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Interpretable AI-Driven Modeling of Plasma Turbulence

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Modeling the nonlinear dynamics of magnetically confined plasmas remains a key challenge in fusion research. Tokamak plasmas exhibit multiscale turbulence and wave coupling, requiring simulations that balance physical accuracy with computational efficiency. Traditional solvers for systems like the Hasegawa–Wakatani or resistive ballooning equations demand fine resolution, leading to high computational costs that hinder real-time diagnostics and large-scale studies. They also often miss secondary but important effects, such as edge transport barrier relaxations in H-mode plasmas [1–2]. To address these challenges, the fusion community has turned to surrogate models, simplified tools trained to replicate key simulation behaviors. Recent AI advances now enable data-driven models that combine speed, accuracy, and physical interpretability, forming hybrid frameworks that blend physics with machine learning for efficient plasma turbulence modeling [3].

We present a unified framework for AI-assisted reduced order modeling (ROM) of plasma turbulence by combining mode decomposition via Singular Value Decomposition (SVD) with neural network-based dynamical inference [4]. Instead of forecasting time-series directly, the network learns the underlying ODE system from a Galerkin projection of the original PDEs, yielding compact and interpretable models of nonlinear plasma dynamics. To enhance interpretability, we introduce Layered Polynomial Neural Networks (LPNNs), a symbolic regression method that hierarchically constructs nonlinear terms and successfully captures dynamics in classical chaotic systems and reduced plasma turbulence models. We apply this framework to systems like the 1D Burgers' equation, where our LPNN-based AiPoG models outperform standard POD–Galerkin ROMs in stability and accuracy. Additionally, we develop a Neural ODE based ROM for edge plasma turbulence governed by the Hasegawa–Wakatani system, accurately reconstructing chaotic trajectories and preserving Lyapunov spectra. A phase-space-aware training strategy enhances generalization across initial conditions, enabling robust extrapolation beyond trained regimes.

In conclusion, combining interpretable AI with reduced order modeling offers a powerful approach for plasma physics. Our SVD-based and neural inference framework captures key turbulence dynamics efficiently, enabling real-time prediction and control while maintaining transparency and scalability.

References

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