PREDICTION AND REAL-TIME CONTROL OF THE TOKAMAK L-MODE DENSITY LIMIT VIA EDGE COLLISIONALITY

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In this study, we show that a dimensionless instability metric, $\nu_{*,edge}\beta_{T,edge}^{0.4}$, significantly improves prediction of the L-mode density limit (LDL) and can enable real-time LDL avoidance in experiment. The density limit is a major risk and limitation for ITER and future tokamak power plants, as most devices must operate near or above the widely utilized Greenwald limit [1] to achieve their fusion power ($P_{fus}\sim n^2$) target. This risk is amplified by major uncertainties: the Greenwald limit is known to not capture the full complexity of the density limit, and there remains no consensus on the casual mechanism of the LDL. By applying machine learning on a multimachine database (ASDEX-Upgrade, Alcator C-Mod, DIII-D, and TCV), we identify a new scaling for the precursor to the LDL involving the effective collisionality and dimensionless pressure at the edge of the plasma (Fig. 1) and show that it achieves 6x fewer false positives than the Greenwald fraction when predicting LDLs. We then demonstrate in experiments at DIII-D that this metric can be used for real-time instability avoidance, successfully achieving higher densities while robustly avoiding the LDL across repeated experiments. This work demonstrates how machine learning can distil more accurate scaling laws from high-dimensional data and enable new control solutions operating near instability limits.

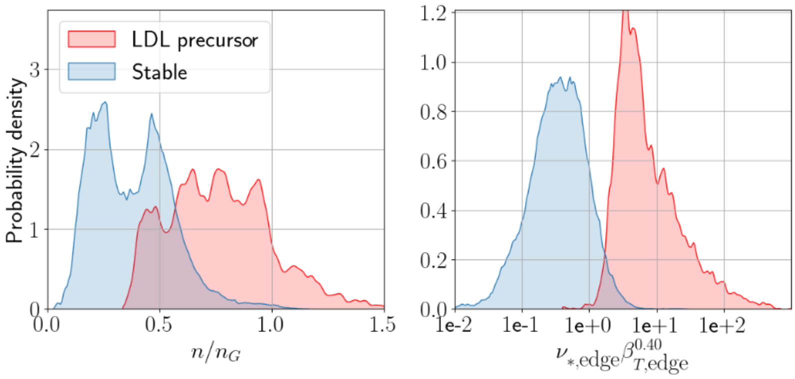

Fig. 1: histograms showing stable time steps versus time steps belonging to the L-mode density limit (LDL) precursor regime in the multimachine database. One can see that the two distributions have more overlap in terms of the Greenwald fraction (left) than the dimensionless instability metric (right). This

The dimensionless scaling is identified from database assembled from 150+ density limit events from tokamaks with a diverse set of wall material, plasma size, and field strength: AUG, C-Mod, DIII-D, and TCV. Unlike past studies of the density limit, we also include over 3000 non-disruptive discharges (primarily from C-Mod and DIII-D due to data availability) to quantitatively determine the false positive rate (FPR) and true positive rate (TPR) of various predictors. We then apply several machine learning approaches to the task of predicting the precursor to the LDL and compare them to three baselines: the (line-averaged) Greenwald fraction, the edge Greenwald fraction, and a model based on linear regression. The machine learning models we compared were Random Forests (RFs), Neural Networks (NNs), and Linear Support Vector Machines (LSVM) trained with recursive feature selection.

We find that the machine learning models all achieve much greater accuracy than the baselines, with the LSVM notably identifying a simple, two-parameter instability metric $\nu_{*,edge}\beta_{T,edge}^{0.4}$. As shown in Table 1, this simple metric achieves the best "Area Under the Curve" (AUC), a commonly used classification performance metric. The instability indicator $\nu_{*,edge}\beta_{T,edge}^{0.4}$ achieves a FPR of only 2.3% (when calibrated to the 95% TPR needed for ITER [2]), which is 6x lower than the Greenwald fraction's FPR, and similar to the FPR of the less explainable RF and NN.

Model	Analytic boundary	AUC	FPR @ TPR = 95%
NN	N/A	0.991	3.0%
RF	N/A	0.996	**1.6%**
LSVM	$\nu_{*,\mathrm{edge}}^{\mathrm{limit}} \sim \beta_{T,\mathrm{edge}}^{-0.40}$	**0.997**	2.3%
Lin. Reg.	$\nu_{*,\mathrm{edge}}^{\mathrm{limit}} \sim \beta_{T,\mathrm{edge}}^{-0.67}\rho_{*,\mathrm{edge}}^{-0.77}$	0.984	6.6%
Greenwald	$\bar{n}^{\mathrm{limit}} \sim \frac{I_p}{\pi a^2}$	0.971	13.9%
Edge Greenwald	$n_{\mathrm{edge}}^{\mathrm{limit}} \sim \frac{I_p}{\pi a^2}$	0.888	43.7%

Table 1: A comparison of data-driven LDL predictors (top four) and three baselines (bottom three). For the task of L-mode density limit with a true positive rate (TPR) of 95% is required, as is the case for ITER [2], the two-parameter, dimensionless instability metric identified by the LSVM achieves a false positive rate (FPR) 6x lower than that of the Greenwald fraction for the same test set.

The LSVM's instability metric was implemented in a real-time control scheme at DIII-D (Fig. 2, left) and enabled robust avoidance of the LDL in several experiments across multiple run days. The instability metric was computed in real-time by the STATIN algorithm in the Plasma Control System and monitored by two controllers: the Proximity Controller [3] and the Off-Normal Fault Response (ONFR) [4] algorithm. After the instability metric surpassed a user-specified threshold, the Proximity Controller modified the density target in feedback with the instability metric and the ONFR increased the NBI power in steps. On each run day, an LDL scenario was reproduced to serve as a testbed for the avoidance scheme, such as in shot 199908 (Fig. 2 right). When the controller was turned on during the flattop, as in shot 199912, the real-time modifications to the plasma trajectory robustly suppressed the LDL precursor. The precursor phase only appeared when the controller response was deliberately limited or during rampdown scenarios, and in all cases the controller intervention extended the plasma lifetime. In fact, LDL disruptions were entirely avoided in 16 out of 17 discharges.

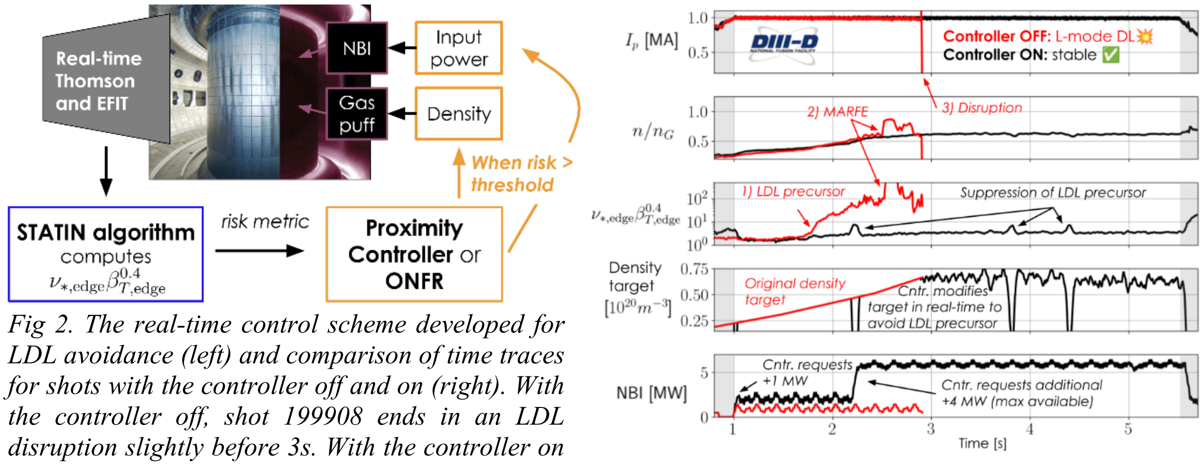

Fig 2. The real-time control scheme developed for LDL avoidance (left) and comparison of time traces for shots with the controller off and on (right). With the controller off, shot 199908 ends in an LDL disruption slightly before 3s. With the controller on during 199912, the plasma survives to the pre-programmed ramp-down. The controller was able to routinely suppress the LDL precursor phase and disruptions by lowering the density target and raising the NBI power in response to this instability metric.

In summary, we find that the precursor to the *density limit* in L-mode is better described as a *collisionality limit*. We identify a more accurate instability metric $\nu_{*,edge}\beta_{T,edge}^{0.4}$ by training an LSVM classifier with recursive feature selection on an extensive multi-machine database. This machine learning workflow, which combines accuracy with interpretability, could applied in other fusion contexts to identify analytic stability boundaries from experimental data. We then demonstrated robust LDL avoidance on DIII-D via real-time feedback control on this instability metric. In addition to improved density limit prediction and control, the LSVM instability metric also clarifies the mechanism for the onset of the density limit precursor. While some studies have suggested the root cause of the density limit is a radiative collapse in the plasma edge, this instability metric is most consistent with theories based on enhanced turbulent transport [5-6]. Additionally, this metric also suggests that burning plasmas with naturally low collisionality will have much larger safety margins to the instability than previously thought, opening up higher density operation. Finally, the control method demonstrated here could be a model for off-normal controllers on near-term devices such as ITER and SPARC where disruption consequences will be more severe.

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