MFRNet: A Unified Digital Twin Framework for Data-Efficient Reconstruction and Optimization of Industrial Combustion Systems

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Industrial combustion systems are foundational to global energy production but face increasing pressure to simultaneously enhance performance and reduce environmental impact. The integration of biomass and other carbon-neutral fuels into these systems introduces complex dynamics due to fuel heterogeneity, geometric complexity, and dynamic operational conditions. As traditional control strategies fall short in adapting to these challenges, digital twins that are virtual replicas of physical systems, have emerged as a transformative approach for real-time monitoring, predictive modeling, and intelligent control.

In this study, we present MFRNet (Multi-field Reconstruction Network), a unified and data-efficient machine learning framework for developing digital twins tailored to industrial-scale combustion systems. MFRNet enables accurate 3D reconstruction of multiple physical fields and multi-objective optimization with minimal reliance on expensive high-fidelity simulation data. This is achieved through three key innovations: (1) Dimension expansion, which extends pretrained 2D models to capture 3D phenomena; (2) Variable extension, allowing prediction of additional fields (e.g., NOx species) from existing learned features; and (3) Dynamic feature fusion, leveraging attention-based mechanisms to enhance scalar prediction accuracy from latent multi-field representations.

We validate this framework using a biomass grate furnace as a case study, where the model is trained on a multi-fidelity dataset combining 288 2D and 48 3D CFD simulations. MFRNet successfully reconstructs key fields such as temperature, flow, and chemical species distribution with high accuracy under complex conditions. Notably, it achieves order-of-magnitude improvements in reconstructing NO, HCN, and NH_3 distributions compared to models trained on limited 3D data alone.

For system-level decision-making, MFRNet is used to develop response surfaces for combustion efficiency (via CO emissions) and pollutant output (NO emissions). These surfaces are then embedded in a Pareto-based optimization loop, enabling real-time exploration of trade-offs between competing objectives. The optimized operating conditions are validated against full-scale CFD simulations, demonstrating MFRNet's reliability and generalizability.

This work establishes a novel and scalable approach for constructing digital twins in industrial energy systems. By drastically reducing the data and computational costs associated with high-fidelity modeling, MFRNet empowers intelligent, self-optimizing control for combustion systems operating under diverse scenarios. The framework is broadly applicable to other multi-physics domains, offering a robust foundation for accelerating the adoption of AI-driven solutions in the pursuit of cleaner, more efficient industrial processes.