INZOR-ND — EXTENDED REPORT · MARCH 2026

A Machine-Agnostic Empirical Law Candidate for Disruption Proximity Based on Plasma Current Dynamics

Discovered with Evolutionary Exploration · Validated on C-Mod, MAST, HL-2A

Dumitru Novic · March 2026 · 1,384 disruptive windows · 4,260 non-disruptive windows · 3 tokamaks

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ABSTRACT

We investigate whether a simple machine-agnostic indicator of disruption proximity can be derived from plasma current dynamics.

Using multi-machine data from C-Mod, MAST and HL-2A together with evolutionary exploration using the inZOR-ND system, we identify a compact empirical relation linking disruption proximity to statistical properties of the plasma current signal.

The resulting candidate law **$\eta \approx -\text{kurtosis} + 0.80 \cdot \text{rate\_ratio} + 0.65 \cdot \text{cv\_ratio}$** combines a structural descriptor of the current signal with two complementary instability channels.

The formula generalizes across machines, passes leave-one-machine-out validation, remains stable under bootstrap resampling and coefficient perturbations, and shows consistent temporal growth approaching disruption.

These results suggest a simple machine-agnostic empirical law candidate describing disruption proximity based on plasma current dynamics.

MAIN EMPIRICAL LAW CANDIDATE (3-TERM)

$$\eta \approx -\text{kurtosis} + 0.80 \cdot \text{rate\_ratio} + 0.65 \cdot \text{cv\_ratio}$$

η increases as plasma approaches disruption · Derived from Ip only · No machine-specific tuning

1.071	min(sep) cross-machine
0.982	Global ROC-AUC
3/3	LOMO folds passed
0.945	Global PR-AUC
>0	Bootstrap CI$_{95}$ min(sep)
3	Tokamaks validated

1. Data and Feature Definitions

All features are derived from plasma current Ip(t) using two windows:

- **D** (late window): 450 samples ending at t_disrupt − 50 ms
- **N** (reference): full shot

Feature	Definition	Physical role
`kurtosis`	Excess kurtosis of Ip in window D	Structural sharpness — decreases before disruption as MHD instabilities flatten the current profile
`rate_ratio`	max|dIp/dt|_D / max|dIp/dt|_N	Dynamic acceleration — late-phase surge in current rate of change
`cv_ratio`	(std/mean)_D / (std/mean)_N	Variability amplification — relative increase in current fluctuations before disruption

Machine	Disruptive windows (D)	Non-disruptive windows (N)
MAST	674	3,647
C-Mod	414	13
HL-2A	296	600
Total	**1,384**	**4,260**

2. Evolutionary Exploration with inZOR-ND

The discovery process relied on the inZOR-ND evolutionary exploration framework, which searches the space of candidate formula structures. Instead of manually proposing models, the system explores low-dimensional slices of the hypothesis space (2D, 3D, 4D) and identifies stable structural attractors.

This exploration revealed recurring formula structures involving kurtosis combined with instability indicators derived from plasma current dynamics. Without this exploratory mechanism the structural relation leading to the final empirical law candidate would likely not have been identified.

Exploration space	Dominant structure discovered
2D	kurtosis + rate_ratio
3D	same attractor (kurtosis + rate_ratio)
4D	kurtosis + cv_ratio + skew

These results indicate the presence of a stable structural core centered on the kurtosis term. The appearance of cv_ratio in the 4D space motivated the dual-instability test, which determined optimal weights a=0.80, b=0.65.

3. Summary of Results

Summary figure

Figure 1 — Summary of the disruption proximity law candidate and its validation across machines. (A) D vs N separation; (B) temporal trajectory η(t) — the disruption clock; (C) formula comparison min(sep); (D) LOMO validation, all 3 folds PASS; (E) bootstrap robustness per machine; (F) law candidate summary.

4. Per-Machine Structural Analysis

Pearson |correlation| between each feature and η reveals the dominant instability regime per machine.

Machine	kurtosis |corr|	rate_ratio |corr|	cv_ratio |corr|	Dominant signal
MAST	~0.60	**~0.80**	~0.55	rate_ratio
C-Mod	~0.55	~0.40	**~0.65**	cv_ratio
HL-2A	~0.58	~0.52	**~0.60**	mixed behaviour

The results indicate two complementary instability channels, which motivates the combined formulation of the final empirical law candidate.

Structural per machine

Figure 2 — Per-machine structural analysis: |Pearson correlation| with η. kurtosis is the universal nucleus; rate_ratio dominates on MAST; cv_ratio dominates on C-Mod and HL-2A.

5. Validation — Formula Comparison (Ablation)

Formula	Terms	min(sep)	Global ROC	Global PR
`kurtosis`	1	0.58	0.96	0.897
`rate_ratio`	1	0.18	0.99	0.957
`cv_ratio`	1	0.50	0.82	0.628
`-kurtosis + rate_ratio`	2	0.68	0.98	0.961
`-kurtosis + cv_ratio`	2	0.95	0.97	0.896
3-term law	**3**	**1.07**	**0.98**	**0.945**

The three-term formulation provides the strongest worst-case separation while remaining structurally simple.

Ablation

Figure 3 — Formula ablation: min(sep) and Global ROC-AUC for all 6 formula variants. Hierarchy 1-term < 2-term < 3-term confirmed.

6. Leave-One-Machine-Out (LOMO)

Fixed coefficients, no retraining. Pass: sep > 0 and ROC > 0.5 on test machine.

Train	Test	sep	ROC-AUC	n_D	n_N	Result
C-Mod + HL-2A	MAST	11.786	0.980	674	3647	**PASS**
MAST + HL-2A	C-Mod	1.071	0.757	414	13	**PASS**
MAST + C-Mod	HL-2A	9.344	0.988	296	600	**PASS**

Overall PASS. C-Mod (hardest: 414 D / 13 N) sep = 1.071 > 0, ROC = 0.757 > 0.5. The formula generalises without retraining.

LOMO

Figure 4 — LOMO validation: sep and ROC-AUC for each left-out machine.

7. Temporal Trajectory η(t)

η computed at −100, −80, −60, −40, −20 ms before disruption shows systematic monotonic growth on all three machines — confirming the disruption clock property.

Temporal eta

Figure 5 — Mean η(t) ± std for C-Mod, HL-2A, MAST. η rises monotonically toward disruption on all machines.

8. Robustness and Sensitivity

Bootstrap (shot-level resampling, 300 replicas)

Metric	Mean	Std	CI 2.5%	CI 97.5%
min(sep)	0.9405	0.2338	0.3730	1.2108
Global ROC-AUC	0.9820	0.0014	0.9789	0.9845

PASS: CI$_{2.5}$% min(sep) = 0.373 > 0. Robust to shot-level resampling.

Sensitivity (coefficients ±20%, 300 replicas)

Metric	Mean	Std	Min	Max
min(sep)	1.0443	0.0930	0.8583	1.2541
Global ROC-AUC	0.9818	0.0011	0.9794	0.9842

PASS: min(sep) ∈ [0.858, 1.254] (always > 0). Formula is insensitive to ±20% coefficient variation.

Robustness

Figure 6 — Bootstrap robustness (left, centre) and sensitivity analysis (right). All results remain positive under perturbation.

9. Conclusion

The analysis reveals a simple empirical relation linking disruption proximity to statistical properties of the plasma current signal.

Across multiple tokamaks, disruption proximity is associated with a reduction in signal structural sharpness (kurtosis decrease) combined with increasing instability reflected in dynamic acceleration and variability amplification.

This yields a compact empirical relation:

$$\eta \approx -\text{kurtosis} + 0.80 \cdot \text{rate\_ratio} + 0.65 \cdot \text{cv\_ratio}$$

While additional validation on further machines would be valuable, the present results demonstrate that disruption proximity can be captured by a simple machine-agnostic statistical relation derived from plasma current dynamics.

10. Reproducibility

Data: MAST (public, CCFE), C-Mod (public, MIT / Zindi), HL-2A (public research dataset). All in HDF5 format.
Convention: D = 450 samples ending at t_disrupt − 50 ms; N = full shot.

```
python3 run_dual_instability_law_test.py   # formula + temporal η(t)
python3 run_priority_tests.py              # LOMO + structural
python3 run_robustness_sensitivity.py      # bootstrap + sensitivity
python3 run_baseline_ablation_test.py      # ablation
python3 generate_publication_figures.py   # all figures
python3 generate_summary_figure.py        # summary figure
```

Scope: Empirical candidate from 3 tokamaks. Not a first-principles law. Real-time deployment and transfer to unseen machines require additional validation. This is a scientific baseline and inZOR-ND demonstration.