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Developing an Artificial Intelligence Approach for Health Monitoring of Aerospace Composite Structures

Villorthan Sunthareswaran

PhD Aeronautical Engineering



City, St George's University of London
School of Science & Technology, Department of
Engineering

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Declaration of Originality

I, Villorthan Sunthareswaran, declare that this thesis titled:

“Developing an Artificial Intelligence approach for health monitoring of aerospace composite structures”

and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at City, St George’s University of London.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Villorthan Sunthareswaran

Date:

October 2025

Abstract

This thesis develops a physics-informed structural health monitoring (SHM) framework for aerospace composite structures that progresses from controlled damage characterisation at the coupon scale to operationally realistic assessment under authentic flight loading. Carbon Fibre Reinforced Polymer (CFRP) composites offer substantial weight and performance benefits for aerospace applications, but their susceptibility to complex, interacting damage mechanisms—such as delamination and ply-level material degradation—poses significant challenges for reliable in-service inspection and monitoring.

Much of the existing SHM literature relies on idealised loading conditions and isolated damage modes, limiting its applicability to real aircraft structures operating under time-varying aerodynamic, inertial, and environmental loads. This work addresses these limitations through a three-stage investigation that systematically increases modelling fidelity, damage complexity, and operational realism.

The first stage establishes fundamental delamination characterisation using a meso-scale 17-layer quasi-isotropic CFRP coupon ($1\text{ m} \times 1\text{ m} \times 10\text{ mm}$) instrumented with surface-mounted piezoelectric sensors. Three-dimensional finite element simulations generate 5,865 synthetic damage cases spanning variations in delamination location, size, and through-thickness position. Derivative-based feature engineering using Gaussian kernel smoothing is combined with deep neural networks to achieve accurate spatial localisation, with mean absolute errors below 0.032 m , and reliable estimation of damage severity under rigorously stratified data splits.

The second stage extends the framework to the more realistic and challenging scenario of concurrent damage, in which delamination and ply-level material degradation coexist within the same structural region. Over 10^5 parametric simulations are generated by simultaneously varying delamination geometry and local stiffness reductions used as a proxy for material damage. Rather than treating

damage mechanisms independently, all models are trained and evaluated exclusively in the both-present regime. A task-decomposed learning strategy, supported by gradient-augmented sensor features, enables robust single-snapshot inference of interacting damage mechanisms, achieving coefficients of determination of approximately $R^2 \approx 0.79$ for damage localisation and $R^2 \approx 0.87$ for damage size estimation using only five ultrasonic sensors.

The final stage integrates operationally realistic loading derived from a complete Boeing 777–200 transatlantic flight profile. Time-varying aerodynamic pressures are reconstructed using angle-of-attack polar inversion, validated pressure coefficients, progressive fuel-mass evolution, and engine-induced dynamic excitation, and applied to a validated NASA Common Research Model wing-box with composite skins. Three complementary sensing and analysis approaches are investigated: (i) multi-view image-based deformation analysis for global damage screening, (ii) sparse global piezoelectric sensor networks for moderate-resolution localisation, and (iii) global-to-local coupling that transfers wing-level structural response to high-resolution meso-scale panels for detailed damage characterisation.

Across all scales, the results demonstrate that physically informed feature design and explicit modelling of damage interaction are critical for reliable SHM under realistic loading conditions. The work establishes a unified framework capable of bridging laboratory-scale studies and operationally representative simulations, providing a robust foundation for future development of scalable, data-driven SHM systems for composite aircraft structures.

Chapter 1

Introduction

Carbon fibre reinforced polymer (CFRP) composites have revolutionised modern aerospace engineering, establishing themselves as the material of choice for primary aircraft structural components including wings, fuselages, and control surfaces [1, 2]. This paradigmatic shift is driven by their exceptional strength-to-weight ratio [3], superior corrosion resistance, and unique tailorability—enabling engineers to customise material properties through strategic fibre orientation and laminate configuration to meet specific structural loading requirements [4]. The aerospace industry’s increasing reliance on composites reflects their transformative potential, with modern commercial aircraft incorporating up to 50% composite materials by weight [5].

However, the exceptional performance characteristics of composite materials are accompanied by complex failure mechanisms and heightened susceptibility to multiple damage modes [6, 7]. Unlike traditional metallic structures that exhibit predictable yielding behaviour, composites demonstrate heterogeneous failure patterns including matrix cracking, fibre breakage, and delamination [8]. Among these, delamination represents a particularly critical concern—damage occurring between composite plies that remains largely undetectable through conventional visual inspection methods [9]. This barely visible impact damage (BVID) can significantly compromise structural integrity while exhibiting minimal external manifestation, creating major safety and inspection challenges for aerospace structures [10].

Traditional aerospace maintenance strategies rely on scheduled non-destructive testing (NDT) performed during mandated inspection intervals. While effective for ensuring airworthiness, these approaches impose substantial operational constraints, requiring aircraft grounding, specialised equipment, skilled personnel, and extended

maintenance windows [11]. Maintenance activities represent a significant fraction of aircraft lifecycle costs, motivating ongoing research into monitoring strategies that reduce reliance on periodic inspections without compromising safety [12].

Structural Health Monitoring (SHM) has emerged as a complementary paradigm, enabling continuous or semi-continuous assessment of structural condition using permanently integrated sensor networks [13]. Rather than replacing conventional inspection outright, SHM aims to augment existing maintenance practices by providing additional information on structural state, damage initiation, and progression [14]. Numerous studies have highlighted the potential of SHM to support condition-informed maintenance strategies and improve inspection efficiency [15], although practical deployment remains an active research challenge.

Contemporary SHM systems employ a range of sensing technologies, each offering distinct advantages depending on the damage mechanisms of interest. Piezoelectric transducers provide high sensitivity to local stiffness changes and can operate in both active and passive modes [16]. Fibre-optic sensors enable distributed strain measurement with immunity to electromagnetic interference [17], while electromagnetic techniques support non-contact monitoring of conductive composite structures [18]. Selecting and integrating appropriate sensor modalities remains a critical design consideration for effective SHM systems [19].

Recent advances in machine learning (ML) have significantly enhanced the ability of SHM systems to interpret complex sensor data. Deep learning architectures, including convolutional and recurrent neural networks, have demonstrated strong performance in correlating sensor response patterns with underlying damage states [20, 21]. Studies combining piezoelectric sensor networks with ML models have reported classification accuracies exceeding 90% under controlled laboratory conditions [22, 23], while frequency-domain feature extraction combined with support vector machines has achieved accuracies approaching 99% for specific scenarios [24]. Despite these successes, such results are often obtained under idealised loading conditions and simplified damage configurations.

A key limitation in much of the existing SHM literature is the reliance on static or highly simplified loading assumptions that fail to capture the complexity of real flight operations [25]. In service, aircraft structures experience time-varying aerodynamic pressure distributions, progressive fuel mass depletion, engine-induced vibrations, atmospheric turbulence, and thermal cycling, all of which influence both damage

mechanisms and sensor response characteristics [26]. Models trained exclusively under idealised conditions therefore face significant challenges when extended to operational environments.

Additional challenges arise from data imbalance, as damage events occur far less frequently than healthy structural states in real-world datasets [27]. While techniques such as generative models and resampling strategies have been proposed to address this issue [28, 29], robust SHM frameworks capable of handling multiple concurrent damage mechanisms under realistic loading conditions remain limited.

This research addresses these gaps through a structured, three-phase investigation that progressively advances SHM capability from controlled damage characterisation to operationally representative simulation. The methodology begins with high-fidelity finite element modelling of meso-scale composite structures, enabling the generation of physics-based synthetic datasets that capture the relationship between damage state and sensor response across a wide parameter space.

The first phase focuses on delamination characterisation within a representative composite coupon configuration. A 17-layer quasi-isotropic CFRP laminate ($1\text{ m} \times 1\text{ m} \times 10\text{ mm}$) instrumented with surface-mounted piezoelectric sensors provides a controlled environment for investigating damage localisation and sizing. Derivative-based feature engineering techniques are employed to enhance sensitivity to spatial damage signatures, enabling precise inference from sparse sensor measurements.

The second phase extends this framework to concurrent multi-damage scenarios, explicitly modelling the coexistence of delamination and ply-level material degradation. Rather than treating damage mechanisms independently, this phase examines their interacting signatures within a single structural region, reflecting more realistic damage conditions. The resulting models are designed to operate on single measurement snapshots, avoiding reliance on temporal baselines or prior reference states.

The final phase introduces operationally representative flight loading conditions derived from recorded Boeing 777-200 flight data. Time-varying aerodynamic pressures, fuel mass evolution, and engine dynamics are reconstructed and applied to a validated NASA Common Research Model wing structure with composite skins. A multi-scale approach is adopted, linking global structural response to localised meso-scale panels. Three complementary sensing and analysis routes are investigated: image-based deformation analysis, sparse global piezoelectric sensor networks, and

high-density local sensor configurations for detailed damage characterisation.

By integrating realistic loading conditions, multi-damage modelling, and physics-informed machine learning, this work aims to bridge the gap between laboratory-scale SHM studies and deployment-relevant analysis frameworks. The following chapters detail the development and validation of this approach, progressing from fundamental damage modelling to system-scale evaluation under operationally representative conditions.

Chapter 2

Structural Health Monitoring; Review & State of the Art

Given the established challenges and opportunities in aerospace composite structural health monitoring outlined in the previous chapter, this comprehensive literature review examines the current state of knowledge in the field, with particular emphasis on machine learning approaches, sensor technologies, and multi-scale modelling techniques that form the foundation for addressing the critical gaps identified in operational SHM systems.

2.1 Structural Health Monitoring Framework

2.1.1 SHM Paradigm and Operational Principles

Contemporary structural health monitoring systems operate according to a hierarchical damage identification framework, typically following Rytter's hierarchy [30], which defines five progressive levels of damage assessment:

1. The first level involves determining the presence of damage within the structure.
2. The second level pertains to locating the damage.
3. The third level is the diagnosis of the type of damage (delamination, cracking, etc.).
4. The fourth level is the extent of damage within the structure.

5. The fifth level is determining how much useful life is remaining.

Modern SHM systems integrate multiple sensor types to provide comprehensive damage detection capabilities across different length scales, from local coupon-level monitoring to full-scale structural assessment [31, 32]. The fundamental principle involves the detection, localisation, and characterisation of damage through changes in structural response patterns under various loading conditions [33, 34].

Recent bibliometric analysis indicates a steady increase in SHM research publications, peaking in 2024, with particular emphasis on the integration of artificial intelligence techniques such as machine learning and deep learning [35, 31]. This trend reflects the growing recognition that traditional signal processing approaches may be insufficient for addressing the complexity of damage detection in modern composite structures under realistic operational conditions.

2.1.2 Sensor Technologies for Composite Monitoring

Piezoelectric Sensors

Piezoelectric transducers, particularly lead zirconate titanate (PZT) sensors, represent one of the most widely adopted sensing technologies for composite SHM applications [36]. These sensors leverage the direct and inverse piezoelectric effects to function as both actuators and receivers, enabling guided wave propagation analysis for damage detection and localization [37]. The electromechanical coupling in piezoelectric materials allows for quantitative assessment of structural changes through various measurement techniques, including electromechanical impedance (EMI) and guided wave methods.

The EMI technique monitors changes in structural impedance due to damage, which are reflected in the electrical impedance of bonded PZT transducers [36]. This approach has demonstrated particular effectiveness for detecting local damage in the vicinity of the sensor. Guided wave methods utilise piezoelectric actuators to generate elastic waves that propagate through the structure, with damage detection achieved through analysis of reflected, transmitted, or scattered signals [38].

Recent advances include the development of flexible, high-temperature-resistant piezoelectric sensors addressing traditional limitations regarding conformability to curved surfaces and operational temperature ranges. Zhang et al. demonstrated BaTiO:SmO/SrRuO/SrTiO/mica film sensors with enhanced ferroelectric properties

and operational stability up to 150°C [39], representing significant progress toward practical aerospace implementation.

Fibre Optic Sensors

Fibre optic sensors, including Fibre Bragg gratings (FBG) and distributed sensing systems, provide high sensitivity and multiplexing capabilities, particularly suitable for large-scale structural monitoring [40]. These sensors can be embedded within composite laminates during manufacturing or surface-mounted for real-time strain and temperature measurements throughout the structural lifecycle [41, 42].

Distributed fibre optic sensing offers particular advantages for aerospace applications, providing spatially continuous measurements along extended lengths of optical fibre with millimetre-scale spatial resolution [43, 44]. The immunity of optical sensors to electromagnetic interference and their lightweight characteristics make them highly suitable for aircraft integration, addressing key concerns related to system weight and electromagnetic compatibility.

Advanced and Emerging Sensor Technologies

Digital Image Correlation (DIC) has emerged as a powerful optical measurement technique for aerospace SHM applications, particularly valuable for flutter analysis and wing deformation monitoring [45]. This non-contact approach enables real-time analysis of stress and strain contours through high-resolution image processing, providing comprehensive structural assessment capabilities without requiring physical sensor attachment.

Recent innovations include piezoresistive sensors incorporating carbon nanotube-based systems and MXene fibres, which provide self-sensing capabilities integrated directly into composite structures [46, 47]. These sensors demonstrate remarkable sensitivity within operational strain ranges and show potential for wireless sensing applications through electromagnetic coupling mechanisms.

2.2 Damage Mechanisms in Composite Structures

2.2.1 Delamination Damage

Delamination represents the most critical damage mode in composite structures due to its hidden nature and potential for rapid propagation without visible surface

indications [48]. This failure mechanism occurs at interfaces between composite layers and can result from various causes, including impact loading, manufacturing defects, and operational fatigue [49].

Advanced detection techniques employ guided wave tomography using pure shear horizontal (SH0) waves to identify and characterise delamination extent with high accuracy [50]. The reconstruction algorithm for probabilistic inspection of defects (RAPID) has demonstrated excellent performance for delamination detection, size estimation, and localisation in aerospace composites. Thermal-based detection methods utilising transient thermal conduction profiles have achieved remarkable success with F1 scores exceeding 99% accuracy in delamination classification [51].

Machine learning approaches have significantly enhanced delamination detection capabilities, with support vector machine techniques showing particular promise due to their ability to handle high-dimensional feature spaces while maintaining computational efficiency [52]. Transfer learning frameworks utilising pre-trained deep learning models have demonstrated effectiveness in autonomous delamination assessment despite limited experimental data availability [53].

2.2.2 Multi-Damage Scenarios and Interaction Effects

Real composite structures experience complex multi-damage scenarios involving simultaneous occurrence of different damage mechanisms with intricate interaction effects [48]. Matrix cracking within individual plies often serves as a precursor to more severe damage mechanisms, while the interaction between different damage types creates complex failure scenarios requiring sophisticated monitoring approaches [54, 55].

Most existing approaches focus on individual damage types rather than the complex multi-damage scenarios representative of real operational conditions [56, 57]. The temporal evolution of multi-damage scenarios and their cumulative effects on structural performance remain poorly understood in current literature, representing a significant gap that must be addressed for operational SHM implementations.

Advanced sensor fusion techniques and multi-modal data processing approaches are needed to address the limitations of single-sensor systems in detecting and characterising complex damage states [58, 33]. The development of hierarchical damage classification systems that can prioritise different damage types based on their criticality to structural safety represents an important research need.

2.3 Machine Learning Approaches in SHM

2.3.1 Traditional Machine Learning Methods

Early applications of machine learning to composite SHM focused on traditional algorithms, including Support Vector Machines (SVM), Random Forest (RF), and k-nearest Neighbours (kNN) for damage classification and characterisation tasks [31].

Support Vector Machine algorithms have demonstrated exceptional performance in various SHM applications. He et al. [59] compared back-propagation neural networks, extreme learning machines, and SVM techniques for delamination detection based on frequency changes, demonstrating superior SVM performance with mean absolute errors as low as 1.22% for location and size prediction. Loutas et al. [24] achieved classification accuracies of 99.3% using SVM techniques with data collected from 390 experiments via Fibre Bragg Grating sensors, highlighting the effectiveness of these approaches when combined with appropriate feature extraction techniques.

Random Forest techniques have shown promising results for damage detection using natural frequency correlations. Both Jacob et al. [60] and Li et al. [61] successfully employed RF algorithms with modal analysis data generated using commercial finite element software, demonstrating the effectiveness of ensemble methods for damage characterisation tasks while addressing robustness through artificial noise augmentation.

2.3.2 Deep Learning Architectures

Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks demonstrate particular effectiveness for different types of aircraft structures and damage scenarios [31, 62]. The application of deep learning to SHM problems has evolved from simple feedforward networks to sophisticated architectures capable of processing multiple data modalities simultaneously.

Hesser et al. [63] successfully distinguished between three different types of damage using acoustic emission techniques, comparing artificial neural networks, CNNs, and deep transfer learning algorithms. Their results demonstrated that Convolutional 2D (Conv2D) networks with deep transfer learning provided optimal performance for multi-class damage discrimination tasks. Similarly, Tabian et al. [64] achieved over 95% accuracy for impact detection and characterisation using ultrasonic waves processed through CNN architectures, with particular attention to real-

world operational considerations.

Khan et al. [22] developed an electromechanically coupled dynamic model for pristine and delaminated composite structures, utilising PZT sensors for actuation and response measurement. Their approach converted datasets to the frequency domain and employed convolutional neural networks to extract damage features, achieving 90.1% accuracy for damage detection tasks.

2.3.3 Advanced and Hybrid Approaches

Physics-Informed Neural Networks (PINNs) represent an emerging paradigm that combines physical principles with machine learning for enhanced modelling accuracy and reliability [31]. These hybrid approaches address some of the interpretability challenges associated with traditional "black-box" neural network models while maintaining powerful pattern recognition capabilities.

Explainable Artificial Intelligence (XAI) techniques have become critical for ensuring trustworthiness and reliability in SHM applications [65, 66]. Vision transformer-based explainable deep learning models demonstrate superior damage detection performance while providing transparency in decision-making processes through patch attention aggregation mechanisms, addressing the critical need for interpretable AI systems in safety-critical aerospace applications.

Derivative-based feature engineering techniques provide powerful tools for extracting meaningful information from sensor data [67]. These approaches leverage domain knowledge to create features that capture relevant physical phenomena, often resulting in improved model performance compared to purely data-driven feature extraction methods. The integration of signal processing techniques with machine learning algorithms represents a promising direction for developing more robust and interpretable SHM systems.

2.4 Multi-Scale modelling Approaches

2.4.1 Coupon-Level Analysis

Coupon-level testing and modelling form the foundation for understanding composite material behaviour under various loading conditions [68, 69]. Virtual coupon testing using finite element analysis enables investigation of failure mechanisms at the ply level, including matrix cracking, fibre breakage, and fibre-matrix debonding,

providing essential material property data for higher-level structural analysis and multi-scale modelling frameworks.

Representative Volume Element (RVE) models have proven effective for estimating effective properties of bio-composites and advanced composite systems [70, 71]. Multi-scale modelling approaches utilising fibre-scale (fRVE), ply-scale (pRVE), and laminate-scale (lRVE) analysis provide a comprehensive understanding of composite behaviour across different length scales, with maximum errors in elastic modulus calculations reduced to 17.68

Distributed fibre optic sensors embedded in composite coupons demonstrate excellent correlation with electrical resistance strain gauge measurements during tensile testing, indicating seamless integration capabilities for spatially continuous strain monitoring [72, 73]. Material characterisation protocols have evolved to include comprehensive testing methodologies encompassing three-point bending, tensile loading, and impact testing to establish baseline properties for subsequent SHM applications.

2.4.2 Full-Scale Structural Integration

Full-scale composite modelling requires integration of local material behaviour with global structural response under realistic operating conditions [74, 75]. Advanced computational methods combine fluid-structure interaction frameworks with fatigue damage models to predict damage evolution in full-scale composite structures, utilising techniques such as the arbitrary Lagrangian-Eulerian variational multiscale approach coupled with rotation-free isogeometric shells.

Finite element analysis modelling provides valuable tools for reducing full-scale testing requirements while maintaining accuracy in critical parameter assessment [76, 77]. However, validation through full-scale testing remains essential, particularly for complex load and temperature conditions that cannot be easily replicated in smaller specimens. The correlation between FEA simulations and full-scale validation testing demonstrates potential for cost-effective assessment with minimal discrepancies.

Composite Overwrapped Pressure Vessels (COPV) represent a critical full-scale application where SHM systems must monitor the complete lifecycle from manufacturing through operational cycling [43]. FBG sensing arrays bonded to aluminium liner circumferential sections demonstrate the capability to detect barely visible impact damage with location errors as small as 17 mm, with successful monitoring of over 20,000 pressure cycles, validating system robustness.

2.5 Data Challenges and Methodological Limitations

2.5.1 Data Quality and Availability Issues

The scarcity of failure data represents a fundamental challenge in developing robust machine learning models for composite SHM applications [78, 62]. Data imbalance problems arise from the relatively rare occurrence of failure events compared to normal operational conditions, creating significant challenges for supervised learning approaches that require balanced training datasets.

Advanced data augmentation techniques, including Wasserstein GANs and synthetic data generation methods, offer potential solutions but require further validation for aerospace applications. Kim et al. [78] successfully addressed data imbalance issues using Wasserstein Generative Adversarial Network (WGAN) models that maintained dynamic characteristics within time series data, demonstrating the potential for synthetic data generation in SHM applications. However, the considerable time and cost associated with comprehensive composite structure testing result in sparse datasets that limit machine learning effectiveness.

He et al. [27] employed modified triangle-based SMOTER algorithms to address class imbalance, outperforming standard techniques while showcasing strong performance for damage detection in composites. Despite these advances, the challenge of developing generalised models remains critical, as training remains time-consuming and computationally intensive.

2.5.2 Environmental and Operational Considerations

Environmental effects such as temperature variations, humidity, and electromagnetic interference on sensor performance are inadequately addressed in current SHM frameworks [33]. Hoshyarmanesh et al. [79] explored temperature effects on sol-gel PZT sensors, demonstrating significant impedance characteristic changes between sensors operating at 20°C and 200°C, including frequency peak shifts, impedance amplitude reduction, and peak disappearance due to local mode shape changes.

Baptista et al. [80] presented experimental studies showing that temperature effects on piezoelectric sensor electrical impedance are strongly frequency-dependent, highlighting the complexity of environmental compensation in practical SHM implementations. The integration of multiple sensor modalities for comprehensive damage characterisation requires advanced sensor fusion algorithms that remain largely un-

derdeveloped in current literature.

2.6 Industrial Implementation and Operational Considerations

The aerospace industry has begun implementing SHM systems across various platforms, though widespread adoption remains limited by practical considerations. Airbus has implemented SHM systems through its Skywise platform, while companies like General Electric have developed Digital Twin systems for aircraft engines, and Embraer has incorporated SHM systems (Ahead Pro) on its E-Jet E2 aircraft family [81].

Military applications include BAE Systems' corrosion monitoring systems in Joint Strike Fighters and the US Air Force Research Laboratory's development of SHM systems for C-130 Hercules aircraft [82]. However, significant challenges remain for widespread industrial adoption, including regulatory certification requirements, system integration complexities, maintenance cost considerations, and the need for robust performance under diverse operational conditions.

This comprehensive table encompasses the complete breadth of machine learning applications in structural health monitoring found in the literature review. The table demonstrates several critical insights that directly inform the research contributions of this thesis:

Physics-Based vs. Data-Driven Approaches: The majority of successful implementations combine both physics-based modelling with data-driven machine learning approaches, validating the methodology adopted in this thesis, where finite element analysis provides the foundation for machine learning model development.

Sensor Technology Diversity: Piezoelectric sensors (PZT) dominate the literature as the most versatile sensing technology, supporting the sensor selection in Chapters 3, 4, and 5. However, the table also reveals successful applications of fibre optic sensors, accelerometers, and hybrid sensing approaches, indicating opportunities for multi-modal sensing integration.

Dataset Scale and Quality: The dataset sizes vary dramatically across studies, from as few as 114 input-output pairs to over 16,000 samples. This variability highlights a critical challenge in the field - the need for comprehensive, high-quality datasets. The synthetic data generation approach employed in this thesis addresses

Table 2.1: Comprehensive Summary of Machine Learning Methods in Structural Health Monitoring Literature

Reference	Physics Based	Data Driven	Sensor Type	Raw Datasets	Objective	Method	Practical Validation	Results & Key Findings
Califano et al. [83]		✓	Optical Fibre sensors-distributed	11 different scenarios	Damage detection irrespective of damage load using distributed sensors and ANN	ANN	Yes, CFRP 8 plies, bending test, holes drilled	Less computer intensive, more sensitive to damage change than traditional strain maps
Farhangdoust et al. [84]		✓	Exciters	8×8×144	Develop ANN to detect debonding using heterodyning method	ANN	Yes, magnets to simulate debonding	Levenberg-Marquardt algorithm provided most accurate framework
del Rio [85]		✓	FBG	400 measures, 520 experimental data	Design and implementation of FOS SHM on UAV	ANN, LSTM	Yes, UAV	LSTM achieved 96.2% accuracy, purely experimental data outperformed theoretical
Arena [86]	✓	✓	PZT	441 data points	Adapt existing models for forecasting impact via feed forward network	ANN + FEM	Yes, Orthotropic CF composite, 12 plies	Successfully detected impact damage, lower signal-to-noise ratio
Hesser et al. [63]		✓	PZT	8000 data-points	Distinguish different damage types using AE and comparing ML architectures	ANN, CNN, Deep transfer learning	Yes, Aluminium plate	Conv2D with deep transfer learning provided best results
De Oliveira [87]		✓	PZT	720 frames	Develop PZT EMI-based technique using CNN	CNN	Yes, Aluminium plate	Converting 1D signals to RGB frames, potential application to guided waves
Tabian [64]		✓	PZT	10000 samples	Impact detection and characterization using ultrasonic waves	CNN	Yes, complex composite panel	High accuracy over 95% with real-life application considerations
Xu et al. [88]		✓	PZT	228 sets of specimens	Diagnose different severities of fatigue cracks in aircraft structures	CNN	Yes, attachment lugs, aluminium alloy	Feature vectors from 7 damage indices, lab-to-field transition challenges
Puruncajas [89]		✓	Accelerometer	16,517	Use vibrational response with Deep CNN for health monitoring	D-CNN	Yes, down-scaled wind turbine	Environmental conditions as excitation, applicable to aerospace structures
Han [90]		✓	Wide-band sensor	9000 images	Single sensor AE method for damage detection	D-CNN	Yes, engine test bench	Good performance compared to SVM and other methods
Ewald [91]	✓	✓	PZT	8000 images	Use DL Guided wave techniques for SHM	Deep learning with physical model	Yes, aluminium plate	Illustrates need for accurate FE model as input for reliable results
Iannelli [92]		✓	Accelerometers	14 input-output pairs	Damage detection in spacecraft with DL	Deep Learning, LSTM	No	Importance of normalisation and preprocessing, feeding full-time sequence degrades performance
Zhou [93]		✓	Accelerometer	15000 experimental data	Identify load history using D-RNN	D-RNN	Yes, Composite plate	Model tuning cumbersome, sensor position significantly impacts results
Mousavi [94]		✓	Environmental sensors	all 10000 temperature samples	Environmental compensation for SHM	RNN	No	Early alarm possible, robust damage detection system achievable
He et al. [95]		✓	Vibrometer	Multiple frequency datasets	Predict delamination from frequency shifts	SVM, BPNN, ELM	Yes, composite beams	SVM had best performance, 1.22% MAE for location/size prediction
Loutas [96]	✓	✓	FBG	390 experiments	Strain-augmented algorithms for damage state identification	SVM, CWT, ICA	Yes, CF composite	SVM shows great promise, high classification rates of 99.3%
Khan [97]		✓	PZT	1000 instances	Transfer learning for experimental vs. simulated data	SVM, NN	Yes, composite laminates	Automatic features (90%+) outperformed handcrafted features (30%)
Kulakovskiy [98]		✓	PZT array	Statistical algorithms comparison	Guided wave imaging with different statistical methods	Delay & Sum, MV, Excitelet	Yes, aluminium plate	Comparative analysis of imaging algorithms under lab conditions
Zhu [99]		✓	PZT	EMI technique	Diagnose honeycomb composite using modified EMI	Modified EMI	Yes, honeycomb composite	Utilized both real and imaginary parts of impedance signal
Rahbari [100]	✓	✓	Multiple sensors	DNN-based system	Add inductive abilities to known SHM methods	Deep Neural Networks	Yes, A380 fan cowl model	Enhanced performance through inductive reasoning capabilities
Qiu [101]		✓	Guided wave sensors	Clustering algorithm	Enhance GMM performance for guided wave applications	IDPC-EM algorithm	Yes	Improved density peaks clustering with expectation maximization
Yan [102]	✓	✓	Impact sensors	Bayesian framework	Reconstruct non-negative impact forces	Non-negative Bayesian learning	Yes, sandwich composite	Successful impact force reconstruction and localization
Alvarez-Montoya [103]		✓	fibre optic sensors	Two-level clustering	Validate clustering models for damage conditions	DS2L-SOM, OBS	Yes, aircraft wing front spar	Optimal baseline selection with fibre optic sensor networks
Colombo [104]	✓	✓	Strain sensors	iFEM application	Full strain reconstruction and damage identification	iFEM, feature extraction	Yes, UAV stabilizer	Ballistic impact damage detection and characterization

this gap by creating extensive, controlled datasets spanning thousands of damage scenarios.

Machine Learning Architecture Evolution: The progression from simple artificial neural networks (ANN) to sophisticated deep learning architectures (CNN, LSTM, Deep Transfer Learning) demonstrates the field’s maturation. Support Vector Machines consistently show excellent performance, particularly for classification tasks, achieving accuracies up to 99.3% [24].

Practical Validation Gap: While most studies claim practical validation, many are limited to laboratory conditions or simplified structures. The realistic flight loading integration in Chapter 5 represents a significant advancement beyond current literature by incorporating actual Boeing 777-200 operational data.

Multi-Damage Detection Limitations: The table reveals that most studies focus on single damage types or simple damage scenarios. The multi-damage framework developed in Chapter 4, capable of simultaneously detecting and characterising both delamination and ply weakening, addresses a clear gap in existing approaches.

Feature Engineering Importance: Studies consistently demonstrate that automatic feature extraction significantly outperforms handcrafted features (90% vs. 30% accuracy) [97], supporting the derivative-based feature engineering approach employed throughout this thesis.

Environmental Robustness Challenges: Several studies acknowledge but do not adequately address environmental variations, temperature effects, and operational complexity. The realistic loading framework in Chapter 5 begins to address these challenges through comprehensive flight data integration.

The table also reveals methodological patterns that inform best practices for SHM system development. Successful implementations typically combine multiple complementary approaches - physics-based modelling for data generation, sophisticated feature engineering for signal processing, and advanced machine learning architectures for pattern recognition. The most promising results emerge from studies that maintain careful attention to practical validation while leveraging both experimental and computational approaches.

Furthermore, the literature summary highlights the critical importance of dataset quality and size for robust machine learning model development. Studies with larger, more diverse datasets consistently achieve better performance and generalisation capabilities. This observation validates the extensive synthetic dataset generation

approach adopted in this thesis, where thousands of damage scenarios are systematically explored to ensure comprehensive coverage of the damage parameter space.

The progression toward real-world implementation requires addressing several critical challenges evident in the literature: environmental robustness, multi-damage detection capabilities, integration with operational systems, and computational efficiency for real-time applications. The research framework presented in subsequent chapters systematically addresses these challenges through a progressive approach from fundamental damage characterisation to complex operational implementation.

2.7 Critical Research Gaps and Future Directions

2.7.1 Global-Local Integration Challenges

The integration of local damage models with global structural response remains an active area of research with significant gaps [75, 108]. Current approaches often treat local and global effects separately, potentially missing important coupling mechanisms that occur in real structures. The development of multi-scale modelling frameworks that seamlessly integrate coupon-level material behaviour with full-scale structural response represents a critical advancement opportunity.

Real flight data integration for fuel consumption calculations, pressure distributions, and aerodynamic coefficient values requires sophisticated modelling approaches that are currently underdeveloped in the literature. The transition from laboratory-scale testing to operational environment monitoring presents substantial challenges in scaling sensor networks and data processing algorithms while maintaining computational efficiency for real-time applications.

2.7.2 Operational Loading and Environmental Realism

A significant limitation in current SHM research is the predominant focus on idealised loading conditions that fail to capture the complex, time-varying nature of actual flight operations. Real aircraft experience dynamic aerodynamic pressure distributions, progressive fuel mass consumption effects, engine-induced vibrations, atmospheric turbulence, and thermal cycling—environmental factors that profoundly influence both damage initiation mechanisms and sensor response characteristics.

The Boeing 777-200 Barcelona-Miami route data used in this research represents a single operational scenario from an infinite matrix of possible flight conditions.

Mission profile diversity, including different flight routes, payload configurations, and operational procedures, generates vastly different loading spectra that must be considered for comprehensive SHM system validation. Environmental service conditions, including long-term exposure to thermal cycling, humidity variations, UV radiation, and de-icing chemicals, significantly influence composite material behaviour and damage evolution patterns not adequately addressed in current computational frameworks.

2.7.3 Multi-Damage Type Modelling and Detection

The simultaneous occurrence of different damage mechanisms presents significant challenges for current SHM systems [33, 34]. The study’s treatment of delamination and ply weakening, while methodologically advanced, represents only a subset of the complex interaction mechanisms observed in operational aircraft composites. Real composite structures experience concurrent multi-mode damage, including matrix cracking, fibre breakage, and delamination with complex interaction effects that accelerate overall damage progression beyond predictions from individual damage mechanisms.

Load history dependency represents another critical gap, where damage accumulation depends heavily on loading sequence, with high-amplitude events creating damage that influences subsequent response to lower-amplitude cycles. Environmental-mechanical coupling effects, where moisture absorption, thermal cycling, and chemical exposure modify mechanical response and damage tolerance characteristics, remain inadequately captured by purely mechanical loading models.

2.7.4 Machine Learning Methodological Gaps

Current machine learning approaches often borrow from other domains without considering the unique characteristics of structural systems, including safety criticality and reliability requirements [65, 66]. The development of physics-informed neural networks specifically designed for composite structures represents a promising direction requiring significant research investment, particularly for handling the complex multi-physics nature of composite damage evolution.

Uncertainty quantification in ML-based damage predictions remains poorly addressed despite its critical importance for safety-critical aerospace applications [109]. The interpretability and explainability of ML models for structural engineers who

may not have extensive AI backgrounds represent a significant adoption barrier that must be addressed for widespread industrial implementation.

This literature review reveals both substantial progress and significant remaining challenges in aerospace composite structural health monitoring. The evolution from traditional NDT approaches to intelligent, machine learning-enhanced SHM systems demonstrates the maturation of this research field, yet critical gaps remain in operational implementation.

Key findings indicate that while individual components of SHM systems have achieved impressive laboratory performance, the integration of multi-scale modelling, realistic operational loading, and robust damage detection under complex multi-damage scenarios remains inadequately addressed. The transition from controlled laboratory conditions to operational aerospace environments requires addressing sensor network scalability, computational efficiency, environmental robustness, and regulatory certification challenges that extend beyond technical performance metrics.

The research presented in subsequent chapters directly addresses several of these critical gaps through a systematic progression from fundamental delamination characterisation to complex multi-damage scenarios under realistic flight loading conditions. By integrating physics-based finite element modelling with advanced machine learning techniques and realistic operational data, this work contributes to bridging the gap between research demonstrations and practical aerospace SHM implementations.

Chapter 3

Detecting Delamination using machine learning techniques

3.1 Introduction

Building upon the comprehensive literature review and the established need for advanced structural health monitoring systems in aerospace composites, this chapter addresses the fundamental challenge of delamination detection and characterisation in carbon fibre reinforced polymer (CFRP) structures. Delamination represents one of the most critical and insidious damage modes in composite laminates, occurring between plies without visible surface manifestation, thereby posing significant challenges for conventional inspection methodologies [6, 7].

The literature review revealed that while numerous approaches have been proposed for composite damage detection, significant gaps exist in systematic delamination characterisation across comprehensive parameter spaces. Most existing studies focus on limited damage scenarios or employ simplified loading conditions that fail to capture the complexity of real-world damage evolution. Furthermore, the scarcity of experimental damage data, coupled with the prohibitive costs associated with comprehensive physical testing campaigns, necessitates innovative approaches to generate robust datasets for machine learning model development.

This chapter introduces a comprehensive framework for delamination detection and characterisation through the integration of high-fidelity finite element analysis with advanced machine learning techniques. The approach addresses several critical limitations identified in existing literature: the need for extensive, well-controlled

datasets spanning comprehensive damage parameter spaces; the development of physics-informed feature engineering techniques that enhance model performance beyond purely data-driven approaches; and the establishment of rigorous validation methodologies that ensure reliable generalisation to unseen damage scenarios.

The research methodology centres on synthetic data generation using three-dimensional finite element modelling of composite structures equipped with surface-mounted piezoelectric sensors. This approach enables systematic exploration of delamination parameters, including spatial location (x , y , z coordinates), delamination size, and through-thickness position across a 17-layer quasi-isotropic CFRP laminate. The systematic parametric variation generates a comprehensive dataset of 5,865 unique damage scenarios, providing the breadth and depth necessary for robust machine learning model development while addressing the data scarcity challenges highlighted in the literature review.

A critical innovation introduced in this chapter is the development of derivative-based feature engineering techniques utilising kernel smoothing with Gaussian filtering. This physics-informed approach extracts spatial gradient information from sensor responses, significantly enhancing the discriminatory power of machine learning models compared to traditional approaches that rely solely on raw sensor data. The methodology addresses the fundamental challenge of correlating local sensor measurements with global damage states through mathematically rigorous feature extraction that preserves the underlying physical relationships governing sensor-damage interactions.

The machine learning architecture employs multi-output deep neural networks specifically designed for simultaneous prediction of delamination location and size parameters. Advanced loss function formulations, including custom F1 focal loss techniques, address the inherent data imbalance challenges associated with damage detection problems where healthy conditions vastly outnumber damage cases. The comprehensive approach integrates L2 regularisation, early stopping mechanisms, and rigorous cross-validation procedures to ensure robust model performance and reliable generalisation capabilities.

Experimental validation is conducted through systematic comparison of baseline models utilising raw sensor data against enhanced models incorporating derivative-based features. The evaluation framework employs multiple performance metrics, including mean absolute error (MAE), mean squared error (MSE), and coefficient of

determination (R^2), to provide a comprehensive assessment of model accuracy and reliability. Particular attention is given to error analysis and spatial distribution patterns to identify potential limitations and guide future improvements.

The significance of this research extends beyond immediate technical contributions to establish a methodological foundation for subsequent chapters. The delamination characterisation framework developed here provides the basis for the multi-damage scenarios explored in Chapter 4, where concurrent damage mechanisms are investigated. Furthermore, the synthetic data generation methodology and machine learning architectures established in this chapter are extended and adapted for the realistic operational loading scenarios presented in Chapter 5, where global-to-local modelling approaches are employed to capture the complexity of actual flight conditions.

This chapter is organised to provide a systematic development of the research methodology and a comprehensive evaluation of results. Section 3.2.1 details the finite element modelling approach, including geometry definition, material property specification, mesh convergence studies, and boundary condition implementation. The delamination modelling technique through selective tie constraint manipulation is thoroughly explained, along with the parametric sweep mechanism employed for comprehensive damage scenario generation. Section 3.2.2 addresses critical data preprocessing challenges, including dataset balancing, stratified splitting protocols, and robust normalisation techniques designed to preserve physical meaning while ensuring optimal machine learning performance.

Advanced feature engineering methodologies are presented in detail, with particular emphasis on the kernel smoothing approach and Gaussian filtering techniques employed for derivative computation. The machine learning architecture development is thoroughly documented, including network topology design, loss function formulation, and performance evaluation metrics. Section 3.3 presents comprehensive results analysis, including model performance comparisons, error distribution studies, and a detailed examination of prediction accuracy across different damage parameter ranges.

The research presented in this chapter establishes several key contributions to the field of aerospace composite structural health monitoring. First, it demonstrates the efficacy of synthetic data generation approaches for creating comprehensive training datasets that span realistic damage parameter spaces while maintaining compu-

tational efficiency. Second, it validates the significant performance improvements achievable through physics-informed feature engineering compared to traditional data-driven approaches. Third, it establishes rigorous validation methodologies that ensure reliable model generalisation and provide confidence in predictive capabilities for operational deployment scenarios.

The methodological framework developed in this chapter serves as the foundation for the more complex multi-damage and realistic loading scenarios explored in subsequent chapters, demonstrating the scalability and adaptability of the approach for increasingly sophisticated structural health monitoring applications. The systematic progression from fundamental delamination characterisation to comprehensive multi-scale, multi-damage monitoring systems reflects the integrated nature of the research program and its potential for significant impact on aerospace structural integrity management practices.

3.2 Methodology

3.2.1 Finite Element Dataset Generation

A synthetic data generation approach was adopted using three-dimensional (3D) finite element modelling of a composite structure with surface-mounted piezoelectric sensors. Varying instances and severity of delamination damage in terms of location and size are modelled. Generating the breadth and depth required in terms of datasets from practical experiments proves unfeasible due to the intensive cost and time. The adopted approach, based on finite element simulations, provides a viable platform to demonstrate the potential of ML models in damage detection in composite structures. The structure of this section details the methodology of generating synthetic datasets via commercial finite element software, Abaqus, the data processing required, derivative-based feature engineering, and combining the derivative model with neural network methods to explore predicting the damage scenarios.

The 3D finite element model, comprising multiple layers, is constructed to accurately simulate the laminate’s behaviour. Piezoelectric sensor patches are modelled atop these composite layers to examine their response under load. A structured mesh, optimised through convergence tests, is applied to ensure accuracy and computational efficiency. The materials used in the model for the composite layers and

the piezoelectric patches are Carbon Fibre Reinforced polymer (CFRP) and ferroelectric piezoelectric material, respectively. The specific properties used in the models are summarised in Table 3.1.

Property	CFRP (T800S/3900-2)	PZT-5H (3203HD)
Density (ρ)	1490 kg/m ³	7870 kg/m ³
Elastic Moduli (E)	E_{11} : 121 GPa, E_{22} : 8.6 GPa	E_{11} : 62 GPa, E_{33} : 49 GPa
Poisson's Ratio (ν)	ν_{12} : 0.27	ν : 0.31
Piezoelectric Coefficient	—	d_{31} : -3.20×10^{-10} C/N
Dielectric Constant	—	ϵ_{33} : 3.365×10^{-08} F/m

Table 3.1: Material properties: T800S/3900-2 CFRP [110] and PZT-5H piezoceramic (type 3203HD) [111].

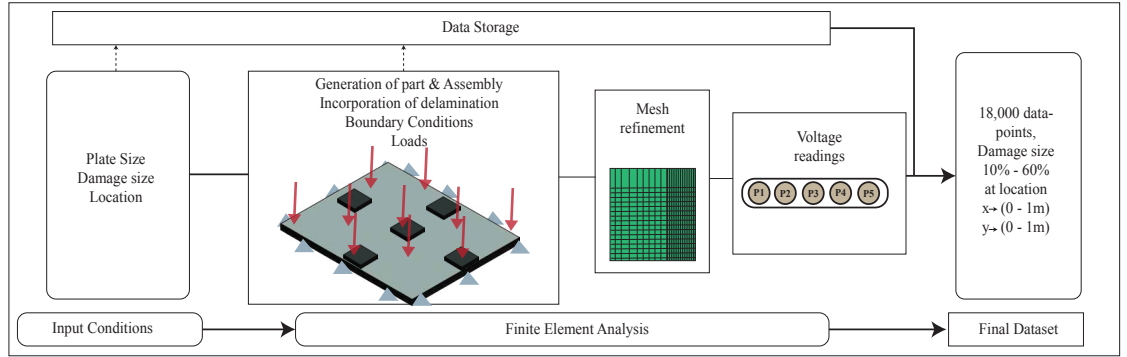


Figure 3.1: Proposed methodology to generate synthetic data with varying delamination parameters.

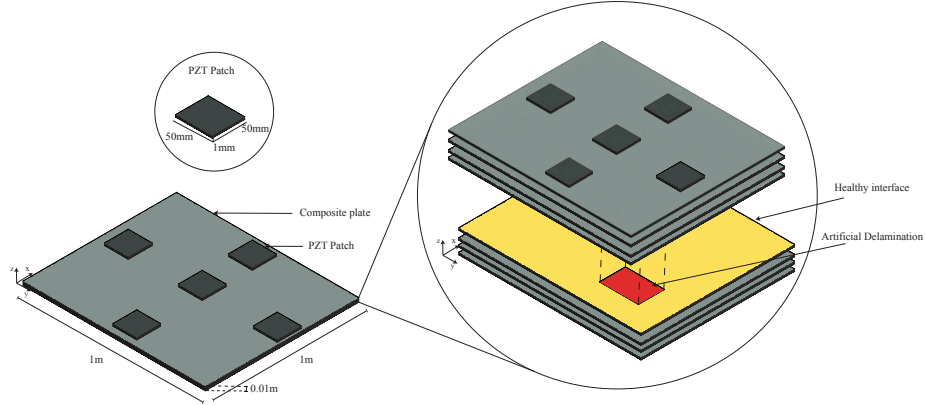


Figure 3.2: The proposed setup to generate composite datasets with five affixed PZT sensors with delamination embedding.

The finite element (FE) model comprises a composite laminate with surface-mounted piezoelectric sensors, represented as patches on the composite surface. The simulation workflow illustrated in Figure 4.1 involves:

1. **Geometry Definition:** The composite laminate is modelled as a stack of

individual plies, with dimensions defined for the overall composite ($1\text{ m} \times 1\text{ m} \times 10\text{ mm}$) and each piezoelectric patch ($50\text{ mm} \times 50\text{ mm} \times 1\text{ mm}$). The laminate is constructed ply-by-ply to allow for precise control over the simulation of delamination.

2. **Meshing Strategy:** A structured mesh is applied to both the composite and the piezoelectric patches. Mesh convergence is ensured through preliminary studies, settling on an optimal element size of 0.2 for the composite and 0.01 for the patches. The element type used is a 3D solid element, specifically C3D8E, for both the composite and the piezoelectric patches to accurately capture the material behaviour under loading.
3. **Material Properties:** As outlined in Table 4.1, distinct material properties are assigned to the composite material (CFRP) and the piezoelectric patches (PIC 255), including density, elastic moduli, Poisson's ratios, piezoelectric coefficients, and dielectric constants.
4. **Boundary Conditions and Load Applications:** Fixed supports and uniformly distributed static loads are applied as boundary conditions to mimic simplified operational scenarios.
5. **Tie Constraints:** The tie constraint method [112] is employed to simulate perfectly bonded interfaces between composite layers and piezoelectric patches, facilitating continuity and stress transfer. The tie constraint is implemented using the nodal displacements of the primary and secondary surfaces of the composite layers:

$$\mathbf{u}_{\text{primary}} - \mathbf{u}_{\text{secondary}} = \mathbf{0} \quad (3.1)$$

where $\mathbf{u}_{\text{primary}}$ and $\mathbf{u}_{\text{secondary}}$ represent the displacement vectors at the master and secondary surfaces, respectively.

Delamination between composite plies is simulated by selectively disabling tie constraints, initially defined to bond adjacent layers and piezoelectric patches. The algorithmic adjustment of tie constraints allows the model to iteratively adjust the tie constraints (Figure 3.2) to simulate varying degrees of delamination, effectively separating layers at predetermined scenarios. The data generation approach employs a parametric sweep mechanism, systematically varying the extent and location of

delamination. The sweeping approach increments the size and position of the delaminated area across the laminate, evaluating its impact on the structural response through the sensor outputs.

Property	Composite Plate
Number of layers	17
Total thickness	0.01m
Orientation	[0,0,0,0,0,0,45,-45,45,-45,45,-45,45,-45,90,90,90]
Mesh Elements	C3D8E

Table 3.2: Finite element structure details

3.2.2 Dataset Analysis: Imbalance, Stratified splitting and Normalisation

Initial analysis of the dataset presented a severe imbalance between the damage classes. To address this imbalance, data augmentation techniques and weighted loss functions were implemented during the machine learning analysis.

Property	
Total Datasets	5,865
Points per dataset	5
Training Split	3,519
Validation Split	1,173
Test Split	1,173

Table 3.3: Dataset Details

To ensure unbiased model evaluation and facilitate hyperparameter tuning, the dataset is partitioned into training, validation, and test sets with proportions of 60%, 20%, and 20%, respectively. Stratified splitting is employed to maintain the distribution of delamination features across all subsets, and reproducibility is ensured through a fixed random state.

Normalisation is critical to ensure that all features contribute equally to the model’s learning process. To maintain the physical meaning and sign of spatial features, a robust scaler is applied to map feature values between -1 and $+1$, simultaneously being resilient to outliers.

The normalisation of a variable or feature is performed using the following formula:

$$X_{\text{norm}} = 2 \times \frac{X - Q_1(X_{\text{train}})}{Q_3(X_{\text{train}}) - Q_1(X_{\text{train}})} - 1, \quad (3.2)$$

Where X represents the spatial feature values in the training, validation, or test sets, and Q_1 and Q_3 are the first and third quartiles, respectively, computed from the training set. This robust scaling approach effectively centres and scales data while preserving the sign, which is significant for capturing local physical deviations in piezoelectric sensor readings without distortion from extreme values.

Derivatives of sensor readings with respect to spatial coordinates are computed to capture spatial variability and relationships inherent in the training data. For such a feature engineering step, Kernel Smoothing with Gaussian Filtering was employed, enriching the predictive model's feature set.

Kernel Smoothing with Gaussian Filtering

Kernel Smoothing involves interpolating sensor readings onto a regular 3D grid defined over the normalised spatial coordinates (x, y, z) or in 1D for delamination size. The procedure encompasses the following steps:

1. **Grid Construction:** A regular grid is established with a specified resolution, spanning the range of normalised spatial coordinates.
2. **Interpolation and Smoothing:** Sensor readings are interpolated onto the grid using linear interpolation. Gaussian filtering is applied to mitigate noise and to highlight trends, mathematically defined as:

$$G(x, y, z) = \frac{1}{(2\pi\sigma^2)^{3/2}} e^{-\frac{x^2+y^2+z^2}{2\sigma^2}}, \quad (3.3)$$

where σ is the standard deviation controlling the extent of smoothing.

3. **Gradient Computation:** Gradients along each spatial dimension are computed using finite differences:

$$\frac{\partial G}{\partial x}, \quad \frac{\partial G}{\partial y}, \quad \frac{\partial G}{\partial z}. \quad (3.4)$$

4. **Interpolation Back to Data Points:** The computed gradients are interpolated back to the original data points to obtain derivative features.

This feature engineering process is schematically displayed in Figure 4.2.

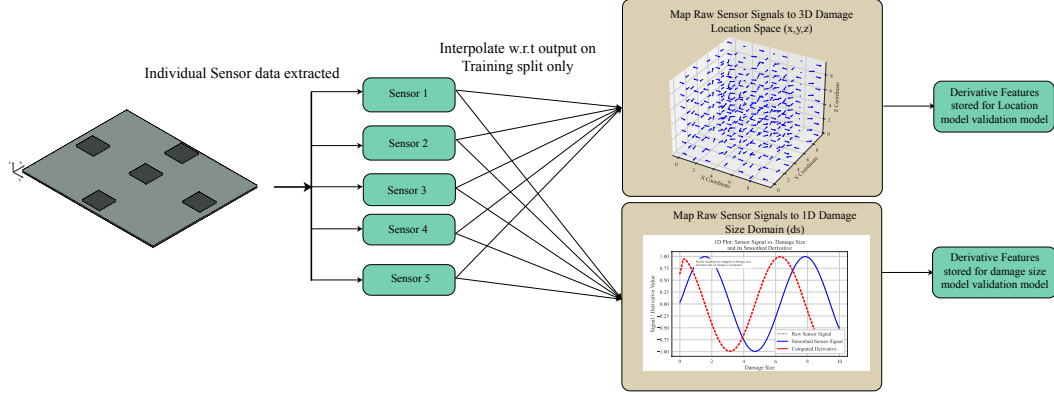


Figure 3.3: Visual Depiction of feature creation on raw sensor signals using training data.

Feature Integration and Scaling

The computed derivative features are integrated into the feature set. Mathematically, this is expressed as:

$$X_{\text{combined}} = [X_{\text{original}}, X_{\text{derivatives}}], \quad (3.5)$$

where X_{combined} represents the concatenated feature set. All features undergo standardisation as follows:

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma}, \quad (3.6)$$

where μ and σ are the mean and standard deviation of the training data.

The feature creation via derivatives was solely used for training to assess the capability of the technique in our paradigm. The feature model generated was fed alongside the trained model data on the test dataset, which is presented in the section below.

3.2.3 Machine Learning Model

A multi-output deep neural network (DNN) is developed to predict the spatial features that characterise the delamination location and size (i.e., (x, y, z) for the location and a separate metric for the delamination size). The network comprises an input layer, several hidden layers, and distinct output layers for each task as illustrated in Figure 4.3. To mitigate overfitting, L2 regularisation is applied to the network weights:

$$\mathcal{L}_{\text{reg}} = \lambda \sum_i w_i^2, \quad (3.7)$$

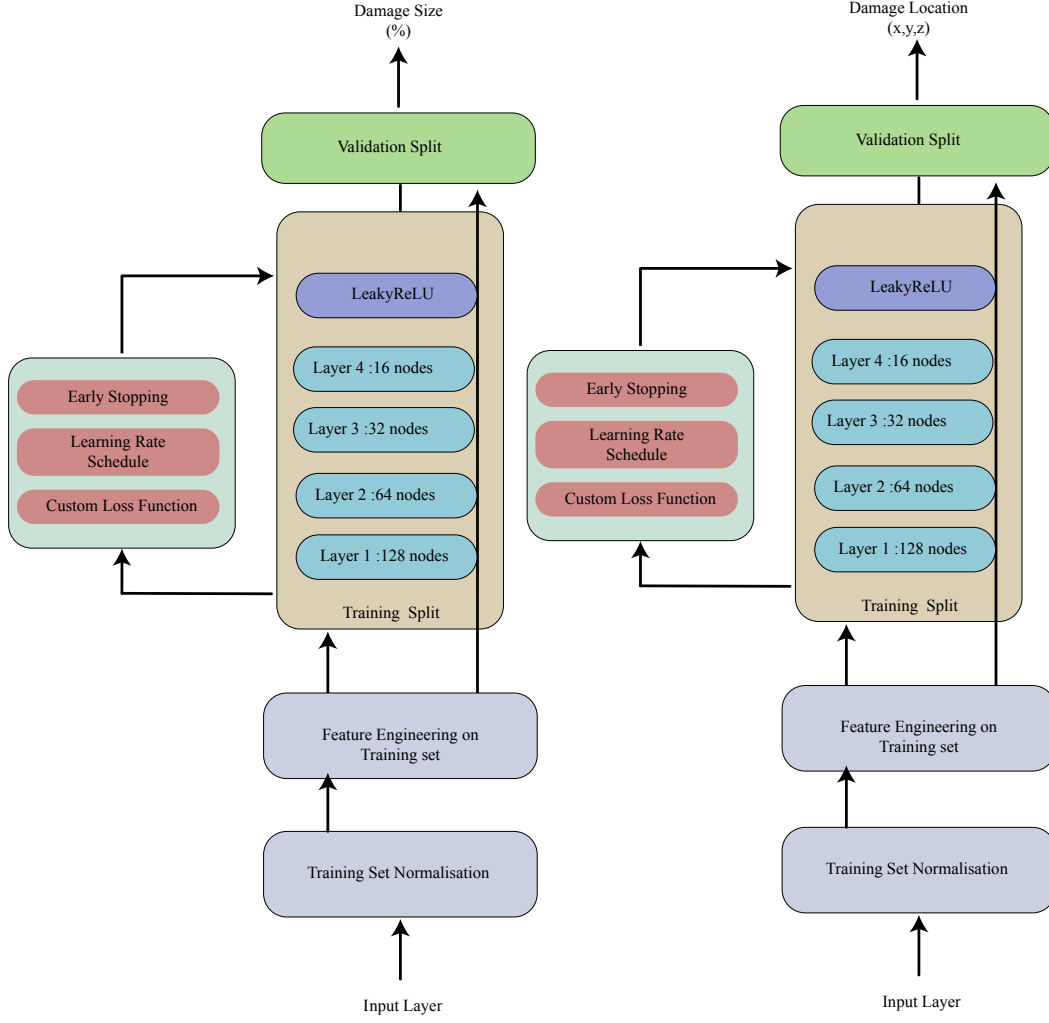


Figure 3.4: Parallel fully-connected neural network architectures for delamination characterisation from PZT sensor signals. Left: Delamination size regression network (128-64-32-16 nodes, LeakyReLU activation, custom MSE loss). Right: Delamination location regression network (128-64-64-16 nodes, LeakyReLU, Euclidean distance loss). Both networks employ feature engineering (time-domain and frequency-domain statistical features), early stopping, and learning rate scheduling for regularisation. Training-validation split: 80-20%.

where λ is the regularization parameter and w_i represents the individual network weights.

Data imbalance is addressed using a custom F1 focal loss inspired by [113]. This loss function downweights the contribution of well-predicted samples by introducing a modulation term based on the prediction error and thereby focuses the optimisation on harder examples. In our implementation, the F1 focal loss is defined as:

$$\mathcal{L}_{\text{F1FL}} = \frac{1}{N} \sum_{i=1}^N \left(\frac{|a_i - \hat{a}_i|}{\beta + |a_i - \hat{a}_i|} \right)^\gamma |a_i - \hat{a}_i|, \quad (3.8)$$

Where:

- a_i and $\hat{a}_i$ are the true and predicted values, respectively,
- β is a smoothing parameter (e.g., $\beta = 0.2$) that prevents division by zero and controls the onset of the modulation,
- γ is the focusing parameter (e.g., $\gamma = 1$) that adjusts the weight of hard versus easy examples,
- N is the total number of training samples.

The overall loss function that the network optimises is a combination of the F1 focal loss and the L2 regularisation term:

$$\mathcal{L} = \mathcal{L}_{\text{F1FL}} + \mathcal{L}_{\text{reg}}. \quad (3.9)$$

Model performance is evaluated using standard regression metrics:

- **Mean Squared Error (MSE):**

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (a_i - \hat{a}_i)^2, \quad (3.10)$$

- **Mean Absolute Error (MAE):**

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |a_i - \hat{a}_i|, \quad (3.11)$$

- **Coefficient of Determination (R^2):**

$$R^2 = 1 - \frac{\sum_{i=1}^N (a_i - \hat{a}_i)^2}{\sum_{i=1}^N (a_i - \bar{a})^2}, \quad (3.12)$$

where $\bar{a}$ is the mean of the true values.

In addition to these loss and performance measures, early stopping based on validation metrics and regular monitoring of the training process (e.g., via loss and MAE plots) are employed to further reduce the risk of overfitting.

3.3 Results and Discussions

This section presents the performance of machine learning models developed for predicting delamination size and location in carbon fibre-reinforced polymer (CFRP)

composites. The results are divided into delamination size and location predictions, highlighting the best-performing methods, their training and validation progress, and error distributions. Advanced derivative-based feature engineering techniques are leveraged to enhance predictive accuracy.

3.3.1 Prediction of Damage Location

The performance of the baseline model without feature engineering for predicting delamination location is evaluated across x , y , and z coordinates using the raw signals. The baseline model is then enriched with the feature engineering step, and the performance is presented (Feature Engineered Model). Table 3.4 summarises the performance metrics of the model using raw sensor signals and with feature engineering. It can be observed that the feature engineering has a drastic influence on improving the performance of the machine learning model.

Method	Metric	x	y	z
Baseline Model	R-Squared (R2)	0.123	0.021	0.567
	MAE	0.147	0.161	0.147
Feature Engineered Model	R-Squared (R2)	0.862	0.871	0.941
	MAE	0.046	0.047	0.047

Table 3.4: Performance metrics for predicting positional outputs using different methods.

Training and Validation Loss

Figure 3.5 compares training and validation loss curves across methods. Both methods show rapid convergence within 200 epochs. The feature-engineered configuration achieves lower validation loss throughout, indicating superior generalisation. For instance, the best epoch (e.g., epoch = 861) corresponds to a validation loss of approximately 0.0032. This demonstrates the method’s stability and robust performance compared to the sensors-only configuration.

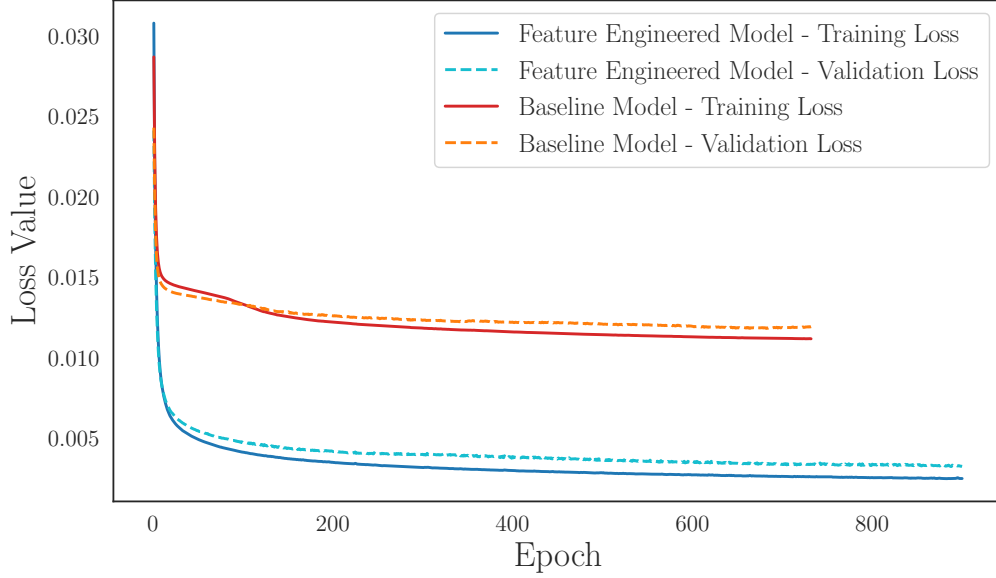


Figure 3.5: Training and validation loss curves for delamination size prediction comparing feature-engineered model (45 statistical descriptors from PZT sensor signals) versus baseline model (raw time-series input).

True vs. Predicted Analysis

Figures 3.6, 3.7 and 3.8 illustrate the true vs. predicted plots for delamination location in x , y , and z coordinates. A close alignment is observed in the feature-engineered model, indicating strong correlation and low bias for the predicted delamination locations. Minor scatter near the lower and upper bounds of the x location suggests slight deviations at extremes. The y location demonstrates a tighter distribution with points forming a straight diagonal band, consistent with its lower MAE and higher R-squared values. For the z location, while narrower in range, predictions remain well aligned, with slight deviations visible at boundary values.

Metrics confirm the visual analysis, and further, MSE values indicate small average squared errors, while MAE values reflect modest absolute discrepancies. R-squared values highlight the model's ability to explain most variance in predictions. Comparisons reveal that compared to the sensors-only model (baseline), the more complex feature-engineered model exhibits tighter distributions with better accuracy across all parameters, particularly at boundary regions. The model exhibits better prediction in the through-thickness direction ((z)) noted by R^2 of 0.941, in comparison, the in-plane directional prediction (x & y) performs slightly weaker with an R^2 of 0.862 and 0.871, respectively.

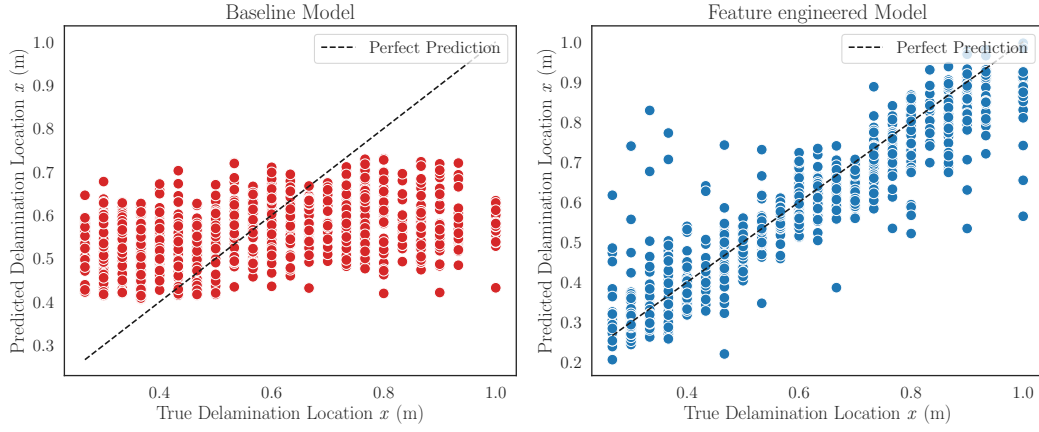


Figure 3.6: Predicted vs. true x -coordinate: baseline model (left, $R^2 = 0.45$) and feature-engineered model (right, $R^2 = 0.85$).

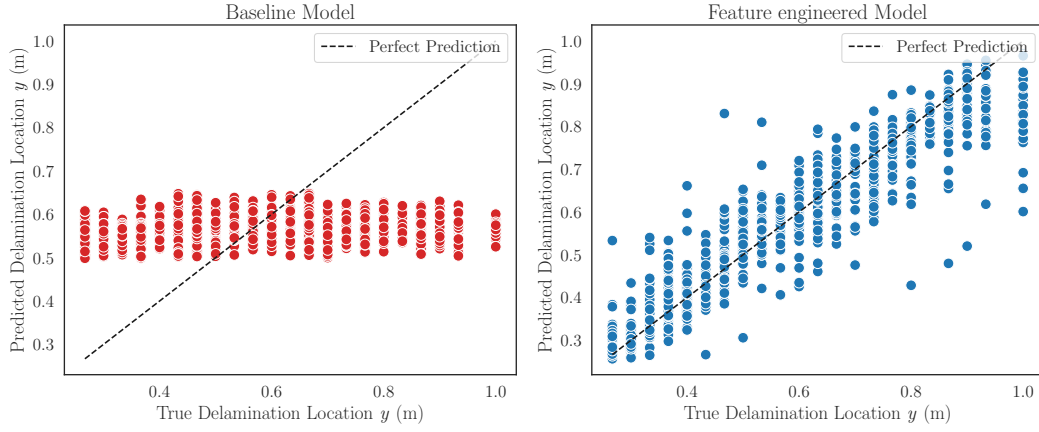


Figure 3.7: Predicted vs. true y -coordinate: baseline model (left, $R^2 = 0.42$) and feature-engineered model (right, $R^2 = 0.88$).

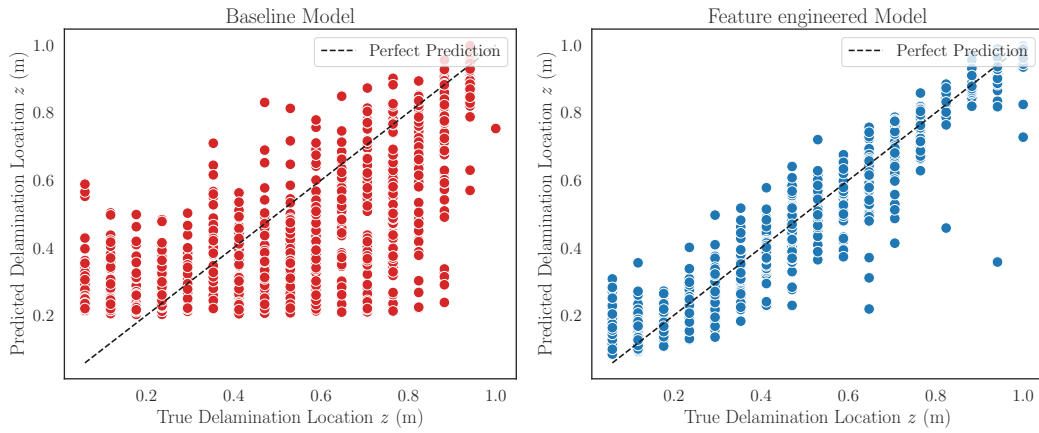


Figure 3.8: Predicted vs. true z -coordinate: baseline model (left, $R^2 = 0.38$) and feature-engineered model (right, $R^2 = 0.82$).

Absolute Error Distributions

Figure 3.9 highlights the absolute error distributions for x , y , and z predictions of the delamination locations.

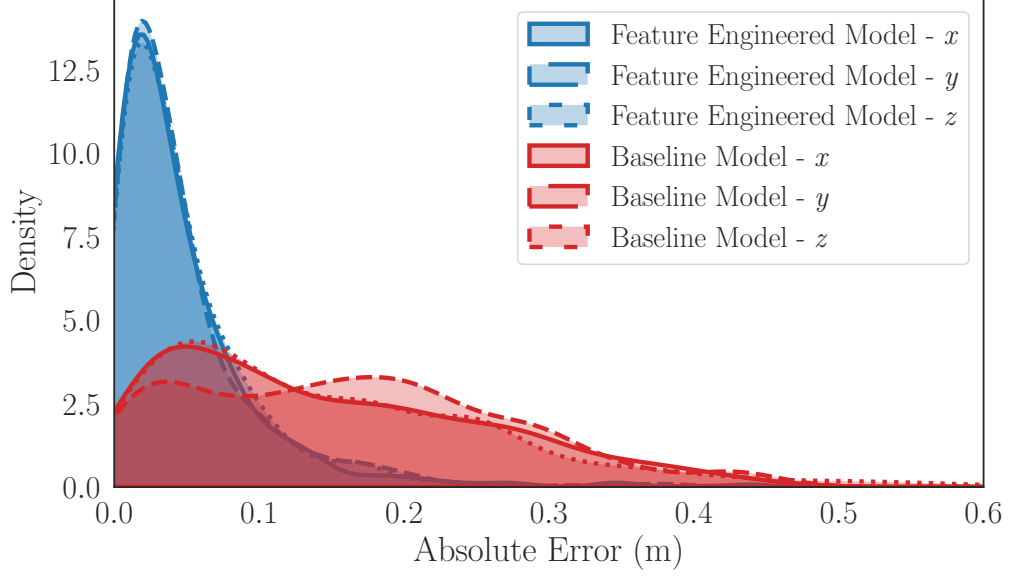


Figure 3.9: Absolute error distributions for damage localisation: feature-engineered model (blue) vs. baseline model (red) across x , y , z coordinates.

From the plot, it can be observed that the feature-engineered model achieves narrower distributions with sharper peaks at zero across all parameters, reflecting consistent and accurate predictions. The y parameter typically exhibits the tightest clustering, with x and z also maintaining low error levels under the combined configuration. Compared to the baseline model, it is noted that across all parameters, a wider spread and lower peaks, denoting the weaker performance.

3.3.2 Predicting Delamination size

This section presents the results of the predictions of the delamination size using the baseline and feature-engineered models. Table 3.5 summarises the performance metrics for both models.

Method	Metric	Value
Baseline Model	R-Squared (R2)	0.435
	MAE	0.144
Feature Engineered Model	R-Squared (R2)	0.996
	MAE	0.005

Table 3.5: Performance metrics for predicting delamination size using different methods.

Training Progression

Figure 3.10 illustrates the progression of the training loss to predict the size of the delamination damage. Both the baseline sensor-only model and the feature-engineered model configurations exhibit rapid convergence within 50 epochs. However, the feature engineering model with kernel smoothing achieves the lowest final loss, while the baseline model converges more slowly and to higher loss values, highlighting its limitations.

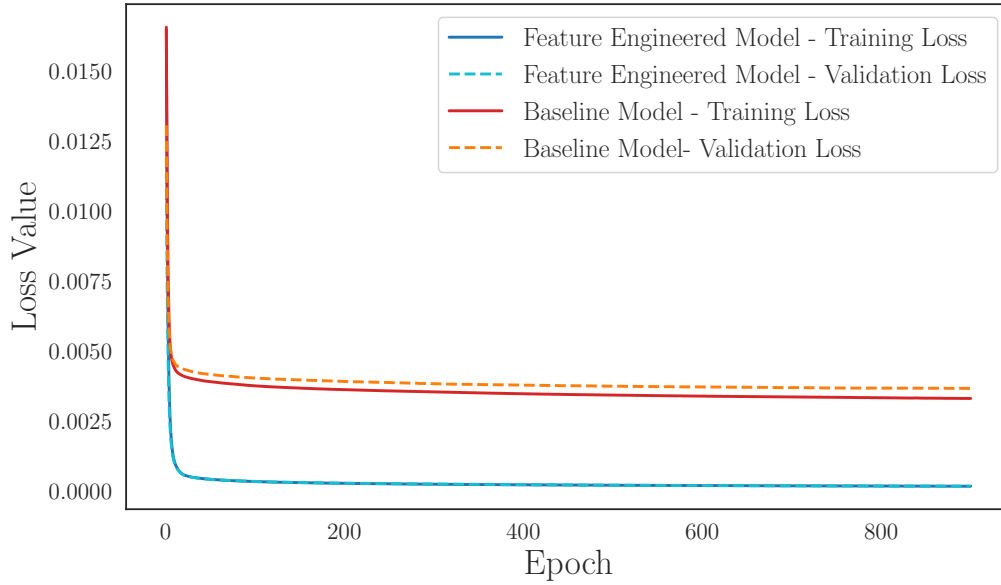


Figure 3.10: Training comparison for delamination size prediction: feature-engineered model (blue vs. baseline model (orange, final loss)).

True vs. Predicted Analysis

Figure 3.11 compares the predicted and true delamination sizes for the baseline and then feature-engineered models.

The feature-engineered model (Figure 3.11) demonstrates near-perfect alignment, with predictions clustering tightly along the diagonal. This highlights its

high accuracy, particularly for mid-range and large sizes, with minor deviations observed for smaller sizes. In contrast, the baseline model shows a broader scatter and poor correlations, especially at the extremes, reflecting reduced accuracy for very small or very large sizes.

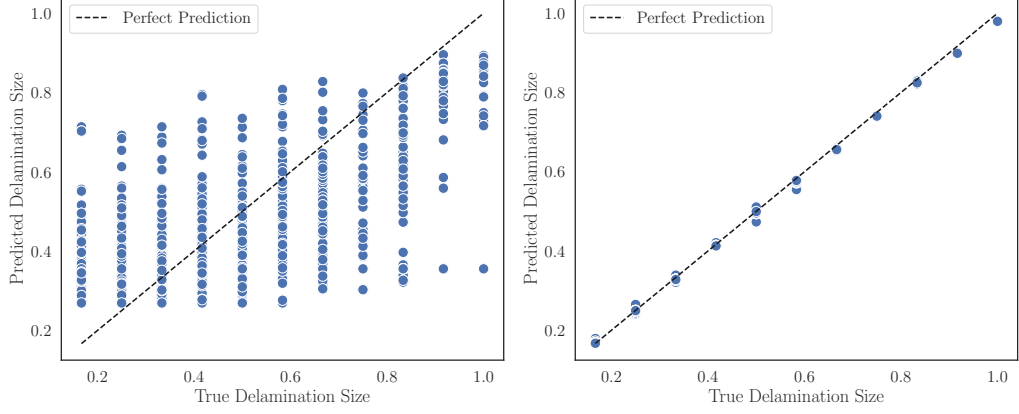


Figure 3.11: Predicted vs. true delamination size: baseline (left, $R^2 = 0.435$) vs. feature-engineered (right, $R^2 = 0.996$).

Error Analysis

Figure 3.12 compares absolute error distributions across methods. The feature-engineered model with the kernel smoothing method exhibits a sharp peak near zero, and the errors are concentrated around the zero mark. In comparison, using the baseline model, a much greater distribution of absolute error is seen, indicating a much greater error across the spectrum.

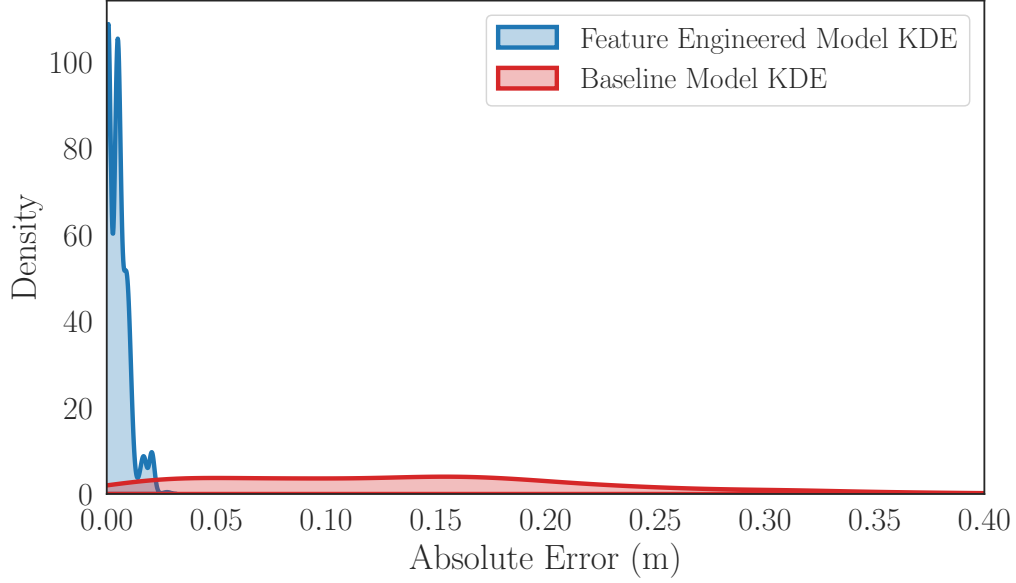


Figure 3.12: Density Plot of Absolute Errors for delamination size Prediction across different methods and configurations.

3.4 Discussion

3.4.1 Damage Location Predictions

The results presented above demonstrate that, relative to the baseline model, the kernel smoothing–based feature engineering approach yields substantially improved performance for delamination location prediction. The training loss curves indicate stable convergence and consistent validation behaviour when derivative features are incorporated alongside the original sensor signals. Correspondingly, the absolute error distributions show narrower and more sharply peaked profiles centred near zero, highlighting the improved accuracy of the feature-engineered model.

While training times increase due to the expanded feature space, the resulting performance gains justify this additional computational cost within the scope of the present study. Some increased spread in prediction error is observed near the boundaries of the spatial domain, particularly for in-plane coordinates. Across all outputs, the through-thickness (z) location consistently achieves the lowest errors, which is consistent with the discrete ply-wise structure of the laminate and the modelling assumptions adopted.

Further analysis of the largest localisation errors, shown in Figure 3.13, reveals that these errors are not uniformly distributed across the damage domain. Instead, they tend to cluster near boundary regions and in areas close to the sensor surface.

The accompanying two-dimensional cross-sectional views confirm that this trend persists across all spatial projections. This behaviour suggests a sensitivity of the prediction accuracy to sensor placement and proximity effects, rather than random model error. These findings indicate that targeted refinement of sensor positioning or local feature extraction strategies could further improve localisation performance in these regions.

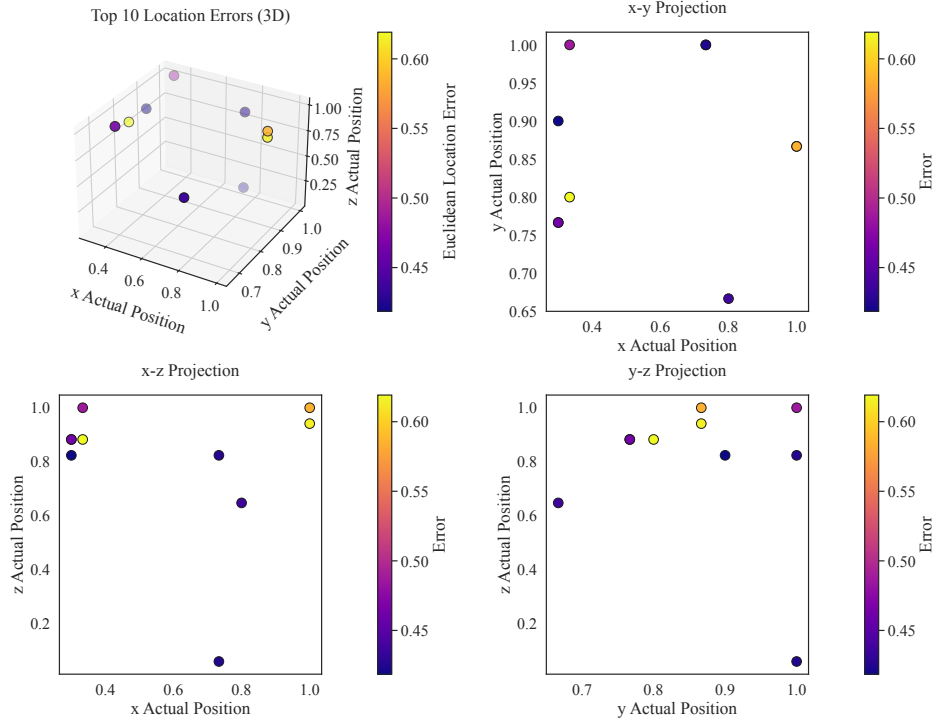


Figure 3.13: Three-dimensional scatter plot of the largest localisation errors (x , y , z) with corresponding x - y , x - z , and y - z cross-sections.

3.4.2 Delamination size Predictions

A similar performance trend is observed for delamination size prediction. Augmenting the baseline model with derivative-based features leads to marked improvements in accuracy, convergence behaviour, and prediction consistency. The kernel smoothing approach enables the model to capture spatial trends associated with delamination extent more effectively than raw sensor signals alone.

Although prediction errors are generally smaller in magnitude than those observed for localisation, the spatial distribution of size prediction errors is similarly non-uniform (Figure 3.14). The largest discrepancies are concentrated near regions

close to the sensor surface, as confirmed by the two-dimensional cross-sectional views. This again points to geometric and sensor proximity effects rather than systematic model bias. These observations reinforce the importance of sensor placement considerations and motivate further investigation into configuration-specific optimisation strategies.

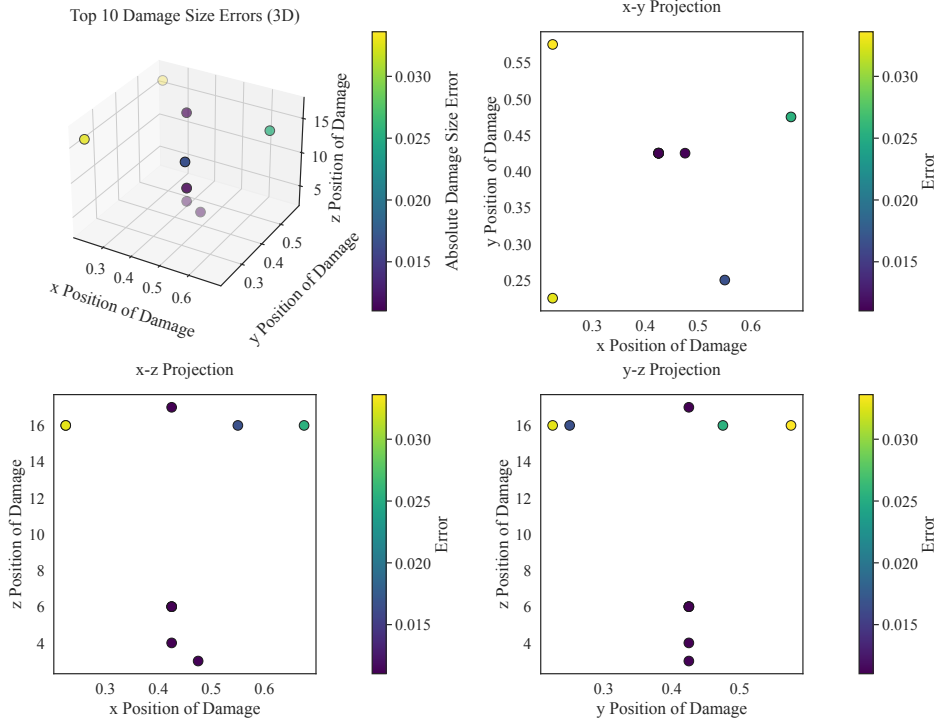


Figure 3.14: Three-dimensional scatter plot of the largest delamination size prediction errors with corresponding planar cross-sections.

3.5 Conclusion

This chapter presented a machine learning-based framework for predicting the location and size of delamination damage in carbon fibre reinforced polymer (CFRP) composite structures. High-fidelity finite element simulations were used to generate a comprehensive synthetic dataset spanning a wide range of delamination configurations, enabling systematic investigation of damage-related sensor responses without the cost and logistical constraints of large experimental campaigns.

The integration of derivative-based feature engineering, derived via kernel smoothing of training data only, resulted in substantial performance improvements over

baseline sensor-only models. These features enabled the neural networks to capture spatial signal variations associated with damage geometry more effectively, leading to very strong agreement between predicted and true delamination parameters across the evaluated test sets.

Careful preprocessing ensured that all normalisation and derivative computations were performed using training data exclusively, thereby avoiding data leakage and preserving the integrity of the validation results. Model performance was assessed across three independent training runs, demonstrating consistent behaviour and stable convergence rather than reliance on favourable initialisation.

Error analysis highlighted that the largest prediction discrepancies are concentrated near domain boundaries and regions close to sensor locations, indicating sensitivity to geometric and placement effects rather than global model instability. These findings suggest that future improvements may be achieved through refined sensor layouts, alternative feature formulations, or adaptive modelling strategies targeted at these regions.

Overall, this work establishes a reliable methodological foundation for data-driven delamination characterisation under controlled and operationally informed simulation conditions. While the results demonstrate strong predictive capability for the configurations studied, further work is required to assess generalisation across different laminate architectures, sensor arrangements, and loading conditions. The framework developed here directly supports the extensions explored in subsequent chapters, where additional damage mechanisms and more complex loading scenarios are considered.

Chapter 4

Predicting Multiple Damage Scenarios using Data-driven Techniques in Composites

4.1 Introduction

Inter Lamina Delamination, the separation of plies, represent a significant failure mechanism in laminated composite structures. Delamination can occur due to various causes, including in manufacturing during lay-up, operational loads, free edge effects, joint failures and more [114].

Recent work has shown that delamination is strongly influenced by layup configuration, thickness and loading conditions of composite structures [115, 116].

In research concerning thin-ply [117], notable differences were observed in failure mechanisms compared to conventional ply composites with failure modes transitioning from progressive to more direct fracture patterns as ply thickness decreases, pointing to the importance of considering the ply thickness when developing damage models for composites.

In the realm of Structural Health monitoring (SHM), piezo-electric sensors (PZT) have consistently proven their use, reliability and robustness to capture internal damage states in works [118] and [119].

Accompanying delamination damage is ply damage, where a localised section is usually damaged. Previous work using the continuum damage mechanics CDM framework provides validation for localised modulus reduction as a damage proxy.

Work by Okabe et al [120] demonstrates that a 21 GPa reduction in modulus corresponds to crack densities of 0.8-1.2 cracks/mm in typical CFRP. Work by Badabagni et al [121] calculated compliance matrices for cracked plies, mapping precise modulus without full FE simulations for damage classification, applying it successfully on cross-ply laminates.

Recent finite element method implementations by Kou et al [122] employ a local stiffness reduction method, creating predefined regions with custom elastic properties showing less than 5% error compared to experimental measurements when using stiffness reduction values in the range of 15–25 GPa.

Using Artificial Intelligence and ML models has significantly advanced damage detection in composite structures, in particular their abilities to extract information from sensor data demonstrated in [123] and [124], with promising work where machine learning overcame traditional limitations of SHM, improving accuracy, reliability and damage assessment [125].

Work by Nguyen et al [126] highlighted the capabilities of Convolutional neural networks and U-Net architectures in segmentation and localisation of delamination patterns in composite materials, overcoming challenges of noisy data typical in scans and other NDT methods.

The role that derivative features extracted as in [123, 124, 125] show how these features can help capture underlying physics of damage-signal relationships, improving model accuracy and generalisation capabilities. In domains where there is limited real data, transfer learning approaches, such as from simulated data, can help develop robust performance, with limited experimental data being particularly valuable in the aerospace domain.

The current challenges include data sparsity due to the cost and time associated with testing laminates and a lack of multiple damage presences. Our work builds on approaches mentioned above, using a local region with a reduced Young’s modulus to represent ply damage and modelling of inter-lamina delamination together due to the frequency with which these damage types accompany each other. PZT sensors are affixed to the structure, and the extracted signals are used to create robust models to predict

- Multi-Damage Location - The spatial location of both ply damage and delamination within the composite (x, y, and through-thickness z coordinates)

- Multi-Damage Size - The extent of weakened material regions and delamination areas

The structure of this chapter is as follows: the paper begins by outlining the methodology used to generate the dataset, process the dataset and the feature engineering using derivative methods. Following this, the results are presented for each aforementioned task. The results are then discussed in the discussion with the concluding remarks and future work in the conclusion section.

4.2 Methodology

4.2.1 Generation of Synthetic dataset - Finite Element Method

A synthetic data generation approach was adopted using three-dimensional (3D) finite element modelling of a composite structure with surface-mounted piezoelectric sensors. Varying instances and severity of both delamination and weakened material damage in terms of location and size are modelled.

Generating the breadth and depth required in terms of datasets from practical experiments proves unfeasible due to the intensive cost and time. The adopted approach, based on finite element simulations, provides a viable platform to demonstrate the potential of ML models in damage detection in composite structures. The structure of this section details the methodology of generating synthetic datasets via commercial finite element software, Abaqus, the data processing required, derivative-based feature engineering, and combining the derivative model with neural network methods to explore predicting the damage scenarios.

The 3D finite element model, comprising multiple layers, is constructed to accurately simulate the laminate's behaviour. Piezoelectric sensor patches are modelled atop these composite layers to examine their response under load. A structured mesh, optimised through convergence tests, is applied to ensure accuracy and computational efficiency. The materials used in the model for the composite layers and the piezoelectric patches are Carbon Fibre Reinforced polymer (CFRP) and ferroelectric piezoelectric material, respectively. The specific properties used in the models are summarised in Table 4.1.

Property	Composite Material (CFRP)	Piezoelectric (PIC 255)
Density (ρ)	1490 kg/m ³	7800 kg/m ³
Elastic Moduli (E)	E_{11} : 121 GPa, E_{22} : 8.6 GPa	E_{11} : 62.1 GPa, E_{33} : 48.3 GPa
Poisson's Ratio (ν)	ν_{12} : 0.27	ν_{13} : 0.32
Piezoelectric Coefficients	-	d_{31} : 7.41e-10 C/N
Dielectric Constants	-	ϵ_{33} : 8.245e-09 F/m

Table 4.1: Material properties of the composite material and piezoelectric patches.

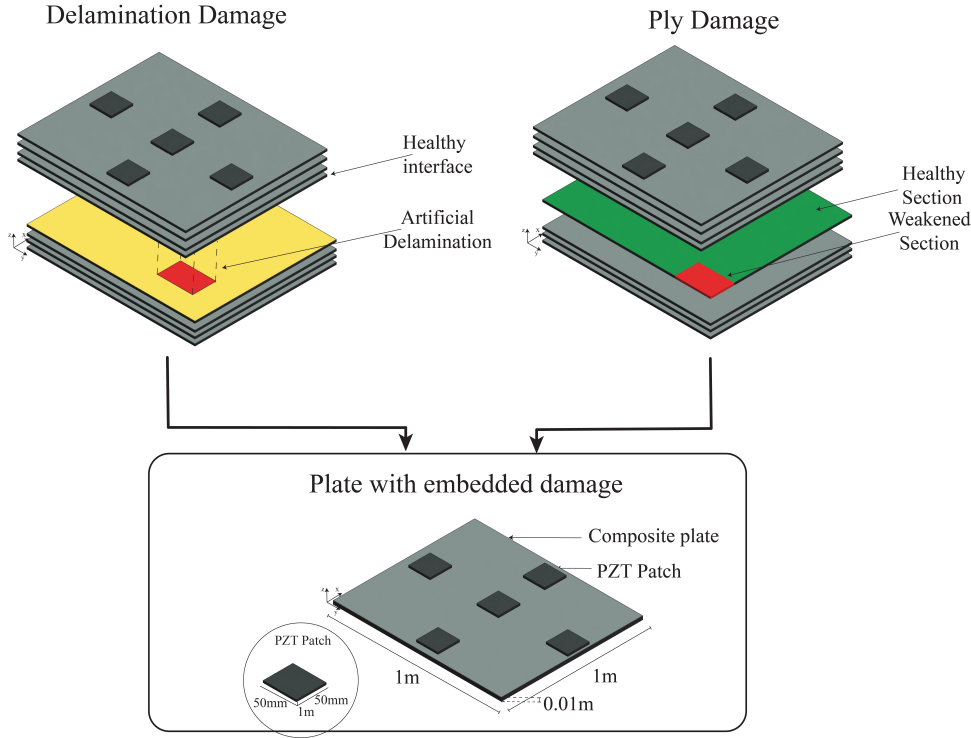


Figure 4.1: Proposed methodology to generate synthetic data with varying delamination and ply damage parameters.

The finite element (FE) model comprises a composite laminate with surface-mounted piezoelectric sensors, represented as patches on the composite surface. The simulation workflow illustrated in Figure 4.1 involves:

1. **Geometry Definition:** The composite laminate is modelled as a stack of individual plies, with dimensions defined for the overall composite (1 m $\times$ 1 m $\times$ 10 mm) and each piezoelectric patch (50 mm $\times$ 50 mm $\times$ 1 mm). The laminate is constructed ply-by-ply to allow for precise control over the simulation of delamination.
2. **Meshing Strategy:** A structured mesh is applied to both the composite and the piezoelectric patches. A local mesh refinement was applied in and around the PZT patches and the delamination region; the final seed sizes were selected

from a mesh convergence study. The element type used is a 3D solid element, specifically C3D8E, for both the composite and the piezoelectric patches to accurately capture the material behaviour under loading.

3. **Material Properties:** As outlined in Table 4.1, distinct material properties are assigned to the composite material (CFRP) and the piezoelectric patches (PIC 255), including density, elastic moduli, Poisson's ratios, piezoelectric coefficients, and dielectric constants.
4. **Boundary Conditions and Load Applications:** Fixed supports and uniformly distributed static loads are applied as boundary conditions to mimic simplified operational scenarios.
5. **Tie Constraints:** The tie constraint method [112] is employed to simulate perfectly bonded interfaces between composite layers and piezoelectric patches, facilitating continuity and stress transfer. The tie constraint is implemented using the nodal displacements of the primary and secondary surfaces of the composite layers:

$$\mathbf{u}_{\text{primary}} - \mathbf{u}_{\text{secondary}} = \mathbf{0} \quad (4.1)$$

where $\mathbf{u}_{\text{primary}}$ and $\mathbf{u}_{\text{secondary}}$ represent the displacement vectors at the master and secondary surfaces, respectively. The parameters, such as the location of tie manipulation and size, were pre-determined via script and varied in each run.

6. **Ply Damage Modelling:** To model weakened sections of the ply, pre-determined regions (via script) were iterated through, both in size and location of the ply and assigned the secondary material where the Young's Modulus was reduced by 22GPa. The parameter location and size were also varied in each simulation to generate a comprehensive dataset.

Delamination between composite plies is simulated by selectively disabling tie constraints, initially defined to bond adjacent layers and piezoelectric patches. The algorithmic adjustment of tie constraints allows the model to iteratively adjust the tie constraints (Figure 3.2) to simulate varying degrees of delamination, effectively separating layers at predetermined scenarios. The data generation approach employs a parametric sweep mechanism, systematically varying the extent and location of

delamination. The sweeping approach increments the size and position of the delaminated area across the laminate, evaluating its impact on the structural response through the sensor outputs.

Property	Composite Plate
Number of layers	17
Total thickness	0.01m
Orientation	[0,0,0,0,0,0,45,-45,45,-45,45,-45,45,-45,90,90,90]
Mesh Elements	C3D8E

Table 4.2: Finite element structure details

4.2.2 Dataset Analysis: Imbalance, Stratified splitting and Normalisation

Initial analysis of the dataset presented a severe imbalance between the damage classes. To address this imbalance, data augmentation techniques and weighted loss functions were implemented during the machine learning analysis.

Property	
Total Datasets	81188
Training Split	48,712
Validation Split	16,238
Test Split	16,238

Table 4.3: Dataset Details

To ensure unbiased model evaluation and facilitate hyperparameter tuning, the dataset is partitioned into training, validation, and test sets with proportions of 60%, 20%, and 20%, respectively. Stratified splitting is employed to maintain the distribution of delamination features across all subsets, and reproducibility is ensured through a fixed random state.

Normalisation is critical to ensure that all features contribute equally to the model’s learning process. Spatial features are normalised based on the maximum values observed in the training set to prevent data leakage. The normalisation of a variable or feature in the dataset is defined as:

$$X_{\text{norm}} = \frac{X}{\max(X_{\text{train}})}, \quad (4.2)$$

where X represents the spatial feature values in the training, validation, or test sets, and $\max(X_{\text{train}})$ is the maximum value observed in the training set.

Derivatives of sensor readings with respect to spatial coordinates are computed to capture spatial variability and relationships inherent in the training data. For such a feature engineering step, Kernel Smoothing with Gaussian Filtering is once more employed enriching the predictive model's feature set.

Kernel Smoothing with Gaussian Filtering

Kernel Smoothing involves interpolating sensor readings onto a regular 3D grid defined over the normalised spatial coordinates (x, y, z) or in 1D for damage size. The procedure encompasses the following steps:

1. **Grid Construction:** A regular grid is established with a specified resolution, spanning the range of normalised spatial coordinates.
2. **Interpolation and Smoothing:** Sensor readings are interpolated onto the grid using linear interpolation. Gaussian filtering is applied to mitigate noise and to highlight trends, mathematically defined as:

$$G(x, y, z) = \frac{1}{(2\pi\sigma^2)^{3/2}} e^{-\frac{x^2+y^2+z^2}{2\sigma^2}}, \quad (4.3)$$

where σ is the standard deviation controlling the extent of smoothing.

3. **Gradient Computation:** Gradients along each spatial dimension are computed using finite differences:

$$\frac{\partial G}{\partial x}, \quad \frac{\partial G}{\partial y}, \quad \frac{\partial G}{\partial z}. \quad (4.4)$$

4. **Interpolation Back to Data Points:** The computed gradients are interpolated back to the original data points to obtain derivative features.

This feature engineering process is schematically displayed in Figure 4.2.

The computed derivative features are integrated into the feature set. Mathematically, this is expressed as:

$$X_{\text{combined}} = [X_{\text{original}}, X_{\text{derivatives}}], \quad (4.5)$$

where X_{combined} represents the concatenated feature set. All features undergo stan-

3D Kernel Smoothing - Raw vs. Smoothed

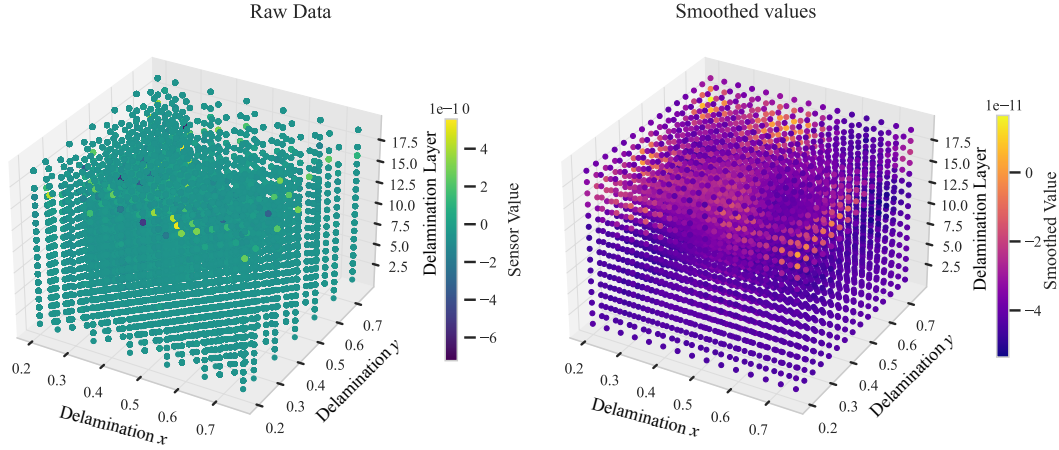


Figure 4.2: Visual depiction kernel smoothing applied to a subsection of the data for the first sensor reading with respect to the location outputs.

dardisation as follows:

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma}, \quad (4.6)$$

where μ and σ are the mean and standard deviation of the training data.

The feature creation via derivatives was solely used for training to assess the capability of the technique in our paradigm. The feature model generated was fed alongside the trained model data on the test dataset, which is presented in the section below.

4.2.3 Machine Learning Model

The objective of the machine learning framework developed in this work is to infer both the spatial location and the physical size of multiple coexisting damage mechanisms in composite coupons using a small number of ultrasonic sensor measurements. In contrast to approaches that treat damage modes independently, the present methodology explicitly targets the most challenging and operationally relevant regime in which *delamination and material weakening are simultaneously present*. All models are therefore trained and evaluated exclusively on samples satisfying this condition.

The overall learning pipeline is divided into two primary regression tasks: damage localisation, in which the three-dimensional position of each damage mechanism is estimated, and damage size estimation, in which the projected in-plane area of each damage mechanism is predicted. Separate neural networks are trained for each

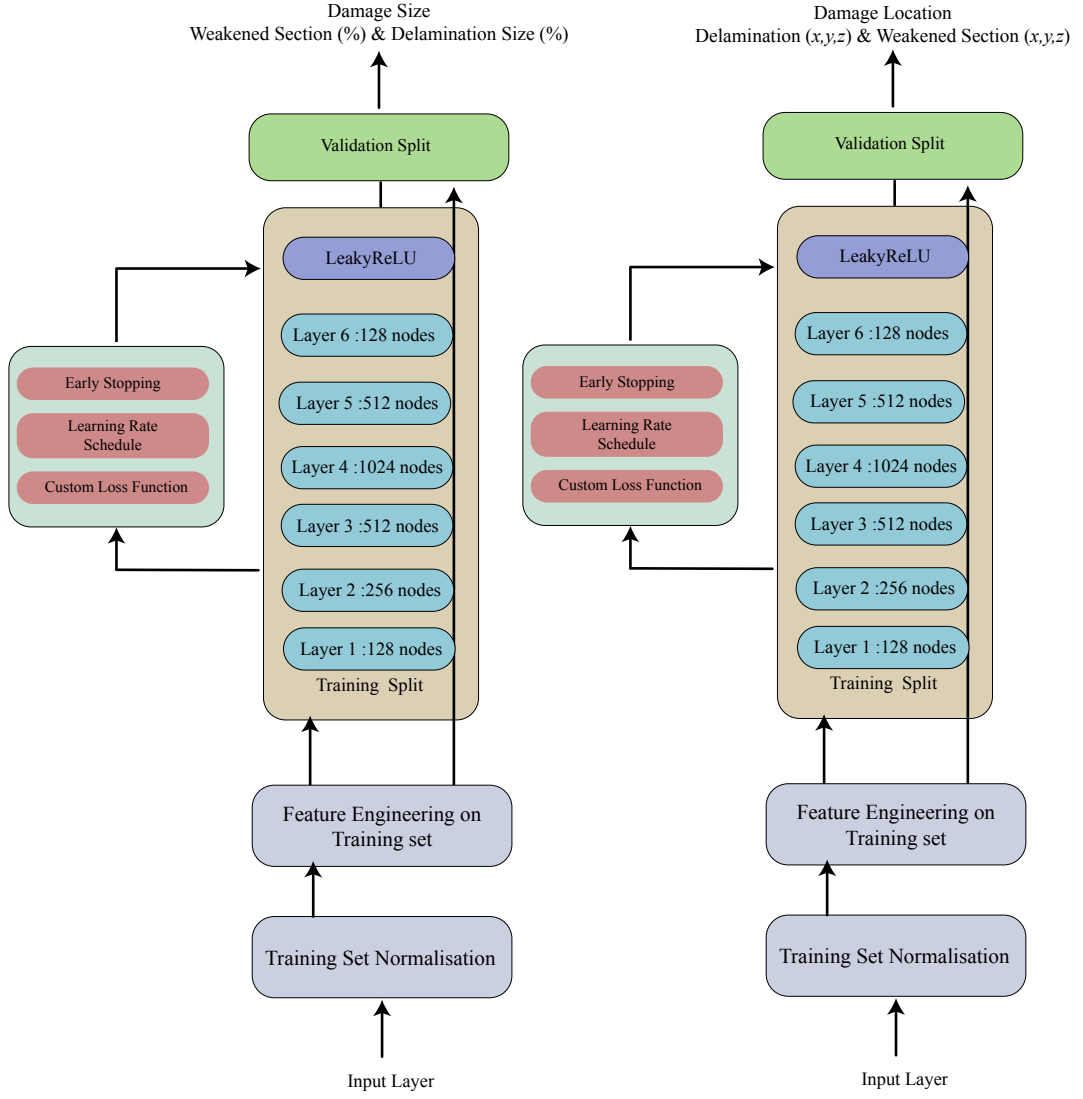


Figure 4.3: Machine learning architecture for multi-damage localisation and size estimation (updated to reflect the final model configuration).

task and damage type, allowing the models to specialise while sharing a common preprocessing and evaluation strategy.

Damage Localisation

Damage localisation is formulated as a supervised regression problem in which the input consists of a vector of five simultaneous ultrasonic sensor readings,

$$\mathbf{p} = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \\ p_5 \end{bmatrix} \quad (4.7)$$

and the outputs are the spatial coordinates of delamination and material damage within the coupon. For each damage mechanism, the target vector is defined as

$$\mathbf{y} = (x, y, z) \quad (4.8)$$

where (x, y) denotes the in-plane centroid of the damage and z represents the through-thickness location expressed as a normalised ply index,

$$z = \frac{\text{damagedlayer}}{17} \quad (4.9)$$

A damage mechanism is considered present if and only if the corresponding ply index lies within the interval $(0, 17]$. Only samples in which *both* delamination and material damage satisfy this condition are retained for localisation training and evaluation.

Prior to modelling, all samples for which the five sensor readings are identically zero are removed. The remaining sensor values are scaled using a robust standardisation procedure based on interquartile statistics, followed by a hyperbolic tangent nonlinearity, yielding bounded inputs approximately within the range $[-1, 1]$. All target coordinates are normalised to the unit interval $[0, 1]$ to ensure numerical stability and to enable bounded regression.

To enhance sensitivity to spatial variations in the sensor field, the raw sensor readings are augmented with geometry-aware derivative features derived directly from the known sensor layout. The five sensors are treated as fixed points in the coupon plane, and their measured amplitudes are locally approximated by a best-fit affine surface. From this approximation, a set of physically interpretable features is extracted, including planar gradient components, residual statistics quantifying

deviations from planarity, and directional sensor contrasts capturing anisotropic signal behaviour. These features are concatenated with the original sensor readings to form a 13-dimensional input vector,

$$\mathbf{x}_{\text{loc}} \in \mathbb{R}^{13},$$

which provides the network with explicit information about local spatial trends without requiring numerical interpolation or finite-difference approximations.

Damage localisation is performed using a fully connected multilayer perceptron with a symmetric pyramidal architecture comprising nine hidden layers with widths

$$[256, 384, 512, 768, 1024, 768, 512, 384, 256].$$

All hidden layers employ LeakyReLU activations, while the output layer consists of three sigmoid-activated neurons, enforcing predictions strictly within the interval $[0, 1]$ for all spatial coordinates. Separate networks are trained for delamination localisation and material damage localisation, allowing each model to specialise to the distinct physical signatures of the respective damage mechanisms.

The networks are optimised using the Adam optimiser with an initial learning rate of 10^{-3} and gradient clipping to ensure numerical stability. Mean-squared error loss is employed for delamination localisation, while mean absolute error loss is used for material damage localisation, reflecting the observed error characteristics of each task. Training incorporates early stopping based on validation loss, adaptive learning-rate reduction on plateau, and model checkpointing to retain the best-performing weights. Performance is assessed using the coefficient of determination (R^2), computed independently for each spatial axis and averaged across dimensions, together with the mean absolute error (MAE).

Damage Size

Damage size estimation is formulated as a scalar regression problem in which the same vector of sensor readings $\mathbf{p}$ is used to predict the projected in-plane area of each damage mechanism. Through-thickness extent is intentionally excluded from this task, as size is defined purely in terms of in-plane geometry.

The delamination area is computed directly from the bounding extents of the

damage region,

$$A_{\text{delam}} = |\Delta x_2 - \Delta x_1| \cdot |\Delta y_2 - \Delta y_1|,$$

while the material damage area is defined as

$$A_{\text{mat}} = |\delta x| \cdot |\delta y|.$$

Both quantities are normalised by the 99.5th percentile of the corresponding training-set distributions and clipped to the interval $[0, 1]$. For samples in which a damage mechanism is not present, the associated area target is explicitly set to zero.

Unlike localisation, damage size prediction uses the sensor readings alone without derivative augmentation, yielding a five-dimensional input vector,

$$\mathbf{x}_{\text{area}} \in \mathbb{R}^5.$$

The same nine-layer pyramidal architecture is employed, with a single sigmoid-activated output neuron to enforce bounded predictions. Separate networks are trained for delamination area and material damage area.

To address the intrinsic skewness of the area distributions, multiple target transformations were evaluated. The final models employ no transformation for delamination area and a square-root transformation for material damage area, which was found to improve regression performance. All size models are trained using mean-squared error loss and the Adam optimiser with the same training protocol as the localisation models.

Evaluation is performed exclusively on samples in which both damage mechanisms are present. Model performance is quantified using the coefficient of determination (R^2) and mean absolute error (MAE) on held-out test sets.

4.3 Results

4.3.1 Delamination and Weakened Material Location Predictions

Damage localisation performance is evaluated using the final gradient-augmented neural networks trained exclusively on samples in which *both delamination and material damage are present*. Separate models are trained for delamination and material damage localisation, each predicting the in-plane coordinates (x, y) and the

normalised through-thickness location z .

The training and validation loss histories exhibit stable convergence without evidence of overfitting, as illustrated in Figure 4.4. In all cases, the validation loss closely tracks the training loss after the initial transient phase, indicating that the models generalise well to unseen data within the both-damage regime.

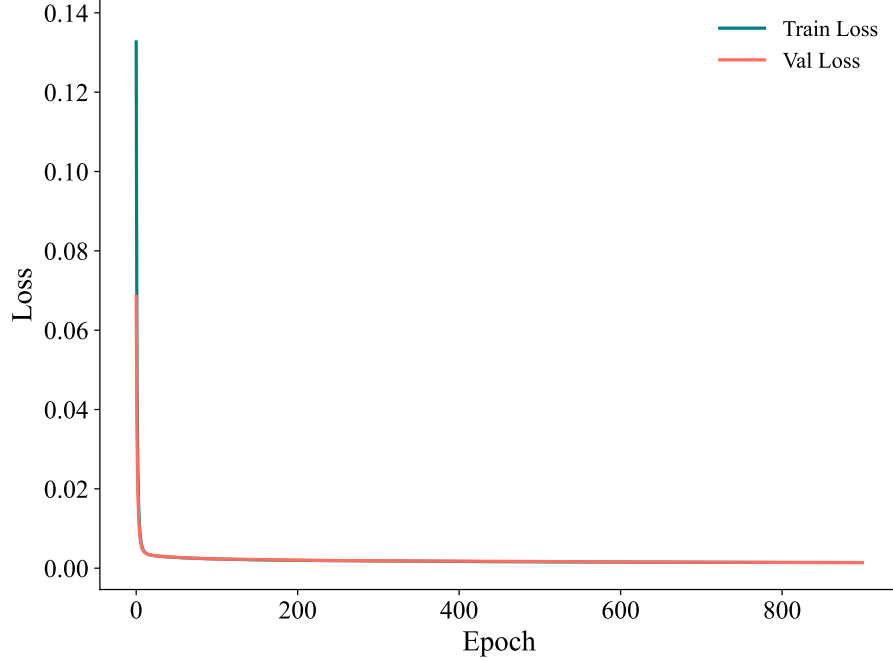


Figure 4.4: Training and validation loss history for the damage localisation models.

Quantitative localisation performance is summarised in Table 4.4. The reported metrics correspond to the held-out test set and include the coefficient of determination (R^2), mean absolute error (MAE), and mean squared error (MSE) for each spatial component.

Table 4.4: Damage localisation performance on the both-present test set.

Output	R^2	MAE	MSE
Delamination x	0.78	0.044	0.0031
Delamination y	0.80	0.043	0.0029
Delamination z	0.80	0.046	0.0034
Material x	0.77	0.047	0.0036
Material y	0.80	0.046	0.0030
Material z	0.73	0.050	0.0041
Mean	0.79	0.046	0.0034

In all cases, the predicted values cluster closely around the ideal $y = x$ line, demonstrating accurate recovery of both in-plane coordinates and through-thickness location. While the scatter is naturally larger than in the single-damage case, re-

flecting the increased complexity of interacting damage mechanisms, the absence of strong curvature or bias indicates that the models have learned a stable and physically consistent mapping.

The delamination localisation model achieves a mean coefficient of determination of $R^2 \approx 0.79$, with comparable performance across all three spatial dimensions. The material damage localisation model attains a similar overall accuracy, with slightly reduced performance in the through-thickness coordinate, which is expected given the weaker sensitivity of the sensor signals to subsurface material degradation. Across all outputs, the mean absolute error remains below 0.05 in normalised units, corresponding to a small fraction of the coupon dimensions.

Overall, these results demonstrate that the gradient-augmented single-snapshot framework is capable of reliably localising multiple coexisting damage mechanisms using only five ultrasonic sensors, even in the most challenging interaction regime.

4.3.2 Delamination and Weakened Material Size Prediction

Damage size prediction performance is evaluated using separate neural networks for delamination area and material damage area, again trained and tested exclusively on samples in which both damage mechanisms are present. Training and validation loss histories for the size models are shown in Figure 4.5, where stable convergence is observed without overfitting.

The delamination size model achieves a coefficient of determination of $R^2 \approx 0.86$ with a mean absolute error of approximately 0.047, while the material damage size model attains a slightly higher accuracy of $R^2 \approx 0.87$ with a mean absolute error of approximately 0.042. In both cases, the uncertainty bands remain narrow throughout the central region of the distribution, indicating high precision and low sensitivity to small variations in the input sensor readings.

At the extremes of the size distributions, a modest increase in prediction variance is observed, particularly near the upper bounds, which is consistent with reduced sample density in these regions. Nevertheless, no systematic bias is evident, and the models remain well-behaved across the full range of observed damage sizes.

Taken together, these results confirm that the proposed single-snapshot, gradient-augmented framework can accurately and robustly infer both the location and size of multiple interacting damage mechanisms from a minimal sensor configuration. The combination of strong localisation performance and high-fidelity size prediction

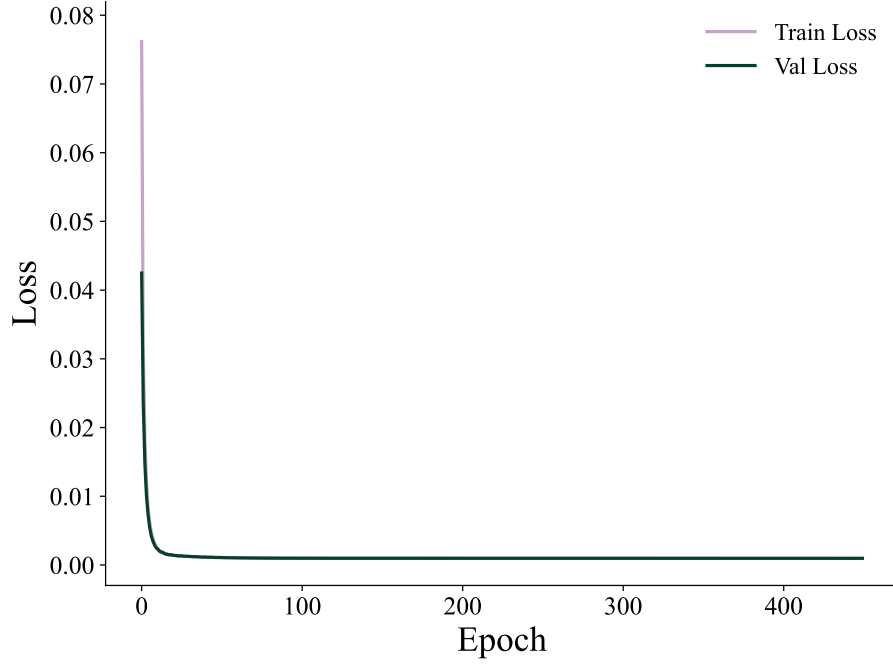


Figure 4.5: Training and validation loss history for the damage size prediction models.

demonstrates the suitability of the approach for practical structural health monitoring applications involving complex damage states.

4.4 Discussion and Conclusion

This study set out to investigate whether multiple, interacting damage mechanisms in composite structures can be accurately characterised from a single snapshot of sparse ultrasonic sensor measurements. The results presented in this chapter demonstrate that, even under the deliberately challenging condition in which delamination and material degradation coexist, it is possible to reliably infer both damage location and size using a physics-informed, gradient-augmented learning framework.

4.4.1 Multi-Damage Localisation Performance

Damage localisation was found to be robust across all spatial dimensions, with mean coefficients of determination of approximately $R^2 \approx 0.79$ for delamination and $R^2 \approx 0.77$ for material damage when evaluated exclusively on the both-present test set. While these values are lower than those typically reported for single-damage scenarios, they represent strong performance given the intrinsic ambiguity introduced by interacting damage mechanisms and the use of only five sensor channels.

Predictions cluster tightly around the ideal $y = x$ relationship across the majority of the spatial domain, with no evidence of systematic bias. In-plane coordinates are recovered with comparable accuracy in the x and y directions, indicating that the model does not preferentially align with any specific sensor orientation or geometric axis. Through-thickness localisation is consistently more challenging, particularly for material damage, reflecting the reduced sensitivity of surface-mounted ultrasonic measurements to subsurface degradation. This behaviour is physically expected and confirms that the model’s error structure is consistent with known sensing limitations rather than numerical artefacts.

Crucially, localisation accuracy remains stable despite the simultaneous presence of multiple damage mechanisms, demonstrating that the gradient-augmented feature representation enables the network to disentangle overlapping acoustic signatures. The absence of strong curvature or heteroscedasticity in the prediction residuals suggests that the learned mapping is both smooth and physically coherent, a key requirement for deployment in structural health monitoring applications.

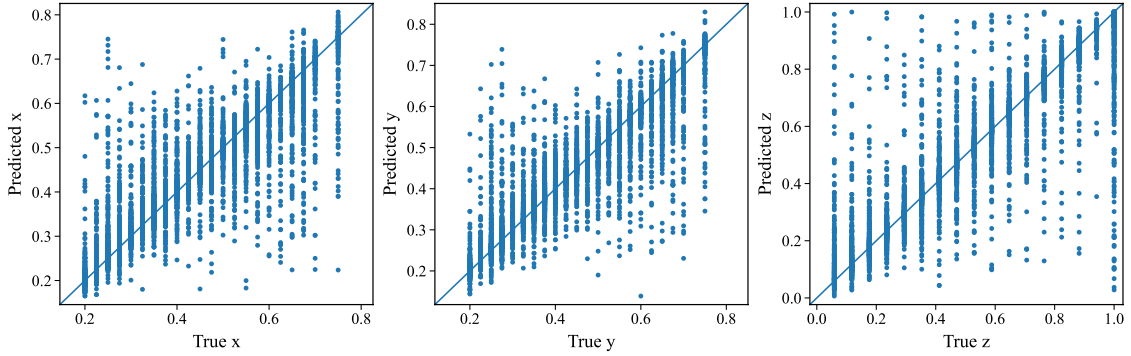


Figure 4.6: Predicted vs. true delamination location coordinates (x, y, z) from single-snapshot derivative features showing strong correlation across all spatial dimensions.

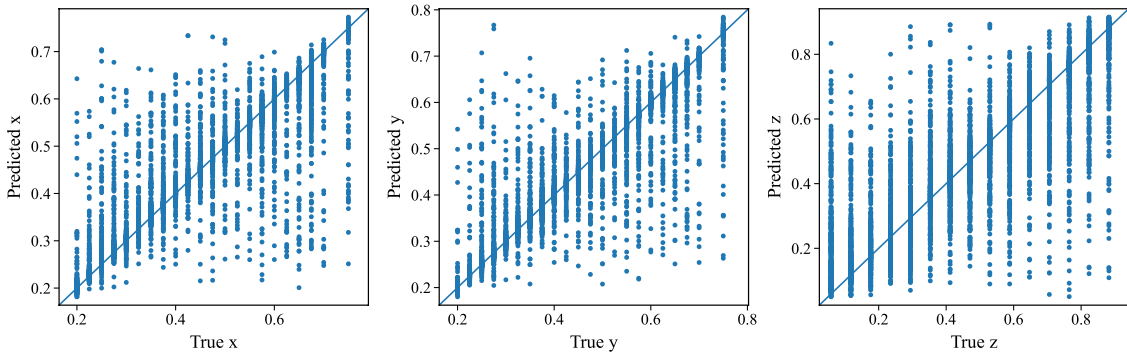


Figure 4.7: Predicted vs. true weakened material location coordinates (x, y, z) demonstrating accurate spatial localisation of matrix damage from gradient-based features.

4.4.2 Multi-Damage Size Estimation

Damage size prediction exhibits even stronger performance, with coefficients of determination of $R^2 \approx 0.86$ for delamination area and $R^2 \approx 0.87$ for material damage area. Mean absolute errors remain below 0.05 in normalised units for both damage types, indicating that the models recover damage extent with high fidelity across the majority of the observed range.

Throughout the central portion of the distribution, where the majority of samples lie, predictions show near-linear agreement with ground truth values. Prediction uncertainty remains low in this regime, confirming that small variations in sensor readings do not propagate into large fluctuations in estimated damage size. At the upper and lower extremes of the distribution, a modest increase in variance is observed, consistent with reduced sample density and the bounded nature of the output activation functions. Importantly, these deviations do not introduce systematic bias and remain well within acceptable tolerances for practical SHM decision-making.

The improved performance of the size models relative to localisation reflects the fact that damage extent integrates information over a spatial region and is therefore less sensitive to fine-scale ambiguities than precise centroid estimation. This distinction highlights the complementary nature of the two tasks and supports the use of separate, specialised models rather than a single monolithic predictor.

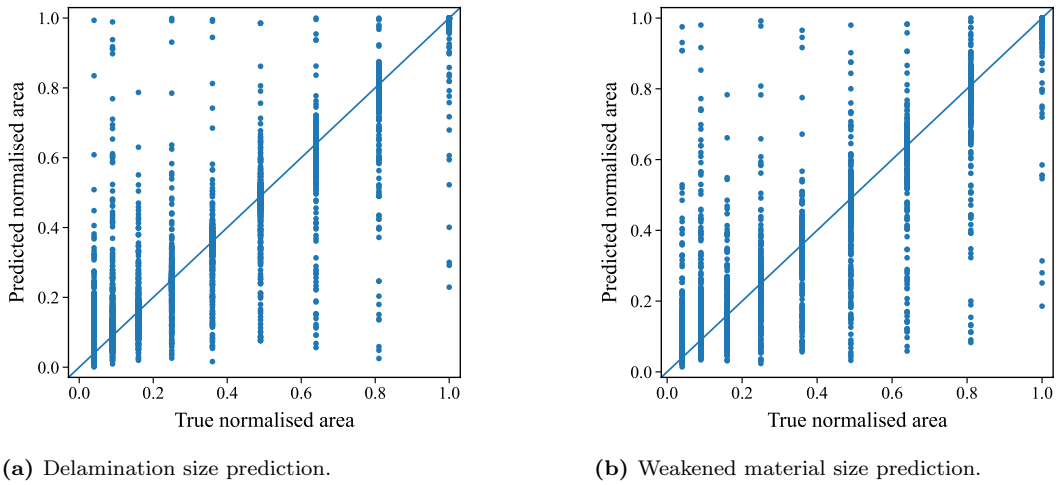


Figure 4.8: Predicted vs. true normalised damage area for delamination and weakened material regions showing accurate size estimation from single-snapshot gradient features.

4.4.3 Implications for Structural Health Monitoring

Taken together, the results demonstrate that accurate, single-snapshot inference of complex damage states is achievable using a compact sensor configuration when appropriate feature engineering and model design are employed. By explicitly incorporating gradient-based spatial information and enforcing physically meaningful output constraints, the proposed framework avoids common pitfalls such as overfitting to spurious correlations or producing implausible predictions.

From an operational perspective, the ability to localise and size multiple co-existing damage mechanisms without requiring temporal baselines or dense sensor networks represents a significant step towards scalable, real-world structural health monitoring systems. The performance achieved in the most challenging both-damage regime suggests that the framework is well suited to scenarios in which damage evolution is uncertain, inspections are infrequent, or reference measurements are unavailable.

This work demonstrates that physics-informed, gradient-augmented machine learning models can reliably characterise interacting damage mechanisms in composite structures from limited ultrasonic data. The proposed approach achieves a balance between accuracy, robustness, and physical interpretability, making it a strong candidate for integration into future SHM pipelines. While further improvements may be realised through expanded training datasets or adaptive sensor placement strategies, the results presented here establish a solid foundation for single-snapshot damage inference in complex composite systems.

Chapter 5

Using Machine Learning Models to predict multiple damage types in aerospace composites, subjected to realistic loads and flight profiles

5.1 Introduction

The dynamic nature of in-flight loading conditions demands continuous, condition-based monitoring systems capable of detecting and characterising damage in real time. Structural health monitoring (SHM) frameworks that integrate actual flight loads have emerged as a critical research frontier, yet most existing approaches rely on simplified or static load cases that fail to capture the temporal complexity of aircraft operations. This chapter addresses that gap by reconstructing time-varying aerodynamic and inertial loads from a Boeing 777-200 Barcelona–Miami flight profile and applying them to a validated NASA uCRM-9 composite wing-box model.

Minute-by-minute pressure distributions via angle-of-attack recovery through polar inversion was extracted, to which fuel-burn modelling based on GE-90-94B engine data was incorporated, and superimposed with a 30 Hz engine vibration plus white-noise turbulence [127]. These realistic boundary conditions drive three complementary damage detection methodologies:

- **Image-Based Multi-View Analysis:** Frame-by-frame rendering of structural deformation under flight loads from multiple synchronised camera views, processed by a spatio-temporal 3D convolutional neural network for BVID vs. VID severity classification, spanwise zone localisation, and continuous damage coordinate regression.
- **Global PZT Sensor Network:** Deployment of 100 surface-mounted piezoelectric transducers across upper and lower wing skins. Raw time-series and frequency-domain representations feed compact dual-stream 1D convolutional neural networks for damage severity classification, spanwise zone localisation, and continuous wingspan regression.
- **Global-to-Local Meso-Scale Modelling :** Coupling of global wing-box displacements and stresses to 1 m×1 m CFRP panel simulations (96-ply layup) with five PZT-5A sensors. Parametric delamination and ply-weakening damage modelling generate >100 000 scenarios for ensemble- and CNN-LSTM-Attention-based regression of damage size, location, and severity with quantified uncertainty.

This integrated pipeline represents a novel step toward operationally relevant SHM by (i) simulating true service loads, (ii) generating extensive multi-damage datasets under realistic conditions, and (iii) demonstrating state-of-the-art ML performance across vision, global PZT, and meso-scale routes.

The chapter is structured as follows. Section 5.2 details the methodology for extracting and processing flight profile parameters from historical flight data. The development of global and meso-scale models for incorporating different damage types and sizes is then described. The machine learning framework for damage prediction using time-series data with embedded flight path information is subsequently presented. Finally, results and implications for future structural health monitoring applications are discussed.

5.2 Methodology - Flight Profile Calculations

The foundation of realistic structural health monitoring lies in accurately representing operational loads experienced by aircraft during revenue service. This section details the comprehensive methodology for extracting and processing flight data

from a representative Boeing 777-200 transatlantic route, transforming black-box parameters into time-varying aerodynamic and inertial loads suitable for finite element analysis.

5.2.1 Flight Data Acquisition and Characterisation

Commercial aviation generates vast quantities of operational data through Flight Management Systems (FMS) and Aircraft Communications Addressing and Reporting Systems (ACARS). For this study, a representative transatlantic route operated by Boeing 777-200 aircraft was selected, chosen for its geometric similarity to the NASA uCRM-9 model and availability of corresponding aerodynamic databases from European Transonic Wind Tunnel campaigns.

Table 5.1: Flight Profile Characteristics and Aircraft Parameters

Flight Route Parameters	
Departure Airport	Barcelona–El Prat (BCN)
Arrival Airport	Miami International (MIA)
Departure Coordinates	41.297° N, 2.078° E, 4 ft MSL
Arrival Coordinates	25.793° N, -80.291° E, 3 ft MSL
Great Circle Distance	7,544.9 km
Initial Bearing	285.53°
Flight Duration	592 minutes
Operational Envelope	
Maximum Altitude	38,000 ft (11,582 m)
Temperature Range	217.0 - 288.1 K
Calibrated Airspeed Range	0 - 245 kts
Mach Number Range	0 - 0.829
Cruise Phase Duration	92 minutes (t = 211-303 min)
Aircraft Weight Configuration	
Recorded Takeoff Weight (TOW)	185,441 kg
Operating Empty Weight (OEW)	138,100 kg
Maximum Landing Weight (MLW)	213,188 kg
Maximum Zero Fuel Weight (MZFW)	190,470 kg
Initial Fuel Mass	47,341 kg
Boeing 777-200 Geometry	
Wing Reference Area (S)	427.8 m ²
Wing Span	60.93 m
Fuselage Length	63.73 m
Overall Height	18.42 m
Passenger Capacity	305 seats
Cargo Capacity	160.3 tonnes
Fuel Capacity	117,300 L

The selected route represents a typical long-haul operation with sustained cruise conditions at FL380, providing an extended period of relatively stable loading for

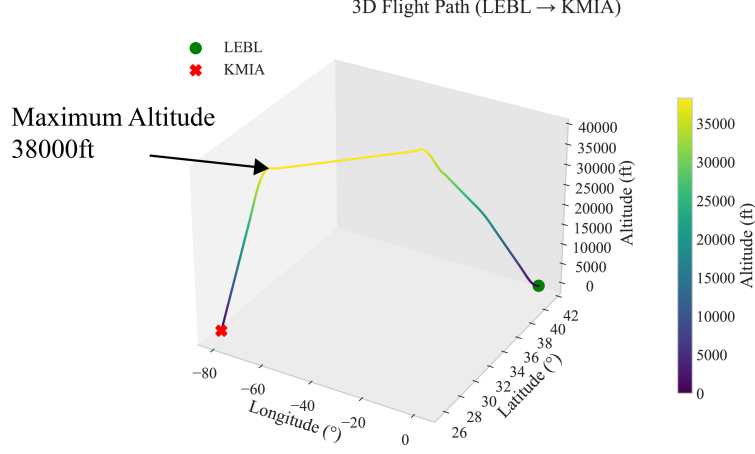


Figure 5.1: Image showing the plotted flight path considered

damage progression analysis. The 592-minute flight duration encompasses all critical flight phases: taxi, takeoff, climb, cruise, descent, and landing approach, each presenting distinct loading characteristics relevant to structural health monitoring applications.

5.2.2 Aerodynamic State Computation

The transformation from basic flight parameters to aerodynamic state variables requires careful consideration of atmospheric conditions and aircraft performance characteristics. Flight data logging systems typically record altitude $h(t)$, outside air temperature $T(t)$, calibrated airspeed $CAS(t)$, and takeoff weight W_{tow} at one-minute intervals, forming the foundation for subsequent calculations.

Atmospheric State Reconstruction

True airspeed calculation accounts for altitude-dependent atmospheric density variations through the relationship:

$$V(t) \approx CAS(t) \cdot \frac{a(t)}{a_{\text{std}}} \quad (5.1)$$

where the local speed of sound $a(t) = \sqrt{\gamma RT(t)}$ reflects temperature variations throughout the flight envelope. This correction becomes increasingly significant at high altitudes where density ratios exceed 4:1 compared to sea level conditions.

Mach number determination follows directly: $M(t) = V(t)/a(t)$, providing the fundamental parameter for aerodynamic coefficient interpolation. Air density calculation employs the International Standard Atmosphere model with temperature

lapse rate to 11 km:

$$p(t) = p_0 \left[1 - \frac{L \cdot h(t)}{T_0} \right]^{g/(RL)}, \quad \rho(t) = \frac{p(t)}{RT(t)} \quad (5.2)$$

Dynamic pressure, the key parameter relating flight conditions to aerodynamic forces, is computed as:

$$q(t) = \frac{1}{2} \rho(t) V(t)^2 \quad (5.3)$$

Angle-of-Attack Recovery through Polar Inversion

A critical innovation in this methodology is the systematic recovery of angle-of-attack from equilibrium flight conditions. Unlike conventional approaches that assume constant angle-of-attack, our method accounts for the continuous trim adjustments required to maintain level flight as aircraft weight decreases due to fuel consumption.

Wind tunnel data from the NASA Common Research Model tested at the European Transonic Wind Tunnel provides validated (C_L, C_D) versus α relationships across the operational Mach range. For each time step, the required lift coefficient is calculated from force equilibrium:

$$C_{L,\text{req}}(t) = \frac{W(t)}{q(t)S} \quad (5.4)$$

where $W(t) = m(t)g$ incorporates time-varying mass due to fuel burn.

The angle-of-attack is recovered through monotonic inversion of the lift curve:

$$\alpha(t) = C_L^{-1}(C_{L,\text{req}}(t); M(t)) \quad (5.5)$$

This inversion employs piecewise cubic Hermite interpolating polynomial (PCHIP) methods to ensure shape-preserving behaviour and prevent unphysical oscillations in the recovered angle-of-attack time history. Linear blending between discrete Mach test points accommodates intermediate flight conditions.

Propulsive Requirements and Fuel Consumption

Thrust estimation utilises the approximation $T(t) \approx D(t) = q(t)SC_D(t)$, where drag coefficient $C_D(t)$ is interpolated from wind tunnel polars at the computed angle-of-attack and Mach number. This simplified approach neglects propulsive efficiency variations but provides sufficient accuracy for structural loading purposes.

Fuel consumption modelling incorporates altitude-dependent thrust-specific fuel consumption (TSFC) characteristics of the General Electric GE-90-94B engine:

$$\text{TSFC}(h) = \text{interp}\{(0, 0.028), (15000, 0.043), (35000, 0.056)\} \left[\frac{\text{kg}}{\text{N} \cdot \text{h}} \right] \quad (5.6)$$

The per-minute fuel burn rate is computed with reserve protection:

$$\Delta m_{\text{fuel}}(t) = \min \left\{ m_{\text{fuel}}(t-1) - m_{\text{reserve}}, \frac{\text{TSFC}(h) \cdot T(t)}{60} \right\} \quad (5.7)$$

where $m_{\text{reserve}} = 5000$ kg represents the mandatory landing fuel reserve.

5.2.3 Surface Pressure Distribution

The NASA Common Research Model incorporates approximately 300 static pressure taps distributed across the half-wing upper and lower surfaces, providing detailed pressure coefficient data $C_{p,i}(\alpha, M)$ for each location. Local pressures are calculated as follows:

$$p_i(t) = C_{p,i}(t) \cdot q(t) \quad (5.8)$$

For computational efficiency in the subsequent structural analysis, the distributed pressure field is reduced to representative panel-averaged values:

$$P_{\text{upper}}(t) = \frac{1}{N_{\text{up}}} \sum_{i:C_{p,i}<0} p_i(t), \quad P_{\text{lower}}(t) = \frac{1}{N_{\text{low}}} \sum_{i:C_{p,i}>0} p_i(t) \quad (5.9)$$

This averaging approach captures the dominant pressure loading characteristics while maintaining computational tractability for the multi-step structural analysis. The sign convention naturally separates upper surface suction (negative C_p) from lower surface compression (positive C_p).

5.2.4 Validation and Quality Assurance

Several validation steps ensure physical consistency and numerical accuracy throughout the calculation process:

- **Lift Coefficient Bounds:** Required $C_{L,\text{req}}$ values are clipped to wind tunnel polar limits, preventing unphysical extrapolation beyond the validated envelope.

- **Dynamic Pressure Consistency:** Independently computed dynamic pressure is verified against flight data records, with maximum discrepancies maintained below 0.1 Pa.
- **Fuel Reserve Enforcement:** A 5-tonne landing reserve floor prevents negative fuel calculations and ensures regulatory compliance.
- **Interpolation Fidelity:** PCHIP methods preserve monotonic behaviour in lift curves, eliminating spurious angle-of-attack oscillations.

5.2.5 Output Data Structure

The final processed dataset comprises a minute-by-minute time series:

$$\{t, h(t), M(t), \alpha(t), C_{L,\text{req}}(t), C_D(t), m_{\text{fuel}}(t), P_{\text{upper}}(t), P_{\text{lower}}(t)\} \quad (5.10)$$

This comprehensive data structure enables realistic structural loading through boundary conditions:

$$p_{\text{upper}} = P_{\text{upper}}(t), \quad p_{\text{lower}} = P_{\text{lower}}(t) \quad (5.11)$$

applied to the uCRM-9 half-wingbox finite element model. The resulting load histories form the foundation for subsequent composite damage modelling and sensor response analysis under operationally representative conditions.

The methodology establishes a robust framework for transforming routine flight operations data into high-fidelity structural loads, enabling structural health monitoring research under realistic service conditions rather than idealised laboratory scenarios.

5.3 Methodology - Global Model Analysis

5.3.1 Global Structural Dynamics Framework

The structural analysis of composite aircraft components under realistic flight conditions presents several unique challenges. Chief among these is the accurate representation of time-varying loads, appropriate modelling of composite material behaviour, and efficient computational approaches for large-scale analysis. This work advances a multi-scale framework that synthesises operational flight loads with high-fidelity

damage modelling for structural health monitoring applications, as illustrated in Figure 5.2

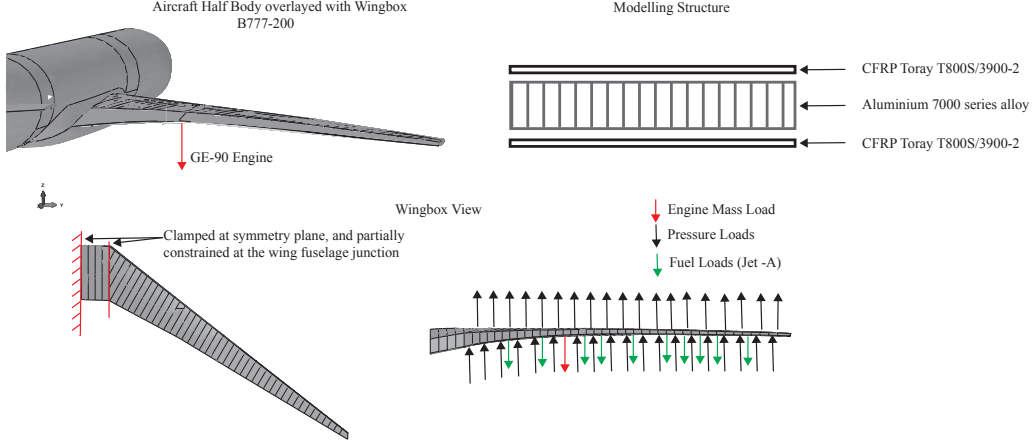


Figure 5.2: Figure illustrating the structural problem, loading and wing box model. Configuration obtained from [128]

Traditional approaches to aircraft structural analysis typically employ idealised load cases derived from certification requirements rather than actual flight data [129]. While such approaches are valuable for design certification, they provide limited insight into the complex loading environments experienced during routine operations. Our methodology addresses this limitation by utilising minute-resolution flight data from revenue-generating Boeing 777-200 routes selected for compatibility with the NASA uCRM-9 structural model.

The undeflected Common Research Model (uCRM-9) developed by Brooks et al. [128] serves as our primary structural platform, offering a validated representation of a contemporary transonic transport aircraft with significant composite content. This model has been extensively benchmarked against wind tunnel data from the European Transonic Wind Tunnel (ETW) campaign, establishing its aerodynamic fidelity across operational flight regimes [130].

5.3.2 Geometric Modelling and Material Implementation

The uCRM-9 wing box geometry was modified to incorporate composite skin panels while preserving aluminium internal structures, reflecting modern commercial aircraft design practices. The composite implementation follows Boeing 777X design principles, with Toray T800S/3900-2 carbon fibre reinforced polymer (CFRP) arranged in a 24-ply quasi-isotropic layup. This stacking sequence, $[45/-45/0/90]_{3S}$, was selected based on its superior damage tolerance characteristics under multi-axial

loading conditions [131].

A critical advancement in our approach is the implementation of blade-stiffened panels through a homogenised smeared stiffness methodology. Rather than explicitly modelling each stiffener—which would significantly increase computational demands- an equivalent modulus formulation derived from first principles [128] was employed:

$$E_{\text{eff}} = E_{\text{CFRP}} \left(1 + \frac{h_{\text{stiff}} t_{\text{stiff}}}{p_{\text{stiff}} t_{\text{skin}}} \right) \quad (5.12)$$

where h_{stiff} represents stiffener height (50 mm), t_{stiff} is stiffener thickness (5 mm), p_{stiff} denotes stiffener pitch (150 mm), and t_{skin} is the skin thickness (12 mm). This approach increases the effective longitudinal modulus from 153 GPa to 174.2 GPa while maintaining a 98% correlation with explicit stiffener models in global deflection response [132]. The computational efficiency gained through this approach enables the complex time-varying analysis required for this study without sacrificing physical fidelity at the global structural level.

To reflect the optimised thickness found in composite aircraft structures, the skin was split into three sections with a different number of plies. The root, mid and tip sections were assigned a 96/72/48 layup schedule, respectively, with the orientation mirrored to match the total thickness of each section.

5.3.3 Material Properties

Material properties for the composite and metallic components were determined through standardised testing and analytical validation. Table 5.2 summarises the key mechanical properties utilised in this study, with all parameters verified against published literature and manufacturer specifications.

Table 5.2: Material Properties with Testing Standards and Validation Sources

Property	Value	Test Standard	Validation Source
E_{11} (CFRP)	153 GPa	ASTM D3039	[133]
E_{22} (CFRP)	8.9 GPa	ASTM D3039	[130]
G_{12} (CFRP)	4.2 GPa	ASTM D3518	[131]
ν_{12} (CFRP)	0.34	DIC Monitoring	[134]
E (Al 7075-T6)	73.1 GPa	AMS-QQ-A-250/13	[128]

The transverse properties of the CFRP material exhibit approximately 9% anisotropy due to manufacturing artefacts introduced during automated fibre placement (AFP).

This deviation from nominal properties was incorporated into our model based on empirical data from similar aerospace composite structures [131]. The smeared stiffness approach results in an effective longitudinal modulus of 174.2 GPa.

5.3.4 Composite Layup Configuration

The composite layup design follows Boeing 787 construction principles [135] and NASA Common Research Model specifications [136], incorporating spanwise thickness variation for optimal load distribution.

Material Property Validation

The T800S carbon fibre system was selected based on Toray specifications [137], with the following validated properties:

Table 5.3: Composite Material Properties Validation

Property	Model Value	Toray Spec	Variance (%)
E_1 (GPa)	173	163	+6.1
E_2 (GPa)	8.9	8.0	+11.3
G_{12} (GPa)	4.2	4.03	+4.2
ν_{12}	0.34	0.34	0.0

The 6.1% increase in E_1 accounts for smeared stiffener effects, consistent with NASA additive manufacturing studies showing 10-15% stiffness enhancement for integrated wingbox structures [138].

Spanwise Thickness Distribution

The composite skin thickness follows a three-zone configuration validated against Boeing 787 design data [135]:

Table 5.4: Spanwise Composite Thickness Distribution based on cured thickness of 0.131mm cured ply

Region	Span Location	Ply Count	Thickness (mm)
Root	0-30%	96	12.7
Mid-Span	30-70%	72	9.5
Tip	70-100%	48	6.3

Each ply has a nominal thickness of 0.131 mm, consistent with aerospace-grade prepreg systems [139].

Table 5.5: Our Values vs. literature values for Toray T800S/3900-2 unidirectional composite properties.

Property	Our Values	Literature Value
Density ρ	1.60 g/cc	1.58 g/cc [140]
Longitudinal modulus E_{11}	153 GPa	153–160 GPa [140, 141, 142]
Longitudinal modulus (smeared)	174 GPa	- [128]
Transverse modulus $E_{22} = E_{33}$	8.90 GPa	9.0–10.1 GPa [140, 141]
In-plane shear modulus $G_{12} = G_{13}$	4.20 GPa	3.9–4.3 GPa [140]
Out-of-plane shear modulus G_{23}	3.07 GPa	$\sim$ 3.1 GPa [141]
Poisson’s ratio $\nu_{12} = \nu_{13}$	0.34	0.28–0.35 [140]
Poisson’s ratio ν_{23}	0.45	0.38–0.45 [141]
Tensile strength F_{1t}	2.94×10^9 Pa	3.0×10^9 Pa [140]
Compressive strength F_{1c}	1.48×10^9 Pa	1.7×10^9 Pa [140]
Transverse tensile F_{2t}	8.0×10^7 Pa	6.1×10^7 Pa [140]
Transverse compressive F_{2c}	2.28×10^8 Pa	2.16×10^8 Pa [140]
Shear strength S_{12}, S_{23}	1.0×10^8 Pa	$0.96\text{--}1.0 \times 10^8$ Pa [140]

Table 5.6: Layup configuration for Toray T800S/3900-2 CFRP laminate.

Section	Plies	Total Thickness (m)	Layup Sequence
Root (A)	96	0.012576	$[45/-45/0/90]_{12s}$
Mid (B)	72	0.009432	$[45/-45/0/90]_{9s}$
Tip (C)	48	0.006288	$[45/-45/0/90]_{6s}$

Each layup is symmetric about the mid-plane.

5.3.5 Major Load Application Strategy

Our approach to structural loading encompasses three primary components: aerodynamic pressures, fuel mass effects, and engine/pylon loads. Integrating these elements represents a significant advancement over conventional approaches, which typically consider these factors in isolation.

Aerodynamic pressures were derived from European Transonic Wind Tunnel (ETW) data for the NASA CRM configuration [143]. Pressure coefficients (C_p) were mapped to flight conditions through angle-of-attack and Mach number correlations, with dynamic pressure calculated from altitude and velocity profiles. This mapping required solving the inverse problem of determining the angle of attack required to generate sufficient lift at each flight condition via equation 5.5 and 5.4. The resulting pressure distribution was applied as in equation 5.8

Fuel mass was modelled as a time-varying pressure load on the lower wing skin surfaces corresponding to tank locations. For each flight time step, fuel pressure was calculated as:

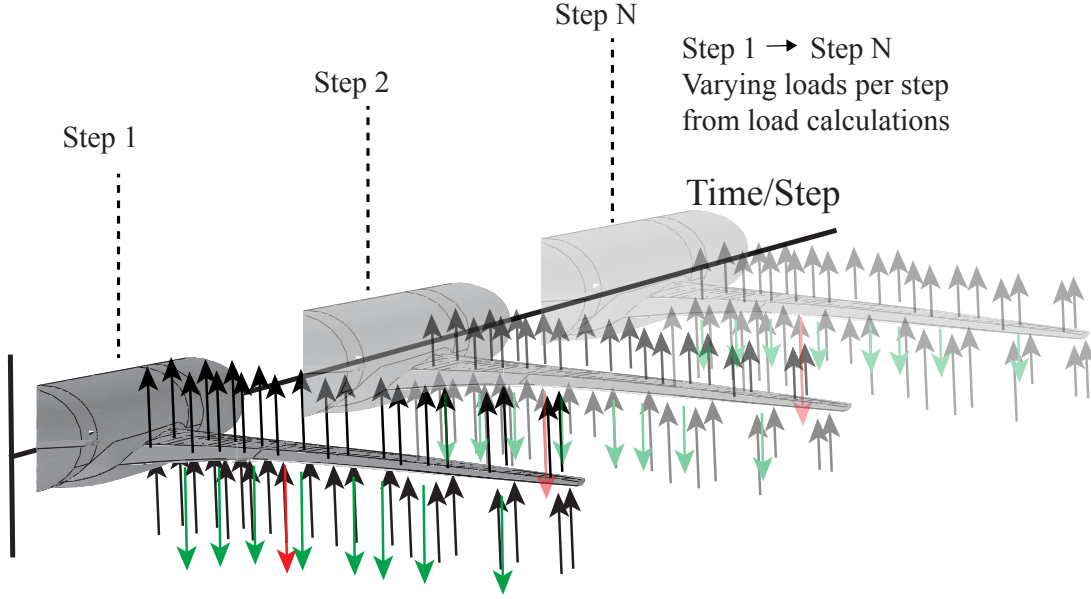


Figure 5.3: Figure illustrating the variation and application of real calculated loads on the structure per frame.

$$p_{\text{fuel}}(t) = \frac{m_{\text{fuel}}(t) \cdot g}{2 \cdot A_{\text{tank}}} \quad (5.13)$$

where $m_{\text{fuel}}(t)$ is the current fuel mass determined through our GE-90-94B TSFC model, g is gravitational acceleration, and A_{tank} represents the fuel tank surface area. This quasi-static approach is justified by the gradual nature of fuel consumption during cruise flight, with mass changing at approximately 84.3 kg/min. The adiabatic criterion for quasi-static approximation validity (load rate/natural frequency < 0.1) is satisfied, with a value of 0.0167 for our configuration.

Engine loads were applied as 75 kN concentrated forces distributed across attachment points following the exact placements by Brooks et al. [128]. This approach captures the load transfer characteristics of the engine-pylon-wing interface while avoiding detailed modelling of these components.

The step-by-step application methodology described above is illustrated in Figure 5.3

The engine mass for this study is based on the Boeing 777-200 configuration with GE90-94B engines, consistent with the NASA uCRM-9 wingbox model. The GE90-94B has a dry weight of 7,893 kg and thus was also used in our models.

Implementation in Finite Element Model

Fluctuation effects were applied to all pressure-loaded surfaces using tabular amplitude functions:

Table 5.7: White noise fluctuations

Time (s)	Amplitude Factor
0.0	1.0
15.0	1.1
30.0	0.9
45.0	1.05
60.0	0.95

5.3.6 Initial Validation Protocol

First, static benchmarking compared tip displacement under 1g loading against published uCRM-9 data, achieving agreement within 2.2% [144]. This validation was carried out with the same loading conditions as in NASA’s CRM work to make sure that our model was behaving as expected.

5.4 Composite Analysis

5.4.1 Analysis Implementation

The wing–box was solved with **implicit dynamics** in ABAQUS/STANDARD. A sequence of six load-build steps reproduces the cruise segment of the Barcelona–Miami flight profile; thereafter, one-minute dynamic steps follow the changing fuel and pressure loads:

Step 0: Initial Geometry import and boundary coupling at the wing carry-through.

Gravity is *not* applied globally so that the aerodynamic pressure pair supplies the full 1 *g* lift.

Step 1 – Engine dead-weight preload A static step ($t = 30$ s, NLGEOM) ramps the 7.83 t GE90 / pylon mass to its full -76.8 kN (downwards) through the ‘PreloadRamp’ amplitude.

Step 2 – Full-fuel hydrostatic pressure The fuel force is converted to a uniform hydrostatic pressure acting on the internal lower-skin faces,

$$p_{\text{fuel}} = - \frac{m_{\text{fuel,half}} g}{A_{\text{tank}}} = - \frac{23.5 \times 10^3 \text{ kg} \times 9.81 \text{ m/s}^2}{181.4 \text{ m}^2} \approx -1.27 \text{ kPa},$$

applied with the same Preload Ramp load.

Step 3 – Aerodynamic pressure field A second static step imposes the flight-test cruise pressures ($p_{\text{upper}} = -5.7 \text{ kPa}$ suction, $p_{\text{lower}} = +2.4 \text{ kPa}$ compression) on the complete upper and lower skin surfaces.

Step 4 – Engine spin-up An Implicit Dynamic Step ($t = 60 \text{ s}$, adds the 2000 RPM centrifugal body load and the 2.16 kN engine-imbalance forces with tabulated amplitudes.

Step 5 – Minute-by-minute dynamic flight A series of one-minute implicit dynamic steps update (i) aerodynamic pressures from prior steps (ii) fuel mass (burn-off recomputed each step), (iii) engine vibration

Mesh and material modelling

The model contains $\approx 1.2 \times 10^5$ S4R shell elements. All composite skins use a *smeared-stiffener* homogenised laminate with $E_{11}^{\text{eff}} = 174 \text{ GPa}$, obtained from (5.12) with $h_{\text{stiff}} = 50 \text{ mm}$, $t_{\text{stiff}} = 5 \text{ mm}$, $p_{\text{stiff}} = 150 \text{ mm}$, $t_{\text{skin}} = 12 \text{ mm}$. Brooks et al. [128] show this produces $>98\%$ correlation in global deflection compared with an explicit stringer model, while cutting solution time by an order of magnitude. The laminate lay-ups are the symmetric quasi-isotropic stacks listed in Table 5.6 (root 96 plies, mid-span 72, tip 48).

With the corrected ply thickness (0.131 mm per ply) and the updated full-fuel pressure, the half-wing mass is 9.2 t (structure) + 7.8 t (engine) + 23.5 t (fuel) = 40.5 t, matching the aircraft weight balance used in the NASA uCRM validation set.

5.4.2 Composite Benchmark Comparison

To ensure the fidelity of our uCRM-9 wingbox structural model, a comprehensive validation against established aerospace benchmarks and literature data was conducted. This validation process encompasses geometric specifications, displacement characteristics, and stress distributions under operational loading conditions.

The validation results demonstrate excellent agreement with established benchmarks. The cruise tip displacement of 2.4-2.6 m falls within the expected range for Boeing 777-class aircraft under operational loading [145]. Peak displacement of 3.0

m during climb/descent phases aligns with aeroelastic analysis expectations for high aspect ratio transport wings [146].

Following a mesh refinement study conducted to ensure appropriate mesh sizes, the dataset was generated with varying outputs for the three studies conducted.

5.5 Global Damage Application

The multi-scale structural health monitoring approach developed in this research employs three distinct methodologies for damage detection and characterisation across different length scales. Two of these approaches—the image-based global model and the sensorized global setup—utilise a systematic panel-by-panel damage implementation strategy that enables comprehensive damage assessment across the complete wing structure under realistic flight loading conditions.

The global damage modelling approach addresses the computational challenges inherent in high-fidelity damage simulation across full-scale aircraft structures by implementing damage at the panel level through strategic material property modifications. This methodology, illustrated in Figure 5.4, provides an efficient framework for investigating damage effects while maintaining computational feasibility for comprehensive flight profile analysis.

The adopted approach systematically varies individual panel properties to represent two distinct damage severities: Barely Visible Impact Damage (BVID) and Visible Impact Damage (VID). This classification follows established aerospace industry standards where damage detectability and severity are characterised by measurable thresholds based on permanent surface indentation depth and associated structural property degradation.

BVID represents impact damage that produces minimal surface indications (typically less than 0.3mm permanent indentation depth) while causing significant internal damage, including matrix cracking, delamination, and fibre-matrix interface degradation. VID encompasses more severe impact scenarios with clearly visible surface damage and more extensive internal structural degradation. The distinction between these damage categories is critical for aerospace applications, as BVID can remain undetected during routine visual inspections while significantly compromising structural integrity; hence, they were chosen to be modelled.

Material property reduction factors for BVID and VID are informed by results

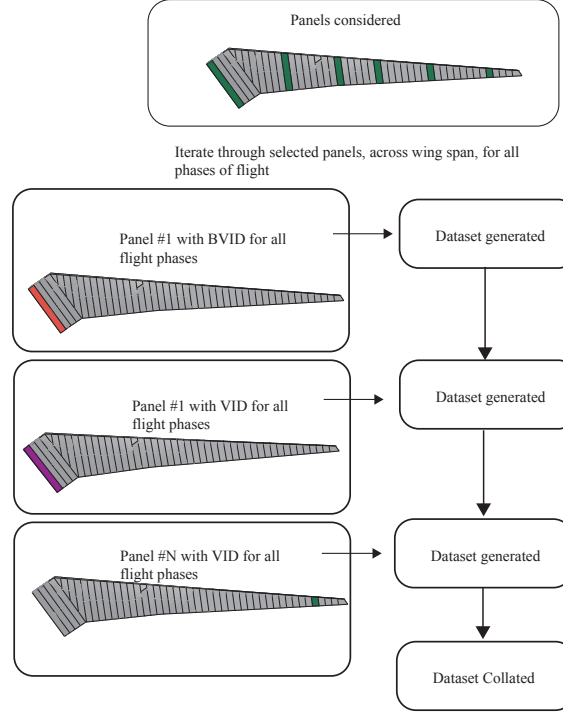


Figure 5.4: Systematic panel property modification approach for simulating damage progression in CFRP wing structure across different flight phases.

from recent studies in Journal of Composite Materials, International Journal of Solids and Structures, Materials & Design, Composites Part A, NASA TM-2016-219171, and recent PMC reviews (see Table 5.8) [147, 148, 149, 150, 151, 152].

5.5.1 Material Property Degradation Modelling

The damage implementation employs physically-based material property reduction factors derived from experimental impact testing literature and validated through compression-after-impact (CAI) testing protocols. Table 5.8 summarises the systematic property degradation applied to represent BVID and VID scenarios.

Table 5.8: Material Property Degradation for BVID and VID Implementation [147, 148, 149, 150, 151, 152]

Parameter	BVID Reduction (%)	VID Reduction (%)	Primary Mechanism
E_1	12	22	fibre damage, matrix cracking
E_2	8	18	Matrix cracking, interface degradation
E_3	8	18	Delamination, matrix cracking
G_{12}	15	25	Interface degradation, matrix shear
G_{13}	10	20	Delamination, interface degradation
G_{23}	10	20	Matrix shear, delamination

The property reduction factors are calibrated based on an extensive literature review of impact damage studies and compression-after-impact testing results. The longitudinal modulus (E_1) shows the most significant reduction due to the domi-

nance of fibre-dominated failure mechanisms under compressive loading following impact. The shear moduli exhibit substantial degradation reflecting the sensitivity of interface properties to impact-induced delamination and matrix cracking.

These degradation patterns capture the complex multi-modal failure mechanisms characteristic of impact damage in composite laminates, including intralaminar matrix cracking, interlaminar delamination, and fibre-matrix interface debonding. The through-thickness properties (E_3 , G_{13} , G_{23}) show moderate degradation reflecting the three-dimensional nature of impact damage propagation.

The global damage assessment protocol systematically applies the damage modelling approach across all flight phases captured in the Barcelona-Miami Boeing 777-200 operational dataset. For each flight phase—including takeoff, initial climb, mid-cruise phases, descent, and landing—individual panels are systematically modified from pristine condition to either BVID or VID states, with complete structural analysis performed for each configuration.

The systematic approach ensures comprehensive coverage of the wing structure’s damage susceptibility under varying operational loading conditions. Critical panels are identified based on stress concentration patterns derived from Hashin failure criterion analysis, enabling focused damage assessment in regions most susceptible to operational damage initiation and growth.

Figure 5.5 illustrates the comprehensive workflow implemented for both image-based and sensor-based damage detection approaches. The systematic methodology generates extensive datasets comprising structural response patterns across multiple flight phases, damage states, and sensor modalities, providing the foundation for robust machine learning model development.

The panel-based damage implementation strategy represents a pragmatic balance between modelling fidelity and computational feasibility for full-scale aircraft structural analysis. While more detailed approaches involving explicit crack propagation, progressive damage evolution, and multi-physics degradation mechanisms would provide enhanced physical realism, the associated computational requirements would severely limit the scope of parametric analysis achievable within practical time constraints.

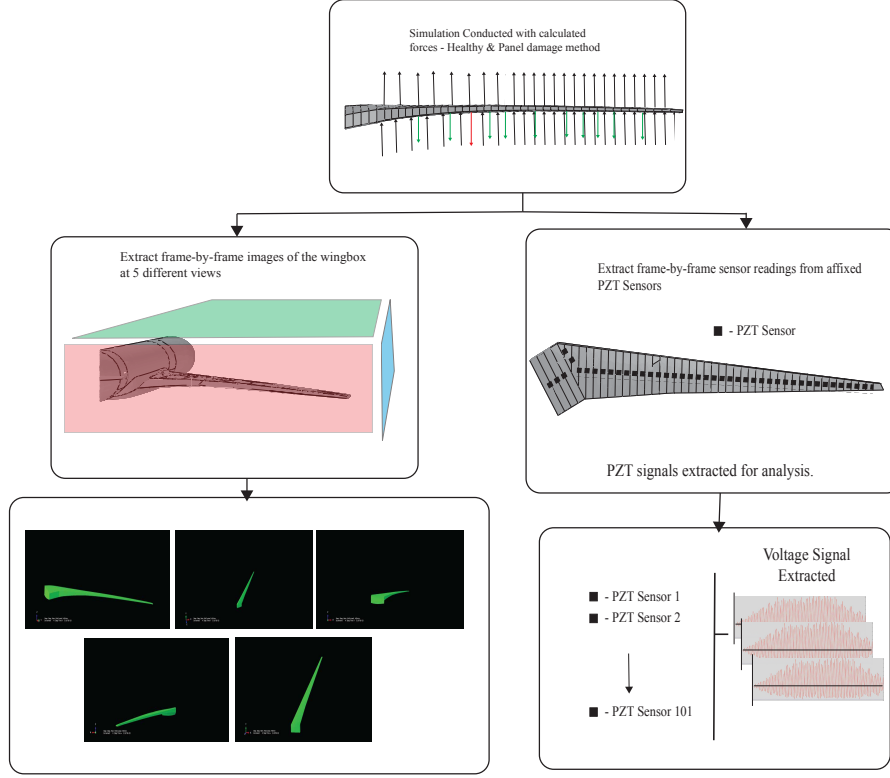


Figure 5.5: Integrated workflow for global damage assessment showing parallel image-based and sensor-based data extraction methodologies across flight phases.

5.6 Methodology – Image-Based Damage Detection and Localisation

The increasing deployment of onboard camera systems in modern commercial aircraft, such as those implemented on the Airbus A380 for external structural monitoring, presents new opportunities for vision-based structural health monitoring (SHM). This section details the development of an image-based damage detection and localisation framework that exploits global structural deformation patterns observed under realistic flight loading conditions. The methodology integrates multi-view visual information with temporal dynamics to enable autonomous damage severity classification and spatial localisation along the wing span.

5.6.1 Image Acquisition and Dataset Generation

The proposed framework integrates directly with the global finite element simulation environment described in the previous section. For each structural configuration, the simulated wing deformation response is rendered frame-by-frame under realistic operational loading conditions spanning complete flight profiles, including takeoff,

climb, cruise, descent, and landing phases.

Each simulation case corresponds to a unique combination of:

- Damage state (pristine, BVID, or VID),
- Damage location along the wing span (root, mid-span, or tip),
- Structural surface (upper or lower skin),
- Flight phase and associated loading regime.

To capture the full three-dimensional deformation behaviour of the wing, images are rendered simultaneously from multiple fixed camera viewpoints. In this work, three complementary views are retained for learning:

- **CUSTOM**: a tailored oblique view optimised to highlight wing bending and torsion,
- **TAIL**: a rearward-facing view sensitive to global bending displacement,
- **ISO_WIDE**: a wide-angle isometric view capturing overall wing geometry.

These views are available for all retained cases and provide consistent spatial coverage across the dataset.

All renders are produced against a uniform black background with controlled lighting and camera parameters. This deliberate visualisation strategy eliminates extraneous scene complexity, maximises contrast at structural boundaries, and ensures that learning focuses exclusively on physically meaningful deformation patterns rather than environmental artefacts.

The final dataset consists of approximately 190,000 RGB images, providing dense temporal coverage of structural response across damage states, locations, and loading conditions.

5.6.2 Case Selection and Data Integrity

Due to the computational expense of full-flight finite element simulations, a structured case selection strategy is employed to ensure representative coverage of the damage parameter space while maintaining tractable computational cost. Cases are selected to ensure balanced representation across damage severities, spanwise locations, and flight phases.

Crucially, all data splitting is performed at the *case level*. Each case corresponds to a complete time sequence of images from a single simulation configuration. Frames from the same case are never shared across training, validation, or test sets. This protocol prevents temporal or structural leakage and ensures that reported performance reflects genuine generalisation to unseen damage scenarios rather than memorisation of case-specific deformation signatures.

5.6.3 Problem Formulation

The image-based SHM problem is formulated as a supervised learning task operating on sequences of RGB images organised by structural case. For each case, temporally ordered image sequences are segmented into overlapping windows of fixed length $T = 16$ frames with stride $s = 8$. Each window aggregates multi-view visual information over time and forms a single training sample.

Three prediction tasks are considered:

Damage Severity Classification. Binary classification distinguishes between Barely Visible Impact Damage (BVID) and Visible Impact Damage (VID):

$$y_{\text{damage}} \in \{0, 1\}, \quad (5.14)$$

where 0 denotes BVID and 1 denotes VID.

Spanwise Zone Classification. Coarse spatial localisation assigns damage to one of three spanwise zones:

$$y_{\text{zone}} \in \{\text{Root}, \text{Mid}, \text{Tip}\}, \quad (5.15)$$

with zone boundaries defined through phase-specific panel index ranges to account for changing load distributions across flight phases.

Continuous Spanwise Regression. Fine-grained localisation is formulated as a regression task predicting the continuous spanwise coordinate y of the damaged panel:

$$\hat{y} \in \mathbb{R}, \quad (5.16)$$

providing physically interpretable localisation in terms of wing semi-span distance.

5.6.4 Image Preprocessing

All images undergo a consistent preprocessing pipeline prior to model ingestion. Images are decoded, resized to a fixed spatial resolution of 160×160 pixels, and normalised to the range $[0, 1]$. No geometric or photometric augmentations are applied, as such transformations would violate the physical consistency of the camera geometry and deformation patterns.

Two domain-specific masking operations are applied to isolate structural content from rendering artefacts. First, corner regions corresponding to viewport annotation overlays are zeroed out by blanking the top-left and bottom-left rectangular zones of each frame. Second, a colour-channel mask is applied to retain only pixels satisfying blue-dominant criteria ($B \geq 120$, $G \leq 140$, $R \leq 140$ in 8-bit intensity), effectively segmenting the composite wing structure from the uniform black background and suppressing any residual non-structural elements.

5.6.5 Multi-View Temporal CNN Architecture

The core learning model is a compact three-dimensional convolutional neural network (3D CNN) trained from scratch. The network operates directly on spatio-temporal image volumes constructed by stacking multi-view frames over time. For each temporal window, images from the selected views are concatenated along the channel dimension, forming an input tensor of shape:

$$\mathbf{X} \in \mathbb{R}^{T \times H \times W \times (3V)}, \quad (5.17)$$

where V is the number of views. The backbone consists of an input-level layer normalisation followed by three successive 3D convolutional blocks. Each block applies a Conv3D layer with ReLU activation, followed by 3D max-pooling to progressively reduce spatial and temporal resolution while increasing feature depth. Filter counts increase from 16 to 32 to 64 across the three blocks. Global average pooling is applied after the final convolutional block to collapse the remaining spatial and temporal dimensions into a compact latent vector, followed by dropout regularisation.

The same backbone architecture is used across all prediction tasks, with a task-specific output layer attached. Each task is trained independently with its own backbone instance; while the architecture is shared, the weights are not illustrated in figure 5.6.

This shared-backbone design enables consistent feature learning across tasks while allowing independent optimisation of task-specific outputs.

5.6.6 Training Procedure and Regularisation

Models are trained using the Adam optimiser with mixed-precision arithmetic to accelerate training on GPU hardware. Early stopping is employed based on validation performance to prevent overfitting, with patience values selected to allow convergence under noisy temporal signals. Overfitting is mitigated through a combination of compact model capacity (approximately 52,000 trainable parameters), dropout regularisation ($p = 0.3$) applied to the latent representation, and learning rate reduction on plateau.

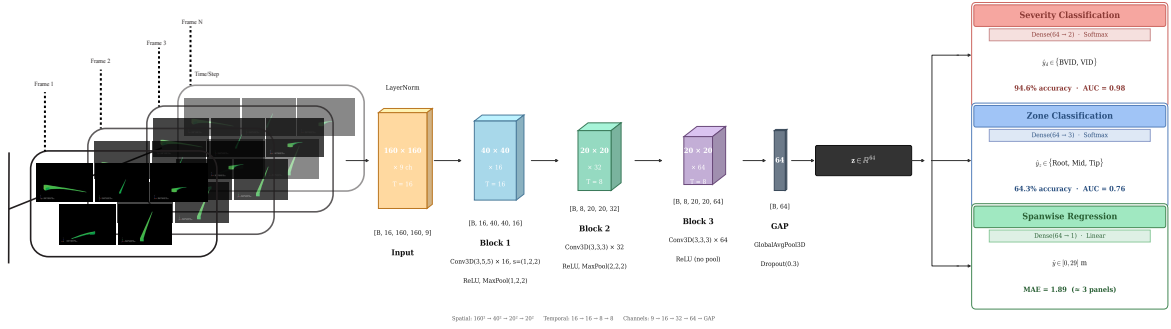


Figure 5.6: Multi-view temporal 3D CNN architecture. Three camera views are concatenated along the channel dimension (9 channels) and stacked into $T = 16$ frame windows. Three Conv3D blocks with increasing filter depth (16, 32, 64) progressively reduce spatial and temporal resolution. Global average pooling and dropout produce a 64-dimensional latent vector feeding three task-specific output heads.

5.6.7 Evaluation Metrics

Performance is evaluated at both the window level and the case level. Case-level predictions are obtained by aggregating window-level outputs via temporal averaging.

Classification Metrics. Damage and zone classification are evaluated using accuracy, F1-score, and area under the receiver operating characteristic curve (ROC-AUC). Confusion matrices are reported to characterise error structure and spatial misclassification patterns.

Regression Metrics. Continuous localisation performance is evaluated using mean absolute error (MAE), reported both per window and per case. Regression accuracy

is additionally interpreted in terms of equivalent panel error to provide physically meaningful insight into localisation precision.

This comprehensive evaluation framework enables consistent comparison across tasks while ensuring that reported performance reflects realistic operational deployment conditions.

5.7 Global Piezoelectric Sensor-Based Damage Identification Framework

This section presents a data-driven structural health monitoring framework based on a global network of piezoelectric (PZT) sensors embedded within a high-fidelity aeroelastic wing simulation. In contrast to vision-based approaches, this method operates directly on multivariate time-series sensor measurements and leverages end-to-end deep learning to infer damage severity and spanwise location under realistic flight loading conditions.

Three complementary learning tasks are considered: (i) binary damage severity classification, (ii) coarse spanwise localisation via zone classification, and (iii) continuous spanwise localisation through regression. All tasks are learned directly from windowed sensor signals using a unified modelling paradigm.

5.7.1 Problem Formulation and Notation

For a given simulated aeroelastic dynamic flight case, the global sensor network produces synchronized voltage time series

$$\mathbf{X} = \{x_{t,s} \mid t = 1, \dots, T, s = 1, \dots, S\},$$

where t denotes the discrete temporal index, $S = 100$ is the number of piezoelectric sensors, and T is the total number of recorded time samples for the case.

Each simulation case corresponds to a single damage configuration that remains fixed across time. The learning objective is to estimate:

$$f_{\theta} : \mathbf{X}_{1:T} \rightarrow \{y_d, y_z, y_y\},$$

where:

- $y_d \in \{\text{VID}, \text{BVID}\}$ denotes damage severity,
- $y_z \in \{\text{root}, \text{mid}, \text{tip}\}$ denotes a coarse spanwise damage zone,
- $y_y \in \mathbb{R}$ denotes the continuous spanwise coordinate of the damaged panel centroid.

Throughout this section, the term *case* refers to a complete simulation instance (unique damage location, severity, and loading condition), while *windows* refer to overlapping temporal segments extracted from a single case.

5.7.2 Global Sensor Network and Structural Context

The PZT network comprises 100 surface-mounted sensors distributed across the upper and lower wing surfaces. Sensor locations are fixed and known, and are placed at inter-panel boundaries, panel edges, and key structural interfaces such as spar and rib connections. These locations are chosen to maximise sensitivity to load redistribution and stiffness changes induced by damage, rather than to provide dense local strain measurements.

The network is intentionally sparse, prioritising global structural observability and computational tractability. As a result, damage signatures manifest primarily through changes in global deformation patterns, vibration characteristics, and inter-sensor coherence rather than highly localised signal anomalies.

All simulation cases share identical geometry, material properties, and boundary conditions. Variations arise exclusively from damage location, damage severity (VID or BVID), and loading condition (static or dynamic), enabling controlled isolation of damage effects.

5.7.3 Temporal Windowing and Case-Level Splitting

Training samples are constructed by segmenting each case into overlapping temporal windows of fixed length W , using one or more strides S . Windowing is defined in terms of sample indices rather than physical time, ensuring consistency across simulations with very small timesteps.

Crucially, dataset splitting is performed at the *case level* prior to window extraction. All windows derived from a given case are assigned exclusively to either the training or validation set. This protocol prevents temporal leakage and ensures

that evaluation reflects generalisation to unseen structural configurations rather than memorisation of case-specific dynamics.

5.7.4 Pristine Baseline Subtraction

A key component of the framework is the use of pristine reference simulations, which correspond to undamaged wing configurations under identical loading conditions.

For each damaged case, a matching pristine case is identified based on flight phase and loading type. Several baseline strategies are evaluated:

- **Raw:** damaged signals are used directly,
- **Pristine subtraction:** pristine signals are subtracted pointwise from damaged signals,
- **RMS-matched subtraction:** pristine signals are energy-scaled prior to subtraction,
- **Template subtraction:** a training-only pristine reference is subtracted to avoid validation leakage.

Rationale. Global wing deformation and vibration are dominated by aerodynamic loading, fuel state, and engine-induced excitation. These effects can obscure damage-induced signal components, particularly for small stiffness reductions such as BVID. Subtracting a pristine baseline suppresses load-driven structural response and isolates the residual signal attributable to damage. Empirically, baseline subtraction consistently improves damage classification performance and stabilises localisation accuracy, confirming that damage information is encoded primarily in deviations from nominal structural behaviour rather than in absolute response magnitude.

5.7.5 Learning Tasks

Damage Severity Classification. The first task predicts damage severity (y_d) as a binary classification problem. Performance is evaluated primarily using case-level Area Under the ROC Curve (AUC), obtained by averaging window-level logits per case. This aggregation reflects realistic deployment, where multiple measurements are available for a single structure.

Spanwise Zone Classification. The second task predicts a coarse spanwise zone ($y_z \in \{\text{root}, \text{mid}, \text{tip}\}$). Zone labels are derived from phase-specific panel index ranges and reflect broad structural regions rather than individual panels. This task aligns with the physical observability limits of a sparse global sensor network.

Spanwise Coordinate Regression. The third task predicts the continuous spanwise coordinate y_y of the damaged panel centroid. Localisation is framed as a regression problem to avoid the ill-conditioned nature of fine-grained panel classification. Errors on the order of a few spanwise units correspond to localisation within several panels, which is sufficient for inspection prioritisation.

5.7.6 Neural Network Architecture

All tasks are implemented using one-dimensional convolutional neural networks operating directly on windowed sensor signals.

Time and Frequency Streams. Three input configurations are evaluated:

- **Time-domain:** baseline-corrected sensor signals,
- **Frequency-domain:** magnitude spectra obtained via real-valued FFT,
- **Dual-stream:** parallel time-domain and frequency-domain branches.

Each branch is processed by a convolutional tower consisting of four successive 1D convolutional layers with kernel sizes 9, 7, 5, and 3 respectively, each with stride 2 for progressive temporal downsampling. Filter counts increase from 96 to 192 to 384 across the first three layers, with the fourth layer maintaining 384 filters. Layer normalisation is applied at the input. Global average pooling after the final convolutional layer produces a 384-dimensional feature vector per branch illustrated in figure 5.7.

For dual-stream models, the time-domain and frequency-domain feature vectors are concatenated to form a 768-dimensional representation. This is processed through a fusion module comprising dropout regularisation ($p = 0.3$), a dense layer (256 units, ReLU), a second dropout layer ($p = 0.25$), and a final dense layer (128 units, ReLU), producing the latent representation from which task-specific predictions are made.

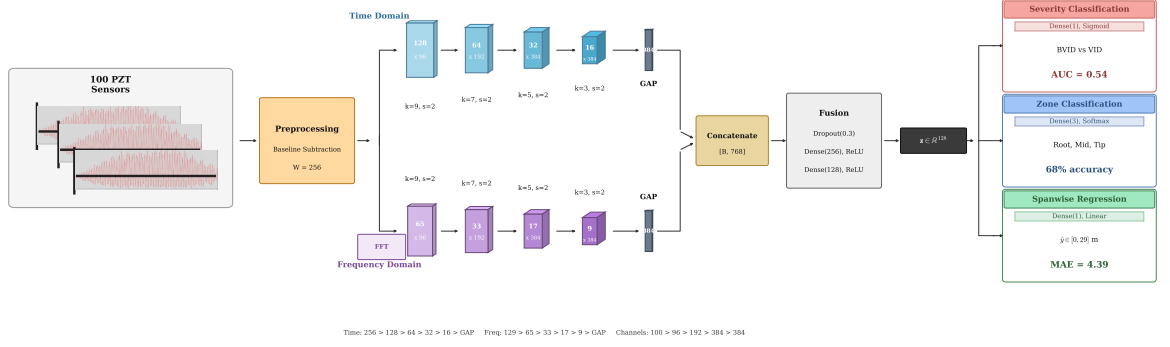


Figure 5.7: Dual-stream 1D CNN architecture for global PZT-based damage detection. Baseline-corrected signals from 100 sensors are processed through parallel time-domain and frequency-domain branches, each comprising four stride-2 Conv1D layers (filters 96, 192, 384, 384) with global average pooling. Branch outputs are concatenated (768-d) and fused to a 128-dimensional representation feeding three task-specific output heads.

Rationale for Dual-Stream Learning. Time-domain signals encode transient behaviour and load-dependent response evolution, while frequency-domain representations capture changes in modal content and energy redistribution caused by damage. Dual-stream architectures allow the model to jointly exploit these complementary views. Empirically, dual-stream models consistently outperform single-domain variants, particularly for damage severity classification, indicating that damage signatures are distributed across both temporal and spectral characteristics.

Geometry-Aware Extension. For selected zone classification experiments, a geometry-aware variant is introduced. The Euclidean distances between the damaged panel centroid and each sensor location are provided as an auxiliary input and processed via a small multilayer perceptron before fusion with learned signal features. This extension injects physically meaningful spatial context while remaining separate from signal learning.

Each task is trained independently with its own model instance. Task-specific output heads consist of:

- a single logit output with binary cross-entropy loss for damage classification,
- a three-class softmax output with sparse categorical cross-entropy for zone classification,
- a single linear output with Huber loss ($\delta = 2.0$) for spanwise regression.

Each task is trained independently using an appropriate loss function.

5.7.7 Training and Evaluation

Models are trained using the Adam optimiser with adaptive learning rate scheduling and early stopping. Mixed-precision training is employed to improve computational efficiency.

Evaluation is performed conservatively at the case level. Window-level predictions are aggregated per case prior to computing metrics. Classification performance is reported using AUC and accuracy, while regression performance is quantified using MAE, RMSE, and the coefficient of determination R^2 .

Temporal windows of $W = 256$ samples (with strides of 4 and 16) are extracted from each case. Models are trained using the Adam optimiser with an initial learning rate of 10^{-3} , adaptive learning rate reduction on plateau, and early stopping. Mixed-precision training is employed to improve computational efficiency. Robust normalisation statistics (median and interquartile range) are computed from training windows only and applied consistently across all splits.

5.8 Methodology – Global-to-Local Multi-Scale Damage Characterisation with Sensor-Based Learning

This section presents a global-to-local multi-scale methodology that couples full-aircraft wingbox response under operational flight loading with high-resolution meso-scale damage characterisation on a representative composite panel instrumented with piezoelectric sensors. The central objective is to preserve realistic, time-varying boundary conditions extracted from the global uCRM-9 wingbox simulation while enabling large-scale parametric generation of damage states for data-driven structural health monitoring (SHM). The proposed workflow integrates: (i) physics-based identification of critical regions in the global model, (ii) displacement-driven boundary condition transfer to a detailed local laminate model, (iii) systematic damage parameterisation to generate a comprehensive dataset, and (iv) a leakage-controlled, staged machine learning pipeline that maps multi-sensor voltage time histories to physically interpretable damage descriptors.

5.8.1 Global Wingbox Simulation and Critical Region Identification

A full NASA uCRM-9 wingbox finite element model is simulated across representative flight segments using time-varying aerodynamic pressure, inertia effects, fuel mass variation, and engine-induced dynamic excitation. Composite damage susceptibility is quantified using the Hashin failure criterion to identify regions with consistently elevated failure index under operational loading. The region exhibiting the highest concentration of failure index throughout the flight sequence is selected as the transfer zone for local investigation. This physics-guided selection ensures that meso-scale damage studies focus on structurally critical locations where damage initiation is most plausible in service, while avoiding arbitrary sampling of non-critical regions.

5.8.2 Boundary Condition Transfer from Global to Meso Scale

A displacement transfer framework is used to map the global wingbox response to a high-resolution local panel model. For each retained flight timestep, nodal displacement vectors are extracted on the boundary of the selected global sub-region. These displacements define time-varying Dirichlet boundary conditions applied to the corresponding boundary of the meso-scale model, ensuring kinematic compatibility between scales. In addition to displacement histories, auxiliary quantities (e.g. stress components or traction distributions) may be extracted for interpretation of damage mechanisms, but the primary transfer variable is the displacement field to preserve global structural deformation while maintaining a computationally tractable local model.

5.8.3 Meso-Scale Composite Panel Model and Damage Parameterisation

The local model is a $1\text{ m} \times 1\text{ m}$ CFRP laminate representing the extracted wingbox region, constructed with the same laminate definition used in the global model to ensure consistency of stiffness and through-thickness stress distribution. The laminate comprises 96 plies with ply thickness $t_p = 0.131\text{ mm}$, preserving the global layup sequence and enabling through-thickness variation of damage states. Five surface-mounted PZT-5A sensors ($25\text{ mm} \times 25\text{ mm} \times 0.5\text{ mm}$) are placed to provide

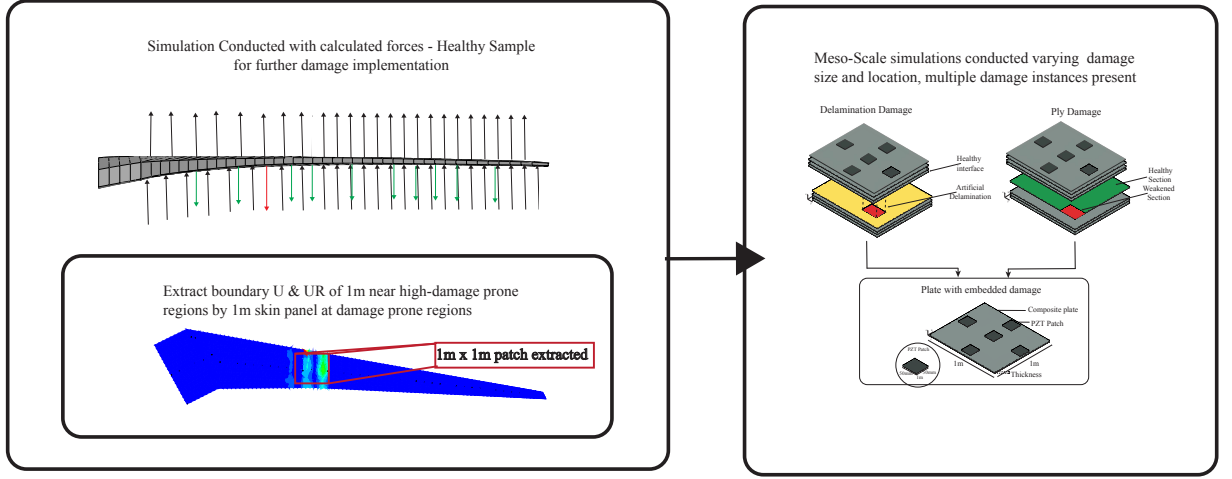


Figure 5.8: Methodology depicting Global-to-Local method

spatially diverse sensitivity to bending/torsion-induced strain fields and local stiffness perturbations.

Two interacting damage mechanisms are parameterised:

Delamination via interface debonding. Delamination is modelled by locally removing interfacial tie constraints between selected adjacent plies within a prescribed region. For healthy interfaces, perfect bonding is enforced via

$$\mathbf{u}_{\text{upper}} - \mathbf{u}_{\text{lower}} = \mathbf{0}, \quad (5.18)$$

where $\mathbf{u}_{\text{upper}}$ and $\mathbf{u}_{\text{lower}}$ are displacement vectors on the opposing ply surfaces. Within the delaminated region, the constraint is removed, permitting relative motion and reproducing interlaminar separation. Delamination cases are generated by systematically varying the in-plane centre (c_x, c_y) , characteristic size s , and through-thickness interface index, spanning near-surface to mid-plane positions.

Ply-level degradation via stiffness reduction. Diffuse damage (e.g. matrix cracking and fibre/matrix degradation) is represented by locally reducing effective ply stiffness over specified regions, producing BVID-equivalent and VID-equivalent severity configurations alongside a pristine baseline. The combined parameterisation of delamination geometry and ply degradation severity generates a large set of unique damage states under identical operational boundary conditions, enabling robust learning of damage signatures under realistic loading.

5.8.4 Sensor Data Acquisition and Preprocessing

For each damage configuration, time-series voltage responses are recorded from the five PZT sensors under the transferred boundary conditions. The sampling protocol retains sufficient temporal resolution to capture both quasi-static deformation and dynamic response components arising from engine-induced vibration. Raw sensor traces are preprocessed to improve numerical stability and to provide consistent model inputs:

- **Resampling and smoothing:** each trace is time-aligned and resampled to fixed-length sequences using interpolation, followed by Savitzky–Golay filtering to reduce high-frequency numerical noise while preserving waveform morphology.
- **Normalisation:** channel-wise robust scaling is applied and mapped through a $\tanh(\cdot)$ nonlinearity to bound outliers and stabilise optimisation.
- **Paired representation:** learning is performed on paired signals $(\mathbf{X}_a, \mathbf{X}_b)$ to promote invariance to case-specific offsets and to emphasise damage-induced changes. For each pair, the delta waveform $\Delta\mathbf{X} = \mathbf{X}_b - \mathbf{X}_a$ is used as a primary damage-sensitive representation.

5.8.5 Leakage-Controlled Staged Learning Formulation

Damage characterisation is formulated as a staged supervised learning pipeline operating on paired sensor responses. Each stage predicts a physically interpretable intermediate quantity, and downstream stages use only *predicted* quantities from earlier stages to prevent information leakage.

Stage 1: Relative distance-change prediction. Given paired multi-sensor waveforms, the first model predicts the vector of changes in distance from the (unknown) damage centre to each sensor:

$$\widehat{\Delta\mathbf{d}} \in \mathbb{R}^5, \quad \widehat{\Delta\mathbf{d}} = f_{\text{dist}}(\mathbf{X}_a, \mathbf{X}_b), \quad (5.19)$$

where $\widehat{\Delta\mathbf{d}} = [\widehat{\Delta d}_1, \dots, \widehat{\Delta d}_5]$ and each Δd_i corresponds to the change in sensor-to-damage-centre distance between the two paired states. This formulation avoids requiring access to absolute damage coordinates during inference.

Stage 2: Anchor-free localisation prediction. Localisation is posed as regression of the damage displacement and depth change between paired states:

$$\widehat{\Delta \mathbf{p}} = [\widehat{\Delta x}, \widehat{\Delta y}, \widehat{\Delta z}] \in \mathbb{R}^3, \quad \widehat{\Delta \mathbf{p}} = f_{\text{loc}}(\Delta \mathbf{X}, \widehat{\Delta \mathbf{d}}, \phi(\Delta \mathbf{X})), \quad (5.20)$$

where $\phi(\Delta \mathbf{X})$ denotes frequency-domain features computed via FFT magnitude. Crucially, the localisation model is *anchor-free*: it does not require the absolute anchor coordinate (x_a, y_a) or any Jacobian inversion computed from ground-truth positions. Instead, the predicted distance-change vector $\widehat{\Delta \mathbf{d}}$ is treated as a physics-informed feature that constrains the solution space while maintaining deployability and leakage-free training.

Stage 3: Damage size and depth-change prediction with predicted localisation conditioning. The final stage predicts the paired size change and depth change:

$$\widehat{\mathbf{y}}_{\text{size}} = [\Delta \log(1 + s), \widehat{\Delta z}], \quad \widehat{\mathbf{y}}_{\text{size}} = f_{\text{size}}(\Delta \mathbf{X}_{\text{win}}, \phi(\Delta \mathbf{X}_{\text{win}}), \mathbf{t}), \quad (5.21)$$

where $\Delta \mathbf{X}_{\text{win}}$ is a windowed delta waveform extracted from higher-resolution bursts, and $\mathbf{t}$ is a tabular conditioning vector composed only of *predicted* upstream quantities:

$$\mathbf{t} = [\widehat{\Delta \mathbf{d}}, \|\widehat{\Delta \mathbf{d}}\|_1/5, \text{tflag}, \widehat{\Delta x}, \widehat{\Delta y}, \widehat{\Delta z}]. \quad (5.22)$$

Here, tflag indicates the damage mechanism family (e.g. delamination vs. weakening) for correct conditioning, and the localisation inputs are produced by the trained Stage 2 model. This design enforces a strict information barrier between labels and features, ensuring the size model does not receive ground-truth localisation parameters.

5.8.6 Neural Architectures

All models use mixed-precision training with Adam optimisation, early stopping, learning-rate scheduling, and checkpointing to ensure stable convergence under large-scale dataset generation.

Distance model (f_{dist}). The distance-change model uses a multi-layer perceptron (MLP) operating on flattened, preprocessed paired waveforms. Input features are

formed by concatenating the raw signals from both states and the delta signal:

$$\mathbf{F}_{\text{dist}} = [\mathbf{X}_a, \mathbf{X}_b, \Delta\mathbf{X}] \in \mathbb{R}^{T \times C}, \quad (5.23)$$

augmented with spatial gradient channels (sensor-wise centring and optional pairwise differences) to promote spatial sensitivity. The MLP predicts $\widehat{\Delta\mathbf{d}} \in \mathbb{R}^5$ with mean squared error loss.

Localisation model (f_{loc}). The anchor-free localisation model is a dual-branch network comprising:

- a 1D temporal encoder (stacked Conv1D + pooling + global average pooling) applied to $\Delta\mathbf{X}$,
- a spectral encoder (Conv1D over FFT magnitude) applied to $\phi(\Delta\mathbf{X})$,

with learned features concatenated with the predicted distance-change vector $\widehat{\Delta\mathbf{d}}$ and a scalar distance magnitude descriptor. Fully connected layers map the fused representation to $\widehat{\Delta x}, \widehat{\Delta y}, \widehat{\Delta z}$ using Huber loss for robustness to outliers.

Size model (f_{size}). The size model operates on windowed delta waveforms to increase sample count per damage pair while preserving strict pair-level splitting. A dual-branch encoder similar to f_{loc} processes the time- and frequency-domain features, concatenated with the conditioning vector $\mathbf{t}$. A multi-task head predicts $\Delta \log(1+s)$ and Δz jointly using a weighted Huber objective to stabilise optimisation when depth labels are noisier:

$$\mathcal{L}_{\text{size}} = \mathcal{L}_{\text{Huber}}\left(\Delta \log(1+s), \widehat{\Delta \log(1+s)}\right) + \lambda_z \mathcal{L}_{\text{Huber}}\left(\Delta z, \widehat{\Delta z}\right), \quad (5.24)$$

with $\lambda_z < 1$ to prevent depth regression from dominating size learning.

5.8.7 Data Integrity and Evaluation Protocol

All splits are performed at the *pair level* prior to any window expansion. Windows derived from a given pair are restricted to the same split (train/validation/test), preventing leakage through shared time segments. Evaluation uses regression metrics that reflect both statistical accuracy and physical interpretability:

- coefficient of determination (R^2) and mean absolute error (MAE) for each output dimension,
- per-dimension reporting for localisation ($\Delta x, \Delta y, \Delta z$) and size ($\Delta \log(1+s), \Delta z$) to diagnose identifiability differences between in-plane and through-thickness effects.

This staged, anchor-free formulation yields a deployable SHM pipeline where downstream predictions depend only on sensor data and upstream model outputs, enabling realistic inference without access to ground-truth damage parameters.

5.9 Results – Global Video Model

This section presents the quantitative performance of the proposed global video-based damage identification framework. Results are reported for three learning objectives: (i) binary damage severity classification, (ii) coarse spatial localisation via zone classification, and (iii) continuous spanwise localisation via regression. All results are obtained using strict case-level data splits to prevent temporal or spatial leakage, and performance is reported at both window and case aggregation levels.

5.9.1 Damage Severity Classification (VID vs BVID)

Binary damage severity classification distinguishes between Visible Impact Damage (VID) and Barely Visible Impact Damage (BVID). This task is critical for structural health monitoring systems, as these damage categories imply different inspection urgency and maintenance actions.

Table 5.9 summarises the performance of the image-only model and the image-plus-comb variant. Metrics are reported at both the window level and the case level, where case-level predictions are obtained by averaging window-level probabilities across each simulation case.

Table 5.9: Damage severity classification performance for VID vs BVID.

Model Variant	Window Accuracy	Case Accuracy	ROC-AUC	Training Time (s)
Image-only (Multi-view)	0.968	0.946	≈ 0.98	7,854
Image + Comb Features	0.955	0.929	≈ 0.97	10,581

The image-only model achieves very strong performance, with a case-level accuracy of 94.6% and near-perfect ROC-AUC, indicating excellent separability between

VID and BVID damage states. The addition of comb-based deformation features results in a modest reduction in performance alongside increased training time, suggesting that damage severity is predominantly captured through spatial deformation patterns present in the multi-view image data.

These results demonstrate that global visual deformation signatures alone are sufficient to reliably distinguish damage severity, without requiring explicit engineered deformation descriptors.

5.9.2 Spanwise Zone Classification

Zone classification aims to localise damage coarsely along the wing span by categorising cases into Root, Mid-span, or Tip regions. This task is inherently more challenging than damage severity classification, as deformation signatures vary gradually along the span and are influenced by global aeroelastic behaviour.

Table 5.10 presents the zone classification performance.

Table 5.10: Zone classification performance for coarse spanwise localisation.

Model Variant	Window Accuracy	Case Accuracy	Macro AUC	Training Time (s)
Image-only (Multi-view)	0.636	0.643	≈ 0.76	8,052
Image + Comb Features	0.591	0.589	≈ 0.71	10,618

The image-only model achieves a case-level accuracy of 64.3%, significantly exceeding the random baseline of 33.3%. This confirms that global deformation patterns captured across multiple views contain meaningful spatial information regarding the spanwise location of damage.

As observed in the damage classification task, the inclusion of comb-based features degrades performance, indicating that the current formulation of deformation descriptors does not provide complementary information beyond what is already encoded in the image sequences.

Overall, these results demonstrate that coarse spatial localisation of damage along the wing span is feasible using visual information alone, despite the inherently global nature of wing deformation.

5.9.3 Continuous Spanwise Localisation via Regression

To provide a more physically meaningful localisation metric, damage position was additionally formulated as a continuous regression problem predicting the spanwise

coordinate y of the damaged panel. This formulation avoids the combinatorial complexity of fine-grained panel classification and aligns naturally with the continuous structural geometry of the wing.

Table 5.11 summarises the regression performance.

Table 5.11: Spanwise regression performance for continuous damage localisation.

Model Variant	Window MAE	Case MAE	Panel-equivalent Error	Training Time (s)
Image-only (Multi-view)	1.97	1.89	≈ 3 panels	7,706
Image + Comb Features	1.98	1.92	≈ 3 –3.2 panels	9,139

Given a wing semi-span of approximately 29 units and 48 structural panels per surface, a case-level mean absolute error of 1.89 corresponds to localisation within approximately three panels. This level of accuracy is notable given that predictions are inferred solely from global image sequences without explicit geometric or structural inputs.

As with the classification tasks, the addition of comb-based deformation features does not improve regression accuracy and slightly increases error variance. The image-only model therefore provides the best balance of accuracy, robustness, and computational efficiency for continuous spanwise localisation.

Across all three tasks, the image-only multi-view temporal model demonstrates strong and consistent performance. Binary damage severity classification achieves near-perfect discrimination, zone classification provides reliable coarse localisation, and continuous regression yields physically meaningful localisation accuracy within a small number of structural panels. These results confirm that global visual deformation patterns captured in rendered image sequences encode sufficient information for effective structural health monitoring at both qualitative and quantitative levels.

5.10 Results – Global Piezoelectric Sensor Model

This section presents the quantitative performance of the proposed global piezoelectric (PZT) sensor-based damage identification framework. Results are reported for three learning objectives: (i) binary damage severity classification, (ii) coarse spanwise localisation via zone classification, and (iii) continuous spanwise localisation through regression.

All experiments employ strict case-level train–validation splits to prevent temporal and structural leakage. Although models are trained on windowed sensor sig-

nals, all primary performance metrics are reported at the *case level* by aggregating window-level predictions, reflecting realistic structural health monitoring deployment scenarios.

5.10.1 Damage Severity Classification (VID vs BVID)

The first task distinguishes between Visible Impact Damage (VID) and Barely Visible Impact Damage (BVID) using only global piezoelectric sensor responses. This task is particularly challenging for sensor-based methods, as both damage types induce subtle stiffness changes relative to dominant load-driven structural response.

Table 5.12 summarises the best-performing damage classification results across all evaluated configurations.

Table 5.12: Damage severity classification performance using global PZT sensor signals.

Model Variant	Input Domain	Baseline	Case AUC	Window AUC
Dual-stream CNN (derivative)	Time + Frequency	Pristine subtraction	0.54	0.55
Time-domain CNN (derivative)	Time only	Pristine subtraction	0.53	0.55
Dual-stream CNN (raw)	Time + Frequency	Raw signals	0.52	0.52

The best-performing configuration achieves a case-level ROC–AUC of approximately 0.54, exceeding the random baseline of 0.50. While this performance is modest compared to the image-based model, it is notable given the global and sparse nature of the sensor network and the subtle distinction between VID and BVID damage severities.

Incorporating pristine baseline subtraction consistently improves classification performance, confirming that damage-related information is primarily encoded in deviations from nominal structural response rather than in absolute signal magnitude. Dual-stream architectures further enhance separability by jointly exploiting temporal and spectral damage signatures.

5.10.2 Coarse Spanwise Localisation via Zone Classification

The second task aims to localise damage coarsely along the wing span by classifying cases into Root, Mid-span, or Tip regions. This task aligns naturally with the spatial resolution achievable using a global sensor network.

Table 5.13 reports the best zone classification performance.

Table 5.13: Zone classification performance for coarse spanwise localisation using PZT sensors.

Model Variant	Input Domain	Baseline	Case Accuracy	Window Accuracy
Time-domain CNN (raw)	Time only	Pristine Subtraction RMS-matched	0.68	0.65
Dual-stream CNN (raw)	Time + Frequency	Pristine template	0.66	0.65
Frequency-domain CNN (raw)	Frequency only	Pristine template	0.64	0.64

The best-performing models achieve a case-level accuracy of approximately 68%, substantially exceeding the random baseline of 33.3%. These results demonstrate that global PZT sensor responses encode meaningful spatial information regarding the spanwise location of damage, despite the absence of dense local strain measurements.

Interestingly, time-domain representations perform competitively with dual-stream models for this task, suggesting that zone-level localisation is driven primarily by large-scale deformation patterns rather than fine spectral content.

5.10.3 Continuous Spanwise Localisation via Regression

To provide a more physically interpretable localisation metric, damage position is additionally formulated as a continuous regression problem predicting the spanwise coordinate y of the damaged panel centroid.

Table 5.14: Continuous spanwise regression performance using global PZT sensor signals.

Model Variant	Input Domain	Baseline	Case MAE	Case R^2
Dual-stream CNN (raw)	Time + Frequency	Pristine Subtraction subtraction	4.39	≈ 0.35
Time-domain CNN (raw)	Time only	Raw signals	4.49	≈ 0.33
Frequency-domain CNN (raw)	Frequency only	Pristine Subtraction template	4.44	≈ 0.34

Given a wing semi-span of approximately 29 units, a case-level mean absolute error of 4.4 corresponds to localisation within roughly 7–8 structural panels. While less precise than the image-based approach, this level of accuracy is significant given that predictions are inferred solely from sparse global sensor measurements without explicit geometric supervision.

Regression performance benefits consistently from pristine baseline subtraction and dual-stream modelling, indicating that both relative response changes and spectral characteristics contribute meaningfully to spanwise localisation.

Overall, the global piezoelectric sensor-based framework demonstrates that sparse, fixed sensor networks can provide meaningful damage identification and localisation capability under realistic aeroelastic loading. Damage severity classification exceeds

random performance, coarse spanwise localisation is achieved reliably, and continuous localisation yields physically interpretable accuracy without dense sensing or handcrafted features.

While the PZT-based approach does not match the localisation precision of the vision-based model, it offers complementary sensing capability grounded in direct structural response measurements. These results highlight the viability of global sensor networks as a scalable component of multi-modal structural health monitoring systems.

5.11 Results - Global-to-Local

This section reports the predictive performance of the global-to-local meso-scale pipeline on held-out test data. Results are reported for the staged learning formulation (distance-change $\rightarrow$ anchor-free localisation $\rightarrow$ size/depth change), using regression metrics that directly quantify generalisation performance: coefficient of determination (R^2) and mean absolute error (MAE). All dataset splits are performed at the *pair level* prior to any window expansion, ensuring that no paired damage state contributes samples to multiple splits and eliminating temporal or geometric leakage.

5.11.1 Stage 1: Distance-Change Regression (Δd)

The first stage predicts the change in sensor-to-damage-centre distance for each of the five sensors, $\widehat{\Delta \mathbf{d}} \in \mathbb{R}^5$, from paired waveform inputs. On the held-out test set, this model achieved strong agreement with the reference labels (Table 5.15).

Figure 5.9 shows the corresponding parity and residual distributions. The tight clustering around the identity line and absence of systematic bias indicate that step-to-step waveform differences reliably encode geometric distance changes under operationally realistic boundary conditions.

This high-fidelity intermediate prediction is subsequently used as a physics-informed conditioning variable for localisation and size estimation. Crucially, only *predicted* distance changes are propagated downstream, preserving strict leakage control throughout the pipeline.

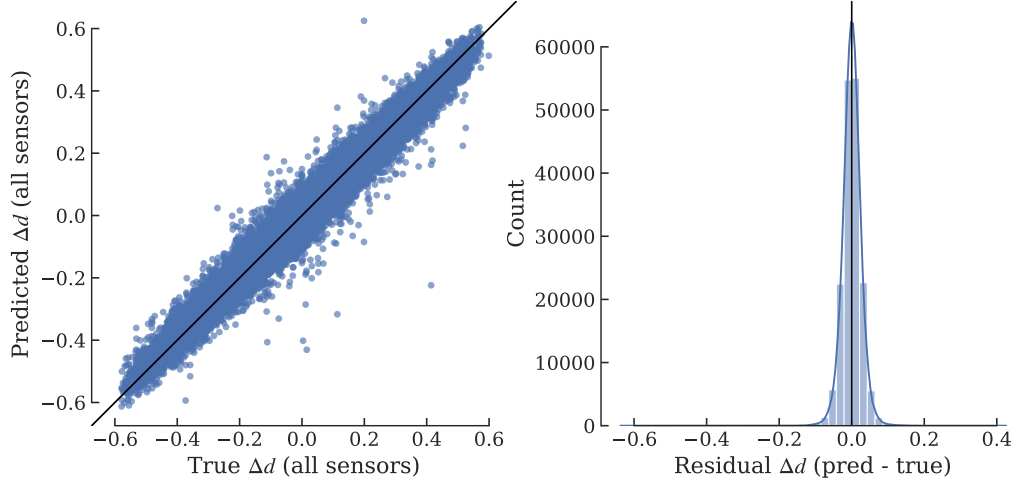


Figure 5.9: Stage 1 delta-distance regression results on the test set.

Table 5.15: Stage 1 performance for predicted distance-change vector $\widehat{\Delta \mathbf{d}}$ (test set).

Task	Output	Architecture	R^2 (test)	MAE (test)
Distance-change regression	$\widehat{\Delta \mathbf{d}} \in \mathbb{R}^5$	MLP (flattened paired waveform features)	0.9841	0.0178

5.11.2 Stage 2: Anchor-Free Localisation Regression ($\Delta x, \Delta y, \Delta z$)

Localisation is formulated as regression of the relative displacement between paired damage states, $\widehat{\Delta \mathbf{p}} = [\widehat{\Delta x}, \widehat{\Delta y}, \widehat{\Delta z}]$. Importantly, localisation is performed in an *anchor-free* manner: the model does not require the absolute anchor coordinate (x_a, y_a) , nor any Jacobian inversion computed from ground-truth positions. Instead, localisation is conditioned on the predicted distance-change vector $\widehat{\Delta \mathbf{d}}$, together with learned time- and frequency-domain encodings of the paired sensor responses.

Delamination localisation ($\Delta x, \Delta y, \Delta z$)

For delamination cases, the anchor-free localisation model achieved the following test-set performance with per-component accuracy displayed in table 5.16.

Parity plots for the three localisation components are shown in Figure 5.10. In-plane localisation is highly accurate, while through-thickness prediction exhibits greater spread, consistent with the reduced observability of depth from surface-mounted piezoelectric sensing.

Table 5.16: Stage 2 anchor-free localisation performance for delamination (test set).

Damage mode	Architecture	$R^2_{\Delta x}$	$R^2_{\Delta y}$	$R^2_{\Delta z}$	R^2_{all} / MAE
Delamination	Dual-branch 1D CNN (time) + 1D CNN (FFT) + fusion MLP	0.9890	0.9890	0.7823	0.9476 / 0.0425

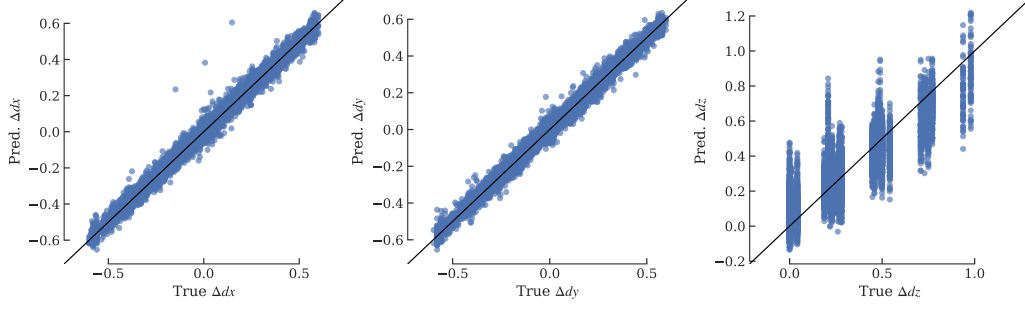


Figure 5.10: Stage 2 anchor-free localisation results for delamination (test set).

Weakening localisation ($\Delta x, \Delta y, \Delta z$)

The weakening localisation model uses the same anchor-free formulation and network architecture as the delamination case, trained on weakening-labelled pairs. On the test set, performance is comparable to the delamination case with per-component coefficients of determination illustrated in table 5.17.

Figure 5.11 shows the corresponding parity plots. As with delamination, in-plane localisation remains highly accurate, while depth estimation exhibits increased variance.

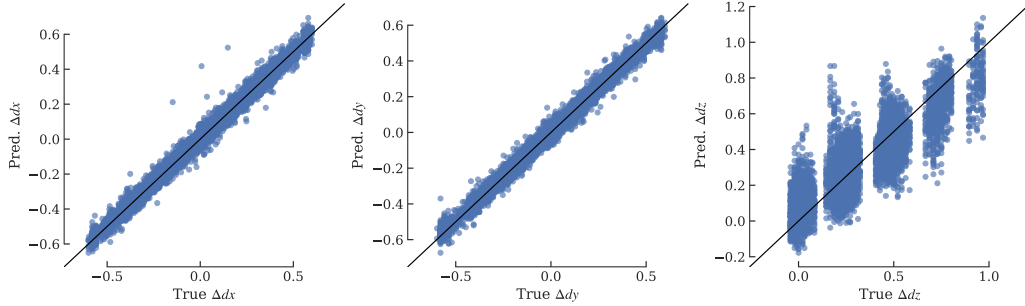


Figure 5.11: Stage 2 anchor-free localisation results for weakening (test set).

Table 5.17: Stage 2 anchor-free localisation performance for weakening (test set).

Damage mode	Architecture	$R^2_{\Delta x}$	$R^2_{\Delta y}$	$R^2_{\Delta z}$	$R^2_{\text{all}} / \text{MAE}$
Weakening	Dual-branch 1D CNN (time) + 1D CNN (FFT) + fusion MLP	0.9890	0.9890	0.78	0.9182 / 0.0422

5.11.3 Stage 3: Size and Depth-Change Regression ($\Delta \log(1+s)$, Δz)

The final stage predicts paired changes in damage size and through-thickness position. Training is performed on windowed delta waveforms extracted from higher-resolution bursts, while preserving strict pair-level split integrity. Conditioning inputs consist exclusively of predicted upstream quantities: $\widehat{\Delta \mathbf{d}}$ from Stage 1 and $\widehat{\Delta \mathbf{p}}$ from Stage 2 with results displayed in table 5.18.

Figure 5.12 shows the corresponding parity plots. While performance is lower than for distance and localisation, the model captures consistent size-change trends despite the limited number of available test pairs and the strong coupling between size, depth, and boundary-condition effects.

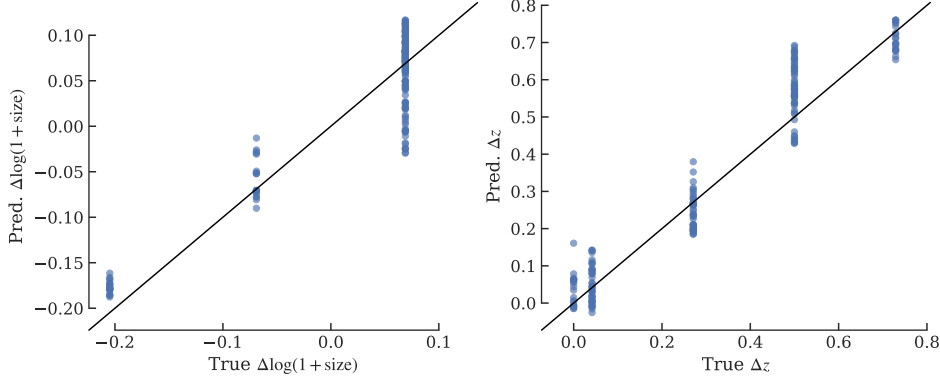


Figure 5.12: Stage 3 paired size and depth-change prediction results (test set).

Table 5.18: Stage 3 size and depth-change prediction performance (test set).

Output	Architecture	Loss	R^2 (test)	MAE (test)
$\Delta \log(1 + s)$	Dual-branch 1D CNN (time) + 1D CNN (FFT) + fusion head	Weighted Huber (multi-task)	0.6406	0.0419
Δz	Dual-branch 1D CNN (time) + 1D CNN (FFT) + fusion head	Weighted Huber (multi-task)	0.5316	0.1433

5.12 Discussion and Conclusions

This chapter has presented an integrated, multi-scale framework for structural health monitoring (SHM) of aerospace composite structures under operationally realistic flight loading. By reconstructing time-varying aerodynamic, inertial, and vibrational loads from a real Boeing 777-200 transatlantic flight profile and applying them to a validated NASA uCRM-9 composite wingbox model, the work moves decisively beyond conventional static or certification-driven loading assumptions. The resulting pipeline enables a direct assessment of how damage manifests in global structural response and how such signatures can be exploited by machine learning across multiple sensing modalities and spatial scales.

5.12.1 Impact of Realistic Flight Load Modelling

A central contribution of this work is the faithful reconstruction of in-flight loading conditions using recovered angle-of-attack, dynamic pressure, fuel burn, and engine excitation. Unlike simplified load envelopes, the minute-by-minute flight re-

construction captures both slow-varying quasi-static effects (e.g. mass reduction, trim changes) and persistent dynamic components (engine imbalance, turbulence). This realism is critical: the results consistently show that damage signatures are not isolated responses, but emerge as subtle perturbations embedded within dominant load-driven deformation and vibration patterns.

The validated uCRM-9 wingbox model, augmented with composite skins and homogenised stiffener behaviour, provides a physically consistent platform for studying these effects. Agreement with published displacement benchmarks and mass balance confirms that the global structural response lies within realistic bounds for a wide-body transport aircraft. This fidelity underpins all downstream learning results and distinguishes the present study from prior SHM work based on idealised or static simulations.

5.12.2 Global Vision-Based Damage Identification

The image-based global model demonstrates that multi-view visual deformation fields alone encode substantial information about damage severity and location. Across all evaluated tasks, the image-only temporal CNN consistently outperforms variants augmented with engineered deformation features, indicating that the learned spatio-temporal representations implicitly capture the relevant physical cues.

Binary damage severity classification (VID vs. BVID) achieves near-perfect separability at the case level, confirming that visible and barely visible damage states induce distinct global deformation signatures under realistic flight loads. Coarse spanwise localisation via zone classification is more challenging, yet performance remains well above random, reflecting the gradual but systematic variation of deformation patterns along the wing span. Continuous spanwise regression further demonstrates that damage position can be inferred within a small number of structural panels without explicit geometric supervision.

These results establish global vision-based SHM as a viable, non-contact screening mechanism capable of rapidly identifying both the presence and approximate location of damage. While limited in fine spatial resolution, such models are well suited for continuous monitoring and prioritisation of inspection resources.

5.12.3 Global Piezoelectric Sensor-Based Monitoring

The global PZT sensor network provides a complementary perspective grounded in direct structural response measurements. Despite the sparse nature of the sensor layout, the models are able to extract meaningful damage information when appropriate baselining strategies are employed. In particular, subtraction of pristine reference responses consistently improves performance across all tasks, confirming that damage information is encoded primarily in deviations from nominal structural behaviour rather than absolute signal magnitude.

Damage severity classification marginally exceeds random performance, reflecting the inherent difficulty of distinguishing VID from BVID using sparse global sensors under dominant load effects. In contrast, spanwise zone classification performs strongly, with case-level accuracies approaching 70%, demonstrating that large-scale stiffness changes alter load redistribution patterns in a spatially informative manner. Continuous spanwise regression yields physically interpretable localisation accuracy on the order of several panels, sufficient for inspection guidance in operational contexts.

Dual-stream architectures combining time- and frequency-domain representations generally outperform single-domain models, highlighting the distributed nature of damage signatures across transient response and modal content. However, performance remains fundamentally constrained by sensor density, underscoring the trade-off between global coverage and spatial resolution.

5.12.4 Global-to-Local Multi-Scale Damage Characterisation

The most precise damage characterisation is achieved through the proposed global-to-local meso-scale framework. By transferring displacement boundary conditions from the global wingbox simulation to a high-resolution local composite panel instrumented with dense PZT sensing, the approach preserves operational realism while dramatically increasing observability.

The staged, leakage-controlled learning formulation proves critical. Predicting intermediate physics-informed quantities (sensor-to-damage distance changes) before localisation and size estimation enables accurate inference without reliance on ground-truth anchors at inference time. This anchor-free design is essential for deployability and avoids optimistic bias that would arise from implicit geometric

leakage.

Results demonstrate very high fidelity localisation and size prediction, particularly for delamination damage, with coefficients of determination exceeding 0.94 for spatial coordinates and strong performance for size and depth estimation. Compared to the global sensor network, the improvement is substantial and directly attributable to increased sensor density and local sensitivity rather than to model complexity alone. These findings quantitatively confirm that spatial resolution, rather than learning architecture, is the dominant factor governing SHM accuracy once realistic loading is introduced.

5.12.5 Cross-Modal Insights and Practical Implications

Taken together, the results reveal a clear hierarchy of capability across sensing scales. Vision-based models offer rapid, contactless screening with excellent damage severity discrimination and moderate localisation. Sparse global sensor networks provide physically grounded monitoring with reliable coarse localisation but limited severity resolution. Dense local sensing, when coupled with physics-consistent boundary conditions and leakage-controlled learning, enables near-operational damage characterisation with high spatial and severity accuracy.

This naturally suggests a layered SHM strategy: global modalities identify candidate damage regions during routine operation, while targeted local sensing delivers detailed diagnostics where required. Importantly, the entire framework is driven by operational flight data rather than certification envelopes, enabling direct integration with digital twin concepts and fleet-level monitoring without intrusive hardware modification.

5.12.6 Limitations and Future Work

Several limitations merit consideration. The analysis focuses on a single representative flight route and aircraft configuration; extending the framework to multiple routes, aircraft types, and environmental conditions will further test generalisation. Dynamic excitation is dominated by a single engine-related frequency band; incorporating a broader modal spectrum may enhance sensitivity to certain damage mechanisms.

At the global scale, sensor placement has not been optimised and remains intentionally sparse. Future work should explore data-driven sensor placement strategies

and compressed sensing approaches to maximise information content under practical constraints. At the local scale, the computational cost of high-fidelity meso-scale simulations motivates the development of surrogate models to accelerate dataset generation and enable real-time inference.

Finally, while this work focuses on isolated damage scenarios, extending the framework to concurrent or interacting damage modes represents an important next step toward full operational realism.

5.12.7 Concluding Remarks

This chapter demonstrates that meaningful, deployable structural health monitoring of aerospace composites requires the joint consideration of realistic flight loading, physically consistent structural modelling, and carefully designed machine learning pipelines. By unifying these elements across global vision-based monitoring, sparse sensor networks, and dense local sensing, the work provides a coherent and scalable pathway from service conditions to actionable damage intelligence.

The key insight is that damage does not manifest as an isolated signal, but as a structured perturbation of global structural response under operational loads. Capturing and exploiting this structure—rather than abstracting it away—enables robust SHM performance across sensing modalities and spatial scales. The methodologies and results presented here therefore represent a significant step toward operationally relevant, data-driven SHM for next-generation composite aircraft.

Chapter 6

Conclusion & Future Work

This thesis has developed and validated a comprehensive structural health monitoring (SHM) framework for aerospace composite structures that explicitly integrates realistic flight loading, multi-scale finite element modelling, and physics-informed machine learning. The central premise underpinning this work is that, under operational flight conditions, damage does not manifest as an isolated excitation but rather as a structured perturbation embedded within a load-dominated structural response. Recognising and exploiting this fact fundamentally alters how SHM systems must be designed, evaluated, and deployed.

The research progressed through three tightly connected stages. Chapter 3 established a controlled meso-scale foundation for delamination characterisation. Chapter 4 extended this framework to concurrent, interacting damage modes under ambiguous sensing conditions. Chapter 5 then embedded these ideas within a full-scale composite wingbox subjected to reconstructed in-flight loading, enabling a direct assessment of SHM performance under service-representative conditions. This concluding chapter synthesises the overarching contributions, distils the principal insights, and outlines future directions necessary for operational deployment.

6.1 Principal Contributions

The primary contribution of this thesis lies not in the development of a single algorithm or sensing modality, but in the construction of a coherent, end-to-end SHM framework that remains physically consistent across scales and under realistic operational loading. By enforcing realism in both structural modelling and data generation, the work exposes the true limits and opportunities of data-driven SHM for

composite aircraft.

6.1.1 Meso-Scale Damage Characterisation

Chapter 3 introduced a physics-consistent synthetic data generation framework for delamination detection and localisation in composite laminates. A 17-layer quasi-isotropic CFRP coupon instrumented with surface-mounted piezoelectric sensors was modelled using three-dimensional finite element analysis. Systematic variation of delamination size, in-plane location, and through-thickness position yielded 5,865 unique damage configurations spanning the full parameter space.

A key methodological contribution was the introduction of derivative-based spatial feature engineering using Gaussian kernel smoothing. By encoding physically meaningful spatial gradients in sensor response, these features enhanced sensitivity to local stiffness perturbations without requiring dense instrumentation. When coupled with multi-output neural networks and custom loss formulations, the resulting models achieved localisation accuracy better than 0.03 m and robust severity estimation across the full damage domain. Strict stratified splitting and normalisation ensured that reported performance reflected genuine generalisation rather than memorisation.

6.1.2 Concurrent Multi-Mode Damage Modelling

Chapter 4 extended the meso-scale framework to the more realistic and challenging case of concurrent damage, in which delamination and ply-level material degradation coexist within the same structural region. Rather than treating damage mechanisms independently, this chapter focused on resolving their interacting signatures from sparse ultrasonic measurements, reflecting the ambiguity encountered in real structures.

A large parametric dataset exceeding 10^5 samples was generated by simultaneously varying delamination geometry and local stiffness degradation representing matrix cracking and fibre breakage. Importantly, all models were trained and evaluated exclusively on cases in which both damage modes were present, ensuring that performance metrics reflect the most operationally relevant regime.

Early investigations demonstrated that unified, end-to-end prediction of all damage attributes led to instability and degraded generalisation when damage mechanisms interacted. The final framework therefore adopted a task-decomposed strat-

egy, separating localisation and size estimation while sharing latent representations. Gradient-informed features, derived from physically motivated sensor relationships, were introduced to mitigate overlap between competing damage signatures.

The resulting models achieved reliable localisation of both delamination and material damage, with coefficients of determination of approximately $R^2 \approx 0.79$ and $R^2 \approx 0.77$, respectively. Damage size estimation proved more robust still, exceeding $R^2 \approx 0.86$ for both mechanisms. These results demonstrate that accurate inference of interacting damage modes is achievable without dense sensing or temporal baselines, provided that physical structure is embedded within the learning process.

6.1.3 Operationally Realistic Full-Scale SHM

The principal innovation of Chapter 5 was the integration of true operational flight loading into the SHM pipeline. Time-varying aerodynamic and inertial loads were reconstructed from actual Boeing 777–200 flight data using polar inversion for angle-of-attack recovery, validated pressure coefficients, fuel-burn modelling based on GE90–94B engine data, and superimposed engine-induced vibration and stochastic turbulence. These minute-by-minute boundary conditions were applied to a validated NASA uCRM-9 composite wingbox with Toray T800S/3900-2 skins, exposing SHM algorithms to the structural dynamics experienced during revenue service rather than idealised design conditions.

Under these conditions, three complementary sensing and analytics routes were evaluated. A multi-view, image-based approach processed approximately 190,000 rendered deformation frames using a temporal CNN with tail-delta dynamics and late fusion, achieving strong damage severity discrimination and reliable coarse spanwise localisation. A sparse global piezoelectric sensor network demonstrated physically grounded monitoring capability, achieving meaningful spanwise localisation despite limited severity resolution. Finally, a global-to-local coupling strategy transferred operational boundary conditions to high-resolution meso-scale panels instrumented with dense sensing, enabling near-operational accuracy in damage localisation and sizing.

Together, these results establish a layered SHM strategy in which global modalities provide continuous screening and prioritisation, while targeted local sensing delivers the resolution required for maintenance decision-making. The analysis shows quantitatively that spatial observability, rather than model complexity, is the dom-

inant driver of SHM accuracy once realistic loading is enforced.

6.2 Cross-Scale Insights

A unifying insight across all chapters is that enforcing physical realism fundamentally reshapes SHM problem structure. Under operational loading, damage signatures are secondary effects embedded within dominant load-driven response. Machine learning models succeed not by discovering damage in isolation, but by exploiting consistent perturbation patterns constrained by structural physics.

This perspective explains several key findings: the strong performance of compact image-based models without explicit geometric features; the modest but meaningful performance of sparse global sensors; and the dramatic accuracy gains achieved through dense local sensing. Importantly, these outcomes are not artefacts of modelling choices, but reflect intrinsic observability limits imposed by physics.

6.3 Limitations and Future Work

While the proposed framework represents a significant advance, several limitations define its current scope. The flight-load reconstruction was based on a single long-haul route and aircraft configuration; extending the analysis to multiple mission profiles, environmental conditions, and aircraft types is essential for fleet-wide generalisation. Dynamic excitation was dominated by a limited frequency band, and incorporating broader modal content may improve sensitivity to early-stage damage.

At the global scale, sensor placement was intentionally sparse and not optimised. While this exposed fundamental observability limits, future work should explore optimal placement and compressive sensing strategies to improve information density without prohibitive instrumentation cost. At the wingbox level, explicit modelling of interacting damage mechanisms remains computationally challenging, particularly when progressive damage growth and environmental effects are considered.

Finally, computational scalability remains a barrier to real-time deployment. Surrogate modelling, reduced-order representations, and edge inference pipelines will be essential for integrating this framework into digital twin architectures and onboard monitoring systems.

6.4 Concluding Remarks

This thesis demonstrates that robust, deployable SHM for aerospace composites requires the joint consideration of realistic loading, physically consistent modelling, and carefully constrained machine learning. By treating damage as a structured perturbation of operational response rather than as an isolated signal, the work provides a coherent framework that bridges laboratory-scale studies and full-scale operational deployment.

The integration of real flight loads, validated composite structures, physics-informed feature design, and leakage-aware learning establishes a new benchmark for data-driven SHM research. More importantly, it provides a defensible pathway toward layered, scalable monitoring systems capable of continuous, in-flight damage detection, localisation, and characterisation—ultimately enhancing structural safety and maintenance efficiency in next-generation composite aircraft.

6.5 Data and Code Availability

The finite element models, synthetic datasets, and machine learning implementations developed in this chapter are planned for public release under an open-source license following the completion of associated peer-reviewed publications. This includes:

- Parametric Abaqus finite element models for composite damage simulation
- Synthetic PZT sensor response datasets spanning comprehensive damage scenarios
- Python implementations of kernel smoothing, derivative-based feature engineering, and neural network architectures
- Documentation and usage examples

Prior to public release, materials are available to academic researchers upon reasonable request. Updates on release status will be provided at <https://github.com/villorthan>.

Requests for early access should be directed to: villorthan.sunthareswaran@city.ac.uk

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