



Scientific Machine Learning for Multi-Fidelity Combustion Modeling

Sili Deng

Massachusetts Institute of Technology, USA

Scientific machine learning (SciML) offers transformative tools for multi-fidelity combustion modeling, bridging experimental data, physics-based insights, and computational efficiency. This talk presents three recent examples ranging from kinetic modeling to system surrogates. First, a Chemical Reaction Neural Network (CRNN) framework quantifies thermal-kinetic uncertainties in lithium-ion battery thermal runaway by leveraging Bayesian inference on differential scanning calorimetry data, improving predictive accuracy for cell-scale models. Second, a PDE-constrained optimization approach extracts kinetic and transport properties from thermal wave dynamics in energetic materials, enabling insights into reaction-transport coupling without full state variable measurements. Third, a digital twin framework, demonstrated for biomass combustion in industrial-scale furnaces, employs a Reactor-Structure-Resembled Network (RSRNet) and incremental learning to reconstruct high-dimensional scalar fields with minimal CFD data, achieving robust predictions under varying conditions. These advancements underscore the power of SciML in addressing critical challenges in combustion modeling and optimization.