

## Ph.D. DISSERTATION DEFENSE

**Candidate:** Ke Xu

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**School:** Charles V. Schafer School of Engineering and Science (SES)

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Title: AI-driven Quality Prediction in Additive Manufacturing based on Multimodal

**Process Monitoring** 

**Chairperson:** Dr. Souran Manoochehri, Department of Mechanical Engineering, SES

Co-advisor: Dr. Chaitanya Krishna Vallabh, Department of Mechanical Engineering, SES

Committee Dr. Robert Chang, Department of Mechanical Engineering, SES Dr. Chang-Hwan Choi, Department of Mechanical Engineering, SES

Members:

Dr. Yi Bao, Department of Civil, Environmental and Ocean Engineering, SES

## **ABSTRACT**

Additive Manufacturing (AM) has emerged as a transformative technology, yet ensuring consistent part quality remains challenging due to complex thermal dynamics, layer-by-layer fabrication, and material microstructure changes. Post-process inspection methods to assure part quality are typically costly, time-consuming, and unable to provide real-time feedback for print process optimization. This dissertation addresses these challenges by developing AI-driven predictive frameworks that integrate multimodal sensor monitoring with Machine Learning (ML) algorithms to enable intelligent quality assessment for both Fused Filament Fabrication (FFF) and Directed Energy Deposition (DED) processes.

For FFF process monitoring, we established Acoustic Emission (AE) sensing as a novel foundation for real-time part and process defect detections such as warpage, nozzle blockage, and over/under extrusion. Recognizing the critical issue of warpage in FFF parts, we quantify the warpage percentages using a sensor fusion methodology that combines data from AE signals and laser scanning of printing layers. This integrated approach, coupled with ML-based prediction models, enables monitoring and quantifying both process quality and geometric deviations.

In the DED studies, we initially investigated the relationships between key process parameters and resulting mechanical properties. By extracting features from AE signals acquired during deposition, we trained multiple ML models to predict part hardness, demonstrating the potential of AE monitoring for non-destructive mechanical property prediction. Advancing beyond single-sensor implementation, we developed a multimodal DED monitoring platform for geometric variation classification and layer-wise quality assessment. This system integrates a camera-based melt pool imaging with AE sensing paired with AI-driven framework capability. To address the critical challenge of subsurface quality prediction, we extended our multimodal framework to characterize part porosity. Recognizing that different sensor modalities capture distinct process characteristics, we developed an optimized weighted ensemble approach that selects feature-specific models to maximize classification accuracy. This novel AI-driven multimodal framework is capable of predicting levels of internal defects (severe, moderate, mild) solely using sensor data.

The contributions of this research demonstrate that AI-driven multimodal sensor integration combined with data augmentation and feature-specific model optimization provides a robust framework for comprehensive AM quality monitoring spanning from surface geometric accuracy to internal microstructural integrity. These methodologies establish a foundation for next-generation intelligent manufacturing systems that enable real-time quality prediction, minimize post-process inspection requirements, and facilitate adaptive process control in both FFF and DED additive manufacturing processes.