Reinforcement Learning-Based Plasma Shape Control via Isoflux scheme on superconductor tokamak

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Plasma shape control is a critical challenge in magnetic confinement fusion devices, where precise regulation of the magnetic flux distribution is essential to achieve stable plasma configurations [1]. Traditional control strategies often rely on linear approximation and decoupling solution based on the physical model, which multiple linear approximations are required to achieve this step by step [2][3]. Now reinforcement learning methods show great potential in solving highly complex, multi-dimensional coupled problems. Stable magnetic control has been achieved on TCV by reinforcement learning [4][5].

This work proposes a reinforcement learning (RL)-based framework to optimize plasma shape control on superconductor tokamak through dynamic magnetic flux regulation. By formulating the control problem as a Markov decision process, the RL agent learns to coordinate the poloidal field coils powersupply to simultaneously stabilize the plasma boundary and minimize flux deviations between boundary and X point. The observation of the RL agent has incorporated historical temporal information to adapt to the complex dynamic response caused by the double-layer vacuum chamber in the fully superconducting tokamak. A new reward design method is proposed to meet the requirements of ISOFLUX scheme[3] and the voltage limited characteristics of superconducting tokamak.

Numerical simulations and experimental validations demonstrate that the RL-driven controller achieves improvement in shape tracking accuracy compared to conventional proportional-integral-derivative (PID) methods. Furthermore, the system exhibits robust performance against magnetic perturbations, maintaining the plasma boundary within 10^{-3} Wb and $2*10^{-4}$ T of the target equilibrium. The figure below shows the simulated control result. Fig (a) is a randomly generated $\Delta\beta_p$ signal. Fig (b) is the curve of the magnetic field intensity in the RZ direction of point X over time, and Fig (c) is the curve of the error between 10 control points and point X over time. This work highlights the potential of data-driven reinforcement learning in bridging the gap between magnetic flux physics and high-precision shape control for next-generation fusion reactors.

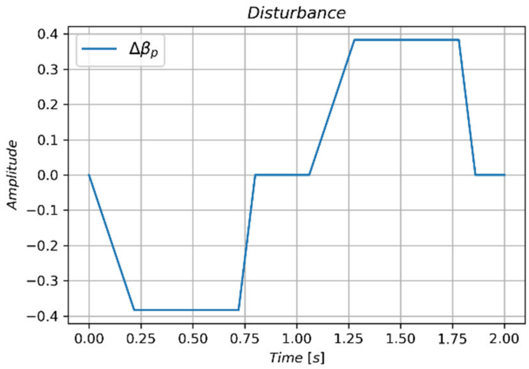

Fig (a) Disturbance of $\Delta\beta_p$

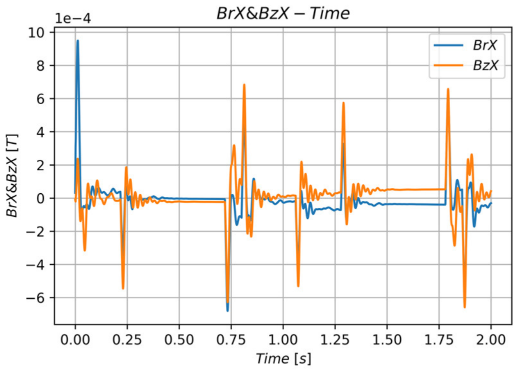

Fig (b) The magnetic field intensity in RZ direction at point X changes with time

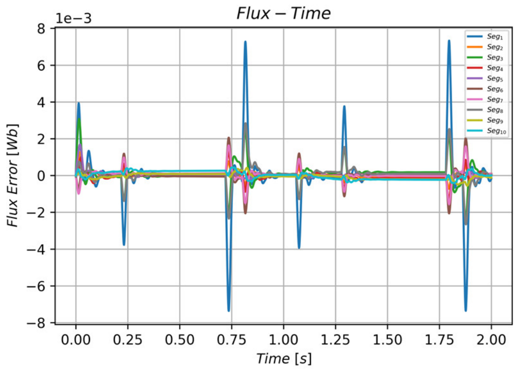

Fig (c) The error of control point and X point varies with time

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