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Adaptive Multi-Fidelity Framework for Defect and Damage Tolerant Composite Structures

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Abstract. This work presents an adaptive multi-fidelity framework for uncertainty quantification in defect-tolerant composite structures. The approach couples the Carrera Unified Formulation (CUF) for generating consistent low- and high-fidelity structural theories with an adaptive Gaussian Process Regression (GPR) surrogate that learns their correlation. High-fidelity simulations are selectively activated in regions of high uncertainty, minimizing computational cost while preserving accuracy. The framework enables probabilistic estimation of stresses and failure indices with confidence intervals and is validated against 3D Abaqus benchmarks.

Introduction

The increasing demand for lightweight and high-performance structures has driven the adoption of advanced composite materials, with manufacturing techniques like Automated Fiber Placement (AFP) enabling highly optimized and complex designs [1-2]. However, the reliability of these components is often compromised by the interplay of manufacturing defects, such as gaps, overlaps and fiber misalignment, and inherent material and load variability [3]. Designing defect and damage-tolerant components therefore requires a rigorous quantification of how these uncertainties shape local stress fields and drive damage evolution, including crack propagation. Traditional deterministic or single fidelity models are either prohibitively expensive for comprehensive probabilistic analysis or too simplistic to capture the governing physics, leaving a critical gap in robust composite design methodologies.

This work proposes a novel Multi-Fidelity (MF) probabilistic framework to overcome these limitations. The methodology is built upon the Carrera Unified Formulation (CUF) [4], which provides a consistent hierarchical basis for generating both computationally efficient Equivalent Single-Layer (ESL) models and highly accurate Layer-Wise (LW) models. An adaptive Gaussian Process Regression (GPR) [5-6] surrogate learns the correlation between these fidelity levels, drastically reducing the need for expensive High-Fidelity (HF) simulations. This intelligent learning process actively queries new HF data only in regions of high predictive uncertainty, maximizing information gain while minimizing computational cost. The conceptual workflow of this adaptive framework is illustrated in Fig. 1. This integrated framework enables an efficient and accurate uncertainty quantification for damage onset assessment, allowing for the direct calculation of key probabilistic metrics such as through-the-thickness stress profiles with confidence intervals, probability distributions of critical failure indices, and the overall probability of failure. To ensure methodological rigor, the framework's predictions are validated against benchmark analyses using high-fidelity 3D models in Abaqus.

Furthermore, the framework extends to progressive damage [7] prediction by combining Low-Fidelity (LF) and high-fidelity models along the damage evolution path. The LF model efficiently captures the global structural response and damage progression, while the adaptive learning strategy selectively deploys HF simulations when approaching critical failure thresholds. A separable GPR surrogate corrects the entire damage history, enabling accurate reconstruction of high-fidelity crack-growth curves across the uncertainty space with minimal computational cost.

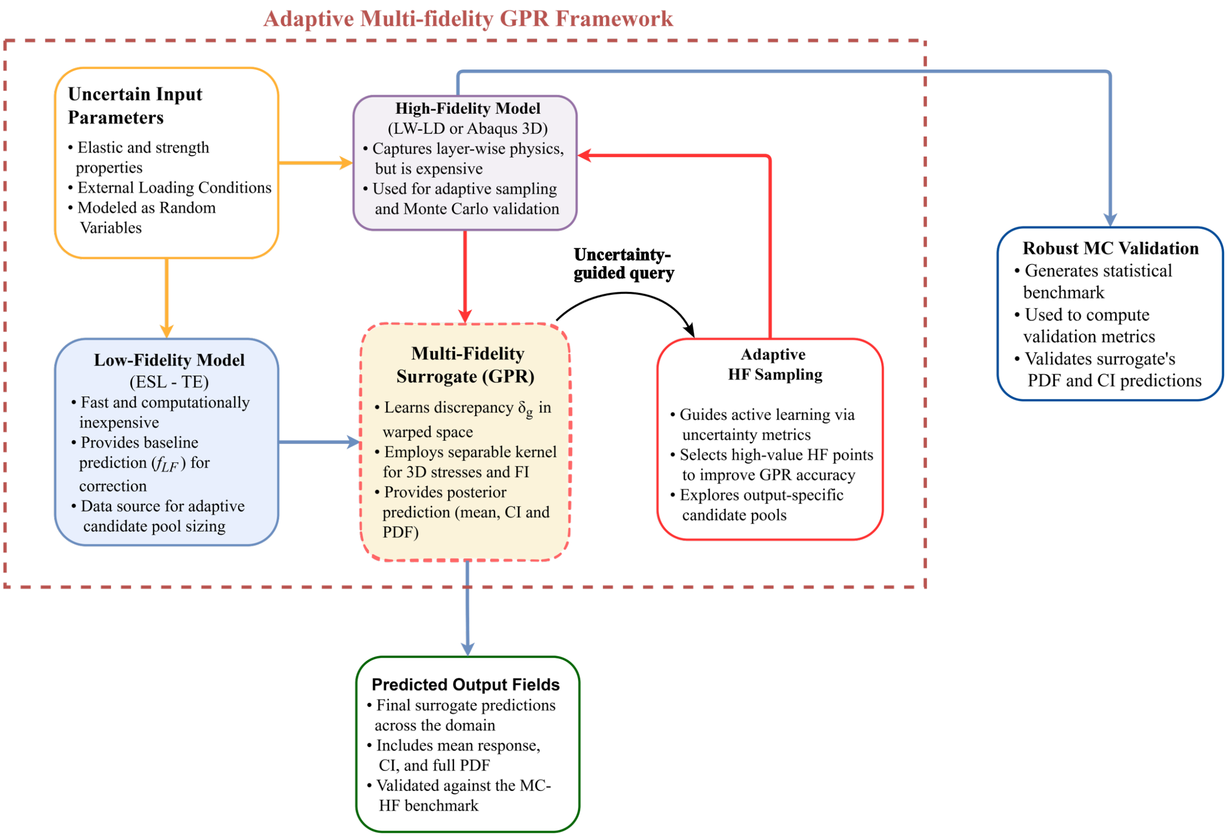

Figure 1. Adaptive multi-fidelity GPR framework combining low-fidelity predictions with selective high-fidelity corrections to provide probabilistic failure and stress predictions validated by Monte Carlo.

Unified finite elements

In this work, CUF formalism is used to implement 2D FE. The 3D displacement field can be expressed using arbitrary through-the-thickness expansion functions $\boldsymbol{F}_{\boldsymbol{\tau}}(\boldsymbol{z})$ as follows:

$$\boldsymbol{u}(x, y, z) = F_\tau(z)\boldsymbol{u}_\tau(x, y). \ \tau = 1, \dots, M \tag{1}$$

The symbol M represents the number of expansion terms, and $\boldsymbol{u}_\tau(x, y)$ represents the vector containing the generalized displacements, with τ indicating summation. Examining multi-layered structures typically employs either an Equivalent-Single-Layer (ESL) or Layer-Wise (LW) approach. In this manuscript, ESL models utilize Taylor polynomials represented by $F_\tau(z)$; while LW employs Lagrange polynomials over individual layers and ensures the continuity of displacements at layer interfaces. Utilizing the FE and shape functions $N_i(x, y)$, the displacement field becomes:

$$\boldsymbol{u}(x, y, z) = N_i(x, y)F_\tau(z)\boldsymbol{q}_{\tau i}(x, y). \ i = 1, \dots, N_n \tag{2}$$

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In Eq. (2), $\boldsymbol{q}_{\tau i}$ are the unknown nodal variables, with N_n denoting the number of nodes per element. This work employs 2D nine-node quadratic elements for the in-plane discretization.

The governing equations are derived using the Principle of Virtual Displacements (PVD), which asserts that the virtual variation of internal strain energy, $\delta\mathcal{L}_{int}$, equals the virtual work of external forces, $\delta\mathcal{L}_{ext}$, minus inertia forces, $\delta\mathcal{L}_{ine}$. Specifically, $\delta\mathcal{L}_{int}$ can be written as:

$$\delta\mathcal{L}_{int} = \delta\boldsymbol{q}_{sj}^T\left[\int_V \boldsymbol{D}^T(N_jF_s)\,\widetilde{\boldsymbol{C}}\boldsymbol{D}(N_iF_\tau)\,dV\right]\boldsymbol{q}_{\tau i} = \delta\boldsymbol{q}_{sj}^T\boldsymbol{k}_0^{ij\tau s}\boldsymbol{q}_{\tau i}, \tag{3}$$

where $\boldsymbol{k}_0^{ij\tau s}$ is the 3×3 Fundamental Nucleus (FN) of the stiffness matrix, invariant regardless of 2D shape function order and through-the-thickness expansion. $\boldsymbol{D}(\cdot)$ is the differential operator matrix with geometric relations, and $\widetilde{\boldsymbol{C}}$ is the material stiffness matrix in the global reference frame, i.e., $\widetilde{\boldsymbol{C}} = \boldsymbol{T}(x,y)^T\boldsymbol{C}\boldsymbol{T}(x,y)$. The global stiffness matrix, $\boldsymbol{K}$, is obtained by iterating over FN's with indices i, j, τ and s to compute element-level matrices, which are then assembled for the global structure.

MF - GPR framework

The approach integrates GPR with a multi-fidelity strategy combining LF (ESL) and HF (LW) simulations. Uncertainties stem from material properties and applied loads, as well as potential manufacturing defects such as fiber misalignments, gaps, overlaps, and resin-rich zones. Random samples are generated using Latin Hypercube Sampling (LHS) to ensure uniform coverage of the input space. GPR models the relationship between input parameters **x** and outputs f(**x**) as a Gaussian Process (GP) defined by a mean function μ(x) and a covariance function κ(x, x′):

$$f(x) \sim \mathcal{GP}(\mu(x), \kappa(x,x')) \tag{4}$$

$$\kappa(x,x') = \sigma_f^2 \exp\left(-\frac{\|x-x'\|^2}{2l^2}\right) \tag{5}$$

where σ_f^2 and l the kernel variance and length scale for each output. Using training data (X, y), the GP predicts outputs at new points by combining the mean and variance derived from the model. The multi-fidelity framework accounts for the discrepancy between low- and high-fidelity simulations. The high-fidelity response $\hat{f}_{HF}(x)$ is expressed as:

$$\hat{f}_{HF}(x) = f_{LF}(x) + \Delta(x) \tag{6}$$

where f_{LF} is the LF response and $\Delta(x)$ is the discrepancy between LF and HF modeled as a GP. This formulation enables accurate and efficient structural predictions under uncertainties by merging LF trends with corrections derived from high-fidelity data.

Damage model

The Hashin 3D criterion predicts the onset of fiber and matrix failure under tension and compression by evaluating stresses in three dimensions. When any failure index reaches unity, the corresponding damage mode is activated, initiating stiffness degradation through an evolution law. Hashin 3D criterion is adopted to evaluate three failure modes: fiber tension, fiber compression, and matrix compression.

$$F_{ft} = \left(\frac{\sigma_{11}}{X_T}\right)^2 + \alpha_f\left[\left(\frac{\sigma_{12}}{S_{12}}\right)^2 + \left(\frac{\sigma_{13}}{S_{13}}\right)^2\right]$$

$$F_{mt} = \left(\frac{\sigma_{22} + \sigma_{33}}{Y_T}\right)^2 + \frac{1}{S_{23}^2}(\sigma_{23}^2 - \sigma_{22}\sigma_{33}) + \left(\frac{\sigma_{12}}{S_{12}}\right)^2 + \left(\frac{\sigma_{13}}{S_{13}}\right)^2$$

$$F_{fc} = \left(\frac{\sigma_{11}}{X_C}\right)^2$$

F quantify the failure, the first subscript indicates whether the failure concerns the matrix (M) or the fiber (F), while the second whether it is tensile (T) or compressive (C). X is the strength of the fiber, if compressive X_C if traction X_T. S_{12}, S_{13} and S_{23} are the shear strengths. Y_T is the tensile strength of the matrix.

Only for matrix compression is considered the Puck criterion according to which the fracture of the matrix is due to stress σ_{nn}, σ_{nl}, σ_{nl}, which are respectively the normal, longitudinal shear and transverse stresses to the fracture plane.

$$F_{mc} = \left(\frac{\sigma_{nt}}{S_{23}^A - \eta_{nt}\sigma_{nn}}\right)^2 + \left(\frac{\sigma_{nl}}{S_{13} - \eta_{nl}\sigma_{nn}}\right)^2$$

η_{nt} and η_{nl} characterize the internal friction of the material while S_{23}^A is the transverse shear strength in the fracture plane.

Once the criterion for the initiation of failure is triggered, the progression of the damage is governed by a linear pattern of damage evolution, so that the stiffness of the material decreases until the final failure. The linear model is based on the equivalent displacements δ_{eq}. Using a unified subscript $P \in \{ft, fc, mt, mc\}$ to represent the four modes of damage, a parameter for the evolution of the damage is defined for each mode d_P,

$$d_p = \frac{\delta_{eq}^u(\delta_{eq} - \delta_{eq}^0)}{\delta_{eq}(\delta_{eq}^u - \delta_{eq}^0)}$$

$\delta_{eq}^0 = \delta_{eq,F=1}$ is the equivalent displacement at the beginning of the damage, while δ_{eq}^u is at the final failure.

The constitutive elastic stress-strain relation during the damage evolution can be written as

$$\sigma = C_{dam}\epsilon$$

where C_{dam} is the stiffness matrix in the damage state, function of damage parameters d_P.

Results

The case study analyzes a composite open-hole plate under tensile loading using the proposed multi-fidelity (MF) framework. The configuration follows a benchmark from Ref. [8] with a symmetric $[45°/90°/-45°/0°]_{3s}$ laminate. Material and load properties are modeled as normal or uniform random variables. LF analyses use an ESL-TE1 model, while HF analyses employ an LW model with one LD1 expansion per ply. Figures 2 and 3 show the probabilistic distributions of the Fiber Tension (FT) and delamination failure indices across the laminate thickness, comparing low-, high-, and multi-fidelity models with their 90% confidence intervals. The MF predictions accurately reproduce the HF trends with a fraction of the computational cost.

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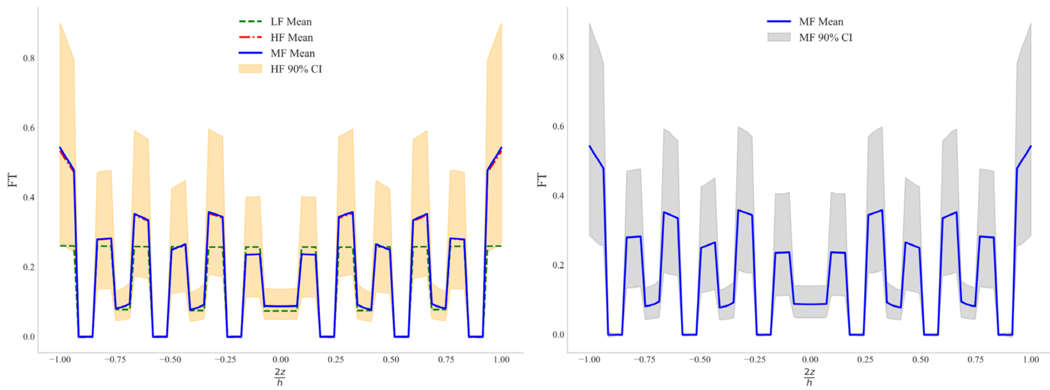

Figure 2. Fiber Tension (FT) failure index through the laminate thickness obtained from LF, HF, and MF models with corresponding 90% confidence intervals.

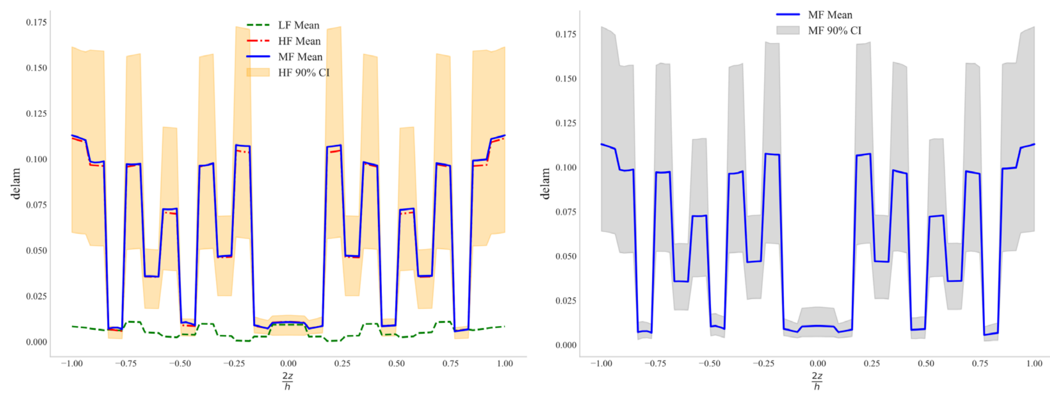

Figure 3. Delamination failure index through the laminate thickness obtained from LF, HF, and MF models with corresponding 90% confidence intervals.

Figure 4 presents the stress–strain response of a composite single element under tension with a symmetric laminate stacking sequence $\theta = [45,90,-45,0]^{\circ}_{4s}$. The uncertainties are applied to the material properties and strength allowables. The MF surrogate accurately reconstructs the high-fidelity (HF) reference using only a limited number of HF simulations (~10%), achieving close agreement with the deterministic curve and providing 90% confidence bounds on the predicted stress field.

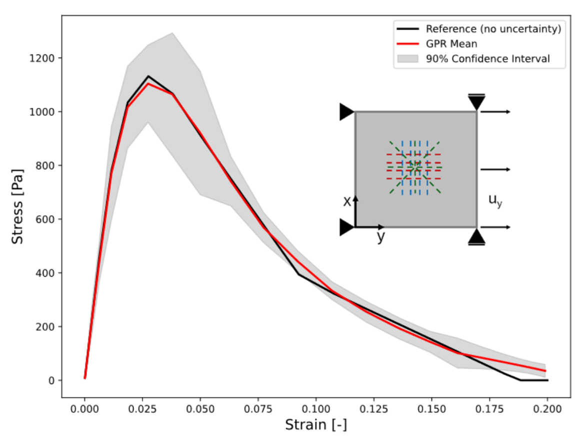

Figure 4. Multi-fidelity stress-strain curve under uncertainties

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Conclusions

The proposed adaptive multi-fidelity framework effectively combines CUF-based structural models with Gaussian Process Regression to quantify the impact of material and manufacturing uncertainties on composite failure. By integrating low- and high-fidelity analyses within an active learning strategy, it achieves high accuracy with a fraction of the computational cost. These results demonstrate its potential for Reliability-Based Design Optimization (RBDO) of lightweight composite structures [9].

Acknowledgments

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