Dissertation Defense Invitation

Advancing Physics-Informed Machine Learning for Process Control in Smart Manufacturing

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You are cordially invited to attend the dissertation defense of Abdelrahman Farrag.

Date: Friday, April 17, 2026
Time: 2:00 PM – 4:00 PM (EDT)
Location: EB-R15 Conference Room *and* Virtual (Zoom)
Zoom Link:
`https://binghamton.zoom.us/j/99363240340?pwd=uCQuLSLd0Rh63MrNLXQEfuYGWvI4t8.1&jst=2`

Dissertation Abstract

Today's manufacturing processes are pushed to their limits to deliver products with ever-increasing quality at low cost. A central challenge lies in the coupling of multiscale and multiphysics interactions among process parameters, materials, and component geometries, which collectively govern final product quality and yield. Despite significant advances in numerical simulation, physics-based models remain limited by high computational cost, complex governing equations, idealized assumptions, and the need for extensive calibration. In contrast, purely data-driven models often suffer from data scarcity, poor extrapolation to unseen operating conditions, and limited physical interpretability.

This dissertation advances *Physics-Informed Machine Learning (PIML)* methods that embed governing physical principles and engineering knowledge of manufacturing systems into artificial intelligence frameworks. The objective is to improve computational efficiency, maintain predictive accuracy under limited data availability, and enhance model generalizability and interpretability.

Three PIML frameworks are developed and validated using real-world case studies from

Surface Mount Technology (SMT), the dominant method for assembling electronic components onto printed circuit boards (PCBs). These studies leverage production data from stencil printing and solder reflow processes to demonstrate the practical applicability of the proposed methods.

The first framework, **SafePrint**, introduces a real-time safe optimization approach for stencil printing during new product introduction. Within a safe Bayesian optimization pipeline, surrogate quality is enhanced using a data-efficient, physics-informed Gated Recurrent Unit kernel learning model that captures solder paste thixotropic behavior and enables accurate, near-optimal parameter selection under limited data.

The second framework, **SRP-PINN**, models the solder reflow process by embedding heat transfer governing equations and boundary conditions directly into the network loss function, enabling accurate prediction of thermal profiles across varying oven recipes and PCB designs.

The third framework, **ThermoDynaSMT**, proposes a sequential operator-splitting formulation of multiphysics-informed neural networks to model Marangoni convection-driven self-alignment of miniaturized passive components during reflow. This framework provides a predictive foundation for optimizing component placement strategies and reduces reliance on empirical, rule-of-thumb adjustments in conventional assembly practices.

The three frameworks are systematically benchmarked against industry standards and state-of-the-art methods in the literature, demonstrating their effectiveness in advancing intelligent, data-efficient, and physics-consistent manufacturing process control.

All are welcome to attend