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Ph.D. DISSERTATION DEFENSE

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Degree:	Doctor of Philosophy
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Title:	Machine Learning for Quantification of Uncertainty in Structural Performance
Chairperson:	Dr. Kishore Pochiraju, Department of Mechanical Engineering
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ABSTRACT

Variability in properties of heterogeneous composites arises from manufacturing processes, service loads, or environmental factors, significantly impacting macroscopic structural performance. Uncertainty Quantification (UQ) offers a framework for measuring these uncertainties and evaluating their effects, enhancing confidence in simulation outcomes. Comprehensive UQ can facilitate certification by simulation for composite materials, manufacturing processes, and aerostructures, where substantial experimental efforts are currently needed.

This research delves into UQ methods for computational efficiency and material variability assessment. It explores innovative artificial intelligence and machine learning approaches for a more versatile and efficient microstructure homogenization framework during UQ. Initially, the study presents a method for reducing the computational load of the Monte Carlo (MC) technique for uncertainty propagation by adopting the Quasi Monte Carlo (QMC) method with various low-discrepancy sampling approaches. The QMC technique demonstrates a significant increase in convergence speed compared to MC. Additionally, convolutional neural networks are shown to infer parameters describing random fields modeling a material's spatial property variability from a limited number of experimental tests with full-field strain measurement. Defining random fields for highly anisotropic materials typically necessitates extensive experimental characterization or computationally intensive multi-scale simulations. Surrogate models utilizing neural networks are often developed for stochastic heterogeneous materials to decrease computational costs. However, these models are usually microstructure-specific, and calibrated models are non-transferable. The research demonstrates that the transformer neural network architecture can generate knowledge about various microstructures and constituents, allowing the transformer to serve as a computationally efficient homogenization surrogate model applicable to multiple microstructures. The transformer network accurately predicts the nonlinear and history-dependent response of elastoplastic composites using a learned and adaptive microstructure encoding. These predictions are considerably faster than finite element method-based approaches, saving orders of magnitude in computational time.