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Presented by

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Topic

Defect identification in composite materials using inverse methods

Supported, on 11 /10 / 2026, before the jury composed of:

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Dedication

To my beloved parents,
whose sacrifices, patience, and unwavering support have been the foundation of everything I
have achieved. Your guidance and belief in me have shaped not only my education but my
character.

To my dear brothers and sisters,
for your constant encouragement, understanding, and the strength we share as a family. You
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moments along the way.

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إلى والديّ العزيزين،

الذين كان لتضحياتهما وصبرهما ودعمهما اللامحدود الأثر الأكبر في كل ما حققته. لقد كان لتوجيهكما وإيمانكما بي دورٌ كبير
في بناء تعليمي وشخصيتي.

إلى إخوتي وأخواتي الأعزاء،

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Abstract

The integrity and reliability of engineering structures are strongly affected by the presence of defects that may develop during manufacturing or service. Among these defects, delamination is one of the most critical damage mechanisms in layered and composite structures, as it reduces stiffness, modifies the dynamic behaviour, and may lead to premature structural failure. Consequently, the development of efficient techniques for the detection and characterization of delamination has become an important topic in structural health monitoring and vibration-based damage identification. This thesis investigates the use of vibration characteristics for the identification of delamination in beam-like structures and presents an inverse analytical approach using natural frequencies. The method is based on the constrained mode model, which is adopted as the forward analytical model to describe the free vibration behaviour of a delaminated beam. By applying the boundary and continuity conditions, a characteristic matrix is established, and its determinant is obtained as a function of the natural frequency and the delamination parameters.

The inverse model is developed directly from the resonance condition of the forward model. For a delaminated beam, the first three natural frequencies are considered as known input data. Each frequency is substituted into the characteristic determinant, and the resonance condition is imposed, generating three nonlinear equations. These equations are written in terms of the delamination location, size, and depth, which constitute the unknown parameters of the inverse problem. The resulting nonlinear system is then solved using a graphical procedure to identify the delamination characteristics.

The proposed approach requires only three natural frequencies and does not rely on optimization algorithms, artificial intelligence techniques, finite element model updating, frequency-shift databases, or reference frequencies from an undamaged beam. The methodology is applied to clamped-clamped, cantilever, and clamped-simply supported beams. The obtained results demonstrate that the proposed inverse model can accurately identify the delamination parameters and provides a simple and efficient analytical framework for vibration-based damage identification.

Keywords. Delamination identification; Inverse analytical model; Natural frequencies; Resonance condition; Constrained mode model; Structural health monitoring.

Résumé

L'intégrité et la fiabilité des structures d'ingénierie sont fortement affectées par la présence de défauts susceptibles d'apparaître au cours de la fabrication ou en service. Parmi ces défauts, le délaminage constitue l'un des mécanismes d'endommagement les plus critiques dans les structures stratifiées et composites, car il réduit la rigidité, modifie le comportement dynamique et peut conduire à une défaillance prématurée de la structure. Par conséquent, le développement de techniques efficaces pour la détection et la caractérisation du délaminage est devenu un sujet majeur dans le domaine de la surveillance de l'état des structures (Structural Health Monitoring) et de l'identification des dommages basée sur les vibrations.

Cette thèse étudie l'utilisation des caractéristiques vibratoires pour l'identification du délaminage dans des structures de type poutre et propose une approche analytique inverse fondée sur les fréquences propres. La méthode repose sur le modèle des modes contraints (Constrained Mode Model), adopté comme modèle analytique direct afin de décrire le comportement en vibration libre d'une poutre délaminée. En appliquant les conditions aux limites et les conditions

de continuité, une matrice caractéristique est établie, dont le déterminant est obtenu en fonction de la fréquence propre et des paramètres du délaminage.

Le modèle inverse est développé directement à partir de la condition de résonance du modèle direct. Pour une poutre délaminée, les trois premières fréquences propres sont considérées comme des données d'entrée connues. Chaque fréquence est substituée dans le déterminant caractéristique, et la condition de résonance est imposée, ce qui conduit à un système de trois équations non linéaires. Ces équations sont exprimées en fonction de la position, de la taille et de la profondeur du délaminage, qui constituent les paramètres inconnus du problème inverse. Le système non linéaire obtenu est ensuite résolu au moyen d'une procédure graphique permettant d'identifier les caractéristiques du délaminage.

L'approche proposée ne nécessite que trois fréquences propres et ne fait appel ni à des algorithmes d'optimisation, ni à des techniques d'intelligence artificielle, ni à la mise à jour de modèles par éléments finis, ni à des bases de données de décalages fréquentiels, ni à des fréquences de référence provenant d'une poutre saine. La méthodologie est appliquée à des poutres encastrées–encastrées, encastrées–libres (porte-à-faux) et encastrées–appuyées simplement. Les résultats obtenus montrent que le modèle inverse proposé permet d'identifier avec précision les paramètres du délaminage et offre un cadre analytique simple et efficace pour l'identification des dommages basée sur les vibrations.

Mots-clés : Identification du délaminage ; Modèle analytique inverse ; Fréquences propres ; Condition de résonance ; Modèle des modes contraints (Constrained Mode Model) ; Surveillance de l'état des structures (Structural Health Monitoring).

ملخص

تتأثر سلامة وموثوقية المنشآت الهندسية بشكل كبير بوجود العيوب التي قد تنشأ أثناء عمليات التصنيع أو خلال فترة الخدمة. ويُعد الانفصال الطبقي من أخطر آليات الضرر في المنشآت الطبقية والمواد المركبة، لما يسببه من انخفاض في الصلابة، وتغير في السلوك الديناميكي، (Delamination) وقد يؤدي في النهاية إلى فشل مبكر للمنشأ. ولذلك، أصبح تطوير تقنيات فعالة للكشف عن الانفصال الطبقي وتوصيفه موضوعاً ذا أهمية كبيرة في مجال والتعرف على الأضرار المعتمد على الاهتزازات (Structural Health Monitoring) مراقبة الحالة الإنشائية

تتناول هذه الأطروحة استخدام الخصائص الاهتزازية للتعرف على الانفصال الطبقي في المنشآت الشبيهة بالعوارض، وتقدم منهجاً تحليلياً عكسياً يعتمد ، الذي يُعتمد بوصفه النموذج التحليلي المباشر (Constrained Mode Model) على الترددات الطبيعية. وترتكز الطريقة على نموذج الأنماط المقيدة لوصف سلوك الاهتزاز الحر لعارضة تحتوي على انفصال طبقي. ومن خلال تطبيق شروط الحدود وشروط الاستمرارية، يتم تكوين مصفوفة مميزة، ويُستخرج محدداتها بدلالة التردد الطبيعي ومعلمات الانفصال الطبقي

وقد تم تطوير النموذج العكسي مباشرة انطلاقاً من شرط الرنين للنموذج المباشر. ففي حالة العارضة المتضررة بالانفصال الطبقي، تُعد الترددات الطبيعية الثلاثة الأولى بيانات إدخال معلومة. ويُعوّض بكل تردد في محدد المصفوفة المميزة مع فرض شرط الرنين، مما يؤدي إلى توليد ثلاث معادلات غير خطية. وتُصاغ هذه المعادلات بدلالة موقع الانفصال الطبقي وحجمه وعمقه، والتي تمثل المعلمات المجهولة في المسألة العكسية. بعد ذلك، يُحل النظام غير الخطي الناتج باستخدام إجراء بياني يتيح تحديد خصائص الانفصال الطبقي

لا يتطلب المنهج المقترح سوى ثلاثة ترددات طبيعية، ولا يعتمد على خوارزميات التحسين، أو تقنيات الذكاء الاصطناعي، أو تحديث نماذج العناصر المحددة، أو قواعد بيانات انزياح الترددات، أو الترددات المرجعية لعارضة سليمة. وقد طبقت المنهجية على عوارض مثبتة من الطرفين، وكابولية

(مثبتة من طرف واحد)، ومثبتة من طرف ومسنودة ببساطة من الطرف الآخر. وتُظهر النتائج المتحصل عليها أن النموذج التحليلي العكسي المقترح قادر على تحديد معلمات الانفصال الطبقي بدقة، ويوفر إطارًا تحليليًا بسيطًا وفعالًا للتعرف على الأضرار اعتمادًا على الخصائص الاهتزازية

الكلمات المفتاحية: التعرف على الانفصال الطبقي؛ النموذج التحليلي العكسي؛ الترددات الطبيعية؛ شرط الرنين؛ نموذج الأنماط المقيدة؛ مراقبة الحالة الإنشائية

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List of abbreviations

Abbreviations	Description
AFP	Automated fibre placement
ATL	Automated tape laying
CTE	Coefficient of thermal expansion
NDE	Non-destructive evaluation
NDT	Non-destructive testing
SHM	Structural health monitoring.
RTM	Resin transfer moulding
VARTM	Vacuum-assisted resin transfer moulding
AFP	Automated fibre placement
T _g	Transition temperature
ATL	Automated tape laying
CMCs	Ceramic-matrix composites
EAC	Environmentally assisted cracking
CFRP	Carbon fibre reinforced polymer
GFRP	Glass fibre reinforced polymer
AFRP	Aramid-fibre-reinforced polymers
BVID	Barely visible impact damage
CNNs	Convolutional neural networks
DIC	Digital image correlation
ESPI	Electronic speckle pattern interferometry
UT	Ultrasonic testing
TOF	The time-of-flight
STFT	short-time Fourier transform
TTU	Through-transmission ultrasonic testing

GUWs	Guided ultrasonic waves
SH	shear-horizontal
LUT	Laser ultrasonic testing
SAFT	Synthetic aperture focusing technique
TFM	Total focusing method
ML	Machine learning
RNNs	Recurrent neural networks
CT	Computed tomography
Micro-CT	Micro- Computed tomography
NR	Neutron radiography
PCI	Phase-contrast X-ray imaging
SRT	Synchrotron radiation tomography
DER	Dual-energy radiography
AE	Acoustic emission
TOA	Time-of-arrival
FEM	Finite element methods
ECT	Eddy Current Testing
PEC	Pulsed eddy current
DC	Direct Current
EIS	Impedance spectroscopy
FBG	fibre Bragg grating
OFDR	Optical frequency domain reflectometry
EMI	Electromagnetic interference
TDR	Time-domain reflectometry
CNTs	Carbon nanotubes
GNPs	Graphene nanoplatelets
TNDT	Thermographic non-destructive testing
PT	Pulsed Thermography

PPT	Step-Heating and Pulse-Phase Thermography
ULT	Ultrasound Lock-in Thermography
LST	Laser Spot Thermography
TWRT	Thermal Wave Radar Thermography
ΔT	Thermal contrast
AI	Artificial intelligence
PINNs	Physics-informed neural networks
PIML	Physics-informed machine learning
SoC	System-on-chip
XAI	Explainable Artificial intelligence
SHAP	Shapley additive explanations
MCMC	Markov Chain Monte Carlo
TSVD	Truncated singular-value decomposition
TV	Total-variation regularization
MAP	Maximum a-posteriori
POD	Proper Orthogonal Decomposition
RB	Reduced-Basis
GCV	Generalized cross-validation
SMC	Sequential Monte Carlo
EnKF	Ensemble Kalman Filter

GA	Genetic Algorithms (GA) and
PSO	Particle Swarm Optimization
GPR	Gaussian process regression
RBFNs	Radial basis function networks
DNNs	Deep neural networks
DeepONets	Deep Operator Networks
EMA	Experimental Modal Analysis
OMA	Operational Modal Analysis
FRF	Frequency Response Function
LDV	Laser Doppler vibrometers
Δf	Natural Frequency Shifts
MSC	Mode Shape Curvature
MAC	Modal Assurance Criterion
FRC	Frequency Response Change
SED	Strain Energy Distribution
EMD	Empirical mode decomposition
ODS	Operational Deflection Shapes
SVM	Support vector machines
CLT	Classical laminate theory

List of symbols

Symbol	Description
$\mathbf{x}$	Unknown or variable
$\mathbf{F}$	Physical model operator
$\boldsymbol{\varepsilon}$	Noise
$\mathbf{y}$	measurement
$\mathbf{u}$	Field variables(displacement, temperature.....
$\mathcal{L}$	Differential operator
$\mathcal{B}$	Boundary operator
$\hat{\mathbf{x}}$	Estimated variable
$\mathbf{y}_{\text{obs}}$	Measurement observed
L	Smoothing operator
ξ	Regularization parameter
λ	Adimensional frequency
$\mathbf{K}(\mathbf{r})=\partial\mathbf{F}/\partial\mathbf{x}(\mathbf{r})$	Sensitivity kernels
$\boldsymbol{\psi}$	Adjoint variable
ϕ	Mode shape
h	Beam Height
$\mathbf{K}$	global stiffness matrix
$\mathbf{M}$	global mass matrix
ω	Natural pulsation
f_i	Natural frequency
$\mathbf{A}_i, \mathbf{B}_i, \mathbf{C}_i \mathbf{D}_i$	Coefficients
ρ	Density
L	Beam length
E	Young modulus

I	Second moment of inertia
a	Delamination horizontal position
b	Delamination size
d	Delamination vertical position(interface)
Z	abscise
P_d	Axial force
A	Continuity matrix 12x12
$D_{11}^{(i)}$	Total Flexural rigidity of sub-beam i
$\overline{D_{11}^{(i)}}$	Bending term for flexural rigidity of sub-beam i
$B_{11}^{(i)}$	coupling term for flexural rigidity of sub-beam i
$A_{11}^{(i)}$	extensional term for flexural rigidity of sub-beam i
b	Beam width
x_k	the distance of the layer edge to the delaminated surface
$\bar{Q}_{11}^k$	the coefficient stiffness of the lamina
E_{11}	Longitudinal Young modulus
E_{22}	Transverse Young modulus
ν_{21}, ν_{12}	Poisson ratio
d_k	Distance from delaminated surface to the midplane of the layer
δ_i	Distance from delaminated surface to the neutral plane of sub-beam i
ϵ_l	Axial deformation caused by the force F

General introduction

Composite materials have become essential in modern engineering applications due to their high stiffness-to-weight and strength-to-weight ratios compared with conventional metallic materials. Their excellent mechanical performance has led to their widespread use in aerospace, automotive, marine, civil engineering, and energy industries. Despite these advantages, composite structures remain vulnerable to various forms of damage that may occur during manufacturing, assembly, or service life. Common defects include porosity, matrix cracking, fibre breakage, foreign inclusions, disbonds, and delamination. Among these defects, delamination is considered one of the most critical forms of damage because it occurs internally between adjacent layers and can significantly reduce the structural stiffness, load-carrying capacity, and fatigue resistance of the material without producing visible surface indications.

The presence of damage in engineering structures represents a major concern for both safety and reliability. Structural degradation may compromise the integrity of critical systems such as aircraft components, bridges, pipelines, rotating machinery, and energy infrastructures. If left undetected, such defects may propagate under operational loads and eventually lead to catastrophic failures, economic losses, and risks to human life. Consequently, the early detection and characterization of damage have become important objectives in structural health monitoring and maintenance strategies. Accurate identification of defects enables timely repair and maintenance actions, reduces operational costs, and extends the service life of engineering structures.

Delamination characterization has therefore attracted considerable attention over the past decades. Various techniques have been developed to detect, locate, and evaluate delamination in composite structures. Conventional non-destructive testing methods, including ultrasonic inspection, radiography, thermography, acoustic emission monitoring, shearography, and other experimental techniques, provide valuable information regarding the internal condition of a structure. These methods can often identify the size and location of defects with good accuracy. However, they frequently require specialized equipment, direct access to the structure, significant inspection time,

and considerable operational costs, particularly when applied to large-scale systems or structures operating under service conditions.

To overcome some of these limitations, researchers have increasingly explored indirect identification techniques based on the analysis of measurable physical responses. Among these approaches, vibration-based damage identification has emerged as an attractive solution. The fundamental principle of these methods is that the presence of damage modifies the dynamic characteristics of a structure, including its natural frequencies, mode shapes, and damping properties. By monitoring variations in these dynamic parameters, it becomes possible to infer the existence and severity of structural defects without direct physical inspection. Vibration-based

techniques offer several advantages, including their non-invasive nature, suitability for continuous monitoring, and potential integration into structural health monitoring systems.

The identification of damage from vibration measurements is generally formulated as an inverse problem. In such problems, the measured structural response is known, whereas the physical parameters responsible for that response must be determined. Inverse problems are often challenging because they may be highly nonlinear, sensitive to measurement noise, and may admit multiple solutions. To address these difficulties, numerous computational techniques have been proposed, including optimization algorithms, surrogate models, machine learning approaches, artificial neural networks, and deep learning techniques. Although these methods have demonstrated significant capabilities for damage identification, they often require extensive computational resources, large training datasets, accurate numerical models, or reference data from undamaged structures. Their performance may also be affected by measurement uncertainties and modelling errors.

In parallel with numerical and data-driven approaches, analytical modelling has played a central role in understanding the dynamic behaviour of damaged structures. Several analytical models have been developed to study the vibration characteristics of delaminated beams. Among these models, the free mode model and the constrained mode model are widely used to describe the

dynamic response of beams containing delamination. These forward models establish the relationship between the physical characteristics of the defect and the resulting vibration behaviour of the structure. While numerous analytical forward models have been reported in the literature, the development of analytical inverse models capable of directly identifying delamination parameters from vibration measurements remains limited.

The present thesis addresses this challenge through the development of a novel analytical inverse methodology for delamination identification in beam structures. The proposed approach utilizes the first three natural frequencies of a delaminated beam as input information to determine the location, size, and depth of the defect. Starting from the constrained mode analytical formulation, a system of nonlinear equations is established from the characteristic equations governing the free vibration behaviour of the beam. Each characteristic equation is obtained from the determinant associated with the continuity and boundary conditions of the model. By introducing the measured natural frequencies into these equations, the inverse problem is formulated directly in terms of the unknown delamination parameters. A graphical solution procedure is then employed to determine the intersection of the resulting nonlinear surfaces and identify the defect characteristics. Unlike many existing approaches, the proposed methodology does not require optimization algorithms, finite element model updating procedures, artificial intelligence techniques, or reference frequencies from an undamaged structure. The method therefore provides a simple, efficient, and physically interpretable framework for vibration-based delamination identification.

The main contribution of this thesis lies in the development of an original analytical inverse model capable of identifying delamination characteristics directly from modal information. In addition to providing an efficient identification strategy, the proposed framework contributes to a deeper understanding of the relationship between structural damage and dynamic behaviour. The methodology also demonstrates the potential of combining analytical modelling and inverse problem theory for structural health monitoring applications.

This thesis is organized into six chapters. Chapter 1 presents the fundamental concepts related to material defects, their classification, formation mechanisms, and influence on structural behaviour,

with particular emphasis on delamination in composite materials. Chapter 2 reviews the principal techniques used for defect identification and structural health monitoring. Chapter 3 introduces the theory of inverse problems and the methodologies commonly employed for parameter identification. Chapter 4 discusses vibration-based damage detection methods and the influence of structural defects on dynamic characteristics. Chapter 5 presents the proposed analytical inverse model for delamination identification, including its formulation, implementation, and validation. Finally, Chapter 6 provides the results, discussion, limitations, and perspectives for future developments.

In summary, this thesis contributes to the field of structural health monitoring by proposing a novel analytical framework for the identification of delamination in beam structures. By combining concepts from composite damage mechanics, vibration analysis, and inverse problem theory, the proposed methodology offers an effective and computationally efficient approach for defect characterization and provides new perspectives for the monitoring and maintenance of engineering structures.

Chapter 1: Defects in materials

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1.1 Introduction

Defects are an essential aspect of materials science because they strongly influence the physical, mechanical, electrical, thermal, and chemical properties of materials. No material is completely free of defect; during processing, manufacturing, or service conditions, imperfections are inevitably introduced into the structure. These imperfections, commonly referred to as defects, can either improve or degrade material performance depending on their nature, concentration, and distribution. Understanding defects is therefore critical for predicting material behaviour and improving the reliability and efficiency of engineering applications.

In the four major classes of materials: metals, ceramics, polymers, and composites-defects appear in different forms and affect its properties. In metals, defects such as vacancies, dislocations, and grain boundaries influence strength, ductility, and conductivity. Ceramic materials are highly sensitive to point defects and cracks, which often control brittleness and thermal resistance. In polymers, chain irregularities, voids, and cross-linking defects affect flexibility, toughness, and durability. This chapter discusses the various types of defects present in these four categories of materials and explains their formation, characteristics, and effects on material properties.

1.2 Defects in metals

For perfect crystals the two main types, edge and screw dislocations, facilitate slip along crystallographic planes and define the metal's yield strength and work-hardening behaviour. Planar defects, such as grain boundaries, twin boundaries, and stacking faults, affect corrosion resistance, creep strength, and recrystallization. In polycrystalline metals, the grain boundary density inversely affects yield strength (Hall–Petch relation). Volume defects, including voids, inclusions, and porosity, act as crack initiation sites, degrading fatigue performance and toughness. These defects are often introduced during solidification, heat treatment, or mechanical processing. For example, inclusions such as oxides or sulphides in steel can reduce fatigue life by serving as stress concentrators. With modern manufacturing processes such as additive manufacturing, defect control has become more challenging issues such as lack-of-fusion porosity and residual stress significantly alter mechanical behaviour. Understanding and controlling the type, density, and

distribution of these defects is fundamental in tailoring metallic materials for applications requiring high strength, ductility, or corrosion resistance.

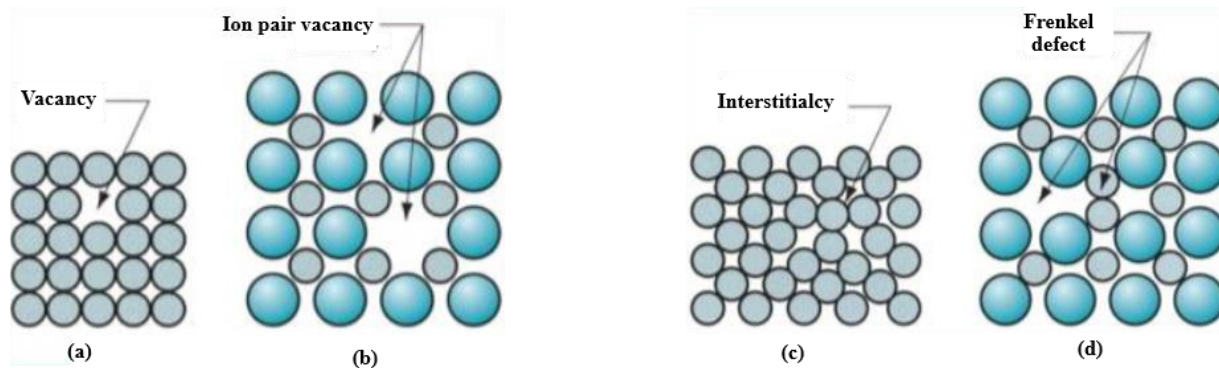


Figure 1.1: Point defects in metals

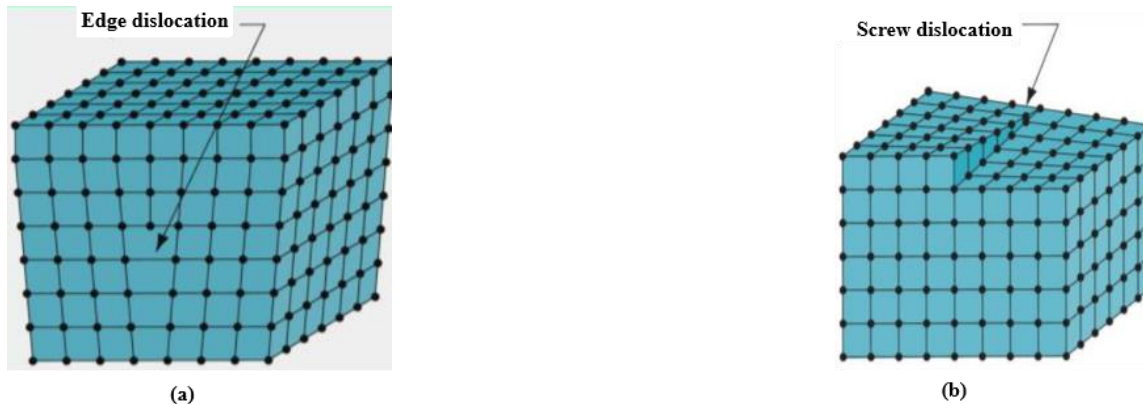


Figure 1.2: Line defects in metals

1.3 Defects in ceramics

Defects in ceramics are intrinsic to their atomic structure and play a decisive role in determining electrical, mechanical, and thermal properties. Unlike metals, ceramics are composed of both metallic and non-metallic ions bonded ionically or covalently, which makes their defect chemistry more complex. The most fundamental defects are point defects, including vacancies and interstitials, which may occur in both the cation and anion sublattices. Depending on charge balance, these point defects are classified as Schottky defects—where equal numbers of cation and anion vacancies are formed—or Frenkel defects as shown in Figure 1.1, which involve a displaced ion leaving a vacancy and occupying an interstitial site. The concentration of such defects

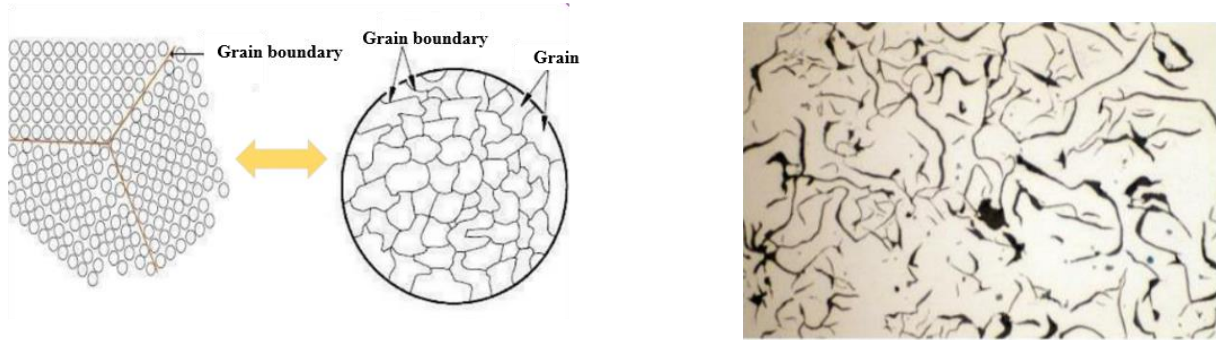


Figure 1.3: Surface and volume defects

strongly depends on temperature and can be described by thermodynamic relationships derived from defect formation energies. In ionic ceramics such as sodium chloride, magnesium oxide, and zirconia, defect equilibria are vital for processes like ionic conductivity, sintering, and diffusion. In nonstoichiometric ceramics (e.g., FeO or TiO_{2-x}), deviations from ideal chemical composition arise due to oxygen vacancies or interstitial cations, which profoundly affect electrical conductivity and oxidation resistance. Extended defects such as dislocations also exist in ceramics, but their movement is limited due to strong ionic or covalent bonding, explaining ceramics' inherent brittleness and low ductility [1]. Grain boundaries and twin boundaries as shown in Figure 1.3, act as barriers to ion migration, affecting mechanical and dielectric behaviour [2]. Microcracks, porosity, and secondary-phase inclusions as shown in Figure 1.3, represent volume defects that originate during powder processing or sintering, serving as initiation sites for fracture under stress [3]. Advanced ceramic systems, such as yttria-stabilized zirconia (YSZ) and barium titanate (BaTiO_3), deliberately introduce controlled defects to tune ionic or electronic conductivity for fuel cells and sensors. Overall, understanding and manipulating defect chemistry in ceramics enables the design of functional materials with optimized performance in extreme environments, from thermal barrier coatings to solid oxide fuel cells.

1.4 Defects in polymers

Defects in polymers arise from irregularities in molecular structure, chain arrangement, and processing conditions, and they significantly impact mechanical, thermal, and chemical performance. Unlike metals and ceramics, polymer defects are not limited to atomic-scale

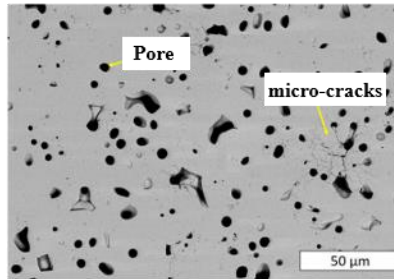


Figure 1.4: Micro-cracks, porosity

irregularities but extend to molecular-scale and mesoscopic imperfections in chain packing and morphology [4]. Structural defects include chain ends, branching, cross-linking irregularities, and stereochemical mismatches as shown in Figure 1.5 which disturb crystallinity and reduce modulus and strength. Point-like defects at the atomic level, such as missing side groups or chain scission sites, can act as centres for chemical attack or photodegradation. At a larger scale, voids, microcracks, inclusions, and gel particles introduced during polymerization or processing lead to stress concentrations and eventual failure under load. Thermoplastics and thermosets exhibit distinct defect behaviours: in thermoplastics, improper cooling or moulding can result in residual stresses, sink marks, and weld lines, while in thermosets, nonuniform curing may cause voids, resin-rich zones, or fibre–matrix debonding in composites. Environmental degradation also introduces defects. Photo-oxidation, hydrolysis, and ozone cracking create chain scission and cross-link breakage, altering molecular weight distribution [5]. In semicrystalline polymers, spherulitic defects such as lamellar misalignment and tie-chain breakage control yield strength and creep response. Processing-induced defects are critical in additive manufacturing and extrusion, where shear-induced voids or poor interlayer bonding decrease fatigue performance [6]. Moreover, chemical inhomogeneities, unreacted monomers, and impurities from catalysts can disturb molecular packing and act as initiation sites for dielectric breakdown or stress cracking. Modern approaches such as in-situ monitoring, nanofiller dispersion control, and defect healing through reversible cross-links are being developed to mitigate these imperfections. Understanding the multiscale nature of defects in polymers—from molecular chain irregularities to macroscopic flaws—is essential for improving durability, reliability, and functionality in structural, electronic, and biomedical applications.

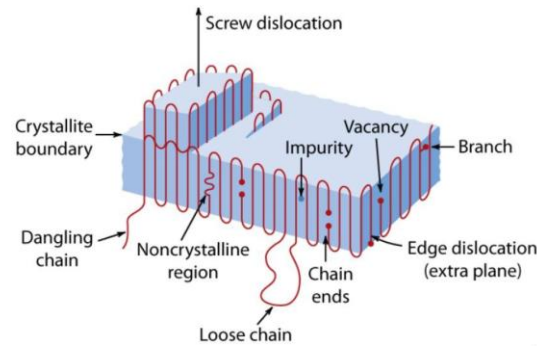


Figure 1.5: Defects in polymers (From the internet)

1.5 Defects in composites

1.5.1 Introduction and Matrix-Related Defects:

Composite materials have become indispensable in advanced structural and functional engineering applications due to their unique combination of light weight, high strength, and tailorability of properties. However, their performance is often constrained by the presence of microstructural imperfections and defects that emerge during manufacturing, handling, or service life. In the broadest sense, defects in composites represent deviations from the intended microstructure, morphology, or bonding configuration, which lead to local variations in stiffness, strength, and damage tolerance. The inherent heterogeneity of composites—including reinforcing phases (fibres, particulates, or whiskers) embedded in a continuous matrix—makes them more susceptible to multi-scale defect formation than monolithic materials such as metals or ceramics. Minor imperfections like voids as shown in Figure 1.6, or interfacial debonding can cause severe stress concentrations, leading to premature failure modes such as delamination or interlaminar cracking as shown in Figure 1.7. The study of defects, therefore, plays a pivotal role in understanding the reliability, safety, and performance of composite structures used in aerospace, automotive, wind energy, and marine industries. At the macroscopic level, the most prevalent defects in composites are broadly categorized into matrix-related, fibre-related, and interfacial defects, each interacting synergistically to influence damage initiation and propagation. Matrix-related defects arise primarily due to incomplete curing, trapped air, void formation, and resin starvation during fabrication, as shown in Figure 1.8. These defects directly compromise the load-transfer efficiency between the matrix and

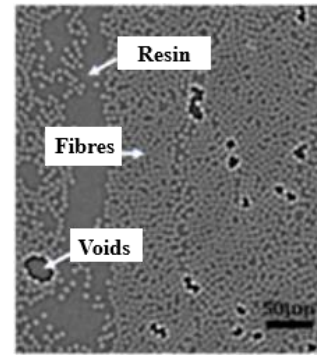
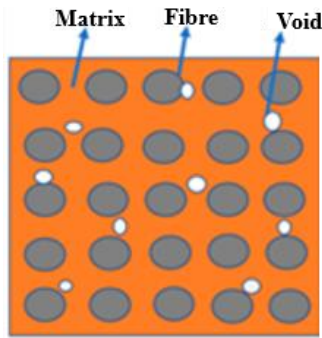


Figure 1.6: Voids in matrix

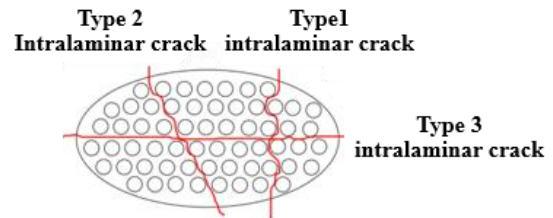
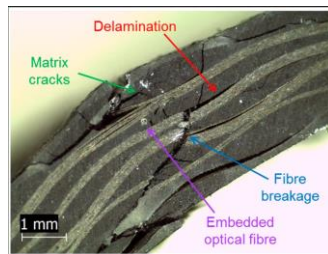


Figure.1.7: Defects in composites (from internet)

reinforcement, often resulting in reduced mechanical stiffness, poor fatigue performance, and lowered interlaminar shear strength [7]. Voids are among the most critical matrix defects and can originate from volatiles, moisture, or trapped gases during resin mixing or curing[7]. Studies have shown that voids exceeding a volume fraction of 1–2% can reduce the tensile strength of carbon fibre-reinforced polymers (CFRPs) by more than 10% [8]. The geometry and distribution of voids strongly affect their impact, spherical voids tend to cause concentrations of local stress, whereas elongated voids aligned along the fibre direction can promote crack propagation. During autoclave processing or vacuum-assisted resin transfer moulding (VARTM), improper control of temperature and pressure gradients can aggravate void formation, particularly in thick laminates. Another class of matrix-related defects includes resin-rich zones and resin-starved areas see Figure 1.11, which occur due to irregular resin flow during impregnation of fibre preforms. Resin-rich zones often show low modulus and act as sites for crack initiation under cyclic loading, whereas resin starvation can expose fibres and diminish interfacial bonding. Such inhomogeneities are particularly problematic in hand lay-up and filament winding processes, where manual impregnation introduces variability in resin distribution. Incomplete or irregular curing is also a frequent cause of matrix defects.

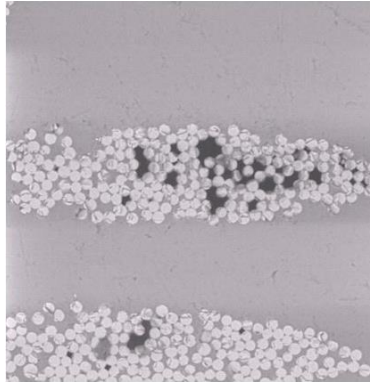


Figure 1.8: Resin starvation

Insufficient cross-linking of thermosetting resins (such as epoxy or polyester) leads to local soft spots and reduced glass transition temperature, while over-curing may generate residual thermal stresses that result in microcracking. Microcracks as shown in Figure 1.10 formed during curing not only reduce matrix cohesion but also facilitate moisture ingress, accelerating environmental degradation and interfacial debonding [9].

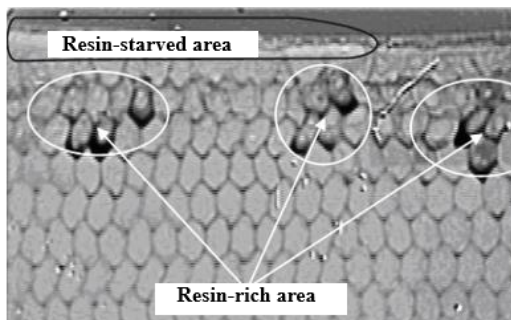


Figure 1.9: Starved and rich resin areas

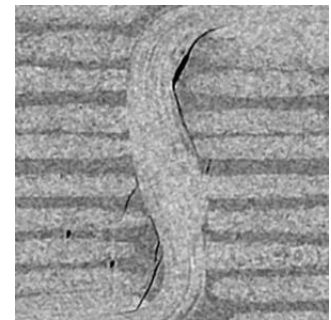


Figure 1.10: Microcracks

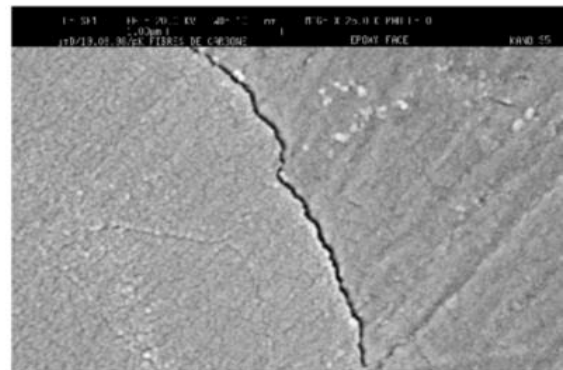
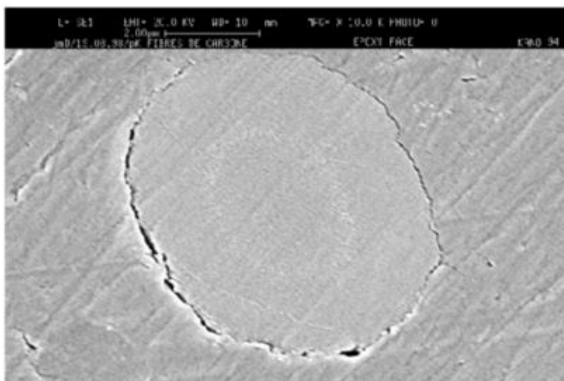


Figure 1.11 :interfacial debonding (from internet)

Porosity as shown in Figure 1.12 represents another major matrix-related imperfection, usually resulting from volatile evolution or insufficient resin compaction. Micro-CT imaging and ultrasonic C-scan analyses have demonstrated that even minimal porosity alters the elastic modulus and energy absorption capacity of composites under compression[10]. Moreover, in high-temperature composites such as carbon/carbon (C/C) systems, porosity serves as a precursor for oxidation pathways, thereby affecting long-term thermal stability. In thermoplastic-based composites, matrix defects can also include fibre pull-out holes and weld-line weaknesses, which form due to incomplete fusion during processing[11]. These regions behave as stress concentrators and contribute to delamination under impact or fatigue loading.

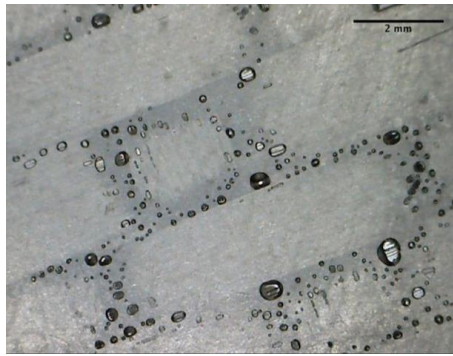


Figure.1.12: Porosity (from internet)

Porosity and voids are both classified as volumetric defects; however, they differ in scale, distribution, and structural impact. Voids generally refers to a large population of microscopic gas-filled cavities that are relatively uniformly distributed within the matrix or along the fibre–matrix interface and are typically formed due to air entrapment, volatile release, or resin reduction during curing. In contrast, porosity is larger, discrete regions where resin is completely absent, resulting from inadequate impregnation, poor fibre wetting, or resin-starved zones during manufacturing. While porosity primarily degrades matrix-dominated properties such as transverse strength, interlaminar shear strength, and fatigue resistance in a cumulative manner, voids act as severe local stress concentrators that can directly initiate matrix cracking, delamination, and premature failure. Consequently, porosity is often treated as a statistical quality parameter with allowable limits, whereas voids are considered critical manufacturing defects requiring corrective action or rejection of the component.

An equally significant defect mechanism is matrix cracking, which typically develops under mechanical loading or thermal fatigue. The brittle nature of many thermoset matrices makes them prone to crack initiation when local stress exceeds their inherent toughness. These cracks can propagate along the fibre–matrix interface, serving as precursors to interlaminar delamination[12]. Matrix cracking also provides pathways for moisture ingress, further degradation under humid or marine environments[13]. Once cracks coalesce or connect to voids and inclusions, the damage transitions into interfacial debonding and laminate delamination, leading to catastrophic failure see Figure 1.13 [14].

Matrix defects are not only negative to static properties but also have a profound influence on fatigue behaviour. Under cyclical loading, micro-voids and matrix cracks act as stress raisers that accelerate fatigue crack initiation. For example, Vassilopoulos and Keller[15] observed that epoxy matrix microcracks in glass fibre composites grew rapidly at room temperature fatigue cycles, reducing the fatigue limit by up to 30%. Similarly, in high-temperature applications such as polymer matrix composites used in turbine blades, oxidative embrittlement and thermo-mechanical cycling induce micro-void growth and coalescence, resulting in matrix fragmentation. In modern research, attention has turned to self-healing matrices that can autonomously repair microcracks via encapsulated curing agents or reversible chemistries[16]. Such systems demonstrate promising recovery of mechanical properties but remain limited by treatment efficiency and temperature sensitivity.

Matrix-related defects thus represent one of the most studied aspects of composite materials science. Their complex origins, processing, curing, environmental, and mechanical influences make them central to any predictive modelling of composite durability. The coupling of experimental techniques such as X-ray computed tomography, digital image correlation, and acoustic emission monitoring with finite element analysis has enabled the mapping of defect-induced stress fields at multiple scales[17]. These approaches have greatly enlarged understanding of how microstructural defects evolve into macroscopic failure, forming the basis for defect-tolerant composite design philosophies.

1.5.2 Fiber-Related and Interfacial Defects

Fibre-related defects represent one of the most influential categories of imperfections in composite systems, as the reinforcing phase is primarily responsible for carrying mechanical loads. Any discontinuity or misalignment in Fibres alters the load transfer and stress distribution within the composite, leading to significant reductions in strength, stiffness, and fatigue resistance. These defects may arise from several sources: manufacturing imperfections, during Fibre production, improper lay-up, during composite fabrication, or damage induced during handling and service life. The most common fibre-related defects include fibre breakage as shown in Figure 1.13, fibre waviness as shown in Figure 1.14, misalignment see Figure 1.15, bundling, and non-uniform fibre volume fraction [18]. Fibre breakage can occur during cutting, weaving, or compaction of preforms, particularly when high-modulus fibres such as carbon are used. Once a fibre fracture initiates, the load is redistributed to surrounding fibres, resulting in stress concentrations that promote local matrix cracking and interfacial debonding[19].

Fibre waviness, often referred to as fibre undulation, occurs when fibres deviate from their intended alignment within the laminate. This defect is highly detrimental to the compressive strength of composites because the misaligned regions act as kink band nucleation sites under compressive loading. Hsiao and Daniel[20] reported that even small deviations in fibre alignment can cause a significant reduction in compressive strength of unidirectional carbon/epoxy composites. Their analytical model and experimental data both showed that fibre waviness severely reduces compressive performance due to local stress concentrations and micro buckling initiation.

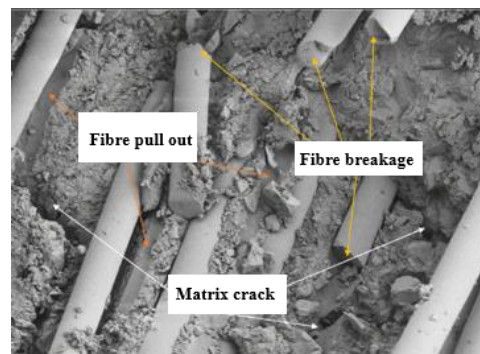


Figure 1.13: Fibre breakage and pull out

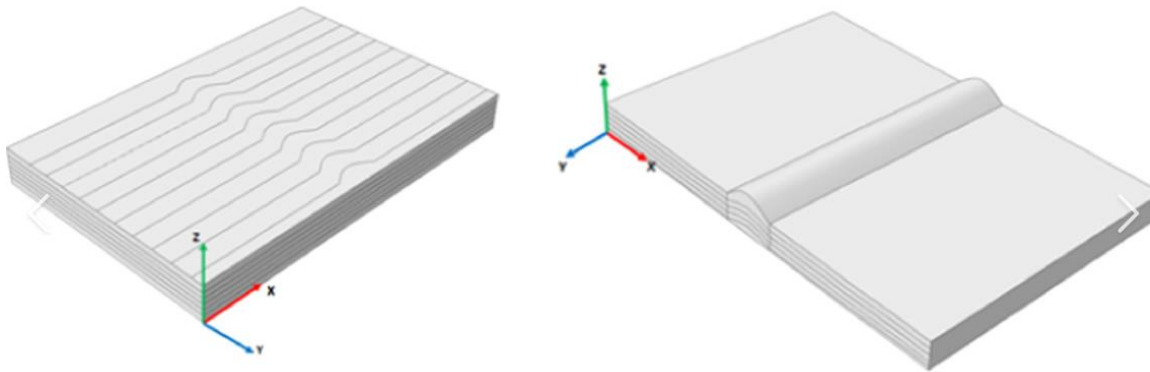


Figure 1.14: Fibre waviness

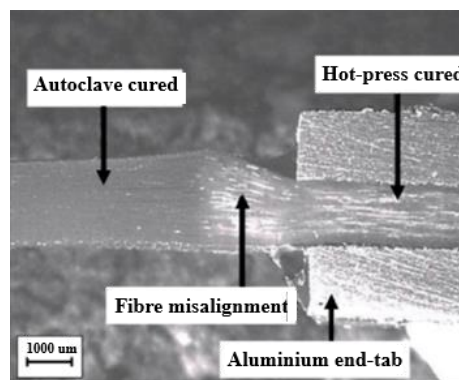


Figure 1.15: Fibre misalignment

Fibre misalignment differs from waviness in that it may be more global, caused by lay-up errors or poor handling during prepreg stacking. Such defects cause anisotropy in stiffness and distort stress fields, promoting early failure under multiaxial loads[21]. Additionally, non-uniform fibre distribution can lead to resin-rich pockets or fibre-free regions, which significantly alter local stress concentrations and reduce fatigue performance. Advanced manufacturing methods such as automated fibre placement (AFP) and automated tape laying (ATL) have reduced human-induced misalignment, but even small deposition errors in AFP can create “tow gaps” and “overlaps” that serve as initiation sites for delamination under cyclic loading.

Fibre surface contamination is another serious defect class. During handling, fibres can accumulate contaminants like dust, lubricants, or moisture that weaken the fibre–matrix interfacial bonding. In high-performance composites, manufacturers employ plasma treatments to improve surface energy and bonding compatibility; however, incomplete treatment or surface oxidation can lead to reduced interfacial shear strength[22]. Fibre fragmentation during loading is also closely related

to the interfacial strength, if the matrix–fibre interface is too weak, load transfer becomes inefficient, leading to debonding and premature fibre pull-out.

Interfacial defects form the critical link between matrix and reinforcement failure mechanisms. The interface in a composite is a mechanically and chemically distinct zone where stress transfer, chemical adhesion, and energy dissipation occur. Imperfections at this boundary, such as debonding, weak adhesion, residual stresses, and incompatible surface chemistry, are among the most common causes of delamination and fatigue failure. As noted by Drzal and Madhukar [23], a strong interface must balance two competing factors: sufficient bonding to transfer stress effectively but enough toughness to resist brittle delamination under cyclic loading. Weak interfaces or poorly wetted fibre surfaces result in localized stress peaks that promote microcrack initiation.

Interfacial debonding may occur due to poor fibre wetting during resin impregnation or from thermal mismatch between the fibre and matrix. For instance, in carbon/epoxy systems, the coefficient of thermal expansion (CTE) mismatch induces tensile residual stresses during cooling, leading to interface microcracks[24]. Similarly, in glass fibre-reinforced composites, hydrolytic degradation at the interface can weaken silane coupling agents, reducing adhesion and causing moisture-assisted debonding. The debonding process is often progressive: initial microcracks form at stress concentrations, which coalesce into larger delamination under cyclic loads [25]. The propagation of this delamination reduces load-bearing cross-sections and leads to interlaminar shear failure.

Delamination itself, a macro-scale manifestation of interfacial failure, is one of the most studied and feared defects in laminated composites. It represents a separation between layers due to weak interlaminar bonding, impact damage, or excessive out-of-plane stresses[26]. Once initiated, delamination tends to propagate rapidly under cyclic loading, thereby making it a primary target for non-destructive evaluation (NDE) and structural health monitoring (SHM).

Residual stresses at the interface also play a central role in defect formation. These arise during curing or cooling due to mismatched thermal expansion or reduction between fibre and matrix. Over time, these stresses lead to microcrack formation, interfacial debonding, and in some cases,

transverse cracking across plies[27]. The degree of residual stress depends on cure kinetics, resin chemistry, and processing parameters such as cooling rate and pressure. Computational models using micromechanics and cohesive-zone methods have been increasingly applied to simulate interfacial fracture and predict delamination growth under mechanical or thermal loading[28].

To improve interfacial performance and mitigate such defects, recent advancements have focused on nano-engineered interfaces, where nanoscale protective material (e.g., carbon nanotubes or graphene nanoplatelets) is grafted onto fibre surfaces to enhance mechanical interlocking and interfacial shear strength. These engineered interphases can significantly delay crack initiation and delamination by improving stress transfer and fracture toughness. For example, Wang et al.[29] demonstrated an 80% increase in interlaminar shear strength in-modified carbon fibre composites compared to unmodified ones. However, achieving uniform nanoparticle dispersion and stable bonding remains challenging and can itself introduce defects if agglomeration occurs.

Overall, both fibre-related and interfacial defects dictate the integrity and long-term performance of composite materials. Their complicated coupling makes it difficult to isolate the effect of each defect type independently, as fibre misalignment may promote matrix cracking, and interfacial debonding can worsen fibre breakage under stress. Advanced diagnostic techniques such as digital volume correlation and acoustic emission monitoring now enable the real-time study of defect initiation and propagation at these interfaces. Understanding these interactions provides a pathway to defect-tolerant design and more reliable next-generation composite systems[30].

1.5.3 Processing, Environmental, and Service-Induced Defects

Processing-induced defects are among the most widespread in composite manufacturing and directly dictate the microstructural quality and reliability of the final product. These imperfections often originate during lay-up, resin infusion, curing, and post-processing, where improper control of temperature, pressure, or resin flow leads to microstructural inhomogeneities. The formation of voids, dry spots as shown in Figure 1.16, resin-rich zones as shown in Figure.1.17, and inclusions is closely related to the manufacturing process. The composite material is fabricated via autoclave processing, resin transfer moulding (RTM)[31], vacuum-assisted resin transfer moulding (VARTM), or automated fibre placement (AFP). Each technique has its own

characteristic defect types. For example, in VARTM, the low-viscosity resin and vacuum-driven impregnation make the process particularly prone to voids and dry fibre regions if the resin front does not fully wet the reinforcement [32]. In autoclave curing, trapped air or volatiles can nucleate as voids under insufficient pressure or improper airing. Tang et al.[33] observed a $\sim 30\%$ reduction in compressive strength by increasing the void content from 5% to 10%.

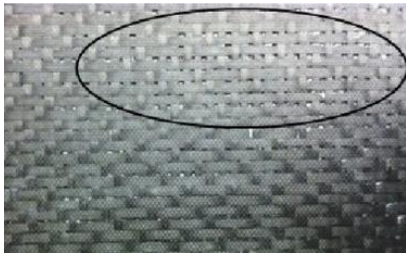


Figure.1.16: Dry spot[34]

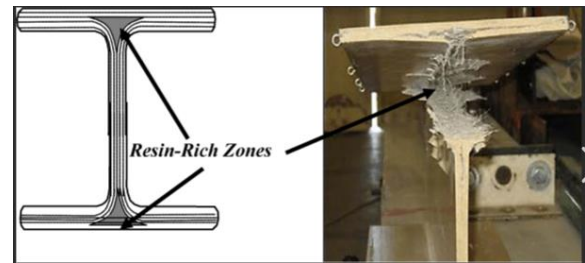


Figure.1.17: Resin-rich zone(from internet)

Curing defects arise due to the complex exothermic reactions in thermosetting matrices, where heat evolution and resin viscosity interact nonlinearly with temperature. Non-uniform curing can result in under-cured or over-cured regions, creating chemical heterogeneity and differential shrinkage. Under-cured regions retain unreacted functional groups, which reduce glass transition temperature (T_g) and lead to poor thermal stability, while over-cured regions accumulate residual stresses that drive microcrack formation[35]. Simulation studies by White and Hahn [36] demonstrated that improper temperature ramping during cure cycles can produce gradients exceeding $10\text{ }^{\circ}\text{C}$ through the laminate thickness, promoting residual stress buildup and micro void formation. To mitigate such defects, modern manufacturing integrates smart cure monitoring using embedded sensors and dielectric analysis to optimize resin crosslinking in real time[37].

Another common manufacturing defect is foreign inclusions, see Figure 1.20, which can be introduced by tooling contamination or operator handling[38]. Metallic particles or free film fragments can act as stress raisers, producing local debonding or galvanic corrosion when in contact with carbon fibres. Similarly, fibre wrinkling and tow overlaps in automated tape laying (ATL) or automated fibre placement (AFP) processes lead to out-of-plane distortions and local stiffness reductions[39]. These wrinkles can initiate delamination under compressive loads, severely compromising structural performance. Wu et al.[40] reported that a fibre wrinkle amplitude-to-wavelength ratio exceeding 0.02 can reduce compressive strength by 35% in

carbon/epoxy laminates. Even in additive manufacturing of polymer composites, layer delamination and incomplete fusion are prevalent, resulting from poor interlayer bonding or thermal gradients[41]. The anisotropic microstructure inherent to 3D printing amplifies the influence of these processing defects on mechanical anisotropy and fatigue behaviour.

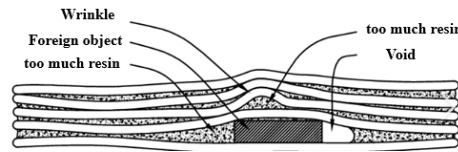


Figure.1.18: Foreign inclusion[42]

Beyond fabrication, environmental and service-induced defects significantly influence the long-term durability of composites. These defects develop gradually under operational exposure to moisture, temperature fluctuations, radiation, or cyclic loading. Moisture absorption, for example, is a critical degradation mechanism in polymer-matrix composites. Water molecules diffuse through the polymer network, causing plasticization, and hydrolysis, which weaken the fibre–matrix interface and reduce mechanical performance[43]. Studies by Dogan et al demonstrated that hygrothermal aging of glass/epoxy composites led to a 25% reduction in interlaminar shear strength after 60 days of immersion at 70 °C. Moisture ingress can also create micro void coalescence, further promoting crack propagation [44]. In carbon/epoxy systems, the mismatch in hygroscopic expansion coefficients between the fibre and matrix generates interfacial stresses that initiate debonding, particularly at elevated temperatures[45].

Thermal degradation is another major service-induced defect mechanism. Repeated thermal cycling can lead to differential expansion and contraction between fibres and matrix, causing interfacial microcracking, delamination, and residual stress buildup [46]. This phenomenon is especially severe in composites used for aerospace applications, where components experience temperature changes from –60 °C to over 200 °C. Additionally, oxidation and UV-induced degradation of polymer matrices result in chain scission, embrittlement, and discoloration, which further intensify crack initiation[47]. In carbon–carbon composites operating in oxidative environments, matrix oxidation produces surface collapse and porosity, reducing load-bearing cross-section and accelerating thermal fatigue[48]. Similarly, ceramic-matrix composites (CMCs)

are vulnerable to oxygen access through microcracks, leading to fibre oxidation and strength loss[49].

Mechanical fatigue during service also induces defect evolution. Under cyclic loads, microcracks nucleate in resin-rich regions, coalesce along fibre–matrix interfaces, and propagate as delamination. Fatigue damage in composites is fundamentally multi-scale: matrix microcracks appear early, followed by fibre–matrix debonding and finally fibre fracture or ply delamination. The accumulation of such damage is often modelled using continuum damage mechanics or cohesive-zone approaches, which capture the gradual stiffness degradation caused by distributed microdefects[50]. In humid or corrosive environments, these mechanisms are further accelerated, giving rise to environmentally assisted cracking (EAC). Studies by De Leon et al.[51] revealed that CFRP laminates exposed to combined mechanical and thermal cycling demonstrated interfacial crack growth rates nearly double those observed under mechanical fatigue alone.

Impact loading, such as low-velocity or high-energy impacts, also generates unique defect morphologies in composites. Even without visible surface damage, internal delamination, matrix cracking, and fibre breakage may develop collectively termed barely visible impact damage (BVID)[52]. BVID is particularly menacing in aerospace composites because it compromises compressive strength without easily detectable external indicators. The size, shape, and depth of impact-induced delamination depend on impact energy, laminate stacking sequence, and fibre orientation. For instance, quasi-isotropic laminates resist through-thickness delamination better than cross-ply laminates due to the more uniform distribution of interlaminar stresses[53]. Repeated low-energy impacts can accumulate damage, creating a network of delamination that eventually coalesce into through-thickness cracks[54].

Chemical degradation and corrosion also contribute to service-induced defects, especially in hybrid metal–composite systems. Galvanic coupling between carbon fibres and metallic fasteners leads to corrosion pitting in the metal and interfacial weakening in the composite[55]. Moisture and electrolytes accelerate these reactions, emphasizing the need for protective coatings and proper insulation. In polymer matrix composites used in marine and offshore structures, osmotic blistering (break out) is a common degradation defect, where water floods and reacts with residual catalysts

or salts in the resin, generating internal pressure and blister formation[56]. Over time, these blisters expand and connect with microcracks, leading to delamination[57].

Environmental and service-induced defects represent the long-term evolution of imperfections initially seeded during manufacturing. They are complex, coupled phenomena involving chemical, mechanical, and thermal interactions. The introduction of smart composites-materials embedded with self-sensing or self-healing capabilities-has emerged as a promising avenue to counteract these defect mechanisms[58]. For example, capsule-based healing systems and reversible Diels–Alder chemistries can repair microcracks and delay delamination beginning, although their long-term stability remains under investigation. Furthermore, hybrid reinforcement architectures (e.g., nano-engineered fibres, enclosed masks, and hierarchical laminates) aim to reduce stress concentrations and slow defect growth. Ultimately, understanding the interplay between processing, environment, and service-induced defects is essential for predictive maintenance and lifecycle management of high-performance composite structures[59].

1.6 Conclusion

Defects are unavoidable features in all materials and play a fundamental role in determining their overall behaviour and performance. Throughout this chapter, the different types of defects found in metals, ceramics, polymers, and composites have been examined, along with their influence on mechanical properties. Although defects are often associated with material weakness or failure, they can also be intentionally controlled to enhance performance and achieve desired material characteristics.

In metals, defects such as dislocations and grain boundaries contribute significantly to plastic deformation and strengthening mechanisms. In ceramics, defects strongly affect fracture behaviour, diffusion, and ionic conductivity. Polymer defects influence molecular arrangement, elasticity, and long-term stability. The study of these imperfections demonstrates that material properties are closely linked to internal structure at the atomic and microscopic levels.

Overall, understanding material defects is essential for improving manufacturing processes, developing advanced materials, and optimizing performance in engineering and technological

applications. Continued research in defect analysis and characterization remains important for the advancement of materials science and the development of innovative materials for future applications.

Chapter 2: Identification techniques

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2.1 Introduction

The demand for reliable defect identification is particularly critical in high-performance composite applications. For instance, in aerospace structures made of carbon-fibre-reinforced polymers (CFRP), the presence of barely visible impact damage (BVID) can lead to catastrophic failures if undetected. Therefore, comprehensive defect detection systems that combine physical sensing, data processing, and decision-making algorithms have become central to the concept of Structural Health Monitoring (SHM)[60].

Historically, inspection of composite materials counts heavily on visual and optical methods such as microscopic examination or holographic interferometry. With advancements in sensor technology and computational capabilities, modern approaches now encompass ultrasonic, thermographic, radiographic, acoustic, electromagnetic, and AI-driven data fusion systems [61], [62], [63]. The convergence of these techniques provides multiscale vision-from microstructural anomalies to macro-level integrity assessments-thus enabling predictive maintenance and life-cycle management.

This chapter reviews and discusses these techniques with particular emphasis on composites used in structural engineering. The goal is to provide a deep technical understanding of their working principles, advantages, limitations, and recent innovations.

2.2 Visual and Optical Techniques

Visual and optical inspection methods represent the most fundamental level of defect identification in composite materials. These techniques are primarily based on the interaction of light (or other electromagnetic waves) with the surface or subsurface regions of a specimen. Although limited to relatively surface depths compared to radiographic or ultrasonic methods, visual and optical methods remain essential for early-stage inspection and quality control during fabrication.

2.2.1 Visual Inspection

Visual inspection is the most direct and low-cost approach for identifying surface defects such as cracks, delamination traces, discolorations, or fibre misalignment. When combined with magnification tools, such as borescopes or endoscopes, it allows the detection of flaws in inaccessible regions of complex geometries. The integration of machine vision and image processing algorithms has significantly enhanced the reliability and repeatability of visual inspection[64]. For instance, convolutional neural networks (CNNs) have been trained to automatically classify surface defects in CFRP laminates based on texture, reflectivity, and pattern variations. Despite its simplicity, the main limitations of visual inspection include its inability to detect subsurface defects and dependence on operator experience. Therefore, visual methods are often used as preliminary screening tools before applying more advanced NDT techniques.

2.2.2 Optical Microscopy

Optical microscopy allows the examination of microstructural features at magnifications up to 1000 $\times$. It is particularly useful for identifying fibre pull-out, void content, and matrix cracking after mechanical testing[65]. In reflective mode, surface topography and resin distribution can be visualized, while in transmitted light mode, the internal structure of thin composite samples can be studied. Recent developments in digital holographic microscopy have improved depth resolution, enabling three-dimensional imaging of micro voids and interfacial degradation. However, optical microscopy requires careful sample preparation-often destructive to the specimen- and is therefore best suited for laboratory characterization rather than in-situ inspection.

2.2.3 Digital Image Correlation (DIC)

Digital Image Correlation as shown in Figure 2.1, is a full-field, non-contact optical measurement technique that evaluates strain and displacement fields on a specimen's surface. By comparing a series of high-resolution images captured before and after deformation, DIC tracks the movement of surface patterns to infer mechanical strain distribution. When applied to composites, DIC provides visions into damage initiation and propagation, such as fibre-matrix debonding or interlaminar shear cracking. The advantage of DIC lies in its ability to detect localized deformation concentrations, which often correlate with underlying defects.

Hybrid DIC–thermography systems have been developed to simultaneously monitor thermal and strain responses, offering multidimensional characterization of composite damage[66].

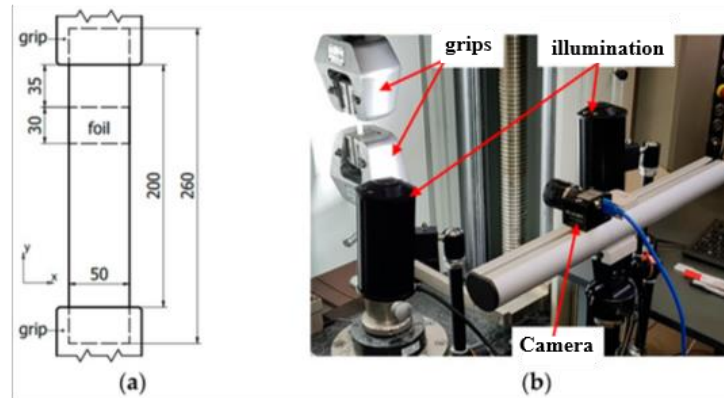


Figure 2.1: Digital image correlation experimental setup

2.2.4 Speckle Shearography

Speckle shearography as shown in Figure 2.2, also known as electronic speckle pattern interferometry (ESPI), is an optical interferometric technique sensitive to minute surface deformations. When a composite specimen is subjected to stress (e.g., thermal, vibrational, or vacuum loading), the resulting deformation causes phase changes in the speckle pattern of reflected laser light. These changes are then analysed to reveal subsurface defects such as delamination, disbands, or impact damage zones.

Shearography's major advantage is its rapid inspection capability over large areas without requiring physical contact. It has been widely used in the aerospace industry for inspecting composite panels and honeycomb structures. Its limitations primarily involve environmental sensitivity (vibration, temperature fluctuations) and the need for controlled illumination conditions [67].

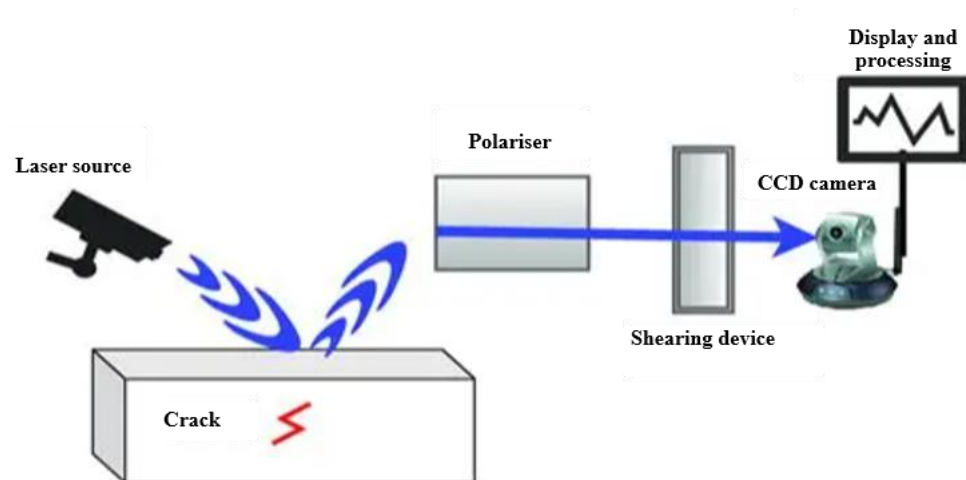


Figure 2.2: shearography

2.2.5 Infrared Thermography

Infrared thermography see Figure 2.3, although often grouped under thermal methods, also possesses an optical nature since it detects infrared radiation emitted from the specimen's surface. Active thermography—where an external heat stimulus is applied—can detect subsurface delamination and voids by analysing transient heat diffusion patterns.

Infrared thermography techniques, including pulse thermography, step heating, and lock-in thermography, are widely applied in detecting disbands and moisture ingress in CFRPs. Recent innovations integrate infrared cameras with AI-based anomaly detection for automated inspection[68].

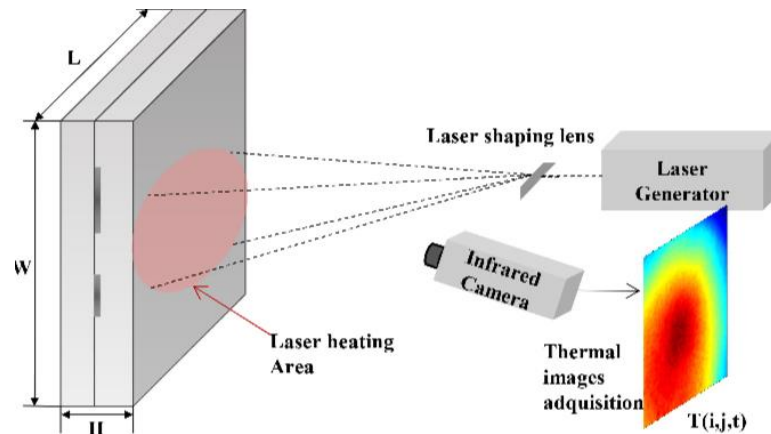


Figure 2.3: Infrared thermography

2.3 Ultrasonic-Based Techniques

Ultrasonic testing (UT) has emerged as one of the most effective and widely adopted non-destructive evaluation (NDE) methods for identifying defects in composite structural materials. Unlike visual or optical methods that primarily detect surface anomalies, ultrasonic techniques can probe deep within the material, providing quantitative information on the size, shape, and location of internal flaws [69].

2.3.1 Fundamentals of Ultrasonic Testing

Ultrasonic testing operates by transmitting high-frequency sound waves (typically 0.5–20 MHz) into a material and analysing the reflections produced by internal discontinuities. The propagation behaviour of ultrasound in composite materials is complex due to their anisotropic and heterogeneous nature. Wave velocity, attenuation, and scattering are influenced by fibre orientation, resin content, and interfacial bonding.

In a typical pulse-echo setup, a transducer emits ultrasonic pulses that travel through the specimen and reflect when encountering an interface (e.g., delamination, void, or inclusion). The time-of-flight (TOF) and amplitude of the reflected signal are analysed to determine the defect's depth and severity. However, due to the layered architecture of composites, wave dispersion often complicates signal interpretation[70].

To overcome these challenges, modern UT employs advanced signal processing, multi-frequency excitation, and imaging algorithms to enhance defect resolution. Time-frequency representations, such as short-time Fourier transform (STFT) and wavelet analysis, are increasingly used to separate overlapping wave modes in complex laminates.

2.3.2 Through-Transmission Ultrasonic Testing (TTU)

Through-transmission ultrasonic testing see Figure 2.4 involves two transducers placed on opposite sides of a specimen, one as a transmitter and the other as a receiver. Defects between

them cause attenuation or phase shift of the transmitted wave, which can be visualized in a C-scan image.

TTU provides reliable detection of large delamination, porosity regions, and inclusions in thin to moderately thick composite laminates. However, its requirement for access to both sides of the specimen limits its use in large or integrated structures such as aircraft wings or wind turbine blades[71].

Recent advancements have focused on air-coupled UT, which eliminates the need for couplings (gel or water) and enables contactless inspection. Air-coupled systems operate effectively at lower frequencies (typically below 500 kHz) and are particularly useful for honeycomb sandwich composites and thermoplastic laminates[72].

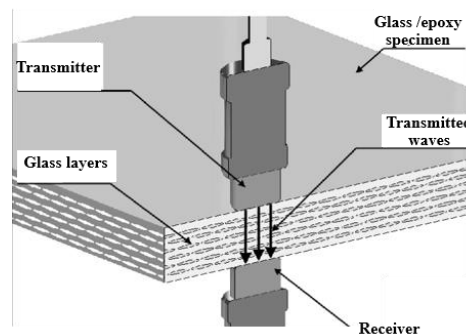


Figure 2.4: Through-Transmission Ultrasonic Testing (TTU)

2.3.3 Pulse-Echo Ultrasonic Testing

The pulse-echo technique see Figure 2.5, is the most common configuration for one-sided inspection, where the same transducer acts as both transmitter and receiver. The amplitude of reflected echoes is compared against reference standards to evaluate defect severity.

In composite laminates, back-wall echo attenuation and multiple reflection patterns are key indicators of internal damage. However, distinguishing between benign features (e.g., resin pockets) and critical flaws (e.g., delamination) often require multi-angle scanning.

Phased-array transducers further enhance the capability of pulse-echo testing by electronically steering and focusing on the ultrasonic beam. This allows for rapid inspection and three-dimensional imaging of complex geometries[72]. For example, phased-array UT has been successfully applied to detect barely visible impact damage (BVID) in carbon/epoxy laminates used in aerospace structures[73].

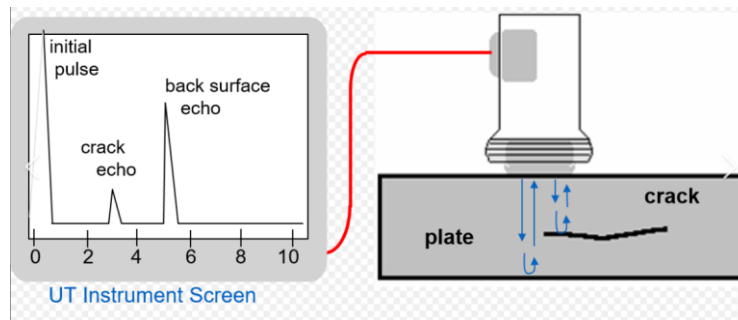


Figure 2.5: Pulse-Echo Ultrasonic Testing[156]

2.3.4 Guided Ultrasonic Waves (GUWs)

Guided ultrasonic waves as shown in 2.6-are low-frequency (10–500 kHz) modes that can travel long distances along a structure's surface or through thin-walled laminates. GUWs provide large-area coverage with minimal instrumentation, making them ideal for Structural Health Monitoring (SHM) of composite structures.

The two principal guided wave modes, Lamb waves and shear-horizontal (SH) waves, are sensitive to delamination, cracks, and debonding defects. By measuring changes in group velocity, mode amplitude, and frequency dispersion, damage can be localized and quantified.

Yaacob et al.[74] demonstrated the application of GUWs in assessing laminated damage in natural fibre-reinforced polymer bio composites. Their study showed that changes in wave energy distribution could accurately correlate with delamination growth, confirming GUWs as a promising tool for in-situ defect monitoring.

Modern implementations of GUW-based testing employ piezoelectric wafer active sensors (PWAS) integrated into the structure for real-time monitoring. Data from multiple sensors are often processed using beamforming or time-reversal algorithms to reconstruct damage maps.

The main limitation of guided wave techniques lies in their dispersion complexity so different modes may interfere, leading to ambiguous interpretations. To address this, researchers use mode-selective excitation and finite element simulations to isolate specific propagation paths and enhance detection accuracy[75].

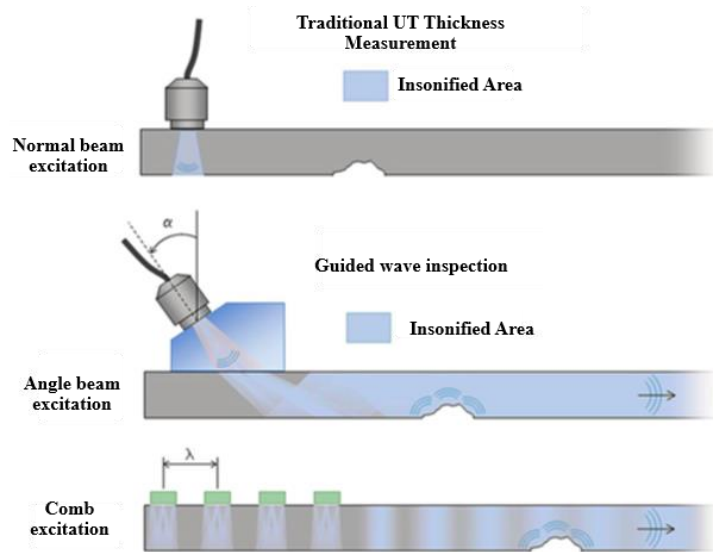


Figure 2.6: Guided Ultrasonic Waves (GUWs)

2.3.5 Air-Coupled and Laser Ultrasonic Techniques

Air-coupled ultrasonic testing as shown in Figure 2.7- uses non-contact transducers that couple sound waves through air rather than a liquid or solid medium. It offers advantages in rapid inspection of moisture-sensitive or curved composite structures. Air-coupled UT systems can detect delamination as thin as 0.2 mm in CFRP panels, although sensitivity decreases with increasing material thickness.

Laser ultrasonic testing (LUT), on the other hand, employs laser pulses to generate ultrasonic waves via thermoelastic expansion. Detection is performed using laser interferometers, making the process entirely non-contact. LUT is particularly advantageous for complex geometries and automated inspection environments, such as aerospace production lines[76].

Recent studies have demonstrated that laser-based ultrasonic imaging can achieve sub-millimetre resolution in detecting porosity and delamination in thick CFRP laminates. When combined with AI-based defect classification, LUT systems represent a state-of-the-art direction in composite defect identification.

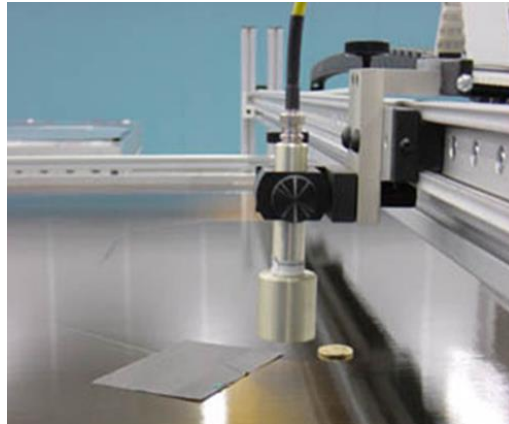


Figure 2.7: Air-Coupled Ultrasonic Techniques [166]

The complexity of ultrasonic wave propagation in composites necessitates advanced data interpretation methods. Techniques such as synthetic aperture focusing technique (SAFT) and total focusing method (TFM) are widely used to enhance image resolution and improve signal-to-noise ratio[77].

Moreover, recent integration of machine learning (ML) in ultrasonic testing allows automated defect classification and quantification. CNNs and recurrent neural networks (RNNs) have been trained to distinguish between delamination, cracks, and fibre fractures based on raw ultrasonic A-scan data. Hybrid approaches combining physics-based models with ML algorithms have shown superior performance, especially in cases with limited labelled data [78].

2.4 Radiographic and Tomographic techniques

Radiographic and tomographic methods play a crucial role in the non-destructive evaluation (NDE) of composite structural materials. These techniques utilize penetrating radiation, such as X-rays or neutrons as shown in Figure 2.8, to produce images that reveal internal features

of the material, enabling the detection and characterization of defects that are often invisible to optical or ultrasonic inspection[79]. Their ability to visualize the internal architecture of composites in high resolution has made them invaluable tools for both laboratory-based analysis and industrial quality assurance.



Figure 2.8: X ray tomography

2.4.1 Principles of Radiographic Inspection

In conventional X-ray radiography, a beam of X-rays is projected through a composite specimen and captured on a detector or photographic plate. Variations in material density and thickness cause differential attenuation of the X-rays as shown in Figure 2.9, which produces contrast in the resulting radiograph. Areas of lower density—such as voids, delamination, or resin-poor regions—appear as darker zones, whereas denser inclusions or fibre appear lighter.

The basic governing law of radiography follows Beer–Lambert’s Law, which defines the exponential attenuation of the beam as a function of material thickness and linear attenuation coefficient. For a composite laminate, the attenuation coefficient varies spatially due to its heterogeneous microstructure and anisotropic fibre orientations. This introduces interpretation challenges, particularly for fibre-reinforced polymers (FRPs), where the fibres and matrix possess significantly different X-ray absorption characteristics[80].

Nevertheless, radiography remains widely used for defect detection in aerospace composites, where voids, inclusions, and foreign object debris can significantly affect mechanical performance.

Digital radiography, using flat-panel detectors, provides real-time imaging capability and higher sensitivity compared to traditional film-based systems.

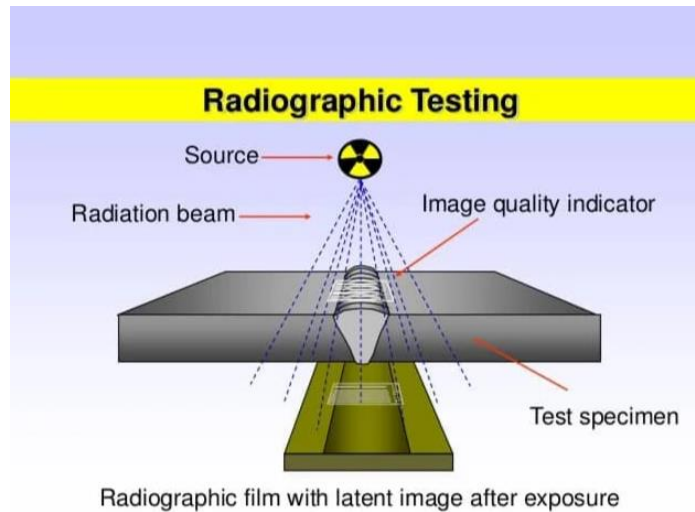


Figure 2.9: Radiographic Inspection

2.4.2 Computed Tomography (CT) and Micro-CT

Computed tomography (CT) as shown in Figure 2.10 represents a major advancement in radiographic NDE. Instead of a single projection image, CT acquires multiple two-dimensional (2D) radiographs from various angular positions around the specimen. These projections are computationally reconstructed to form a three-dimensional (3D) representation of the internal structure [81].

In micro-computed tomography (micro-CT), the X-ray source and detector are optimized to achieve micrometre-scale resolution, making it possible to visualize fibre orientations, void distributions, microcracks, and delamination networks in composite laminates. Micro-CT has become an indispensable tool for evaluating additive-manufactured and fibre-reinforced components where conventional techniques lack sufficient depth resolution.

Mehdikhani et al. [82] presented the use of micro-CT to analyse porosity evolution during the curing of carbon-fibre/epoxy laminates, revealing correlations between curing parameters and

defect formation. Similarly, three-dimensional CT analysis has been used to monitor impact damage propagation in CFRP panels, enabling accurate mapping of internal delamination growth[83].

The primary advantages of CT include its quantitative imaging capabilities, non-destructive cross-sectional analysis, and ability to visualize complex geometries. However, the high cost, long scanning times, and substantial data processing requirements limit its widespread adoption in large-scale industrial applications.

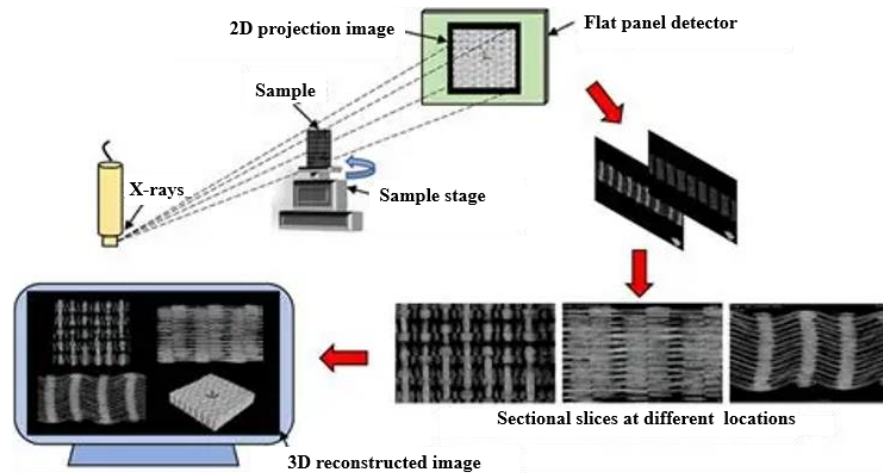


Figure 2.10: Computed Tomography (CT) and Micro-CT

Recent developments in machine learning–assisted computed tomography (CT) have focused on reducing reconstruction time while maintaining or improving image quality. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated the ability to reconstruct high-quality images from sparse or limited-angle projection data, substantially accelerating inspection workflows. Reported performance varies depending on the dataset and experimental conditions. For example, CNN-based reconstruction methods have achieved structural similarity index measure (SSIM) values exceeding 0.95 and peak signal-to-noise ratio (PSNR) values above 35–40 dB on publicly available datasets such as LoDoPaB-CT (Low-Dose Parallel Beam Computed Tomography) and Mayo Clinic Low-Dose CT, while testing under sparse-view (typically 60–120 projections) and low-dose acquisition conditions. In industrial CT

applications, similar approaches have reported reconstruction accuracies exceeding 95% for defect detection and image restoration when evaluated on simulated and experimental datasets using cross-validation and independent test sets, demonstrating their potential for fast and reliable non-destructive inspection.[84].

2.4.3 Neutron Imaging

While X-rays are primarily sensitive to atomic number and material density, neutron imaging as shown in Figure 2.11, provides complementary information because neutrons interact differently with atomic nuclei. This makes neutron imaging particularly effective for detecting hydrogen-rich materials, such as moisture ingress or resin degradation within composites[85].

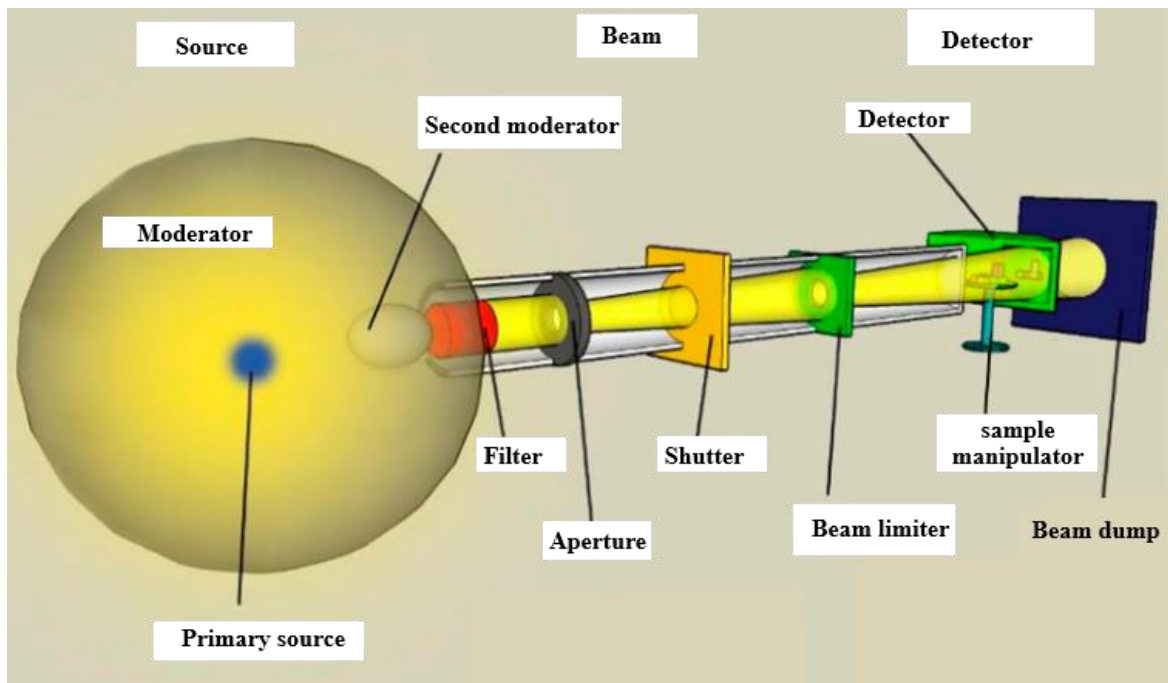


Figure 2.11: Neutron imaging

Neutron radiography (NR) and neutron tomography (NT) have been used to study water absorption and delamination in glass-fibre and carbon-fibre composites. Unlike X-rays, which are strongly attenuated by high-density fibres, neutrons can penetrate fibre-reinforced regions more uniformly, providing enhanced contrast for the polymeric matrix and interfacial zones. Despite their

advantages, neutron-based techniques are limited by restricted facility access (often requiring nuclear reactors) and long exposure times. Therefore, their applications are typically confined to research laboratories and critical aerospace component testing[85].

2.4.4 Advanced Radiographic Methods

Several advanced radiographic modalities have been developed to address the limitations of conventional X-ray and CT systems.

Phase-contrast X-ray imaging (PCI): This technique enhances contrast at material interfaces by detecting phase shifts rather than attenuation, which is especially useful for composites with low-density variations[86]. PCI has proven effective in visualizing fine cracks, fibre-matrix disbands, and early-stage delamination in thin laminates.

Synchrotron radiation tomography (SRT): Utilizing high-brightness X-ray beams from synchrotron sources, SRT enables nanometre-scale imaging of microstructural defects. SRT studies have revealed complex void morphologies and crack propagation mechanisms in aerospace-grade composites[87]. Dual-energy radiography (DER): By capturing images at two different X-ray energies, DER can differentiate between constituent materials, allowing detection of inclusions or adhesive disbands between dissimilar composite layers.

2.4.5 Industrial Applications and Case Studies

In industry, radiographic and tomographic inspection systems are integral to the manufacturing quality assurance of aerospace, automotive, and wind turbine composites. Automated X-ray scanning systems detect delamination or foreign inclusions during the layup and curing stages, preventing costly failures in service.

For example, the aerospace sector uses digital radiography and CT for periodic inspection of aircraft fuselage panels, where even minor inclusions or porosity clusters can compromise safety[88]. In wind turbine blade production, micro-CT is employed to evaluate adhesive bond integrity and detect voids within thick fibre-reinforced regions[89].

Integration of AI-driven defect segmentation algorithms further enhances reliability and inspection. Deep learning architectures such as U-Net and Mask R-CNN have been trained on CT datasets to automatically segment voids and delamination, achieving accuracy levels exceeding 95% in controlled studies[90].

Emerging real-time radiographic systems with robotic manipulators are now capable of performing inline inspection during production. These systems combine digital X-ray imaging and automated defect recognition (ADR) for continuous quality control[91].

2.4.6 Limitations and Future Trends

Despite their powerful visualization capabilities, radiographic and tomographic methods face several challenges when applied to large-scale composite structures. These include:

- Limited penetration depth in thick, multi-layered laminates
- High cost and complex calibration requirements
- Radiation safety constraints for human operators
- Data management challenges due to massive 3D image datasets

Future trends point toward the integration of hybrid imaging systems combining X-ray CT with ultrasonic or thermographic data, providing multi-modal insights into defect morphology and mechanical implications[92]. The use of AI-assisted reconstruction algorithms, compressed sensing, and quantum-enhanced detectors is expected to reduce scanning time while improving defect detectability.

2.5 Acoustic Emission

Acoustic emission (AE) analysis is a dynamic non-destructive evaluation (NDE) method that have proven highly effective for identifying and monitoring defects in composite structural materials. Unlike traditional inspection techniques that require external excitation (e.g., ultrasound or X-rays), AE method rely on the stress wave energy released during damage initiation or growth within the material itself. Similarly, vibration analysis detects structural irregularities by analysing

deviations in modal parameters such as natural frequencies and damping ratios. Together, these techniques enable real-time damage monitoring and are integral to structural health monitoring (SHM) frameworks for composite systems[93].

2.5.1 Fundamentals of Acoustic Emission (AE)

Acoustic emission see Figure 2.12, refers to the transient elastic waves generated by the rapid release of localized strain energy within a material. In composites, AE signals are commonly associated with processes such as matrix cracking, fibre breakage, fibre-matrix debonding, and delamination.

The AE phenomenon is typically monitored using piezoelectric sensors that convert the elastic waves into electrical signals. These sensors, attached to the composite surface, capture features such as signal amplitude, rise time, counts, and energy, which can then be correlated with specific damage mechanisms[93].

One of AE's principal advantages is its ability to detect active damage progression in real-time under service loads, rather than requiring off-line testing. This makes AE a powerful tool for in-situ monitoring of aerospace, automotive, and wind turbine structures [93].

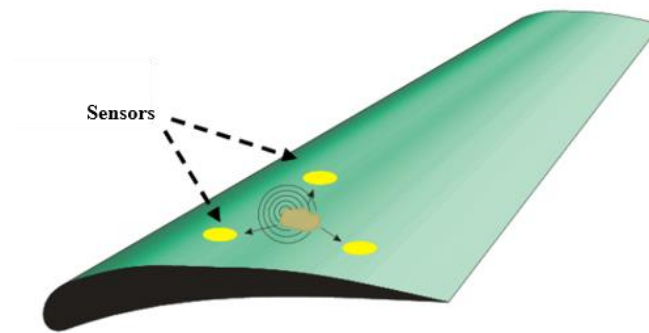


Figure 2.12: Passive SHM acoustic emission (From internet)

2.5.2 Signal Analysis and Feature Extraction

AE data are inherently complex, often containing overlapping signals from multiple damage sources. Effective interpretation requires advanced feature extraction and pattern recognition techniques. Commonly analysed AE features include:

- Amplitude (dB): related to energy release magnitude
- Duration and rise time: linked to crack propagation speed
- Counts: number of threshold crossings, indicative of activity level
- Frequency content: distinguishes between matrix cracking (low-frequency) and fibre breakage (high-frequency) events.

Wavelet transforms and short-time Fourier transforms (STFT) are used to analyse AE signals in both time and frequency domains. These analyses provide valuable insights into damage evolution and help separate concurrent events.

Recent studies employ machine learning algorithms such as k-means clustering, support vector machines (SVMs), and convolutional neural networks (CNNs) to automatically classify AE signals into categories representing different failure modes[94]

2.5.3 AE Source Localization

Accurate localization of AE sources is critical for locating the spatial position of defects within a composite structure. AE localization relies on measuring the time-of-arrival (TOA) differences of signals at multiple sensors. Triangulation algorithms are then used to reconstruct the source location [95].

Due to the anisotropic nature of composite materials, wave propagation velocities vary with fibre orientation and laminate stacking sequence. Therefore, traditional isotropic localization models are inadequate. To address this, velocity calibration maps and numerical simulations using finite element methods (FEM) are often incorporated into AE localization frameworks.

Advanced approaches utilize sensor networks and beamforming algorithms to enhance localization accuracy. For example, integrating beamforming with time-reversal techniques significantly improved delamination detection in CFRP panels under fatigue loading[96].

2.5.4 Damage Mechanism Identification

AE can provide not only the location but also the nature of damage mechanisms. By analysing the frequency–energy and rise time–amplitude relationships of AE signals, distinct patterns corresponding to specific failure modes can be identified. Typical correlations include:

- Matrix cracking: low amplitude (<60 dB), short duration
- Fibre-matrix debonding: intermediate amplitude (60–75 dB)
- Fibre fracture: high amplitude (>75 dB), high-frequency content
- Delamination: wideband frequency with moderate amplitude

Statistical clustering and unsupervised learning methods, such as principal component analysis (PCA) and independent component analysis (ICA), are increasingly applied to AE datasets for automatic damage mechanism discrimination[97].

2.6 Electrical and Electromagnetic techniques

Electrical and electromagnetic non-destructive testing (NDT) techniques as shown in Figure 2.13-provide valuable insight into the electrical, magnetic, and dielectric properties of composite structural materials. These properties are strongly influenced by material composition, fibre orientation, and internal defects such as cracks, delamination, and voids. By monitoring variations in electrical impedance, capacitance, or electromagnetic field response, such methods enable both surface and subsurface defect identification without requiring physical contact or mechanical loading [98].

Electrical methods are especially well-suited for carbon-fibre-reinforced polymer (CFRP) composites, which possess inherent electrical conductivity due to the carbon fibre network. In contrast, glass- or aramid-fibre-reinforced polymers (GFRP/AFRP), which are insulating, often

require integration with conductive protective material or embedded sensors to enable similar diagnostic capability[99].

2.6.1 Eddy Current Testing (ECT)

Eddy current testing operates by inducing localized alternating currents in a conductive material using a time-varying magnetic field. Defects disturb these currents, causing measurable changes in coil impedance that can be correlated with defect type and size. While ECT is traditionally applied to metals, it has been adapted for conductive composites such as CFRPs. The challenge lies in the anisotropic electrical conductivity of CFRPs, which varies with fibre orientation and stacking sequence. To address this, researchers have developed multi-frequency eddy current probes and orthogonal coil configurations capable of detecting delamination and fibre breakage despite directional conductivity variations[100].

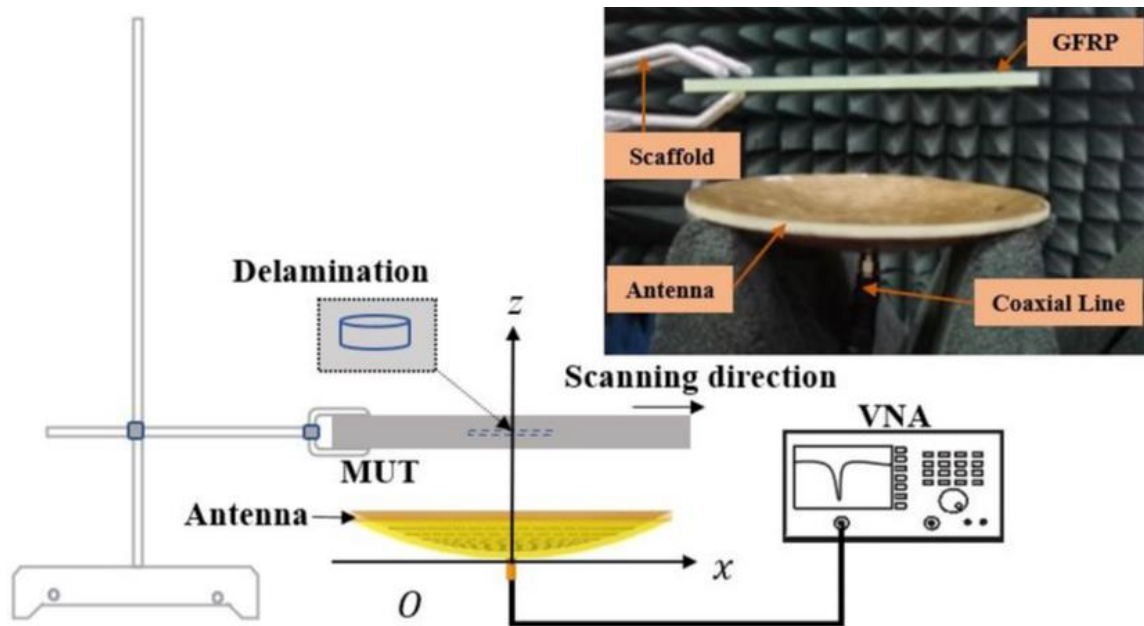


Figure 2.13: Defect detection using electromagnetic technique

High-frequency ECT allows detection of surface-breaking and near-surface defects, while pulsed eddy current (PEC) systems extend the depth of penetration by analysing transient responses.

Studies have demonstrated that PEC imaging can visualize subsurface delamination and impact damage zones in CFRP laminates with improved sensitivity compared to conventional ECT.

Furthermore, array-based ECT systems with automated scanning have enabled high-resolution mapping of large composite structures. Integration of machine learning algorithms-such as convolutional neural networks (CNNs)-has further improved defect classification accuracy by learning characteristic impedance patterns[101].

2.6.2 Electrical Impedance and Resistance Measurements

Electrical impedance and resistance measurements are particularly suitable for CFRP composites due to their intrinsic conductivity. Defects such as fibre breaks, resin cracks, and delamination interrupt conductive pathways, resulting in measurable changes in electrical resistance[102]. Two main approaches are used:

- Direct Current (DC) resistance monitoring – sensitive to large-area defects or damage accumulation.
- Alternating Current (AC) impedance spectroscopy (EIS) provides frequency-dependent information that can differentiate between matrix, fibre, and interfacial degradation.

For instance, Wang et al[103] reported that in CFRP laminates subjected to cyclic fatigue, an increase in through-thickness resistance corresponded closely to delamination growth observed via ultrasonic C-scans. EIS measurements have also been shown to detect moisture absorption and interfacial debonding in polymer matrices, as these phenomena alter dielectric relaxation characteristics. Recent research has explored embedded electrode networks and printed conductive circuits within composites to achieve distributed sensing capabilities. Such smart structures can continuously monitor their own integrity during service[104]

2.6.3 Fibre Bragg Gratings (FBG) and Optical Impedance Sensors

Although primarily optical, fibre Bragg grating (FBG) sensors also operate on principles related to impedance variation and can thus be categorized under hybrid electromagnetic techniques. FBG sensors are embedded or surface-bonded optical fibres that reflect specific

wavelengths of light based on strain and temperature changes. Damage or delamination alters the strain field, resulting in a measurable wavelength shift[105]. In multi-FBG networks, distributed sensing along an optical fibre allows for precise damage localization and quantification in complex composite geometries. Hybrid FBG–electrical impedance systems combine high spatial resolution (from FBG) with sensitivity to electrical conductivity changes, achieving superior defect identification performance.

Advanced interrogation systems using optical frequency domain reflectometry (OFDR) now enable detection of micro-scale defects, such as local resin cracks or early-stage delamination, with spatial resolutions below 1 mm[106].

2.6.4 Electromagnetic Interference (EMI) and Microwave Testing

Microwave and electromagnetic interference (EMI) testing rely on the interaction between electromagnetic waves and composite materials. When a composite component contains defects—such as delamination, voids, or moisture ingress—the dielectric constant and loss tangent are altered, leading to measurable changes in reflection or transmission coefficients.

Microwave NDT offers several advantages over lower-frequency eddy current or impedance methods, including greater penetration depth in non-conductive materials and the ability to inspect multilayer composite assemblies. Both frequency-domain and time-domain reflectometry (TDR) techniques are used to identify internal discontinuities. In one notable study, Saif et al[107] demonstrated that near-field microwave imaging could detect delamination regions as small as 5 mm within thick GFRP panels. Moreover, integrating synthetic aperture(space) radar (SAR) processing with microwave data significantly improved image clarity and defect resolution. Microwave-based sensors are also attractive for in-situ health monitoring, as they can operate through protective coatings and function under harsh environmental conditions, such as high humidity and elevated temperatures[108].

2.6.5 Conductive Nanomaterials for Self-Sensing Composites

Recent advances in nanotechnology have led to the development of self-sensing composites, which incorporate conductive nanomaterials-such as carbon nanotubes (CNTs),

graphene nanoplatelets (GNPs), or metallic nanowires-into the polymer matrix[109]. These nanofillers form permeating networks that provide enhanced electrical conductivity while maintaining mechanical performance. Defect formation disrupts these networks, altering the composite's electrical impedance. By measuring these variations, damage can be detected and quantified in real time. For example, Wang et al. [110] developed a CNT-reinforced epoxy laminate that exhibited linear resistance increases with applied strain, enabling both damage detection and strain monitoring. Similarly, graphene-enhanced GFRP composites demonstrated improved sensitivity to delamination and impact damage due to increased dielectric contrast between damaged and intact regions. The integration of nanomaterial-based self-sensing elements is paving the way for autonomous structural health monitoring (SHM), where composites can self-diagnose and report their condition without external sensors[111].

2.6.6 Hybrid Electrical–Electromagnetic Systems

Hybrid approaches combine multiple sensing mechanisms to overcome the limitations of individual methods. For example, integrating electrical resistance measurement with eddy current imaging enhances both sensitivity and defect localization accuracy.

Emerging AI-driven hybrid systems can correlate electrical, magnetic, and optical sensor data in real time to reconstruct three-dimensional defect maps. These systems leverage deep learning architectures to classify defects and predict their growth trends under operational loading conditions[112].

2.6.7 Limitations and Future Perspectives

Despite significant progress, several challenges remain in the application of electrical and electromagnetic techniques for composite defect detection:

- Anisotropy of electrical conductivity complicates calibration and interpretation.
- Contact quality between sensors and composite surfaces affects measurement repeatability.
- Environmental factors (temperature, humidity) can influence dielectric and impedance properties.

- Signal processing complexity, especially for multi-sensor arrays, requires sophisticated algorithms.

Future directions include the integration of wireless sensor networks, energy-harvesting sensor nodes, and quantum-enhanced electromagnetic sensing, which could radically improve sensitivity and operational autonomy. Moreover, the convergence of AI, digital twins, and embedded sensor technologies promise a new generation of intelligent composite structures capable of self-monitoring, predictive maintenance, and adaptive control[113].

2.7 Thermographic and Infrared Techniques

Thermographic non-destructive testing (TNDT)-also known as infrared (IR) thermography-has emerged as one of the most powerful and versatile techniques for detecting defects in composite structural materials. This method is based on measuring the temperature distribution on the surface of a specimen and interpreting temperature variations as indicators of subsurface anomalies. Because defects such as delamination, voids, or inclusions disrupt the flow of heat through the material, they create detectable thermal contrasts on the surface when subjected to an external or internal heat stimulus.

Infrared thermography offers the advantages of full-field, non-contact inspection, rapid scanning over large areas, and compatibility with automated or in-service monitoring systems. It has found widespread application in aerospace, wind energy, and automotive composite structures, where it is used for quality control, damage assessment, and maintenance diagnostics[114].

2.7.1 Principles of Thermographic Inspection

Thermographic inspection relies on the fundamental principles of heat conduction and diffusion. When heat is applied to a composite surface, it propagates through the thickness of the material according to the Fourier heat equation. Any internal defect alters local thermal conductivity or diffusivity, leading to measurable differences in surface temperature profiles[115].

Thermography systems typically consist of an infrared camera (detector), heating source, and control unit. The temperature data captured by the IR camera are processed to generate

thermograms, which display surface temperature as a function of time and position. The two main modes of thermographic inspection are:

- Passive thermography, where natural temperature differences (e.g., from sunlight or operational heat) are monitored.
- Active thermography, where an external heat source (flash, halogen lamp, laser, or ultrasound) is applied to stimulate a transient thermal response.

2.7.2 Influence of defect depth diffusivity and heating conditions on thermal contrast

The thermal contrast observed in thermography is strongly influenced by defect depth, the thermal diffusivity of the material, and the applied heating conditions. Defects located closer to the inspected surface generally produce higher thermal contrast and are detected earlier because they more effectively disrupt heat flow, whereas deeper defects generate weaker and delayed thermal responses due to increased heat diffusion through the surrounding material. Thermal diffusivity governs the rate at which heat propagates within the specimen, thereby affecting both the magnitude and temporal evolution of the thermal contrast; materials with higher diffusivity exhibit faster heat dissipation and shorter-lived temperature gradients, while lower diffusivity enhances heat retention and can improve defect visibility over longer observation periods. In addition, heating conditions—including the heating mode, excitation energy, pulse duration, and heating uniformity—play a critical role in determining the quality of the thermal response. Appropriate selection of these parameters maximizes the temperature differential between defective and sound regions, thereby enhancing defect detectability, whereas insufficient or excessive heating may reduce contrast or introduce measurement artifacts.

2.7.3 Active Thermography Methods

Active thermography as shown in Figure 2.14, is subdivided into several excitation methods, each suited to different applications and defect types.

- Pulsed Thermography (PT)

In pulsed thermography, a short, intense thermal pulse (typically <10 ms) is applied to the specimen surface. The transient temperature decline is recorded, and subsurface defects are

identified by analysing the cooling rate. Defects closer to the surface produce faster and more pronounced contrasts[116].

PT is especially effective for detecting near-surface delamination and impact damage in thin composite laminates. Modern systems employ high-speed IR cameras and data inversion algorithms to estimate defect depth and size quantitatively.

- **Lock-in Thermography (LT)**

Lock-in thermography (also called modulated or periodic thermography) uses a sinusoidal heating source. By synchronizing the thermal excitation with the IR camera acquisition, phase and amplitude images can be generated. Phase images are less sensitive to non-uniform heating and surface emissivity variations, making LT highly reliable for subsurface defect detection. The phase delay between thermal excitation and surface response provides direct information on defect depth[117]

- **Step-Heating and Pulse-Phase Thermography (PPT)**

Step-heating thermography applies longer, constant heating, while pulse-phase thermography combines PT and LT principles through Fourier analysis of transient thermal signals. PPT has been shown to improve signal-to-noise ratio and detect defects at multiple depths simultaneously[118]

2.7.4 Advanced Thermographic Techniques

Recent advancements have introduced several sophisticated thermographic methods designed to enhance sensitivity and depth resolution in composite materials.

- **Ultrasound Lock-in Thermography (ULT):** In this hybrid method, ultrasonic waves induce localized frictional heating at defect sites, which is captured thermographically. ULT is particularly effective for identifying touching bonds and microcracks that produce minimal optical or ultrasonic contrast.

- **Laser Spot Thermography (LST):** Uses focused laser heating to achieve high spatial resolution and rapid scanning. LST systems can detect millimetre-scale delamination or disbands in aerospace CFRP panels.

- **Thermal Wave Radar Thermography (TWRT):** Employs a linearly modulated heat flux to probe varying depths, generating 3D maps of subsurface defects[119].

- Infrared Shearography Integration: Combined thermography–shearography systems measure both temperature and deformation gradients, improving accuracy in defect size estimation [120].

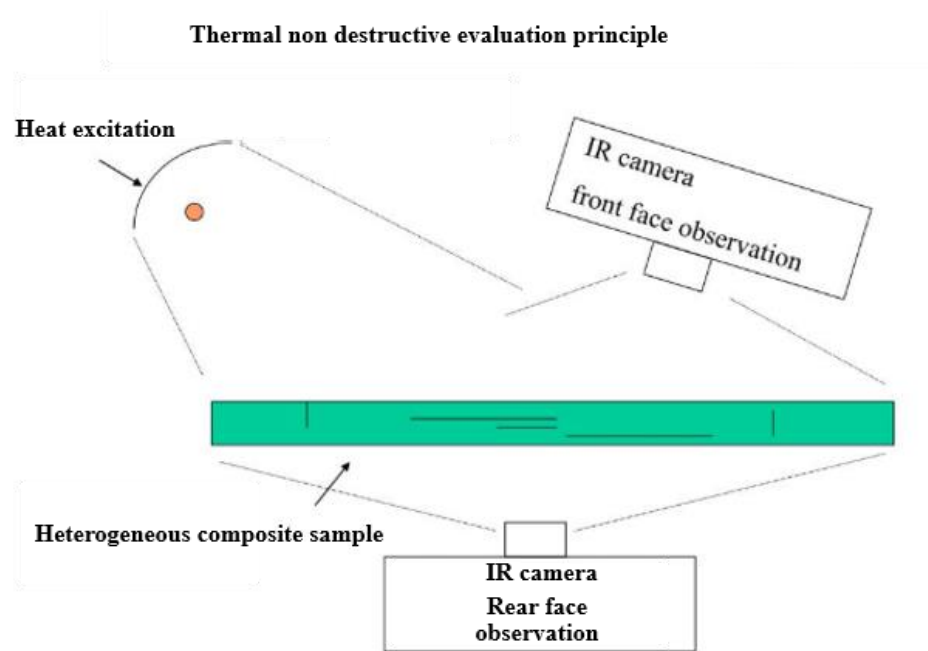


Figure 2.14: Thermal NDE principle (From internet)

Quantitative analysis of thermal data is essential for determining defect geometry and depth. Two primary analytical models are widely used:

1. One-dimensional heat diffusion model: Assumes uniform heat flow through the material thickness; suitable for simple geometries.
2. Three-dimensional finite element (FE) models: Used for complex laminates and anisotropic materials, accounting for thermal conductivity variations along fibre directions.

The thermal contrast (ΔT) between defective and sound regions decreases with defect depth; thus, time-domain analysis or phase-delay evaluation can estimate the location and extent of defects. Advanced inverse problem algorithms-including genetic algorithms and neural networks-have been used to automate defect reconstruction from thermographic data [121].

2.7.5 Thermography for Composite Damage Types

Thermography can detect a variety of defect types in composites, including:

- Delamination: Appearing as localized cooling delays due to reduce through-thickness conduction.
- Matrix cracks: Producing fine linear anomalies in phase or amplitude images.
- Fibre breakage: Causing fine, orientation-dependent heating differences.
- Impact damage: Identified through irregular hot spots correlating with energy absorption regions.
- Moisture ingress or adhesive disbands: Detected via changes in emissivity and heat transfer properties.

For thick laminates, step-heating or modulated thermography is preferred, while pulsed and laser thermography are ideal for thin, high-sensitivity inspections[122].

2.7.6 AI and Data-Driven Thermography

Modern thermographic analysis increasingly incorporates artificial intelligence (AI) and machine learning (ML) to enhance defect interpretation and automate diagnostics. Convolutional neural networks (CNNs) can identify complex patterns in thermal images and classify defect types with high accuracy. Deep learning architectures, such as U-Net and Res-Net, have been applied to segment defect regions in composite thermograms, outperforming traditional threshold-based methods. Additionally, physics-informed neural networks (PINNs) integrate thermal diffusion equations into ML models, improving generalization to new materials and defect geometries[123]. AI-driven thermography also enables real-time inspection in manufacturing environments, where continuous monitoring of curing processes and surface bonding quality is required.

2.7.7 Limitations and Future Trends

Despite its many advantages, thermographic inspection has several essential limitations:

- Depth sensitivity is limited by thermal diffusion; deeper defects produce weaker contrasts.
- Surface emissivity variations and environmental conditions can affect measurement accuracy.
- Quantitative analysis requires calibration and may depend on complex inverse models.

- High computational demand for large-scale 3D data analysis.

Future developments are expected to focus on multi-modal thermography, combining IR data with ultrasound, microwave, or optical coherence tomography for enhanced defect detectability. Additionally, portable IR systems, drone-based inspection, and embedded micro-thermal sensors will extend thermography's reach to in-field and real-time monitoring [124].

Emerging quantum infrared detectors and AI-enhanced image reconstruction are also expected to drastically improve spatial resolution and defect sensitivity beyond the capabilities of current Machine Learning and Data Fusion for Defect Identification

The increasing complexity of composite materials and the vast quantity of data produced by advanced non-destructive evaluation (NDE) systems have driven the integration of machine learning (ML) and data fusion methodologies in defect detection. Traditional signal-based and image-based analyses, though effective, are often time-consuming, subjective, and limited in handling multi-modal datasets. In contrast, ML enables the automated extraction of features, classification of defect types, and prediction of material degradation trends from heterogeneous data sources [296].

Machine learning-driven NDE has transformed defect identification from a diagnostic task into a predictive, real-time structural health monitoring (SHM) process, enabling early fault detection and lifecycle prognosis of composite structures.

2.7.8 Physics-Informed and Hybrid Machine Learning Models

A major limitation of purely data-driven models is their dependency on large, labelled datasets. Physics-informed machine learning (PIML) seeks to overcome this limitation by embedding physical laws-such as wave propagation, heat transfer, or stress-strain relationships-into ML models[125]. PIML enhances generalization and interpretability, ensuring that predictions comply with established physical principles. For example, physics-informed neural networks (PINNs) integrate governing equations directly into the network's loss function, improving accuracy for unseen materials and loading conditions[126].

Hybrid ML simulation models have been developed that combine finite element modelling (FEM) outputs with real experimental data. This approach accelerates model training and allows defect scenarios to be simulated under diverse environmental and loading conditions. Such hybrid frameworks are particularly promising for digital twin (DT) applications, where real-time data from sensors update a virtual model of the structure to predict future damage progression [127].

2.7.9 Real-Time and Edge-Based Implementation

Recent advances in edge computing -edge of the network and sensing devices-and embedded artificial intelligence (AI) hardware have accelerated the deployment of machine learning (ML)-based defect detection systems that operate in real time[128]. Traditional approaches often rely on transmitting sensor data to remote servers or cloud platforms for processing, which introduces communication delays and bandwidth constraints. By contrast, edge-based implementations perform inference directly on embedded platforms located near the sensors, significantly reducing latency and enabling near-instantaneous decision making on the device itself. This architecture supports high-throughput and low-latency processing of time-series data from diverse sensors, such as accelerometers, strain gauges, and acoustic emission (AE) transducers, which is crucial for applications requiring rapid detection of structural anomalies or equipment faults. Real-time edge analytics also minimizes reliance on centralized computation resources and reduces network traffic and energy consumption in distributed monitoring networks[129].

In structural health monitoring (SHM) for aerospace and other safety-critical domains, the transition toward real-time analytics on embedded hardware has been propelled by efficient ML frameworks and lightweight models tailored to resource-constrained devices[130]. Microcontrollers and system-on-chip (SoC) platforms can now host tinyML or EmbeddedAI models that continuously process sensor streams directly at the edge. These systems classify normal versus anomalous structural responses in real time and can trigger alerts or control actions when predefined thresholds are exceeded, thereby enabling prompt interventions.

2.7.10 Explainability, Trust, and Model Validation

For machine learning (ML)-based non-destructive evaluation (NDE) techniques to achieve widespread adoption in safety-critical industries-such as aerospace, nuclear energy, and automotive manufacturing-explainability, transparency, and rigorous validation are essential. Regulatory agencies and industry standards bodies mandate that predictive models not only demonstrate high accuracy but also provide interpretable results that can be traced to underlying physical phenomena[131]. Without this level of transparency, ML systems may be considered “black boxes,” damaging confidence in their deployment for safety-critical inspections.

Emerging explainable AI (XAI) methodologies address this challenge by offering tools to interpret model predictions and link them to physically meaningful features. Techniques such as saliency mapping allow visual identification of the input regions most influential in defect detection within images, while SHAP (Shapley additive explanations) quantitatively attributes the contribution of each feature to a specific prediction. For example, in composite structure inspection, SHAP can highlight which ultrasonic signal characteristics or sensor readings drive the classification of delamination or porosity defects, enabling engineers to validate that the model is relying on physically plausible cues rather than spurious correlations[131].

In addition to explainability, rigorous model validation is critical to ensure reliability under real-world operational conditions. Approaches such as cross-validation provide a systematic way to evaluate performance across diverse datasets, while uncertainty quantification techniques-such as Bayesian neural networks or Monte Carlo dropout-offer insight into the confidence of each prediction. Similarly, outlier detection frameworks help identify inputs for which the model may be unreliable, preventing false alarms or missed defects in critical applications. Together, these methods help establish the robustness of ML-based NDE systems across varying material properties, loading conditions, and environmental factors[132].

The integration of XAI techniques with digital twin environments further enhances trust and traceability. Digital twins, which are high-fidelity virtual replicas of physical systems, can simulate inspection scenarios and compare AI predictions with physically modelled responses. This combination allows for continuous validation and performance monitoring of the ML models,

creating a certifiable and auditable inspection workflow. In the context of next-generation composite structures, this fusion of XAI, uncertainty quantification, and digital twins is expected to enable fully traceable, explainable, and certifiable AI-based NDE systems, meeting the strict safety requirements of modern engineering applications and accelerating the adoption of intelligent inspection technologies[133].

2.7.11 Prospects

The convergence of artificial intelligence (AI), big data analytics, and advanced smart materials is composed to revolutionize the field of non-destructive evaluation (NDE), piloting to a new era of intelligent defect detection and structural health monitoring. This evolution will enable predictive, real-time assessment of material integrity, reducing reliance on traditional periodic inspections and increasing operational safety and efficiency. Several key future directions are emerging:

- **Federated Learning Frameworks:** Future NDE systems are expected to influence federated learning, which allows machine learning models to be trained across multiple facilities or organizations without the need to share sensitive or proprietary data. This approach ensures data privacy while enabling models to benefit from a larger, diverse dataset, improving detection accuracy and generalizability across different composite structures[134].

Autonomous Robotic Inspection Systems: The deployment of autonomous robotic platforms equipped with adaptive machine learning algorithms will enable comprehensive inspection of complex structures with minimal human intervention. These systems can navigate confined or hazardous environments, perform high-resolution sensing, and dynamically adjust inspection parameters based on detected anomalies, ensuring more efficient and reliable defect identification[135].

Multimodal Neural Networks: Advanced neural network architectures capable of fusing multiple types of sensor data-visual imaging, acoustic emissions, electromagnetic signals, and thermal measurements-will provide a more complete understanding of structural health. By integrating these diverse data streams, NDE systems can achieve higher sensitivity, differentiate between

defect types, and detect hidden or subsurface anomalies that would be missed by single-modality approaches.

Self-Evolving AI Models: The next generation of AI in NDE will involve self-evolving models that continuously learn from new inspection data collected during the operational lifetime of structures. These models will adapt to changes in material behaviour, environmental conditions, and usage patterns, enabling predictive maintenance strategies and early intervention before critical failures occur[136].

Ultimately, the integration of machine learning, data fusion, and autonomous sensing technologies will transform NDE from a reactive, periodic inspection paradigm into a continuous, intelligent monitoring system. For next-generation composite structures, this transformation promises enhanced safety, reduced maintenance costs, and extended service life, positioning AI-driven NDE as a cornerstone of modern materials engineering and structural management.

2.8 Conclusion

Defect identification and characterization techniques play a critical role in materials science and engineering because they provide essential information about the structure, integrity, and performance of materials. Throughout this chapter, various methods used to detect and analyse defects have been presented. Each technique offers unique advantages depending on the type of material, the scale of observation, and the nature of the defect being investigated. Non-destructive testing methods, including ultrasonic testing, radiography and eddy current testing, enable defect detection without damaging the material, making them highly important in industrial applications and quality control. Table 2.1 summarizes the most used techniques for all materials.

The study of defect identification techniques demonstrates that no single method is sufficient for all materials and defect types. In practice, combining multiple characterization techniques often provides more accurate and reliable analysis. Advances in modern instrumentation, digital imaging, and automated analysis continue to improve the precision, speed, and efficiency of defect detection. Overall, defect characterization techniques are essential for ensuring material reliability,

improving manufacturing processes, preventing failures, and supporting the development of advanced materials for engineering applications.

Table 2.1: Comparison between identification techniques

Technique	Principle	Typical Detectable Defects	Advantages	Limitations	Best Applicability
Visual Testing (VT)	Direct or remote visual inspection	Surface cracks, corrosion, deformation, misalignment, weld defects	Lowest cost, fast, simple, no equipment (or minimal), first-line inspection	Only visible surface defects, operator dependent	Initial inspection of all components, welds, pipelines, structures
Liquid Penetrant Testing (PT)	Dye penetrates surface-breaking discontinuities	Surface cracks, porosity, seams, laps	High sensitivity, inexpensive, portable, suitable for complex shapes	Detects only surface-breaking defects, requires clean non-porous surface	Metals, ceramics, plastics, welds, castings
Magnetic Particle Testing (MT/MPI)	Magnetic flux leakage attracts magnetic particles	Surface and near-surface cracks, laps, seams	Very sensitive, rapid, inexpensive	Only for ferromagnetic materials, limited penetration depth	Steel structures, forgings, welds, railway components
Ultrasonic Testing (UT)	High-frequency sound waves reflect from discontinuities	Internal cracks, inclusions, delamination, lack of fusion, thickness loss	Deep penetration, high accuracy, immediate results, portable	Skilled operator required, coupling medium needed, difficult on rough surfaces	Thick metals, composites, pressure vessels, pipelines
Phased Array Ultrasonic Testing (PAUT)	Electronically steered ultrasonic beam	Same as UT with improved imaging	High resolution, rapid scanning, 3D imaging, better sizing	Higher equipment cost, advanced training required	Critical welds, aerospace, nuclear, oil & gas
Time-of-Flight Diffraction (TOFD)	Measures diffracted ultrasonic waves	Crack sizing, fatigue cracks, weld defects	Excellent crack sizing accuracy, permanent digital records	Less effective for volumetric defects, requires access to both sides	Pressure vessels, pipelines, structural weld inspection
Radiographic Testing (RT)	X-rays or gamma rays produce internal images	Porosity, inclusions, cracks, voids, lack of fusion	Permanent image, excellent internal visualization	Radiation hazards, expensive, access restrictions, orientation sensitivity	Weld inspection, castings, aerospace components
Digital Radiography (DR)	Digital X-ray detector replaces film	Same as RT	Faster results, image enhancement, no film processing	High equipment cost, radiation safety required	Manufacturing, aerospace, automated inspection
Computed Tomography (CT)	Multiple X-ray projections reconstructed into 3D image	Internal cracks, porosity, inclusions,	Complete 3D characterization, quantitative defect analysis	Very expensive, slow, limited part size	Aerospace, additive manufacturing,

		dimensional defects			electronics, research
Eddy Current Testing (ECT)	Electromagnetic induction	Surface and near-surface cracks, corrosion, conductivity changes	No contact required, rapid, excellent for conductive materials	Conductive materials only, shallow penetration	Aircraft skins, tubing, heat exchangers
Alternating Current Field Measurement (ACFM)	Electromagnetic field disturbance	Surface cracks through coatings	Works through coatings, crack sizing capability	Mainly surface defects, specialized equipment	Offshore structures, marine applications
Remote Field Eddy Current (RFEC)	Low-frequency electromagnetic fields	Corrosion, wall thinning, internal defects in tubes	Inspects ferromagnetic tubes from one side	Mainly tubular components, lower resolution	Heat exchanger and boiler tubes
Infrared Thermography (IRT)	Detects temperature variations	Delamination, disbands, corrosion, moisture, impact damage	Large-area inspection, non-contact, fast	Environmental effects, shallow depth, thermal contrast required	Composites, concrete, electrical systems
Shearography	Laser interferometry detects strain anomalies	Delamination, debonding, impact damage	Large-area inspection, very sensitive for composites	Requires loading, vibration-sensitive	Aerospace composites, wind turbine blades
Acoustic Emission (AE)	Detects transient elastic waves from active damage	Crack growth, fibre breakage, leak detection	Monitors entire structure in real time, detects active defects	Does not detect dormant defects, complex interpretation	Pressure vessels, bridges, storage tanks
Guided Wave Ultrasonics (GWUT)	Guided ultrasonic waves propagate long distances	Corrosion, wall loss, large cracks	Long-range inspection (tens of meters), minimal insulation removal	Limited defect characterization, requires confirmation	Pipelines, rails, long tubular structures
Laser Ultrasonics	Laser generates and detects ultrasonic waves	Internal defects, delamination	Non-contact, suitable for hot or moving parts	Expensive, sensitive to surface conditions	Aerospace, automated manufacturing
Microwave Testing	Microwave interaction with dielectric properties	Moisture, delamination, voids	Non-contact, suitable for non-metallic materials	Limited penetration, material dependent	Composites, concrete, dielectric materials
Terahertz Testing	Terahertz electromagnetic waves	Delamination, inclusions, coating thickness	High resolution, non-ionizing	Limited penetration in conductive materials, costly	Composites, polymers, coatings
Leak Testing (LT)	Detects escaping fluid or gas	Leaks in pressure boundaries	Highly sensitive, quantitative	Does not identify structural flaws directly	Pressure vessels, pipelines, vacuum systems

Chapter 3: Computational Inverse Techniques

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3.1 Introduction

Computational inverse techniques have emerged as indispensable tools for quantitative damage assessment and defect characterization in composite materials. Through the integration of physics-based modelling, optimization, and statistical inference, these methods allow the reconstruction of hidden internal states, such as delamination, fibre-breakage zones, and matrix cracks-from measured non-destructive testing (NDT) data. The evolution of numerical computation, machine learning, and multi-physics modelling has enabled inverse formulations that can efficiently link sensor signals to material degradation phenomena. This section outlines the theoretical framework and computational foundations supporting inverse methods, emphasizing deterministic, stochastic, and hybrid artificial-intelligence-assisted approaches[137].

Direct interpretation of NDT data often fails to provide quantitative information about the internal defect state because the mapping from measured responses to material properties is essentially indirect and ill-posed. To overcome this limitation, computational inverse techniques have been developed to reconstruct the internal physical parameters of a structure from external or surface measurements. These approaches aim to solve an inverse problem in which the governing equations of elasticity, heat transfer, or wave propagation are inverted to estimate unknown material or geometric parameters[138].

Inverse problem formulation is fundamentally rooted in mathematical physics. For a general forward model

$$\mathbf{y} = F(\mathbf{x}) + \boldsymbol{\varepsilon}, \quad (3.1)$$

where $\mathbf{x}$ represents unknown material or defect parameters, F is the physical model operator, and $\boldsymbol{\varepsilon}$ is noise, the objective of inverse analysis is to recover $\mathbf{x}$ from the measurements of $\mathbf{y}$. The difficulty arises because F is often nonlinear and ill-conditioned; small measurement errors can lead to large variations in reconstructed parameters. Regularization strategies and computational optimization algorithms are therefore required to stabilize the inversion[139]

Early inverse analysis techniques in composite materials relied primarily on deterministic optimization, where the inverse problem was reformulated as a minimization of an error functional between measured and simulated data. Gradient-based approaches, adjoint sensitivity analysis, and finite-element-assisted optimization became standard tools. As computational power increased, stochastic and probabilistic frameworks-particularly Bayesian inference and Markov Chain Monte Carlo (MCMC) algorithms-emerged to quantify uncertainty in defect reconstructions. These methods treat material properties as random variables with prior distributions, enabling probabilistic estimates of defect characteristics rather than single deterministic values.

Modern developments have expanded the field toward hybrid and data-driven inversion. With the integration of artificial intelligence (AI) and machine learning, it is now possible to develop surrogate models that approximate the forward operator (F) with high fidelity while significantly reducing computational cost. Neural networks, Gaussian process regressors, and variational autoencoders have been employed to accelerate iterative inversion or to directly infer defect geometry from measured fields. Recent studies demonstrate that physics-informed machine-learning architectures can embed governing equations into the network training process, thereby maintaining physical consistency while learning from sparse data.

In the context of composite structures, these computational inverse strategies are applied to multiple sensing modalities. Thermographic inversion exploits transient heat diffusion to localize subsurface delamination. Ultrasonic inverse scattering reconstructs stiffness variations from reflected wave fields. Electromagnetic and eddy-current inversions reveal conductive anomalies in carbon-fibre-reinforced composites[140]. The fusion of such multi-physics data through inverse modelling has substantially improved the accuracy and reliability of defect detection.

Industrial applications increasingly demand real-time and automated defect identification frameworks. AI-enhanced inversion software, integrated with robotic NDT setups, enable autonomous scanning, signal interpretation, and feedback-based repair operations[141]. These developments represent a fundamental transition from traditional post-processing toward closed-loop digital twins that continuously update the structural state of composite systems during their lifecycle. Overall, computational inverse techniques form the analytical support of modern

composite inspection systems. Their evolution from classical regularized optimization to probabilistic and machine-learning-assisted methods reflects both the complexity of composite behaviour and the growing availability of computational resources. Subsequent sections of this chapter will examine the mathematical structure of inverse problems, present detailed algorithmic frameworks, and analyse emerging hybrid approaches for accurate and efficient defect reconstruction.

3.2 Fundamentals of Inverse Problem Theory

Inverse problem theory provides the mathematical pillar for modern computational defect-identification frameworks. In the context of composite materials, inverse problems arise whenever one seeks to infer hidden material parameters—such as elastic moduli, delamination geometry, or thermal diffusivity—from limited measurement data. The forward problem, by contrast, computes observable quantities (e.g., displacements, temperatures, or wavefields) from known parameters and boundary conditions.

3.2.1 Mathematical Formulation

Let the governing physics of a composite system be described by a set of partial differential equations (PDEs)

$$\mathcal{L}(\mathbf{u}, \mathbf{x}) = \mathbf{f} \text{ in } \Omega, \mathcal{B}(\mathbf{u}) = \mathbf{g} \text{ on } \Gamma, \quad (3.2)$$

where $\mathbf{u}$ denotes the field variables (displacement, temperature, or potential), $\mathbf{x}$ represents spatially varying material parameters, and $\mathcal{L}$ and $\mathcal{B}$ are differential and boundary operators, respectively.

The forward operator $F: \mathbf{x} \mapsto \mathbf{y}$ maps these parameters to measurable responses $\mathbf{y} = F(\mathbf{x})$. The inverse problem seeks an estimate $\hat{\mathbf{x}}$ such that $F(\hat{\mathbf{x}})$ reproduces the measured data $\mathbf{y}_{\text{obs}}$.

In general, F is nonlinear and non-invertible. Small perturbations in $\mathbf{y}_{\text{obs}}$ may produce large deviations in $\hat{\mathbf{x}}$, revealing the ill-posedness of the inverse problem. According to Hadamard's definition, a problem is well-posed only if a solution exists, is unique, and depends continuously

on the data. Inverse NDT formulations often violate one or more of these conditions, motivating the development of regularization techniques[142].

3.2.2 Well-Possedness and Regularization.

The instability of inverse formulations manifests in noise amplification and non-uniqueness of reconstructed material fields. Regularization introduces auxiliary information or constraints to restore stability. The most common approach is Tikhonov regularization, in which one minimizes the functional:

$$J(\mathbf{x}) = \| F(\mathbf{x}) - \mathbf{y}_{\text{obs}} \|^2 + \xi^2 \| L(\mathbf{x} - \mathbf{x}_0) \|^2, \quad (3.3)$$

where L is a smoothing operator, ξ is the regularization parameter, and $\mathbf{x}_0$ is an a priori estimate. The optimal ξ balances fidelity and smoothness and is typically determined via the L-curve or generalized cross-validation methods[143]

Alternative strategies include truncated singular-value decomposition (TSVD), total-variation (TV) regularization for piecewise-constant parameters, and sparsity-promoting L_1 norms suited for localized defects. Total variation (TV) regularization is particularly well suited to composite materials because it preserves sharp spatial gradients associated with interfaces, defects, and ply boundaries while effectively suppressing measurement noise, thereby maintaining the integrity of structural features that are essential for accurate defect characterization.[144].

3.2.3 Sensitivity Analysis and the Adjoint Method

Inverse analysis requires gradients of the objective function with respect to the unknown parameters. Finite-difference gradient evaluation is computationally expensive for high-dimensional problems; thus, adjoint-state methods are employed. The adjoint approach solves an auxiliary PDE derived from the Lagrangian of the constrained optimization problem, allowing efficient computation of sensitivities with respect to thousands of variables at the cost of one additional PDE [145]. This efficiency has made adjoint formulations central to finite-element-based inversion of thermographic and ultrasonic NDT data.

Sensitivity kernels $K(\mathbf{r}) = \partial F / \partial x(\mathbf{r})$ describe how local parameter changes affect global responses. Understanding these kernels provides physical insight into defect detectability: regions with weak sensitivity indicate areas where inversion results are unreliable. Sensitivity-based weighting is often embedded within regularization matrices to enhance spatial resolution.

3.2.4 Variational and Statistical Interpretation

Deterministic regularization methods can be reinterpreted in a Bayesian statistical framework. Minimizing $J(\mathbf{x})$ corresponds to computing the maximum a-posteriori (MAP) estimate under Gaussian noise and prior assumptions. This link between deterministic and probabilistic formulations bridges the coming discussion of stochastic inversion in the following sections. Variational formulations also enable multi-physics coupling. For instance, simultaneous minimization of thermal and acoustic misfits allows joint reconstruction of stiffness and conductivity fields, improving overall robustness[146].

3.2.5 Summary

The mathematical concepts presented before provide the theoretical foundation for solving inverse problems encountered in non-destructive testing (NDT). Because inverse NDT problems are typically ill-posed, regularization techniques are required to obtain stable and physically meaningful solutions, while adjoint-based formulations enable efficient gradient evaluation for large-scale optimization. Furthermore, variational frameworks establish a unified perspective that bridges deterministic optimization methods and probabilistic inference. Building upon these theoretical principles, the following sections examine their implementation in inverse NDT applications, highlighting deterministic, stochastic, and hybrid approaches for defect characterization and material property reconstruction.

3.3 Deterministic Inverse Techniques

3.3.1 Overview

Deterministic inverse techniques approach defect identification as a well-defined optimization problem in which the objective is to minimize the difference between experimentally measured responses and model-predicted signals. Unlike stochastic or probabilistic schemes that

treat model parameters as random variables, deterministic methods compute a unique parameter set that best satisfies a defined cost function. These strategies remain the most widely applied category in computational NDT for composite materials because of their mathematical tractability, efficient gradient computation, and compatibility with finite-element (FE) solvers[147]

3.3.2 Gradient-Based Optimization

Let the misfit functional be:

$$J(\mathbf{x}) = \frac{1}{2} \| F(\mathbf{x}) - \mathbf{y}_{\text{obs}} \|^2 + \frac{\xi^2}{2} \| L(\mathbf{x} - \mathbf{x}_0) \|^2, \quad (3.4)$$

Where $F(\mathbf{x})$ is the forward operator, and L and ξ denote the regularization operator and weight as introduced in 3.2.2. Gradient-based minimization uses the derivative $\nabla_{\mathbf{x}} J$ to iteratively update material parameters:

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - \alpha^{(k)} \nabla_{\mathbf{x}} J(\mathbf{x}^{(k)}), \quad (3.5)$$

with step size $\alpha^{(k)}$ determined through line search. Common algorithms include steepest-descent, conjugate-gradient, and quasi-Newton methods. The Gauss–Newton approach linearizes the forward model about the current iterate,

$$F(\mathbf{x}) \approx F(\mathbf{x}^{(k)}) + J_F(\mathbf{x}^{(k)})(\mathbf{x} - \mathbf{x}^{(k)}),$$

leading to normal equations $(J_F^T J_F + \lambda^2 L^T L) \Delta \mathbf{x} = J_F^T (\mathbf{y}_{\text{obs}} - F(\mathbf{x}^{(k)}))$. With J_F is the Jacobian of function F . This formulation is particularly effective for small-to-moderate nonlinearities.

Regularization plays a crucial role in ensuring convergence to physically meaningful solutions. Adaptive or *iterative* regularization methods modify ξ during optimization based on residual statistics or curvature information. In composite NDT, gradient-based inversion has been used to reconstruct spatially varying stiffness and density fields from ultrasonic wave-propagation data or to identify local thermal diffusivity using transient thermography[148].

3.3.3 Adjoint-State Implementation

Direct evaluation of gradients by finite differences becomes impractical for high-dimensional material models. The adjoint-state method bypasses this by solving an auxiliary PDE that yields gradients at computational cost independent of the number of parameters. For an objective function $J_B(\mathbf{x}, \mathbf{u})$ constrained by governing equations $\mathcal{L}(\mathbf{u}, \mathbf{x}) = \mathbf{f}$, the Lagrangian is:

$$\mathcal{L}_a(\mathbf{x}, \mathbf{u}, \boldsymbol{\psi}) = J_B + \boldsymbol{\psi}^T (\mathcal{L}(\mathbf{u}, \mathbf{x}) - \mathbf{f}), \quad (3.6)$$

where $\boldsymbol{\psi}$ denotes the adjoint variable. Differentiating $\mathcal{L}_a$ with respect to $\mathbf{u}$ yields the adjoint equation, which, once solved, provides gradients $\partial J_B / \partial \mathbf{x}$. This technique is implemented within FE frameworks for ultrasound and guided-wave simulations, enabling full-field inversion of large-scale composite structures[145].

Adjoint-based sensitivity analysis also enables topological and shape optimization for defect detection. By defining design variables representing void regions or damage zones, the method iteratively refines their geometry to minimize residual misfit, providing both localization and quantitative characterization[149]

3.3.4 Finite-Element-Based Inversion

Finite-element (FE) discretization offers flexibility for modelling anisotropy, complex boundaries, and multilayered configurations typical of composite laminates. In deterministic inversion, the FE model serves as the forward operator F . The Jacobian matrix J_F linking parameter perturbations to response variations is computed either analytically or via the adjoint formulation. Robust FE-based inversion frameworks incorporate mesh adaptivity, model-order reduction, and parallel solvers to reduce computational cost.

Recent research combines FE modelling with model-reduction techniques such as Proper Orthogonal Decomposition (POD) or Reduced-Basis (RB) methods to speed up iterative optimization while maintaining high accuracy[150]. These strategies are critical for 3D wave-

propagation problems in large composite panels, where full-scale simulations are computationally expensive.

3.3.5 Regularization-Parameter Selection

The choice of the regularization weight λ strongly influences reconstruction quality. Several deterministic criteria are employed:

- L-curve method: plotting the residual norm versus solution norm to locate the corner point
- Generalized cross-validation (GCV): minimizing prediction error under data perturbations.
- Discrepancy principle: adjusting ξ until the residual equals the expected noise level.

Hybrid methods automatically tune ξ during optimization using Levenberg–Marquardt or trust-region strategies that combine gradient and curvature information. Adaptive selection is especially valuable when spatial noise statistics vary across the domain, as in thermographic imaging of composites[151].

3.3.6 Practical Implementation and Limitations

Despite their mathematical rigor, deterministic inversions are sensitive to model inaccuracies and measurement noise. The quality of results depends on initial guesses, boundary-condition fidelity, and linearization assumptions. Local minima may occur when the objective surface is highly non-convex, motivating stochastic extensions discussed in Section 3.4. Nevertheless, deterministic techniques remain indispensable for high-resolution quantitative reconstructions, providing the core around which probabilistic and hybrid algorithms are built [152].

3.4 Stochastic Inverse Techniques

3.4.1 Overview

While deterministic methods provide single best-fit estimates of unknown material parameters, they often fail to quantify the uncertainty associated with reconstruction results. In practice, experimental noise, modelling errors, and limited data coverage introduce significant ambiguity in inverse solutions. Stochastic inverse techniques address this issue by interpreting the

inverse problem probabilistically, representing unknowns as random variables with probability distributions conditioned on measured data[153]. These techniques not only estimate the most likely solution but also provide confidence intervals and probability maps of defect characteristics, which are critical for risk-informed decision-making in structural health monitoring of composites.

3.4.2 Bayesian Inference Framework

The foundation of stochastic inversion lies in Bayesian inference, where the goal is to determine the *posterior distribution* $p(\mathbf{x} | \mathbf{y}_{\text{obs}})$ of the unknown parameters $\mathbf{x}$ given the observed data $\mathbf{y}_{\text{obs}}$:

$$p(\mathbf{x} | \mathbf{y}_{\text{obs}}) = \frac{p(\mathbf{y}_{\text{obs}} | \mathbf{x}) p(\mathbf{x})}{p(\mathbf{y}_{\text{obs}})}. \quad (3.7)$$

Here, $p(\mathbf{x})$ is the prior distribution encoding pre-existing knowledge, $p(\mathbf{y}_{\text{obs}} | \mathbf{x})$ is the likelihood function describing measurement uncertainty, and $p(\mathbf{y}_{\text{obs}})$ is the normalization constant[154]. For linear-Gaussian systems, the posterior is analytically tractable, yielding the classical Tikhonov regularization as the maximum a posteriori (MAP) estimator. However, for nonlinear or non-Gaussian systems-typical in composite NDT-sampling-based approaches such as Markov Chain Monte Carlo (MCMC) are used. MCMC generates an ensemble of samples approximating the posterior distribution without requiring direct evaluation of the normalization term.

Recent studies in ultrasonic and thermographic imaging have implemented Hamiltonian MCMC and Langevin dynamics to explore high-dimensional parameter spaces efficiently. These methods combine gradient information with stochastic sampling, accelerating convergence relative to traditional algorithms[155]. The resulting posterior ensembles enable direct visualization of uncertainty distributions in defect geometry, stiffness, and anisotropic damage parameters.

3.4.3 Sequential and Ensemble-Based Methods

When real-time or large-scale problems are considered, full MCMC sampling becomes computationally too expensive. Sequential Monte Carlo (SMC) and Ensemble Kalman Filter

(EnKF) algorithms provide efficient alternatives by updating the posterior distribution iteratively as new data arrive.

In composite defect identification, EnKF has been successfully coupled with finite-element forward solvers for adaptive damage tracking, where the ensemble mean represents the current best estimate and the ensemble spread quantifies uncertainty. Ensemble-based techniques are particularly advantageous in online monitoring scenarios, such as fatigue damage evolution under cyclic loading[156].

3.4.4 Evolutionary and Nature-Inspired Algorithms

Besides Bayesian sampling, stochastic inversion can also be achieved via evolutionary computation, where the solution space is explored by population-based search heuristics. The most widely used are Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)[157].

- Genetic Algorithms mimic natural selection, evolving a population of candidate solutions through crossover, mutation, and selection operations. In composite NDT, GAs have been applied to locate multiple delamination in carbon-fibre-reinforced polymer (CFRP) laminates from ultrasonic response data. Their advantage lies in global search capability, avoiding entrapment in local minima typical of gradient-based schemes.
- Particle Swarm Optimization, inspired by collective motion in biological swarms, updates particles' positions and velocities in the search space according to personal and global best experiences. PSO has been effectively employed to estimate ply-wise material properties and defect sizes from thermal wavefront measurements, providing faster convergence than full Monte Carlo searches[158]
- Hybrid stochastic approaches combining GAs, PSO, and Bayesian inference-termed meta-inference algorithms-have recently gained traction. These combine the robustness of population-based search with the statistical rigor of posterior analysis[159].

3.4.5 Uncertainty Quantification and Reliability

Quantifying uncertainty is essential for translating inverse results into engineering decisions. Stochastic inverse analysis naturally provides variance measures that can be propagated through structural models to assess the reliability of predictions. Uncertainty maps can highlight regions with insufficient data sensitivity or model fidelity, guiding sensor placement and experiment design[160].

Bayesian credible intervals (or confidence bounds) are used to express uncertainty in reconstructed parameters, while variance-based sensitivity indices, such as coefficients, identify dominant sources of uncertainty in the forward model. These metrics form a foundation for probabilistic design and maintenance strategies in composite structures[161].

3.4.6 Computational Considerations

The main limitation of stochastic inversion is computational cost, as thousands of forward simulations may be required for convergence. Recent advancements in parallel computing, GPU acceleration, and surrogate modelling have mitigated this issue by approximating the forward model with reduced-order representations.

To further improve scalability, variational Bayesian methods approximate the posterior by optimizing a tractable distribution, balancing accuracy and efficiency. Such methods have been integrated with finite-element and thermographic models for near-real-time defect detection in aerospace-grade composites[162]

3.4.7 Summary

Stochastic inverse techniques provide a probabilistic framework for defect identification, enabling comprehensive uncertainty quantification and robust reconstruction under noisy and incomplete data. Bayesian inference offers a principled theoretical basis, while evolutionary and ensemble-based algorithms provide computational flexibility. These methodologies complement deterministic approaches by extending inversion capabilities to complex, uncertain, and dynamically evolving composite structures[163].

3.5 Machine Learning–Assisted Inverse Techniques

3.5.1 Overview

The rapid evolution of machine learning (ML) and artificial intelligence (AI) has transformed the landscape of inverse problem-solving. Conventional deterministic and stochastic approaches, though mathematically rigorous, are often computationally demanding due to the need for repeated forward simulations. Machine learning–assisted inverse methods aim to bypass or accelerate these computations by constructing *data-driven surrogates* that approximate the forward or inverse mappings. These approaches leverage the representational power of neural networks, regression models, and hybrid physics-informed systems to estimate defect characteristics such as location, geometry, and severity from sensor measurements in composite materials[164].

3.5.2 Surrogate Modelling

A surrogate model is a computationally inexpensive approximation of the forward operator $F(\mathbf{x})$, trained on a database of simulated or experimental input–output pairs. Popular surrogate modelling techniques include Gaussian process regression (GPR), radial basis function networks (RBFNs), and deep neural networks (DNNs). Once trained, the surrogate can be inverted directly via optimization or closed-form evaluation-to recover unknown material parameters. For example, GPR-based surrogates have been employed to reconstruct delamination depth profiles from guided-wave dispersion data, achieving substantial reductions in computational cost compared to full finite-element analyses. Similarly, RBFN models have demonstrated efficient mapping from thermographic image features to local thermal conductivity variations[165]

A critical challenge lies in training-data representativeness: if the surrogate is trained on a limited parameter range or specific defect geometries, it may generalize poorly. Adaptive sampling and active learning techniques address this issue by selectively generating new simulations in regions of high model uncertainty.

3.5.3 Neural Network–Based Inverse Modelling

Deep learning models-particularly convolutional neural networks (CNNs) and autoencoders have proven effective for high-dimensional image-based inversion. CNNs can directly process raw ultrasonic, acoustic, or thermographic images to predict defect maps without explicit physical modelling. Autoencoder architectures compress measurement data into a low-dimensional latent space, from which the inverse mapping to defect parameters is performed through a decoder network. This approach captures complex, nonlinear relationships that traditional inversion methods struggle to represent.

In composite materials, CNN-based models have been trained on synthetic thermographic sequences to identify voids and delamination with over 95% accuracy, while transfer learning enables adaptation to new laminate configurations using limited experimental data[166].

3.5.4 Physics-Informed Neural Networks (PINNs)

A significant advancement in machine learning for inverse problems is the emergence of Physics-Informed Neural Networks (PINNs). These networks integrate governing physical equations-such as elasticity, heat conduction, or wave propagation-into the neural network loss function[167]. This integration allows PINNs to learn inverse mappings even from sparse or noisy data, as the embedded physical laws act as a form of regularization[168].

For composite defect detection, PINNs have been implemented to estimate local stiffness and anisotropy parameters by enforcing equilibrium and compatibility constraints in the learning process. Unlike black-box neural networks, PINNs provide physically consistent reconstructions and reduce dependency on large, labelled datasets.

Recent extensions, such as DeepONets (Deep Operator Networks), generalize the concept of PINNs by learning mappings between function spaces, thereby enabling the prediction of full-field responses from partial measurements. These models have been applied to detect multiple subsurface defects under varying thermal loading conditions[169]

3.5.5 Hybrid FEM–AI Frameworks

Hybrid frameworks that combine finite-element modelling (FEM) with machine learning leverage the strengths of both data-driven and physics-based paradigms. In such frameworks, FEM simulations generate large training datasets under controlled variations of material properties, boundary conditions, and defect morphologies. Machine learning models then serve as fast surrogates or correction layers that compensate for model discrepancies [170].

A prominent example involves the FEM–DNN hybrid inversion for ultrasonic NDT, where neural networks predict material parameter corrections based on mismatches between simulated and measured waveforms. Similarly, thermography-based hybrid models integrate deep networks with analytical heat diffusion models to reconstruct defects in large composite panels within milliseconds.

Such hybridization facilitates real-time defect monitoring, which is otherwise infeasible with purely iterative inversion. Moreover, by integrating uncertainty quantification modules these frameworks can produce probabilistic confidence maps for detected defects[171]

3.5.6 Generalization, Explainability, and Challenges

Despite their promise, machine learning–based inverse models face notable challenges. The generalization problem—ensuring reliable predictions under unseen conditions—remains critical, particularly when environmental or material variability is high. Data absence in experimental NDT further limits the availability of high-fidelity training datasets[172]

Explainable AI (XAI) techniques, such as saliency maps and layer-wise relevance propagation, are increasingly being integrated to interpret the internal reasoning of neural inverse models. This transparency is essential for gaining industrial trust in automated inspection systems. Future directions include transfer learning, multi-task learning, and physics-guided data augmentation, which aim to improve adaptability and robustness of ML-assisted inversions in complex composite structures[173]

3.5.7 Summary

Machine learning assisted inverse methods have redefined the paradigm of defect identification in composites, offering rapid, accurate, and interpretable solutions. By merging data-driven learning with physical modelling, these techniques overcome the limitations of classical inversion and pave the way for real-time, adaptive, and autonomous diagnostic systems.

3.6 Multi-Physics and Hybrid Approaches

3.6.1 Overview

Modern composite materials demonstrate coupled physical behaviours-mechanical, thermal, electrical, and acoustic, which interact during both service and damage evolution. Multi-physics inverse techniques aim to exploit these couplings by integrating multiple sensing modalities and physical models into a unified inversion framework. Unlike single-domain inversion, which may provide incomplete information about complex defect morphologies, multi-physics approaches achieve greater robustness and sensitivity by combining complementary datasets such as ultrasonic time-of-flight, thermal transients, and electromagnetic impedance signatures.

The coupling between distinct physical phenomena requires both consistent mathematical formulation and efficient numerical implementation. Recent developments in hybrid inverse solvers, data-fusion schemes, and multi-domain regularization have made such integration computationally feasible for practical composite inspection systems[174].

3.6.2 Coupled Physical Inversion Frameworks

In multi-physics inverse modelling, multiple forward models $F_i(\mathbf{x})$ corresponding to different physical processes are solved simultaneously, each producing measurement predictions $\mathbf{y}_i$. The global objective function becomes:

$$J(\mathbf{x}) = \sum_{i=1}^N w_i \| F_i(\mathbf{x}) - \mathbf{y}_{i,\text{obs}} \|^2 + \xi^2 \| L(\mathbf{x} - \mathbf{x}_0) \|^2, \quad (3.8)$$

where w_i are weights balancing the contribution of each physics domain.

This formulation has been implemented for thermo-elastic and acoustic-ultrasonic coupling, where heat diffusion and elastic wave propagation share correlated defect signatures. Thermal anomalies indicate low-conductivity regions, while ultrasonic reflections localize discontinuities. Combining these responses improves the reconstruction accuracy of subsurface delamination and micro-cracks in CFRP panels.

Electro-mechanical and electromagnetic-thermal coupling have also been used for conductive composite materials reinforced with carbon fibres. Electrical impedance tomography (EIT) and eddy-current thermography are integrated through joint inversion schemes, capturing both conductivity and stiffness degradations[175]

3.6.3 Data Fusion and Multi-Modal Learning

Beyond physics-based coupling, data fusion combines heterogeneous experimental measurements to enrich the information content of inverse analyses. Fusion strategies are classified as:

- Signal-level fusion, integrating raw temporal or spatial data before inversion.
- Feature-level fusion, merging extracted features such as texture descriptors, time–frequency signatures, or modal parameters.
- Decision-level fusion, combining separate inversion outcomes via probabilistic weighting or Bayesian updating[176].

For instance, thermal and ultrasonic features fused through principal component analysis (PCA) and fed into neural inverse models have achieved higher detection rates for barely visible impact damage (BVID) in aerospace composites. Deep learning architectures such as multi-modal CNNs and cross-attention transformers further enhance this process by learning inter-domain correlations automatically.

These strategies form a bridge between the deterministic, stochastic, and machine-learning models discussed earlier yielding hybrid solutions that incorporate physical constraints and data-driven adaptability simultaneously.

3.6.4 Multi-Physics Case Studies

Several studies demonstrate the efficacy of multi-physics inversion:

- Thermo-Ultrasonic Joint Inversion: Simultaneous reconstruction of defect depth and delamination area by coupling transient heat diffusion and ultrasonic scattering equations[177].
- Electromagnetic–Thermal Coupling: Eddy-current excitation induces localized heating near subsurface flaws, with inverse thermal analysis revealing conductivity loss zones.
- Acousto-Optic Hybrid Systems: Integration of laser ultrasonics and digital holography to infer both surface and subsurface damage fields with micrometre precision[178].

These case studies consistently demonstrate improved detection reliability, reduced ambiguity, and enhanced quantitative estimation of defect parameters compared with single-physics inversions.

3.6.5 Computational and Practical Challenges

The primary challenges in multi-physics inverse analysis include computational cost, data synchronization, and inter-model calibration. Disparate temporal and spatial resolutions between sensing modalities necessitate co-registration and scale normalization. Efficient solvers employing domain decomposition, reduced-order modelling, and parallel GPU implementations have been developed to address these bottlenecks[179].

Furthermore, hybrid inverse solvers require rigorous uncertainty propagation across coupled domains. Bayesian hierarchical models and ensemble Kalman filters are increasingly adopted to quantify joint uncertainty and improve confidence in reconstructions. As computational resources and multi-sensor instrumentation continue to advance, fully integrated digital twins for composite structures are expected to become practical within the next decade[180].

Computational inverse methods have become powerful tools in modern defect identification and characterization, enabling the accurate estimation of hidden material defects from experimental or simulated response data. Throughout this chapter, various inverse approaches used in materials science have been discussed, including optimization-based methods, finite element model updating, statistical and probabilistic techniques, regularization methods, machine learning approaches, and artificial intelligence-based algorithms. These techniques provide efficient ways to solve complex defect detection problems that are often difficult or impossible to address using direct experimental methods alone.

3.7 Conclusion

The application of inverse techniques has significantly improved the ability to detect, localize, and quantify defects in different classes of materials and structures. By combining computational modelling with experimental measurements such as ultrasonic signals, thermal responses, electromagnetic data, or imaging information, inverse techniques allow researchers to reconstruct internal material conditions with high precision. Their use has become increasingly important in non-destructive evaluation, structural health monitoring, quality control, and predictive maintenance.

Despite their advantages, inverse problems are often mathematically complex, ill-posed, and computationally demanding. Challenges such as sensitivity to noise, non-uniqueness of solutions, and high computational cost require careful model formulation and advanced numerical strategies. Recent developments in high-performance computing, data-driven modelling, and machine learning have greatly enhanced the robustness and efficiency of these methods, opening new possibilities for real-time defect identification and automated material inspection.

Overall, computational inverse methods represent a rapidly advancing field that bridges materials science, applied mathematics, and computational engineering. Their continued development will contribute to more reliable defect detection systems, improved material performance, and the advancement of intelligent diagnostic technologies for future engineering applications.

Chapter 4: Vibration-Based Methods

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4.1 Introduction

Vibration-based defect identification is a non-destructive technique that evaluates changes in the dynamic response of composite structures, such as natural frequencies, damping ratios, and mode shapes-to detect and localize damage. Because defects alter the local stiffness, mass distribution, or boundary conditions of a structure, they produce measurable changes in its vibrational characteristics. These changes can be used as diagnostic features to judge the presence, type, and severity of defects.

Compared with localized inspection methods (ultrasonic or thermographic), vibration-based techniques are global approaches, they can assess the overall integrity of large composite components without scanning every region individually. This makes them especially suitable for aerospace panels, wind-turbine blades, and automotive chassis, where full-field inspection is otherwise time-consuming or impractical[181].

4.2 Fundamental Principle

The vibration behaviour of a composite structure is governed by the generalized eigenvalue problem:

$$(K - \omega^2 M)\phi = 0, \quad (4.1)$$

where K and M denote the global stiffness and mass matrices, ω the natural frequency, and ϕ the mode shape vector. A defect such as delamination, matrix cracking, or fibre breakage reduces local stiffness, leading to a decrease in natural frequencies and alterations in mode shapes[182].

The essence of vibration-based defect identification lies in comparing measured modal parameters with baseline (healthy) data or with predictions from a finite-element (FE) model. The difference between the two provides the input for inverse algorithms that estimate defect characteristics.

4.3 Modal Parameter Extraction

Accurate defect detection depends on reliable extraction of modal properties from experimental data. The most widely used techniques include:

- Experimental Modal Analysis (EMA): Uses impact hammer or shaker excitation and measures acceleration or strain responses at multiple locations.
- Operational Modal Analysis (OMA): Extracts modes under ambient excitation (e.g., wind or engine vibration), suitable for in-service monitoring.
- Frequency Response Function (FRF) Analysis: Computes transfer functions between input and output signals to identify resonant peaks.

Modern methods employ Laser Doppler vibrometers (LDV) and 3D scanning systems to capture full-field vibration data without physical contact[183]. These provide high-resolution modal information essential for inverse identification.

4.4 Modal-Based Defect Indicators

Defects are typically identified using one or more of the following vibration-based indicators:

1. Natural Frequency Shifts (Δf): Damage reduces local stiffness, causing measurable decreases in natural frequencies. Although sensitive, this method is global.
2. Mode Shape Curvature (MSC): The curvature of mode shapes is proportional to bending strain energy. Local anomalies in MSC indicate stiffness reductions near defects.
3. Modal Assurance Criterion (MAC): Quantifies the correlation between healthy and damaged mode shapes. A drop in MAC value at specific sensor locations signals local damage[184]
4. Frequency Response Change (FRC): Compares changes in FRF magnitude and phase across frequencies. FRC provides a broadband signature sensitive to multiple defect types[185].
5. Strain Energy Distribution (SED): Identifies energy concentration zones that deviate from baseline due to delamination or debonding[186].

4.5 Inverse Algorithms for Damage Localization

Once vibration features are extracted, inverse techniques are applied to determine defect parameters. Several computational approaches are employed:

- **Sensitivity-Based Methods:** The sensitivity of modal parameters to stiffness changes is computed using derivatives of eigenvalues with respect to material properties. By solving the inverse sensitivity equation, the defect location and severity can be estimated.
- **Model Updating Techniques:** A finite-element model of the composite structure is iteratively updated to minimize differences between measured and predicted frequencies or mode shapes. Regularization ensures stability against measurement noise[187].
- **Optimization and AI-Based Methods:** Genetic algorithms (GAs), particle swarm optimization (PSO), and neural networks (NNs) have been widely employed to establish relationships between measured vibration features and defect parameters, enabling automated defect identification and characterization in complex anisotropic composite structures. Their ability to capture highly nonlinear interactions and explore large, multimodal solution spaces makes them particularly effective for inverse problems involving heterogeneous materials and intricate geometries. However, the computational cost of these approaches varies considerably. Population-based optimization algorithms, such as GAs and PSO, often require a large number of objective function evaluations to achieve convergence, making them computationally demanding when each evaluation involves a high-fidelity finite element or Multiphysics simulation. This challenge becomes more pronounced in large-scale inverse problems or when real-time damage assessment is required. In contrast, neural network-based methods typically incur substantial computational expense during the training phase, as they require extensive datasets and iterative parameter optimization. Once trained, however, they provide rapid inference, enabling near real-time prediction of defect characteristics with minimal computational overhead. To address the high computational demands of optimization-based inversion, recent studies have increasingly integrated surrogate models, reduced-order models, and

parallel computing techniques to accelerate convergence while maintaining acceptable levels of accuracy [188]

4.6 Advanced Methods and Innovations

4.6.1 Wavelet and Time–Frequency Analysis

Wavelet transforms and empirical mode decomposition (EMD) decompose vibration signals into localized time–frequency components. Local anomalies in wavelet coefficients indicate the presence of defects without requiring a baseline.

4.6.2 Operational Deflection Shapes (ODS):

ODS techniques visualize real-time deformation patterns under harmonic excitation. Variations in deflection amplitude across the structure reveal stiffness discontinuities caused by delamination or cracks[189].

4.6.3 Machine Learning and Data-Driven Fusion

Recent developments integrate vibration features (natural frequencies, curvatures, wavelet energies) with machine learning algorithms—such as support vector machines (SVM), convolutional neural networks (CNN), and autoencoders—to classify defect types. These models can identify multi-site damage and generalize across varying boundary conditions.

4.6.4 Smart Sensors and Distributed Monitoring

Distributed piezoelectric sensors and fibre Bragg grating (FBG) arrays enable continuous vibration monitoring. These systems feed real-time data to inverse algorithms, forming the basis for digital twin–enabled SHM[190].

4.7 Advantages and Limitations

Advantages:

- Global coverage with relatively simple instrumentation.
- Sensitive to early stiffness degradation.

- Compatible with online or operational monitoring.

Limitations:

- Limited spatial resolution compared to ultrasonic imaging.
- Requires accurate boundary-condition modelling.
- Influenced by environmental variations (temperature, humidity, load).

Hybridizing vibration-based detection with thermographic or ultrasonic inversions can overcome these limitations by combining global sensitivity with local accuracy.

4.8 Conclusion

Vibration-based defect identification remains one of the most versatile and scalable diagnostic approaches for composite materials. Through modal analysis, inverse modelling, and emerging AI integration, it provides a non-intrusive pathway to assess structural integrity in real time. Continued advancements in sensor networks, data fusion, and digital twin modelling are expected to enhance its role in next-generation structural health monitoring systems.

Chapter 5: Present approach for delamination identification in beams

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5.1 Introduction

Delamination characterization in composite laminates is a crucial aspect of structural analysis, aiming to understand the nature and implications of this form of damage. Various methods are employed to quantify and assess delamination, including non-destructive techniques such as ultrasonic testing[191], thermography[192], and acoustic emission monitoring[193]. These methods allow for the identification of delamination size, location, and progression without causing further harm to the material. Additionally, non-destructive testing methods like microscopy and shearography provide in-depth insights into the morphology of delamination, aiding in understanding initiation mechanisms and failure modes. Characterization also involves employing fracture mechanics concepts, such as assessing the mode of delamination, to predict crack growth and devise effective repair strategies. Material property evaluations such as Interlaminar Shear Strength (ILSS)[194] contribute to a comprehensive understanding of delamination behaviour. Ultimately, delamination characterization plays a pivotal role in ensuring the structural integrity and reliability of composite laminates, guiding decisions on maintenance, repair, and future material development.

The dynamic behaviour of delaminated beams has been investigated analytically. For example, Wang and Liut [195] have studied the free vibration of split beams, Mujumdar and Suryanarayan[196] have presented an analytical forward model for isotropic beams with delamination. There are several analytical forward models available in the literature. For example, there are the free mode model and the constrained mode model. In the free mode model, it is assumed that the four sub-beams move freely[195]. In the constrained mode model, the sub-beams above and below the delamination are constrained to move together. This model is more accurate, especially for delamination located on the midplane of the beam[196]. For identifying delamination parameters using modal frequencies, an inverse model is necessarily based on the forward analytical models (constrained and free mode models). According to our research in the literature, there are no analytical inverse models available in the literature.

In this chapter, we present our approach which seeks to identify delamination in beams using an analytical inverse model. In this model, the first three natural frequencies, which correspond to a real delaminated beam, are given as input to find the delamination position and size. Based on the

forward constrained mode model, we compose a system of nonlinear equations from three characteristic equations. Each characteristic equation is the determinant of the continuity and boundary conditions matrix. These characteristic equations are in terms of four independent parameters: horizontal position a , vertical position d , delamination size b and natural frequency λ , where the fourth parameter λ is a given parameter. The solution of the system of nonlinear equations represents the desired delamination parameters (a , d and b). We use a graphical technique in order to find the solution as in [197]. The main advantage of this inverse model is to find an accurate solution rapidly without using frequencies of pristine beams or comparing with modal models.

5.2 Methodology

The natural frequency-based method is a well-known technique for identifying delamination in materials. It operates on the principle that the presence of delamination alters the stiffness and mass distribution of the structure, leading to changes in its natural frequencies. The present approach uses natural frequencies f_i as inputs for an inverse model based on analytical system of equations. This approach consists of two stages: forward modelling and inverse modelling.

The forward modelling stage begins by defining the geometry, material properties, boundaries and environment conditions surrounding the structure. The calculation of natural frequencies involves solving the equation where the determinant of a coefficient matrix A equals zero. This determinant is a function of the delamination parameters X and the frequency.

The inverse modelling begins by considering a set of natural frequencies obtained from experimental measurements. Using the same determinant function $F_1(A(X, \lambda))$, built in the forward modelling stage, an equation is formed for each frequency. Solving the system of equations F_2 in terms of the delamination parameters allows the identification of these parameters. The details of this approach are provided in the synoptic scheme in Figure 5.1.

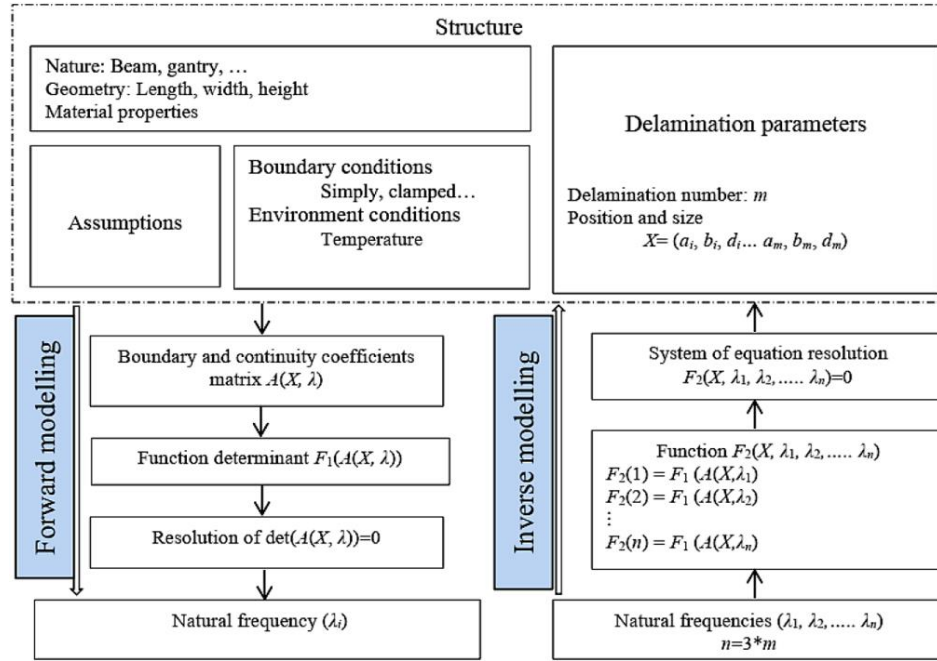


Figure 5.1: Present new inverse approach

5.3 Model of isotropic beams

To validate the proposed inverse approach a beam with a single delamination is considered as shown in Figure 5.2. In the forward modelling phase, the constrained mode model is employed, and three different boundary conditions are examined: clamped-clamped, cantilever and clamped-simply supported beams. For this model, eight continuity conditions are considered: continuity of displacement, slope, bending moment, and internal shear force. Each side of the delamination introduces four continuity conditions. Additionally, boundary conditions are applied, leading to a system of twelve equations in total. The details of direct and inverse modelling are explained in the following sections.

5.3.1 Forward modelling

The investigation of the free vibration behaviour of delaminated beams has garnered scholarly attention spanning over five decades, commencing with important works documented in references[195] and up to contemporary research efforts[198] [199]. Consequently, various analytical models have been proposed and discussed in the literature[195] [196]. Among these models, the constrained mode model presented in reference[196] appears to be particularly simple.

This section presents key aspects of the constrained mode model's development, starting from foundational assumptions and ending with the delaminated beam natural frequencies.

5.3.2 Assumptions

To avoid complexities in modelling and analysis, the following assumptions are made:

- The beam is homogeneous and isotropic.
- Only a single delamination is considered.
- There is no gap between layers at the delamination region.
- The beam is subdivided into four segments as shown in Figure 5.2, where each segment is considered as a Euler–Bernoulli beam.
- The two segments of the delaminated region have the same transverse displacement.
- The rotational displacement is neglected compared to the vertical displacement.

5.3.3 Modelling

The beam has three regions, the delamination region and two integral regions, as shown in Figure 5.2. The left integral region is the segment 1, and the right integral region is the segment 4. The delamination region contains two segments: the segment 2 above the delamination plane, and the segment 3 below the delamination plane. The calculation of the natural frequency of the delaminated beam involves satisfying the boundary conditions at the ends of the beam and the continuity conditions (displacement, slope, bending moment, and shear force) at the junctions between the integral and delaminated regions. In the constrained mode model, a contact pressure distributed between the adjacent layers is considered to avoid overlapping of each layer over the other layer. This pressure distribution P ensures the compatibility and constrains the two adjacent layers to deform simultaneously. The dynamic equilibrium of an infinitesimal element leads to:

$$V - \left(V + \frac{\partial V}{\partial z} dz \right) + q(z, t) dz = \rho A dz \frac{\partial^2 u}{\partial t^2}$$

Simplifying:

$$\left(-\frac{\partial V}{\partial z}\right) + q(z, t) = \rho A \frac{\partial^2 u}{\partial t^2}$$

Substitute: $V = \frac{\partial M}{\partial z}$ and knowing that: $M = -EI \frac{\partial^2 u}{\partial z^2}$

The equation of motion is become:

$$EI \frac{\partial^4 u}{\partial z^4} + \rho A \frac{\partial^2 u}{\partial t^2} = q$$

For the sub-beam 1 and 4 the equation of motion is:

$$EI \frac{\partial^4 u}{\partial z^4} + \rho A \frac{\partial^2 u}{\partial t^2} = 0 \quad (5.1)$$

The separation of variables leads to: $u(z, t) = \phi(z).T(t) \Rightarrow EI \frac{\phi''''}{\phi} = -\rho A \frac{\ddot{T}}{T} = cte$

The temporal equation becomes: $\ddot{T} + \omega^2 T = 0 \Rightarrow T(t) = k_1 \cos(\omega t) + k_2 \sin(\omega t)$

The spatial equation becomes: $\phi'''' - \lambda^4 \phi = 0$, $\lambda^4 = \frac{\rho A \omega^2 L^4}{EI}$

The general solution is given by:

$$\bar{u}_i(z_i) = A_i \sinh(\lambda_i \bar{z}_i) + B_i \cosh(\lambda_i \bar{z}_i) + C_i \sin(\lambda_i \bar{z}_i) + D_i \cos(\lambda_i \bar{z}_i), \quad (5.2)$$

Where:

- A_i, B_i, C_i and D_i are coefficients.
- $\lambda_i = \rho A (2\pi f_i)^2 L^4 / (EI)$
- ρ : Density
- A : Beam cross section
- L : Beam length

- E : Young modulus
- I : Second moment of inertia of the considered segment.

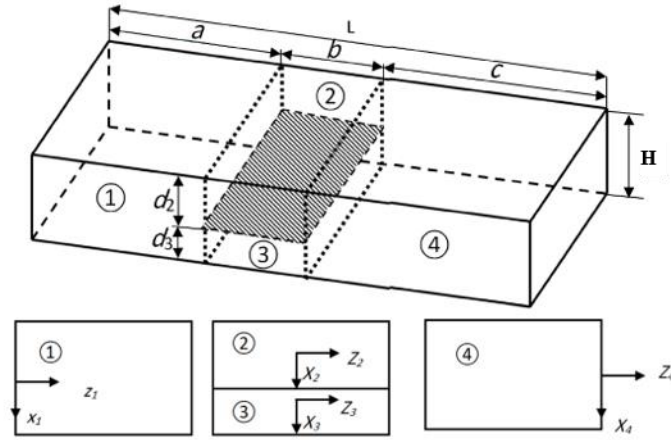


Figure 5.2: Beam divided into four segments.

5.3.4 Boundary conditions

The type of boundary condition applied depends on the end support. Table 5.1 presents the appropriate boundary conditions.

For example, let's consider a clamped-clamped beam. The boundary conditions of this beam are clamped at both ends. Using Table 5.1 above, we can write:

- At the left side $z_1=0$ we have:

$$u_1(0) = 0, \frac{\partial u_1}{\partial z}(0) = 0$$

- At the right side $z_4=0$, (see Figure 5.2) we have

$$u_4(0) = 0, \frac{\partial u_4}{\partial z}(0) = 0$$

By substituting in (1), we obtain:

$$B_1 + D_1 = 0, \quad (5.3)$$

$$A_1 + C_1 = 0, \quad (5.4)$$

$$B_4 + D_4 = 0, \quad (5.5)$$

$$A_4 + C_4 = 0, \quad (5.6)$$

Table 5.1: Boundary conditions.

Support type	Boundary condition
Free	$\frac{\partial^2 u_i}{\partial z^2} = 0, \frac{\partial^3 u_i}{\partial z^3} = 0$
Simple	$u_i = 0, \frac{\partial^2 u_i}{\partial z^2} = 0$
Sliding	$\frac{\partial u_i}{\partial z} = 0, \frac{\partial^3 u_i}{\partial z^3} = 0$
Clamped	$u_i = 0, \frac{\partial u_i}{\partial z} = 0$

5.3.5 Continuity conditions

The continuity conditions are applied between the delaminated region and integral regions. These conditions are displacement continuity, slope continuity, shear force and bending moment continuity. The continuity conditions are expressed for the continuity between the segments 1, 2 and between the segments 1 and 3. By similarity, the continuity conditions between segment 4 segments 2 and 3 are found.

- Displacement continuity:

$$\bar{u}_1(\bar{a}) = \bar{u}_2\left(-\frac{\bar{b}}{2}\right), \quad (5.7)$$

- For the same example of a Clamped-Clamped beam, this condition at the point

$(z_1 = \bar{a}, z_2 = -\bar{b}/2)$ can be written as:

$$\begin{aligned}\bar{u}_1(\bar{a}) - \bar{u}_2\left(-\frac{\bar{b}}{2}\right) &= A_1 \sinh(\lambda_1 \bar{a}) + B_1 \cosh(\lambda_1 \bar{a}) + C_1 \sin(\lambda_1 \bar{a}) + D_1 \cos(\lambda_1 \bar{a}) \\ -A_2 \sinh\left(-\lambda_2 \frac{\bar{b}}{2}\right) - B_2 \cosh\left(-\lambda_2 \frac{\bar{b}}{2}\right) - C_2 \sin\left(-\lambda_2 \frac{\bar{b}}{2}\right) - D_2 \cos\left(-\lambda_2 \frac{\bar{b}}{2}\right) &= 0,\end{aligned}$$

- Using the same method, the displacement continuity for a Clamped-Clamped at the point $(z_2 = \frac{\bar{b}}{2}, z_4 = -\bar{c})$ can be expressed.
- Slope continuity:

$$\frac{\partial \bar{u}_1}{\partial \bar{z}}(\bar{a}) = \frac{\partial \bar{u}_2}{\partial \bar{z}}\left(-\frac{\bar{b}}{2}\right), \quad (5.8)$$

- Shear forces continuity:

$$-EI \frac{\partial^3 \bar{u}_1}{\partial \bar{z}^3}(\bar{a}) = -E(I_2 + I_3) \frac{\partial^3 \bar{u}_2}{\partial \bar{z}^3}\left(-\frac{\bar{b}}{2}\right), \quad (5.9)$$

- Or in dimensionless form:

$$\frac{\partial^3 \bar{u}_1}{\partial \bar{z}^3}(\bar{a}) = (\bar{d}_2^3 + \bar{d}_3^3) \frac{\partial^3 \bar{u}_2}{\partial \bar{z}^3}\left(-\frac{\bar{b}}{2}\right), \quad (5.10)$$

- Bending moment continuity:

$$\frac{\partial^2 \bar{u}_1}{\partial \bar{z}^2}(\bar{a}) = (\bar{d}_2^3 + \bar{d}_3^3) \frac{\partial^2 \bar{u}_2}{\partial \bar{z}^2}\left(-\frac{\bar{b}}{2}\right) - \frac{P_d L^2}{2EI}, \quad (5.11)$$

With:

$$\frac{P_d L^2}{2EI} = 3(\bar{d}_2 \bar{d}_3 / \bar{b}) \left(\frac{\partial \bar{u}_1}{\partial \bar{z}}(\bar{a}) - \frac{\partial \bar{u}_4}{\partial \bar{z}}(-\bar{c}) \right),$$

In conclusion, our delaminated beam model involves four boundary equations at the two ends. Alongside these, we have eight continuity equations, making a total of twelve equations with twelve unknowns.

- The unknowns are: $Y = (A_1, B_1, C_1, D_1, A_2, B_2, C_2, D_2, A_4, B_4, C_4, D_4)^T$.
- The system of equations is:

$$AY = 0. \quad (5.12)$$

Such that matrix A is a 12×12 which depends on a , b , d , and f_i (the frequency), for the same example (clamped-clamped beam), the non-zero values of the first line of A are:

$$A(1,2)=1; A(1,4)=1;$$

the non-zero values of lines 2, 3, 4, and 5 are :

$$A(2,1)=1; A(2,3)=1;$$

$$A(3,10)=1; A(3,12)=1;$$

$$A(4,9)=1; A(4,11)=1;$$

$$A(5,1)=(\sinh(\lambda_1 a)); A(5,2)=\cosh(\lambda_1 a); A(5,3)=\sin(\lambda_1 a); A(5,4)=\cos(\lambda_1 a);$$

$$A(5,5)=-\sinh(\lambda_2(-b/2)); A(5,6)=-\cosh(\lambda_2(-b/2)); A(5,7)=-\sin(\lambda_2(-b/2)); A(5,8)=-\cos(\lambda_2(-b/2))$$

The other lines of A are found by the same way, while the frequency λ_2 is calculated by (10)

5.4 Model of composite beams

The free vibration behaviour of delaminated composite beams has been the subject of substantial research, beginning with foundational works[200][201][202]and continuing through contemporary studies[203]. Unlike isotropic beams, composite laminated beams exhibit anisotropy, layer-dependent mechanical properties, coupling effects between bending and extension, and geometry-dependent stiffness that must be carefully incorporated into the modelling framework. Various analytical models have been proposed in the literature[200], [204]. Among these, the constrained mode model is adopted here for its relative simplicity and suitability for extension to the laminated case.

5.4.1 Assumptions

To make the problem tractable while retaining the essential physics of composite delaminated beams, the following assumptions are considered:

- The beam is composed of linearly elastic, orthotropic laminae stacked along the thickness direction.
- Each lamina has fibre orientation defined in the laminate stacking sequence.
- Only a single delamination, lying parallel to the laminate mid-plane, is considered.
- There is no gap or contact pressure between the delaminated sub-laminates other than the distributed constraint pressure introduced by the constrained mode assumption.
- The beam is subdivided into four segments as shown in Figure 5.2, where each segment is treated as an equivalent Euler-Bernoulli beam governed by Classical Lamination Theory (CLT).
- Within the delaminated region, the two sub-laminates (segments 2 and 3) are constrained to undergo the same transverse displacement (constrained mode assumption), preventing interpenetration.
- Rotary inertia and transverse shear deformation are neglected (thin beam assumption, valid when $L/h \gg 1$). For thick composites, a higher-order shear deformation theory should be used instead.
- The delamination is assumed to be perfectly flat and located at a distance d from the top surface, measured through the laminate thickness h .

5.4.2 Modelling

The beam geometry and segment definitions follow identically to the isotropic case see Figure 5.2. The left integral region is segment 1, the right integral region is segment 4, and the delaminated region contains segment 2 (upper sub-laminate) and segment 3 (lower sub-laminate).

The fundamental difference from the isotropic model lies in the effective stiffness of each segment. For a composite laminated beam governed by CLT, the bending behaviour is characterised by the laminate stiffness matrices A_{II} , B_{II} and D_{II} , corresponding to extensional, bending-extension coupling, and bending stiffness, respectively. For a general unsymmetric laminate, bending and stretching are coupled through B . However, for a symmetric laminate (the most common engineering case), $B_{II} = 0$, and the effective bending stiffness reduces to the D_{II} term of the D matrix.

For segment i , the effective flexural rigidity is:

$$(EI)_i^{eff} = D_{11}^{(i)} \cdot b \quad (5.13)$$

where $D_{11}^{(i)}$ is the (1,1) component of the $\mathbf{D}$ matrix for the sub-laminate constituting segment i , and b is the beam width.

For the integral regions (segments 1 and 4), $D_{11}^{(i)}$ is computed for the full laminate stacking sequence. For the delaminated sub-laminates (segments 2 and 3), $D_{11}^{(i)}$ is computed separately for the upper sub-laminate (plies from the top surface to the delamination plane) and the lower sub-laminate (plies from the delamination plane to the bottom surface), each referenced to their own mid-plane.

For an asymmetric split (delamination not at the laminate mid-plane), each sub-laminate will have a different neutral axis location. The effective D_{11} for each sub-laminate must account for the shift of the neutral axis from the sub-laminate geometric mid-plane using the parallel axis theorem see Figure 5.3:

$$D_{11}^{(i)} = \overline{D_{11}^{(i)}} - \frac{(B_{11}^{(i)})^2}{A_{11}^{(i)}} \quad (5.14)$$

where $\overline{D_{11}^{(i)}}$, $B_{11}^{(i)}$ and $A_{11}^{(i)}$ are the bending, coupling, and extensional terms referenced segment neutral plane considering x_k the vertical position of the layer k .

$$A_{11}^{(i)} = b \cdot \sum_{k=1}^{n_i} (\bar{Q}_{11}^k)_k (x_k - x_{k-1}) \quad (5.15)$$

$$B_{11}^{(i)} = \frac{b}{2} \cdot \sum_{k=1}^{n_i} (\bar{Q}_{11}^k)_k (x_k^2 - x_{k-1}^2) \quad (5.16)$$

$$\overline{D_{11}^{(i)}} = \frac{b}{3} \cdot \sum_{k=1}^{n_i} (\bar{Q}_{11}^k)_k (x_k^3 - x_{k-1}^3) \quad (5.17)$$

$$\text{Where:} \quad \bar{Q}_{11}^k = Q_{11}^k \cos^4 \theta + Q_{22}^k \sin^4 \theta + 2(Q_{11}^k + 2Q_{66}^k) \cos^2 \theta \sin^2 \theta \quad (5.18)$$

$$Q_{11} = \frac{E_{11}}{1 - \nu_{12}\nu_{21}}, Q_{22} = \frac{E_{22}}{1 - \nu_{12}\nu_{21}}, Q_{66} = G_{12}, \nu_{21} = \frac{\nu_{12}E_{22}}{E_{11}} \quad (5.19)$$

$$EA_l = b \cdot \sum_{k=1}^{n_i} (\bar{Q}_{11}^k)_k (x_{k-1} - x_k) \quad (5.20)$$

b is the beam width. θ is this orientation of fibres of layer k . The summation of the moment exerted by each layer should equal the moment caused by F multiplied by the distance δ_i from the delaminated surface.

$$F\delta_i = \sum_{k=1}^{n_i} d_k \sigma_k b \cdot t^k = \sum_{k=1}^{n_i} d_k \epsilon_l \bar{Q}_{11}^k b \cdot t^k = \sum_{k=1}^{n_i} d_k \frac{F}{EA_l} \bar{Q}_{11}^k b \cdot t^k \quad (5.21)$$

In which:

$$d_k = x_{k-1} + 0.5(x_k - x_{k-1}) \quad (5.22)$$

This results in:

$$\delta_i = b \cdot \sum_{k=1}^{n_i} \frac{d_k \bar{Q}_{11}^k t^k}{EA_l} \quad (5.23)$$

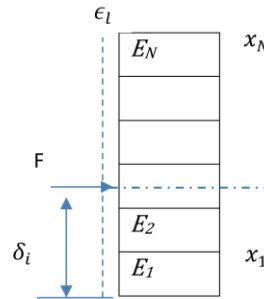


Figure 5.3: Neutral surface position determination

The general solution for the transverse displacement of each segment i (i from 1 to 4) retains the same form as in the isotropic model:

$$\bar{u}_i(z_i) = A_i \sinh(\lambda_i \bar{z}_i) + B_i \cosh(\lambda_i \bar{z}_i) + C_i \sin(\lambda_i \bar{z}_i) + D_i \cos(\lambda_i \bar{z}_i),$$

where the frequency parameter λ_i is now defined using the effective composite stiffness of segment i :

$$\lambda_i^4 = \rho_i A_i \omega^2 L^4 / D_{11}^{(i)} \quad (5.25)$$

with:

- ρ_i : Effective mass density of segment i , computed as the mass-weighted average through the laminate thickness
- A_i : Cross-sectional area of segment i
- ω : Natural frequency
- $D_{11}^{(i)}$: Effective flexural rigidity of segment i as defined above

In this equation λ_2 cannot be rewritten in the dimensionless transversal delamination location d anymore. For λ_2 the following relation is found:

$$\lambda_2^4 = \lambda_3^4 = \frac{\lambda_1^4 * D_{11}^{(1)}}{D_{11}^{(2)} + D_{11}^{(3)}} \quad (5.26)$$

The effective density is computed as:

$$\rho_i = (1/h_i) \sum_k^{n_i} \rho_k t_k \quad (5.27)$$

where n_i is the number of plies in segment i , and ρ_k and t_k are the density and thickness of the k -th ply.

5.4.3 Boundary Conditions

The boundary conditions are identical in form to the isotropic case and are applied using Table 5.1. For a clamped-clamped composite beam, the conditions are:

- At the left end ($z_1 = 0$): $u_1 = 0, \quad u_1' = 0$
- At the right end ($z_4 = 0$): $u_4 = 0, \quad u_4' = 0$
- Substituting into equation (1) yields:
 - $B_l + D_l = 0$
 - $A_l \lambda_l + C_l \lambda_l = 0$
 - $B_4 + D_4 = 0$
 - $A_4 \lambda_l + C_4 \lambda_l = 0$

The form of these equations is the same as for the isotropic beam. Only the frequency parameter λ_i changes, now carrying the composite material information through $D_{11}^{(1)}$.

5.4.4 Continuity Conditions

The continuity conditions at the junctions between the integral and delaminated regions are applied for displacement, slope, shear force, and bending moment. The displacement and slope conditions are the same with respect to the isotropic beam case. Their mathematical form is the same as in the isotropic case. However, for the bending moment and shear force expressions must now use the effective composite stiffnesses.

- **Displacement continuity:**

$$u_i(a) = u_2\left(-\frac{b}{2}\right), \quad i = 1, 4$$

- **Slope continuity:**

$$\frac{\partial u_i}{\partial z}(a) = \frac{\partial u_2}{\partial z}(a)\left(-\frac{b}{2}\right), \quad i = 1, 4$$

- **Bending moment continuity:** The bending moment is distributed between the two sub-laminates (2 and 3) according to their stiffness:

$$\frac{\partial^2 \bar{u}_i}{\partial z_i^2} = \frac{D_{11}^{(2)} + D_{11}^{(3)}}{D_{11}^{(1)}} \frac{\partial^2 \bar{u}_2}{\partial z_2^2} + \frac{PL^2(\delta_2 + \delta_3)}{dD_{11}^{(1)}} \quad i = 1, 4 \quad (5.28)$$

To ensure compatibility of axial displacement at the two junctions the following condition must be satisfied [196]:

$$(\delta_2 + \delta_3) \left[\frac{\partial \bar{u}_1}{\partial \bar{z}_1}(\bar{a}) \right] = [w_2 - w_3]_{z_2 = -\frac{b}{2}} \quad (5.29)$$

$$(\delta_2 + \delta_3) \left[\frac{\partial \bar{u}_4}{\partial \bar{z}_4}(-\bar{c}) \right] = [w_2 - w_3]_{z_2 = -b/2} \quad (5.30)$$

So we have:

$$\begin{aligned} (\delta_2 + \delta_3) \left[\frac{\partial \bar{u}_1}{\partial \bar{z}_1}(\bar{a}) - \frac{\partial \bar{u}_4}{\partial \bar{z}_4}(-\bar{c}) \right] \\ = [\bar{w}_3(\bar{b}/2) - \bar{w}_3(-\bar{b}/2)] - [\bar{w}_2(\bar{b}/2) - \bar{w}_2(-\bar{b}/2)] \end{aligned} \quad (5.31)$$

Knowing:

$$[\bar{w}_i(\bar{b}/2) - \bar{w}_i(-\bar{b}/2)] = \frac{P \cdot b}{EA_i} - \int_{-\frac{b}{2}}^{\frac{b}{2}} \left[\frac{\partial u_i}{\partial z_i} \right]^2 dz_i \quad (5.32)$$

The integral term in the precedent expression represents the end shortening caused by the bending of beam segments. Knowing that $\bar{w}_i = w_i/d$ These terms cancel and we will have

$$d(\delta_2 + \delta_3) \left[\frac{\partial \bar{u}_1}{\partial \bar{z}_1}(\bar{a}) - \frac{\partial \bar{u}_4}{\partial \bar{z}_4}(-\bar{c}) \right] = Pb \left[\frac{1}{EA_2} + \frac{1}{EA_3} \right] \quad (5.33)$$

Finally, we have:

$$P = \frac{\bar{d}(\delta_2 + \delta_3)}{\bar{b}L} \left[\frac{1}{EA_2} + \frac{1}{EA_3} \right]^{-1} \left[-\frac{\partial \bar{u}_1}{\partial \bar{z}_1}(\bar{a}) + \frac{\partial \bar{u}_4}{\partial \bar{z}_4}(-\bar{c}) \right] \quad (5.34)$$

- **Shear force continuity:** In the composite case, the total shear force is shared between the two sub-laminates proportionally to their respective effective stiffnesses:

$$\frac{\partial^3 \bar{u}_i}{\partial \bar{z}_i^3} = \frac{D_{11}^{(2)} + D_{11}^{(3)}}{D_{11}^{(1)}} \frac{\partial^3 \bar{u}_2}{\partial \bar{z}_2^3} \quad i = 1, 4 \quad (5.35)$$

5.4.5 Assembly and Frequency Equation

As in the isotropic case, the system comprises 4 boundary equations (2 at each end) and 8 continuity equations (4 at each junction), giving a total of 12 equations with 12 unknowns:

$$Y = (A_1, B_1, C_1, D_1, A_2, B_2, C_2, D_2, A_4, B_4, C_4, D_4)^T$$

The system is:

$$A(\lambda, a, b, d) Y = 0$$

The matrix A is a 12×12 matrix that depends on the delamination parameters a, b, d , the frequency parameter λ . For the non-zero entries of the matrix are structured identically to those of the isotropic model, except those rows corresponding to shear force and bending moment. The natural frequencies are obtained by searching for the values of ω (equivalently λ) that make the determinant of A equal to zero:

$$\det[A(\lambda)] = 0$$

5.4.6 Key differences from the isotropic model

The Table 5.2 summarises the principal differences between the isotropic and composite laminated beam models:

Table 5.2: Differences between the isotropic and composite laminated beam models:

	Isotropic Beam	Composite Laminated Beam
Flexural rigidity	EI (uniform)	$(EI)_i^{eff} = D_{11}^{(i)} \cdot b$
Frequency parameter λ_i	Uses EI, ρ, A	Uses $D_{11}^{(i)}, \rho_i, A_i$
Neutral axis of sub-laminates	Always at geometric mid-plane	Shifts with ply stacking; parallel axis correction required
Coupling effects	None	$B_{11} \neq 0$ for unsymmetric laminates; reduced stiffness must be used
System matrix A	Function of λ, a, b, d	Function of λ, a, b, d

5.5 Inverse modelling

The inversion procedure involves determining the delamination parameters (a , b and d) based on natural frequencies (f_1 , f_2 and f_3). In the forward modelling phase, it is stated that at resonance, the determinant of the matrix A equals zero. This determinant depends on the delamination parameters and the frequency. Since the three delamination parameters are the unknowns of the inverse model, only three independent equations are needed. The characteristic equations corresponding to the first three frequencies can be used such that:

$$\begin{cases} \det(A(a, b, d, f_1)) = 0 \\ \det(A(a, b, d, f_2)) = 0 \\ \det(A(a, b, d, f_3)) = 0 \end{cases} \quad (5.36)$$

It is important to note that with this approach, we do not need the natural frequencies of the pristine beam to identify delamination parameters. Additionally, there is no need for a database representing frequency shifts as a function of position and size.

5.6 Graphical technique

The graphical technique for solving a system of nonlinear equations involves visualizing the solutions by plotting the equations and identifying the points of intersection as shown in Figure 5.4, which represent the solutions to the system. In this method, each equation is treated as a curve. By plotting the curves on the same graph, the graphical technique allows us to observe where the

curves intersect providing solution. This method is particularly useful when analytical methods become impractical, and it gives an intuitive understanding of how the solutions behave. However, it may require iterative refinement to achieve higher accuracy, especially in systems with complex interactions between variables. The graphical technique can be applied using tools like Python, or specialized plotting software, making it a versatile method in various scientific and engineering fields.

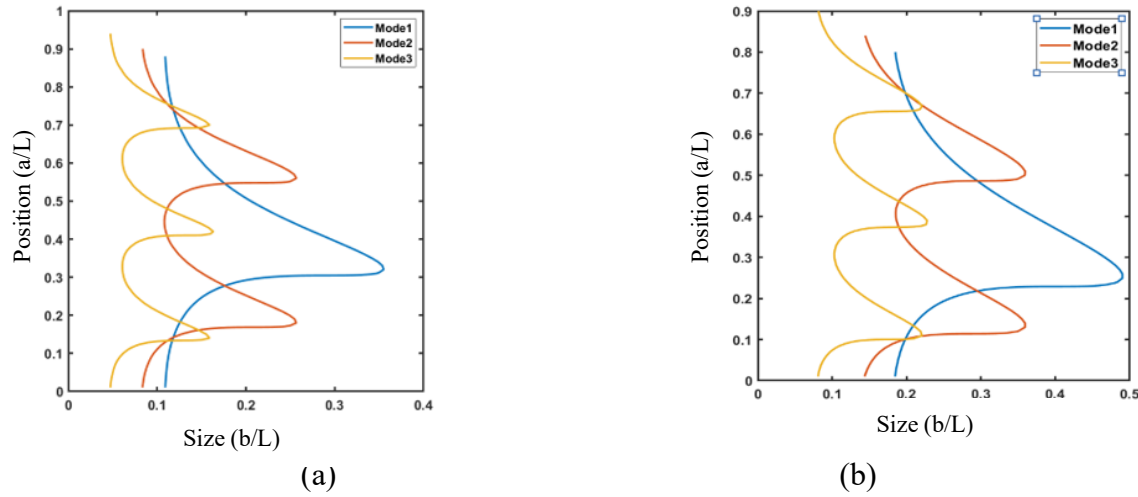


Figure 5.4: Curves of intersection of the determinant with plane $z = 0$. (a) d must be changed, (b) d corresponds to a delamination

5.7 Conclusion

This chapter presented a new inverse analytical approach for delamination identification in beams based exclusively on a limited set of natural frequencies. The proposed approach combines the constrained mode analytical model with an inverse formulation derived directly from the resonance condition of the structural system. By expressing the determinant of the continuity and boundary-condition matrix as a nonlinear function of the delamination parameters and the measured frequencies, a system of nonlinear equations was established and solved graphically to determine the delamination characteristics.

Chapter 6: Results and discussion

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6.1 Introduction

This chapter is devoted to the application of the proposed method developed in the previous chapter, as well as to the presentation and analysis of the obtained results. The chapter focuses on the identification of delamination in laminated beams under different mechanical configurations. The first part addresses the case of delaminated isotropic beams, whereas the second part investigates the more general case of delaminated composite beams. For both cases, the adopted forward and inverse models are validated through comparisons with numerical, analytical, and experimental results available in the literature. The obtained results are presented in the form of tables and curves illustrating various physical and numerical quantities, including the identified delamination size and location, natural frequencies, mode shapes, determinant intersection curves.

6.2 Delamination identification in isotropic Beams

This section investigates the vibration behaviour and delamination identification of isotropic beams under different boundary conditions. Attention is given to the influence of the delamination size and its horizontal and vertical positions on the natural frequencies and mode shapes of the structure. The proposed approach is assessed through comparisons with published numerical results, followed by the application of the inverse procedure to identify the delamination parameters from the measured vibration frequencies. The obtained results are analysed using tables, frequency evolution curves, and determinant intersection curves to evaluate the performance and accuracy of the developed models.

6.2.1 Forward Model Validation

The clamped-clamped beam shown in Figure 6.1 is considered in this section to validate the forward model. Our results of this model are compared with those obtained by Lee J. [201], who used the finite element method. Firstly, the dimensionless frequency of the first three vibration modes is calculated for fixed central delamination with different sizes, as shown in Table 6.1. Then, the horizontal delamination position and size are changed to calculate the dimensionless frequency of the first mode, as presented in Table 6.2. To conclude the forward model validation, the vertical delamination position is varied along the symmetric axis for different sizes, as

displayed in Table 6.3. Figures 6.2, 6.3 and 6.4 show the frequency in terms of size and horizontal position for different modes and vertical positions.

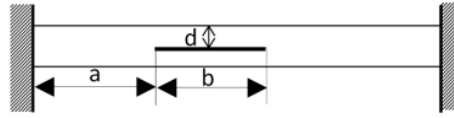


Figure 6.1: Clamped-Clamped beam

A first observation is that the forward model results are in good agreement with the FEM results, as shown in Tables 6.1 and 6.2. In Table 6.3, the difference is notable when the delamination vertical position d is near zero. This difference can be explained by the fact that this model is built upon the assumption that beam segments 2 and 3 have the same displacement (the delamination is always closed), which is not always the case. Experimental tests show that the delamination breathes (opens and closes), with each segment having its own displacement. On the other hand, the frequency decreases with the increase of delamination size, as shown in all tables. Additionally, the horizontal delamination position has a smaller effect on the frequency for small delamination sizes compared to larger sizes (see Table 6.1). In Figures. 6.2, 6.3, and 6.4, we observe that the frequency has semi-sinusoidal shapes in terms of delamination position when the delamination size is more significant. Moreover, there is one hump for the first mode, two humps for the second mode, and three humps for the third mode.

Table 6.1: The first three frequencies for a clamped-clamped beam.

Delamination size (b/L)	λ^2					
	1 st mode		2 nd mode		3 rd mode	
	Forward model	FEM [201]	Forward model	FEM [201]	Forward model	FEM [201]
0.1	22.37	22.36	60.81	60.74	120.83	120.62
0.2	22.36	22.35	56.00	55.95	118.87	118.69
0.3	22.24	22.23	49.00	48.97	109.16	109.03
0.4	21.83	21.82	43.89	43.86	93.59	93.51
0.5	20.89	20.88	41.52	41.50	82.29	82.23
0.6	19.30	19.28	41.04	41.01	77.69	77.64
0.7	17.23	17.22	40.82	40.80	77.18	77.12
0.8	15.05	15.05	39.07	39.04	75.43	75.39

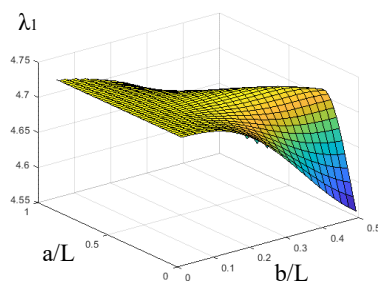
0.9	13.00	12.99	35.39	35.39	69.19	69.16
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Table 6.2: Variation of frequencies λ^2 in function of delamination size and horizontal position for a clamped-clamped beam $d/H=0.5$

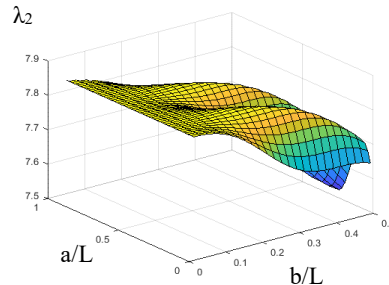
Delamination size (b/L)	First frequency (λ^2)							
	Delamination position (a/L)							
	0.1		0.2		0.3		0.4	
	Forward model	FEM[195]	Forward Model	FEM[195]	Forward model	FEM[195]	Forward model	FEM[195]
0.1	22.16	22.16	22.22	22.23	22.30	22.31	22.36	22.37
0.2	21.00	21.00	21.55	21.55	22.10	22.11	22.35	22.36
0.3	19.34	19.33	20.78	20.78	22.03	22.04	22.03	22.04
0.4	18.18	18.17	20.49	20.49	21.83	21.83	20.49	20.49

Table 6.3: : Variation of frequencies λ^2 in function of size and vertical position for a clamped-clamped beam

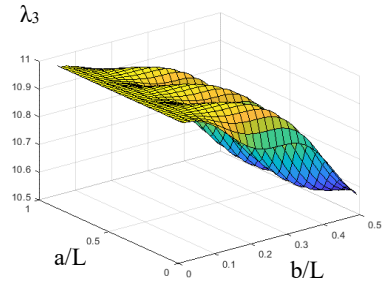
Delamination size (b/L)	First frequency (λ^2)							
	$d/H = 0.1$		$D/H = 0.25$			$D/H = 0.5$		
	Forward Model	FEM	Forward Model	Reference [195]	FEM	Forward Model	Reference [195]	FEM
0.05	22.37	22.38	22.37	22.37	22.38	22.37	22.37	22.38
0.1	22.37	22.38	22.37	22.37	22.38	22.37	22.37	22.38
0.2	22.37	22.31	22.36	22.35	22.36	22.35	22.35	22.36
0.3	22.36	21.43	22.31	22.16	22.17	22.24	22.24	22.25
0.4	22.31	13.8	22.14	21.37	21.38	21.83	21.83	21.83



(a)



(b)



(c)

Figure 6.2: First three dimensionless frequency modes λ for $d = 0.1$. (a) Mode I. (b) Mode II. (c) Mode III.

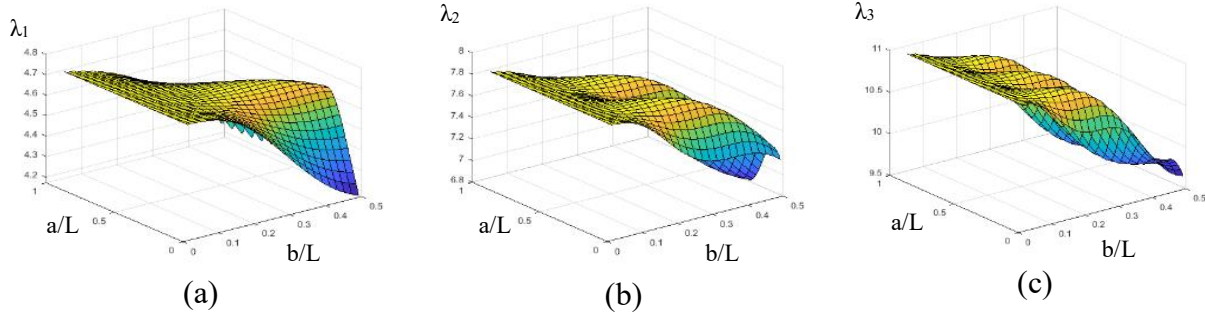


Figure 6.3: First three dimensionless frequency modes λ for $d = 0.3$. (a) Mode I. (b) Mode II. (c) Mode III

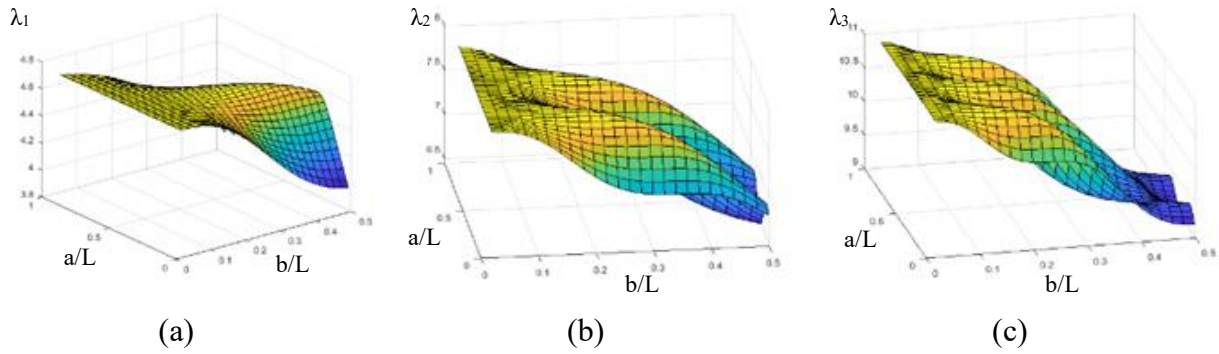
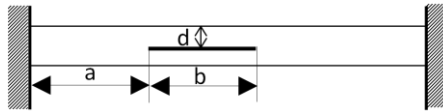


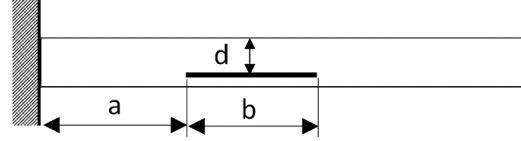
Figure 6.4: First three dimensionless frequency modes λ for $d = 0.5$. (a) Mode I. (b) Mode II. (c) Mode III

6.2.2 Application of the present inverse model

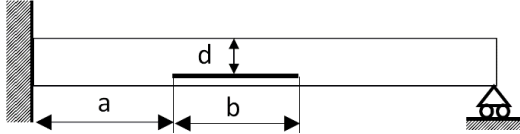
Three examples are considered to apply the present inverse model. The first example is the previous Clamped-Clamped beam. The second and third examples are Cantilever and Clamped-simply supported beams as presented in Figure 6.5. The delamination in the Clamped-Clamped beam is studied by Wang et al. [195], where the delamination size and position are given to calculate the three first frequencies. These frequencies are used in this example (Example 1) as inputs in order to find the delamination parameters which are shown in Table 6.4. For Examples 2 and 3, the three frequencies are selected in descending order starting from the frequencies of the pristine beam. Table 6.5 and Table 6.6 showcase the corresponding results.



(a) Clamped-Clamped



(b) Cantilever



(c) Clamped-Simply supported beam

Figure 6.5: Beams boundary conditions

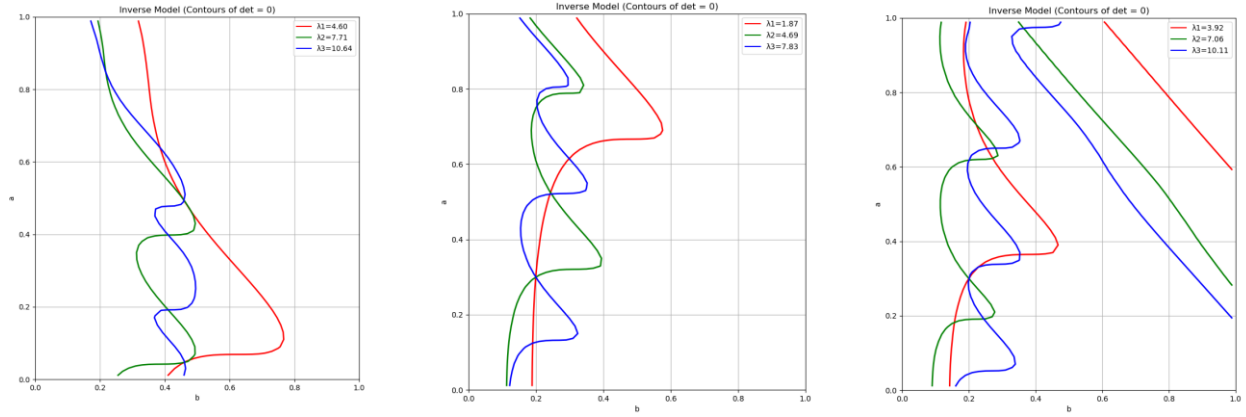


Figure 6.6: Intersection curve for Example 3 (Clamped-Simply supported beam).

Table 6.4: Example 1, Results for Clamped-Clamped beam

case	λ^2			Delamination parameters [195]			predicted delamination parameters		
	λ_1^2	λ_2^2	λ_3^2	d/H	a/L	b/L	d/H	a/L	b/L
1	22.370	60.810	120.830	0.5	0.45	0.10	0.50	0.45	0.10
2	22.350	56.000	118.870	0.50	0.40	0.20	0.50	0.40	0.20
3	22.240	49.000	109.160	0.50	0.35	0.30	0.50	0.35	0.30
4	21.830	43.870	93.570	0.50	0.30	0.40	0.50	0.30	0.40
5	20.880	41.450	82.080	0.50	0.25	0.50	0.50	0.25	0.50

Table 6.5: Example 2, Results for a cantilever beam

case	First three frequencies			Predicted delamination parameters		
	λ_1	λ_2	λ_3	a/L	b/L	d/h
1	1.875	4.690	7.840	0.76	0.10	0.31
2	1.855	4.600	7.120	0.45	0.36	0.50
3	1.845	4.550	6.930	0.42	0.42	0.50
4	1.835	4.500	6.790	0.40	0.46	0.50
5	1.825	4.450	7.100	0.09	0.69	0.17

Table 6.6: Example 3, Results for clamped- simply supported beam

Case	First three frequencies			Predicted delamination parameters		
	λ_1	λ_2	λ_3	a/L	b/L	d/L
1	3.910	7.000	10.110	0.10	0.11	0.40
2	3.900	6.950	10.000	0.08	0.12	0.50
3	3.890	6.900	9.900	0.05	0.14	0.40
4	3.880	6.800	9.700	0.29	0.35	0.22
5	3.870	6.970	9.600	0.23	0.33	0.20

The results of Example 1 in Table 6.4 show total agreement between the inverse model and Ref. [195], proving that the delamination position and size can be identified accurately by the present inverse model. Table 6.5 shows results for a cantilever beam. The corresponding delamination size shows an increasing trend, whereas the vertical position is predominantly located around the median plane of the beam. The vertical position drops from 0.5 to 0.17, indicating that the delamination is approaching the edge of the beam. The horizontal position decreases, representing the movement of the delamination towards the left side of the beam. Table 6.6 showcases the delamination parameters for a clamped-simply supported beam. As the first three frequencies decrease simultaneously, the delamination size increases while the horizontal and vertical positions fluctuate. According to Figure 6.6, the intersection curves are nonlinear with high orders.

6.3 Delamination identification in composite beams

This section investigates the delamination identification in composite beams subjected to different boundary conditions. The study begins with the validation of the proposed analytical model through comparisons with available results from the literature, demonstrating its accuracy in predicting the dynamic response of delaminated composite beams. Subsequently, a parametric analysis is conducted to examine the influence of delamination characteristics, including its size and horizontal and vertical locations, on the natural frequencies of the structure. The sensitivity of the vibration response to these parameters is analysed for various boundary conditions. Finally, an inverse identification procedure is used to estimate the delamination parameters from natural frequencies. To assess the robustness and applicability of the proposed approach, several composite beams with different material and geometric properties are considered under different support conditions. The obtained results are presented and discussed through tables, frequency variation surfaces, highlighting the accuracy and effectiveness of the developed approach.

6.3.1 Analytical forward model validation

The validation process is carried out through a series of comparisons with benchmark results available in the literature, as well as with numerical simulations based on the Finite Element Method (FEM). First, the natural frequencies obtained from the present formulation are compared with the results reported by Shen and Grady[205], whose work is widely recognized as a reference for the vibration analysis of delaminated composite beams. This comparison allows the evaluation of the model's capability to accurately capture the effects of delamination on the structural dynamic response. Subsequently, additional validation is performed through finite element simulations, providing an independent numerical benchmark for various delamination configurations and boundary conditions.

6.3.1.1 Validation with experimental and analytical results

To validate the analytical free-vibration model for composite beams, the predicted natural frequencies are compared with benchmark results reported in the literature. The study of Shen and Grady (1992) [368] is selected as the reference because it provides widely recognized solutions

for the free vibration behaviour of delaminated composite beams based on beam theory. This reference present both experimental and analytical results.

For validation purposes, the same geometric dimensions, material properties, laminate configuration, boundary conditions, and delamination parameters reported by Shen and Grady are adopted in the present simulations. Figure 6.7 presents the beam geometry, boundary conditions, material properties, and laminate layup used in the analysis.

The reference specimen is a cantilever laminated composite beam manufactured from graphite/epoxy (T300/934). The laminate consists of eight plies arranged in a symmetric cross-ply stacking sequence, $[0/90]_{2s}$. Each ply has a thickness of approximately 0.127 mm, resulting in a total laminate thickness of 1.016 mm. The beam dimensions are 254 mm in length and 12.7 mm in width. During the vibration experiments, the specimen was clamped at its midspan, creating an effective cantilever length of 127 mm. The orthotropic material properties of each lamina used in the analysis are $E_{11} = 134\,450\text{ MPa}$, $E_{22} = 10\,340\text{ MPa}$, $G_{12} = 4\,999\text{ MPa}$, Poisson's ratio $\nu_{12} = 0.33$, and mass density $\rho \approx 1530\text{ kg/m}^3$. These geometric parameters, stacking sequence, and material properties were adopted in the present simulations to ensure a consistent comparison with the results reported in the literature.

A through-width delamination was introduced at the midspan region by inserting a 0.025 mm thick Teflon film between selected plies before curing. Different delamination lengths, ranging from 0 to 101.6 mm, were investigated, and the delamination was positioned at various ply interfaces through the laminate thickness. The same delamination configurations are considered in the present model to enable a direct comparison of the predicted natural frequencies with the results reported by Shen and Grady. The results are organized in three tables, Table 6.7-6.9, each corresponding to a different interface configuration. In their study [368] Three specimens are considered for each delamination parameters and frequencies are presented from Specimen 1 to Specimen 3 under experimental row. In the same reference there is results corresponding to analytical models. Model A is based on the assumption that longitudinal/flexural coupling exists along the entire length of the delamination, and model B assumes that coupling exists only at the two delamination tips. The numerical values obtained from the present formulation are then

directly compared with those reported by Shen and Grady (1992) under identical conditions to evaluate the accuracy and reliability of the developed model.

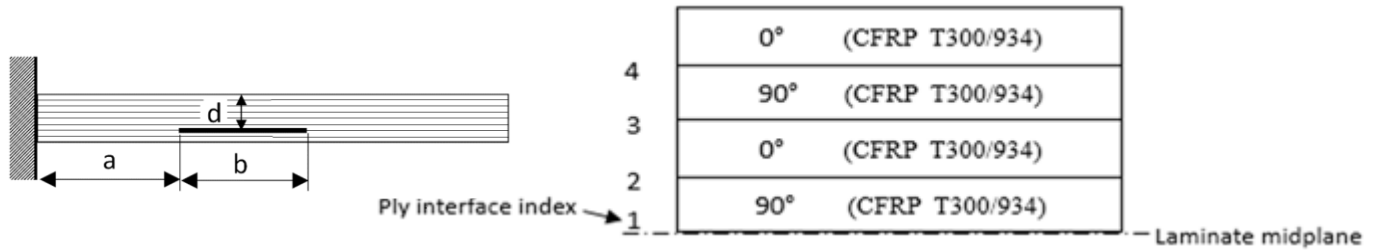


Figure 6.7: Boundary condition and composite beam layup configuration

The comparison between the predicted natural frequencies obtained from the present model and those reported by Shen and Grady (1992) shows a generally good agreement as shown in Table 6.7-6.9. For delamination located at interface 1 and interface 2, the numerical results obtained in this study are very close to both the analytical predictions and the experimental measurements reported in the reference. In the case of interface 3, a slight deviation can be observed between the present results and the values reported in the literature, particularly for larger delamination lengths. This small difference may be attributed to changes in modelling assumptions, numerical approximations, or sensitivity of the vibration response to the delamination position within the laminate thickness. Nevertheless, the overall trend of the natural frequencies with respect to delamination size and location is well reproduced.

Table 6.7: Fundamental resonant frequency for delamination along interface 1

b (mm)	a (mm)	Experimental[205]			Analytical		
		Spec 1	Spec 2	Spec 3	Model A[205]	Model B[205]	Present model
0	0	79.87	79.87	79.75	82.04	82.04	82.91
25.4	50.8	78.37	79.12	77.00	80.13	67.36	80.26
50.8	38.1	74.37	75.00	76.75	75.28	56.47	74.46
76.2	25.4	68.25	66.25	66.37	66.93	47.89	65.3
101.6	12.7	57.62	57.50	57.50	57.23	50.58	55.22

Table 6.8: Fundamental resonant frequency for delamination along interface 2

b (mm)	a (mm)	Experimental[205]			Analytical		
		Spec 1	Spec 2	Spec 3	Model A[205]	Model B[205]	Present model
0	0	79.87	79.87	79.75	82.04	82.04	82.91
25.4	50.8	78.37	78.37	76.62	81.38	68.77	81.6
50.8	38.1	75.12	75.25	75.00	78.10	59.43	77.06
76.2	25.4	64.00	70.00	69.87	71.15	51.18	68.67
101.6	12.7	45.75	49.75	49.50	62.12	43.86	58.70

Table 6.9: Fundamental resonant frequency for delamination along interface 3

b (mm)	a (mm)	Experimental[205]			Analytical		
		Spec 1	Spec 2	Spec 3	Model A[205]	Model B[205]	Present model
0	0	79.87	79.87	79.75	82.04	82.04	82.09
25.4	50.8	78.37	78.37	76.62	81.38	68.78	80.23
50.8	38.1	75.12	75.25	75.00	78.10	59.44	76.76
76.2	25.4	64.00	70.00	69.87	71.15	51.18	72.06
101.6	12.7	45.75	49.75	49.50	62.12	43.86	66.35

6.3.1.2 Validation with FEM

A second validation of the present analytical free-vibration model is performed by comparing its predictions with finite element (FE) results. Unlike the previous validation, which was based on analytical and experimental benchmark results, this case assesses the model against numerical simulations obtained by two independent FEM codes. The structure is a cantilever laminated composite beam manufactured from E-glass/epoxy (GFRP) and composed of eight plies arranged in a symmetric stacking sequence ($[0/-45/45/90]_s$). The beam has a length of 0.244 m, a width of 0.01918 m, and a thickness of 0.00246 m. The orthotropic material properties used in the analysis are summarized in Table 6.10. The results of the present model and the FEM simulation are presented in Table 6.11. Figure 6.8 illustrates the variation of the first three natural frequencies in terms of delamination position and size for different delamination interfaces. The comparison between results indicates that the implemented analytical model can capture the dynamic behaviour of the laminated composite beam with delamination

Table 6.10: Beam physical properties

Material	E-glass/Epoxy
Lay up	[0/-45/45/90] _s
L (Length)	0.244
H (Thickness)	0.00246
W(width)	0.01918
E ₁₁	92.5
E ₂₂	8.04
G ₁₂	2.88
Density	1429
μ ₁₂	0.33

Table 6.11: Comparison with FEM simulations

		1	2	3	4
<i>a(mm)</i>		44.9	45.3	105.1	43
<i>b(mm)</i>		28	31	60.2	43.5
<i>d(mm)</i>		1.23	0.923	0.615	0.308
F1	Present Analytical Model	43.909	43.906	42.985	43.613
	FEM1	45.261	45.209	45.230	45.306
	FEM2	42.887	42.834	42.445	42.898
F2	Present Analytical Model	263.491	261.222	276.396	258.966
	FEM1	276.881	274.648	284.258	279.728
	FEM2	260.44	258.91	266.9	253.19
F3	Present Analytical Model	754.458	754.596	626.576	755.078
	FEM1	784.334	783.616	741.519	792.146
	FEM2	736.36	736.3	611.45	739.57

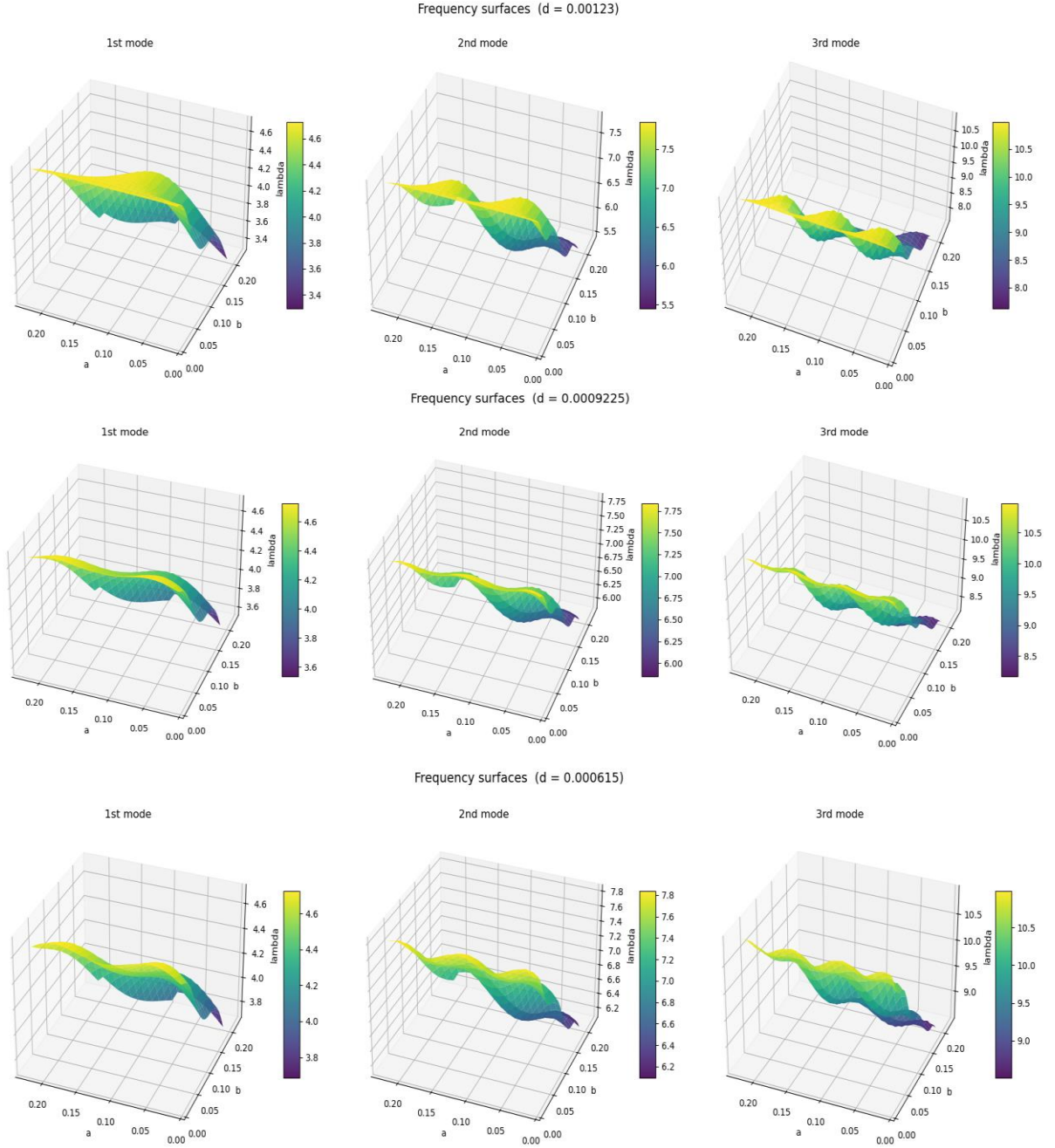


Figure 6.8: Frequency variation in terms of delamination position and size

The differences between experimental results and analytical model arise from several interconnected factors. Analytical model is based on simplifying assumptions for instance, Classical Laminate Theory (CLT) neglects transverse shear deformation and is therefore less accurate for thick laminates or higher-frequency responses, whereas more refined theories such as Timoshenko beam or higher-order shear deformation models account for these effects and

generally provide better agreement with experiments. In practice, experimental boundary conditions also deviate from the ideal constraints assumed in models, introducing additional stiffness that alters the system response. Moreover, damping effects present in real structures reduce natural frequencies and are often simplified or neglected in analytical formulations. Finally, the presence of sensors and their attached mass can locally modify the dynamic properties of the structure, leading to a measurable shift in the natural frequencies. Together, these factors contribute to the observed differences between theoretical predictions and experimental measurements. The overall agreement demonstrates that the developed formulation provides reliable predictions of the vibration characteristics of delaminated composite beams. Therefore, the present model can be considered validated and suitable for further parametric studies and dynamic analyses of composite beam structures.

6.3.2 Inversion

In this section, the inverse frequency-based delamination identification approach is applied to composite laminated beams to determine the delamination parameters from three set of natural frequencies. Therefore, the main objective is to investigate the capability of the proposed inverse approach to identify the delamination position (a), delamination length (b), and delamination depth (d) using only the first three natural frequencies (F_1 , F_2 , and F_3) as input data. Unlike the direct problem, where the dynamic response is computed for known damage characteristics, the inverse problem seeks to estimate the damage parameters from the vibration frequencies.

To evaluate the robustness and applicability of the present approach three composite beam configurations with different material properties, laminate stacking sequences, and geometric properties are considered, as summarized in Table 6.12. Beam 1 is a carbon-fibre-reinforced polymer (CFRP) beam with a unidirectional $[0]_8$ layup and material properties taken from Sadarang et al. (2018). Beams 2 and 3 are glass-fibre-reinforced polymer (GFRP) laminates adopted from Ju-Fen (2005), with stacking sequences $[0/90/90/0]_s$ and $[\pm 45]_s$, respectively. These beams cover a wide range of stiffness characteristics, anisotropy levels, laminate architectures, and geometric dimensions, allowing a comprehensive assessment of the inverse identification procedure under different structural conditions.

Furthermore, several boundary conditions are investigated to evaluate their influence on the sensitivity of the inverse solution. For Beam 1, four classical support configurations are considered: cantilever (C-F), clamped–clamped (C-C), clamped–simply supported (C-S), and clamped–sliding (C-G) beams. For Beams 2 and 3, cantilever boundary conditions are examined. For each case, numerous first three natural frequencies are imposed, and the corresponding delamination parameters are calculated. The results are summarized in Table 6.13-6.15, which presents the identified intervals of (a,b,d) associated with different frequency triplets (F_1, F_2, F_3) .

Table 6.12: Beams physical characteristics

	Beam 1	Beam 2	Beam 3
Reference	J Sadarang(2018)[206]	Ju-Fen(2005)[207]	Ju-Fen(2005)[207]
Material	CFRP	GFRP	GFRP
Lay up	[0] ₈	[0/90/90/0] _s	[±45] _s
L (Length) m	0.275	0.266	0.25
H (Thickness)m	0.0022	0.001778	0.008
W(width)m	0.03	0.0254	0.015
E ₁₁ (GPa)	140	42.34	42.34
E ₂₂ (GPa)	4.8	11.72	11.72
G ₁₂ (GPa)	7.1	4.14	4.14
μ ₁₂	0.3	0.27	0.27
Density(kg/m ³)	1696	1901.5	1901.5

Table 6.13: Results for Beam 1

Beam 1	F_1 (HZ)	F_2 (HZ)	F_3 (HZ)	$b(m)$	$a(m)$	$d(m)$
-----Cantilever beam-----						
Isotropic Intact case	42.696	267.572	749.210	0	0	0
Composite	42.6	268	700	0.049-0.053	0.092-0.102	0.0011
	42.3	268	610	0.073-0.075	0.1-0.108	0.0011
	42	260	610	0.0832-0.0844	0.0776-0.079	0.0011
	42	255	710	0.0475-0.0505	0.1050-0.1070	0.0008

	42.6	255	700	0.065-0.072	0.0174-0.0182	0.0008
	41.6	268	540	0.096-0.106	0.090-0.102	0.0011
	40	230	580	0.146-0.158	0.106-0.12	0.0011
	40	215	540	0.175-0.205	0.11-0.1275	0.0011
-----Clamped-Clamped-----						
Isotropic Intact case	271.686	748.914	1468.170	0	0	0
Composite	270	740	1450	0.023-0.0255	0.024-0.033	0.001
	260	725	1400	0.0495-0.051	0.0379-0.0381	0.0009
	250	700	1350	0.071-0.064	0.029-0.036	0.001
	240	675	1300	0.082-0.083	0.0249-0.0259	0.0008
	230	650	1250	0.0918-0.0926	0.0174-0.0184	0.0008
	220	625	1200	0.09975-0.10175	0.0095-0.0125	0.0006
	210	600	1150	0.096-0.101	0.165-0.174	0.0009
	200	575	1100	0.1035-0.105	0.17225-0.174	0.0009
	190	550	1050	0.1088-0.1104	0.1735-0.1750	0.001
	180	525	1000	0.1435-0.1465	0.128-0.136	0.0009
	170	500	950	0.147-0.152	0.144-0.152	0.0012
-----Clamped-Simply supported-----						
Isotropic Intact case	187.228	606.740	1265.9	0	0	0
Composite	185	600	1260	0.025-0.05	0.0375-0.055	0.001
	180	580	1220	0.04-0.065	0.025-0.05	0.0011
	175	560	1180	0.045-0.08	0.015-0.045	0.0011
	170	540	1140	0.0965-0.10005	0.0195-0.0230	0.004
	150	520	1030	0.10128-0.10140	0.0187-0.018875	0.0011
-----Clamped-Sliding beam-----						
Isotropic Intact case	67.92	367.04	906.365	0	0	0
Composite	67	360	900	0.0495-0.0520	0.0585-0.0620	0.0011

	65	350	860	0.071-0.075	0.049-0.055	0.0011
	63	340	820	0.085-0.091	0.041-0.049	0.0011
	61	330	780	0.098-0.103	0.035-0.042	0.0011
	59	320	740	0.109-0.0115	0.029-0.036	0.0011
	58	310	720	0.117-0.119	0.0265-0.0305	0.0011
	56	300	680	0.1282-0.1286	0.0238-0.0246	0.0011
	54	290	640	0.137-0.1405	0.019-0.025	

Table 6.14:Results for Beam 2

-----Cantilever beam-----						
Beam 2	$F_1(\text{HZ})$	$F_2(\text{HZ})$	$F_3(\text{HZ})$	$b(m)$	$a(m)$	$d(m)$
Isotropic Intact case	19.154	120.040	336.117	0	0	0
	16.2	102	280	0.096-0.106	0.124-0.136	0.0007
	16.15	100	270	0.1102-0.1116	0.1250-0.1264	0.0007
	16.05	98	260	0.146-0.156	0.116-126	0.00010
	16	96	250	0.1522-0.1530	0.1132-0.1138	0.0012
	15.9	94	240	0.140-0.146	0.1125-0.1155	0.0008
	15.75	92	230	0.1582-0.1590	0.1098-0.1103	0.0009
	15.6	90	220	0.1715-0.1750	0.1038-0.1054	0.0009

Table 6.15:Results for Beam 3

-----Cantilever beam-----						
Beam 3	$F_1(\text{HZ})$	$F_2(\text{HZ})$	$F_3(\text{HZ})$	$b(m)$	$a(m)$	$d(m)$
Isotropic Intact case	97.57	611.46	1712.112	0	0	0
	56	350	750	0.098-0.104	0.053-0.058	0.004
	54	340	700	0.126-0.134	0.09-0.095	0.004
	52	330	650	0.151-0.159	0.077-0.083	0.004
	51	320	620	0.166-0.168	0.0716-0.0732	0.004
	50	310	550	0.1630-0.1650	0.033-0.037	0.004

6.3.3 Discussion of Results

The results presented in Tables 6.13-6.15. Show that in all investigated cases, reductions in the natural frequencies are associated with the presence and growth of delamination, reflecting the progressive loss of structural stiffness induced by interlaminar separation. The identified intervals of delamination position and size indicate that a given set of modal frequencies can be used to localize the damaged region and estimate its extent with a relatively thin uncertainty range.

6.3.3.1 Comparison Between CFRP and GFRP Beams

The comparison between Beam 1 (CFRP) and Beams 2 and 3 (GFRP) highlights the strong influence of material properties and laminate architecture on the vibration. Beam 1 possesses the highest longitudinal modulus ($E_{11}=140$ GPa), resulting in significantly higher natural frequencies than the GFRP beams. Consequently, even relatively small delamination generates measurable frequency shifts. Beam 2, with a cross-ply $[0/90/90/0]_s$ laminate and lower stiffness ($E_{11}=42.34$ GPa), exhibits largely lower frequencies. The frequency variations induced by delamination remain detectable; however, the relative changes are smaller than those observed in Beam 1. Beam 3, characterized by a $[\pm 45]_s$ layup, presents the largest difference between intact isotropic and composite frequencies. This behaviour reflects the strong coupling effects and reduced bending stiffness associated with angle-ply laminates. Despite the lower frequency levels, the inverse procedure remains capable of identifying delamination parameters. Accuracy and Uniqueness of the Inverse Solution

Taking in consideration that the frequency triplets are chosen facultatively. The identified parameters ranges reported in Tables 6.13-6.15 demonstrate that these of three frequencies considerably improves the uniqueness of the inverse problem. While a single frequency could correspond to numerous delamination scenarios, the simultaneous use of the first three vibration modes significantly reduces the number of admissible solutions.

6.3.3.2 Overall Assessment

The results confirm that the proposed inverse approach provides a reliable and efficient tool for delamination identification in composite laminated beams. The first three natural

frequencies contain sufficient information to estimate the delamination location, size, and depth for a wide range of beams, laminate configurations, and boundary conditions. The study therefore demonstrates the feasibility of frequency-based identification for composite structures and highlights the importance of considering both boundary conditions and laminate architecture when developing inverse damage detection strategies.

General conclusion

This research has developed a new approach for the delamination identification in beams by using analytical approach. While the FEM formulation enabled accurate modelling of complex anisotropic behaviour, interlaminar effects, and boundary conditions, the analytical approach provided physical insight into the influence of delamination on structural dynamics. The analytical model successfully captured the reduction in stiffness and the corresponding changes in natural frequencies caused by delamination. A strong agreement between analytical predictions, FEM results, and established literature validates the accuracy of the used model. Furthermore, the study highlights that vibration-based analytical techniques offer a computationally efficient alternative for preliminary damage assessment and can serve as a valuable complement to numerical methods. Overall, this work contributes to the field by providing an integrated understanding of composite beam dynamics and establishing a practical framework for delamination detection using natural frequencies.

The novelty in this work exists in the formulating of the new system of nonlinear equations modelling the relationship between natural frequencies and delamination parameters. Despite the using of advanced techniques like DL and ANN the delamination identification was a hard task. This can be explained by the present work, so the system of equation formulated contains at least three highly nonlinear equations, each equation is the determinant of 12×12 matrix which is a sum of hundreds of nonlinear terms. This fact leads to the high sensitivity of the phenomena.

For more complex structures, the analytical forward model becomes complex and may not represent the real dynamic behaviour. For structures that present symmetry multiple solutions are found. To resolve this problem, we propose to add equations by changing boundary conditions or by adding supports along the beam and modify the forward model, this will shift the natural frequencies and allow delamination identification. Another difficulty may be encountered will be in the resolution of the system of equations. The numeric solvers used depend on initial solution and the highly nonlinear system of equations presents a great number of local picks that can cause

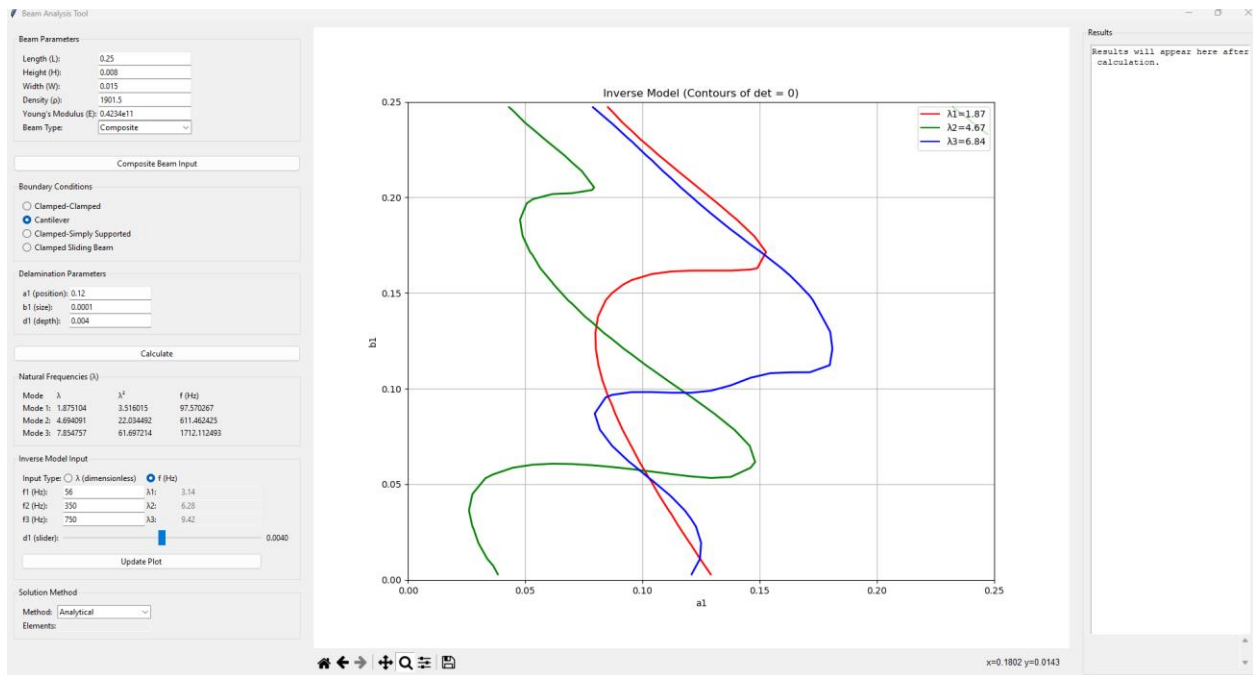
convergence to local minima. This problem can be resolved by integrating an ANN algorithm for selecting initial solution, by combining ANN with numerical solvers allow to eliminate this problem and make a fast and accurate solver.

Perspectives

Although the present study has demonstrated the effectiveness of analytical modelling for delamination detection, several opportunities exist for further advancement. First, the analytical model can be extended to include multiple and interacting delamination, which remain challenging due to increased complexity in continuity conditions. Second, future work should focus on hybrid analytical–data-driven approaches, where analytical solutions are combined with machine learning techniques to improve damage identification accuracy and enable real-time monitoring. Additionally, experimental validation using modal testing and advanced sensing technologies (e.g., piezoelectric sensors) would strengthen the applicability of the proposed model in structural health monitoring systems. Another important direction is the extension of the analytical formulation to plates, shells, and more complex composite structures, where delamination behaviour is more complicated. Finally, improving the sensitivity of analytical methods for detecting small or incipient delamination remains a key challenge, requiring refined formulations and possibly coupling with high-resolution signal processing techniques.

Annexes

1. Graphical user interface: The application is a computational application developed in python for the identification of delamination in beam structures, particularly composite beams, using vibration-based inverse analysis. It allows users to define beam geometry, material properties, and boundary conditions, and then simulate the presence of delamination by specifying parameters such as location, size, and depth. The tool computes natural frequencies for different vibration modes. For the inversion and uses frequency inputs in an inverse model, where contour plots of characteristic equations (determinant = 0) are generated. By analysing the intersection of these modal curves, the application estimates the most probable delamination parameters. With its interactive interface and real-time visualization, the tool provides an efficient and non-destructive approach for structural health monitoring and damage detection in beams.



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