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Abstract. The Carrera Unified Formulation, CUF, provides variable kinematic structural theories to handle 3D strain and stress fields with superior computational efficiency [1]. The accuracy of a CUF model depends on the number of generalized variables used to describe the unknown fields, which is a free parameter typically chosen through convergence analyses. Additionally, accuracy can vary from node to node, as each node in a CUF-based finite element model may employ a different structural theory. Node-dependent kinematics is useful for optimizing computational effort by limiting the use of higher-order variables to regions where significant 3D effects are expected.
Recently, machine learning (ML) techniques have been used in the CUF framework for multiple purposes, namely, to obtain guidelines on the correct choice of generalized variables for a given set of problem parameters [2], to build a training dataset composed of a blend of low-fidelity and high-fidelity models [3], to develop adaptive learning approaches and handle model uncertainties [4]. This paper presents the latest developments in the synergistic use of CUF and ML to tune model fidelity and optimize computational cost.

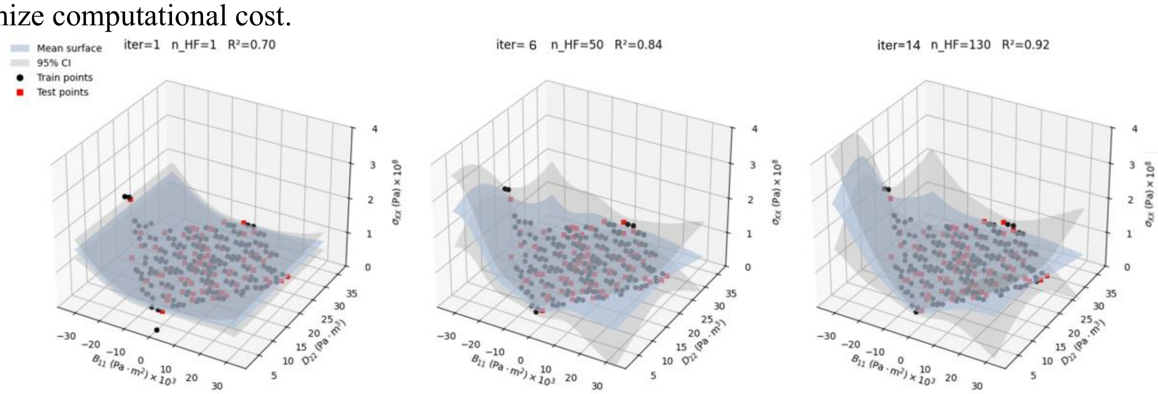

Figure 1: Multi-fidelity GPR predictive surface with iterative replacement of low-fidelity (LF) points by high-fidelity (HF) points, and comparison with the 95% confidence bands

Figure 1 illustrates an example of CUF-ML results for assessing residual stresses caused by the curing process in an eight-layer, cross-ply composite part. The horizontal axes display stiffness coefficients for each combination of 0° and 90° layers, while the vertical axis shows the residual stress. Gaussian Process Regression (GPR) was employed to create a surrogate model that offers response surfaces based on the stacking sequence. GPR was trained using a mix of low-fidelity (LF) and equivalent single-layer models, along with high-fidelity (HF) layer-wise models. The goal was to reduce the number of HF models to cut down on computational costs. The three plots depict how the response surface changes as the number of HF models increases, demonstrating a significant boost in accuracy. Additional results will focus on mapping problem features and applying explainable machine learning techniques to assess the impact of a generalized variable on the solution.

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