Machine Learning-Based Framework for Navigating Plasma State

Fusion devices operate in high-dimensional state spaces where plasma behavior emerges from complex interactions between transport processes, self-generated currents, and external actuators [1]. The challenge of controlling such systems lies not only in their dimensionality but in identifying controllable pathways through state space that respect physical constraints while achieving desired operational regimes [2]. This contribution introduces a learning-based control framework that leverages transport simulations to efficiently navigate plasma states, with transport modelling serving as the learning environment for controller development.

Control of complex systems requires understanding both the system's structural controllability and the practical control effort required to navigate between them [2]. For tokamak plasmas, this challenge is compounded by the highly self-organized nature of burning plasma regimes, where parameters form interdependent feedback loops [3]. Traditional control approaches struggle to identify efficient trajectories through this coupled state space, particularly when operating in advanced scenarios such as those with high bootstrap fraction where the plasma exhibits strong self-organization [3].

We propose a framework inspired by recent advances in learning optimal control of dynamical systems through neural network parameterization [4]. The key insight is that neural controllers can implicitly minimize control energy while exploring the system's natural dynamics in a "go-with-the-flow" manner, without requiring explicit energy regularization terms [4]. By parameterizing control inputs as neural ordinary differential equations, the controller learns to exploit the underlying vector field of the plasma transport system, identifying low-energy pathways through the state space that would be intractable to discover through traditional optimization methods.

The transport simulator serves as the learning environment for controller development, incorporating actuator inputs through transport equations to plasma state evolution. This enables gradient-based training of neural controllers, where gradients flow through the time-unfolded transport dynamics [4], allowing the controller to learn how actuator adjustments propagate through the complex physics of heat, particle, and current transport. The transport model captures the essential physics [5], providing a sufficiently high-fidelity environment for controller learning while remaining computationally tractable.

The framework could naturally integrate with model-based control architectures proposed for ITER and beyond [6] where the controller could provide feedforward trajectories optimized through the transport model. At the same time, this framework could allow the development of model-based observers for real-time state estimation despite limited

diagnostic availability [3]. This combination addresses the fundamental challenge of controlling systems where measurements are sparse, but physics models are available.

This work introduces a systematic methodology for developing controllers that efficiently navigate high-dimensional plasma states by learning from physics-based transport models. The approach is particularly relevant for advanced scenarios in spherical tokamaks and burning plasma regimes where strong self-organization and limited actuator authority demand intelligent exploitation of the system's natural dynamics.

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[5] Citrin et al, *arXiv:2406.06718*, 2024