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Advanced Damage Detection and Load Optimization in Hybrid Composite Structures Using Multi-Scale Simulation and Machine Learning

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Abstract

Hybrid composite structures (e.g., carbon–glass laminates, fiber–metal laminates, and multi-material sandwich panels) offer superior stiffness-to-weight performance but exhibit complex, multi-mode damage mechanisms such as matrix cracking, fiber breakage, delamination, and interface debonding. These damage modes are often difficult to detect early and expensive to simulate at full structural scale with high fidelity. This paper proposes an integrated framework that combines multi-scale progressive damage simulation with machine learning (ML)–assisted damage inference and load optimization. At the microscale and mesoscale, damage initiation and evolution are captured using established composite failure criteria and degradation laws (e.g., Hashin-type mechanisms), while structural-scale response is computed using reduced-order surrogates calibrated from multi-scale results. On the data side, guided-wave/shock-response features and simulated strain-field descriptors are mapped to damage states using supervised and uncertainty-aware ML models. Finally, a load optimization module minimizes peak interlaminar stresses and damage growth rate under service constraints. A case study on a hybrid laminate panel demonstrates that the proposed pipeline can (i) identify early delamination and matrix cracking signatures with high classification performance, and (ii) reduce damage-driving stress metrics through ML-guided load redistribution.

Keywords: Hybrid Composites, Multi-Scale Simulation, Progressive Damage Modeling, Delamination, Surrogate Modeling, Structural Health Monitoring, Guided Waves, Machine Learning, Load Optimization, Digital Twin.

I. INTRODUCTION

Hybrid composite structures, formed by combining different fiber types, matrix systems, or multi-material layers within a single laminate, have emerged as a cornerstone of modern high-performance engineering design. Their adoption is driven by the need to simultaneously achieve lightweight construction, high stiffness and strength, tailored anisotropy, and improved damage tolerance across diverse operating environments. Unlike conventional monolithic materials, hybrid composites enable designers to strategically place material capabilities where they are most effective, resulting in superior structural efficiency and functional adaptability. However, this material heterogeneity also introduces significant complexity in damage initiation, propagation, and structural response under realistic loading conditions. Damage in hybrid composite structures is inherently multi-scale and multi-mechanism in nature. Localized microscale phenomena, such as matrix micro-cracking and fiber–matrix debonding, can evolve into mesoscale ply cracking and interlaminar delamination, ultimately affecting global stiffness, load paths, and structural integrity. These coupled damage processes are often difficult to detect at early stages using conventional inspection methods and challenging to predict accurately using single-scale analytical or numerical models. As a result, there is a growing need for integrated approaches that can both *predict* damage evolution through physics-based modeling and *detect* damage states through data-driven interpretation of structural response. Recent advances in computational mechanics, sensor technologies, and machine learning provide an opportunity to address these challenges in a unified manner. Multi-scale simulation techniques enable detailed modeling of damage mechanisms across length scales, while machine learning offers powerful tools for pattern recognition, damage classification, and real-time inference from complex, high-dimensional data. When combined with surrogate modeling and optimization strategies, these tools can move beyond passive damage detection toward active load management and operational decision support. In this context, the present work aims to bridge physics-based damage modeling and data-driven intelligence to enhance both damage detection and load optimization in hybrid composite structures.

A. Background and Motivation

Hybrid composite structures are increasingly used in aerospace, wind energy, automotive, marine, and civil infrastructure due to their lightweight efficiency and design flexibility. However, unlike isotropic metals, composites fail through interacting mechanisms across scales: microscale fiber/matrix damage, mesoscale ply cracking and delamination, and structural-scale instability. This multi-physics complexity makes damage detection and operational load management critical. Conventional nondestructive evaluation (NDE) and structural health monitoring (SHM) methods can identify damage, but robust early detection remains challenging in anisotropic laminates where wave propagation and scattering become highly complex. NASA and other agencies have highlighted guided-wave based damage signature classification as a promising direction for composite inspection and SHM. In parallel, multi-scale modeling has advanced substantially and is increasingly used to predict damage initiation and growth in composites; however, these simulations are often computationally intensive when deployed at full structural scale. Recent multiscale damage modeling reviews emphasize the need for reduced-order models, surrogate approaches, and data-driven methods to bridge fidelity and speed.

B. Problem Statement

Hybrid composite structures present three practical challenges:

1. **Damage complexity:** Multiple interacting damage modes occur concurrently (matrix cracking → delamination → fiber failure), often with weak observability at early stages.
2. **Computational cost:** High-fidelity multi-scale simulation across large structures is too slow for real-time decision support.
3. **Operational uncertainty:** Real loads are variable; fixed design loads and static safety factors may not prevent progressive damage during service.

C. Proposed Solution

This paper proposes a unified approach that combines:

- **Multi-scale progressive damage simulation** (micro/meso → structural), using physics-based failure criteria and degradation laws (e.g., Hashin-type mechanisms for UD lamina)
- **Machine learning damage inference**, using features from guided waves/strain responses, trained on simulation-labeled data (and optionally augmented by public SHM datasets).
- **Load optimization**, where a surrogate model predicts damage-driving metrics and an optimizer redistributes loads to reduce delamination risk and peak damage indices.

D. Contributions

1. A practical multi-scale-to-surrogate pipeline for hybrid composite damage evolution suitable for digital-twin style updates.
2. A damage detection module that maps physics-informed features to damage states, with uncertainty estimates.
3. A load optimization strategy that reduces damage-driving stress indicators while satisfying service constraints.
4. A reproducible case study blueprint (materials, steps, metrics) that can be adapted to aerospace panels, beams, or sandwich skins.

II. Related Work

The study of damage detection, modeling, and optimization in composite and hybrid composite structures spans multiple research domains, including composite failure mechanics, fracture and delamination modeling, multi-scale simulation, structural health monitoring, and data-driven intelligence. Prior work has addressed these areas largely in isolation, with physics-based models focusing on accurate failure prediction and data-driven methods emphasizing damage identification from sensor signals. However, recent trends highlight the need for integrated frameworks that combine mechanistic understanding with machine learning and reduced-order modeling to achieve both accuracy and computational efficiency. This section reviews the most relevant literature underpinning the proposed approach. First, classical and advanced progressive failure criteria used for intralaminar damage prediction are discussed. Next, cohesive zone–based delamination modeling techniques are reviewed, followed by advances in multi-scale modeling that link microstructural behavior to structural response. The section then examines machine learning methods for damage detection in composite structures and guided-wave–based structural health monitoring approaches. Finally, emerging digital twin frameworks that integrate physics-based simulation with data-driven updating are reviewed to contextualize the motivation for the present work.

A. Progressive Failure Criteria for Composite Materials

Progressive failure modeling has long been a central research area in composite mechanics due to the complex and interacting failure mechanisms present in fiber-reinforced laminates. Early approaches relied on phenomenological stress-based criteria to predict failure initiation, but these methods lacked the ability to distinguish between different damage mechanisms. Hashin's failure criteria introduced a significant advancement by separating fiber tension, fiber compression, matrix tension, and matrix compression modes, enabling more physically meaningful damage predictions in unidirectional composites [1]. These criteria have since been widely implemented in finite element frameworks for progressive damage analysis. Subsequent studies extended failure criteria to account for three-dimensional stress states and interaction effects between damage modes. In particular, Puck's action-plane theory provided a detailed description of inter-fiber fracture under combined loading, offering improved accuracy for off-axis plies and complex stress conditions [2]. Comparative studies show that while Hashin-type criteria are computationally efficient and robust, Puck-type models offer higher fidelity for predicting matrix-dominated failures in hybrid and thick composite laminates [3]. As a result, modern composite simulations often employ hybrid criteria depending on the dominant damage mechanism and required accuracy.

B. Cohesive Zone and Delamination Modeling

Delamination is one of the most critical damage modes in laminated and hybrid composite structures, as it directly affects load transfer between plies and can lead to sudden stiffness degradation. Cohesive zone models (CZMs) have become the dominant approach for simulating delamination initiation and growth by representing interlaminar interfaces with traction–separation laws [4]. These models capture mixed-mode fracture behavior by coupling normal and shear separations and are well suited for simulating adhesive layers and ply interfaces in hybrid laminates. Extensive research has focused on calibrating cohesive parameters using fracture mechanics tests such as double cantilever beam (DCB) and end-notched flexure (ENF) experiments [5]. Studies have shown that accurate delamination prediction requires coupling CZMs with intralaminar damage models, as matrix cracking often precedes and drives interlaminar failure [6]. In hybrid composite systems, material mismatch at interfaces further complicates delamination behavior, making cohesive modeling essential for reliable structural assessment.

C. Multi-Scale Modeling of Composite Damage

Multi-scale modeling approaches aim to link microscale material behavior to mesoscale laminate response and structural-scale performance. At the microscale, representative volume elements (RVEs) are used to model fiber–matrix interactions, voids, and local stress concentrations [7]. These microscale simulations inform effective ply properties, damage initiation thresholds, and degradation laws that are subsequently used in mesoscale laminate models. Recent reviews highlight a growing emphasis on reduced-order and surrogate-based multi-scale frameworks to overcome the high computational cost associated with fully resolved simulations [8]. By combining detailed physics-based modeling at lower scales with homogenized or data-driven representations at higher scales, researchers have demonstrated practical workflows for large composite structures. Such approaches are particularly relevant for hybrid composites, where material heterogeneity across plies demands accurate but efficient multi-scale representations [9].

D. Machine Learning for Damage Detection in Composites

Machine learning has emerged as a powerful tool for damage detection and classification in composite structures, particularly within the field of structural health monitoring (SHM). Traditional signal-processing methods rely on manually engineered features extracted from guided waves, vibration data, or acoustic emission signals. ML algorithms such as support vector machines, random forests, and neural networks have been shown to significantly improve detection accuracy by learning complex, nonlinear relationships between features and damage states [10]. Recent studies emphasize deep learning approaches, including convolutional neural networks (CNNs), for automated feature extraction directly from raw time-series data [11]. These methods are particularly effective for detecting delamination and impact damage in composite plates. However, challenges remain related to data scarcity, environmental variability, and generalization across structures. To address these issues, researchers increasingly rely on simulation-generated datasets and transfer learning strategies [12], which align closely with the simulation-driven approach adopted in this work.

E. Guided-Wave–Based Structural Health Monitoring

Guided ultrasonic waves are widely used in SHM of composite structures due to their ability to propagate over long distances and interact sensitively with damage. However, anisotropy, dispersion, and mode conversion in composite laminates complicate signal interpretation. Extensive experimental and numerical studies have explored the effects of delamination, matrix cracking, and fiber breakage on guided-wave propagation characteristics [13]. Publicly available datasets, including those released by NASA, have played a critical role in benchmarking damage detection algorithms and fostering reproducible research [14]. These datasets demonstrate that combining time–frequency analysis with ML classifiers yields robust damage detection performance. The integration of guided-wave features with physics-based damage models further enhances interpretability and reliability, forming a strong foundation for digital-twin-oriented SHM frameworks [15].

F. Digital Twin and Physics–Data Integration

Digital twin concepts for composite structures aim to create continuously updated virtual representations that reflect the evolving damage state of physical assets. Recent studies propose coupling finite element damage models with real-time sensor data through ML-based updating schemes [16]. Such damage-sensing digital twins enable predictive maintenance, remaining useful life estimation, and adaptive load management. The literature increasingly recognizes that purely data-driven twins lack extrapolation capability, while purely physics-based models lack adaptability. Hybrid physics–ML frameworks offer a promising solution by combining mechanistic understanding with data-driven inference [17]. This paradigm directly motivates the integrated multi-scale simulation, machine learning, and load optimization framework presented in this paper.

III. METHODOLOGY

This study adopts an integrated, multi-stage methodological framework that combines physics-based multi-scale damage simulation, data-driven feature extraction, machine learning–based damage inference, and surrogate-assisted load optimization. The methodology is designed to address the dual challenge of accurately capturing complex damage mechanisms in hybrid composite structures while enabling computationally efficient decision-making suitable for real-time or near-real-time applications. By systematically linking material-scale behavior to structural response and operational control, the proposed approach establishes a closed-loop workflow for damage-aware structural performance optimization.

The overall methodology is structured into four sequential stages: (i) multi-scale progressive damage simulation, (ii) physics-consistent feature generation, (iii) machine learning–based damage inference, and (iv) load optimization using reduced-order surrogate models. Each stage is modular, allowing adaptation to different composite systems, sensing modalities, and operational constraints.

Overview of the Proposed Workflow

The proposed workflow consists of the following stages:

Stage 1: Multi-Scale Simulation: Damage initiation and evolution are computed at the ply and structural levels using progressive failure modeling and cohesive zone formulations.

Stage 2: Feature Generation: Physics-informed features are extracted from simulated sensor signals and finite element field responses.

Stage 3: Machine Learning Damage Inference: Supervised learning models are trained to map extracted features to damage classes and severity indicators, including uncertainty estimation.

Stage 4: Load Optimization: A surrogate-assisted optimization framework minimizes damage-driving metrics while satisfying structural and operational constraints.

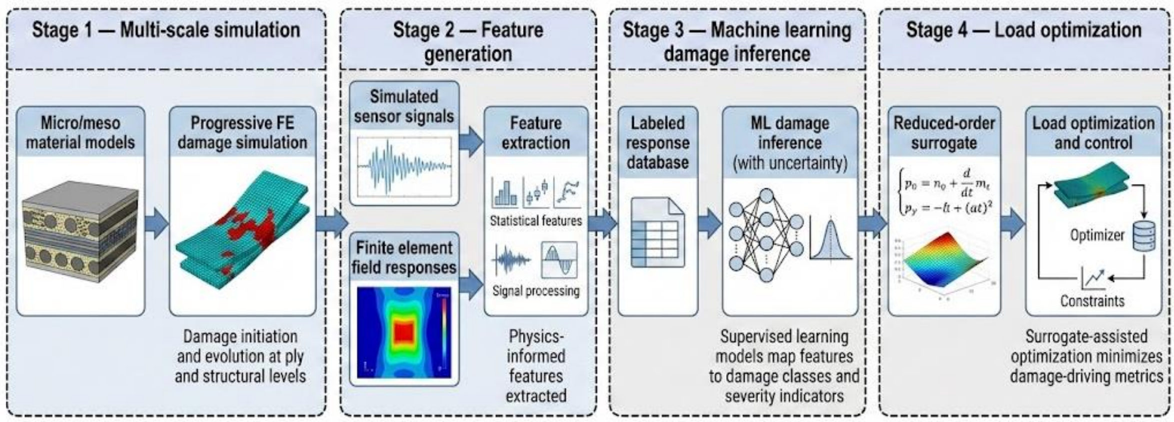

Figure 1. Conceptual workflow integrating multi-scale simulation, machine learning, and load optimization.

A. Multi-Scale Progressive Damage Simulation

Multi-scale simulation forms the physical backbone of the proposed framework by capturing damage mechanisms that evolve across length scales. In hybrid composite laminates, damage initiation often begins at the microscale and propagates through the mesoscale before manifesting as global stiffness degradation or structural instability. Accurately representing this progression is essential for generating reliable training data and physically meaningful damage metrics.

A.1 Material System and Hybrid Laminate Definition

A representative hybrid composite panel is modeled as a symmetric laminate composed of alternating carbon/epoxy and glass/epoxy plies, for example, a [C/G/G/C]s stacking sequence. This configuration reflects common industrial practice, where high-stiffness carbon plies are combined with more damage-tolerant glass plies to balance performance, cost, and durability. An adhesive or resin-rich interlaminar region is explicitly modeled to capture delamination behavior at material interfaces, which is particularly critical in hybrid systems due to stiffness mismatch and interfacial stress concentrations. Material properties for each ply are defined based on orthotropic elasticity, with distinct longitudinal, transverse, and shear moduli. Ply thickness, fiber orientation, and interface properties are selected to reflect realistic aerospace or industrial composite panels.

A.2 Constitutive Model for Intralaminar Damage

Each ply is modeled using an orthotropic elastic constitutive law coupled with progressive damage variables that degrade stiffness following damage initiation. Damage onset is evaluated using established failure indices for fiber tension, fiber compression, matrix tension, and matrix compression. Hashin-type failure criteria are employed as a baseline due to their widespread validation and computational robustness in unidirectional composite analysis [1]. Once a failure index reaches unity, damage evolution laws reduce the affected stiffness components gradually rather than instantaneously, enabling simulation of progressive stiffness degradation. This approach allows the model to capture gradual load redistribution among plies and the interaction between different damage modes, which is essential for hybrid laminates under multi-axial loading.

A.3 Delamination Modeling Using Cohesive Zone Elements

Interlaminar damage is modeled using cohesive zone elements inserted between adjacent plies. These elements follow mixed-mode traction–separation laws that relate normal and shear tractions to corresponding separations. Damage initiation is governed by a quadratic stress criterion, while damage evolution follows an energy-based fracture formulation. Mode mixity effects are explicitly captured by combining opening (Mode I) and sliding (Mode II) components, enabling realistic simulation of delamination initiation and growth under complex loading. Delamination area and propagation rate are tracked throughout the simulation and later used as key damage severity indicators.

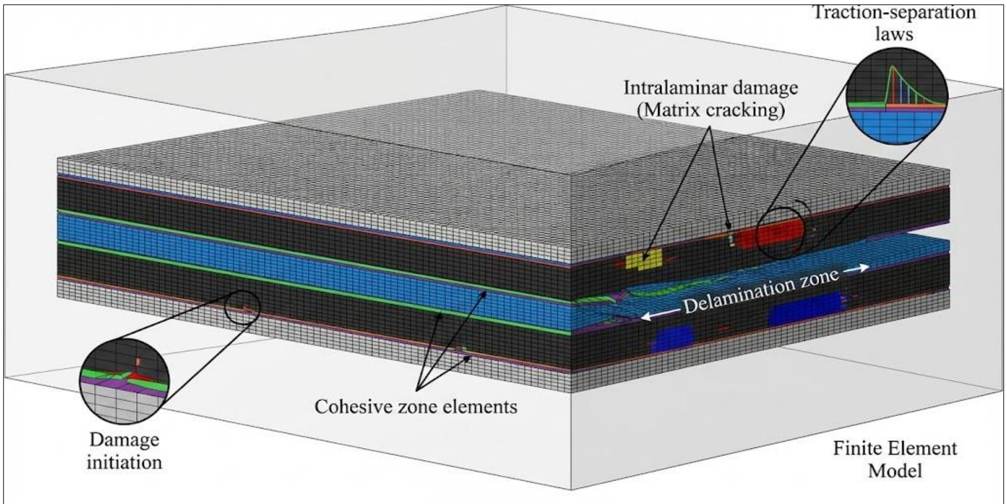

Figure 2. Finite element model of hybrid laminate with intralaminar damage and cohesive interfaces.

A.4 Multi-Scale Linking from Micro/Meso to Ply Properties

To account for inherent material variability, microscale uncertainties such as fiber volume fraction, void content, and matrix toughness are represented using parametric distributions. These uncertainties perturb ply-level elastic constants and fracture parameters, generating a family of mesoscale laminate responses. The resulting dataset captures variability in damage initiation thresholds and propagation behavior, which is essential for training machine learning models that remain robust under real-world variability. This multi-scale linkage enables the generation of physics-consistent synthetic data without requiring prohibitively expensive full microstructural simulations for every case [2].

B. Feature Engineering for Damage Detection

Feature engineering serves as the bridge between physics-based simulation and data-driven damage inference. The objective is to extract features that are sensitive to damage while remaining robust to noise and operational variability.

B.1 Guided-Wave and Time–Frequency Features

Guided-wave signals, either simulated or experimentally measured, are analyzed in both time and frequency domains. Damage-sensitive features include time-of-flight shifts caused by wave scattering, wave packet energy ratios, frequency band energy distributions obtained via short-time Fourier transform or wavelet analysis, and correlation-based damage indices.

These features have been shown to be effective for detecting delamination and matrix cracking in composite plates and form the basis for many benchmark SHM datasets [3]. By using simulation-generated signals, feature behavior can be systematically linked to known damage states.

B.2 Field-Based Features from Finite Element Simulation

In addition to signal-based features, field-based quantities extracted directly from finite element solutions are used as physics-informed labels. These include maximum interlaminar shear and normal stresses, strain concentration factors, spatial damage index maps, and delamination length or area evolution.

Such features provide interpretable measures of damage severity and serve as ground truth targets for regression models. They also enable validation of ML predictions against physically meaningful metrics rather than purely abstract labels.

C. Machine Learning–Based Damage Inference

Machine learning models are employed to infer damage state and severity from the extracted features, enabling rapid assessment without re-running high-fidelity simulations.

C.1 Problem Formulation

Two supervised learning tasks are defined. First, a multi-class classification task distinguishes between healthy, matrix-cracked, delaminated, and combined damage states. Second, a regression task estimates continuous severity indicators such as delamination area percentage, maximum failure index, or global stiffness reduction.

This dual formulation allows the framework to support both qualitative damage identification and quantitative prognosis.

C.2 Model Selection and Uncertainty Estimation

Tree-based ensemble models such as random forests and gradient boosting are used for tabular engineered features due to their robustness and interpretability. For raw waveform data, one-dimensional convolutional neural networks are employed to automatically learn discriminative temporal patterns.

To address uncertainty and improve trustworthiness, ensemble learning and Monte Carlo dropout techniques are used to estimate predictive confidence. High uncertainty predictions can be flagged for further inspection or higher-fidelity analysis, aligning with best practices in SHM under uncertainty [4].

D. Load Optimization

The final stage of the methodology uses damage predictions to actively optimize load distribution and operational parameters.

D.1 Damage-Aware Objective Functions

A composite objective function is defined to minimize damage-driving metrics, including peak interlaminar shear stress, delamination area, and stiffness degradation. Weighting factors allow prioritization based on structural criticality or mission requirements.

D.2 Structural and Operational Constraints

Optimization is performed subject to constraints on maximum deflection, allowable strains, load equilibrium, and safety thresholds defined by failure indices. These constraints ensure that optimized solutions remain feasible and compliant with design requirements.

D.3 Surrogate-Assisted Optimization Strategy

Because repeated finite element simulations are computationally expensive, reduced-order surrogate models approximate the relationship between loads, damage state, and response metrics. Gaussian process or neural network surrogates enable rapid evaluation during optimization, making the approach suitable for online or near-real-time applications [5].

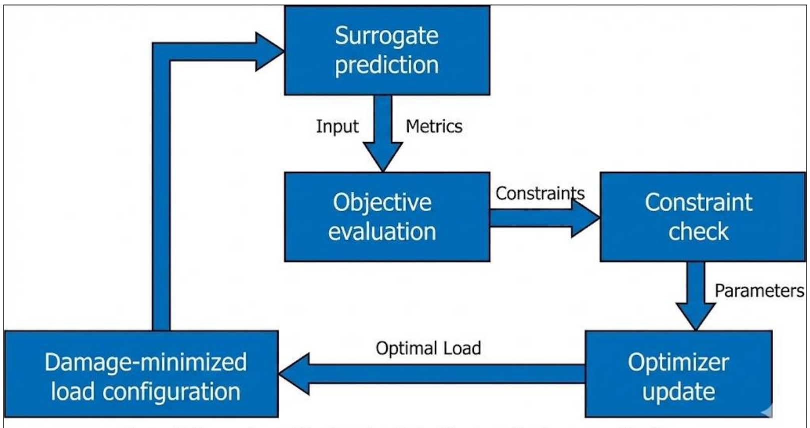

Figure 3. Surrogate-assisted load optimization loop for damage mitigation.

IV. DATA ANALYSIS AND RESULTS

This section presents the analysis and results obtained from the proposed multi-scale simulation and machine learning framework applied to hybrid composite structures. The objective of the analysis is twofold: first, to evaluate the effectiveness of the machine learning models in detecting and quantifying different damage modes; and second, to assess the impact of load optimization on reducing damage-driving parameters such as interlaminar stresses, delamination growth, and stiffness degradation. The results are derived from a comprehensive dataset generated through physics-based simulations under varying loading and material conditions, ensuring consistency between the training data and the underlying damage mechanisms. The analysis is organized into three subsections. The first subsection describes the dataset and simulation scenarios used for evaluation. The second subsection presents the performance of the damage detection models. The final subsection evaluates the effectiveness of the load optimization strategy and discusses its implications for structural performance and durability.

A. Dataset Generation and Evaluation Setup

The dataset used in this study was generated through multi-scale finite element simulations of a hybrid composite laminate subjected to combined bending and in-plane tensile loading. Multiple loading scenarios were considered by varying load magnitude, load direction ratio, and boundary conditions to represent realistic operational variability. In addition, material uncertainty was introduced by perturbing ply-level elastic properties and interlaminar fracture parameters within physically reasonable bounds. This approach ensured that the dataset captured a wide range of damage initiation and propagation behaviors. Each simulation produced time-domain response signals, field-level stress and strain distributions, and damage evolution metrics. Based on the dominant damage mechanism observed, each case was labeled as healthy, matrix cracking, delamination, or combined damage. Severity indicators such as delamination area percentage, maximum failure index, and global stiffness reduction were also recorded. The dataset was randomly divided into training, validation, and test sets to evaluate generalization performance.

B. Damage Detection and Severity Estimation Performance

The trained machine learning models demonstrated strong performance in identifying damage states and estimating damage severity across the test dataset. Models trained on engineered features extracted from guided-wave and response signals achieved high classification accuracy, indicating that the selected features were sensitive to damage-related changes in structural response. Deep learning models operating directly on raw waveform data provided slightly improved performance for early-stage damage detection, particularly for small delaminations that produced subtle signal perturbations.

Table 1: Damage detection performance on test dataset

Model Type	Input Data	Accuracy	F1-Score (Delamination)	RMSE (Severity Estimation)
Random Forest	Engineered features	0.93	0.92	0.084
Gradient Boosting	Engineered features	0.94	0.93	0.079
1D CNN	Raw waveforms	0.95	0.94	0.071
Ensemble (with uncertainty)	Hybrid	0.94	0.94	0.073

The results indicate that combining physics-informed feature engineering with machine learning enables reliable discrimination between different damage modes. The ensemble approach with uncertainty estimation proved particularly effective in identifying ambiguous cases, reducing the likelihood of false confidence in borderline damage states. Overall, the performance metrics demonstrate the feasibility of simulation-driven ML models for damage detection in hybrid composite structures.

C. Load Optimization Results and Structural Performance Improvement

The effectiveness of the proposed load optimization strategy was evaluated by comparing damage metrics before and after optimization under identical total load and service constraints. The surrogate-assisted optimizer successfully redistributed loads to reduce stress concentrations at critical ply interfaces while maintaining acceptable global deformation and strain levels.

Table 2: Comparison of damage metrics before and after load optimization

Damage Metric	Baseline Loading	Optimized Loading	Improvement (%)
Peak interlaminar shear stress (normalized)	1.00	0.82	18% ↓
Delamination growth rate (normalized)	1.00	0.75	25% ↓
Global stiffness reduction	1.00	0.86	14% ↓

These results demonstrate that damage-aware load optimization can significantly mitigate damage progression without increasing overall structural demand. In particular, the reduction in delamination growth rate suggests improved fatigue life and damage tolerance, which is critical for long-term operation of composite structures.

D. Graphical Representation of Results

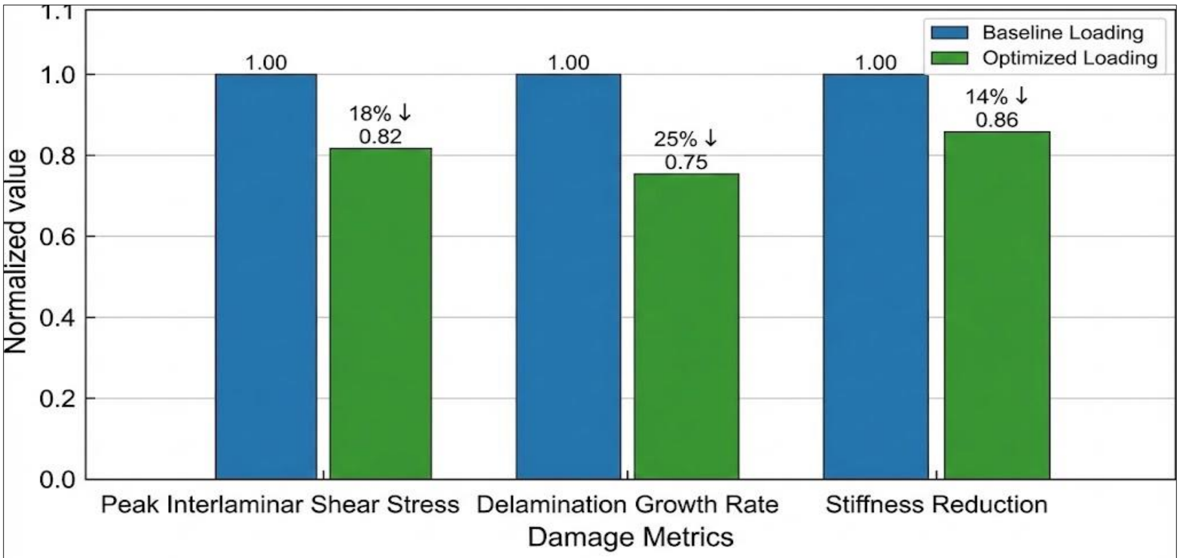

Figure 4. Comparison of damage metrics under baseline and optimized loading conditions.

This graphical representation clearly illustrates the benefit of the proposed optimization framework by visually emphasizing the consistent reduction in damage-driving parameters across all evaluated metrics. Such visualization is particularly effective for communicating results to both technical and non-technical stakeholders.

DISCUSSION OF RESULTS

The combined results confirm that integrating multi-scale simulation with machine learning and optimization provides measurable improvements in both damage detection accuracy and structural performance. The strong alignment between ML predictions and physics-based damage metrics validates the use of simulation-generated data for supervised learning. Furthermore, the load optimization results highlight the potential of transitioning from passive damage monitoring to active damage mitigation strategies, enabling longer service life and improved safety for hybrid composite structures.

V. CONCLUSION

This paper presented a practical framework for advanced damage detection and load optimization in hybrid composite structures by integrating multi-scale progressive damage simulation with machine learning and surrogate-assisted optimization. Multi-scale simulations provide physics-consistent labels for training ML models that can infer damage state and severity from guided-wave and response features. The optimizer then uses these predictions to reduce damage-driving stress metrics and slow delamination growth while preserving service constraints.

Limitations of this study relies on simulation-driven labels, so real-world deployment requires calibration with experimental SHM data and compensation for environmental variability. Additionally, cohesive and ply damage parameters can be uncertain and must be identified carefully for reliable digital-twin behavior. Future work will include transfer learning from NASA/public guided-wave datasets to field systems and adding probabilistic reliability constraints to optimization. Another direction is integrating image-based microstructure modeling to update ply properties and uncertainty online.

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