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Advancing Transparent Deep Learning for Modeling Turbulence in Fusion Plasmas

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In response to the increasing intricacy of plasma behaviors within magnetically confined fusion systems, we propose a comprehensive approach leveraging interpretable artificial intelligence (AI) to enhance modeling, system reduction, and diagnostic analysis. The presented framework integrates a range of machine learning methods designed to uphold both physical insight and computational reliability.

A central feature of this research is the introduction of Layered Polynomial Neural Networks (LPNNs), a symbolic regression method tailored to reconstruct governing dynamical equations from trajectory data. Unlike traditional black-box models, LPNNs retain a clear polynomial structure, enabling transparent interpretation of nonlinear relationships. Their architecture builds complexity hierarchically, allowing them to outperform conventional networks in capturing chaotic dynamics observed in benchmark systems such as Lorenz, Rössler, and Lotka–Volterra models, as well as in reduced models relevant to L–H mode transitions in fusion plasmas.

This interpretability extends to model reduction. Using LPNN-based reduced-order modeling (termed Ai-PoG), we address canonical problems like the one-dimensional Burgers'equation, achieving more stable and physically meaningful solutions than those obtained through conventional Proper Orthogonal Decomposition (POD) combined with Galerkin projection. The results underscore superior fidelity in resolving both advective and dissipative dynamics.

Simultaneously, we develop a hybrid Reduced-Order Model based on Neural Ordinary Differential Equations (NODEs) to simulate edge turbulence governed by the Hasegawa–Wakatani equations. This NODE-ROM model is built atop Galerkin-reduced modes and captures key dynamical features such as Lyapunov exponents, ensuring long-term trajectory fidelity and preserving system invariants—critical for real-time forecasting and potential feedback control in plasma operations.

Recognizing the challenges posed by chaotic regimes, especially regarding generalization, we introduce a novel phase-space-aware training strategy for NODEs. This method enhances extrapolation capability and stabilizes predictions over long time horizons by incorporating varied initial conditions during training. The approach proves effective in maintaining the structure of sensitive attractors like those in the Lorenz system.

Altogether, this work demonstrates how physically grounded AI tools can bridge simulation and theory offering new capabilities in modeling and understanding fusion plasma systems. These advances hold particular promise for improved control, monitoring, and design of next-generation fusion experiments.

Speaker's email address

sadruddin.benkadda@univ-amu.fr

Speaker's Affiliation

Aix Marseille University

Member State or International Organizations

France

Author: Prof. BENKADDA, Sadruddin (Aix Marseille University- CNRS)

Co-authors: Mr GARRIDO-GONZALEZ, David (Aix Marseille University); Dr SAURA, Nathaniel (Aix Marseille University); BEYER, Peter (Aix Marseille University)

Presenter: Mr GARRIDO-GONZALEZ, David (Aix Marseille University)

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