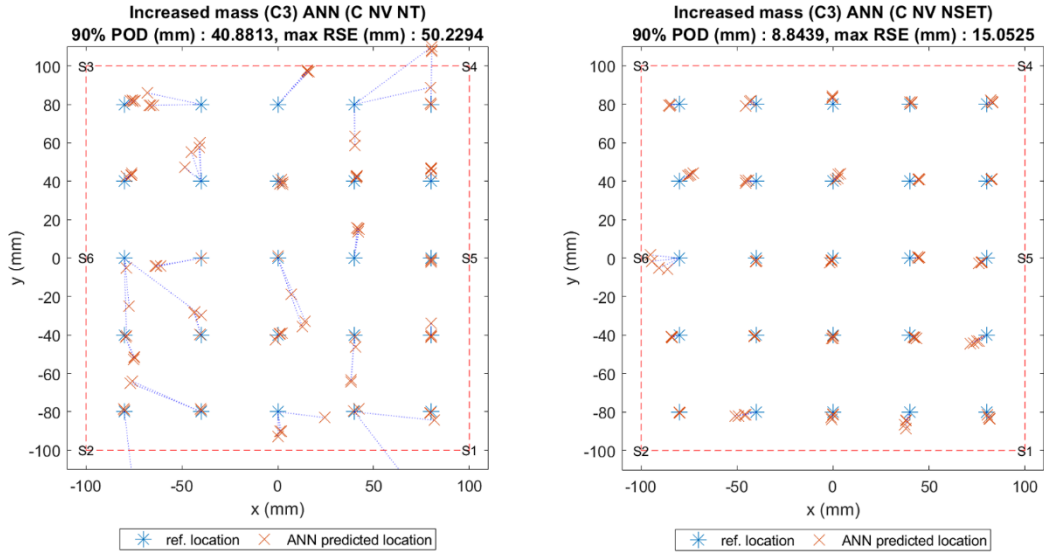


Figure 3.1. 13 Curved plate impact localisation results comparison between NT and NSET ANNs for impact case C3 (increased mass)

Figure 3.1. 15 and Figure 3.1. 16 show the impact localisation CDFs and detection range (90% POD) for ANNs with vibration filtering (ANN [F V NT],

ANN [F V NSET], ANN [C V NT], ANN [C V NSET]). In general, the trend is similar to the results from ANNs without vibration filtering (Figure 3.1. 10 and Figure 3.1. 11) where the training sets (F1 and C1) are fitted very well but accuracy drops for the test cases (F4 – F11 and C2 – C5) and intermediate locations (F2 and F3). It also confirmed that NSET ANNs are more accurate for test cases than the NT ANNs which, demonstrates better generalisation. For the same test cases as the ANNs without vibration (F2, F4 – F10), the maximum detection range for the flat plate is 20.23 mm (F5) for the NT ANN versus 7.52 mm (F5) for the NSET ANN (a 62.84% improvement). For the curved plate, the maximum detection range is 24.36 mm (C2) for the NT ANN versus 6.02 mm (C2) for the NSET ANN (a 75.31 % improvement) for cases C2 – C4. For these cases, the ANNs with vibration filtering for the flat plate (ANN [F V NT] and ANN [F V NSET]) showed lower accuracy compared to ANNs without vibration filtering (ANN [F NV NT] and ANN [F NV NSET]) whilst for the curved plate it was the other way around which gives no particular indication of the effect of vibration filtering on the accuracy of the result.

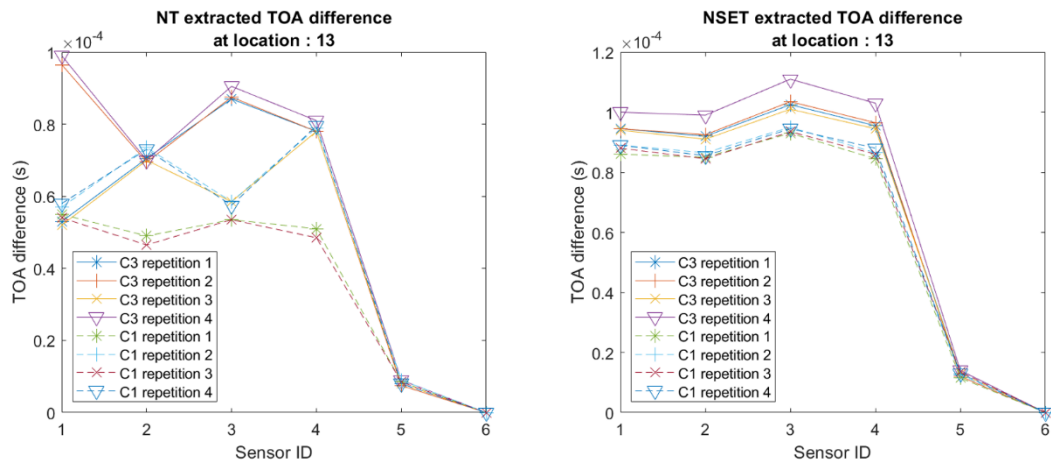


Figure 3.1. 14 Comparison of extracted TOA differences between NT and NSET method for curved plate location 13 (centre of plate) case C3 and C1

Unlike the ANNs without vibration filtering (Figure 3.1. 10 and Figure 3.1. 11), the largest drop in accuracy for ANNs with vibration filtering (Figure 3.1. 15 and Figure 3.1. 16) is caused by angled impacts (F5 and C2). This suggests that the variation caused by increased mass (F6 and C3) affects the low frequency

components of the signal that is filtered out along with the vibration noise. This is in line with the finding that higher impact mass generates more low frequency components [18,81] and thus variation caused by increased mass will be in the low frequency range which is visible in Figure 3.1. 6. This also may suggest that angled impacts generate high frequency variation (possibly from sliding contact) that may have been masked by the low frequency components when no vibration filtering was applied.

Comparison between plate geometries for ANNs with vibration filtering (Figure 3.1. 15 and Figure 3.1. 16) for cases F2, F4 – F10 and C2 – C4 (same as ANNs without vibration filtering, Figure 3.1. 10 and Figure 3.1. 11) shows that for the NT ANNs (maximum detection area percentage to sensing region area : 6.70 % for flat and 4.66 % for curved) and NSET ANNs (maximum detection area percentage to sensing area : 0.93 % for flat and 0.28 % for curved) the difference in curvature does not significantly affect the accuracy.

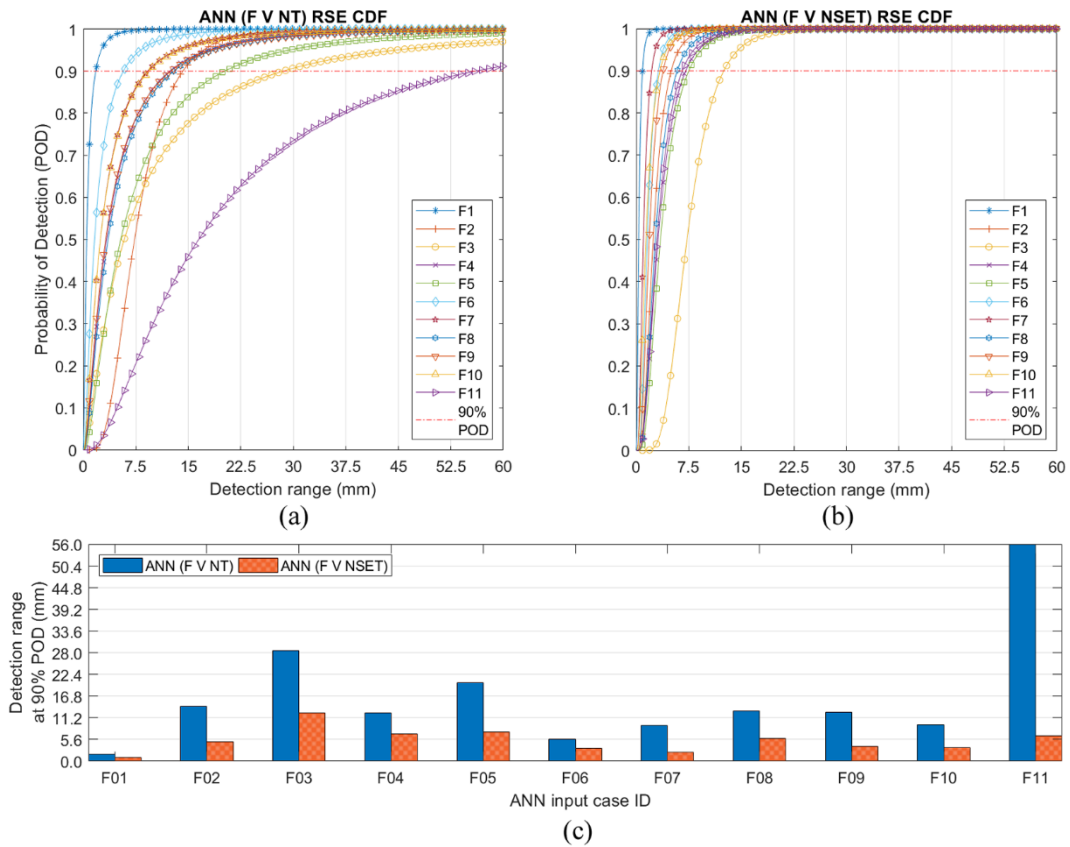


Figure 3.1. 15 Flat plate ANN localisation (with vibration filtering) CDFs for NT (a) versus NSET (b) extraction methods and detection range comparison at 90% POD (c)

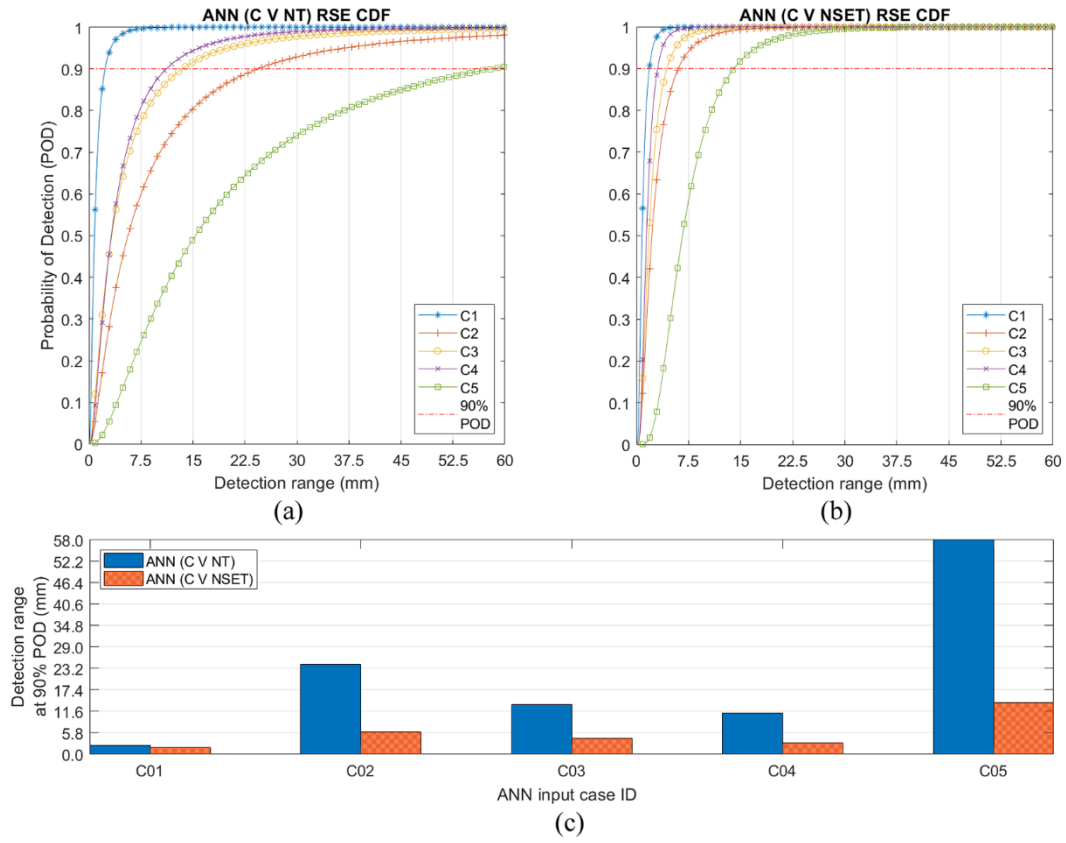


Figure 3.1. 16 Curved plate ANN localisation (with vibration filtering) CDFs for NT (a) versus NSET (b) extraction methods and detection range comparison at 90% POD (c)

The vibration test case (F11 and C5) combines the presence of vibration, with very small impact magnitude (small taps with maximum amplitude of 5 V compared to 30 V impacts, Figure 3.1. 3) and randomness in impact (variation in angle and energy) due to operation of the hammer by hand. Therefore, it contains very large variation from the training baseline case (F1 and C1) and should be more difficult to detect accurately. Figure 3.1. 17 and Figure 3.1. 18 show the impact localisation results for the vibration cases for both plates where it can be seen that the NT ANNs give very poor accuracy in locating the impacts (detection range : 56.08 mm for flat and 58.10 mm for curved). On the other hand, the NSET ANNs give much more accurate location predictions for both the flat (6.59 mm detection range, an 88.26 % improvement) and curved panels (14.03 mm detection range, a 75.85 % improvement).

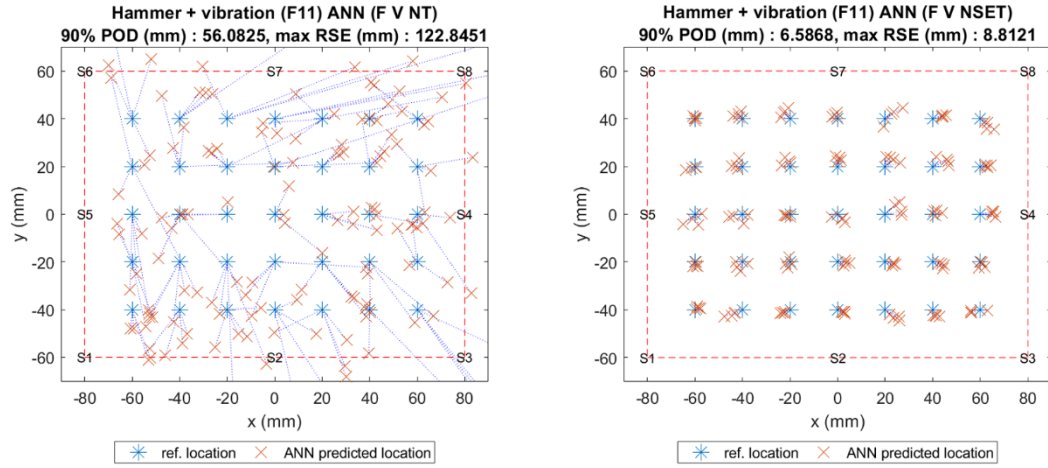


Figure 3.1. 17 Flat plate impact localisation results comparison between NT and NSET ANNs for impact case F11 (hammer + vibration)

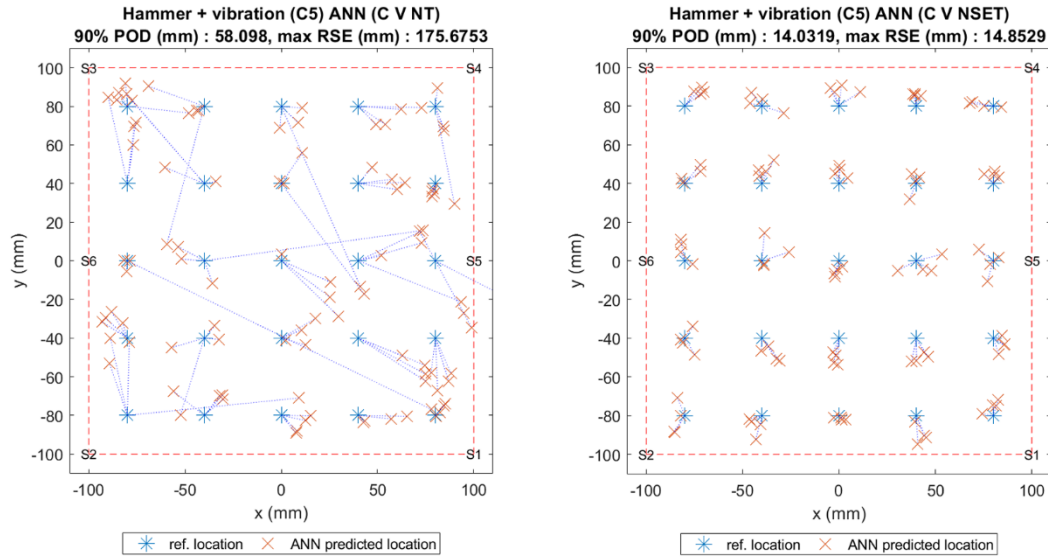


Figure 3.1. 18 Curved plate impact localisation results comparison between NT and NSET ANNs for impact case C5 (hammer + vibration)

For the NT ANNs, the detection area for cases F11 and C5 in terms of percentage of sensing region area is 56.08 % for the flat plate (F11) and 26.51 % for the curved plate (C5). For the NSET ANNs the values were 0.71 % for the flat plate (F11) and 1.55 % for the curved plate (C5). It can be seen that the effect of geometry on accuracy is relatively small for NSET ANNs whilst for NT ANNs the accuracy is higher for curved plates. Comparing the previously mentioned detection ranges for all NT ANNs gives a spread of 0.99 – 56.08 % whilst for

NSET ANNs the spread is 0.28 – 1.55 %. This shows that the NSET method gives better consistency in terms of accuracy for variation of all parameters (impact condition, vibration noise filtering and plate geometry) given.

Additionally, as the flat and curved plates had different numbers of sensors (8 for flat and 6 for curved), it can be seen that for consistent TOA inputs produced by the NSET method, the number of sensors does not significantly affect the accuracy of localisation (accuracy of flat plate not significantly different than curved plate). Thus, it can be said that the NSET methods allows for further optimisation of number of sensors used leading to less added weight and acquisition system requirements [88,89].

3.1.6 Conclusion

In this chapter, a novel feature extraction is proposed for developing a meta-model for impact localization. The developed ANN is trained with only one data set (one impact scenario) but can localize impacts under varying conditions. Observation of test data collected under variation of impact conditions (temperature, angle, mass and energy) showed significant variation in recorded impact signals. This prevented consistent TOA extraction using available methods such as the Normalised Threshold (NT) method and resulted in localisation with much higher uncertainty and lower accuracy. Factors that generated a change in the signal waveform such as temperature, impactor mass and angle seemed to have the largest effect in this regard. Unfortunately, due to limitations of the experimental setup, only high temperature conditions were able to be tested, while low temperature conditions need to be evaluated in future works. For the problem of vibration noise, high pass filtering was proposed due to the wide band signal generated by impacts which usually have much higher impact frequencies than operational vibration noise.

A Normalised Smoothed Envelope Threshold (NSET) method was proposed as a more robust alternative to the NT method. Observation of TOA extracted using the NT method and the NSET method showed that the NSET method gave much more consistent TOA difference profiles for impact case repetitions and also for different impact cases. Therefore, by using the NSET method the TOA

profiles were generalised for the different impact cases resulting in significantly higher accuracy location predictions (detection area 0.99 – 56.08 % of sensing region area for NT method versus 0.28 – 1.55 % for NSET method for all impact cases) by the trained ANNs for test impact cases that differ from the original training set. Vibration filtering, number of sensors and difference in plate geometry (curvature) did not significantly affect the accuracy of NSET ANNs.

Therefore, by using the NSET TOA extraction method preceded by high pass filtering for vibration noise, an ANN can be trained using only 1 impact case training set but can accurately predict the location of impact cases with variable impact conditions (variable temperature, mass, angle and energy) and added vibration noise presence. This allows for a large reduction in the amount of training data needed and gives consistent accuracy for ANNs trained using TOA extracted by the NSET method making ANN based impact localisation much more feasible for real life implementation. Additionally, compared to more common signal processing methods for ToA extraction (such as the Hilbert transform [27]), the proposed method can be done entirely using analog filters [38], saving much computational requirements for onboard data acquisition systems and allowing them to be much simpler in design. This is an important step forward for application of meta-models to real structure under operational conditions.

Chapter 3 : Part 2

Impact Localisation in Composite Plates with Different Stiffness Impactors²

In Chapter 3 : **Part 1**, a novel signal processing and ANN based passive sensing method was developed for impact location estimation under simulated environmental and operational conditions. However, the simulated conditions did not include the effect of impactors with differing materials. This is important as impacts on aircraft structures come from a variety of objects that vary in their materials. Thus, in this chapter a novel data driven method is developed for impact location estimation under the simulated conditions in Chapter 3 : **Part 1**, as well as impactors with different materials.

3.2.1 Introduction

In Chapter 3 : **Part 1** [16], it was found that minute variations (amplitude, waveform, etc.) in the generated Lamb waves between different impact cases (energy, mass, angle, temperature) may cause variation in extracted features depending on the extraction methods used, not necessarily because of actual change in the Lamb wave propagation characteristics. A feature extraction method was then developed for artificial neural network (ANN) based impact localisation that was able to extract consistent features (or eliminate variations) for impacts of different cases whilst filtering out operational vibration noise. This meant that by using data from a single impact case, it was possible to accurately locate impacts under various combinations of the mentioned parameters, leading to a significantly smaller initial data set required and allowing feasible localisation of real life impact cases.

² Chapter published as : Seno, A. H., & Aliabadi, M. H. (2019). Impact localisation in composite plates of different stiffness impactors under simulated environmental and operational conditions. *Sensors*, 19(17), 3659. Published under CC BY license.

However, besides the parameters assessed in the study [16], variation of impacts can also come from differences in impactor stiffness caused by different impactors (debris, bird strike, tools, etc.) [90]. Out of the few studies that have investigated the effect of impactor stiffness on the generated Lamb waves, it was found that lower impactor stiffness generates significantly lower frequency lab waves [66,90–92]. These differences can significantly affect feature extraction [66,90], which in turn affects the accuracy of data driven localisation, as the difference in stiffness of a test case compared to the initial training case becomes larger [92].

Thus, in order to improve on the results of Chapter 3 : **Part 1** [16], here a novel data driven impact localisation methodology is developed that is not only robust for previously studied cases (velocity, mass, angle, temperature, vibration noise) but also robust for detecting impacts of different stiffness whilst using an initial data set from only one impact case. In order to accomplish this, a novel parametric comparison is conducted of experimental data on impacts for the cases of interest. The observation results are then used to develop a methodology, which was tested against the previously developed method in Chapter 3 : **Part 1** as benchmark. Emphasis is placed on using methods that are less computationally expensive/complex than common methods such as Hilbert [27] or wavelet transforms [68], such that it is applicable to miniaturized data acquisition systems with limited computational power [38] for application in real structures.

3.2.2 Experimental Setup

Experimental impact data under different scenarios (impactor stiffness, angle, mass, energy) and conditions (temperature, vibration) were gathered using a multiparametric impact setup designed in a Chapter 3 : **Part 1**. The setup consisted of a drop impact tower, a fixture for holding specimens, two composite plate specimens (flat and curved) with piezoelectric (PZT) sensors and an oscilloscope to measure the voltage from the PZT sensors, as shown in Figure 3.2. 1.

The impact fixture (Figure 3.2. 1 a,b) was made up of steel bars, which held the plates via clamps on to a base. Both plates were made of M21 T800s carbon fibre prepregs with a 16 layer quasi-isotropic lay up $([0/+45/-45/90/0/+45/-$

45/90]s) resulting in a thickness of 4 mm. The flat plate was 200×290 mm with eight PZT sensors bonded (but only six were used in this study to match the curved plate) to the top side of the plate (impact side) and had a silicone heating pad on the bottom side for temperature control (Figure 3.2. 1 a). The curved plate was 290×285 mm with six PZT sensors bonded to the underside of the plate (opposite to the impact side) to mimic the conditions of an aircraft panel (Figure 3.2. 1 b). The layout of the sensors and the impact locations of both plates can be seen in Figure 3.2. 2.

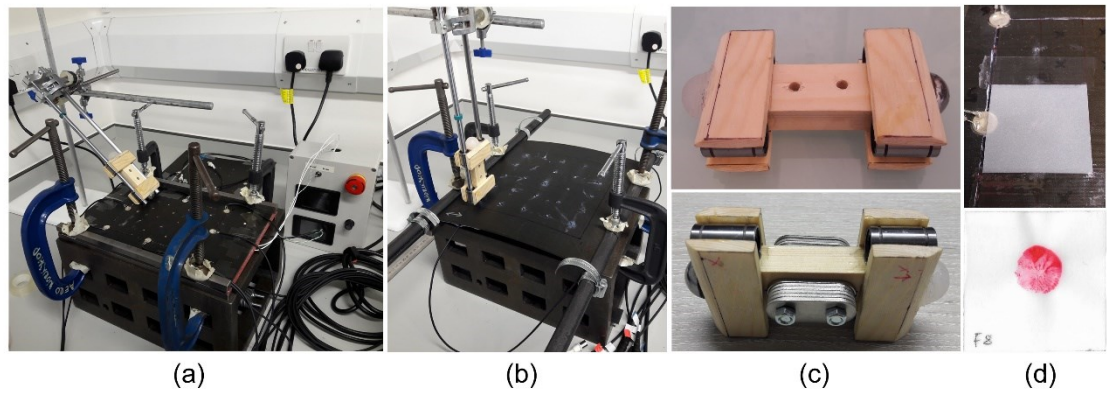


Figure 3.2. 1 Impact setup: impact tower (a,b), flat plate (a), curved plate (b), impactor (c, top) with 2 heads (steel and silicone) and added mass (c, bottom), paper for contact area measurement (d, top) and example scan from soft impact (d, bottom).

The impact tower consisted of the tower itself and the impactor (Figure 3.2. 1). The impactor (Figure 3.2. 1c) had an original mass of 100 gr and could be increased to 200 gr with added weights. There were two impact heads (both spherical, 20 mm diameter) with differing materials (silicone and steel) to simulate impacts from different stiffness materials (silicone ~ 0.1 GPa, steel ~ 200 GPa [93]). Impacts were generated by lifting the impactor to a certain height (controlling the energy) and then letting the impactor drop onto the plate. The rails of the impact tower guided the trajectory, thus allowing for angled impacts (Figure 3.2. 1 a and Figure 3.2. 2). To measure the contact area during impact, the impactor heads were painted, and a 40×40 mm piece of paper was placed on the impact surface (held in place lightly with two strips of adhesive tape) to capture the print of the contact area (Figure 3.2. 1 d top). Each print was then scanned

(Figure 3.2. 1 d bottom), and the contact area silhouette was extracted for further comparison.

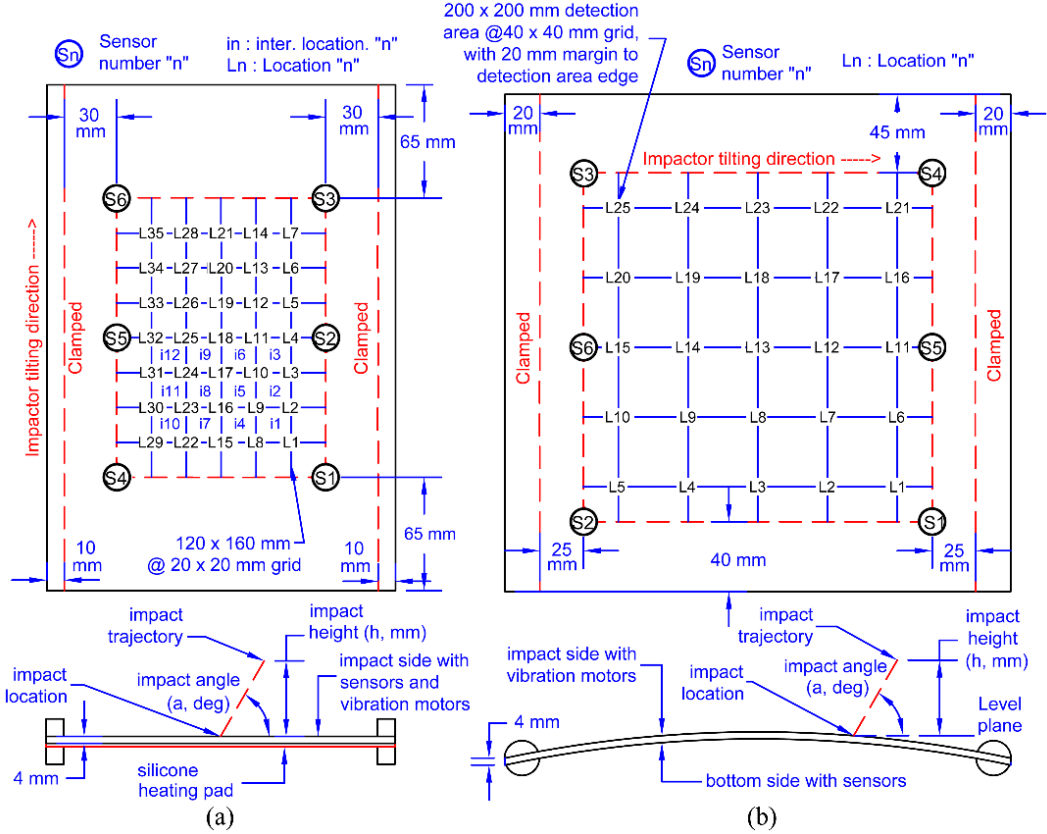


Figure 3.2. 2 Layout of flat (a) and curved (b) composite plates.

Lamb waves caused by impact were transformed into voltage signals by the PZT sensors, which were recorded using an National Instruments (Austin, Texas) PXI 5105 8 channel oscilloscope. The sensors were connected to the oscilloscope via probes, which were also used to attenuate (10x) the signals from hard impacts (impacts with the steel head), as the voltage magnitudes were too high for the oscilloscope. No attenuation was used for soft impacts (impacts with the silicone head). Signals from each of the six sensors were recorded at 2 MS/s sampling rate with a length of 100,000 samples using National Instruments (Austin, Texas) SignalExpress software. All data processing and localisation algorithms were done using MathWorks MATLAB.

Table 3.2. 1 and Table 3.2. 2 give the list of impact case data sets recorded for the flat and the curved plates under various impact scenarios and conditions. For

each plate, a reference impact case (F1 and C1) was used as the baseline, whereas all other impact cases were a deviation (change of one or two parameters) from the said reference. These reference cases also served as the training data sets for the localisation algorithms later on.

Table 3.2. 1 Impact cases for the flat plate.

Case	Case Name	Parameters ¹	Number of Samples	Energy (J)
F1	Reference Impact Case	Head = steel, h = 25, a = 90, m = 100, T = RT, n = none	140 (loc. 1-35 x 4 rep.)	0.025
F2	Increased Impact Height	Head = steel, h = 50, a = 90, m = 100, T = RT, n = none	140 (loc. 1-35 x 4 rep.)	0.050
F3	Angled Impact	Head = steel, h = 25, a = 45, m = 100, T = RT, n = none	140 (loc. 1-35 x 4 rep.)	0.025
F4	Increased Impact Mass	Head = steel, h = 25, a = 90, m = 200, T = RT, n = none	140 (loc. 1-35 x 4 rep.)	0.050
F5	Increased Impact Temperature	Head = steel, h = 25, a = 90, m = 100, T = 65, n = none	140 (loc. 1-35 x 4 rep.)	0.025
F6	Intermediate Impact Locations	Head = steel, h = 25, a = 90, m = 100, T = RT, n = none	48 (int. loc. 1-12 x 4 rep.)	0.025
F7	Reference Case + Artificial Noise	Head = steel, h = 25, a = 90, m = 100, T = RT, n = 500Hz 3V	140 (loc. 1-35 x 4 rep.)	0.025
F8	Soft Impact	Head = silicone, h = 50, a = 90, m = 100, T = RT, n = none	140 (loc. 1-35 x 4 rep.)	0.050
F9	Soft Impact + Artificial Noise	Head = silicone, h = 50, a = 90, m = 100, T = RT, n = 500Hz 0.1V	140 (loc. 1-35 x 4 rep.)	0.050

¹Notes: Head = impactor head material, h = vertical drop height (mm), a = impact angle (deg.), m = impactor mass (gr), T = temperature (°C, RT: room temperature, 22–24), n = noise (frequency [Hz], amplitude [V]).

Table 3.2. 2 Impact cases for the curved plate.

Case	Case name	Parameters ¹	Number of samples	Energy (J)
C1	Reference Impact Case	Head = steel, h = 25, a = 90, m = 100, T = RT, n = none	100 (loc. 1-25 x 3 rep.)	0.025
C2	Angled Impact	Head = steel, h = 25, a = 45, m = 100, T = RT, n = none	100 (loc. 1-25 x 4 rep.)	0.025
C3	Increased Impact Mass	Head = steel, h = 25, a = 90, m = 200, T = RT, n = none	100 (loc. 1-25 x 4 rep.)	0.050
C4	Reference Case + Artificial Noise	Head = steel, h = 25, a = 90, m = 100, T = RT, n = 500Hz 3V	100 (loc. 1-25 x 4 rep.)	0.025
C5	Soft Impact	Head = silicone, h = 50, a = 90, m = 100, T = RT, n = none	100 (loc. 1-25 x 4 rep.)	0.050
C6	Soft Impact + Artificial Noise	Head = silicone, h = 50, a = 90, M = 100, T = RT, n = 500Hz 0.1V	100 (loc. 1-25 x 4 rep.)	0.050

¹Notes: Head = impactor head material, h = vertical drop height (mm), a = impact angle (deg.), m = impactor mass (gr), T = temperature (°C, RT : room temperature, 22–24), n = noise (frequency [Hz], amplitude [V]).

Unlike in Chapter 3 : Part 1 [16] when this setup was first used, vibration noise was not generated physically but rather added artificially in MATLAB, as this allowed for simulation of more severe noise magnitude (3V for hard impacts and 0.1V for soft impacts) and with a controlled spectrum (as stated in RCTA/DCO-160C [48]). Noise was generated using the randn random number generating function to create a vector with the same length as the impact signal with values between -1 to 1 taken from a normal distribution. The noise signal was then low pass filtered to produce the desired bandwidth. Finally, the maximum amplitude (chosen instead of RMS to limit relative magnitude with real signal) is scaled to the desired amplitude for each signal (soft and hard impacts).

3.2.3 Impact Signal and Contact Behaviour from Hard and Soft Impacts

3.2.3.1 Effect of Impact Case on Impact Signal and Contact Behaviour

As mentioned in Section 3.2.1, minute variation in Lamb wave amplitude and waveform due to differing impact cases was found to significantly affect Lamb wave feature extraction for impact localisation [16]. To compare the effects of variation in impact case on the contact behaviour and the subsequent Lamb waves, one impact location from the flat plate (as it had the complete set of parameter variations) was chosen to act as a reference point. Figure 3.2. 3 shows the comparison of recorded impact signals and measured contact area between the reference case (F1) and the cases F2–F5 at impact location 15 measured from sensor 6. As the soft impacts (F8) were conducted with a higher impact height than the reference case (due to the very weak signal produced by the soft impact), the comparison was conducted with case F2, as the heights (and energy) were the same (Figure 3.2. 4).

Comparison between signals from case F1 and F2 showed that an increase in impact height (and subsequently velocity and energy) only affected the amplitude of the signal but not the waveform [16]. Comparison of the contact area revealed that, although the impact energy was higher, the area was mostly unchanged.

Since the vertical impact height for cases F1 and F3 were the same (25 mm), the initial potential energy and the resulting velocity (and thus kinetic energy) of

the impactor at contact was also the same. However, for the angled impacts (F3), the transverse component of velocity was smaller compared to perpendicular impacts (F1) and thus resulted in a less severe impact, as can be seen by the smaller amplitude of the impact signal [2,16]. Observation of the contact area of the angled impact (F3) indicated a similar initial contact area proceeded by sliding contact due to the velocity components parallel to the contact surface, possibly generating the differences observed in the impact signal waveform. However, as both velocity components (transverse and parallel) were equal due to the 45° impact angle, it seems that the transverse contact was still the dominant source of the Lamb wave, as the change in waveform was relatively small (possibly due to low friction coefficient between impactor and contact surface).

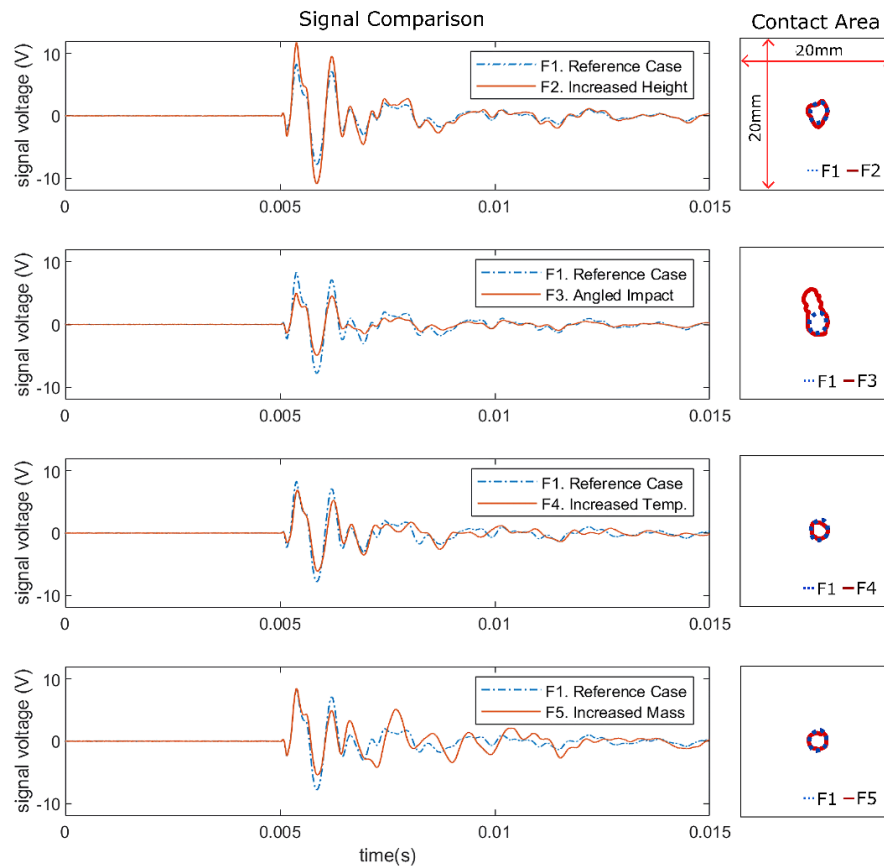


Figure 3.2. 3 Comparison of impact signals (from sensor 6) and contact area from impacts at location 15 of the flat plate for hard impact cases (F1–F5).

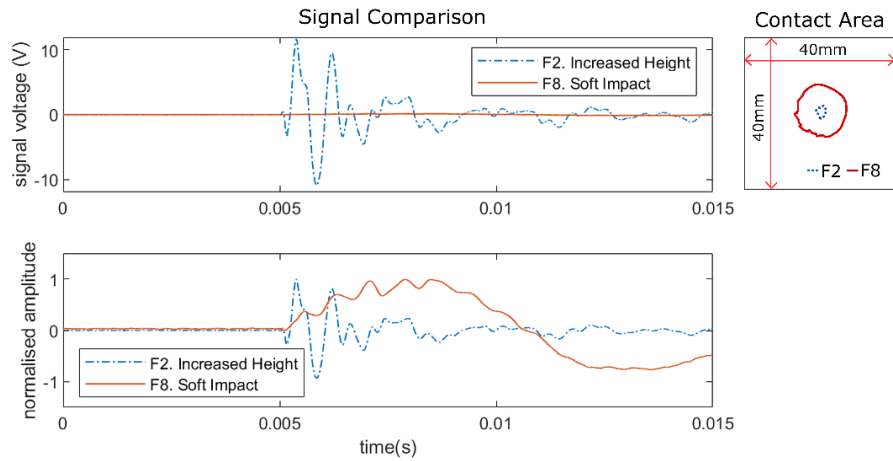


Figure 3.2. 4 Comparison of impact signals (from sensor 6) and contact area from impacts at location 15 of the flat plate for cases F2 and F8.

Comparison of impact signals between case F1 and F4 showed that increasing temperature induced as a slight shift in waveform due to changes in wave propagation velocity [94] and reduction in amplitude due to reduction in adhesive stiffness [95]. Observation of the contact area showed that the variation in temperature did not affect the contact area significantly.

Cases F1 and F5 both had the same impact height, thus the resulting impact velocity was the same (due to constant gravitational acceleration), which seemed to be mirrored in the first portion (up to the first positive peak) of both signals. However, as the impactor had larger mass in case F5, the momentum of the impactor was larger, and thus the momentum transfer differed from the reference case (F1), as shown by the significant difference in waveform of both signals after the first positive peak. Similar to the previous cases, the contact area was not significantly affected, even though the impact energy was larger. Thus, it could be concluded that, for hard impacts, the deformation of the impactor head was small and was not significantly affected by variations in impact case.

Figure 3.2. 4 shows the comparison between two identical impacts but with different stiffness impact heads (F2: steel, F8: silicone). Observation of the contact area revealed that the soft impact (F8) had a significantly larger contact area than the hard impact (F2) due to larger deformation of the impact head. This led to significantly smaller impact signal amplitude (Figure 3.2. 4), as the kinetic energy was partially absorbed by the soft impactor head rather than transferred to

the plate. This possibly also acted as a dampener for the impact signal, as the impact energy was transferred gradually when the impactor deformed, leading to a much lower frequency impact signal (as can be seen from the normalised signals in Figure 3.2. 4). Contrast this to the hard impact, where the deformation was small and thus the energy transfer occurred faster, resulting in a high frequency signal. This difference in contact behaviour resulted in differences in impact signal amplitude and waveform that were far greater than any other impact case variation previously observed (cases F1–F5) and could create difficulties in consistent feature extraction, which is necessary for accurate localisation [16,66,92].

3.2.3.2 Simulation of Random Vibration Noise and Noise Filtering

As mentioned in Section 3.2.2, artificial random noise was added to the impact signals to simulate vibration noise during operation. This noise was generated for each impact signal using MATLAB, where a series of random numbers was generated (creating noise with bandwidth up to 1 MHz or half the sampling frequency) with the same length as the signal (100,000 samples), after which a 500 Hz low pass Butterworth filter was applied to limit the bandwidth of the random noise (although some small components just after the 500 Hz cut off frequency, around 700 Hz, still existed, as the filter had not reached maximum attenuation). This bandwidth was chosen from the frequency limit of the soft impacts, as is demonstrated later on. The amplitude was then scaled to 3 V for the hard impacts and 0.1 V for the soft impacts (due to the much smaller amplitude of soft impacts collected) to give a moderate magnitude of noise. This noise was then superimposed to the impact signals of the reference cases (F1 and C1) and also the soft impacts (F8 and C5) from both the flat and the curved plates (creating impact cases F7, F9, C4, C6). Figure 3.2. 5 shows the noise added to the signals measured from sensor 6 of the reference case (F1) and the soft impact (F8) at location 15 of the flat plate. It can be seen that the noise masked the signal, especially the start, which is vital for feature extraction such as time of arrival (ToA) for localisation purposes.

As impacts generate signals with a wide bandwidth [9,16,96], high pass filtering is commonly used to remove vibration noise, as it usually has a lower bandwidth limit [16,38,48]. Here, a 700 Hz Butterworth high pass filter was applied to completely remove all components of the previously added vibration noise. As can be seen in Figure 3.2. 5, for the hard impact after high pass filtering, there was still a significant portion of the impact signal left to be able to identify the start of the signal. However, as soft impacts generated impact signals with lower frequency (narrower bandwidth), there was little left of the signal after high pass filtering, making it more challenging to pick the start of the signal accurately. Thus, the frequency bandwidth of soft impacts (near 700 Hz for this data set) limited how much noise filtering could be done before the impact signal itself was completely lost and the impact became undetectable using this method.

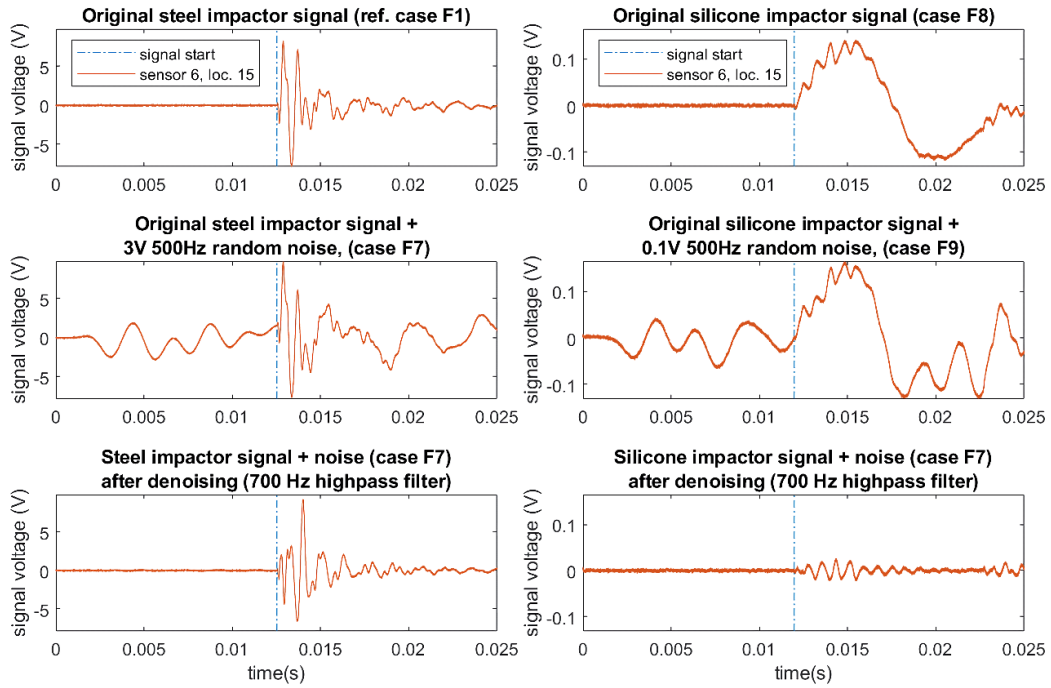


Figure 3.2. 5 Comparison between hard (F1) and soft (F8) impacts at location 15 measured from sensor 6 of the flat plate: original (top), with random noise (middle), and after noise filtering (bottom).

3.2.4 Feature Extraction from Hard and Soft Impacts for Localisation

For localisation algorithms, especially data driven methods, the main interest is to lower the amount of initial data required for training or building a reference

database, as collecting large amounts of data (from the large combination of different impact scenarios and conditions) is not practical for large and complex structures such as aircrafts [16,43,92,97]. To obtain accurate results by using an initial data set from only one impact case, the features extracted from impacts under different cases must be as consistent as possible to match that of the initial reference data set [16].

From previous studies, it has been shown that wave ToA difference (as the actual time of impact is unknown, thus it is in terms of difference towards the first arriving signal) is the best feature for localisation [27], followed by signal amplitude ratios [27,98]. Thus, in this section, extraction of these two features is investigated. In Chapter 3 : Part 1 [16], a ToA extraction method was developed that could homogenize the waveform and the amplitude variations (Section 3.2.3.1) and obtain consistent ToA for hard impacts under various impact cases. However, as shown in Section 3.2.3, soft impacts generate impact signals that are significantly different than hard impacts and thus may have significant effects on consistent feature extraction. Thus, in this section, methods to obtain consistent feature extraction are developed based on observation of the effect of differing impactor stiffness.

3.2.4.1 Normalised Smooth Envelope Threshold Method for ToA Extraction

The normalised smooth envelope threshold (NSET) algorithm was developed to extract consistent ToA from hard impact under various impact cases (differing energy, mass, angle, and temperature) [16]. The algorithm first converts the signals into absolute values, and then an envelope is constructed by running the absolute valued signals through a low pass filter. This removes all the small peaks at the start of the signal and creates a smooth initial rising edge. Afterwards, the amplitude of each signal envelope is normalised by the largest amplitude of the envelopes from all sensors. The ToA value is then determined from the envelope using thresholding (the signal is said to arrive when the amplitude surpasses a certain threshold). The extracted ToA is more consistent, as it is less sensitive to the threshold value due to the smoothing done by the low pass filter.

It was found that this method coupled with high pass filtering to remove vibration noise was successful in extracting consistent ToA for hard impacts under various impact cases (F1–F5), as can be seen in Figure 3.2. 6. However, when tested on soft impacts (F8), it was found that, although the ToA profile/pattern was similar to hard impacts, the ToA value showed significant variation between hard and soft impacts (Figure 3.2. 6). This was most likely due to the greater difference in impact signal waveform caused by differing impact stiffness (as observed in section 3.2.3.1) compared to any other parameter variance (energy, temperature, mass, and angle), which could not be completely homogenized by the normalisation and the low pass filter envelope used in the NSET method.

This difference in ToA caused large localisation errors for soft impacts (F8) when using ANNs, as the features were not consistent with the reference case (F1), which was used to train the localisation algorithm [16,88]. Thus, either a more consistent ToA extraction method or a less sensitive localisation algorithm was needed (in this chapter, the latter was chosen).

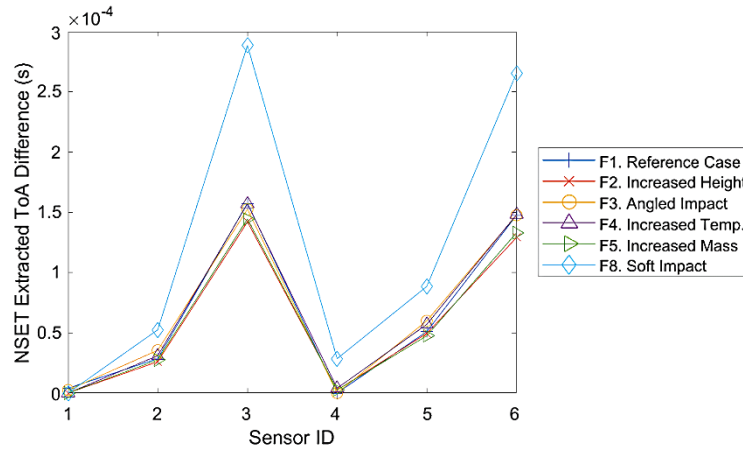


Figure 3.2. 6 Figure 6. Comparison between time of arrival (ToA) difference extracted from hard (F1–F5) and soft (F8) impacts at location 15 of the flat plate using the normalised smoothed envelope threshold (NSET) method (2 kHz low pass filter, 2.5% of maximum amplitude threshold).

Additionally, since this method relies on a threshold value to determine the start of the signal, it is not suitable for very small signals with low signal to noise ratio (SNR), as in these cases, the threshold has to be very low to detect signals

and then has high risk of false detection due to noise. As shown previously in Figure 3.2. 5, the signals left behind after high pass filtering soft impacts were very small and thus not feasible to detect using this method. Thus, a new ToA extraction method was required that was more robust in extracting the signal ToA of very small signals.

For the purpose of validating new methodologies, the NSET method was used as a benchmark. A Butterworth 2 kHz low pass filter was used for smoothing, and a threshold was set at 2.5% of the maximum amplitude of the signals in the array.

3.2.4.2 Modified Akaike Information Criterion Method for ToA Extraction

A signal can be divided into a number of locally stationary processes that can be stochastically approximated using autoregressive models [21,99]. In the case of an impact signal, it can be divided into two segments—the period before the impact signal arrives, which is noise, and the period after the impact signal arrives, which is dominated by the impact signal itself (as can be seen in Figure 3.2. 3, Figure 3.2. 4, Figure 3.2. 5). As the two segments are stochastically different, the best possible fit of the autoregressive models is achieved when the selected separation point between the two segments coincides with the arrival time (ToA) of the signal. Thus, using this criterion, the ToA of a signal could be determined by finding the separation point that produced the best fit for the autoregressive models.

The Akaike Information Criterion (AIC) gives the relative quality of fit between different statistical models for a given data set [21,99]. By calculating the AIC for differing separation points along the length of the signal, the point where the AIC value is minimum can be found, which indicates best fit of the autoregressive models and subsequently the ToA. Thus, unlike other ToA pickers [16,92,100,101], the determination of ToA was not dependent on a predefined magnitude threshold, making it more feasible for ToA picking of small signals with low SNR [102].

Equation (3.2. 1) shows how the AIC value was calculated (as derived by Maeda [99] and Simone [21]) :

$$AIC(t) = t \ln(\text{var}(x_1 \sim t)) + (L - t - 1) \ln(\text{var}(x_{t+1} \sim L)), \quad (3.2. 1)$$

$$t = 1, 2, \dots, L,$$

for each possible separation point (t) along a signal (x) with a certain length “ L ”. For each step, the lengths of each segment ($x_1 \sim t$ and $x_{t+1} \sim L$) changed as the tested separation point (t) moved from the start of the signal to the end. The AIC value at each step was calculated to evaluate the goodness of fit for the given separation point (t).

Figure 3.2. 7 shows the AIC values calculated for the high passed signal from the soft impact with added noise (F9) shown in Figure 3.2. 5. To save computational time, a rough threshold above the noise level (4 V for hard impacts and 0.125 V for soft impacts) was used on the original (not filtered) signal to obtain a rough estimate of the region where the signal started. Then, a window of 10,000 sample points before and after the triggered point was taken as a short window for AIC calculation. It can be seen that the minimum value of the calculated AIC (thus the predicted ToA) was near the start of the signal. However, it can also be seen that the minimum of the AIC was not clearly pronounced and showed a “flat” region where the AIC values were similar and led to uncertainty in choosing the minimum point. This occurrence was most likely due to the very small amplitude of the signal, which was difficult to discern from noise.

Previous studies [21,101] developed characteristic functions (CF) to enhance certain features of the signal (amplitude, SNR, etc.) in order to gain more accurate ToA. Examples of CFs include signal absolute value, squared signal, signal gradient, and Hilbert transform [21,101]. However, for signals such as those shown in Figure 3.2. 7 where the area of interest (the start of the signal) is much smaller in amplitude than the rest of the signal, CFs such as absolute value, signal gradient, and Hilbert transform [21,101] may not always significantly affect the said area of the signal. Moreover, squaring the signal may instead minimise the start of the signal (as it is small in amplitude) and amplify the larger peaks instead.

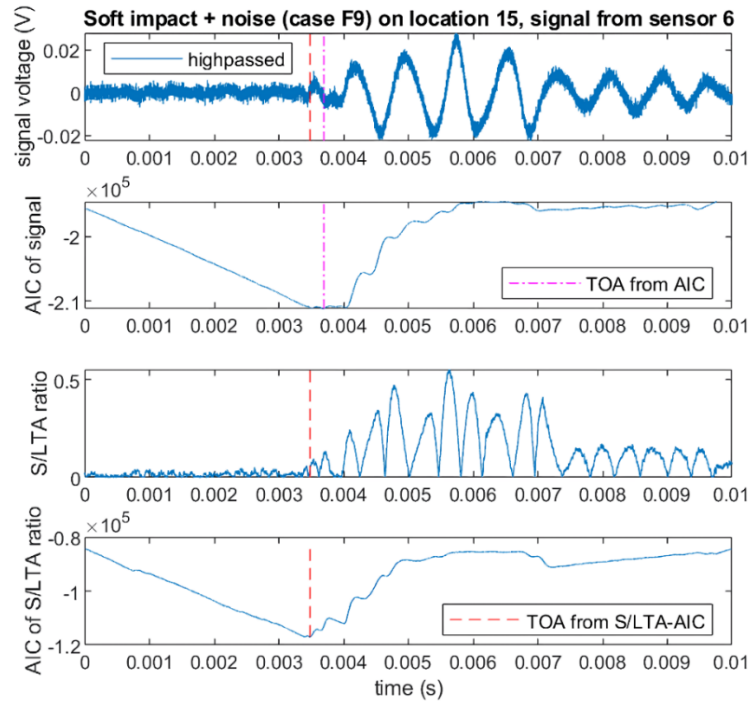


Figure 3.2. 7 Comparison of ToA extracted using Akaike Information Criterion (AIC) and Short Term/Long Term Average ratio (S/L TA) AIC for high passed filtered signal from soft impact with noise (F9) measured by sensor 6 at location 15 of the flat plate.

Thus, a novel CF is proposed that could enhance the sudden changes caused by the arrival of the impact signal. The proposed CF was based on the Short Term/Long Term Average ratio (S/L TA) picker [100], where two averages with different sliding window lengths (short and long) are calculated for the length of the signal, and a ratio is calculated between them. The short term average reacts to sudden changes in the signal, whilst the long term average has a more stable value. Thus, when the short term average is divided by the long term average, sudden changes at the start of the signal (where the long term average is still low since it is all mostly still noise) are enhanced, whilst larger amplitudes later on (where the long term average is higher due to the signal) with less change are not. However, for the small signals, as in Figure 3.2. 7, it was found that the calculation of the ratio was prone to instabilities due to the averages (especially the long term as the denominator) having very small values at some areas of the signal. Thus, before calculation, the original signal (x) was shifted by 1.5, the maximum absolute amplitude, resulting in a positive signal (x_p) where no

amplitude was near zero. Equation (3.2. 2) shows how the CF (named the S/L TA ratio) was calculated :

$$S/LTA\ ratio(t) = \frac{mean(xp_{t-ws \sim t})}{mean(xp_{t-wl \sim t})} - 1, \quad t = 1, 2, \dots, L, \quad t > wl, \quad (3.2. 2)$$

for a positive signal (xp) of length “L” with short window length “ws” and long window length “wl” (in this study, 25 and 500 sample points were used for the short and the long window lengths).

Figure 3.2. 7 shows the S/L TA ratio calculated for the high passed soft impact signal shown in Figure 3.2. 5, where the resulting signal had less noise and a more pronounced peak at the arrival of the impact signal. When the AIC was calculated for the S/L TA ratio instead of the original signal, it could be seen that the AIC minimum was much clearer, and the corresponding ToA was more accurate. From here on, this method is called the S/L TA-AIC method. Figure 3.2. 8 shows the comparison of ToA profiles for all six sensors between soft (F9) and hard impacts (F1) obtained using the AIC and the S/L TA-AIC method for impacts at location 15 (Figure 3.2. 2) of the flat plate. It can be seen that the S/L TA-AIC method gave more consistent ToA profiles between the soft and the hard impacts, which resulted in more accurate localisation of soft impacts. Thus, this method gave a robust way of determining the ToA from high pass filtered soft impact signals that had very low amplitude. However, significant variation between ToA of hard and soft impacts remained, which significantly affects localisation accuracy.

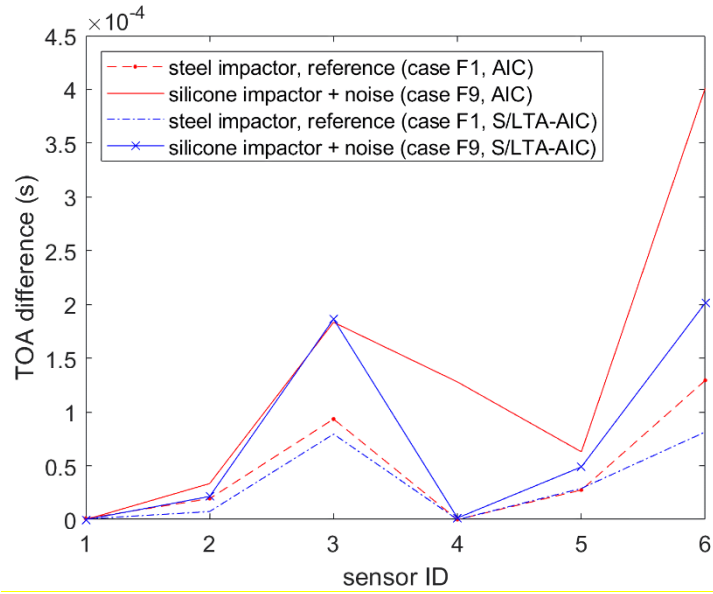


Figure 3.2. 8 Comparison between ToA of the reference case (F1) and the soft impact with noise (F9) extracted using AIC and S/L TA-AIC method.

3.2.4.3 Signal Amplitude

As shown in Sections 3.2.4.1 and 3.2.4.2, soft impacts generated significant variation in ToA between hard and soft impacts, which may cause significant reduction in localisation accuracy. Thus, here, an alternative feature to be used for localisation of impacts with differing stiffness was investigated. Besides ToA, signal amplitude has been shown to be a good feature for localisation [27,98], as there is strong correlation between impact distance from a sensor and signal amplitude (closer impacts generate larger amplitude signals and vice versa) [98]. As the signal amplitude itself changes with differing impact cases (energy, mass, etc.), the amplitudes (here the minimum amplitude was used) are normalised such that the input is the ratio of impact signal amplitudes between sensors in an array.

With respect to vibration noise, for severe impacts (which are of the main interest for localisation), the noise level should be much smaller than the amplitude of the signal and thus possibly negligible. Therefore, the amplitudes from the original signal rather than the filtered signal were used, as the frequency bandwidths of different impact cases differed (especially soft and hard impacts), and the consistency of the amplitude ratios may have change when some components of the waves are filtered.

3.2.5 Impact Localisation Methods

In Section 3.2.4, the developed feature extraction methods were discussed that can improve the feasibility and the consistency of feature extraction for hard and soft impacts. However, significant variation of extracted features still exists, which may significantly reduce localisation accuracy using data driven methods [16,88]. Thus, a localisation method that was less sensitive to input feature variations was developed.

3.2.5.1 Artificial Neural Networks

ANNs are a network of mathematical operations between an input and an output that are linked together via weighted connections [16,86,96]. ANNs can create a meta-model mapping given input and output via training using a previously known input and output data set. During training, the ANN is given the input from the training data, and the weights of the connections are optimized to fit the output of the ANN to the output of the training data.

From previous studies [16,22,66,82,88,92,96,98], it was found that ANNs are able to accurately locate the position of an impact using input in the form of impact signal features such as ToA and signal amplitude. However, the accuracy is significantly reduced when there is variation between input features from an impact at a given location that differs from the features for the said location in the original training set. As the mapping of the ANN is only calibrated to what is included in the training set, when given an input that is outside of what is contained in the training set, the ANN may not be able to map it accurately [16,22,66,82,88,92]. Thus, to ensure the accuracy of localisation, either a training set containing all possible variations of the signal features or a method to ensure consistency of extracted features is needed. This is a significant problem for real life application, as there are multiple parameters that may alter the recorded impact signal and subsequently the extracted features (as shown in Section 3.2.3) [16,66,88]. The possible combination of these parameters is very large and would require collecting an impractically large training set.

In Chapter 3 : **Part 1** [16] a method to extract ToA consistently for hard impacts under various impact scenarios and conditions was developed, which allows for accurate localisation of these impacts using ANNs with a training set consisting of only a single impact case. However, for soft impacts, the same level of consistency was not achievable, and thus an alternative localisation method is required.

For validation purposes of new localisation methods, ANNs were used as benchmark for comparison. The ANNs had a single hidden layer with 12 neurons with ToA as input and the predicted impact coordinates (x,y) as output. To account for random initial weights, each ANN training (done using the Levenberg–Marquardt algorithm) was repeated 500 times, and the best performing iteration was chosen as the ANN to use [16].

3.2.5.2 Reference Database Method

The reference database (DTB) method [24,43,80,103] is similar to ANNs, as it also utilizes an initial data set/database of previously known inputs and outputs to predict the location of an impact. Features of an incoming impact wave are compared to the known features corresponding to different impact locations stored in a reference database. The reference location, which has corresponding features that have the least difference compared to the features of the incoming wave, is considered to be the location where the impact most likely occurred. As the determination of impact location is based only on similarity, this method is less sensitive to variation in input features and should be able to give acceptable location prediction provided there is some degree of similarity between the input features and the features stored in the database. In Section 3.2.4, it is shown that there is a degree of similarity between the features extracted from hard and soft impacts with variation occurring to differing degrees on each sensor. Thus, the reference database method was used as an alternative to ANNs for localisation of hard and soft impacts.

The difference between the input and reference features is given in Equation (3.2. 3) :

$$D_i = \sum_{j=1}^{Ns} |y_j^{in} - y_{j,i}^{ref}|, \quad i = 1, 2, \dots, Nr, \quad j = 1, 2, \dots, Ns, \quad (3.2.3)$$

where D_i is the difference between the input features (y_j^{in}) and the reference features ($y_{j,i}^{ref}$) from “Ns” number of sensors stored in a database containing “Nr” number of reference features. The value of D_i was calculated for all sets of reference features stored in the database, where the location coordinates (x_i, y_i) corresponding to the set of reference features that minimized D_i were said to be the impact location.

As noted in Section 3.2.4, the degree of variance between hard and soft impact features differs between sensors. Thus, a novel comparison method was proposed where, rather than determining the location using all the sensors at once ($j = 1, 2, \dots, Ns$), the sensors are split into groups of combinations of “Ncs” number of sensors (for example, $Ns = 1-6$, $Ncs = 5$, $j_1 = 1, 2, 3, 4, 5$, $j_2 = 1, 2, 3, 4, 6$, $j_3 = 2, 3, 4, 5, 6$, etc.) and produced multiple impact location predictions (x_1, y_1 ; x_2, y_2 ; x_3, y_3 ; etc.). These predictions were then averaged to obtain the final impact location prediction (x, y). The idea was that, by using different combinations, the probability of having a combination of exactly all sensors with large feature variation was smaller than the probability of having a combination where one or more of the sensors with large variation was not included. Thus, out of all the location predictions produced, most were likely to have originated from combinations with less feature variation and subsequently had better accuracy.

As the reference database consists of discreet locations and their corresponding features, to predict impact locations over a continuous area, there needs to be an interpolation method between the reference locations. This is commonly done by either interpolating the impact location from a set of reference locations with the highest similarity to the input features [24,80] or by interpolating the reference database entries to gain a smoother discretisation (thus approximating continuity) of the sensing area [103]. Here, interpolation of the database entries was chosen due to the simplicity, where the grid shown in Figure 3.2. 2 was discretised by the order of two using bicubic interpolation (Figure 3.2. 9).

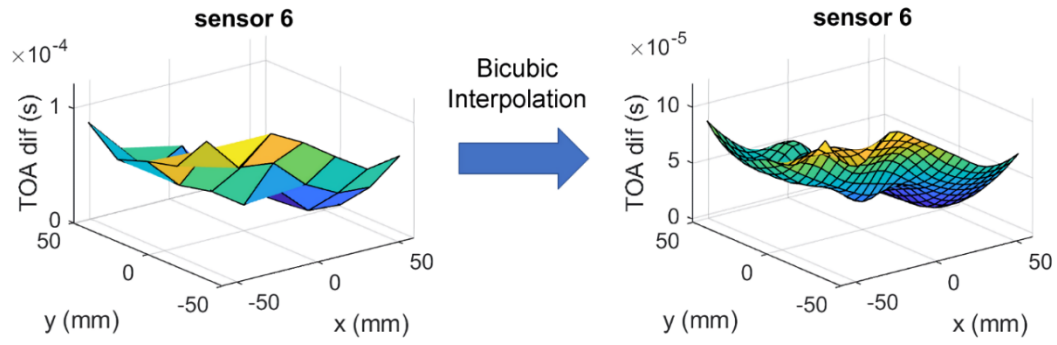


Figure 3.2. 9 Bicubic interpolation of ToA extracted using the S/L TA-AIC method from sensor 6 of the flat plate for the reference case (F1).

3.2.6 Impact Localisation Results

In this section, localisation of the impacts collected in Section 3.2.2 (Table 3.2. 1 and Table 3.2. 2) was conducted using the methodologies developed in Sections 3.2.4 and 3.2.5 based on observations done in Section 3.2.3. In order to validate these methods, comparisons of these methodologies were conducted with a benchmark method which, in this case, was the localisation method using ANNs with ToA extracted using the NSET method (Sections 3.2.4.1 and 3.2.5.1). The main objective was to see if the proposed methodologies could improve localisation of impacts with different stiffness using training/reference data only from impacts with a single stiffness compared to the benchmark method.

The data set used for the ANN training set and the reference database in this section was taken from the reference impact cases (F1 and C1) where one out of four repeated impacts at each location (35 and 25 impacts for the flat and the curved plates, respectively) were collected into a training/reference data set. The extracted features from these impacts were then interpolated (as mentioned in Section 3.2.5.2) to produce a fine discretisation for the reference database and at the same time produce a large enough database for training the ANN. The rest of the impacts from the reference cases (105 and 75 impacts for the flat and the curved plates, respectively) were used as testing data for cases F1 and C1.

Impact localisation accuracy was quantified using the Root Square Error (RSE) of the predicted impact location towards the actual impact location [16,27,88]. To express the general localisation accuracy of a whole data set, a gamma distribution was fit (as there were cases of zero error, the commonly used

lognormal distribution could not be fit) [16,27,88] to the RSE of all predicted impact locations in the data set and the RSE value corresponding to 90% on the cumulative distribution function (CDF) of the fitted distribution was taken. The RSE value was defined as the range around the predicted impact location where there is 90% confidence that the actual impact location was located within (smaller value is better) or 90% Probability of Detection (POD) [16,27,88].

3.2.6.1 Comparison between Localisation Methods

In this section, the accuracy of the benchmark localisation method was compared with the proposed reference database method with varying amounts of sensor combinations when tested with impacts with different stiffness (soft impacts, F8 and C5) from the training/reference database (Table 3.2. 3). The input used was ToA extracted using the NSET for all cases to isolate the localisation accuracy improvements due to the localisation method alone.

The results of the comparison can be seen in Figure 3.2. 10 and Figure 3.2. 11, which show that, when using the benchmark method (ANN with NSET ToA), the localisation error for soft impacts was very high. However, when the same input was given to the reference database method without sensor combinations (all six sensors), the error dropped significantly. This suggested that the ANN was very sensitive to the variations in ToA between the training case (F1 and C1) and the soft impact test case (F8 and C5), whereas the reference database was much less sensitive due to the mapping being based on similarity only.

Table 3.2. 3 Test cases for comparison between localization methods

Test Impact Case	Noise Filtering	Feature Used	Localisation Method	Training/Reference Database ¹
Soft impact (F8 and C5)	No	ToA (NSET)	ANN, 1 × 12 hidden layer	F1 and C1
Soft impact (F8 and C5)	No	ToA (NSET)	Database, 6 sensors	F1 and C1
Soft impact (F8 and C5)	No	ToA (NSET)	Database, 5 sensor comb.	F1 and C1
Soft impact (F8 and C5)	No	ToA (NSET)	Database, 4 sensor comb.	F1 and C1
Soft impact (F8 and C5)	No	ToA (NSET)	Database, 3 sensor comb.	F1 and C1

¹Note: F1 for flat plate impacts and C1 for curved plate impacts.

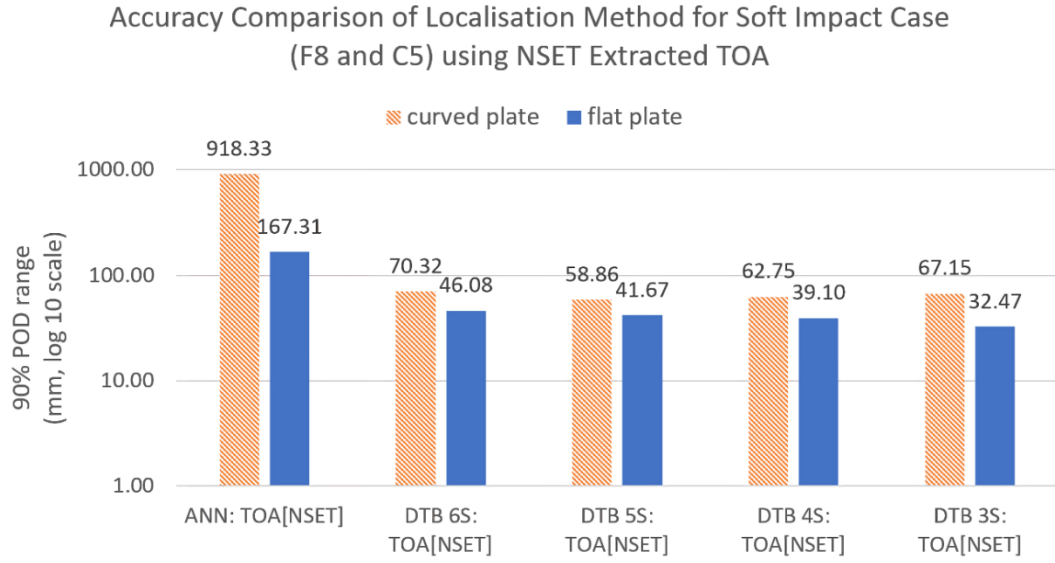


Figure 3.2. 10 Comparison of localisation accuracy for different methods trained with the reference case (F1 and C1) and tested with the soft impact (C5 and F8).

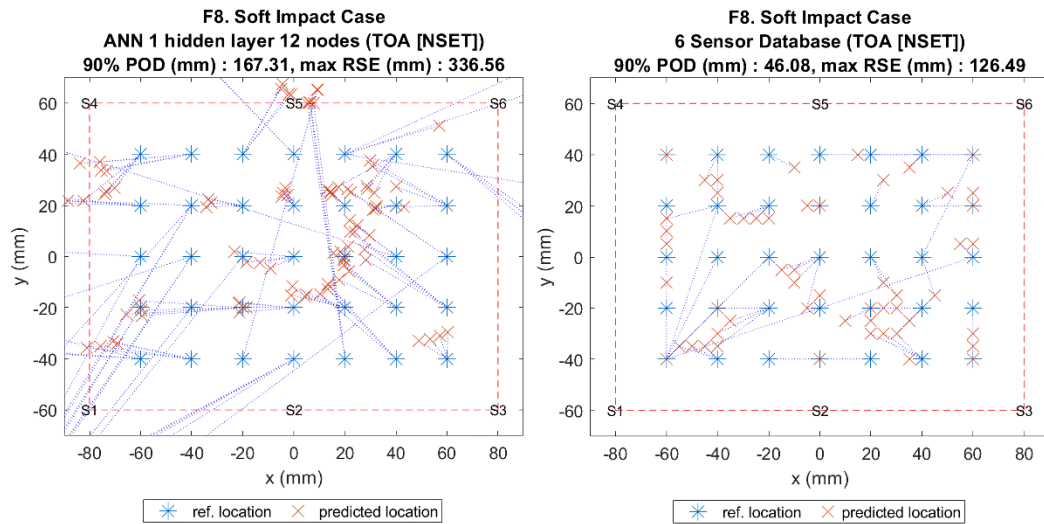


Figure 3.2. 11 Visualisation of impact localisation for soft impacts (F8) using different methods: ANN (left) and reference database (right).

When tested using the reference database with varying degrees of sensor combinations, it can be seen that using sensor combinations decreased the error further. However, although it was found that the error decreased with increasing number of sensor combinations for the flat plate, for the curved plate, the largest decrease was achieved with five sensor combinations. This suggested an optimum number of sensor combinations dependent on the structure. For later comparisons,

five sensor combinations were used for the reference database to ease comparison between the flat and the curved plates.

3.2.6.2 Comparison Between Input Features for Localisation

In this section, the effect of different input features on soft impact (F8 and C5) localisation accuracy was compared. To isolate the effect of various inputs, the localisation method used for all cases was the same (reference database method with five sensor combinations, Table 3.2. 4). For the case of multiple input features, such as ToA with minimum amplitude ratio (Table 3.2. 4), two separate reference databases were used for each input feature with the sensor combinations done separately for each database. The predicted coordinates of these separate reference databases were then averaged to obtain the final prediction. The localisation results using the benchmark method (ANN with NSET ToA) were also included as reference for comparison.

Table 3.2. 4 Test cases for comparison between input features for localisation.

Test Impact Case	Noise Filtering	Feature Used	Localisation Method	Training/Reference Database ¹
Soft impact (F8 and C5)	No	ToA (NSET)	ANN, 1x12 hidden layer	F1 and C1
Soft impact (F8 and C5)	No	ToA (NSET)	Database, 5 sensor comb.	F1 and C1
Soft impact (F8 and C5)	No	ToA (S/L TA - AIC)	Database, 5 sensor comb.	F1 and C1
Soft impact (F8 and C5)	No	Min. amp. ratio ToA	Database, 5 sensor comb.	F1 and C1
Soft impact (F8 and C5)	No	(S/L TA - AIC) + Min. amp. ratio	Database, 5 sensor comb.	F1 and C1

¹note : F1 for flat plate impacts and C1 for curved plate impacts. ANN = artificial neural network.

Figure 3.2. 12 and Figure 3.2. 13 show the comparison results of localisation accuracy for various input features. Comparing the different ToA extraction methods, it can be seen that, for the flat plate, the S/L TA-AIC method gave lower localisation error than the benchmark NSET method. However, the same was not observed in the curved plate, where the accuracy was roughly unchanged. Comparing between ToA and minimum amplitude ratios, it can be seen that ToA extracted using the S/L TA-AIC method gave lower error than using the signal

amplitude ratios. When combined, both features gave lower localisation error than when used separately and were thus used for further comparison.

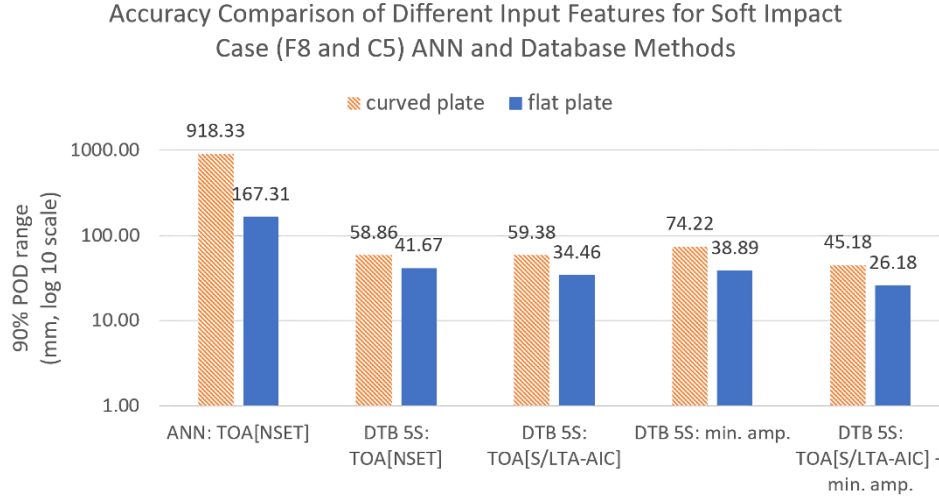


Figure 3.2. 12 Comparison of localisation accuracy for different input features, all trained with features from the reference case (F1 and C1) and tested with the soft impact (C5 and F8).

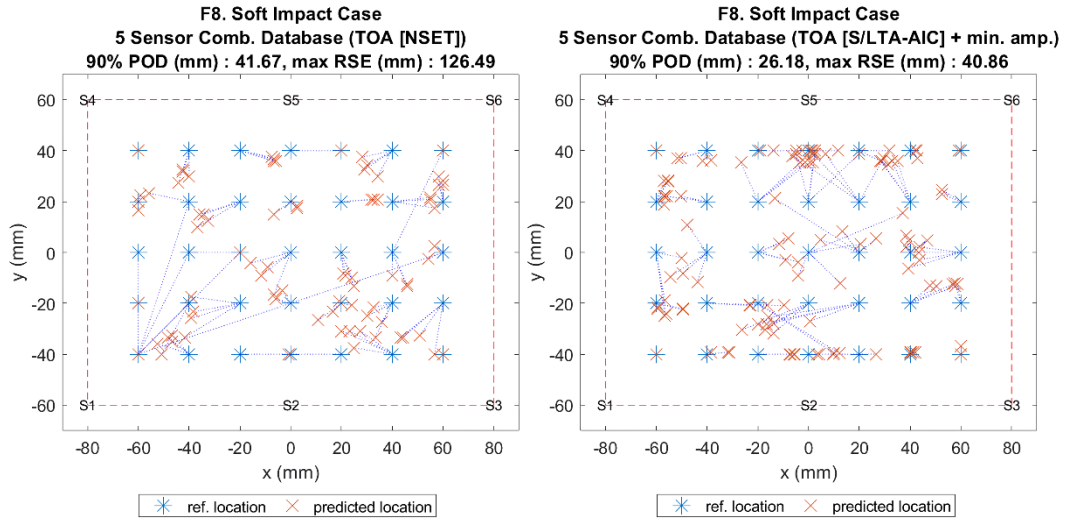


Figure 3.2. 13 Visualisation of impact localisation for soft impacts (F8) using different input features NSET extracted ToA (Left) and S/LTA-AIC extracted ToA with normalised minimum amplitude (right).

3.2.6.3 Comparison Between Reference Method and Proposed Method

As the proposed method must be able to detect other impact cases besides soft impacts with acceptable accuracy, in this section, we compare the localisation accuracy between the benchmark method (ANNs with NSET ToA as input) and

the proposed method (reference database with five sensor combinations with S/L TA-AIC ToA and minimum amplitude ratios as input) for all the cases collected in Section 3.2.2 (Figure 3.2. 5). As it is known that the benchmark method is able to detect hard impacts (F1–F7 and C1–C4) with good accuracy [16], thus it would be desirable for the proposed method to have comparable accuracy with the benchmark method for these cases. Additionally, the localisation error of soft impacts were compared with hard impacts to see the effects of impactor stiffness on localisation accuracy.

To account for the cases with added noise (F7, F9, C4, and C6), high pass filtering (>700 Hz, Section 3.2.3.2) was conducted prior to ToA extraction. As the NSET method cannot reliably extract ToA for soft impacts (C5 and C6) when high pass filtering is conducted (Section 3.2.4.1), localisation for soft impacts was not conducted using the benchmark method (Figure 3.2. 5).

Table 3.2. 5 Test cases for comparison between reference and proposed method.

Test Impact Case	Case ID	Noise Filtering	Reference Method ^a	Proposed Method ^b	Training/Reference Database ^c
Reference Impact Case	F1 and C1	>700 Hz	Yes	Yes	F1 and C1
Increased Impact Height	F2	>700 Hz	Yes	Yes	F1 and C1
Angled Impact	F3 and C2	>700 Hz	Yes	Yes	F1 and C1
Increased Impact Mass	F4 and C3	>700 Hz	Yes	Yes	F1 and C1
Increased Impact Temperature	F5	>700 Hz	Yes	Yes	F1 and C1
Intermediate Impact Locations	F6	>700 Hz	Yes	Yes	F1 and C1
Reference Case + Artificial Noise	F7 and C4	>700 Hz	Yes	Yes	F1 and C1
Soft Impact	F8 and C5	>700 Hz	-	Yes	F1 and C1
Soft Impact + Artificial Noise	F9 and C6	>700 Hz	-	Yes	F1 and C1

Note: a. Reference method: ANN (1 x 12 hidden layer) with ToA (NSET) input; b. Proposed method: database (five sensor combination) with ToA (S/L TA-AIC) and minimum amplitude ratio.; c. F1 for flat plate impacts and C1 for curved plate impacts.

Figure 3.2. 14, Figure 3.2. 15, Figure 3.2. 16 and Figure 3.2. 17 show the results of the comparison between the benchmark and the proposed method for all impact cases collected. It can be seen that, for hard impacts, the error level was similar for the flat plate (Figure 3.2. 14, F1–F7), whilst for the curved plate (Figure 3.2. 16, C1–C4), the error level was also similar except for the case with added noise (C4), where the proposed method was less accurate. However, the

error for these hard impacts was significantly lower than that of the soft impacts (F8, F9 and C5, C6) suggesting that variation caused by impactor stiffness was the limiting factor for localisation accuracy, as predicted earlier (Sections 3.2.4 and 3.2.5). From Figure 3.2. 10, Figure 3.2. 14 and Figure 3.2. 16 it can be seen that the proposed method was able to suppress the increase in error due to the variations from soft impacts to an acceptable level compared to the benchmark method. Additionally, it can be seen that there was little effect of added noise on soft impact localisation error (F9,C6), suggesting that the proposed method was able to accommodate for vibration noise.

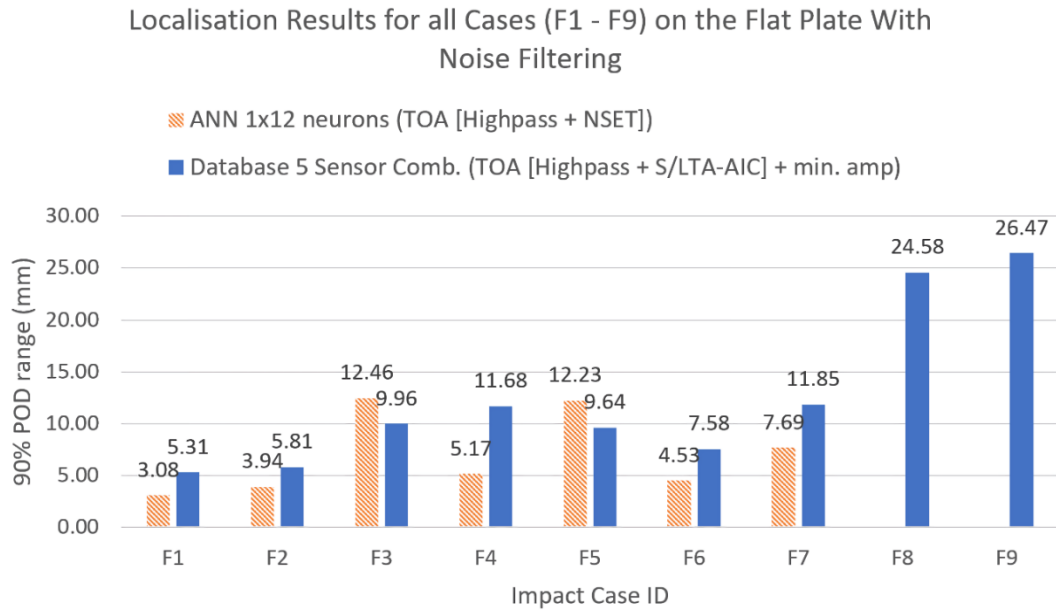


Figure 3.2. 14 Comparison of localisation accuracy between the reference method (ANN with NSET extracted ToA input) and the proposed method (reference database with S/LTA-AIC extracted ToA and normalised minimum amplitude input) for the flat plate.

To compare the localisation accuracy between plates with differing sensing area dimensions, the 90% POD range was converted into a circular detection area around the predicted impact location as a percentage of the whole sensing area [16,27]. For hard impacts, the maximum detection areas were 2.30% (F7) and 2.72% (C4) for the flat and the curved plates, respectively, indicating that the difference in configuration had no effect on localisation accuracy. For soft impacts, the maximum detection areas were 11.46% (F9) and 17.69% (C6) for the flat and the curved plates, respectively, suggesting that the difference in

configuration in both plates influenced localisation accuracy. For these cases, the 90% POD ranges were 26.47 mm and 47.46 mm for the flat and the curved plates, which were similar to the experimental data point distances of the reference impact cases (20 mm and 40 mm for the flat and the curved plates, Figure 3.2. 2) indicating that, for soft impacts, the accuracy was mostly dictated by the discretisation of the original data set of the reference database even though interpolation was applied.

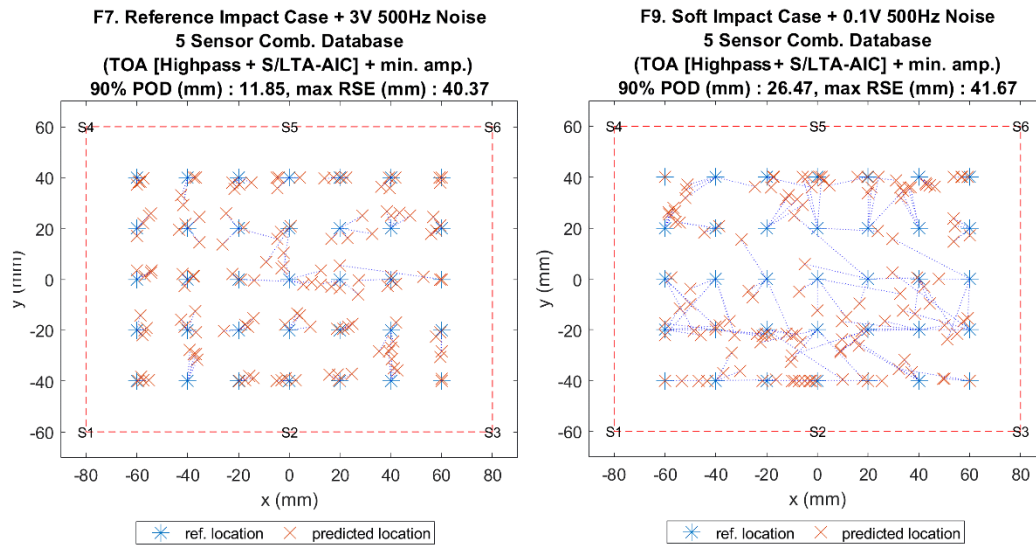


Figure 3.2. 15 Visualisation of impact localisation for impacts with added noise for hard (F7, left) and soft (F9, right) impacts on the flat plate.

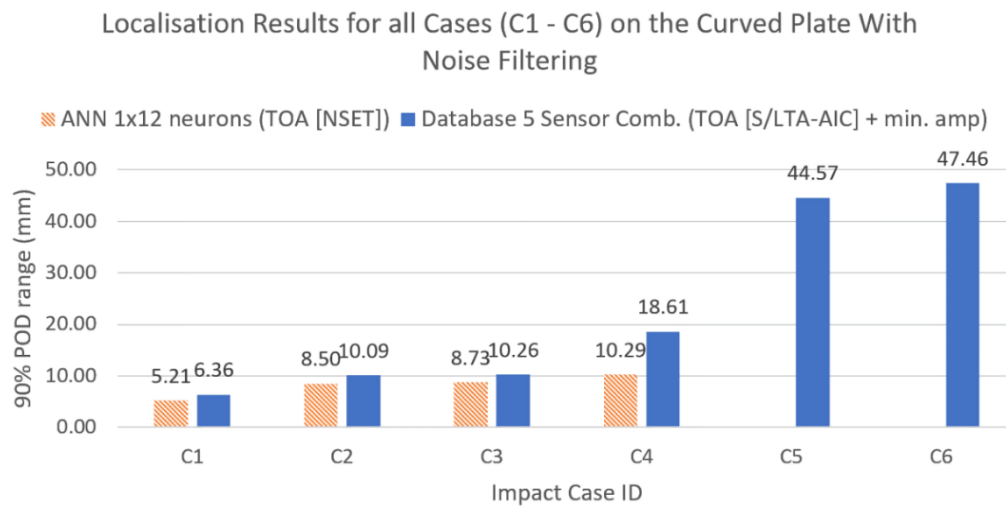


Figure 3.2. 16 Comparison of localisation accuracy between the reference method (ANN with NSET extracted ToA input) and the proposed method (reference database with S/LTA-AIC extracted ToA and normalised minimum amplitude input) for the curved plate.

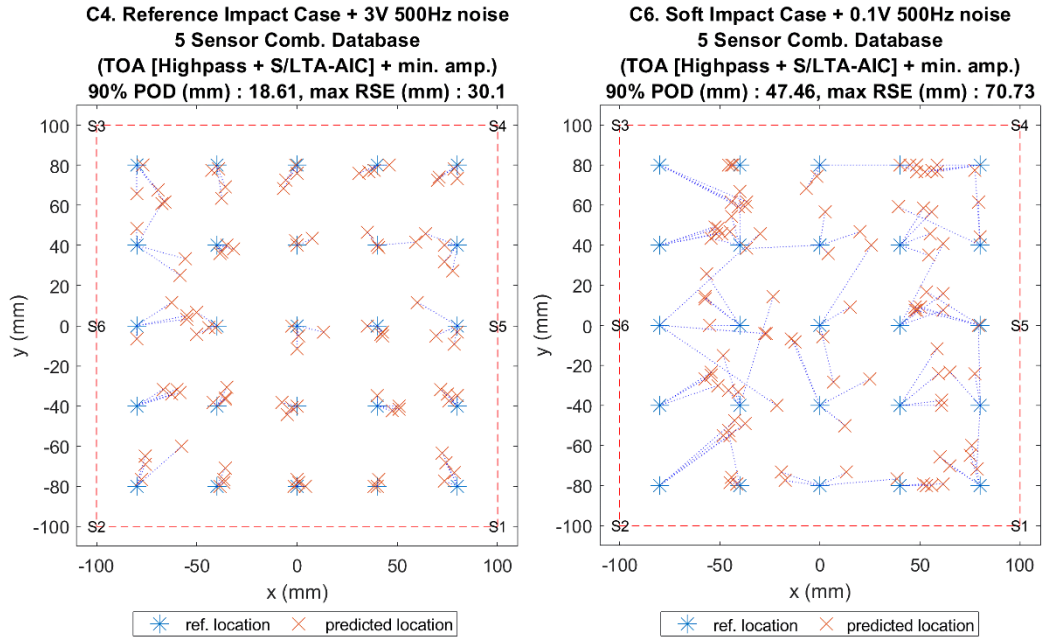


Figure 3.2. 17 Visualisation of impact localisation for impacts with added noise for hard (C4, left) and soft (C6, right) impacts on the curved plate.

3.2.7 Conclusion

A parametric investigation of the effect of impactor stiffness as well as environmental and operational conditions on impact contact behaviour and the subsequently generated Lamb waves in composite structures was conducted. From the tests carried out, it was observed that lower impactor stiffness generated a larger contact area (due to deformation) and subsequently generated a Lamb wave with much lower amplitude and frequency due to said contact behaviour.

These observations were utilised to develop a novel impact localisation method based on the reference database method and AIC ToA picker that is robust towards the variations due to differences in impactor stiffness. The proposed method was compared against a benchmark method based on ANNs and the NSET ToA extraction method, which is known to have good accuracy in locating impacts under various environmental and operational conditions but untested for different impactor stiffness. The results indicate that the proposed method had comparable accuracy (11.85–18.61 mm detection range) to the benchmark method (10.29–12.46 mm detection range) for hard impacts under various environmental and operational conditions when trained only using a single

hard impact case. However, when tested with soft impacts, the benchmark method had very low accuracy (167.31–918.33 mm detection range) whilst the proposed method was able to maintain its accuracy at an acceptable level (26.18–45.48 mm detection range). It can be concluded that the proposed method is capable of detecting the location of impacts of varying stiffness and environmental and operational conditions using data from only a single impact case.

Chapter 4

A Novel Method for Impact Force Estimation in Composite Plates under Simulated Environmental and Operational Conditions³

In Chapter 3 : **Part 1** and Chapter 3 : **Part 2**, novel robust data driven impact location estimation methods were developed that can provide accurate impact location estimation under simulated environmental and operational conditions using minimum initial data. In this chapter, a novel data driven impact severity (specifically impact force) estimation method was developed that is robust towards the same environmental and operational conditions in previous chapters. This method complements the methods developed in previous chapters to provide robust estimation for both impact location and severity.

4.1 Introduction

Impact damage in composite structures initiate at a specific threshold force [2], thus one of the main interests of impact monitoring systems is to estimate the impact force to determine the severity of the impact (estimate possibility of damage) [14,36,45,104,105]. Many methods have been developed using passive Lamb wave measurements from sensors at discrete points to reconstruct the impact force profile [12,14,36,45,104–107]. Analytical solutions to such inverse problems exist but may be impractical to apply for complex structures [108,109].

A popular alternative approach is to find the function which maps the recorded Lamb wave response directly onto the impact force for a specific location [14,36,45,105,106,110]. This way the actual geometric complexities of the structure can be disregarded, although there is now a requirement to store

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characteristic functions of each location [14,111]. Many methods have been developed to find these characteristic functions, with transfer function based methods (deconvolution [12,14,50,77,112] and state space models [15,107,110]) and data driven [36,45,106,113] based works being the most common in recent studies.

Data driven based methods can directly map the recorded Lamb wave to the impact force via a meta model trained with a known training data set [36,45,106,113]. They have the flexibility to map most forms of input and outputs, but the drawback is that extrapolation for inputs that are not included in the training set yield lower accuracy [16,34,45]. This is vital for application in real life applications as the variation of possible impact cases may require an impractical amount of training data to achieve robust accuracy [34].

Deconvolution and state space models use the transfer function between the recorded signal and the impact force profile [12,14,50,77,104,110–112]. These methods allow reconstruction of any form of impact profile using the transfer function obtained from a single impact force and Lamb wave pair and are thus able to accommodate the many variations in possible impact cases. However, they can be unstable especially for noisy signals [77,104] and many regularisation methods have been developed to give more robust results [77,104,105,112]. Additionally, these methods may require large amounts of storage for transfer functions of multiple locations.

A few studies have discovered a simpler relationship between signal features (energy, amplitude, etc.) with impact severity (force, energy, etc.) [10,12,35] which have the potential to be used as simplified severity indicators. It was found that there is a linear relationship between signal energy and impact energy [35] that was affected by impactor stiffness. A linear relationship was also found between signal amplitude and maximum impact force [10,12] with varying gradient depending on location.

Development of methods to identify impact force need to follow the capabilities of the data acquisition (DAQ) systems being developed for operation on aircraft structures [29,38,114]. These systems tend to be simple to minimise weight and energy required for computing especially if they are to be deployed on

the entire structure. In this chapter a novel impact force identification method is proposed that is robust for simulated environmental and operational conditions experienced by an aircraft structure which is feasible for integration with current DAQ systems and requires minimum initial data. The method expands on previous linear relations found between the impact signal magnitude and the impact force to create a robust and simplified estimation method. The more established deconvolution method was used as a benchmark to assess the performance of the proposed method.

4.2 Experimental Setup

Experimental measurements were acquired from two different setups : i) a low energy non-damaging impact test setup for collecting large amounts of impact data under various simulated environmental and operational conditions, and, ii) a high energy impact test setup for collecting data on high energy damaging impacts. Data from both setups are then used to develop and test impact force estimation methods that can identify damaging impact events as well as being robust towards simulated environmental and operational conditions. All data processing was done in MathWorks MATLAB 2018a.

4.2.1 Non-damaging impact setup

The non-damaging impact setup consists of a flat carbon fibre plate (M21 T800s, [0/+45/-45/90/0/+45/-45/90]s layup) and 2 types of impactors : an impact hammer and a small drop impactor setup as can be seen in Figure 4. 1. Both impactors were used to generate impacts from differing sources (manually actuated vs dropped mass) as well as random (hammer) vs controlled parametric impacts (drop impactor). The drop impactor, however, has no apparatus to measure the impact force directly and as such the impact force was estimated using methods discussed later in Section 4.4.

The impact hammer (PCB Piezotronics 086C03, Figure 4. 1b) can measure the impact force at the tip and was used to generate impacts with random force. It has interchangeable tips (10 mm diameter) with different materials (metal, plastic, hard rubber and soft rubber) and as such can simulate impacts from different stiffness impactors. On the other side of the hammer head there is an attachment

which allows the addition of a 100 g extra mass for simulating variation in impactor mass.

The drop impactor setup consists of a rail and the impactor itself which can generate repeatable impacts of specific energy by dropping the impactor from a controlled height. The impactor has 2 tips (steel and soft rubber, 20 mm diameter) to simulate impacts from impactors of different stiffness. The impactor itself weighs 100 g, with attachments to add extra weights to a maximum of 200 g. The rail that guides the impactor can be tilted to generate impacts with controlled angles.

The carbon fibre plate dimensions were 290 x 200 x 4 mm, had a silicone heating mat underneath to control the temperature and steel clamps on 2 sides to secure the specimen. The layout of the 6 PZT sensors (only 6 out of 8 used as oscilloscope only had 8 channels and 1 channel was required to measure the impact force as mentioned later on, Figure 4. 1) and impact locations are shown in Figure 4. 1c. The PZT sensors convert the Lamb waves generated by impact into a voltage signal which were recorded using an NI PXI 5105 8 channel oscilloscope at 2 MS/s with a signal length of 100000 samples. Each sensor was connected to the oscilloscope via probes with 10x attenuation.

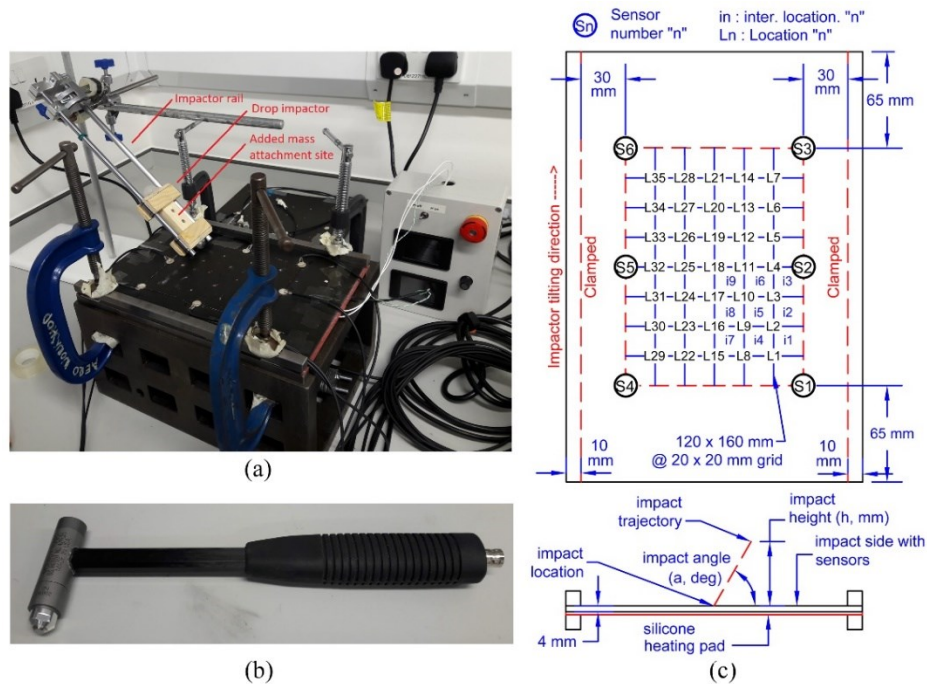


Figure 4. 1 Non-damaging impact setup : (a) composite plate and impactor, (b) impact hammer, (c) layout of composite plate

Table 4. 1 shows the various impact cases collected using the non-damaging impact setup using the hammer and impactor which encompasses a wide variety of possible cases in real life. For all cases, impacts at each location (shown in the layout, Figure 4. 1c) were repeated 4 times. All the impacts generated using this setup are non-damaging.

Table 4. 1 Impact cases collected from non-damaging impact setup

Case ID	Impactor	Impact case	Force	Parameters	Number of impacts
H1	hammer	steel, reference	Measured	a : rn, m : ref, t : 24, E : rn	35 loc. x 4 rep.
H1a	hammer	steel, intermediate locs.	Measured	a : rn, m : ref, t : 24, E : rn	9 loc. x 4 rep.
H2	hammer	steel, added mass	Measured	a : rn, m : ext, t : 24, E : rn	35 loc. x 4 rep.
H3	hammer	steel, increased temp.	Measured	a : rn, m : ref, t : 70, E : rn	35 loc. x 4 rep.
H4	hammer	plastic	Measured	a : rn, m : ref, t : 24, E : rn	35 loc. x 4 rep.
H5	hammer	hard rubber	Measured	a : rn, m : ref, t : 24, E : rn	35 loc. x 4 rep.
H6	hammer	soft rubber	Measured	a : rn, m : ref, t : 24, E : rn	35 loc. x 4 rep.
I1	impactor	steel, reference	Estimated	a : 90, m : 100, t : 24, E : 25	35 loc. x 4 rep.
I2	impactor	steel, angled	Estimated	a : 45, m : 100, t : 24, E : 25	35 loc. x 4 rep.
I3	impactor	steel, added mass	Estimated	a : 90, m : 200, t : 24, E : 25	35 loc. x 4 rep.
I4	impactor	steel, increased height	Estimated	a : 90, m : 100, t : 24, E : 50	35 loc. x 4 rep.
I5	impactor	steel, increased temp.	Estimated	a : 90, m : 100, t : 70, E : 25	35 loc. x 4 rep.
I6	impactor	Rubber	Estimated	a : 90, m : 100, t : 24, E : 100	35 loc. x 4 rep.

Note : a = angle, deg, m = mass, g, t = temperature, °C, E = energy, mJ, loc. = locations, rep. = repetitions, “ref” : no added weights, “rn” = random, “ext” = added 100 g weight

4.2.2 Damaging impact setup

The damaging impact setup (Figure 4. 2) was used to generate impacts of much larger energy which may create barely visible damage on composite specimens. The setup consists of composite plate specimens and an impact tower. The impact tower (INSTRON CEAST 9350) has a drop impactor with a mass of 2.41 kg and a steel tip with 20 mm diameter. The impactor was dropped from a specific height to generate impacts with energies of 1, 7, 9 and 11 J resulting in 4 impact tests. The 1 J impact acts as the non-damaging reference impact whilst the rest are the damaging impact cases. The impact force was measured from the force sensor on the impactor tip which was recorded at 500 KS/s and a length of 25000 samples.

For each impact test, an individual composite plate (8552-33%-134-IM7-12K, $[0/+45/-45/90]_{2s}$ layup) with dimensions 250 x 250 x 2 mm was used (4 in total for all tests). The specimens were held in place by a steel fixture which clamps all 4 sides of the plates (Figure 4. 2b). Each plate has 1 PZT sensor (as can be seen in the layout in Figure 4. 2c) to measure the impact generated Lamb wave which was recorded using a GW Instek GDS-2074A oscilloscope with 10x attenuation at 500 KS/s and a length of 25000 samples. All plates were impacted at the same location (Figure 4. 2c) and after impact an ultrasound scan using a CF08 Dolphicam was done to ascertain the extent of damage.

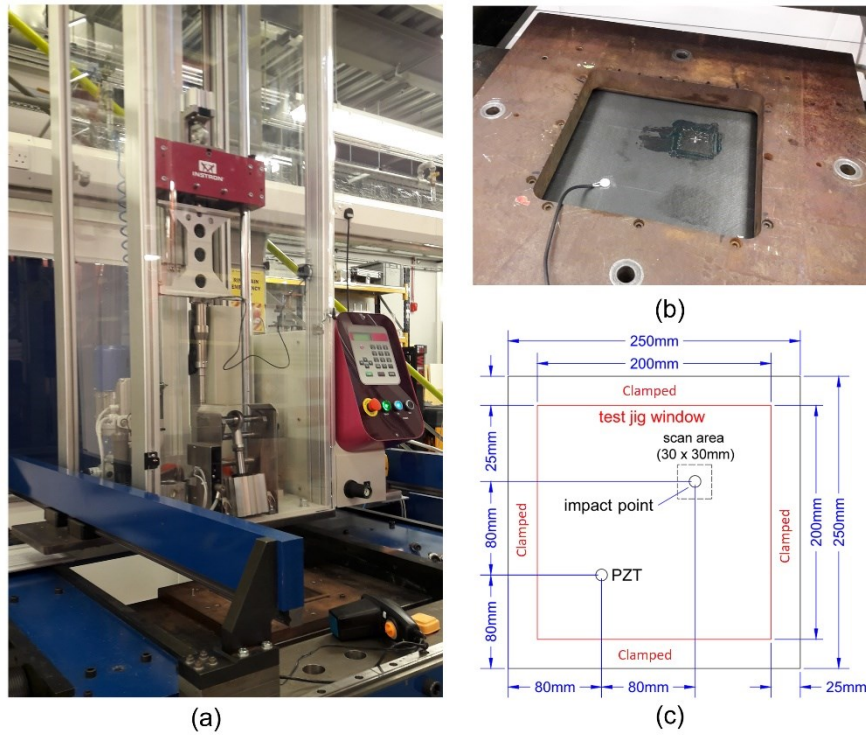


Figure 4. 2 High energy impact setup : (a) impact tower, (b) composite plate and fixture, (c) plate layout

4.3 Signal deconvolution for impact force profile reconstruction

In signal deconvolution, it is assumed that the measured response of a system (in this case the measured Lamb wave) is equal to the input signal (in this case the impact force) that is convoluted as it propagates through the system [14,36,79], as can be seen in equation (4. 1) :

$$s(t) = \int_0^t c(t - \tau)f(\tau)d\tau, \quad (4. 1)$$

where s is the recorded time (t) series response, c is the convoluting function and f is the original input signal.

In order to obtain an unknown original input (f) from a measured response (s) deconvolution of the input signal is required by finding the inverse of the convolution [14,36,79]. As the convolution is a time series integral, it is often transformed into the Fourier domain for ease. This transforms the integral into multiplication of spectral components [14,36] as seen in equation (4. 2) :

$$S = C \cdot F \rightarrow H \cdot S = F, \quad (4. 2)$$

where S , C and F are the spectral components of s , c and f respectively.

In this form, the inverse of the spectral convolution (C) can be expressed in terms of the transfer function (H) as seen in equation (4. 2). If the transfer function is known, the original input signal (f) may be found from the measured response (s) through multiplication of the spectral components of the response (S) with the transfer function (H) followed by an inverse Fourier transform.

For deconvoluting impact force profiles from measured Lamb waves on a structure with a specific configuration (geometry, material and boundary conditions), the transfer function depends on the location as it is affected by the propagation path of the wave source to the sensors [14]. The transfer function may be obtained experimentally by measuring the force profile and subsequent response of an impact at each location [14,50] or through estimation [62,79]. Once the transfer function is known for a specific location, impact profiles of any form (different impactor energies, masses, materials, angles) may be reconstructed from the measured response provided that the structure configuration is constant (thus constant transfer function) and the bandwidth of the input profile is covered by the transfer function [50,112]. This property makes deconvolution a promising method for robust reconstruction impact force profiles under varying operational and environmental conditions.

4.3.1 Reconstruction of impact force profiles under simulated environmental and operational conditions

Here the deconvolution method is tested for reconstructing the impact force profile measured from the non-damaging impact setup (Figure 4. 1) with the impact hammer under simulated environmental and operational conditions as listed previously in Table 4. 1 (H1 – H6, except H1a as locations differ). The first impact repetition from each location (1 x 35) of the reference case (H1) was used to find the transfer function for these locations (1-35, Figure 4. 1c and Figure 4. 3). The rest of the impact repetitions (3 x 35) of the reference case (H1) as well as the other impact cases (H2 – H6) were then used as other test cases to see the robustness of the obtained transfer functions.

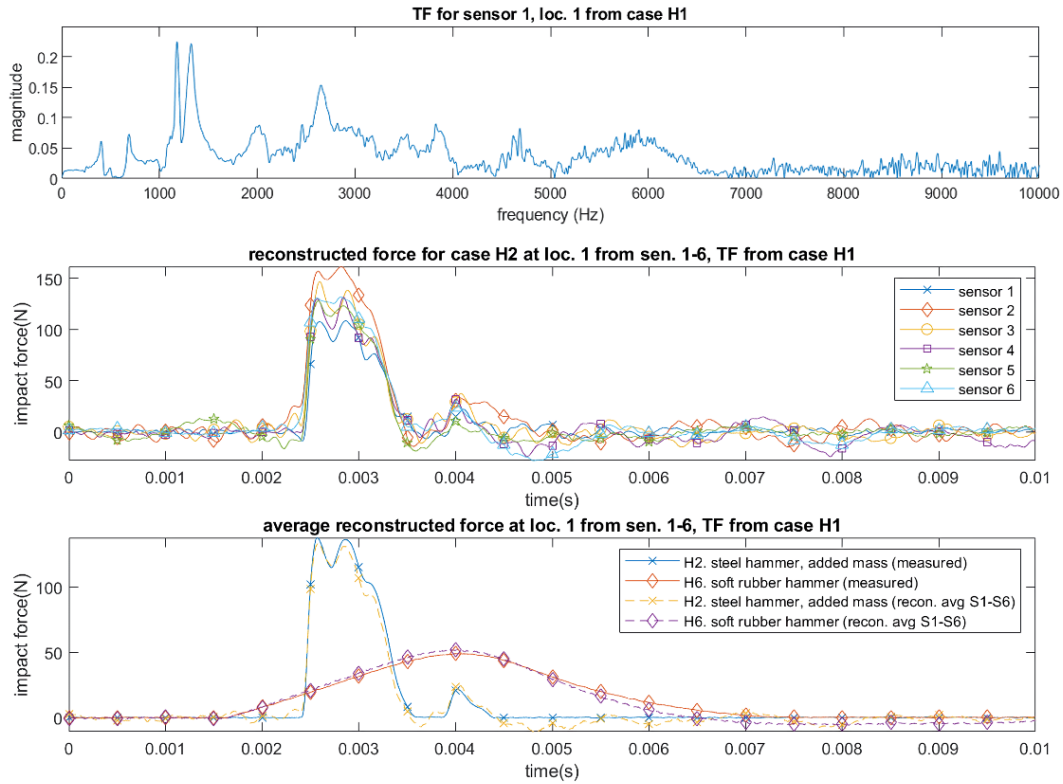


Figure 4. 3 Impact force profile reconstruction using deconvolution for case H2 and H6 at location 1 using transfer function from case H1 : transfer function (top), reconstruction from individual sensors (middle) and average reconstruction results (bottom)

As mentioned previously, deconvolution results can be unstable [105,112] as the scaling factors of the transfer function may vary largely. It is important that

the frequency components are sampled with enough resolution to prevent scaling up the wrong component, resulting in noise or reconstruction errors. To achieve this, the signal was downsampled by a factor of 4 (by keeping only 1 in every 4 samples) as it was highly oversampled and used a 10^6 point Fourier transform to ensure the spectrum contains less noise (only frequency components of the signal) and has sufficient resolution. As there were 6 sensors on the plate, the transfer function for each sensor was obtained and the impact force profile was reconstructed for each sensor individually (Figure 4. 3). Afterwards, all 6 reconstructed impact force profiles were averaged to obtain a robust final result.

Figure 4. 3 shows the impact force profile reconstruction results for case H2 (added mass) and H6 (soft rubber tip) at location 1 using the transfer function (TF) obtained from case H1. It can be seen that the deconvolution results match very closely to the measured force profiles even though they have significantly different shapes and values. For severity estimation, as the interest is to know whether the damage threshold force is passed, the maximum impact force reconstruction results for all the test cases (H1 – H6) are summarised in Table 4. 2. It can be seen that the estimated maximum force using the single transfer function obtained from case H1 has good accuracy when compared to the measured force for all cases except H3 (increased temperature).

Table 4. 2 Maximum force reconstruction for cases H1 - H6 using deconvolution

case ID	impactor	Case	Number of impacts	Max. force reconstruction error from H1 TF (%)
H1	hammer	steel, reference	35 x 4	-2.5 ± 2.22
H2	hammer	steel, added mass	35 x 4	-8.3 ± 2.73
H3a	hammer	steel, increased temp. (no comp.)	35 x 4	-15.01 ± 4.1
H3b	hammer	steel, increased temp. (w. comp.)	35 x 4	-3.06 ± 4.68
H4	hammer	plastic	35 x 4	5.92 ± 2.09
H5	hammer	hard rubber	35 x 4	3.75 ± 5.87
H6	hammer	soft rubber	35 x 4	-2.45 ± 6.67

It is known from previous studies that increased temperature decreases the amplitude of the recorded response [16,17,46]. In Table 4. 2 (case H3a) and Figure 4. 4 it can be seen that this temperature effect causes the maximum force to be underestimated when not compensated. Using the impactor (Figure 4. 1a), controlled impacts were generated at different temperatures to see the pattern of

amplitude reduction. The results can be seen in Figure 4. 5 where it shows a linear trend of reduction [46] from the reference room temperature (24⁰C). Using this linear trend, the correction factor (Figure 4. 5) was obtained to compensate for the reduction in amplitude which improved the maximum impact force estimation accuracy (case H3b, Table 4. 2 and Figure 4. 6) to similar levels as other cases.

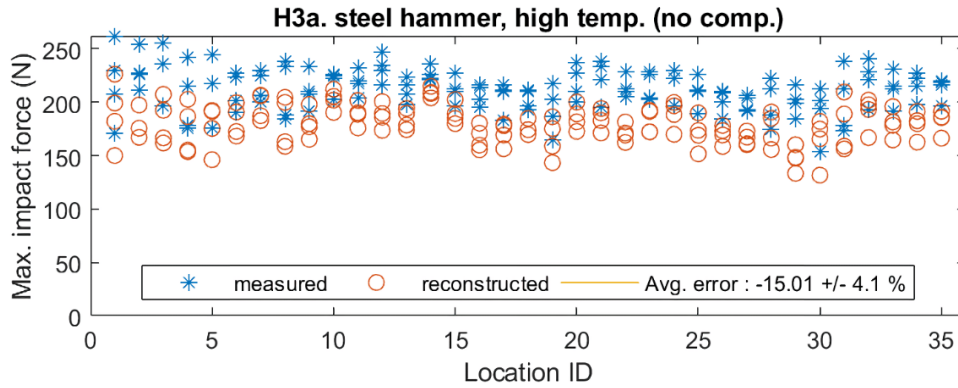


Figure 4. 4 Maximum impact force estimation using deconvolution for increased temperature no amplitude compensation (H3a)

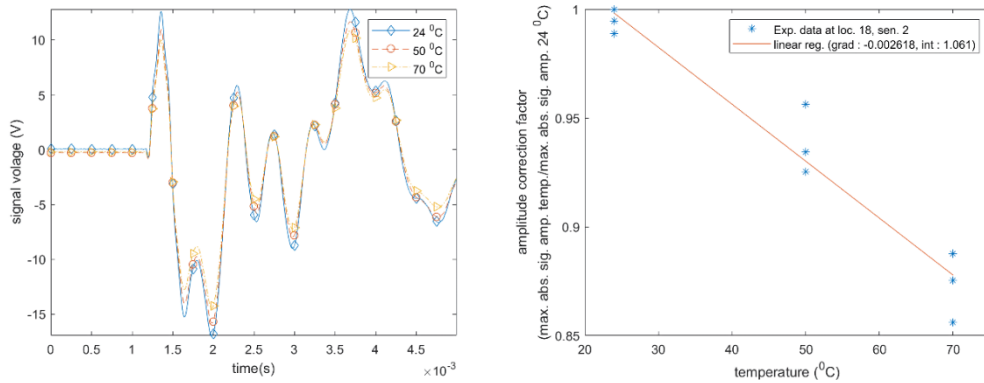


Figure 4. 5 Reduction of signal maximum absolute amplitude with temperature

From these results it is concluded that for the simulated environmental and operational cases tested the deconvolution method can give a robust and accurate reconstruction of the impact force profile using transfer functions obtained from a single impact case (H1). However, the data storage (transfer functions of all locations) and computational requirements (Fourier transforms, etc.) may not necessarily be suited for the capability of current data acquisition systems [29,38,114], especially if applied to the entire structure. As the concern is mostly the maximum impact force for severity assessment and not necessarily the whole

impact force profile, most of the processing effort in deconvolution is not required. Thus, in the next section a simple yet robust novel method is proposed for estimating the maximum impact force under simulated environmental and operational conditions.

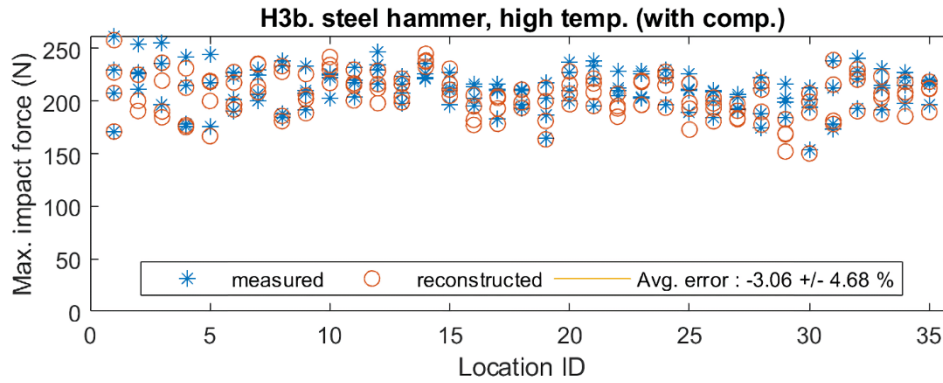


Figure 4. 6 Maximum impact force estimation using deconvolution for increased temperature with amplitude compensation (H3b)

4.4 Novel gradient method for maximum impact force estimation

Previous studies [10,12,35] have found simple linear relationships between impact severity (energy or force) and impact signal features (energy, amplitude). The work here builds on these findings to establish if there is a consistent relation between the impact force and signal features which can be used to accurately estimate the maximum impact force under the simulated environmental and operational conditions. To accomplish this, the impacts collected on the non-damaging impact setup (as shown in Table 4. 1) were used.

It was established in Section 4.3.1 that the deconvolution method is able to give an accurate reconstruction of the maximum impact force regardless of the original impact force profile. Thus, the obtained transfer functions were used to estimate the impact force from the impactor cases (case I1 – I6, Table 4. 1) as the impactor does not have a direct force measurement system. Along with the hammer impacts (H1-H6), this adds a comparison between 2 types of impact actuation sources (manually actuated and free drop). It also gives a data set of controlled parametric variations (angle, energy, etc.) not possible with the hammer.

Figure 4. 7 shows the relation between the maximum absolute (MA) signal amplitude and maximum impact force for the specific specimen configuration (geometry, material and boundary condition) at a single location for all impact cases (H1 – H6 and I1 – I6). It can be seen that there is indeed a consistent linear relationship between the MA signal amplitude and the maximum impact force for most cases (except H5, H6 and I6). Using this relationship, it is possible to estimate the maximum impact force from the MA signal amplitude provided the gradient of this relationship is known, as shown in equation (4. 3) :

$$F_{max}(x,y) = G(x,y)A, \quad (4. 3)$$

where F_{max} is the maximum impact force, A is the MA signal amplitude and G is the maximum impact force gradient. It is known that the gradient changes with location (x,y) [12] and thus it must be obtained for all locations. Similar to the transfer functions for deconvolution, the gradient may be obtained using a known pair of signal and impact force measurements.

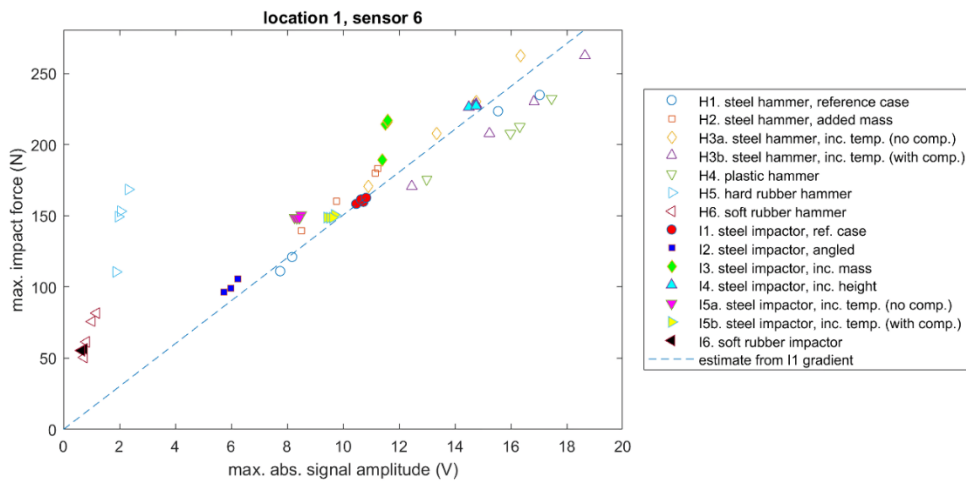


Figure 4. 7 Linear relationship between maximum absolute (MA) signal amplitude and maximum impact force for impacts tested on the non-damaging impact setup

From Figure 4. 7, it can be seen that for impact cases using the rubber (soft and hard) impact tip (H5, H6 and I6), the gradient of the linear relationship is significantly different to that of the other cases with stiffer impact tips (steel and plastic). Other studies have found a similar phenomenon when correlating signal

energy and impact energy of differing stiffness impactors [35]. The difference in gradient deters us from being able to estimate the maximum impact force accurately for a large range of impactor stiffness (steel ~ 200 GPa, plastic ~ 10 GPa, silicone rubber ~ 0.1 GPa, [93]). For aircraft structures, impacts may come from various sources such as tool drop (steel), hail (stiffness similar to plastic) and ground service equipment (with rubber bumpers) [2]. Thus, it may be necessary to find an alternative signal feature other than the MA signal amplitude that is consistent for a wider range of impactor stiffness.

4.4.1 Gradient method for impact force estimation in different stiffness impactors

The response of a structure to transient loading (impact, etc.) can be expressed as the components of the response of a nonhomogeneous differential damped mass spring system which consists of the particular and general response [2,115] as shown in equation (4. 4) :

$$y_{t=i} = yp(f, \omega f, p, s_{t=i-1}) + yg(\omega n, p, s_{t=i-1}) \quad (4. 4)$$

$$s = y, \dot{y}, \ddot{y} \quad p = k, m, c$$

where y is the total structural response, yp is the particular response and yg is the general response. The particular response is the transient response of the structure (with mass m , stiffness k , and damping c , dependant on the structures geometry, material and boundary conditions) towards the particular transient load (f) along its bandwidth (ωf). The general response is the response of the system that is mostly independent of the transient load (only implicitly affected through the change of state, s , due to the particular response) and only occurs at the structure specific (based on configuration) natural frequencies (ωn). The components of the particular and general responses that are near to the structures natural frequencies are scaled up due to resonance [116]. In a Lamb wave signal from impact, the particular response is most notable when the impact load is applied causing the structure to undergo forced vibration (Figure 4. 8). When there is no more load,

the structure freely vibrates at its natural frequencies (the general response) until the kinetic energy is dissipated through damping [2].

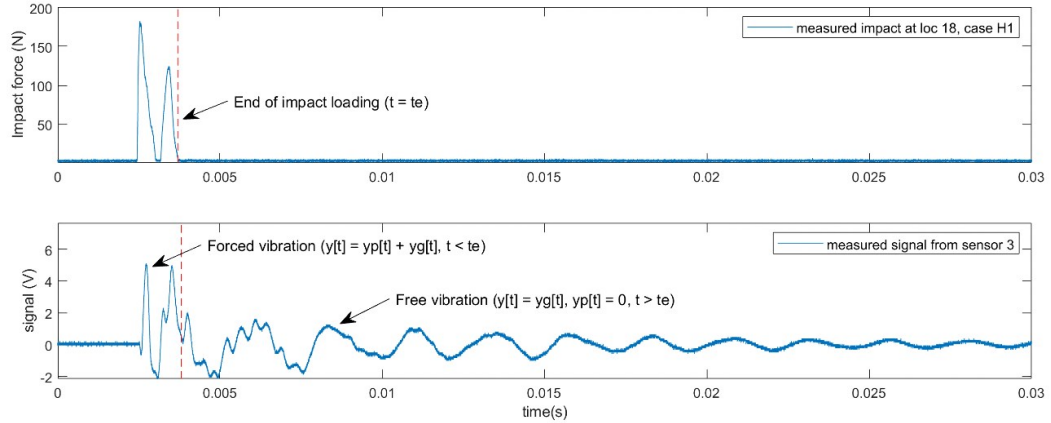


Figure 4. 8 Forced and free vibration phases in a Lamb wave signal caused by impact

For second order systems such as simple vibrating structures, it is known that the particular response (yp) amplitude is a linear function of the force (f) magnitude independent from the force profile [2]. Similarly, in Figure 4. 7 it is found that the recorded MA signal (y) amplitude scales linearly with the impact force (f) magnitude for all cases but show a difference in gradient (G) between stiffer and less stiff impactors. If the particular response (yp) amplitude has a consistent linear relation to the impact force (f) magnitude irrespective of the input force profile, then the variable that may cause a change in gradient (G) is the general response (yg) which interacts implicitly with the particular response (yp).

It is known that impacts generate a wideband impact force profile (and subsequent impact signal), with a lower bound of 0 Hz and an upper bound dependent on the impactor stiffness [50]. As can be seen in Figure 4. 3, stiffer impactors trigger higher frequency responses (small peaks and short contact time) compared to less stiff impactors (smoother response with longer contact) [50]. The particular response of the structure (yp) will follow the bandwidth of the impact force profile (ωf) whilst the general response (yg) will only occur at the frequency components that match the natural frequencies (ωn) of the structure. For stiff impacts, as the bandwidth of the impact forces (ωf) are comparable, the generated general response (yg) profile will also have similar bandwidths. As such,

it will interact with the particular response (y_p) in a similar way, causing comparable gradients (G) between the amplitude of the response (y) and the magnitude of the impact force (f). However, for less stiff impactors, the impact force profile (f) does not trigger the higher natural frequency modes (only the 1st mode as the main flexural mode) and thus the bandwidth of the general response (y_g) differs from stiffer impactors. This causes a difference in the reaction between the particular (y_p) and general (y_g) response as compared to stiffer impactors which ultimately leads to differing gradients (G). This is why the problem of different impactor stiffnesses is not encountered in deconvolution (as seen in Section 4.3.1) as the transfer function captures the complex interaction between all the frequency components.

Thus, in order to have a consistent gradient between differing stiffness impactors, the general response (y_g) needs to be removed from the total response (y). A crude but simple way of accomplishing this is by filtering out the natural frequencies (ω_n) as it is known that the general response (y_g) only occurs at these frequency bands. However, this will also filter out components of the particular response (y_p) at the same frequency bands. As will be shown later on in Section 4.4.2, this turns out to be an acceptable loss in terms of accuracy of results.

To identify the natural frequency bands of the flat plate used in the non-damaging impact setup, the transfer functions obtained previously in Section 4.3.1 were used. Figure 4. 9 shows the average magnitude for the transfer functions (TF) for all sensors due to impacts at all 35 locations of the flat plate (Figure 4. 2). The natural frequency bands were identified as the peaks in the transfer function signifying resonance [116]. Using these frequency bands, the signal was filtered (using IIR Butterworth bandpass filters) from the steel and soft rubber impact hammer cases (H1 and H6) as a test case (shown in Figure 4. 10). The 1st natural frequency band (filtering starts from the 2nd band onwards) was not filtered out as this was the main flexural mode for all impacts regardless of stiffness.

Figure 4. 10 shows that as more frequency modes are filtered, the MA signal amplitude of the steel hammer signal (H1) decreases approaching the value of the soft rubber hammer signal (H6). This happens as the filtering removes the high frequency components only present in the stiffer impactor signal (H1). The result

is that the force gradient (G) of the steel hammer impact (H1) becomes much closer to that of the soft rubber hammer impact (H6), thus removing the differences in gradient (Figure 4. 10). However, as mentioned previously the method of filtering also removes components of the desired particular response (yp) which is why the gradient (G) values do not match up completely. By applying the filtering to the impacts shown in Figure 4. 7, a new linear relationship between the filtered MA signal amplitude and the maximum impact force is obtained, which is now consistent for all cases as shown in Figure 4. 11. Thus, by substituting the maximum absolute (MA) signal amplitude in equation (4. 3) with the filtered maximum absolute (FMA) signal amplitude it is possible to estimate the maximum impact force from impacts of all cases tested (Table 4. 1).

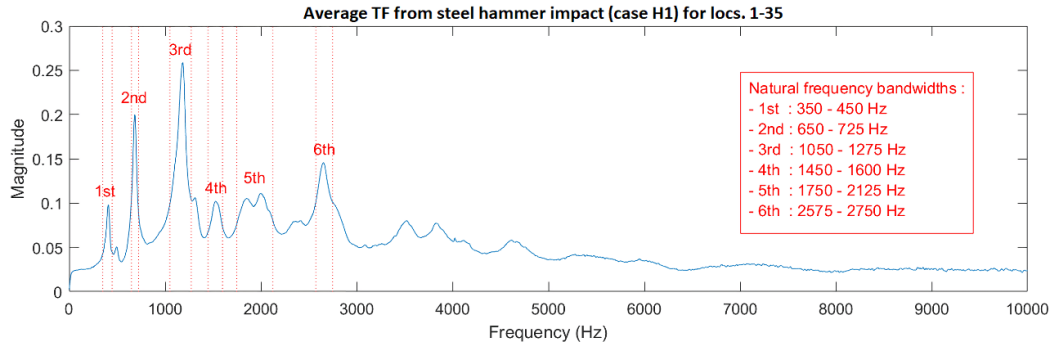


Figure 4. 9 Average transfer function (TF) magnitude from case H1 for all sensors and impact locations of the non-damaging impact plate, showing natural frequency bands

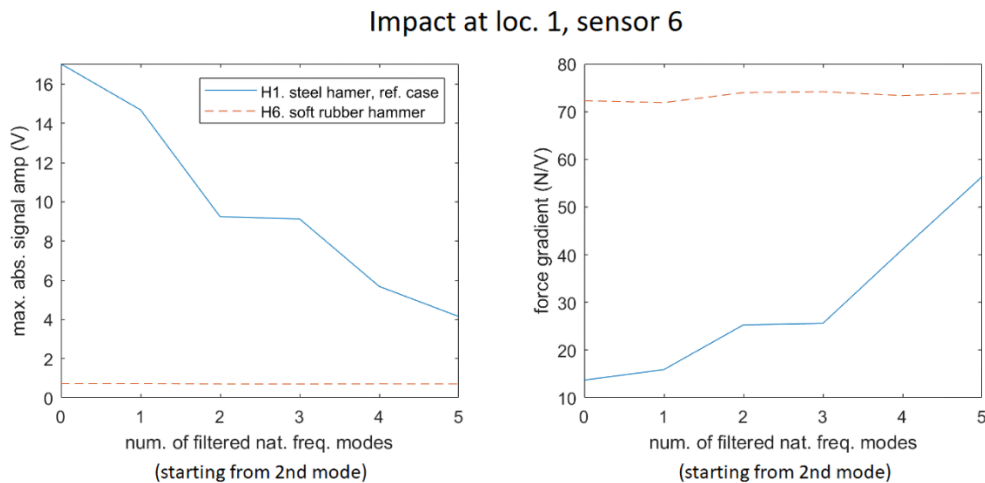


Figure 4. 10 Change in signal amplitude and force gradient for stiff (case H1) and non stiff (cse H6) impactors due to filtering of natural frequency components of the signal

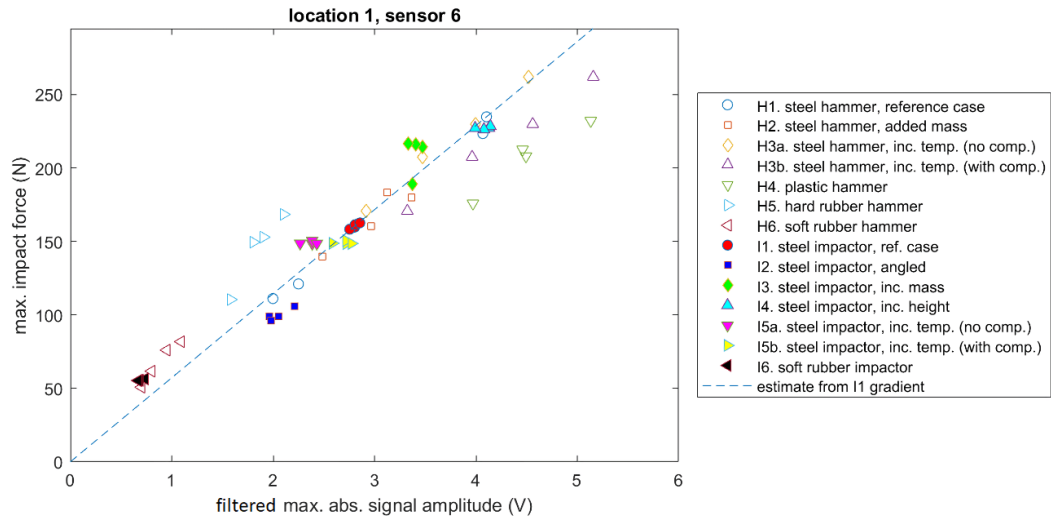


Figure 4. 11 Linear relationship between filtered maximum absolute (FMA) signal amplitude and maximum impact force for impacts tested on the Inon-damaging impact setup

4.4.2 Gradient method for impact force estimation in simulated environmental and operational conditions

Here the accuracy of the gradient method in estimating the maximum impact force under the environmental and operational conditions simulated in the impact cases taken from the non-damaging impact setup (H1 – H6, I1 – I6, Table 4. 1) is investigated. The first repetition of the reference impactor case (I1) was used as a reference to obtain the maximum impact force, MA signal amplitude and FMA signal amplitude for all impact locations (Figure 4. 1). From these values the reference impact force gradient for MA and FMA signal amplitudes were obtained and used to estimate the maximum impact force of all other cases collected (H1 – H6, I1 – I6). As there were 6 sensors on the flat plate, an estimate was generated from each sensor signal which is then averaged to obtain a robust final estimation. For impact cases with increased temperature (H3a, H3b, I5a and I5b), the correction factor obtained in Section 4.3.1 was used on the signal before extracting the MA and FMA signal amplitude values.

Table 4. 3 shows the results of the maximum impact force estimation using both the MA and FMA signal amplitude accompanied by a comparison with the deconvolution method established in Section 4.3. It can be seen that the deconvolution method in general has a higher accuracy compared to both gradient methods (MA and FMA) even though the difference is not too large. As

postulated in Section 4.4.1, the gradient method using the MA signal amplitude is able to give an accurate estimate of the maximum impact force for all cases except for the non-stiff impactors (H4 – H6, I6; Table 4. 3, Figure 4. 12) where it is severely underestimated. With the FMA signal amplitude, the gradient method is able to accurately estimate the maximum impact force of non-stiff impactors (Table 4. 3, Figure 4. 13) as well as retaining a similar level of accuracy to the MA signal amplitude for other cases. The removal of components of the particular response due to filtering mentioned in Section 4.4.1 does not seem to significantly reduce the accuracy of estimation. This is likely due to the final estimation being an average from all sensors thus being more robust. It is concluded that the gradient method with the FMA signal amplitude is able to accurately and robustly estimate the maximum impact force for impact cases under the simulated environmental and operational conditions using gradient values obtained from a single impact case.

Table 4. 3 Maximum impact force estimation results using the gradient method

case ID	impactor	case	gradient method error (%)		deconvolution error (%)
			MA	FMA	
H1	hammer	steel, reference	-1.47 ± 7.24	-7.3 ± 8.08	-2.5 ± 2.22
H2	hammer	steel, added mass	-7.02 ± 6.57	-1.27 ± 6.97	-8.3 ± 2.73
H3a	hammer	steel, increased temp. (no comp.)	-6.86 ± 6.25	-18.31 ± 7.34	-15.01 ± 4.1
H3b	hammer	steel, increased temp. (w. comp.)	6.24 ± 7.13	-6.82 ± 8.38	-3.06 ± 4.68
H4	hammer	plastic	9.09 ± 6.76	-2.72 ± 9.07	5.92 ± 2.09
H5	hammer	hard rubber	-45.31 ± 4.63	4.13 ± 10.12	3.75 ± 5.87
H6	hammer	soft rubber	-52.44 ± 5.05	-4.56 ± 9.98	-2.45 ± 6.67
I1	impactor	steel, reference	0.14 ± 1.94	-0.4 ± 2.8	
I2	impactor	steel, angled	-3.79 ± 5.81	0.95 ± 6.61	
I3	impactor	steel, added mass	-6.35 ± 7.89	9.91 ± 8.09	
I4	impactor	steel, increased height	0.93 ± 4.89	-1.65 ± 4.59	
I5a	impactor	steel, increased temp. (no comp.)	-8.29 ± 5.48	-7.24 ± 5.64	
I5b	impactor	steel, increased temp. (w. comp.)	4.61 ± 6.26	5.8 ± 6.43	
I6	impactor	rubber	-55.86 ± 5.41	-3.42 ± 9.41	

Compared to the deconvolution method, the data storage requirement of the gradient method is much lower as only a single gradient value (as opposed to a

transfer function) needs to be stored for each location. The process of filtering out natural frequencies may potentially be conducted using analog circuitry [29,38,114] once the frequency bands have been identified. Moreover, the calculation involved in the estimation of the maximum impact force is much simpler (only multiplication) compared to the deconvolution method which involves large matrix operations and Fourier transforms. Thus, it can be concluded that the gradient method is more feasible to integrate with current DAQ systems.

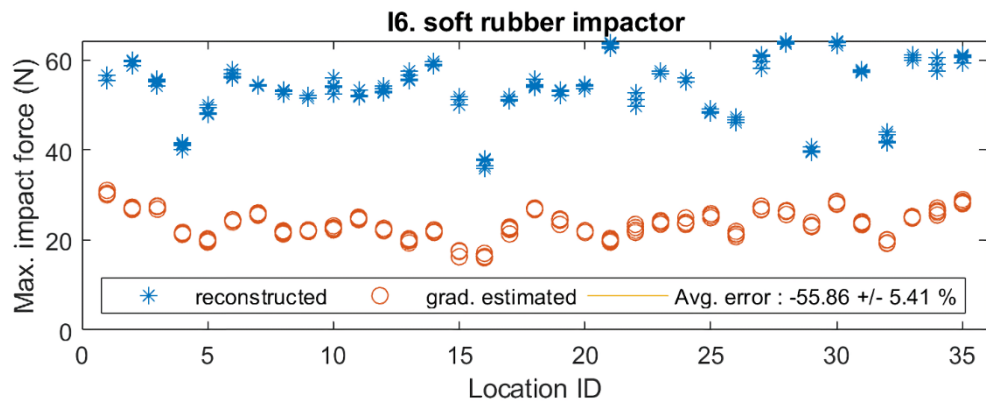


Figure 4. 12 Maximum impact force estimation using gradient method with MA signal amplitude for the soft rubber impactor (case I6)

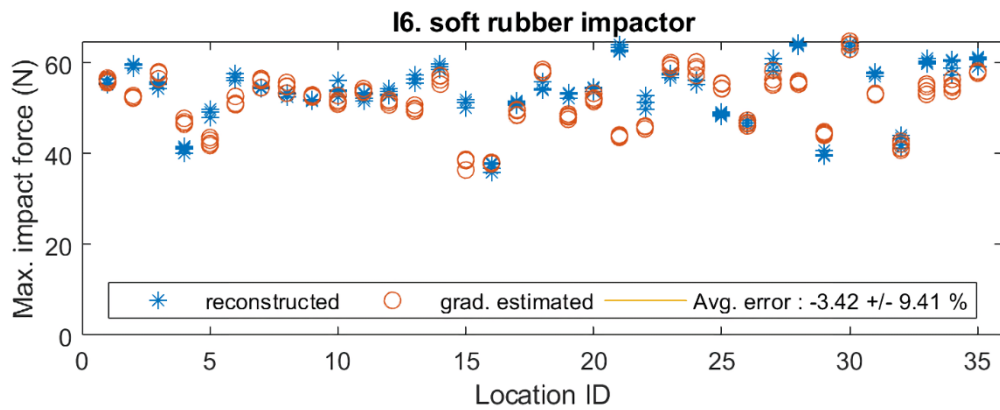


Figure 4. 13 Maximum impact force estimation using gradient method with FMA signal amplitude for the soft rubber impactor (case I6)

4.5 Effect of localisation and noise towards gradient method force estimation

As the characteristics used for impact force estimation (transfer functions or force gradients) are location dependent, the monitoring of impact force with these

methods is thus coupled and preceded by localisation of the impact event. Many methods have been developed for such purpose including data driven methods which use signal features such as time of arrival and amplitude in a reference database (for pattern matching or neural networks) as used here for impact force estimation [16,17].

The maximum impact force estimation results from the deconvolution and gradient methods in Sections 4.3 and 4.4 were based on the condition where the exact impact location is known and it coincides with the location where the reference characteristics (gradient or transfer function) was measured. In reality, most cases will not follow those conditions because of 2 reasons : (1) it is not possible to feasibly measure the reference characteristics at all possible locations for a continuous structure and (2) all impact localisation methods have some degree of error such that the reference characteristic used may not be entirely correct. Additionally, there may be noise in the form of vibrations [16,17] which may interfere with the signal amplitude. Here robustness of the proposed gradient method is tested towards these effects using impacts collected on the non-damaging setup.

To address the issue of reference characteristic collection on all locations, most studies using reference databases for either localisation or impact force estimation commonly use some form of interpolation between sampled reference locations to get a continuous map of values [14,17,111]. This is based on the assumption that the characteristics of a structure should change in a relatively gradual manner and can be captured by interpolation provided there are enough sampled reference points. Here the gradient values collected in Section 4.4.2 from the reference impactor case (I1) for the FMA signal amplitude were interpolated using cubic interpolation by a factor of 2 between the original impact locations (Figure 4. 1).

To test the accuracy of the interpolated gradients, they were used to estimate the maximum impact force of the steel hammer impacts on intermediate locations (case H1a, Table 4. 1) between the original reference impact locations (Figure 4. 1). Figure 4. 14 shows the results where it can be seen that the interpolated

gradient values are able to give an accurate estimation of maximum impact force estimation on locations outside the original reference locations.

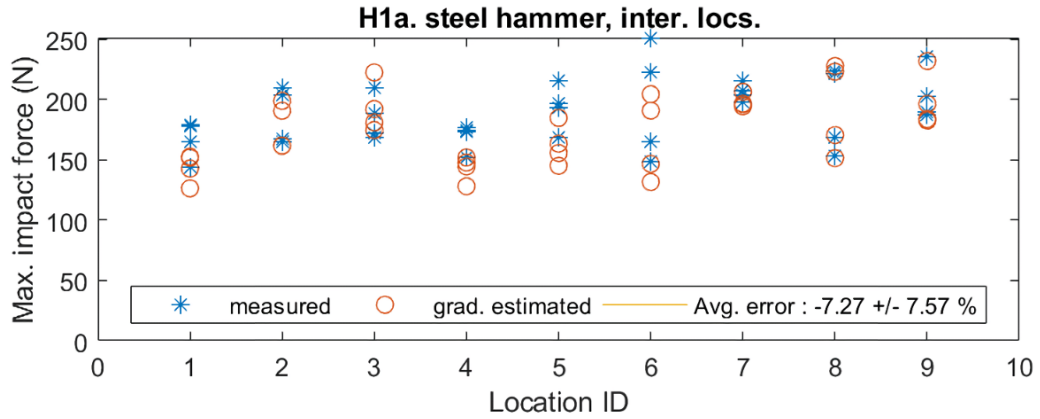


Figure 4. 14 Maximum impact force estimation using gradient method with FMA signal amplitude for the steel hammer at intermediate locations (case H1a)

To test the robustness of the gradient method towards localisation inaccuracy, random localisation errors were simulated (to maintain focus on impact force estimation methods) with relatively severe magnitude (-20 to 20 mm range, based on results from previous chapters on the same specimen [16,17]) on the x and y coordinates of the reference impactor case (I1a) as shown in Figure 4. 15. Using the interpolated gradients from before, the maximum impact force was estimated for the impacts of case I1 but with these new locations. Figure 4. 16 shows the results, where it can be seen that the gradient method is able to retain a good level of accuracy despite significant localisation inaccuracy.

With regards to noise, here the robustness of the gradient method was tested by adding random noise with a magnitude range of -20 to 20% of signal amplitude to the extracted FMA amplitude values of the reference impactor case (I1b) to simulate vibration noise [16,17]. The gradient values were then used with the new FMA amplitude to estimate the maximum impact force of case I1. Figure 4. 17 shows the results, where it can be seen that despite a quite severe noise level, the gradient method still retains a good level of accuracy for maximum impact force estimation.

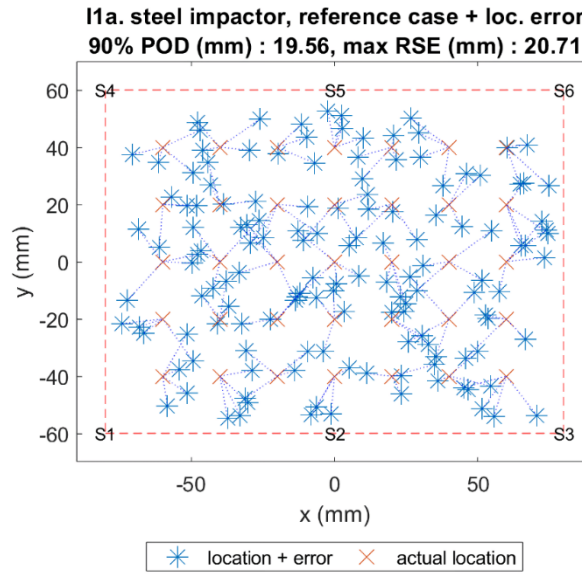


Figure 4. 15 Random localisation errors simulated on the reference impactor case (I1)

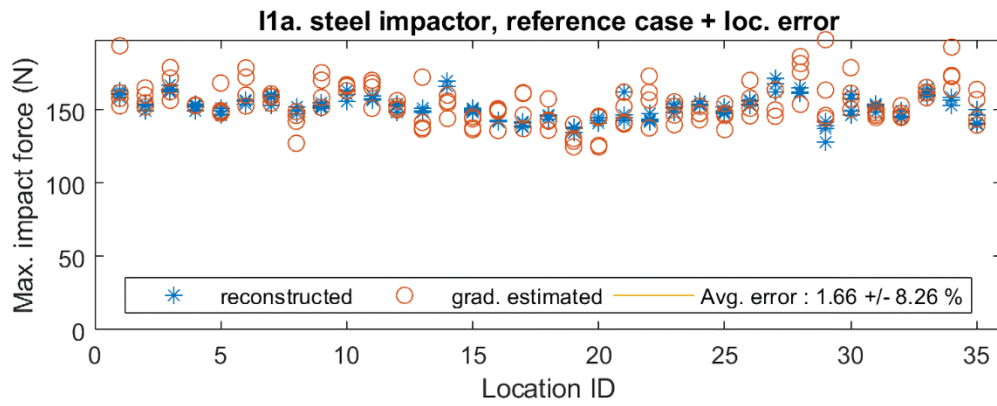


Figure 4. 16 Maximum impact force estimation using gradient method with FMA signal amplitude for the reference impactor case with simulated localisation errors (case I1a)

Table 4. 4 summarizes the results of testing the robustness of the gradient method towards localisation and noise using gradient values obtained from case I1. It can be concluded that the gradient method is able to retain a good level of accuracy despite relatively severe levels of noise and localisation error. In terms of localisation, this suggests that the gradient values are not so sensitive towards change in location for the specimen configuration used. For the addition of noise, it is postulated that the accuracy is also retained at a good level because the maximum impact force estimations were obtained from the average of all the sensors on the plate. If the noise is random (as it is here), then by averaging the

estimate of multiple sensors it is effectively averaging the random errors of estimation at each sensor caused by the given noise.

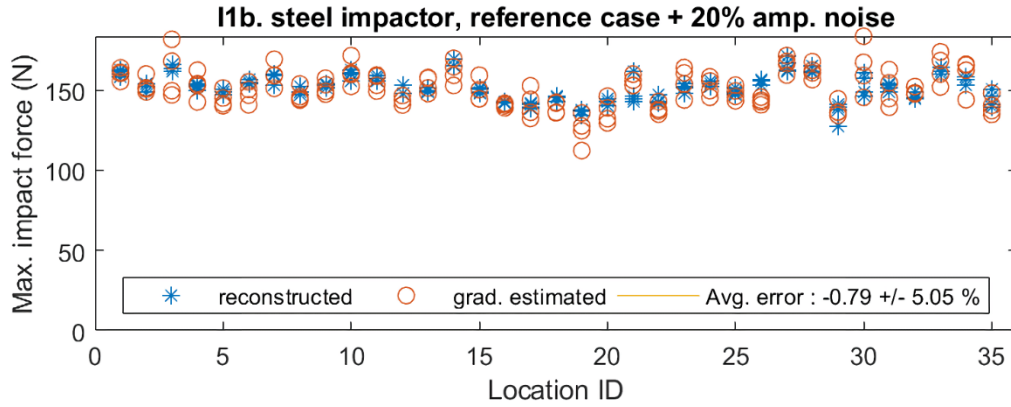


Figure 4. 17 Maximum impact force estimation using gradient method with FMA signal amplitude for the reference impactor case with simulated amplitude noise (case I1b)

Table 4. 4 Summary gradient method testing towards localisation and noise effects

case ID	Impactor	Case	Gradient method (FMA amplitude) error (%)
H1a	hammer	Steel reference, intermediate locs.	-7.27 ± 7.57
I1	impactor	steel, reference	-0.4 ± 2.8
I1a	impactor	steel, reference + loc. Error	1.66 ± 8.26
I1b	impactor	steel, reference + 20% amp. Noise	-0.79 ± 5.05

4.6 Gradient method for damage assessment

In previous sections, the accuracy of the gradient method under various impact cases and scenarios (Sections 4.4 and 4.5) was investigated. However, all of these impacts are low energy non-damaging impacts with impact force levels ranging around 50 to 250 N. As the interest is to use this method for damage assessment, it is necessary to test if the linear relationship that forms the base of the gradient method still holds for much larger impact forces that can cause damage and whether effects such as large nonlinear deformation have any effect [36]. Thus, here the impact tests from the high energy impact setup (1 J, 7 J, 9 J and 11 J) were used to investigate the relationship between amplitude and impact force at a higher range of forces.

Figure 4. 18 shows the recorded impact force profiles, subsequent signals and the ultrasound scan of the impact area indicating whether damage had formed. For all cases except the 1 J impact, impact damage is produced in the test specimens. From previous studies [2,63,75], it is known that the threshold force to produce damage is consistent and is characterised by the first discontinuity in the impact force profile as stiffness is lost during damage formation. In Figure 4. 18 it can be seen for these tests that the damage threshold force (characterised by a “dip” in the impact force profile) value for the plate specimens is consistently around 2 kN regardless of impact energy.

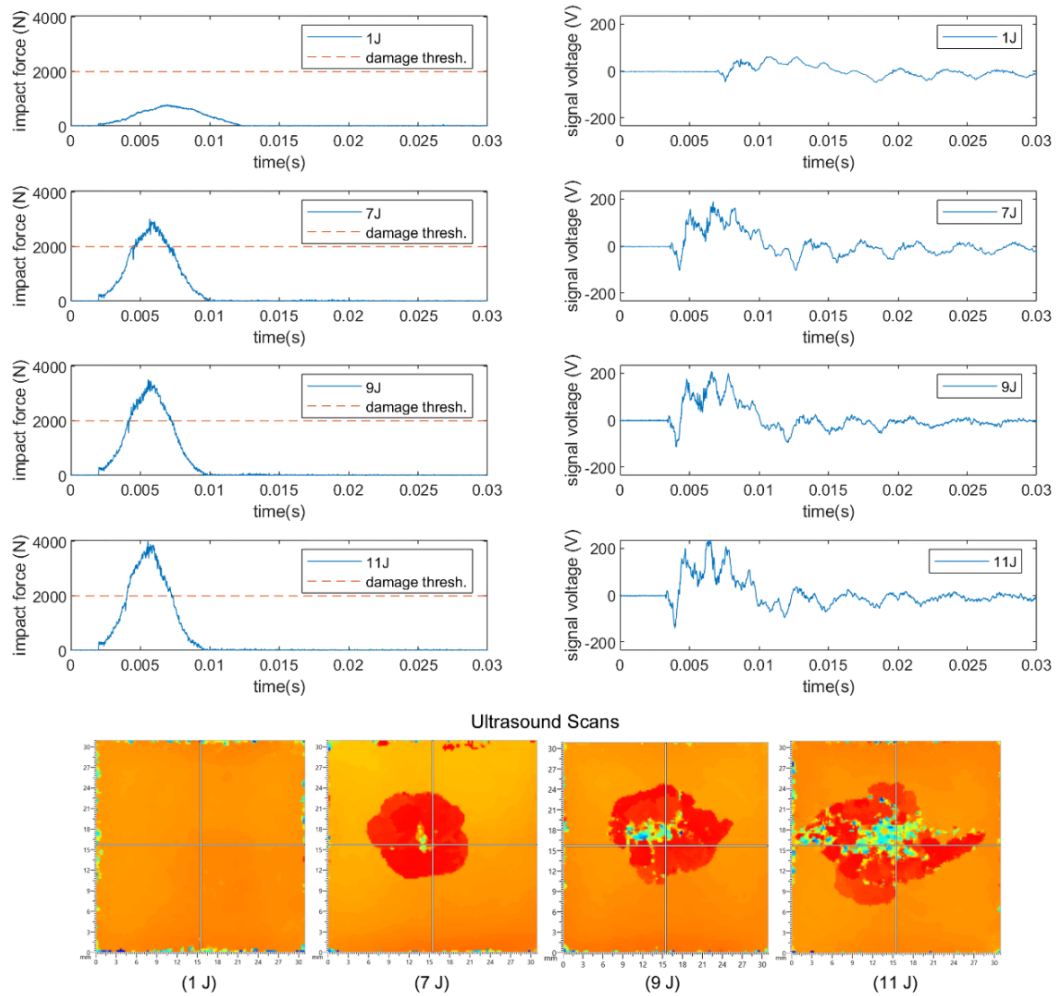


Figure 4. 18 Impact force profile, impact signal and ultrasound scan results for impact test on the high energy impact setup

Plotting the MA signal amplitude vs the maximum impact force (Figure 4.19), it can be seen that there is indeed a linear relationship as seen for the impacts with the on-damaging impact setup. Thus, it can be concluded that the gradient method is valid for impact forces at least up to the damage threshold (prior to damage formation) and thus can be used for reliable severity assessment. For forces above the damage threshold, the consistency of the linear relation found here may be affected by the relatively small damage size (<30mm radius for 200 x 200 mm plate), although larger damage may result in more than BVID and thus can be found without the need of a monitoring system. Additionally, as the boundary conditions differ between the damaging and non-damaging impact setups (2 side vs 4 side clamp), it can be said that the boundary conditions tested do not have an effect on the linear relation used in the gradient method and only changes the value of the gradient.

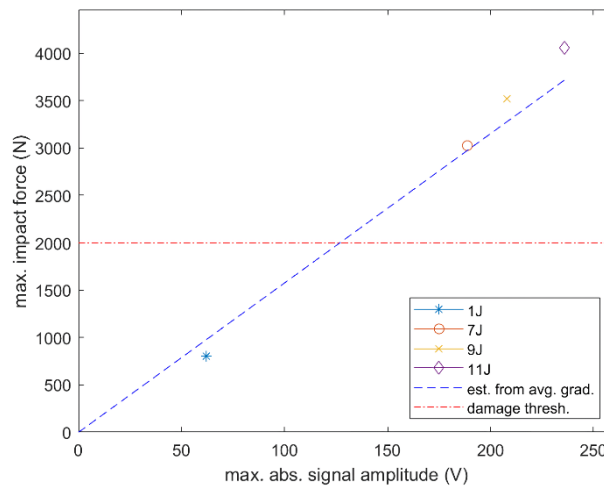


Figure 4. 19 Linear relationship between maximum absolute (MA) signal amplitude and maximum impact force for impact cases tested on the high energy impact setup

4.7 Impact monitoring of structures using the gradient method

With knowledge from previous sections, it is possible to conduct severity assessment in 2 ways provided the damage threshold force is known (through testing or modelling) or there is an estimate of the level of forces that should be given attention (usually in the kN range). First, the gradient method can be used to estimate the maximum force of an impact, after which the value is compared with the threshold to see if it is a critical impact which warrants structural inspection.

Alternatively, the linear relationship of the gradient method can be used in reverse to determine the threshold signal amplitude level (MA or FMA, depending on range of impactor stiffnesses expected) of critical impacts. This further reduces the processing requirements as severity assessment is then done by simply comparing the signal amplitude value to the threshold amplitude.

Similar to any data driven method, the gradient method requires initial data to be collected on the structure that is to be monitored. By having a robust method towards the various possibilities of environmental and operational conditions, it is possible to minimise the required data into that of a single impact case. However, as the characteristics of a structure (transfer function and impact force gradients) may differ when the configuration changes (boundary condition, geometry, material), there is currently still the need to collect a new data set for each structure type monitored. Thus, to further reduce initial data collection needs and increase feasibility for complex structures (with multiple substructures), future development should be aimed at either reducing the amount of data required per structure or understanding the change in characteristics as the structural configuration changes. Additionally, the effect of pre-existing damage on the structural properties (stiffness, boundary condition, etc.) may have significant effect on the transfer functions or gradient values (although it may need to be severe enough that it surpasses BVID in the end). Thus, quantification of the effect of damage on the structural characteristics is also a necessary next step.

4.8 Conclusion

In this chapter two new methods for maximum impact force estimation have been explored, deconvolution and novel gradient method, for the purpose of reliable severity assessment in composite aircraft structures under simulated environmental and operational conditions. It was shown that both methods allow accurate and robust estimation of the maximum impact force from various cases of impacts using minimum initial data (transfer function or gradient) from a single impact case. From further testing it was found that the gradient method is robust towards the effects of impact localisation errors and noise. The gradient method also has much less computational and storage requirements and is thus more

feasible to integrate with current DAQ systems being developed for structural health monitoring. Thus, it is concluded that the proposed gradient method is feasible for impact force monitoring and severity assessment in composite aircraft structures in real life conditions.

Chapter 5

Uncertainty Quantification for Impact Location and Force Estimation in Composite Structures⁴

The work in Chapter 3 : **Part 1**, Chapter 3 : **Part 2** and Chapter 4 has produced novel data driven methods for impact location and severity estimation that are robust towards simulated environmental and operational conditions. However, providing a deterministic estimate alone does not always provide enough information for the operator to assess the structure and make appropriate maintenance decisions as there may be errors in the estimate. To address this, in this chapter a novel uncertainty quantification method is developed for the data driven algorithms developed in previous chapters.

5.1 Introduction

In thin structures (as is usually found in composite airframe), impact events generate Lamb waves which propagate across the structure and can be recorded using strain sensors or accelerometers [1,16,17,81,117]. Features of these recorded Lamb wave signals (such as Time of Arrival and amplitude) contain information that can be used to estimate the location [1,13,16–18,43,54,118] and severity of impacts [8,55,57,117] and many methods have been developed for this purpose. However, these features are subject to variation arising from measurement uncertainty [13,54,55,57] as well as changes in environmental and operational conditions [8,16,17]. Coupled with the inherent limit of accuracy in impact location and force estimation algorithms (as no algorithm is ever exact) [8,16–18,34,57,117], results in uncertainty in the final estimations.

So far, most methods developed for impact location and severity estimation are deterministic [1,8,8,14,16,22,34,36,43]. This poses a problem for operators, as

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an estimate with an unknown degree of uncertainty is not reliable information for assessing the condition of a structure or locating damage that needs to be repaired. Thus, it is necessary to develop impact location and severity estimation algorithms with quantified uncertainty [13,54,57,117]. For this purpose, uncertainty estimates must be reliable (e.g. wide enough) such that the actual value reliably falls within the predicted range. On the other hand, the predicted range must be as narrow as possible to not be vague and give enough certainty for assessing the impact location and severity.

For impact location estimation, the most basic form of uncertainty quantification can be seen in imaging methods [42,64,119]. These methods generate contour maps that highlight regions with the highest likelihood of the impact to be located. Other methods involve strategies for multiple sampling (e.g. Monte Carlo simulations) to approximate the distribution of uncertainty within measurements of signal features and estimation algorithms [13,57,117,120]. Morse, et al. [18] trained multiple localisation neural networks on the same data set to capture the uncertainty of neural network estimates. This is then followed by the use of Kalman filters or Bayesian updating to combine the estimates of these neural networks and form the final uncertainty distribution of the impact location coordinates. Niri, et al. [54] and Sarego, et al. [13] captured measurement uncertainties of impact localisation features which were then propagated through localisation algorithms (via Monte Carlo simulations or Kalman filters) to obtain multiple location estimations that form the final uncertainty distribution of the estimated impact location coordinates.

Similarly, for impact severity estimation previous studies have propagated measurement uncertainties through impact force estimation algorithms (e.g. with Monte Carlo simulations) [55,120] or iterative sampling to generate multiple estimations which are combined using Bayesian updating [57,117]. These studies, however, have focused on reconstruction of the complete impact force history [55,57,117,120] which is not completely necessary for impact damage monitoring as the main parameter for force-based damage assessment is the maximum/peak impact force which is evaluated against the threshold force of damage formation [2,8].

The work in Chapter 3 : **Part 1**, Chapter 3 : **Part 2** and Chapter 4, has produced data-driven deterministic impact location [16,17,34] and maximum impact force [8] estimation algorithms that are accurate and robust for various simulated environmental and operational conditions (temperature, vibration noise, different impact configurations). Here an extension to these methods is proposed using a different approach to uncertainty quantification/estimation with a novel application of the kriging technique [121]. The proposed method takes advantage of the relationship between the data points [121] used in the reference database of the data-driven methods to quantify the uncertainty without the need for expensive Monte Carlo simulations.

In this chapter the robustness and accuracy of the estimates on simple (flat panel) and complex (stiffened panel) composite specimens under simulated environmental and operational conditions are assessed. For benchmarking, a comparison is made with the previously developed methods for impact location and force estimation with the proposed modified methods to assess the improvement in accuracy and robustness.

5.2 Experimental Setup

Experimental impact data was collected using a handheld instrumented impact hammer (PCB Piezotronics 086C03) that is able to record impact forces (Figure 5. 1a). The hammer has 2 tips, steel and plastic, to simulate impacts from different stiffness objects. The back of the hammer head also has space for a 100 gr weight attachment to generate impacts with differing weight.

Handheld impacts (with random angle and energy, ranging from 50 – 250 N maximum force) were imparted on 2 sensorised composite specimens, a simple flat (M21 T800s, [0/+45/-45/90/0/+45/-45/90]s layup) and a more complex stiffened (M21 T800s, [45/-45/0/0/90/0]s layup) panel, following the layout shown in Figure 5. 1 and Figure 5. 2. The flat panel has a silicone heating mat underneath and a temperature control system to simulate increased temperatures (Figure 5. 1). To simulate vibration noise, artificial 1 kHz random noise at 20% of the maximum recorded signal amplitude was generated through band filtering of

white noise [8,17] and superimposed to the impact signals of the reference case (Figure 5. 1c).

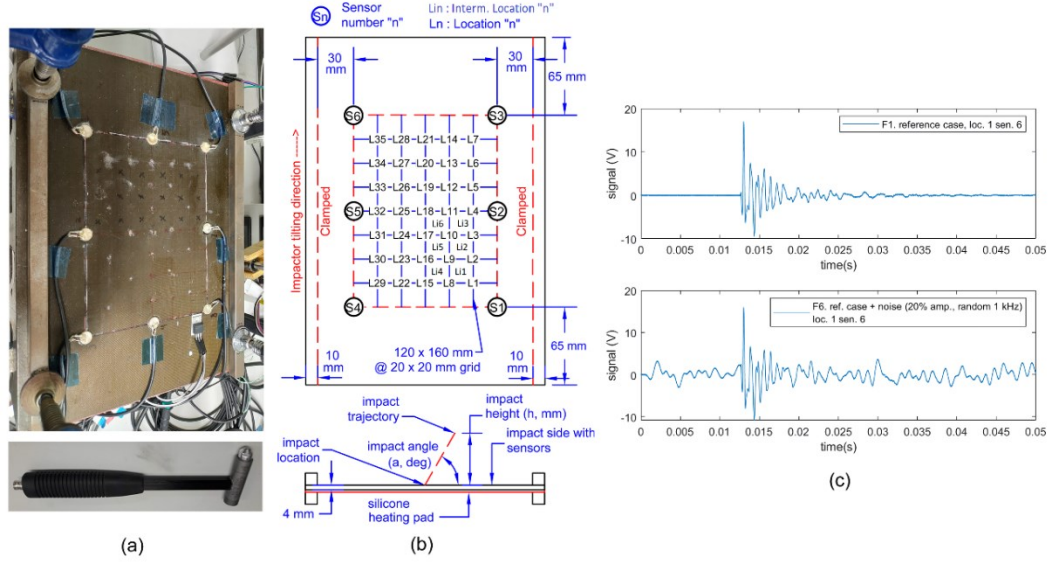


Figure 5. 1 Flat panel experimental impact setup : (a) flat panel and impact hammer, (b) layout of flat panel, and (c) example of impact signals

Impact induced Lamb wave signals were recorded via the attached PZT sensors on each plate (Figure 5. 1 and Figure 5. 2), which are connected to an 8 channel PXI-5105 oscilloscope through 10x attenuation probes. Signals were recorded at 2 MS/s with a length of 100000 sample points. As the force measurement from the impact hammer requires 1 oscilloscope channel, thus not all 8 PZT sensors are used on each panel. For the flat panel, 6 sensors were used as shown in Figure 5. 1, whilst only 5 sensors were used (Figure 5. 2) on the stiffened panel due to damaged sensors from previous testing campaigns. All data processing was done using MathWorks MATLAB.

In total, data from 6 impact cases (F1 – F6) representing parametric variations (reflecting simulated environmental and operational conditions) from a reference case (F1) were collected from the flat panel, whilst 1 case (S1) was collected from the stiffened panel as listed in Table 5. 1. For each case, impacts were conducted at each location shown in Figure 5. 1 and Figure 5. 2 with 4 repetitions each, resulting in the total shown in Table 5. 1. For the reference case of each panel (F1 and S1), 1 impact from each location (35 impacts) was used to build the reference

database [17] of each plate for the impact location and force estimation algorithms, whilst the rest of the impact data were use as test data.

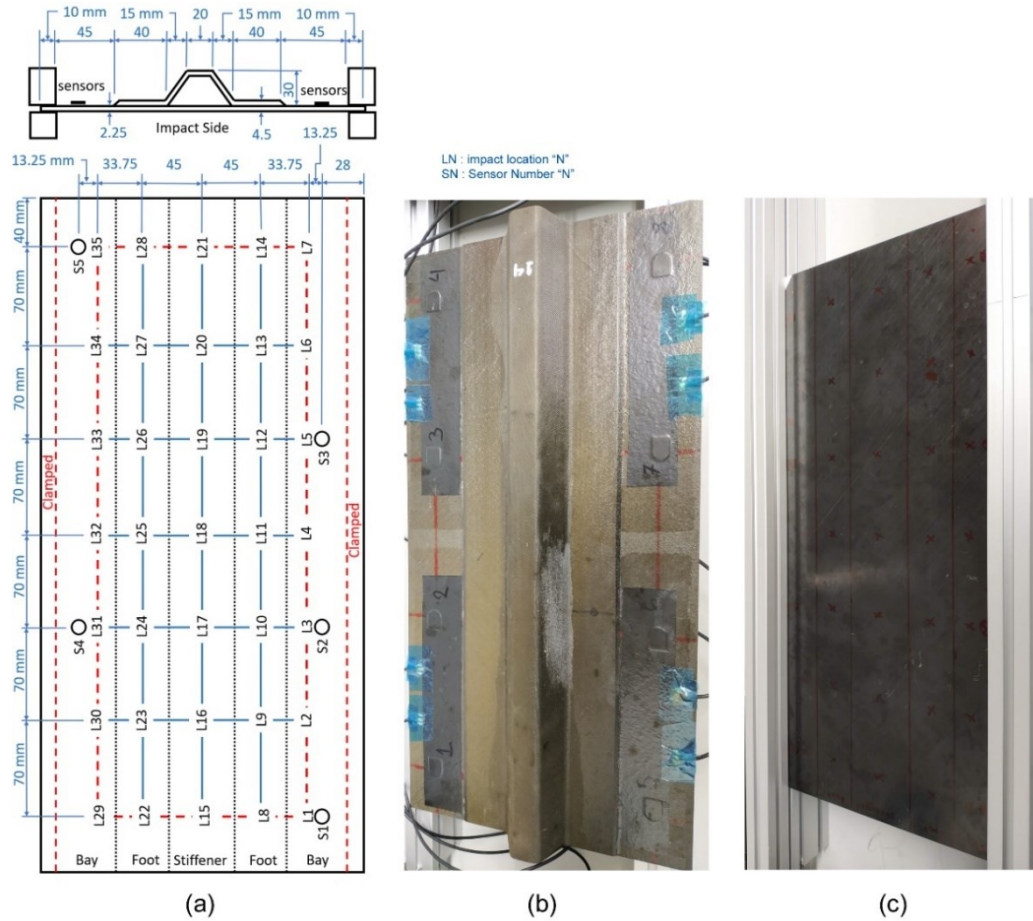


Figure 5. 2 Stiffened panel experimental impact setup : (a) layout, stiffened panel bottom where the sensors are located (b) and top side where the impacts are conducted (c)

Table 5. 1 Experimental impact cases collected on flat and stiffened panel

ID	Case	Parameters	Number of Impacts
Flat Panel			
F1	Reference case	Tip : steel, Temp. : 24°C, mass : hammer only	140 (35 loc. x 4 rep.)
F2	Increased mass	Tip : steel, Temp. : 24°C, mass : added 100 gr	140 (35 loc. x 4 rep.)
F3	Increased temp.	Tip : steel, Temp. : 70°C, mass : hammer only	140 (35 loc. x 4 rep.)
F4	Plastic tip	Tip : plastic, Temp. : 24°C, mass : hammer only	140 (35 loc. x 4 rep.)
F5	Reference + noise	Tip : steel, Temp. : 24°C, mass : hammer only	140 (35 loc. x 4 rep.)
F6	Intermediate locs.	Tip : steel, Temp. : 24°C, mass : hammer only	24 (6 loc. x 4 rep.)
Stiffened Panel			
S1	Reference case	Tip : steel, Temp. : 24°C, mass : hammer only	140 (35 loc. x 4 rep.)

5.3 Signal Features for Impact location and Maximum Force Estimation

For the purpose of impact localisation, the Time of Arrival (ToA) difference of the Lamb wave signals from each sensor towards the earliest signal from the sensor set (as the actual impact event time is unknown) was chosen as the input feature. To mitigate the effect of the simulated vibration noise (case F5) in masking the start of the signal (Figure 5. 1c), all signals were highpass filtered with a 2 kHz Butterworth IIR filter prior to ToA extraction. The ToA was then extracted using the Normalised Smoothed Envelope Threshold (NSET) method developed in Chapter 3 : **Part 1** [16]. First the signal was converted into its absolute values, then it was lowpass filtered with a 250 Hz IIR Butterworth filter. Afterwards, the amplitude of the signals from each sensor are normalised with respect to the largest amplitude in the set of sensors. The ToA was then taken when the resulting envelope passes a predetermined threshold (0.05 used here).

For maximum impact force estimation, the Maximum Absolute (MA) signal amplitude was used as the input feature. No highpass filtering was done beforehand even in the presence of simulated random vibration noise (case F5) as the maximum impact force estimation method developed in Chapter 4 has been shown to be robust towards the change in amplitude [8]. The maximum measured impact force together with the MA signal amplitude at the reference database points were used to calculate the force gradient for the maximum impact force estimation as will be explained in Section 5.4.2.

5.4 Benchmark Impact Location and Maximum Force Estimation Methods

The benchmark data-driven impact location method (reference database method [17]) and maximum impact force estimation method (force gradient method [8]) were taken from Chapter 3 : **Part 1**, Chapter 3 : **Part 2** and Chapter 4 which have proven to be accurate and robust for simple structures under simulated environmental and operational conditions using minimum initial data.

5.4.1 Reference Database Method for Deterministic Impact Location Estimation

The reference database method is essentially a pattern matching method where the impact location estimate is given based on the similarity of features (ToA differences used in this study) of the incoming signal to that of signal features known for specific locations in a reference database (obtained from the reference impact cases F1 and S1) [17,43]. To do so, first the absolute difference between the incoming signal's features and the known features in the reference database are calculated, as shown in Equation (5. 1) :

$$Df_i = \sum_{j=1}^{Ns} |f_j^{in} - f_{j,i}^{ref}| \quad i = 1, 2, \dots, Nr, j = 1, 2, \dots, Ns, \quad (5. 1)$$

where f^{in} is the incoming signal features, f^{ref} is the reference database features and Df_i is the absolute difference between features for all sensors (Ns) and all reference database points (Nr). The location estimate is then taken as the location of the database point with minimum difference (Df).

By the above definition, the location estimation is limited to points that exist in the reference database. To achieve a more thorough coverage of locations without requiring too many initial data points to build the reference database, cubic spline interpolation is done to approximate the features at locations between the reference database points (2 points between reference points interpolated in this study).

To increase the robustness of the final estimate, rather than calculating a single difference value for each reference point (Df_i) using all the features available at once, multiple values are generated by creating different combinations of features used (e.g. if there are 6 sensors, than using combinations of 5 yields 12345, 12346, 12456, and so on, resulting in 6 feature sets and location estimates in the end). The location estimates are then averaged to obtain the final estimate. Here combinations of 5 (out of 6) ToA difference values for the flat panel and 4 (out of 5) for the stiffened panel were used.

5.4.2 Force Gradient Method for Deterministic Maximum Impact Force Estimation

The force gradient method is based on the linear relation between the maximum impact force and the MA signal amplitude, as shown in equation (5. 2) :

$$F_{max}(x, y) = G_{MA}(x, y) A_{MA}(x, y) (1 - \alpha[T - T_{ref}]), \quad (5. 2)$$

where F_{max} is the maximum impact force, A_{ma} is the MA signal amplitude, G_{MA} is the impact force gradient and α is the temperature (T) compensation factor relative to a reference temperature (T_{ref}). It is a faster and more simple way of estimating the maximum impact force than reconstructing the whole impact force history [8]. Once the gradient (G_{ma}) is known, it is possible to estimate the maximum impact force from signals with varying amplitude. The gradient of this linear relation has been found to be constant for most simulated environmental and operational conditions (except very soft impactor materials, e.g. silicone) as well as low (non-damaging impacts) or high (damaging) energy impacts, but its location (x,y) and temperature (T) dependent [8].

Lamb wave amplitude is known to have an inverse linear relation with temperature (T) [8,46], thus it is necessary to apply a compensation factor (α) relative to a certain reference temperature (T_{ref}). For the panel used in this study, the linear relation has been determined in Chapter 4 ($\alpha = -0.0026$, $T_{ref} = 24^0$ C [8]) and the results were used here, mostly for the increased temperature case (case F3). As the gradient is also location dependent, for the reference database the measured maximum impact force and MA signal amplitude from the reference case (F1 and S1) were used to obtain the gradient value at each location. As each sensor can give an estimate, the final force estimate was taken from the average from all sensors.

Similar to the localisation method in section 5.4.1, to ensure a thorough coverage of the reference database, cubic spline interpolation is done to approximate the gradient values points at locations outside of the original reference points. As the gradient values are location dependent, in order to obtain

the appropriate value, the impact location must be known beforehand. Here the location estimate results from the localisation algorithm in section 5.4.1 were used. This has a disadvantage as the error of the location estimation is brought over to the estimated maximum force gradient values. Figure 5. 3 illustrates how the deterministic localisation and force estimation methods combine.

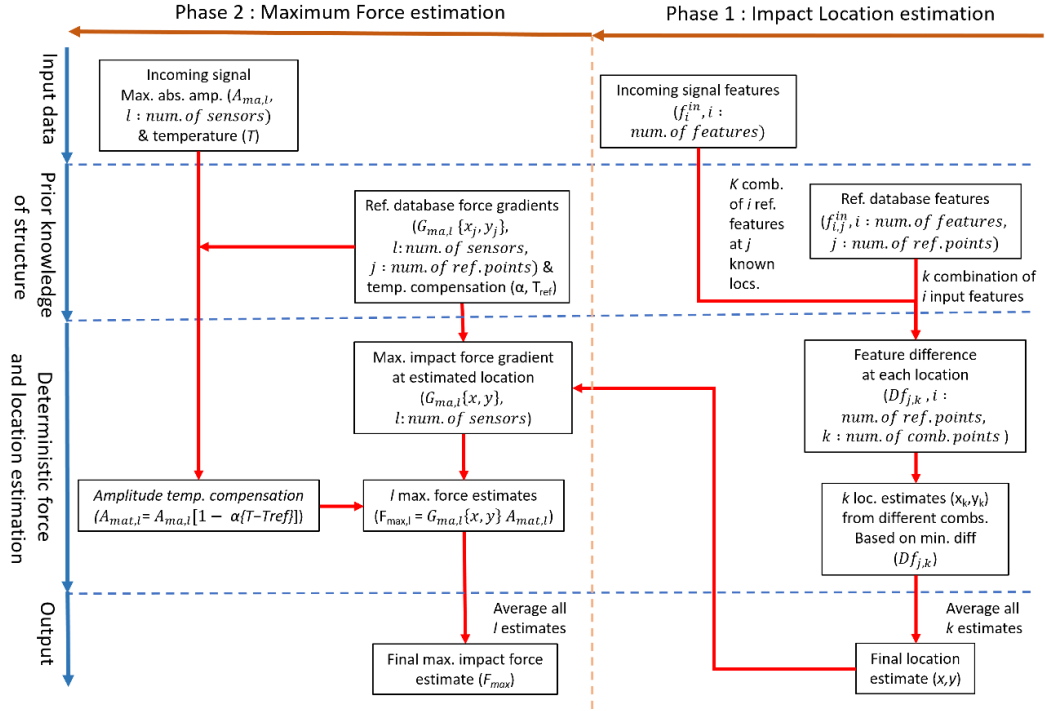


Figure 5. 3 Diagram of benchmark deterministic impact location and maximum force estimation algorithm

5.5 Uncertainty Quantification Method for Impact Location and Maximum Force Estimation

To provide estimates to the uncertainty obtained using the benchmark location and maximum force estimation algorithms given in section 5.4, a modification is proposed by incorporating a novel application of the kriging technique [121]. Originally, kriging is used for spatial interpolation of geostatistical data, however here a novel application is proposed to modify it for statistical pattern matching between the incoming impact features and the features of the reference database points to estimate the location and maximum force of impacts. Using the proposed method, it is possible to not only able to obtain an estimate but also the

uncertainty of the estimate based on the relationship between data points used in the reference database [121].

5.5.1 Kriging Method for Spatial Interpolation

Kriging was originally developed for spatial interpolation of geostatistical data, using the spatial correlation between existing reference data points to determine weights for use in a linear combination of the available data points to determine the interpolated value [121]. The spatial correlation between data points may be expressed in many forms [121], but one of the most widely used is the semivariance between data points, as shown in equation (5. 3) :

$$\gamma(h^{ref}) = \frac{1}{2N_h} \sum_i^{Nr} \sum_j^{Nr} (z_i^{ref,h} - z_j^{ref,h})^2. \quad (5. 3)$$

Semivariance values ($\gamma[h^{ref}]$) for a certain distance (h^{ref}) are calculated for each data point pair combination that is separated by that distance ($z_i^{ref,h}, z_j^{ref,h}$) and are averaged based on the number of data pairs that share the same distance (N_h). This is done for all the reference data points (N_r) in their possible pair combinations. It quantifies how the variance between data points change (usually increasing) as their respective distance (h^{ref}) increases (or how the correlation is higher between closer data points). As the distance (h^{ref}) between data pairs may not always be exactly the same, they are usually grouped into bins (20 bins used in this study) to allow averaging [121]. Afterwards, a semivariance function ($\gamma^{fc}[h]$) is fitted to the discrete empirical semivariance values ($\gamma[h^{ref}]$) to allow approximation of the semivariance at a continuous distance range (h)[121].

To estimate the value of an interpolated point, first the distance between the point and the existing reference data points (h^{in}) are calculated. Afterwards, using the previously obtained semivariance function ($\gamma^{fc}[h]$), the approximate semivariance values for the reference ($\gamma^{fc}[h^{ref}]$) and interpolated ($\gamma^{fc}[h^{in}]$) data point pairs are calculated based on their respective distances (h^{ref} and h^{in}). Equation (5. 4) provides the relation between the semivariance of the reference and interpolated data point pairs :

$$\begin{bmatrix} \gamma_{ij}^{fc}(h^{ref}) & I_i \\ I_j^T & 0 \end{bmatrix} \begin{bmatrix} w_i \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma_i^{fc}(h^{in}) \\ 1 \end{bmatrix} \quad i, j = 1, 2, 3 \dots Nr, \quad (5.4)$$

where h^{ref} and h^{in} are the respective data point distances between reference and input data, γ^{fc} is the interpolated semivariance, and I_j is a column vector of 1's with j number of rows (for Nr number of reference points). The equation is solved to obtain the kriging weights (w_i) and the Lagrange parameter (μ).

With the obtained kriging weight and Lagrange parameter values, the interpolated value and uncertainty (in the form of a standard deviation from the interpolated value) can be calculated from equation (5.5) :

$$z^{est} = \sum_{i=1}^{Nr} w_i z_i^{ref} \quad \sigma^{est} = \sqrt{\mu + \sum_{i=1}^{Nr} w_i \gamma_i^{in}(h^{in})}, \quad (5.5)$$

where z^{est} is the estimated value, σ^{est} is the uncertainty of the estimate, μ is the Lagrange parameter, with w_i and $\gamma^{in}(h^{in})$ as the kriging weight and semivariance of the interpolated point (relative to the Nr reference points). As the semivariance values are always positive, to ensure that the estimated uncertainty is real valued, the kriging weights and Lagrange parameter need to be positive valued. Thus, a non-negative constrained linear least square solver (MATLAB lsqnonneg) is used to solve equation (5.4).

5.5.2 Kriging Application for Impact Location and Maximum Force Estimation

In section 5.4, it is shown that the impact location is determined by simply choosing the point in the reference database that has the minimum difference in features compared to the incoming impact signal [17]. In turn, the maximum impact force gradient is then taken as the value known for the said reference point. This way, there is a significant amount of information discarded as only the information from 1 database point is used in the end. Here it is proposed to substitute this criterion with the kriging technique which can interpolate the location and also the maximum impact force gradient using the information from all of the reference database points whilst also estimating the uncertainty.

Contrary to the original application of kriging as shown in section 5.5.1, in our case the value at the point of interest (in the form of the incoming impact signal features) is already known, and what is to be estimated instead is the location of the point. Here, it is proposed to substitute the actual spatial distance between data points, (which is the difference in spatial coordinates) with the difference in feature values (calculated by the L2 norm of the difference vector). Thus, here data points are grouped not based on spatial closeness but by the similarity of their features. The values to be interpolated are then the actual spatial coordinates (x,y) of the data point locations and the respective maximum impact force gradients ($G_{ma}[x,y]$). Thus, by using the features of the incoming impact signal it is possible to estimate the location of the impact event and the maximum impact force.

Here the L2 norm of the ToA difference vector between the reference and interpolated data points was used to calculate their respective “distances” (h^{ref} and h^{in}). Using the location coordinates and the maximum impact force gradients for each sensor as the estimated variable (z), the semivariance ($\gamma[h^{ref}]$) of the reference database points were calculated using equation (5. 3) as shown in Figure 5. 4. A linear function ($\gamma^{fc}[h] = G_\gamma h$) was then fit for all estimated variables to obtain the approximate semivariance values for equation (5. 4). Then, equation (5. 4) was solved to obtain the kriging weights and Lagrange parameter to calculate the final estimate and uncertainty of the impact location coordinates and maximum impact force gradients for each sensor using equation (5. 5). A normal probability distribution function (P) was then formed using the estimate (z^{est} , as mean) and standard deviation (σ^{est}) for all estimated variables.

Following the benchmark localisation method in section 5.4.1, here the ToA difference values were also used in combinations rather than all at once, resulting in multiple estimate distributions of the impact location coordinates and the maximum impact force gradients. For each of these combinations, there is a further set of maximum impact force gradients from each sensor. The maximum impact force estimate distributions are obtained by multiplying the obtained gradient distributions with the signal amplitude for each sensor, following equation (5. 2).

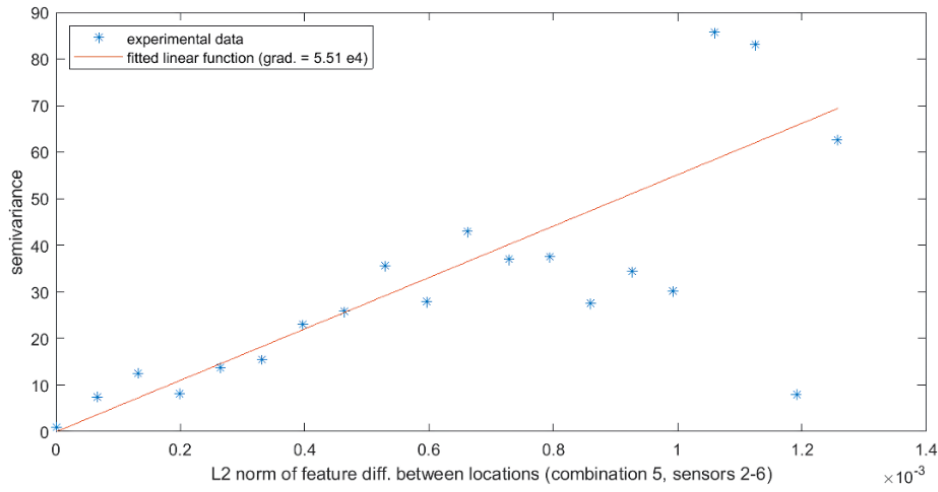


Figure 5. 4 Semivariance of sensor 5 maximum impact force gradient vs L2 norm of Time of Arrival difference from sensors 2-6 (combination 5) for the stiffened panel

It must be noted that using this approach, the maximum impact force gradients ($G_{ma}[x,y]$) are determined independently from the estimated location unlike in the benchmark method (section 5.4, Figure 5. 3), thus the localisation error is not imposed on the maximum impact force estimation. Additionally, the kriging method is able to interpolate values between the reference data points due to the fitted semivariance functions, thus there is no need for the cubic interpolation done in the benchmark method.

5.5.3 Fusion of Impact Location and Maximum Force Distributions

As the kriging method given in section 5.5.2 results in multiple estimate distributions for each output variable, here the methods to fuse them together are outlined. The first alternative is to simply take the mean of the estimates (as is done with the benchmark method) to obtain a wider and more conservative final estimate distribution as shown in Figure 5. 5. To ensure that the total probability of the distribution is unity, it is divided by the area under the mean probability density function.

Another method is to apply Bayesian updating [18], treating multiple estimates as new information that can update prior estimates as shown in equation (5. 6) :

$$P_i(O|N) = \frac{P_i(N|O)P_i(O)}{P_i(N)} \quad (5.6)$$

$$P_i(N|O) = P_{i-1}(O|N) \quad i = 1, 2, 3 \dots Ne.$$

It starts with an initial/prior assumption of the estimated variables ($P[O]$), which in this study was taken as a uniform distribution as there was no initial knowledge of their values [18]. The estimates from kriging were then used to “update” ($P[N|O]$) the prior assumption to obtain a more “informed” estimate ($P[O|N]$). Here $P(N)$ is a normalising factor (obtained from the area under the distribution of $P[N|O]$ $P[O]$) to ensure that the total probability of $P(O|N)$ is unity. The informed estimate ($P[O|N]$) then becomes the new prior ($P[O]$) and is updated with the next available estimate ($P[N|O]$). This goes on until all of the available estimate distributions (Ne) have been used to obtain the final estimate distribution. This method results in a more narrow final estimate distribution compared to the original data (Figure 5. 5) as the confidence of the estimation increases when updated with new information.

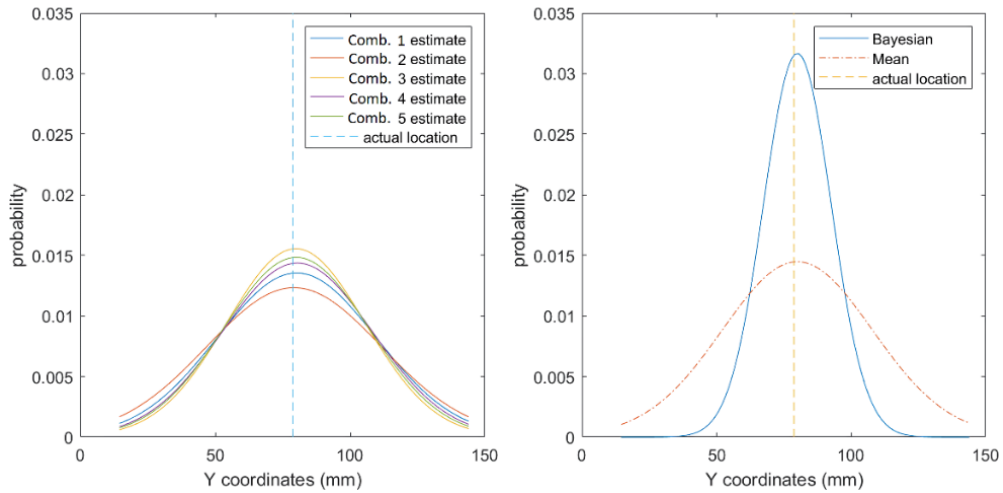


Figure 5. 5 Estimate distributions for Y coordinate from sensor combinations 1-5 (left) and fused final estimates using mean and Bayesian updating (right)

As stated in section 5.1, the estimated range must be wide enough to ensure that the actual value reliably lies within the bounds of the distribution whilst at the same time must be narrow enough to give an estimate that is as precise as possible. Both the mean and Bayesian approaches have different characteristics

and are thus both tested to compare their performance with the test data. For the maximum impact force, as there are multiple estimates not only from multiple sensors but also from the multiple feature combinations, there are 2 stages of fusion. Here both the mean and Bayesian approach were tested for both stages, as well as a 3rd combination where the estimates from all sensors are first fused using the mean approach and the resulting estimates are finally fused using the Bayesian approach. Figure 5. 6 shows the outline of the proposed kriging method accompanied by uncertainty fusion for both impact location and maximum force estimation.

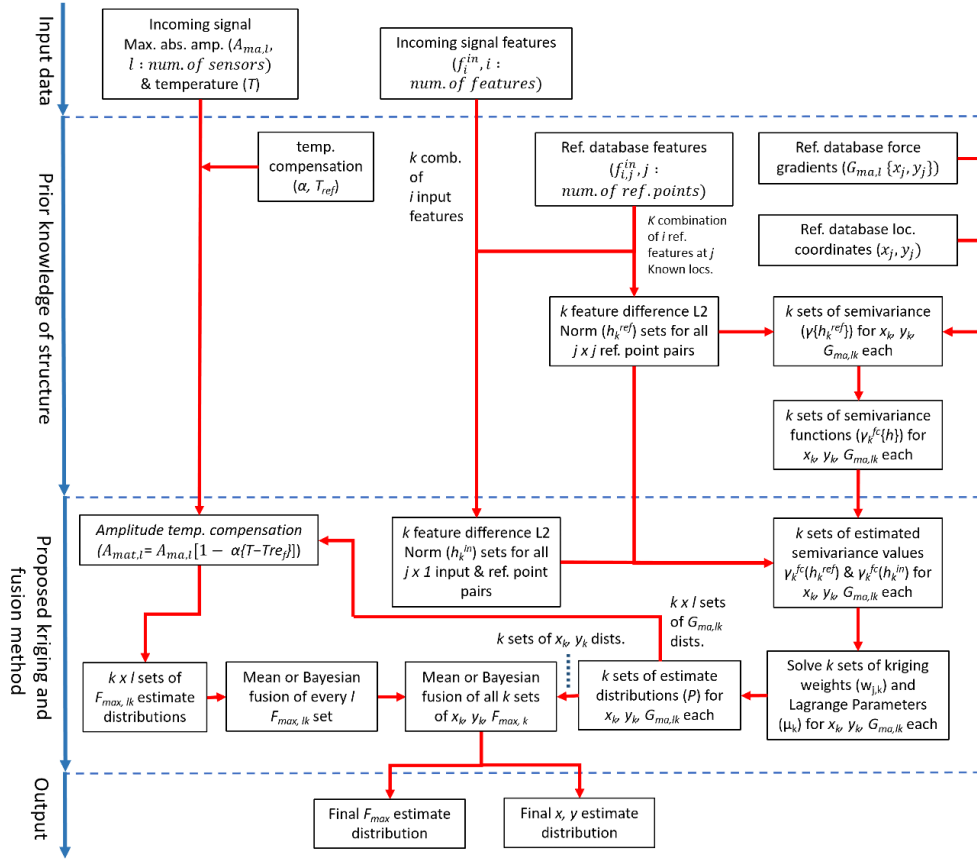


Figure 5. 6 Diagram of proposed stochastic impact location and maximum force estimation algorithm

Once the final distribution has been obtained, the upper and lower bound of the estimate range is determined within the 95% confidence interval of the distribution. For the impact location, an oval area is drawn around the estimated coordinates (x^{est} , y^{est}) using the estimate range of the x and y coordinates as the

semi-major axes to mark the area at which there is 95% confidence that the impact location is located within.

5.6 Performance Evaluation and Comparison of Benchmark and Proposed Methods

To evaluate and compare the performance of the proposed methods against the benchmark methods, the metrics used to measure the accuracy of the estimates are defined here. To compare the deterministic accuracy of both methods directly, the error of the estimated values from the benchmark and proposed methods towards the actual values for each test impact in Table 5. 1 was compared.

For maximum impact force, the error in estimation is given in equation (5. 7) :

$$F_{max,error} = \frac{(F_{max,est} - F_{max,act})}{F_{max,act}} 100\% \quad (5. 7)$$

where $F_{max,error}$ is the difference between the estimate ($F_{max,est}$) from either algorithm towards the actual value ($F_{max,act}$). As the maximum impact force is random (ranging from 50 – 250 N), the error was taken as percentage towards the actual value. To summarise the error for a whole impact case, the mean ($F_{max,mean}$) and standard deviation ($F_{max,std}$) of the maximum force error for all impacts in the said case were calculated [8].

For impact location, the error of the estimates is given by the Root Square Error (RSE) as shown by equation (5. 8) :

$$RSE = \sqrt{(X^{act} - X^{est})^2 + (Y^{act} - Y^{est})^2} \quad (5. 8)$$

where x^{est}, y^{est} are the estimated coordinates and x^{act}, y^{act} are the actual location coordinates. To summarise the localisation errors (RSE) for an impact case (Table 5. 1), a gamma distribution was then fit on the RSE values and the 90th percentile of the cumulative distribution function (RSE_{90th}) was then taken as the range from the actual location that encompasses 90% of the localisation errors [16,17].

To evaluate the reliability of the uncertainty estimates, the error of the estimate range (upper and lower bounds based on 95% confidence interval) for

both the maximum impact force and location was calculated. For the estimated maximum impact force range, this is shown in equation (5. 9) :

$$F_{max,Error} = \begin{cases} \frac{(F_{max,range(-)} - F_{max,act})}{F_{max,act}} 100\% , F_{max,act} \leq F_{max,range(-)} \\ 0 , F_{max,range(-)} \leq F_{max,Ract} \leq F_{max,range(+)} \\ \frac{(F_{max,range(+)} - F_{max,act})}{F_{max,act}} 100\% , F_{max,range(+)} \leq F_{max,Ract} \end{cases} . \quad (5. 9)$$

The estimate range error ($F_{max,Error}$, spanning from $F_{max,range(-)}$ to $F_{max,range(+)}$) is defined to be 0 when the actual force ($F_{max,act}$) is within the estimated range. However, when the actual force is outside of the estimated range, then the error is calculated similar to the deterministic error in equation (5. 7), but relative to the nearest bound (upper or lower) as shown in equation (5. 9). To summarise the estimated range error for a whole impact case, the mean ($F_{max,Rmean}$) and standard deviation ($F_{max,Rstd}$) for all the impacts in the said case were calculated as is done with the deterministic errors.

For the estimated impact location range, the error is determined based on the range given in equation (5. 10) :

$$RSE_{lim}(\theta) = \frac{x_{sm} y_{sm}}{\sqrt{(y_{sm} \cos[\theta])^2 + (x_{sm} \sin[\theta])^2}} \quad (5. 10)$$

$$\sin(\theta) = \frac{y_{err}}{RSE} , \cos(\theta) = \frac{x_{err}}{RSE}$$

The location estimate range was defined as an oval area around the estimated location (x^{est}, y^{est}) with the upper ($x_{range(+)}, y_{range(+)}$) and lower bounds ($x_{range(-)}, y_{range(-)}$) of the coordinates as the semi-major axes (x_{sm}, y_{sm} as the distance from x^{est}, y^{est} to bounds). The radius of the oval area (RSE_{lim}) at any angle (θ) is given by equation (5. 10). The coordinates of the actual impact location relative to the estimated location (in other words the location error, x_{err}, y_{err}) can also be defined in polar coordinates (RSE, θ). When the radius of the location error (RSE) is smaller than the radius of the oval area limit (RSE_{lim}) for a given angle, the actual location (x, y) is located inside the estimated oval range and thus the error is 0. When the radius of the location error is larger than the radius of the oval area limit,

the actual impact location is outside the estimate range and the error of the oval range is calculated as $RSE_{range} = RSE - RSE_{lim}$. To summarise the localisation error for an impact case, a gamma distribution is fitted to the range error and the 90th percentile value (RSE_{R90th}) of the cumulative distribution function is taken as done for the deterministic location error.

5.7 Results

Table 5. 2 shows the comparison of the deterministic impact location estimation for both the benchmark and the proposed kriging method (using mean [K+M] and Bayesian [K+B] fusion methods). It can be seen that all 3 methods are considerably accurate for all cases tested (F1 – F6 and S1) and there is no significant difference between the accuracy of the deterministic location estimates between these methods.

Table 5. 2 Benchmark vs proposed kriging method deterministic location estimation

Impact Case	BM RSE_{90th} (mm)	K+B RSE_{90th} (mm)	K+M RSE_{90th} (mm)
Flat Panel			
F1. steel hammer, ref case	5.1	5.9	5.9
F2. steel hammer, incr. mass	6.7	6.9	7
F3. steel hammer, incr. temp.	6.3	6.7	6.5
F4. plastic hammer	7.6	8	7.9
F5. steel hammer, + noise	5.2	6	5.9
F6. steel hammer, interm. loc.	8.6	7.3	7.4
Stiffened Panel			
S1. steel hammer, ref. case	25.3	25.7	26.5
Note : BM : Benchmark Method, K+B = Kriging + Bayesian, K+M = Kriging + Mean			

Similarly, comparing the deterministic maximum impact force estimation (Table 5. 3) of the benchmark and proposed kriging method (with mean – mean [K+M+M], Bayesian-Bayesian [K+B+B], and mean – Bayesian [K+M+B], fusion methods), it was found that all methods were considerably accurate for all cases tested (case F1 – F6) apart from the stiffened panel (S1). This is due to the stiffened panel having more spatial variation of the maximum impact force gradient (and thus higher sensitivity) due to the stiffness difference from each stiffener zone (Figure 5. 2). As the benchmark method requires the location estimate to determine the maximum impact force gradient, the maximum force estimation also includes the localisation errors which shows in the lower accuracy

of the benchmark estimates compared to the proposed kriging method (which determines the maximum force gradient independent of localisation) for the stiffened panel (S1).

Although the deterministic estimates for both impact location and maximum force are mostly accurate, some level of error exists from the various sources of uncertainty that cannot be captured deterministically, especially as shown by the maximum impact force estimates of the stiffened panel (S1, Table 5. 3). Table 5. 4 and Table 5. 5 show the estimate accuracy for the stochastic approach using the proposed kriging method to define estimates in terms of a range (instead of a deterministic point) encompassing the estimated degree of uncertainty. For impact location (Table 5. 4), it can be seen that both kriging methods (with mean [K+M] and Bayesian [K+B] fusion methods) have very high reliability, with all actual impact locations being situated within the estimated uncertainty range (cases F1-F6) or being only slightly outside (case S1). Looking at the uncertainty range, it can be seen that by using the Bayesian updating method the estimated location coordinates (x,y) had significantly smaller uncertainty ranges (more than 2x) compared to the mean fusion method, with only a small trade off in accuracy. Thus, the Bayesian method is the better of the 2 fusion methods for location estimation as it allows for reliable and precise location estimation.

Table 5. 3 Benchmark vs proposed kriging method deterministic impact force estimation

Impact Case	BM avg. $F_{\max, \text{error}} (\%)$	K + B + B avg. $F_{\max, \text{error}} (\%)$	K+ M + M avg. $F_{\max, \text{error}} (\%)$	K + M + B avg. $F_{\max, \text{error}} (\%)$
Flat Panel				
F1. steel hammer, ref case	0.2 ± 3.8	0 ± 4	-0.3 ± 4	-0.3 ± 4
F2. steel hammer, incr. mass	-4.5 ± 4.5	-6.8 ± 4.5	-7.3 ± 4.3	-7.3 ± 4.3
F3. steel hammer, incr. temp.	9.3 ± 4.4	9.7 ± 5.1	8 ± 5.1	8.1 ± 5.2
F4. plastic hammer	12 ± 4.4	10.7 ± 4.5	10 ± 5	10 ± 5
F5. steel hammer, + noise	0.9 ± 4.7	0.5 ± 5.1	0.2 ± 5.5	0.2 ± 5.4
F6. steel hammer, interm. loc.	7.1 ± 8	4.4 ± 4.3	3.8 ± 4.2	3.8 ± 4.2
Stiffened Panel				
S1. steel hammer, ref. case	8 ± 17.5	5.5 ± 15.9	3.7 ± 16.3	4.2 ± 16.6
Note : BM : Benchmark Method, K + B + B = Kriging + Bayesian + Bayesian, K + M + M = Kriging + Mean + Mean, K + M + B = Kriging + Mean + Bayesian				

Table 5. 4 Evaluation of proposed kriging method location uncertainty estimation

Impact Case		K+B RSE _{R90th} (mm)	K + M RSE _{R90th} (mm)	K+B avg. x unc. (mm)	K+B avg. y unc.. (mm)	K+M avg. x unc. (mm)	K+M avg. y unc. (mm)
Flat Panel							
F1	steel hammer, ref case	0	0	22.4 ± 5.1	14.5 ± 3.3	50.6 ± 11.4	32.9 ± 7.4
F2	steel hammer, incr. mass	0	0	24.1 ± 4.7	15.7 ± 3	54.6 ± 10.2	35.6 ± 6.7
F3	steel hammer, incr. temp.	0	0	28.9 ± 7.1	18.7 ± 4.6	65.6 ± 16.5	42.6 ± 10.5
F4	plastic hammer	0	0	25.8 ± 6.1	16.8 ± 4	58.5 ± 13.9	38.2 ± 9
F5	steel hammer, + noise	0	0	22.3 ± 5.1	14.5 ± 3.3	50.6 ± 11.5	33 ± 7.4
F6	steel hammer, interm. loc.	0	0	31 ± 3.6	20 ± 2.3	69.2 ± 7.9	45.1 ± 5.1
Stiffened Panel							
S1	steel hammer, ref. case	1.3	0	74.2 ± 18.4	29.5 ± 7.3	159.5 ± 40.4	64.7 ± 16.5
Note : K+B = Kriging+Bayesian, K+M = Kriging+Mean, unc = uncertainty range (upper – lower bound)							

Table 5. 5 Evaluation of proposed kriging method impact force uncertainty estimation

Impact Case		K + B + B F _{max,Error} (%)	K+ M +M F _{max,Error} (%)	K+ M +B F _{max,Error} (%)	K + B + B avg. F _{max} unc. (N)	K+ M +M avg. F _{max} unc. (N)	K+ M +B avg. F _{max} unc. (N)
Flat Panel							
F1	steel hammer, ref case	-0.3 ± 1.7	0 ± 0	0 ± 0.2	12.1 ± 3.8	82.1 ± 31.2	28 ± 8.2
F2	steel hammer, incr. mass	-4.1 ± 3.7	0 ± 0	-1.3 ± 2	12.5 ± 3	102.6 ± 39.7	33.4 ± 9.5
F3	steel hammer, incr. temp.	5.5 ± 3.9	0 ± 0	0.8 ± 1.7	18.9 ± 6	153.6 ± 66.7	47 ± 13.9
F4	plastic hammer	6.8 ± 3.7	0 ± 0	1.9 ± 2.5	16.4 ± 5.7	125.5 ± 51.3	40.8 ± 11.7
F5	steel hammer, + noise	0.1 ± 2.7	0 ± 0	0 ± 0.6	12.2 ± 3.8	89.8 ± 30.7	32.2 ± 9.2
F6	steel hammer, interm. loc.	1.6 ± 2.4	0 ± 0	0.1 ± 0.3	17.3 ± 2.6	119.9 ± 16.9	43.7 ± 6
Stiffened Panel							
S1	steel hammer, ref. case	2.4 ± 10.3	-0.1 ± 0.7	0.7 ± 5.3	20.6 ± 8.5	142.6 ± 68.9	51.6 ± 29.6
Note : K + M + M = Kriging + Mean + Mean, K + B + B = Kriging + Bayesian + Bayesian, K + M + B = Kriging + Mean + Bayesian, unc. = uncertainty range (upper – lower bound)							

For maximum impact force estimation, Table 5. 5 shows the estimation accuracy using the proposed kriging method accompanied by 3 different fusion methods (Bayesian – Bayesian [K+B+B], mean – mean [K+M+M], and mean – Bayesian [K+M+B]). Using the Bayesian – Bayesian fusion method, the estimated uncertainty range is very narrow up to the level where it becomes inaccurate as

some of the actual maximum force values are not encompassed in the estimated range. On the other hand, using the mean – mean fusion method results in a very reliable (most actual values encompassed in estimated range) but very wide (up to 6 x wider than the Bayesian – Bayesian method) and imprecise uncertainty range which may not be useful for impact severity assessment. Using a combined mean – Bayesian method, a balance of good reliability and uncertainty range precision is achieved, making it more reliable than the Bayesian – Bayesian approach as well as more precise than the mean – mean approach. The proposed stochastic approach gives a much higher reliability of maximum impact force estimation compared to the deterministic method, especially for cases such as the stiffened panel (S1) which are sensitive and difficult to estimate deterministically.

Figure 5. 7 and Figure 5. 8 illustrate an example of the impact location and maximum force estimation using the benchmark and proposed kriging method (K+B for location and K+M+B for impact force). It can be seen that although the deterministic method is quite accurate, there is some degree of inaccuracy stemming from various sources of uncertainty, more so in some cases (such as in location 7 [Figure 5. 8], bottom left of the stiffened panel [S1]) than others. On the other hand, the proposed kriging method is able to reliably estimate the uncertainty of the impact location and maximum force estimation (all actual locations and maximum impact force encompassed in estimated range), giving a more robust output for users to locate and assess the severity of an impact event.

As mentioned in section 5.1 there are 2 main sources of uncertainty : measurement errors and algorithm inaccuracy [57,117]. The measurement errors are encoded in the reference database points, whilst the algorithm inaccuracy is represented in the multiple outputs given by feature combinations (section 5.5) which are merged with the proposed fusion methods. Because of this, the uncertainty range can be accurate and reliable, even though it is estimated only from the reference database points and not based on actual error measurements of the output. This highlights the suitability of data driven methods for uncertainty quantification by taking advantage of the information contained in their reference database without the need for expensive simulations often use for this purpose (e.g. Monte Carlo simulations) [13,54].

5.8 Conclusion

A novel data driven stochastic kriging based method for impact location and maximum force estimation was developed. Comparison with a deterministic benchmark method developed in prior studies [8,16,17] indicates that the proposed method gives more reliable estimates for experimental impacts under various simulated environmental and operational conditions by estimating the uncertainty. The developed method highlights the suitability of data driven methods for uncertainty quantification by taking advantage of the relationship between data points in the reference database that is a mandatory component of these methods (and is often seen as a disadvantage). By quantifying the uncertainty, it gives more information for operators to reliably locate impacts and estimate the severity for making maintenance decisions.

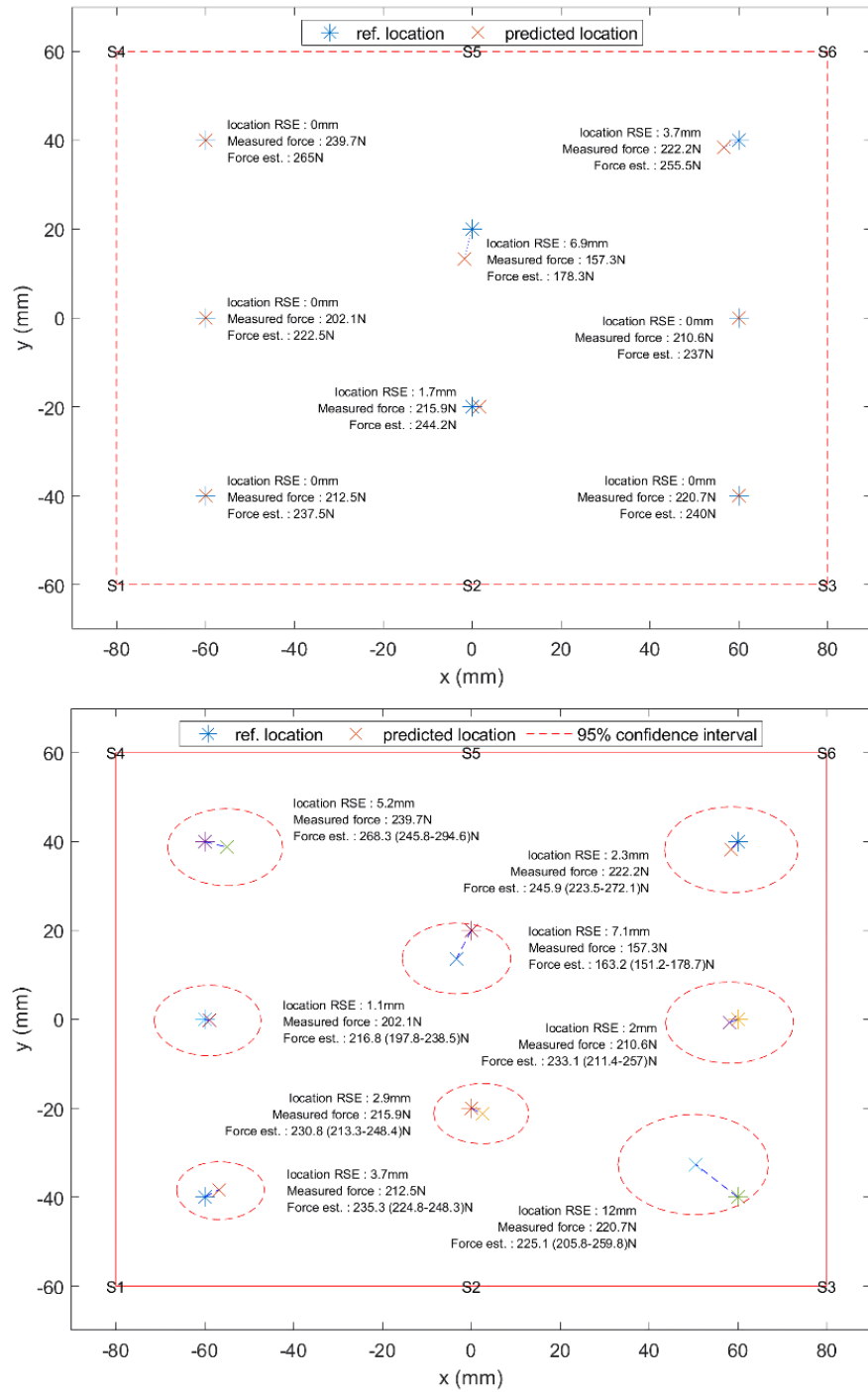


Figure 5. 7 Example of location and maximum impact force estimation for plastic hammer tip (case F4) impacts on the flat panel using the benchmark deterministic method (top) and the proposed kriging stochastic method (bottom)

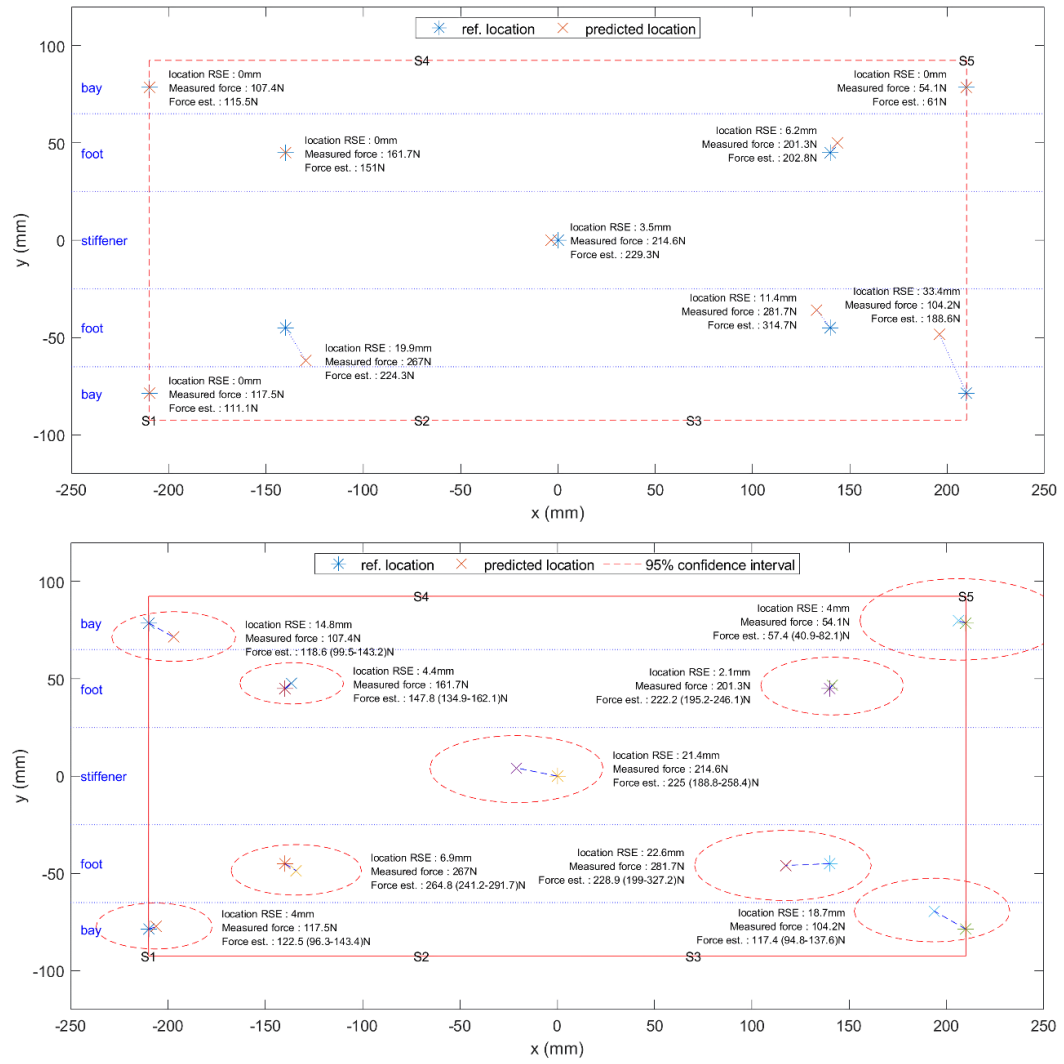


Figure 5. 8 Example of location and maximum impact force estimation for impacts (case S1) on the stiffened panel using the benchmark deterministic method (top) and the proposed kriging stochastic method (bottom)

Chapter 6

Multifidelity Data Augmentation for Data Driven Passive Impact Location and Force Estimation in Composite Structures

The work from previous chapters has produced data driven methods for impact location and force estimation that are reliable and robust towards simulated environmental and operational conditions that require minimum initial data. However, even a small amount of data sampling per component may lead to unfeasible amounts of experimental data collection in real life structures as they are much larger and complex than the lab specimens used up to now. Thus, in this chapter a multifidelity approach is developed to augment the initial data requirements with alternative sources to direct experimental sampling.

6.1 Introduction

Data driven methods do not take into account the behaviour of the wave propagation and for the most part just form a meta model (e.g. neural networks, pattern matching models) that connects certain inputs (in this case Lamb wave features) to certain outputs (in this case the impact location and severity) [16,27,36,52]. Because of this, these models are not affected by the change in complexity of a structure, as long as there is still correlation between the input and output variables [16,27,36,52]. They have been demonstrated to work in complex structures (e.g. stiffened structures or structures with cut-outs that obscure direct propagation paths) with little to no change in general application compared to simple coupons [16,27,36,52]. Thus these methods, due to their adaptability, have potential for deployment in structures in real life, which may contain various sources of complexity [16,27,36,52].

However, as these methods do not take into account the wave propagation behaviour, the only way they are able to form a meta model to connect an input and output is to provide a reference database or train the algorithm with an initial known set of input and output data pairs [16,17,27,52]. This is considered by many as the Achilles's heel of data driven methods which prevents them from being used in real life, as collecting initial data for large structures, as well as including all possible variations caused by operational and environmental conditions, results in an unfeasible amount of initial data required [16,17,34].

Data driven methods for impact location and maximum force estimation that are robust towards variations caused by simulated environmental and operational conditions have been developed in previous chapters [8,16,17,34], thus these factors need not be included in the reference database. This reduces the amount of initial data points required to just the spatial sampling along the structure [8,16,17], which as mentioned before will be a problem for large structures (e.g. an entire aircraft).

Previous studies have demonstrated that Finite Element (FE) models can generate simulated Lamb waves with features that can be used to estimate the location and severity of simulated impacts, similar to what is done with experimental data [27,36]. However, no attempt has been made to see whether simulated Lamb waves are good enough to substitute actual experimental data samples for use in estimating the location and severity of an actual impact on a real structure.

There are various sources of variation and uncertainty that may not be captured in an FE model [54,117,120,122]. Thus, rather than including all these factors and increasing the complexity of an FE model, a multifidelity approach using cokriging is presented to combine a “cheaper” but less accurate (lower fidelity) data source (FE models) with more “expensive” but more accurate (higher fidelity) data (experimental sampling) using the correlation of the data in the 2 datasets is proposed [59,121,123]. The aim is to generate as much data using the “cheaper” source to gain spatial coverage and then to calibrate it using the least amount of “expensive” experimental data. This reduces the “cost” of constructing a reference database for data driven methods, thus making them more

feasible for real life application. Here we, take advantage of both datasets to obtain a cheaper yet more accurate final database than can be achieved by each dataset alone.

In this study a comparison of the performance of impact location and maximum force estimation under simulated environmental and operational conditions with methods developed in previous chapters is conducted for different reference databases: purely experimental samples, purely FE samples and a multifidelity combination of FE and experimental samples. The purpose is to observe how the multifidelity approach can create a right balance between reduced number of experimental data sampling needed and FE simulations while maintaining a reasonable level of accuracy.

6.2 Experimental Setup

The experimental impact data (for use as the high fidelity data set) was collected from, 2 carbon fibre composite specimens were used : a flat panel (M21 T800s prepreg, [0/+45/-45/90/0/+45/-45/90]s layup, Figure 6. 1) and a more complex stiffened panel (M21 T800s prepreg, [45/-45/0/0/90/0]s layup, Figure 6. 2). The flat panel has a silicone heating mat underneath with a temperature control unit to simulate elevated temperatures. Each Panel has 8 PZT sensors attached, however not all were used due to limitations of measurement channels. Only 6 sensors were used for the flat panel and 5 on the stiffened panel (not 6, due to sensor damage from previous testing campaigns) as shown in the layout in Figure 6. 1a and Figure 6. 2a, respectively.

The impacts with random energies and angle were generated and recorded with a PCB Piezotronics 086C03 handheld instrumented. The hammer has space for a 100 g attachment to simulate impacts of varying mass. The hammer tip was interchangeable with 2 materials available, plastic and steel, to simulate impacts from different stiffness materials.

The signals were recorded from PZT sensors on each panel via 10x attenuation oscilloscope probes attached to an NI PXI-5105 8 channel oscilloscope. Signals were recorded at 2 MS/s and with a length of 100000

samples. A channel of the oscilloscope was used to measure the impact force from the hammer.

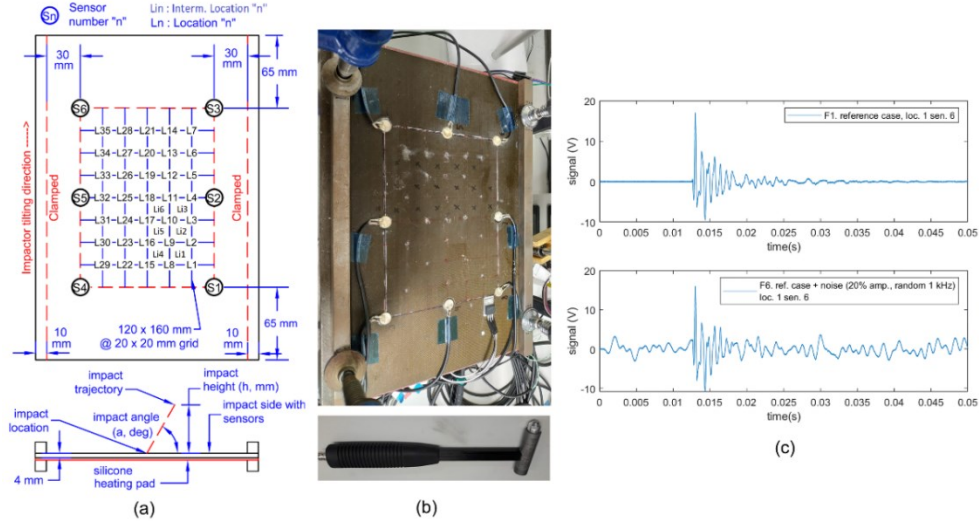


Figure 6. 1 Flat panel specimen used for collecting experimental impact data : (a) layout of impact and sensor locations, (b) photo of flat panel and impact hammer, (c) example of signals recorded from the reference case (F1) and with artificial noise (F6)

Impact data was collected from the locations laid out in Figure 6. 1a and Figure 6. 2a for cases described in Table 6. 1 with four repetitions for each location. For the flat panel, these cases represent parametric changes (case F2 – F6) from a reference case (F1) and simulate the common environmental and operational conditions encountered in operation [8,16,17]. To simulate vibration noise (case F5), artificial 1 kHz random noise was generated through lowpass filtering of white noise and then scaled to 20% of the maximum absolute amplitude of the signals in the reference case (F1).

Table 6. 1 Experimental impact cases collected on flat and stiffened panel

ID	Case	Parameters	Number of Impacts
Flat Panel			
F1	Reference case	Tip : steel, Temp. : 24°C, mass : hammer only	140 (35 loc. x 4 rep.)
F2	Increased mass	Tip : steel, Temp. : 24°C, mass : added 100 g	140 (35 loc. x 4 rep.)
F3	Increased temp.	Tip : steel, Temp. : 70°C, mass : hammer only	140 (35 loc. x 4 rep.)
F4	Plastic tip	Tip : plastic, Temp. : 24°C, mass : hammer only	140 (35 loc. x 4 rep.)
F5	Reference + noise	Tip : steel, Temp. : 24°C, mass : hammer only	140 (35 loc. x 4 rep.)
F6	Intermediate locs.	Tip : steel, Temp. : 24°C, mass : hammer only	24 (6 loc. x 4 rep.)
Stiffened Panel			
S1	Reference case	Tip : steel, Temp. : 24°C, mass : hammer only	140 (35 loc. x 4 rep.)

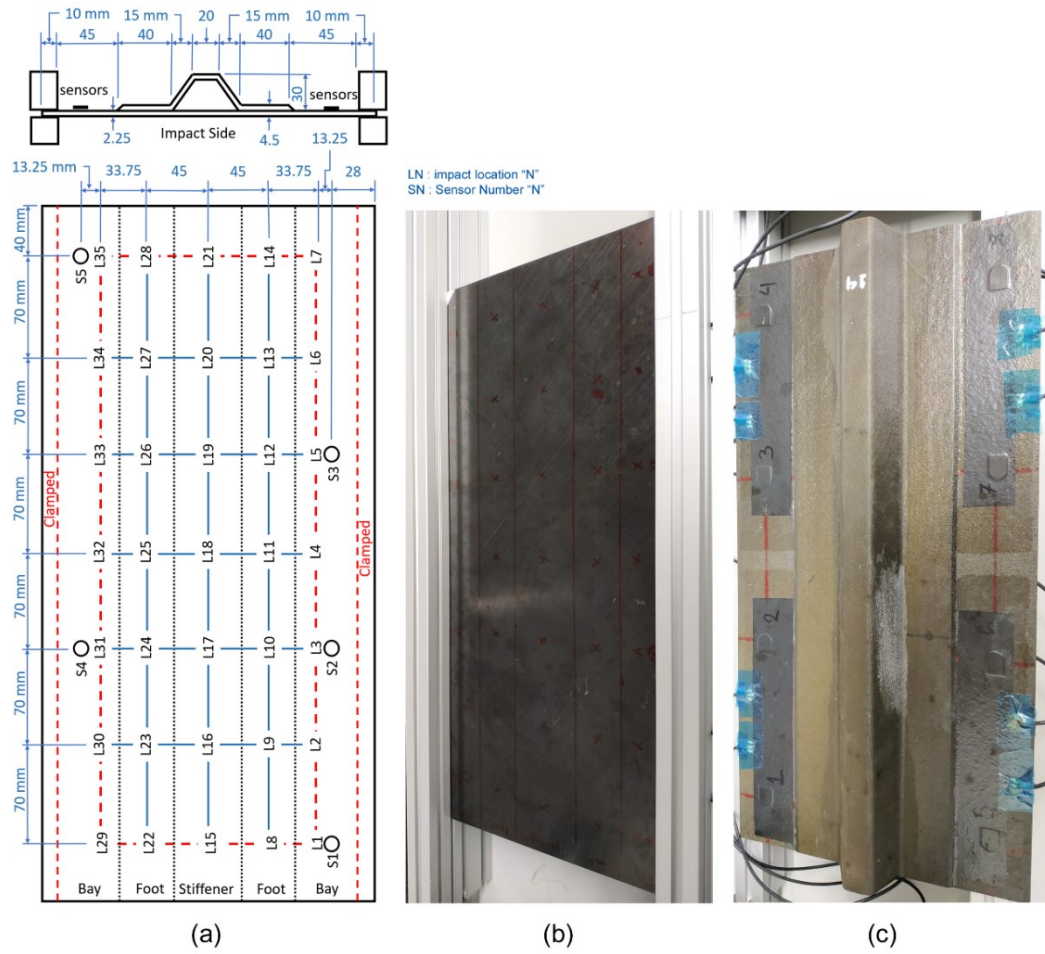


Figure 6. 2 Stiffened composite panel specimen for collecting experimental impact data : (a) layout of impact and sensor locations, (b) photo of specimen impact side, (b) photo of bottom side with stiffener

6.3 Finite Element Modelling of Impacts

Finite Elements (FE) modelling was conducted as a source of low fidelity data. The target of the simulation was to be as “cheap” as possible whilst achieving the best possible correlation with experimental data. Next, the simulation and calibration of the FE model is discussed.

6.3.1 Finite Element Model

To simulate impacts and the induced Lamb waves, ABAQUS commercial FE software with explicit solver was used. The flat panel was modelled as a solid and was meshed with continuum shell elements (Figure 6. 3). The material was modelled as a composite layup following the stacking sequence mentioned in

section 6.2 using the property values shown in Table 6. 2 [124,125]. As the flat panel had a silicone heating mat attached underneath, this was modelled as a uniformly spread non-structural mass of 213 g (obtained from weighing the panel minus the weight from the density of the material). The PZT sensors were modelled as single rectangular membrane elements (8.86 mm x 8.86 mm x 1 mm, equivalent area as the 10 mm diameter circular sensors used) and attached to the panel surface with tie constraints (Figure 6. 3) to match nodal displacements. The thickness (t) was defined in the section of the membrane. The isotropic PZT sensor properties are given in Table 6. 2 [126]. The clamps were modelled as analytical rigid surfaces and placed in contact with the panel surface and given full displacement and rotation constraints to hold the panel in place through contact and friction (Figure 6. 3).

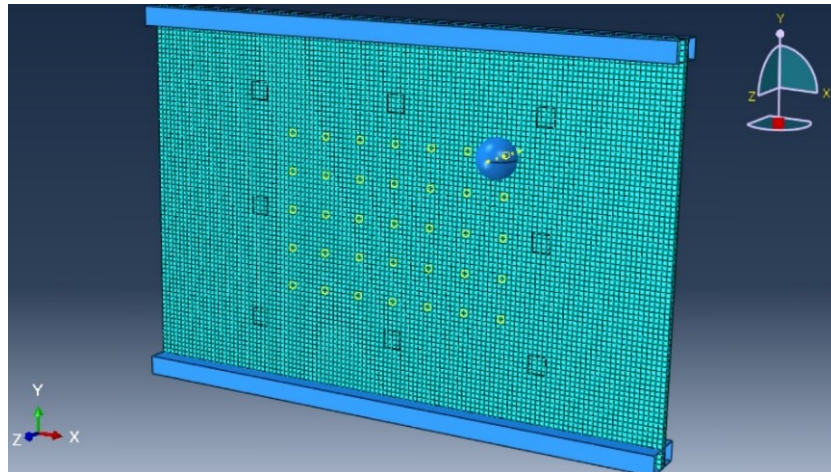


Figure 6. 3 Finite element model of flat panel showing impactor, sensors and impact locations

Table 6. 2 Material properties used in finite element model

Property	Value	Property	Value
M21 T800S Prepreg (lamina model) [124,125]		Piezo ceramic (PIC 255, isotropic) [126]	
Longitudinal stiffness, E_{11} (MPa)	171000	Stiffness, E (MPa)	62100
Transverse stiffness, E_{22} (MPa)	11470	Poisson's ratio, ν	0.34
Shear Modulus, G_{12} (MPa) & G_{13} (MPa)	4830	Density, ρ (tonne/mm ³)	7.8e-9
Shear Modulus, G_{23} (MPa)	3720	Piezo. coefficient, d_{31} (C/N)	0.18e-9
Poisson's ratio, ν_{12}	0.35	Permittivity, ϵ (F/m)	14.6e-9
Density, ρ (tonne/mm ³)	1.6e-9	Contact/interaction	
Mass damping coefficient, α (calibrated)	500	Contact stiffness, k (calibrated)	500
		Friction coefficient	0.3

The same approach was followed for the stiffened panel (Figure 6. 4), with the difference that the panel consisted of 2 solids, the base and the stiffener. Both were meshed with continuum shell elements and coupled through tie constraints. The base plate and stiffener were given the same stacking sequence following what was mentioned in section 6.2, with all material property values listed in Table 6. 2.

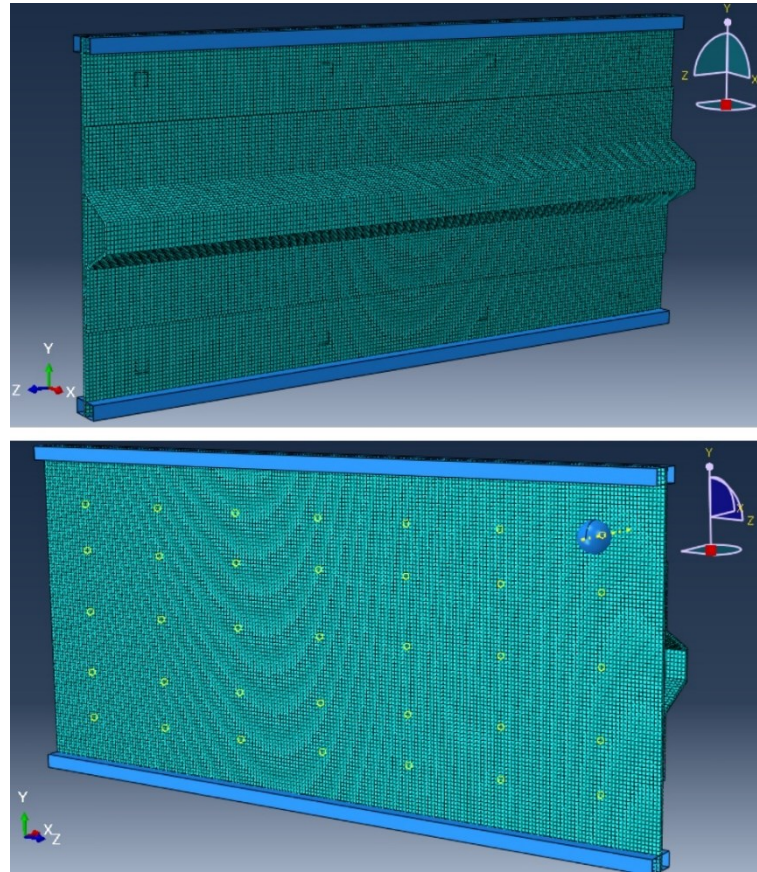


Figure 6. 4 Finite element model of stiffened panel : (top) bottom side with stiffener and sensors, (bottom) top side with impactor and impact locations

As previously mentioned in section 6.2 the main source of experimental data were hammer impacts. This was done as it was a quick and simple way of obtaining experimental data points with measured force and is most likely what experimental data sampling on actual structures in operation would look like. However, these impacts are difficult to model as they are random due to the nature of handheld actuation. In this case however, the main features that are used in the impact location and maximum force estimation (Time of Arrival and

maximum force gradient [8,16,17]) later on (section 6.6) are independent of impact case (impactor mass, angle, energy, etc.), and as such it does not matter whether the modelled impact case does not match that of the experiments.

Because of that, here the choice of impactor model design was based on simplicity and also for calibration purposes to find missing parameter information later on in section 6.3.2. An analytical rigid sphere surface (20 mm diameter) was defined to simulate an impactor (Figure 6. 3 and Figure 6. 4) and was given a lump mass of 100 g at the reference point in the centre. Displacement and rotation constraints were also applied at the reference point to prevent any movement except for translation transverse to the panel surface. The impactor was situated on the impact side of each panel at a distance of 0.01 mm from the surface to simulate the moment prior to contact. An initial velocity of 0.707 m/s was given to simulate impacts of 50 mJ energy. The impactor was moved to whichever location it was needed to simulate impacts, following the laid out locations (same as the experimental tests) in Figure 6. 1a and Figure 6. 2a, respectively resulting in 35 x 1 impacts.

Contact was defined through the general contact option for all contacts between components (panel, clamps and impactor) with a friction coefficient of 0.3 and a linear pressure-overclosure contact behaviour [127]. Two vital parameters that were not readily available from literature were the contact stiffness and damping coefficient (Table 6. 2), both which were obtained through calibration using experimental data as will be explained in the next section.

The output of the FE model was the acceleration of the impactor at the reference point and the principal strain components of the membrane elements of each sensor, all of which were sampled at 2 MS/s. The simulation itself was run for 20 ms from start of impact to collect a reasonable duration of measurements. The impact force history was obtained by multiplying the acceleration with the mass of the impactor. The signal voltage (V) from the sensors were obtained from equation (6. 1) :

$$V = \frac{E d_{31} t}{\epsilon} (1 - \nu)(\epsilon_{11} + \epsilon_{22}) , \quad (6. 1)$$

using the principal strain components (ϵ_{11} , ϵ_{22}) from the FE model, the piezo material properties (E , d_{31} , ϵ , ν) in Table 6. 2 and sensor thickness (t) [128].

6.3.2 Finite Element Model Calibration

To obtain the property values for contact stiffness and damping coefficient (Table 6. 2), calibration was done using experimental data gathered from 1 impact on the flat panel using a controlled drop impactor as shown in Figure 6. 5. The impactor has a steel 20 mm diameter spherical tip, a total mass of 100 g, and was dropped from a height of 50 mm to produce an impact of 50 mJ energy as is simulated in the FE model. As the impactor has no force measurement system, the impact force history was obtained from deconvolution of measured signals as was done in Chapter 4 [8]. To do so, first the actual force (F) and measured signal (S) spectral components from the hammer impact (F_1) at the target location (here it was calibrated from location 1, Figure 6. 1a) were used to obtain the spectral transfer function ($TF = F/S$). Afterwards, the obtained transfer function was used to obtain the impact force history spectral components ($F_{\text{drop}} = TF S_{\text{drop}}$) from the drop impact signal spectral components (S_{drop}). Finally, the drop impact force history was obtained by inverse Fourier transform of the obtained force spectral components. As there are 6 sensors, 6 impact force histories were produced, all of which were averaged to obtain the final impact force history (Figure 6. 6).

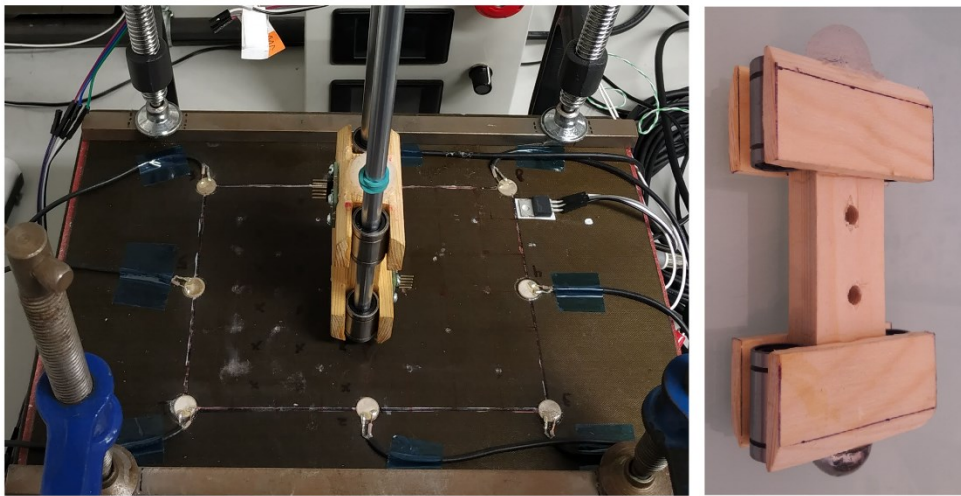


Figure 6. 5 Drop impactor used to collect experimental drop impact data on the flat panel for finite element model calibration

As both the impactor (analytical rigid) and plate (continuum shell) are rigid in the transverse direction, the interaction between impactor and plate during contact needs to be modelled [27]. Here, a linear contact stiffness (k) approach is used to define the relation between the transverse displacement of the contact area and the contact pressure. As the value of k is not readily available in literature for the materials used, calibration is done to find the appropriate value of k using the experimental sample as the reference. Figure 6. 6 shows the effect of different contact stiffness values on the impact force history. It can be seen that with a completely “hard” impact where the stiffness is infinite, the impact force was overestimated. Lowering the contact stiffness reduced the impact force until it became close to the experimental data at a stiffness value of $k = 500$ (Figure 6. 6).

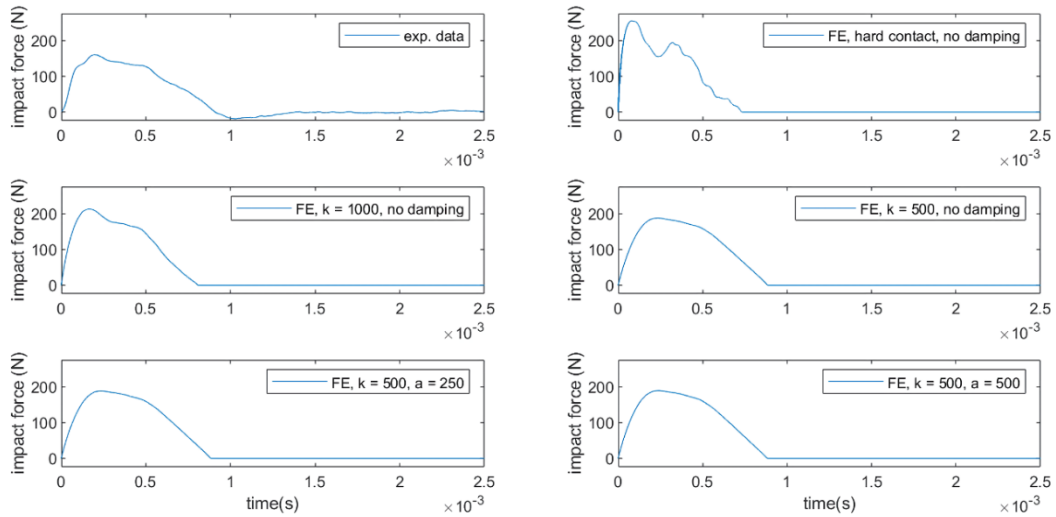


Figure 6. 6 Experimental drop impact force history and finite element results with various values of contact stiffness (k) and damping coefficient (α)

In the experimental signal (Figure 6. 7), it can be seen that after the initial forced response [8], the residual free vibrations attenuate rapidly. On the other hand, the signal from the “hard” FE model showed very low attenuation of the free vibration. Using a lower contact stiffness introduced some slight attenuation, but not as much as the experimental signal. Thus, here mass proportional Rayleigh damping (α) [127] was added to damp the low frequency (based on natural frequencies of the structure [8]) free vibrations. From Figure 6. 7, increasing the

damping coefficient (α) increases the attenuation of the signal, until at a coefficient value of 500 it approaches the level seen in the experimental signal. Although the amplitude of the signal itself differs between FE and experimental data, this will be rectified by the multifidelity approach later on in section 6.5. The obtained values for contact stiffness and damping coefficient were then used for all FE simulations.

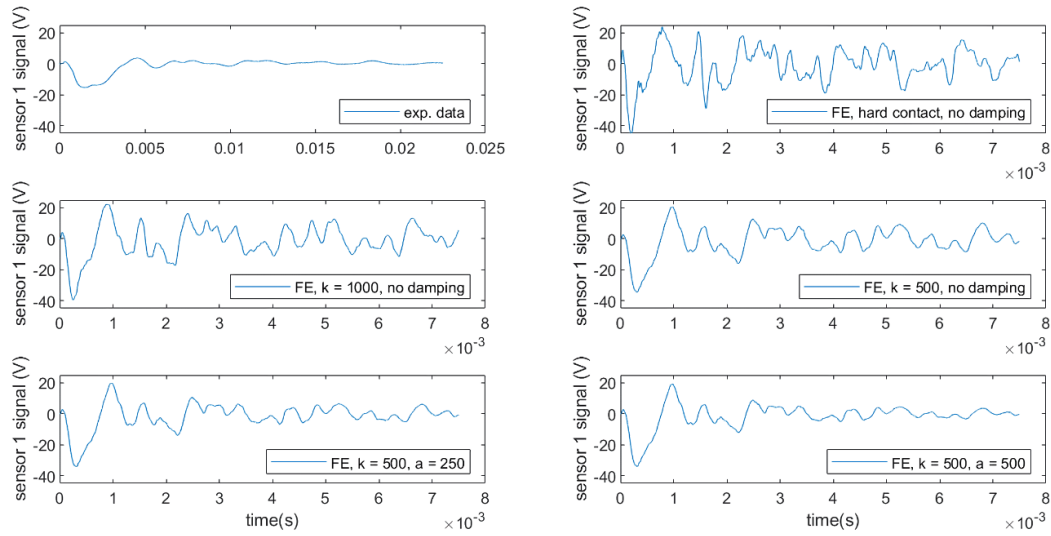


Figure 6. 7 Experimental drop impact signal from sensor 1 and finite element results with various values of contact stiffness (k) and damping coefficient (α)

6.4 Signal Feature Extraction for Impact Location and Maximum Force Estimation

Here, the data driven impact location (kriging based localisation [129]) and maximum force estimation (maximum impact force gradient method [8]) methods developed in previous chapters were used (will be described later on in section 6.6). One impact from each location in the experimental reference case of both panels (F1 and S1) was taken to form the high fidelity reference database of these algorithms whilst the rest of the experimental data (Table 6. 1) were used as test cases. The FE signals were used to form a lower fidelity reference database. Specific features were then extracted from the experimental and FE signals to be used as inputs for the impact location and maximum force estimation algorithms.

For impact localisation, the signal Time of Arrival (ToA) was used as the input feature and was extracted using the NSET (Normalised Smooth Envelope

Threshold) method [16]. To mitigate vibration noise (case F5), the signals were first highpass filtered using a 2 kHz IIR Butterworth filter. Afterwards, the signals were rectified and then lowpass filtered to generate the NSET envelope using a 250 Hz IIR Butterworth lowpass filter. Finally, the signals were normalised using the maximum absolute amplitude from the set of sensors. The ToA was taken as the time when the envelope surpasses a threshold value of 0.05. As the actual time of impact is unknown, the ToA is defined in the form of the difference between signal arrivals from the first arriving signal in the set of sensors [16].

For the maximum impact force estimation, the maximum absolute amplitude (A_{MA}) of the measured signals (without any signal processing) were used as the input feature [8]. As the maximum impact force estimation requires the knowledge of the impact maximum impact force gradients (G_{MA}) beforehand [8], the measured impact force from impacts used for the reference database (case F1 and S1) were combined with the subsequent maximum absolute amplitude (A_{MA}) to calculate the gradients.

The final test database consisted of the ToA and A_{MA} of each sensors for all test impacts, whilst the reference database (both high and low fidelity) consisted of ToA and G_{MA} (to be used with the A_{MA} from the test databases) of each sensors for the selected impacts [8,17,129]. The high and low fidelity reference databases were then the subject of the proposed multifidelity approach as elaborated in section 6.5.

6.5 Multifidelity Reference Database Augmentation using Cokriging

Cokriging works by looking at the spatial correlation between data points in multiple datasets (e.g. z , v), to interpolate a data point that is a member of one of the datasets (z) at a point/location using a weighted linear combination of all the data points in the known datasets (z , v) [121]. Having additional datasets (v) that are more densely sampled than the dataset to be interpolated (z), gives better interpolation than using a single dataset (e.g. ordinary kriging) as the additional correlated datasets provide more information regarding the behaviour of the data points in between the known points in the target dataset [121]. This way, cokriging can be used to construct a reference database with just a limited amount

of “expensive” experimental high fidelity data (z), aided by “cheap” and more densely sampled low fidelity (v) FE simulations to achieve similar levels of accuracy to a reference database constructed using purely high fidelity data.

The spatial (x,y) correlation between known/reference points are commonly described in the form of semi-variance (γ), as shown in equation (6. 2) [121] :

$$\gamma(r^{ref}) = \frac{1}{2N_h} \sum_i^{Nr} \sum_j^{Nr} (A_i^{ref,r} - B_j^{ref,r})^2 \quad (6. 2)$$

which captures how the correlation between data points decreases (or semivariance, γ , increases) with increasing distance ($r = \sqrt{x^2 + y^2}$) between them. When looking at the semivariance between data points in the same dataset (e.g. $A = B = z$), the semivariance was calculated for all possible data point pairs (z_i, z_j , N_r number of points) in the dataset. When looking at the semivariance between datasets (e.g. $A \neq B$, $A = z$, $B = v$), the semivariance value was calculated between all possible data point pairs at locations that were concurrently sampled for both datasets (z_i, v_j , N_r number of concurrently sampled locations). The semivariance was then averaged by the number of data point pairs that share the same distance (N_h). As data point pairs do not always share uniform distances, the distances are grouped into bins to allow averaging (here 20 bins were used). A linear semivariance function ($\gamma^f[r] = G_\gamma r$) was then fitted over the discrete semivariance points to obtain a continuous expression of the semivariance with distance. Figure 6. 8 shows an example of the semivariance and fitted functions for the G_{MA} of sensor 6 of the flat panel using the experimental data (γ^{zz}), FE (γ^{vv}) data and combination of both (γ^{zv}).

To interpolate a data point at a certain location (x^{in}, y^{in}), first the distances between the known data points (r^{ref}) as well as the distance between the input point to the known data points (r^{in}) were calculated. Using the fitted functions ($\gamma^{zz}[r]$, $\gamma^{vv}[r]$, $\gamma^{zv}[r]$) and distances (r^{in} , r^{ref}), the semivariance values were calculated for the known ($\gamma^{zz}[r^{ref}]$, $\gamma^{vv}[r^{ref}]$, $\gamma^{zv}[r^{ref}]$) data pairs as well as the input and known ($\gamma^{in}[r^{in}]$) data point pairs (N_z number of high fidelity points and N_v

number of low fidelity data points). The system of equations (6. 3) [121,130] (I is a vector of 1s and O is a vector of 0s) :

$$\begin{bmatrix} \gamma_{i,j}^{zz}(r^{ref}) & \gamma_{i,l}^{zv}(r^{ref}) & I_{i,1} & O_{i,1} \\ \gamma_{k,j}^{zv}(r^{ref}) & \gamma_{k,l}^{vv}(r^{ref}) & O_{k,1} & I_{k,1} \\ I_{1,j} & O_{1,l} & 0 & 0 \\ O_{1,j} & I_{1,l} & 0 & 0 \end{bmatrix} \begin{bmatrix} w_i^{zz} \\ w_j^{zv} \\ \mu^{zz} \\ \mu^{zv} \end{bmatrix} = \begin{bmatrix} \gamma_i^{in}(r^{in}) \\ \gamma_j^{in}(r^{in}) \\ 1 \\ 0 \end{bmatrix} \quad \begin{matrix} i, j = 1, 2, \dots, Nz \\ k, l = 1, 2, \dots, Nv \end{matrix} \quad (6. 3)$$

was then solved to obtain the cokriging weights (w^{zz} , w^{zv}) and Lagrange parameters (μ^{zz} , μ^{zv}). Using equations (6. 4) and (6. 5) [121,130] :

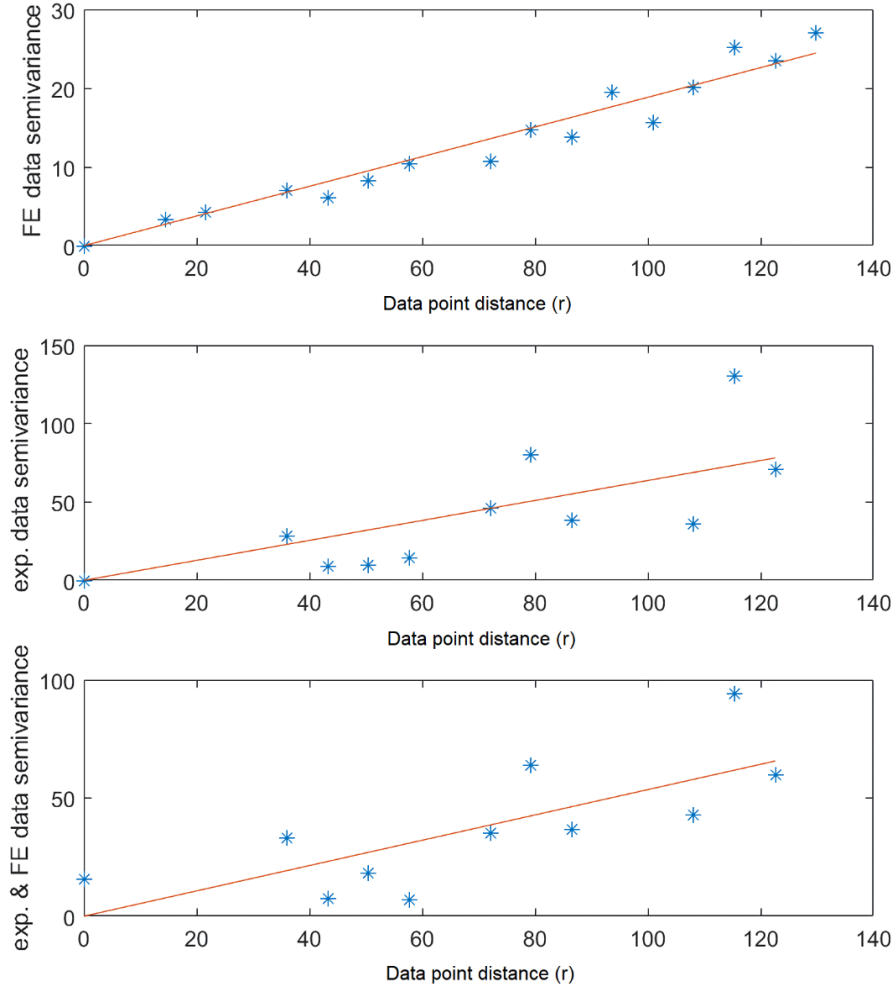


Figure 6. 8 Semivariance of data points within the reference databases of the flat panel from the finite element (FE) simulations (top), experimental data samples (middle) and combination of both (bottom), including fitted linear functions for each

$$z^{est} = \sum_{i=1}^{Nz} w_i^{zz} z_i^{ref} + \sum_{j=1}^{Nv} w_j^{zv} v_j^{ref} , \quad (6.4)$$

$$\sigma^{est} = \sqrt{\mu^{zz} + \sum_{i=1}^{Nz} w_i^{zz} \gamma_i^{in}(r^{in}) + \sum_{j=1}^{Nv} w_j^{zv} \gamma_j^{in}(r^{in})} . \quad (6.5)$$

the estimated data point (z^{est}) and the associated variance/uncertainty (σ^{est}) were then calculated. As the semivariance (γ) always has a positive value, the kriging weights (w^{zz} , w^{zv}) and Lagrange parameters (μ^{zz} , μ^{zv}) solved from equation (6.3) were constrained to be positive (MATLAB `lsqnonneg` solver used here) so that the variance always has a real value.

To build a reference database, interpolation was done for the signal features (ToA and G_{MA}) for all 35 impact locations on the flat and stiffened panel as shown in Figure 6.1a and Figure 6.2a using a limited number of experimental samples as well as the full FE reference database (35 points). The number of experimental samples was varied starting from 5 (all 4 corners and middle point) all the way up to 35 points (all experimental data) to see the effect on impact localisation and maximum force estimation accuracy. Here, only the estimate value was used in the reference database whilst the variance was used to determine the sampling strategy. When increasing the experimental points from 5 (starting with locations 1,7,18,29,35, Figure 6.1a and Figure 6.2a) to 35, the selection of which location to sample next was based on the points with the highest variance (if there were multiple points with the same level of variance, then all points were sampled simultaneously) as it shows the area with highest uncertainty. By sampling these locations, it was expected to reduce the uncertainty of the estimated values and give the best spatial coverage.

6.6 Impact Location and Maximum Force Estimation Methods

6.6.1 Kriging Based Impact Localisation Method

The kriging based impact localisation method uses similar principles to the cokriging method for reference database interpolation in section 6.5. It uses kriging, which is the single dataset form of cokriging as the base [121], but instead of interpolating data points based on their location, it uses the “distance”

or difference between impact signal features to interpolate characteristics of the impact. For localisation, the characteristics interpolated were the impact location coordinates (x,y), using the ToA as the input feature [129].

Similar to cokriging, first the semivariance (γ^{ToA}) was calculated for the impact location coordinates (x,y) using the difference (L2 norm) in ToA (h^{ref}) for all possible reference database pairs (Nr number of database points) as shown previously in equation (6. 2). Then a linear semivariance function was fitted ($\gamma^{f,ToA}[h] = G_{ToA} h$) to the discrete semivariance values. To estimate the location of an incoming impact, the L2 norm of the input ToA (h^{in}) was calculated against the ToA of the reference database points. Using the fitted function and the L2 norm of the reference database points and the input point, the semivariance values ($\gamma^{ToA,in}$) were obtained from the fitted semivariance function. Equation (6. 6) :

$$\begin{bmatrix} \gamma_{ij}^{ToA}(h^{ref}) & I_{1,i} \\ I_{1,j} & 0 \end{bmatrix} \begin{bmatrix} w_i^{ToA} \\ \mu^{ToA} \end{bmatrix} = \begin{bmatrix} \gamma_i^{ToA,in}(h^{in}) \\ 1 \end{bmatrix} \quad i, j = 1, 2, \dots, Nr, \quad (6. 6)$$

is the single dataset form of equation (6. 3), and was solved (with the same lsqnonneg solver as cokriging in section 6.5) to obtain the kriging weights (w^{ToA}) and Lagrange parameter (μ^{ToA}). The location estimate (c^{est}) as well as the uncertainty/variance (σc^{est}) was then calculated using equation (6. 7).

$$c^{est} = \sum_{i=1}^{Nr} w_i^{ToA} c_i^{ref} \quad \sigma c^{est} = \sqrt{\mu^{ToA} + \sum_{i=1}^{Nr} w_i^{ToA} \gamma_i^{ToA,in}(h^{in})}. \quad (6. 7)$$

$c = x \text{ or } y \text{ coordinates}$

Here, the ToA was not used all at once in 1 input vector, rather it was split into multiple smaller input vectors containing permutations of the possible combinations of sensors [17] to obtain a more robust estimation (e.g. permutations of 5 sensors out of 6 gives 12345, 12346, 12356 and so on). This resulted in multiple final estimates depending on the number of combinations used (a combination of 5 sensors out of 6 for the flat panel and a combination of 4 sensors

out of 5 for the stiffened panel was used). To combine the final estimate distributions (constructed with the estimate as mean and uncertainty as standard deviation), Bayesian updating was used, as shown in equation (6. 8) [18,129] :

$$P_i(O|N) = \frac{P_i(N|O)P_i(O)}{P_i(N)} \quad (6. 8)$$

$$P_i(N|O) = P_{i-1}(O|N) \quad i = 1,2,3 \dots Ne$$

with a random initial prior distribution (P[O]) that was updated by the Ne number of estimate distributions (P[N|O]) to obtain an informed final estimate (P[O|N]).

From the resulting distribution, an estimate range was taken using a 95% confidence interval for each coordinate (x,y). An elliptical uncertainty range was then taken around the estimate point using the range for the x and y coordinates as the semimajor axes (x_{sm}, y_{sm}), designating the area where there is 95% confidence the real impact was located in [129]. Equation (6. 9) was used to calculate the error bounds of this range :

$$RSE_{lim}(\theta) = \frac{x_{sm} y_{sm}}{\sqrt{(y_{sm} \cos[\theta])^2 + (x_{sm} \sin[\theta])^2}} \quad (6. 9)$$

$$\sin(\theta) = \frac{y_{err}}{RSE} \quad \cos(\theta) = \frac{x_{err}}{RSE} .$$

The Root Square Error ($RSE = \sqrt{x_{err}^2 + y_{err}^2} = \sqrt{(X^{act} - X^{est})^2 + (Y^{act} - Y^{est})^2}$) between the estimated (x^{est}, y^{est}) and actual (x^{act}, y^{act}) impact location was calculated and then compared with the estimated uncertainty range ($RSE_{lim}[\theta]$) for the angle between the estimate and actual location (θ), as shown in. If the RSE was smaller than the uncertainty range (thus the actual location is located inside the uncertainty range), the error of the uncertainty range (RSE_{range}) was taken as 0. If not, the uncertainty range error was calculated from the edge of the uncertainty range ($RSE_{range} = RSE - RSE_{lim}$). To summarise the uncertainty range errors for multiple impacts in each case (Table 6. 1), a gamma distribution was fit to the errors and the 90th percentile of estimation range error (RSE_{R90th}) was used as the summarising metric [16,17,129].

6.6.2 Maximum Impact Force Gradient Method

Similar to location estimation (section 6.6.1), the maximum impact force estimation also uses kriging to determine the G_{MA} (estimate and uncertainty) of the incoming impact using the ToA as input [129]. After obtaining the G_{MA} distribution for each sensor, the maximum impact force distribution (F_{max}) was calculated from $F_{max}(x, y) = G_{MA}(x, y) A_{MA}(x, y) (1 - \alpha_T[T - T_{ref}])$. For the flat panel, the temperature (T) compensation parameter ($\alpha_T = -0.0026$, $T_{ref} = 24^0$ C) has been characterised in Chapter 4 [8] and the results were used here (the stiffened panel did not have a different temperature case, thus no need for temperature compensation). As each sensor produces 1 maximum impact force distribution, they were combined together by taking the mean of the distributions [129].

Here, the ToA was also used in combinations as is for localisation, resulting in a maximum impact force distribution for each combination. These distributions were also combined using Bayesian updating to obtain the final maximum impact force distribution. The final estimated maximum impact force range was determined using a 95% confidence interval. As shown in equation (6. 10) :

$$F_{max,Error} = \begin{cases} \frac{(F_{max,range(-)} - F_{max,act})}{F_{max,act}} 100\% , F_{max,act} \leq F_{max,range(-)} \\ 0 , F_{max,range(-)} \leq F_{max,act} \leq F_{max,range(+)} \\ \frac{(F_{max,range(+)} - F_{max,act})}{F_{max,act}} 100\% , F_{max,range(+)} \leq F_{max,act} \end{cases} \quad (6. 10)$$

if the actual measured impact force ($F_{max,act}$) was within the estimated range, then the maximum impact force estimate range error ($F_{max,Error}$) was taken as 0. If not, the estimate range error was calculated from the bounds of the estimate range ($F_{max,range(-)} - F_{max,range(+)}$). Averaging was done to summarise the maximum impact force range errors ($F_{max,Rmean} \pm F_{max,Rstd}$) for each case (Table 6. 1).

6.7 Results

Figure 6. 9 shows the comparison between the maximum impact force gradient (G_{MA}) of sensor 6 on the flat panel for the reference database of the low fidelity FE data and the high fidelity experimental data. It can be seen that there is

only a limited correlation between the FE and experimental data. Taking some experimental data samples (11 out of 35) and applying cokriging (Figure 6. 9) shows a significant increase in correlation of the cokriged data with experimental data. This demonstrates how effective the proposed approach can increase the correlation of signal features using a small sample of high fidelity data. This increased correlation should result in improved accuracy for impact location and maximum force estimation.

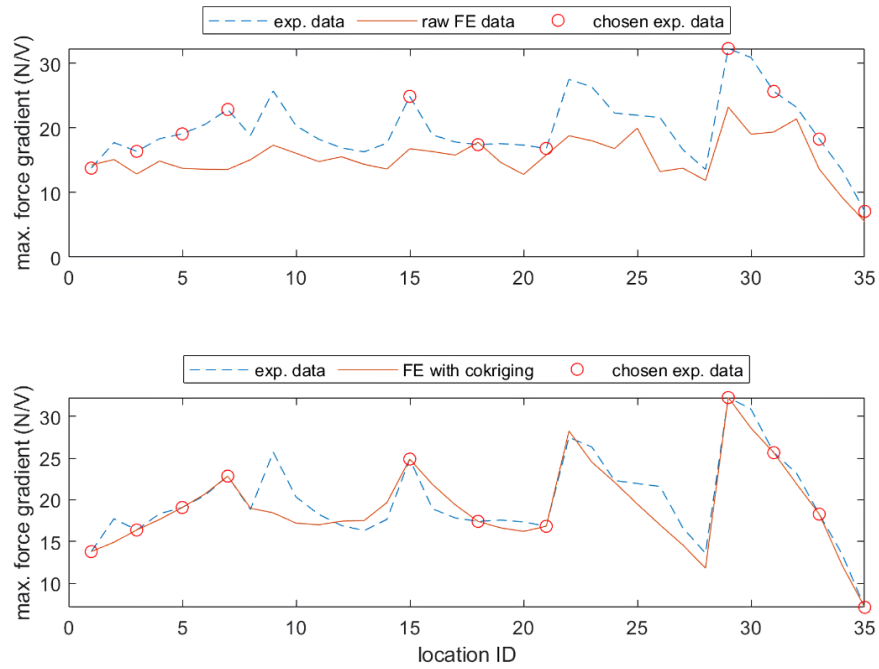


Figure 6. 9 Comparison between maximum impact force gradient for sensor 6 on the flat panel for : (top) finite element data vs experimental data, (bottom) cokriged finite element data (using 11 experimental data samples) vs experimental data

Figure 6. 10 and Figure 6. 11 shows the impact location and maximum force estimation results for the reference case (F1) of the flat panel, using different reference databases with varying amounts of experimental points (maximum is 35 points, 0% indicates full FE data, 100% indicates full experimental data). Here it can be seen that when using only FE data, the error and uncertainty of both location and maximum impact force estimation was very high compared to when using all experimental data. However, when cokriging was applied and experimental samples were gradually added, the error for both location and

maximum impact force estimation decreased significantly and started to approach full experimental data error levels starting from 31.4% (11 out of 35 samples) experimental data sample usage, which here is taken as the optimum percentage (best “cost” to accuracy ratio).

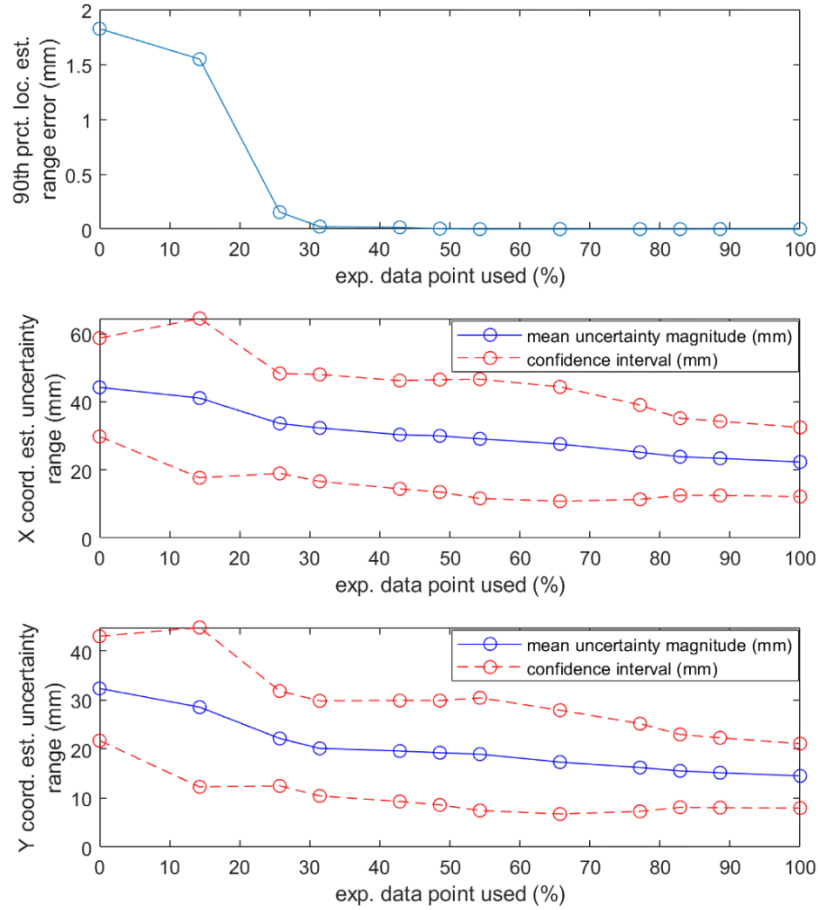


Figure 6. 10 Change in flat panel impact location estimation error and uncertainty as experimental high fidelity data is gradually added to cokrig low fidelity finite element data

Table 6. 3 shows the errors for both the impact location and maximum force estimation on the flat panel for other test cases (F2 – F6) besides the reference case (F1) for full FE data, full experimental data and optimum percentage of experimental data usage. Here, it can be seen that the accuracy at the optimum percentage was robust for the environmental and operational conditions simulated in the test cases.

Figure 6. 12 and Figure 6. 13 shows the impact location and maximum force estimation results for the reference case (S1) of the stiffened panel, using

databases with varying amounts of experimental data samples. Similar to the flat panel, with purely FE data, the error and uncertainty was high for both location and maximum impact force estimation. As the amount of experimental data samples was gradually increased, the error for both location and maximum impact force estimation decreased to levels near full experimental data usage at 65.7% experimental data samples (23 out of 35). The uncertainty decreased slightly for the localisation but remained relatively constant for the maximum impact force. This shows how the FE model was less able to capture the behaviour in the stiffened panel compared to the flat panel, most likely due to the added geometrical complexity, and resulted in a higher optimum percentage.

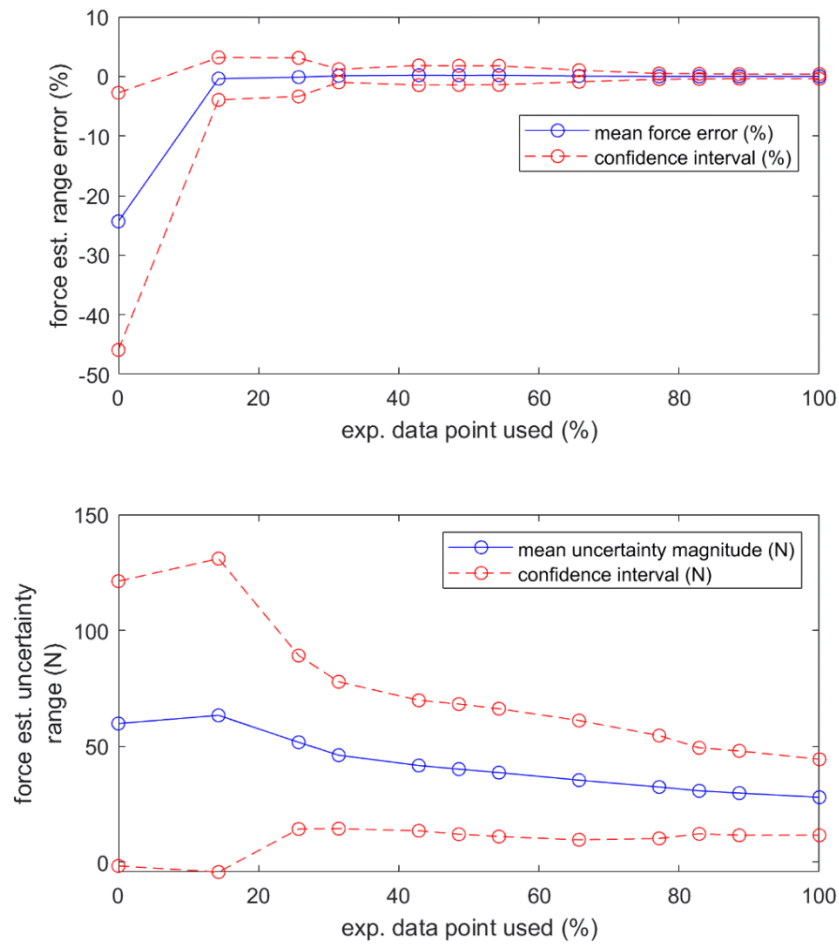


Figure 6. 11 Change in flat panel maximum impact force estimation error and uncertainty as experimental high fidelity data is gradually added to cokrig low fidelity finite element data

Table 6. 3 Impact location and maximum force estimation for all flat panel cases

Impact Case		RSE _{R90th} (mm)	RSE _{R90th} (mm)	RSE _{R90th} (mm)	F _{max,Error} (%)	F _{max,Error} (%)	F _{max,Error} (%)
Exp. data usage		0%	31.4%	100%	0%	31.4%	100%
F1	steel hammer, ref case	1.82	0.02	0	-24.3 ± 10.8	0.1 ± 0.6	0.0 ± 0.2
F2	steel hammer, incr. mass	1.28	0	0	-31.9 ± 9.2	-1.2 ± 2.1	-1.3 ± 2.0
F3	steel hammer, incr. temp.	1.02	0.01	0	-20.4 ± 11.8	1.3 ± 2.8	0.8 ± 1.7
F4	plastic hammer	2.03	0.37	0.01	-18.1 ± 11.8	1.9 ± 3.6	1.9 ± 2.5
F5	steel hammer, + noise	1.82	0.02	0	-24.3 ± 10.8	0.1 ± 0.7	0.0 ± 0.6
F6	steel hammer, interm. loc.	0.36	0	0	-25.6 ± 8.6	0 ± 0	0.0 ± 0.3

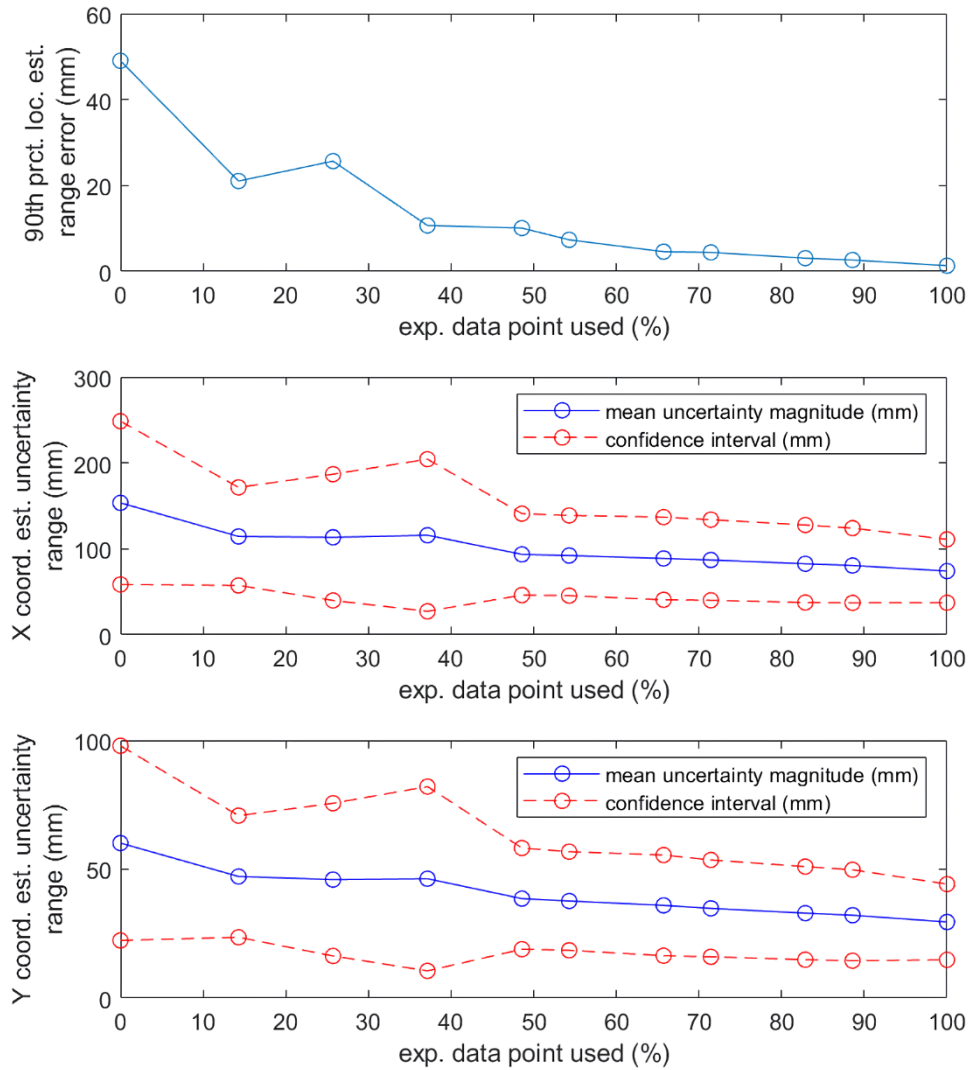


Figure 6. 12 Change in stiffened panel impact location estimation error and uncertainty as experimental high fidelity data is gradually added to cokrig low fidelity finite element data

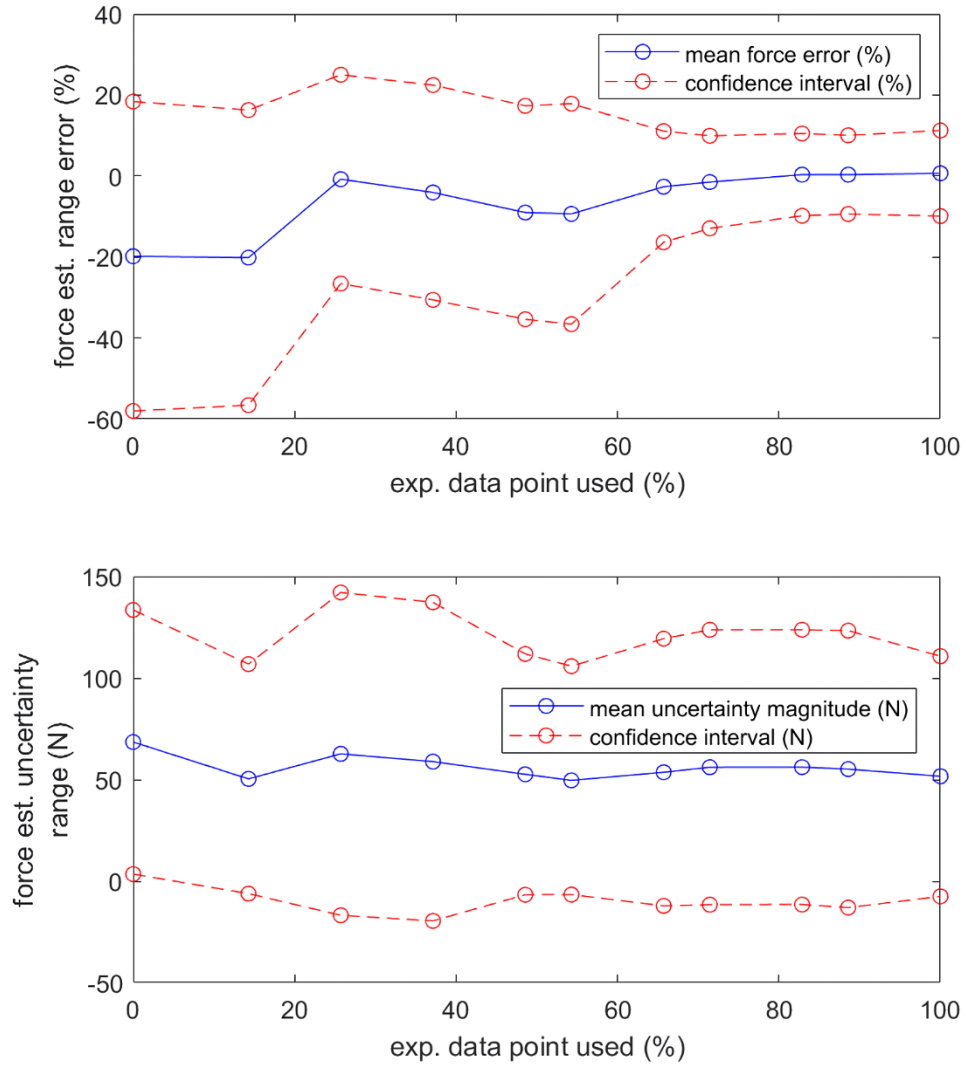


Figure 6. 13 Change in stiffened panel maximum impact force estimation error and uncertainty as experimental high fidelity data is gradually added to cokrig low fidelity finite element data

Figure 6. 14 and Figure 6. 15 illustrates the comparison between the location and maximum impact force estimation between full FE data and optimum percentage of experimental samples for both flat and stiffened panels. Here it can be seen how at the optimum percentage the accuracy of the estimation is significantly increased compared to using pure FE data.

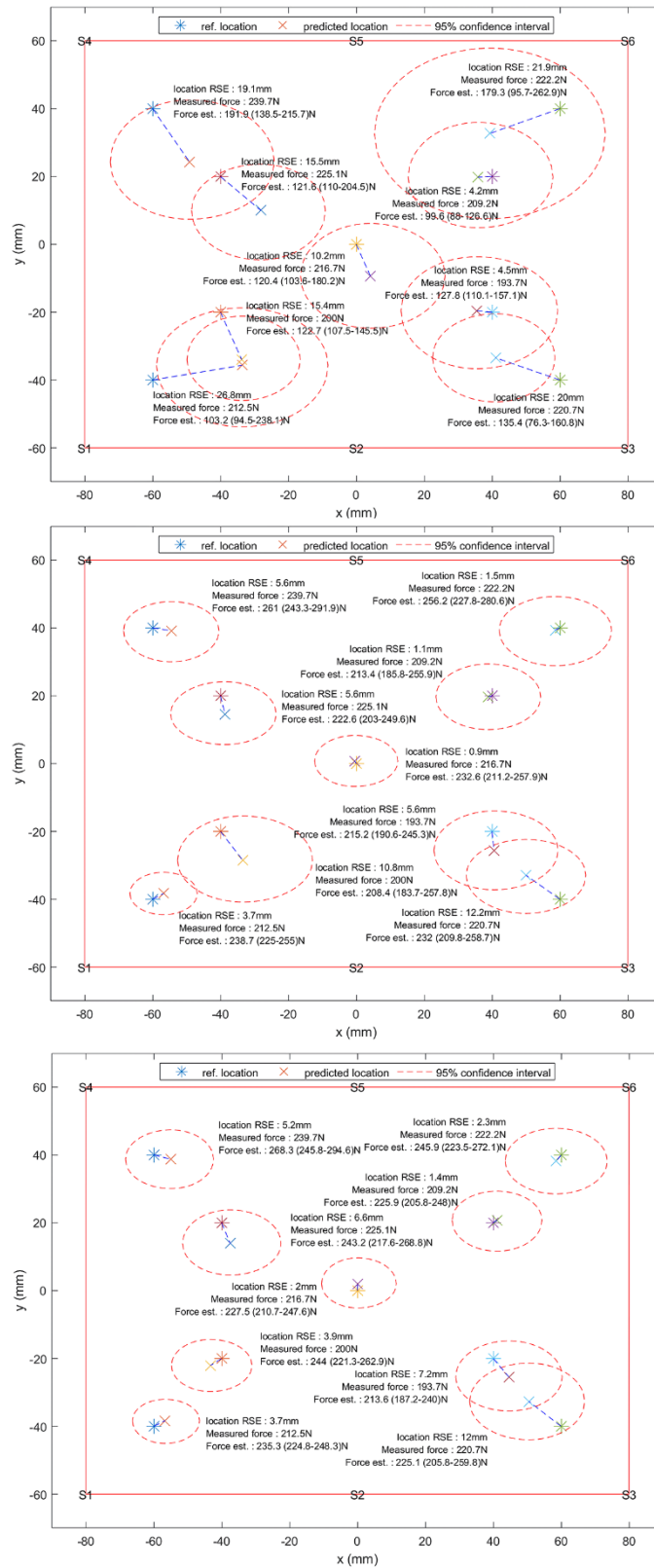


Figure 6. 14 Impact location and maximum force estimation for plastic impact case (F4) on the flat panel using different reference databases : (top) all FE data, (middle) cokriging with 31.4% experimental samples, (bottom) all experimental data

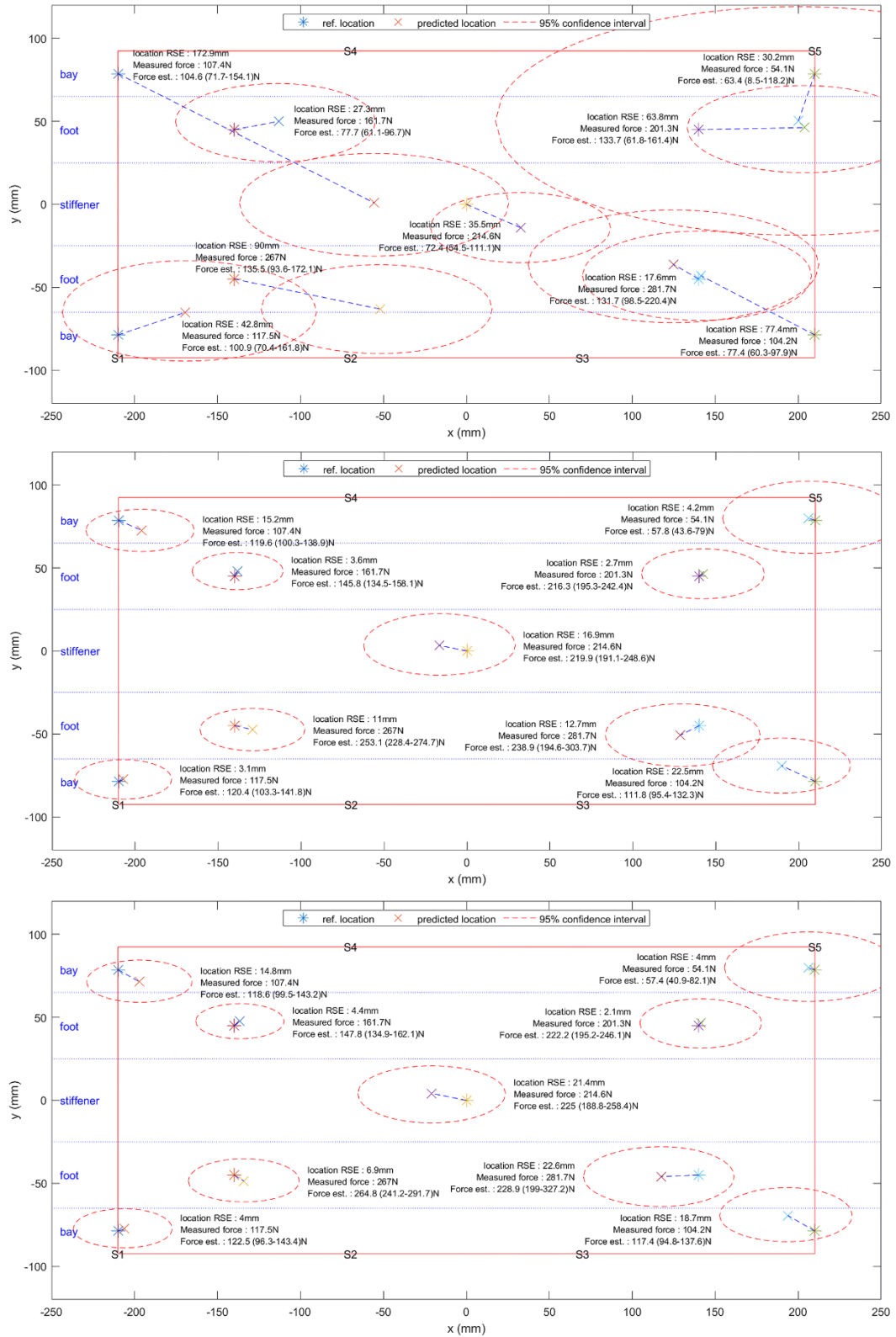


Figure 6. 15 Impact location and maximum force estimation for reference impact case (S1) on the stiffened panel using different reference databases : (top) all FE data, (middle) cokriging with 65.7% experimental samples, (bottom) all experimental data

6.8 Possible Extension of Multifidelity Approach and Future Work

Here the multifidelity approach has been demonstrated to be an effective way to combine different sources of data to achieve reduction of “cost” in constructing a reference database for data driven impact location and maximum impact force estimation methods. Although the example given here is a combination between FE and experimental test data from structural coupons, the cokriging method given here is able to combine data from a wider range of sources, such as tests from different levels of coupon/structure complexity, simulations (e.g. FE), data from similar components, inspection history as well as data from sister/fleet assets (e.g. aircraft, civil structures) as shown in Figure 6. 16.

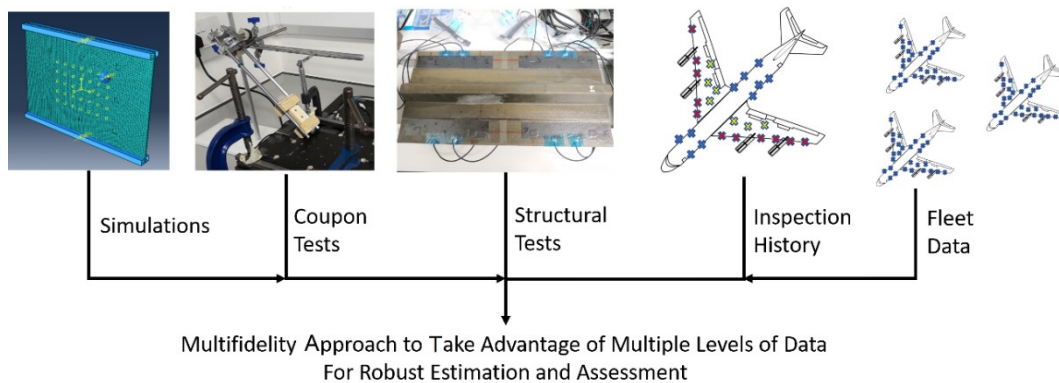


Figure 6. 16 Possible expansion of multifidelity approach to encompass multiple sources of data

By being able to combine data from similar components (e.g. similar geometry panels), it may be possible to reduce the overall amount of data required for a large scale structure. The capability to include inspection history may enable the reference database to become more and more accurate as time goes on and the structure experiences more impacts that are identified through inspection and logged into the reference database. By being able to share the data between sister/fleet assets, it is possible to integrate the operational experience from a large number of assets to obtain a large amount of data.

As mentioned previously in section 6.5, only the estimate is used from the cokriging results for the reference database. In future studies, it may be possible to take advantage of the variance to construct a stochastic (rather than deterministic)

reference database to possibly increase the accuracy of the location and maximum impact force estimates. Improvement of the FE model accuracy or improved high fidelity sampling strategy may also improve overall accuracy and lower the optimum percentage of high fidelity data needed, especially for complex structures.

6.9 Conclusion

In this chapter a multifidelity approach was shown to reduce the “cost” of constructing the reference database necessary for data driven impact location and severity estimation methods by combining “cheap” FE data with a limited number of “expensive” experimental samples. The results showed that using pure FE data for points used, it was shown that the accuracy increases significantly approaching levels near pure experimental data at only 31.4% and 65.7% of experimental data usage for flat and stiffened composite panel test specimens, signifying a reduction in the need for “expensive” experimental data. Further tests were carried out for impacts under simulated environmental and operational conditions, which showed that the accuracy is robust for the simulated conditions. Thus, by using the proposed approach, it is possible to significantly reduce the “cost” of constructing reference databases with the help of “cheaper” sources of data, thus bringing data driven methods much closer to real life application.

The amount of experimental “cost” reduction depends on how well the FE model can capture the behaviour of the actual structure. This is manifested in 2 aspects : the number of points spatially that can be feasibly evaluated with the model as well as the accuracy of the modelling of the physical structure itself. The accuracy of the FE model can potentially be increased by exploring potential improvements, such as more realistic modelling of the impactor and boundaries (currently modelled as rigid) to better capture the behaviour load transfer, wave generation and reflection [27,36,131,132]. On the other hand, the FE model itself can be made “cheaper” to run by mirroring the FE results from one section to its symmetrical counterpart or using a dynamic point load as input as opposed to modelling the impact and contact event itself [70]. Thus, there is still potential for

improvement in the magnitude of experimental “cost” reduction compared to what was obtained in this study.

Finally, the wider context of data fusion is also explored, highlighting the possibility to combine various sources of data (including inspection history as well as data from sister assets) can possibly be used to create a data driven framework that requires less initial data whilst also being robust and self-improving.

Chapter 7

Real-time Impact Location Estimation with Uncertainty Quantification using an Event Driven Miniaturized Passive Sensing Data Acquisition Unit

The work from previous chapters have developed reliable and robust impact location and impact severity algorithms. However, no matter how good an algorithm is, it's applicability will inevitably be limited by the equipment that it works on. Any Data Acquisition (DAQ) system installed on an aircraft must be as light as possible and thus will usually have to sacrifice performance to some degree. Thus, in this chapter the developed impact localisation algorithm is tested in real time on a prototype miniaturized DAQ system to demonstrate it's applicability in representative real life equipment.

7.1 Introduction

Thus, there is high interest in developing automated impact monitoring systems to alleviate the cost through condition based maintenance [28,30,37,38,60,61,133–137]. One of the main components of such systems is the data acquisition unit, which records signals from sensors (e.g., PZT sensors, accelerometers) attached to the structure [28,30,37,38,60,61,133–137]. These signals are then relayed and processed to give the operator information regarding the location and severity of the impact . To be applicable to aircraft structures, these systems need to be small, lightweight and require low energy to maintain the balance of weight and cost savings by the addition of the system [28,30,37,38,60,61,133–137].

Currently, many prototype systems have been developed using microcontrollers (e.g. STM32) [38,61,133,134,137] or FPGAs (Field

Programmable Gate Arrays) [37,60] allowing for small size and light weight. To reduce weight further, some systems are designed to be wireless and battery operated to reduce the amount of wiring needed [37,38,61,133]. Providing continuous monitoring, even when the aircraft is not in operation, leads to a very large energy cost and is especially critical for battery operated systems [37,38,61,133]. Although the system must always be alert towards possible impact events, it does not need to continuously measure data when there are no impacts. Thus, some systems [37,38,133] are designed to “sleep” during inactivity and only “wake up” to record data when an impact event occurs, saving significant amounts of energy (commonly called event driven systems).

However, this causes a lag time between “waking up” to recording data, thus there will inevitably be some data loss at the start of signals recorded closer to the impact location (as the travel of the wave to the sensor is shorter) [37,38,133]. This portion of the signal contains information regarding the Time of Arrival (ToA) of the signal, which is one of the main signal features used to estimate the impact location [16,17,129]. This loss of data coupled with the general performance limitations (sampling rate, amplitude limitation, etc.) of current microcontrollers (compared to lab oscilloscopes) results in most systems running simplified localisation algorithms (e.g. location estimated at sub-region level, rather than actual coordinates) or increased number of sensors [28,37,133] to compensate. This also prevents the implementation of more advanced features such as uncertainty quantification [54,129], reducing the robustness of the location estimates.

Here a simple data reconstruction method is presented for estimating the lost portion and the ToA of impact signals recorded from a miniaturized event driven passive data acquisition system called WIPASS (Wireless Passive Sensing System) [29,38]. When the signal is cut, it can be expressed as the original signal that is superimposed by a pulse that negates the starting portion of the original signal. As this pulse only negates a portion of the signal, it must be shorter than the signal itself and will most likely contain higher frequency components than the original signal [138]. The proposed method utilizes filters to remove these high frequency components and estimate the original lower frequency signal. The ToA estimates

are then fed into a kriging based impact location estimation algorithm [129] to test whether it is good enough for robust impact localisation with uncertainty quantification. Lastly, the system is demonstrated to be able to locate impacts accurately in real-time.

7.2 Experimental Setup

Figure 7. 1 shows the event driven data acquisition unit, named WIPASS (Wireless Passive Sensing System), that is driven by an STM32 microcontroller and supports 12 ADC channels for recording signals at a sampling frequency of 90.27 kS/s each with a 1000 sample length [29,38]. The system was designed primarily to record voltage signals from PZT sensors which are self powering, saving energy and also allowing the sensors to wake the system up when an impact occurs. As impacts may generate high voltage signals from PZTs (above the 3V limit of the STM32 MCU) [29,38], 6 channels were equipped with 10x attenuators to allow high energy impact recording. However, here only the other 6 channels without attenuation were used as the impacts generated were small (in future iterations the attenuation level would be adjustable).

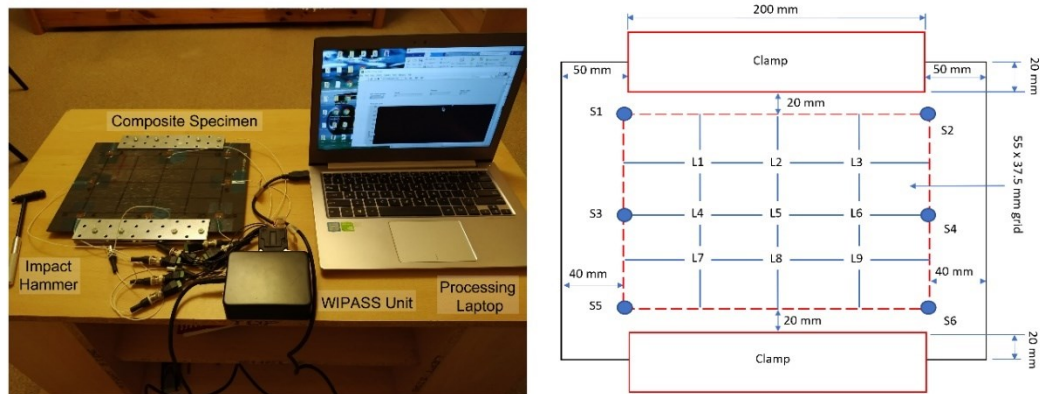


Figure 7. 1 Impact setup (left) consisting of processing laptop, WIPASS unit, impact hammer and composite specimen (with layout of composite specimen on the right)

When activated, the system is always in “sleep” mode unless an impact occurs that generates a signal that is higher than a set digital threshold (here it was set at 5 out of 255), which will trigger a signal comparator that will send a signal to wake up the microcontroller to start recording [29,38]. To prevent accidental

waking up due to disturbance that is not an impact (e.g. vibration [16,17]), each channel was equipped with a 2 kHz analog single order highpass filter. Once the signal had been recorded, it was relayed through a serial USB connection (wireless Zigbee module not used here as programming was still in progress) to a computer, where it was received by an NI LabView GUI and converted into a text file containing the signals from all channels. The data was then processed in MathWorks MATLAB to produce location estimates.

To simulate impacts, a flat carbon fibre panel (M21 T800s, [+45/-45/0/90/0]_s layup) was used as a test specimen with 8 PZT sensors attached (only 6 were used due to the limitation of non-attenuated channels available) as shown out in Figure 7. 1. A small steel hammer (Figure 7. 1) was used to generate impacts (random angle and energy) on the panel, which were then picked up by the PZT sensors and WIPASS unit. A total of 9 impacts with 3 repetitions were generated on the locations shown in Figure 7. 1. One impact from each location (9 x 1 impacts) was taken to form the reference database for the impact location estimation algorithm [129], while the rest were used as test data. To test real-time impact localisation, 3 impacts were conducted on the plate in random locations and the signals are recorded, passed on by the system as well as processed by the localisation algorithm directly, as demonstrated in a video provided in section 7.6.

7.3 Data Reconstruction and Feature Extraction for Impact Localisation

Figure 7. 2 shows an example of the signal recorded by the WIPASS system at channel 1 for an impact at location 1 (Figure 7. 1). It can be seen that the signal is cut in the beginning, with an unknown Time of Arrival (ToA). As mentioned in section 7.1, all signals are comprised of a combination of a number of spectral components [138]. Here, the signal itself is comprised of lower frequency components, while the cut portion is akin to a localised high frequency signal superimposed on the original signal. Thus to “remove” it and estimate the original beginning of the signal it is proposed to apply a low pass filter in MATLAB on the signals passed on from the WIPASS unit.

Specifically, here the Normalised Smoothed Envelope Threshold (NSET) method [16] was employed. The signal was first padded with 100 zero sample

points at the beginning to allow space for the cut portion of the signal. As the WIPASS system records the signals in rectified form, the initial step of the NSET method (rectifying [16]) was already done by the recording system. A low pass 2 kHz IIR Butterworth filter was then applied to the rectified signal to “remove” the cut. To obtain the ToA, the signals were first normalized with respect to the maximum amplitude of all the signals from the set of sensors. The ToA was then determined as the time when the signal amplitude first exceeds a certain threshold (a value of 0.025 used here). As the exact time of signal excitation from impact is unknown (as is the conditions in real life monitoring), the ToA was defined as the ToA difference relative to the first arriving signal (first arriving signal has a ToA of 0 [16,17]). To assess the effectiveness of this proposed method, it is compared to simple reconstruction of the signal using a moving mean (50 sample window), which was found to produce a decent estimate of the start of the signal in a previous study (although untested for location estimation) [29].

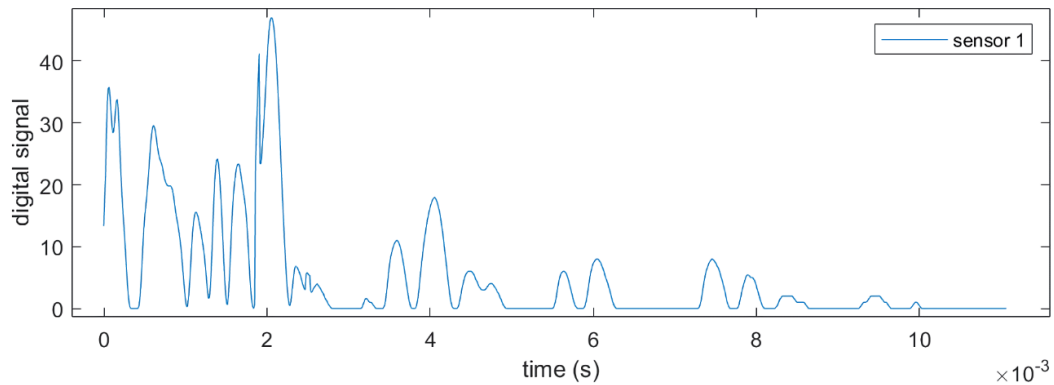


Figure 7. 2 Impact signal recorded at sensor 1 from an impact at location 1 using the WIPASS unit

An impact was done in location 1 with the hammer and an NI PXI 5105 oscilloscope (instead of the WIPASS unit) to obtain an example of a complete signal (shown rectified in Figure 7. 3 and Figure 7. 4) at 2MS/s. The signal was then artificially “cut” (amplitude set to zero) at different segments at the beginning of the signal to simulate different degrees of data loss (Figure 7. 3 and Figure 7. 4). It can be seen from Figure 7. 3 and Figure 7. 4 that both the proposed NSET method and the benchmark moving mean method, are able to estimate the

start of the signal with very similar levels of accuracy even with significant loss of data. The ToA from all of the impact signals collected (9 x 3 impacts) using the WIPASS unit (as described in section 7.2) were then extracted (using both the moving mean and NSET methods) and split into a reference database (9 x 1 impacts) and a test database (9 x 2 impacts). It was then tested with the kriging based impact localisation method [129] to see if the estimated ToA was good enough for accurate location estimation.

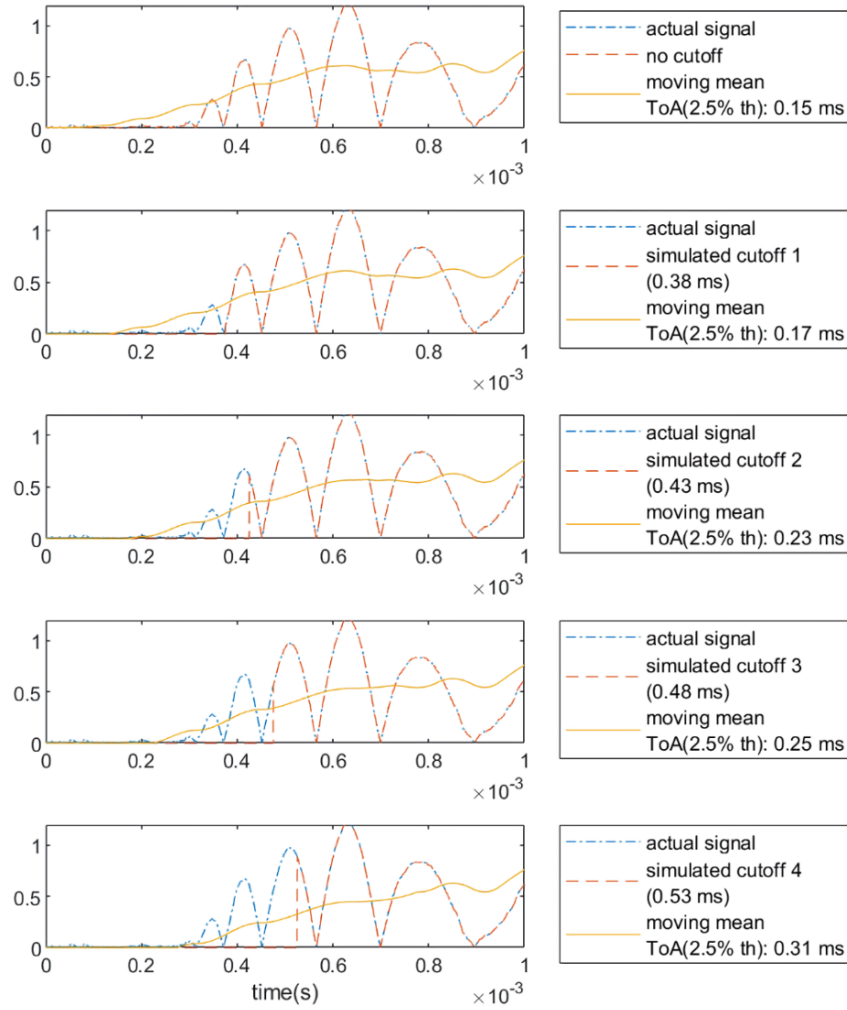


Figure 7. 3 Reconstruction of signal with varying degrees of simulated cuts/data loss using the moving mean method

7.4 Kriging Based Impact Location and Uncertainty Estimation Method

Equation (7. 1) shows the impact location estimation method :

$$z^{est} = \sum_{i=1}^{Nr} w_i z_i^{ref} \quad \sigma^{est} = \sqrt{\mu + \sum_{i=1}^{Nr} w_i \gamma_i^{in}(h^{in})}, \quad (7.1)$$

which uses kriging to interpolate the location of an impact ($z^{est} = x, y$ coordinates) and the associated uncertainty (expressed as standard deviation, σ^{est}) using a weighted linear combination of the coordinates of known reference points (z_i^{ref}) [129].

The weights (w_i) and Lagrange operator (μ) are determined by the relation between known reference data points as well as the incoming signal expressed in the form of semivariance (γ) vs the “distance” (h) between data points. The “distance” here is defined as the difference in features (ToA is used here) between two data points, calculated as the L2 norm between the feature vectors of 2 data points. Equation (7.2) shows how the empirical semivariance (γ) is calculated :

$$\gamma(h^{ref}) = \frac{1}{2N_h} \sum_i^{Nr} \sum_j^{Nr} (z_i^{ref,h} - z_j^{ref,h})^2, \quad (7.2)$$

from all the possible pairs (Nr amount of pairs) of reference database points (z_i^{ref} and z_j^{ref}), including averaging for point pairs (Nh amount of pairs) with the same “distance” (h^{ref}). It is common to group the semivariance points into bins based on their “distance” (20 bins used here) to allow averaging and get a better representation of the semivariance for a given “distance”. Afterwards, a semivariance function (γ^c) is fitted on to these discrete points (linear function, $\gamma^c(h) = gh$, used here) to obtain a continuous relation of semivariance with “distance”.

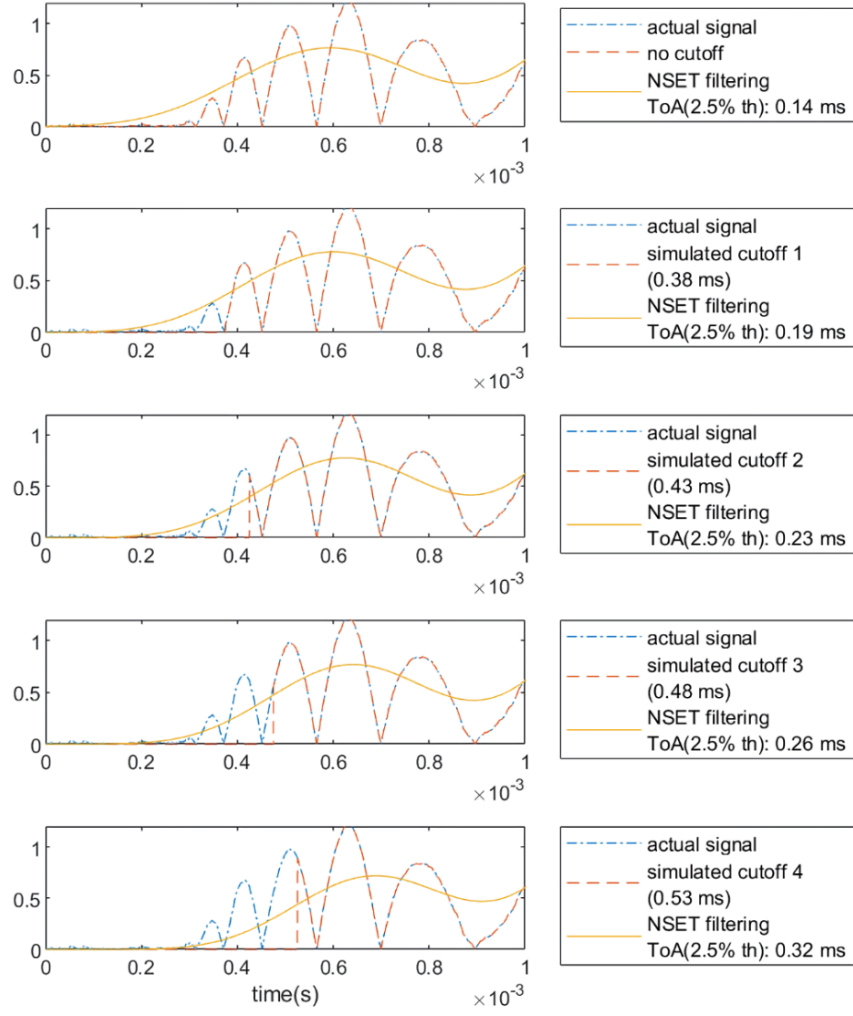


Figure 7. 4 Reconstruction of signal with varying degrees of simulated cuts/data loss using the NSET method

To calculate the parameters (w_i, μ) for estimating the impact location (z^{est}) and uncertainty (σ^{est}) from an incoming impact signal, first the “distance” of the features (h^{ref} and h^{in}) for all the incoming signal and reference database point pairs (z_i^{ref}, z_i^{in}) are calculated and the semivariance values ($\gamma^c(h^{ref}), \gamma^c(h^{in})$) calculated using the fitted semivariance function. Afterwards, equation (7. 3) is solved (I_i is an i length column vector of zeros) :

$$\begin{bmatrix} \gamma_{ij}^{fc}(h^{ref}) & I_i \\ I_j^T & 0 \end{bmatrix} \begin{bmatrix} w_i \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma_i^{fc}(h^{in}) \\ 1 \end{bmatrix} \quad i, j = 1, 2, 3 \dots Nr, \quad (7. 3)$$

to obtain the weights (w_i) and Lagrange operator (μ), which are then fed into equation (7. 1) to obtain the impact location estimation and the associated uncertainty, both of which are used to form a normal distribution (P) for the estimated coordinates.

To increase robustness, rather than using all sensors at once, the sensors are used in combinations (here combinations of 5 out of 6 sensors were used : 12345, 12346, 12356 etc.) and the location estimation distributions from each sensor combination (P_i) are combined using Bayesian updating [18,129]. This is shown in equation (7. 4) :

$$P_i(O|N) = \frac{P_i(N|O)P_i(O)}{P_i(N)} \quad (7. 4)$$

$$P_i(N|O) = P_{i-1}(O|N) \quad i = 1,2,3 \dots Ne$$

where an initial estimate ($P(N|O)$) is updated using the kriging estimate ($P(O)$) from 1 sensor combination set to obtain a more informed estimate ($P(O|N)$). The term $P(N)$ is a normalising factor to ensure that the total probability of the informed estimate distribution is one, obtained by the area under $P(N|O)P(O)$. For the very first initial estimate, a uniform distribution is used as a starting point. The informed estimate then becomes the new initial estimate and is updated with the kriging estimate of the next sensor combination set and so on until all sensor combinations have been used. Once a final informed estimate is obtained, the estimated location (x^{est} and y^{est}) is obtained from the mode of the final distribution whilst the uncertainty range ($x_{range(-)}$, $x_{range(+)}$, $y_{range(i)}$ and $y_{range(+)}$) is obtained from the 95% confidence interval range.

The estimated impact location coordinates (x^{est} and y^{est}) are used as the centre point of the estimate and the associated uncertainty ($x_{range(-)}$, $x_{range(+)}$, $y_{range(i)}$ and $y_{range(+)}$) for both coordinates are used as the semi-major axis (x_{sm} and y_{sm}) of an oval area around the centre point that defines the range at which there is 95% certainty the impact is located within. The error of the location estimate between the actual and estimated location is calculated as the Root Squared Error (RSE) as shown by equation (7. 5) :

$$RSE = \sqrt{x_{err}^2 + y_{err}^2} = \sqrt{(X^{act} - X^{est})^2 + (Y^{act} - Y^{est})^2}. \quad (7.5)$$

To see if the actual impact location is situated inside the estimated oval range, the radius (RSE_{lim}) at any given angle (θ) relative to the estimated location is given by equation (7.6) :

$$RSE_{lim}(\theta) = \frac{x_{sm} y_{sm}}{\sqrt{(y_{sm} \cos[\theta])^2 + (x_{sm} \sin[\theta])^2}}, \quad \sin(\theta) = \frac{y_{err}}{RSE}, \quad \cos(\theta) = \frac{x_{err}}{RSE}. \quad (7.6)$$

When RSE is smaller than $RSE_{lim}(\theta)$, the actual impact location is located inside the uncertainty range and the uncertainty range error is taken as zero. When RSE is larger than the oval radius ($RSE_{lim}(\theta)$) than the actual impact location is situated outside of the estimated range and the error ($RSE_{rg,error}$) is calculated as $RSE_{rg,error} = RSE - RSE_{lim}(\theta)$. To summarise the error for all of the test impacts, a gamma distribution is fitted onto the errors (RSE and $RSE_{rg,error}$) and the 90th percentile of the cumulative distribution is taken [129].

7.5 Results

Figure 7.5 and Figure 7.6 show the localisation results for 1 test impact for each location (defined in Figure 7.1) using the moving mean and the proposed NSET method. It can be seen that although both methods are able to generate estimates for ToA that allow robust estimation of the impact location, the NSET method gives more accurate results with higher certainty. Table 7.1 shows the summary of the localisation results for all of the test impacts conducted (2 for each location). Here, it is also seen that by using the NSET method the overall error (point error, RSE , and uncertainty range error, $RSE_{rg,error}$) and the level of uncertainty (σ^{est}) is reduced significantly. Although in section 6.3 both the moving mean and the NSET method were shown to produce similar results for reconstructing the ToA of a cut signal, the NSET method gives better consistency of ToA extraction for varying impacts (such as the random test impacts used here)

as it creates a smooth rising edge for the signal (Figure 7. 4) which aids in thresholding [16].

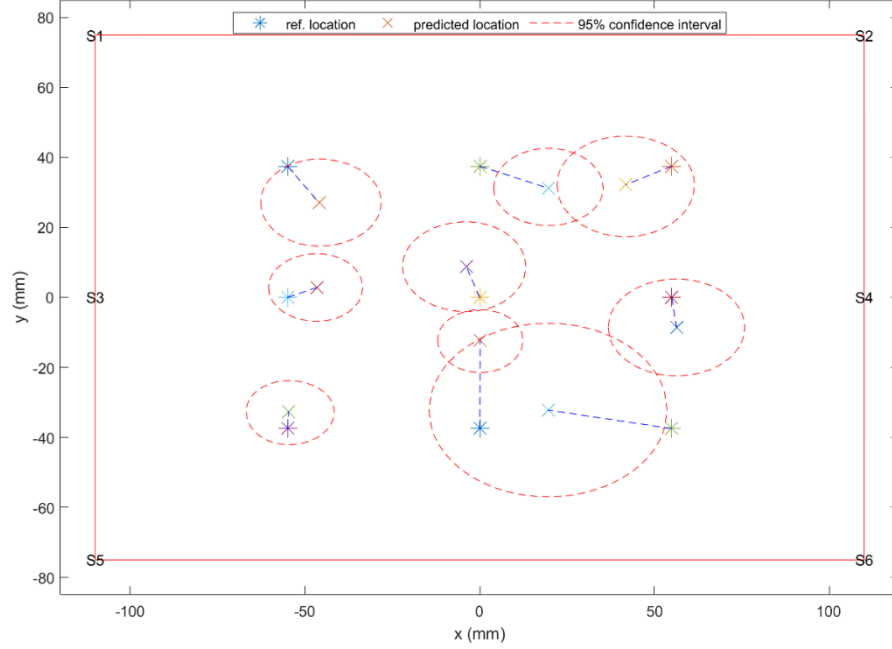


Figure 7. 5 Impact localisation results (1 impact at each location) using time of arrival estimated with the moving mean method

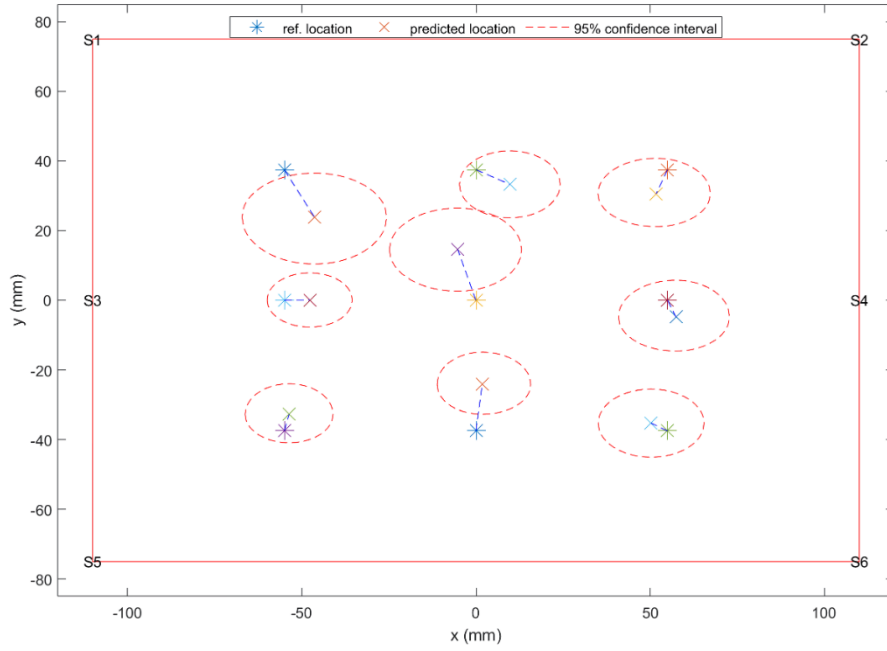


Figure 7. 6 Impact localisation results (1 impact at each location) using time of arrival estimated with the NSET method

Table 7. 1 Summary of impact localisation results for all test impacts

Case	90th percentile RSE (mm)	90th percentile $RSE_{rg,error}$ (mm)	Avg loc. est. X uncertainty, σ_x^{est} (mm)	Avg loc. est. Y uncertainty, σ_y^{es} (mm)
Moving mean (50 samples)	28.51	10.44	35.13 +/- 10.25	25.26 +/- 7.42
NSET (2000 Hz)	19.58	5.09	33.06 +/- 6.62	21.09 +/- 3.86

7.6 Real-time Impact Localisation

To demonstrate that the whole flow of impact localisation is computationally light enough to be conducted in real-time, a video demonstration is attached in the supplementary material or can be accessed through this [link](#) and a screenshot is given below in Figure 7. 7 to illustrate the setup. The process from impacting, recording signals in Signal Express, processing in Matlab to the final location estimate takes approximately 3 seconds per impact and the impact locations are estimated accurately within the uncertainty region.

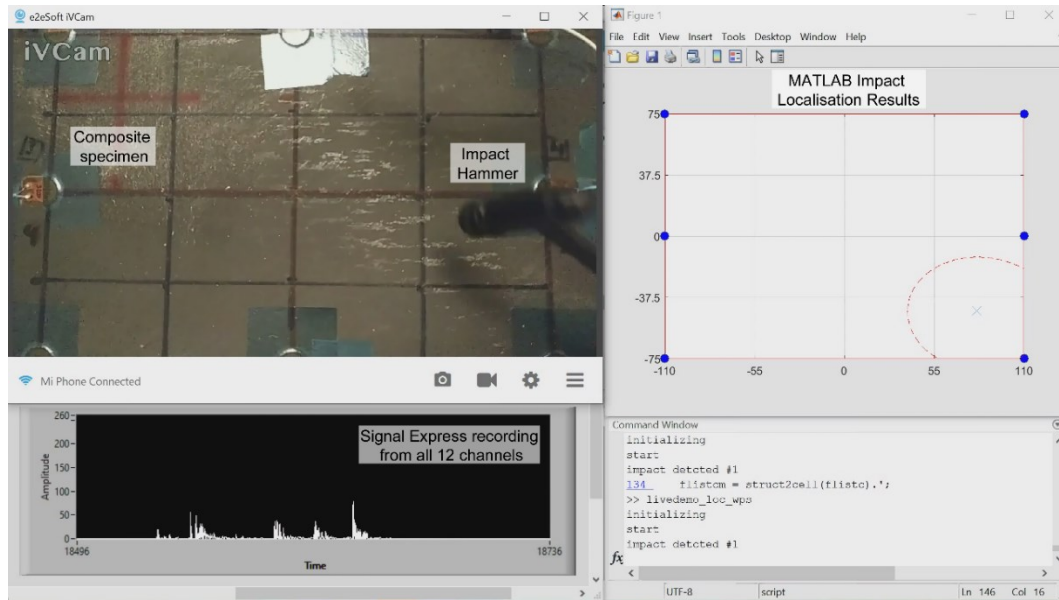


Figure 7. 7 Real-time impact localisation setup : video of impact setup (top left), recorded signal from WIPASS unit (bottom left) and Impact localisation results (left)

7.7 Conclusion

The proposed NSET and moving mean methods are able to reconstruct and estimate the ToA from cut impact signals recorded using the miniaturized WIPASS system, allowing the application of ToA based impact localisation methods commonly used with signals from higher performing oscilloscopes [16,18,54,129] with a relatively small amount of sensors [37,133]. Using the kriging based localisation method [129], the ToA obtained from the NSET and moving mean methods are able to give robust location estimates with accurate uncertainty quantification, which has not been previously demonstratable in miniaturised data acquisition systems [37,133,134]. The localisation results were found to be more accurate and with lower uncertainty compared to the moving mean method. Finally, it is also demonstrated that the proposed method is computationally light enough to be run in real-time. Thus, using the proposed NSET and kriging based algorithm, it is possible to conduct accurate and robust impact localisation using a miniaturized data acquisition system that can potentially (following further development of the hardware) be integrated to aircraft structures.

Chapter 8

Conclusion and Future Work

8.1 Conclusion

Data driven Structural Health Monitoring (SHM) provides the flexibility of scaling up from simple coupons to more complex structures, thus have the potential for application in real life structures. However, they have a few weaknesses, due to the fact that they require a reference database of known impact data to operate. The requirement to collect impact data may be unfeasible for large structures due to the amount of data sampling (especially if experimental) required. Additionally, these methods do not perform accurately when given a case that is outside the data provided in the reference database. This is especially crucial when considering the variation of in service environmental and operational conditions faced which is unfeasible to include comprehensively in the reference database due to the large number of combinations.

In this thesis novel methodologies and improvements to the data driven passive SHM approach for low velocity impact location and severity estimation were developed to increase accuracy, robustness, reliability, and feasibility when applied to prepreg carbon reinforced composites in in-service environmental and operational conditions. The Normalised Smoothed Envelope Threshold (NSET) method (Chapter 3) and the ST/LT-AIC method (Chapter 4) were developed to significantly increase the consistency of Time of Arrival (ToA) extraction which coupled with a novel reference database method allows higher robustness and accuracy compared to established methods (up to ~95% improvement compared to ToA thresholding and shallow neural networks). This is achieved using reference data from only 1 impact case and tested with various combinations of temperature, energy, mass and angle parameters thus greatly improving feasibility.

A novel impact severity estimation method was also developed for estimating the maximum impact force which is a known indicator of delamination in composites. The developed force gradient method (Chapter 5) is able to provide

robust and accurate (average error $< 10\%$) maximum impact force estimation regardless of the environmental and operational conditions using only the impact force – amplitude gradient from a single impact case. Thus, the method provides improvement of robustness and feasibility in the same manner as the developed impact location estimation methods. Additionally, the force gradient method is able to provide estimates using significantly less computational effort compared to established methods such as deconvolution.

In Chapter 6, a novel kriging based method was developed as an extension to the impact location and maximum impact force estimation methods developed earlier (Chapter 3 and 4). This method allows the quantification of the uncertainty range of the estimated location coordinates or maximum impact force, which provides the operator with more information on how sure the estimate is and possibly what maintenance action should be taken. The method was able to provide very reliable uncertainty ranges (number of predictions outside estimated range $< 5\%$) regardless of environmental and operational conditions tested.

Although the data driven methods developed are accurate and robust, they still require initial data to build the reference database. Although the developed methods have minimised the data required, it is still unfeasible to collect data in large real life structures. Thus a multifidelity approach was developed (Chapter 7) to allow the combination of alternative data sources (in this case finite element simulations) to reduce the amount of experimental data samples needed (to just 31% and 65% for simple and complex specimens) whilst achieving similar level of accuracy to that of full experimental sampling. This method may also potentially be used to combine data from other alternative sources such as sister structures, similar components etc.

Finally, even though the methods developed are accurate, robust and feasible data-wise, it must also need to be able to run on in-service hardware. Thus, in Chapter 8, the impact localisation method was demonstrated to run in real time using a prototype miniaturized data acquisition system which has less performance (but is much smaller and lighter) than the previously used lab equipment. The results show that the algorithm works accurately and is fast enough for real time use.

Thus, in conclusion the work in this thesis has successfully provided novel methodologies and improvements aimed at improving the accuracy, robustness, reliability and feasibility of data driven passive SHM methods in real life structures under in-service conditions. These methods are hoped to bring the application of passive SHM methodologies to real life application a step closer to insure better safety and efficiency of aircraft structures.

8.2 Future Work

Overall, the work in this thesis has successfully addressed some of the main challenges related to real life application of data driven passive SHM systems for low velocity impact monitoring in quasi-isotropic prepreg carbon reinforced composites. For further development, the following points may be necessary to verify the capability and reliability of these methods:

1. Testing the effects of humidity on the structural response (specifically Lamb waves) towards impact and how it affects the developed methods.
2. Test alternative sources for dataset development other than finite element simulations, specifically subcomponents of a structure that share similar geometry/configuration. This may reduce the data requirements for structures with many repetitive components (e.g. fuselage that consist of similar panels).
3. Test the impact force estimation method using the miniaturized data acquisition system.
4. Test validity of approaches developed on different material systems (e.g. different layup, not carbon reinforced composites, out of autoclave manufactured, or vertically reinforced) as they may respond differently than quasi-isotropic prepreg carbon reinforced composites.
5. Test the effect of higher impact velocities and strain rates towards the structural response (as it may alter the behaviour, e.g. softer impactors behaving like hard at high strain rates) and the robustness of the developed methods compared to low velocity impact.

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