

# REAL-TIME FEEDBACK CONTROL OF RADIATION FRONT POSITION FOR DETACHMENT IN MULTI-DEVICE STUDIES: APPLICATION OF MACHINE LEARNING ON DIII-D AND KSTAR

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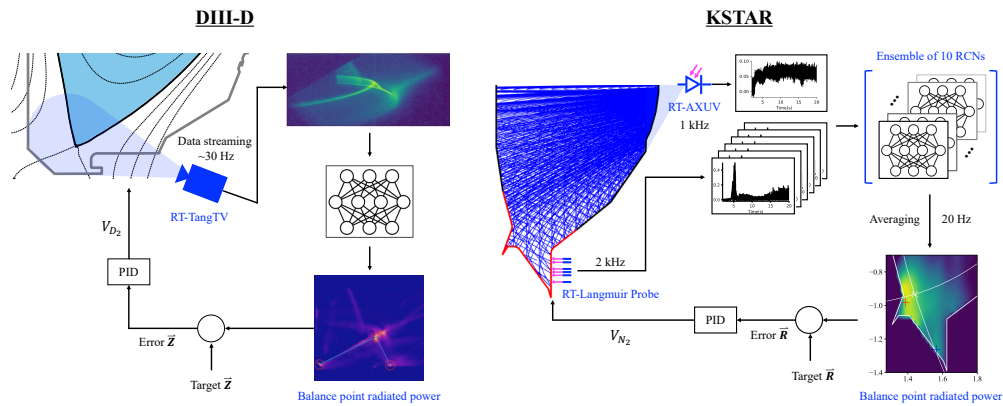
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**For the first time, real-time control of the radiation front position for detachment in H-mode plasma has been successfully demonstrated on DIII-D and KSTAR using Machine Learning (ML).** This enables precise detachment control, which is vital for protecting plasma-facing components (PFCs) in fusion devices like ITER and future power plants (FPPs). Detachment reduces heat flux but can degrade confinement. Therefore, a feedback control system is required to achieve an optimal detachment level while minimizing performance degradation. Previous detachment control using probes has been successful for direct heat flux regulation but has limitations in future devices due to its inflexibility in varying striking point configuration, making it unsuitable for ITER and FPPs. Here, 2D imaging offers a novel path for direct detachment control. The radiation front serves as a reliable global indicator of detachment by capturing major power dissipation in seeded discharges [1]. On DIII-D, an ML model extracted the radiation front position from 2D images measured by the tangential imaging system (Tang TV) [2], which provides a poloidal reconstruction of C-III line emission in the divertor region. On KSTAR, ML was used to reproduce the radiation front position measured by the Infrared Video Bolometer (IRVB) [3] using AXUV and Langmuir probes in real time, representing a more advanced ML application in diagnostics. By applying ML techniques and adapting diagnostics to each device's requirements, this work highlights the flexibility and universality of radiation front-based detachment control. These results represent progress toward integrating such methods into next-generation fusion reactors and demonstrate that ML can enhance the flexibility of plasma diagnostic design for future devices.



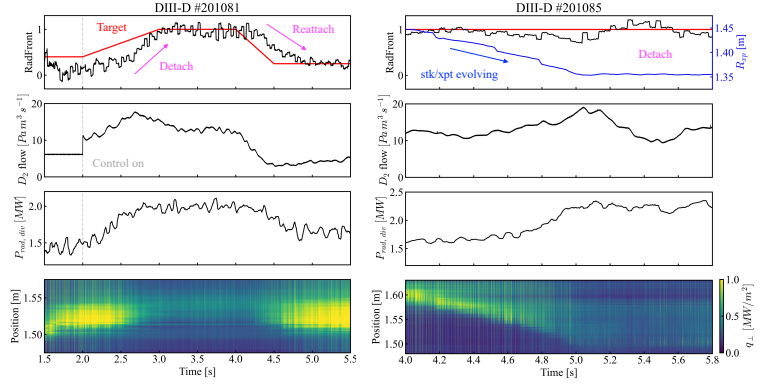
**Figure 1.** Schematic representation of the real-time feedback control system for regulating the radiation front position in DIII-D (left) and KSTAR (right).

To control the radiation front position in DIII-D and KSTAR, systems were developed using camera-based process variables, PID controllers, and impurity seeding as the control variable, configured for each device's requirements, as shown in Figure 1. Both systems used the balance-point radiated power approach, which represents the radiation front by averaging the weighted distribution of radiated power rather than tracking a single peak. This mitigates a limitation of camera diagnostics, where exposure periods may capture both attached and detached states during marginal detachment. By averaging radiation peaks, the radiation front remains positioned between the X-point and strike point, even during high-frequency events such as edge-localized modes (ELMs) and detachment clifing. On DIII-D, the

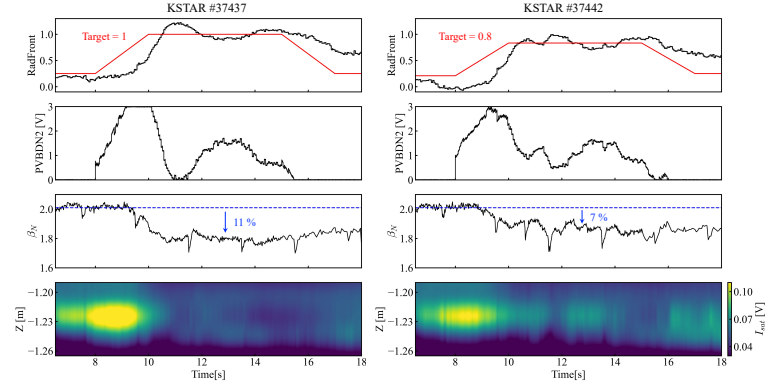
RT-Tang TV system enabled direct measurement with an ML model for real-time control, while on KSTAR, real-time control was achieved through AI-driven diagnostic coupling using RT-AXUV and RT-Langmuir probes. **Despite differences in diagnostics, both systems use a common detachment control metric through appropriate parameterization with advanced ML techniques, highlighting the flexibility and universality of this approach.**

On DIII-D, the system demonstrated rigorous control of the radiation front. By fine-tuning the PID controller, we achieved reliable detachment in H-mode, as shown in Figure 2 (left). The target for RadFront, the normalized radiation front position relative to the X-point, was set to cycle from 0 to 1 and back to 0. The radiation front followed this trajectory with a reasonable delay, achieving both detachment and reattachment within a single discharge. Infrared television (IRTV) observations confirmed a significant heat flux reduction, and bolometers detected an increase in dissipative radiated power in the divertor region during detachment. **Despite changes in the X-point and strike point, the system successfully regained and maintained detachment control after temporarily losing control during the initial phase of evolution, as shown in Figure 2 (right).**

A successful demonstration was also conducted on KSTAR. The ML model [4] accurately reconstructed the 2D radiation information, establishing RadFront as a reliable process variable. The experiment targeted complete and partial detachment, as shown in Figure 3. The radiation front followed the target with a longer delay than in DIII-D due to valve response limitations, but control remained effective. Plasma performance degradation was reduced and maintained in partial detachment, decreasing from 11% to 7%, which is the main goal of precise detachment control. Offline Langmuir probe measurements confirmed that RadFront reliably represents the degree of detachment. **This marks the first real-time application of AI-driven diagnostic coupling for feedback control on KSTAR.**



**Figure 2.** Demonstration of the DIII-D radiation control system: (left) fixed strike point and X-point; (right) evolving strike point and X-point.



**Figure 3.** Demonstration of the KSTAR radiation control system for (left) complete detachment and (right) partial detachment.

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