Third Technical Meeting on Plasma Disruptions and their Mitigation

Combining Adaptive Learning and Physics-Guided Machine Learning for Prediction and Control of Anomalies and Disruptions in Tokamaks

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on behalf of JET Contributors and the EUROfusion Tokamak Exploitation Team

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Work funded by Riccardo Rossi EUROfusion Researcher Grant “Development and implementation of a physics-based multi-machine plasma instability detection and classification system for disruption avoidance, prevention, and mitigation”, AWP22-ERG-ENEA/Rossi

Outline

1. Aim of the Work
2. Paths to Disruption Considered
3. Database
4. System Architecture
5. Single Anomaly Classifier
   - Magnetic anomaly Detection
   - Electron Temperature Anomaly Detection and Classification
   - Radiative Pattern Anomaly Detection and Classification
6. Alarm and Control Logic and System Architecture
7. Statistical Analysis
8. Conclusions

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Aim of the work

Development of a not a simple disruption predictor, but a **system** for **anomaly detection** and **classification**.

Main Features

Multiclass

Detection and Classification of Plasma Anomalies, providing useful information for the control system and DMS

Physics-informed machine/deep learning

Physics-informed deep learning allows to constrain model with both data and physics, allowing for more reliable predictors with the capability to extrapolate using physical models, improving also transferability.

Ensemble of predictors

Instead of one deep model, simpler detector/classifier have been developed for specific anomalies. This improves the explainability of the model, reduce the data requirements for training, and the transferability to other tokamaks.

Adaptive learning

Adaptive learning allows to update the training set pulse by pulse, avoiding performance degradation (obsolescence)

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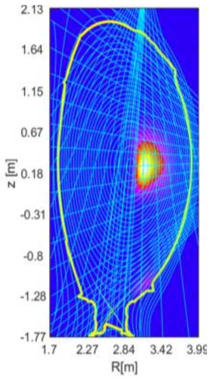
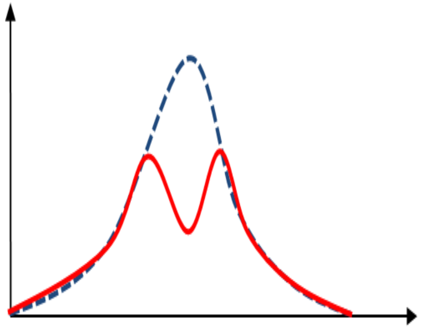
Typical Paths to Disruptions

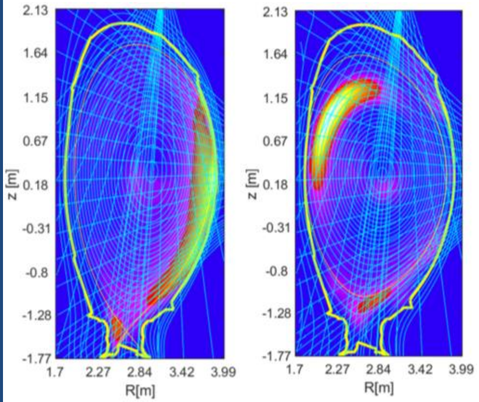
Core Radiation



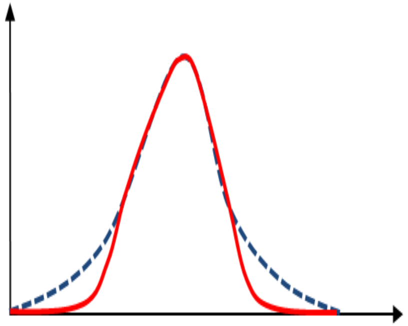
Electron temperature hollowness



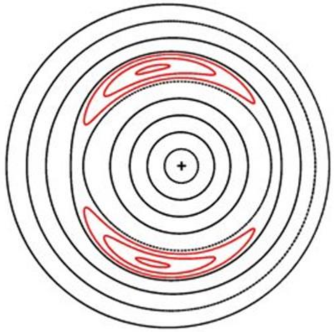
Edge radiation



Electron temperature Edge cooling



MHD mode destabilisation



Disruption

Pucella G. et al. "Onset of tearing modes in plasma termination on JET: the role of temperature hollowing and edge cooling", Nuclear Fusion, 2021

Rossi R. et al. "A systematic investigation of radiation collapse for disruption avoidance and prevention on JET tokamak", Matter and Radiation at Extremes, 2023

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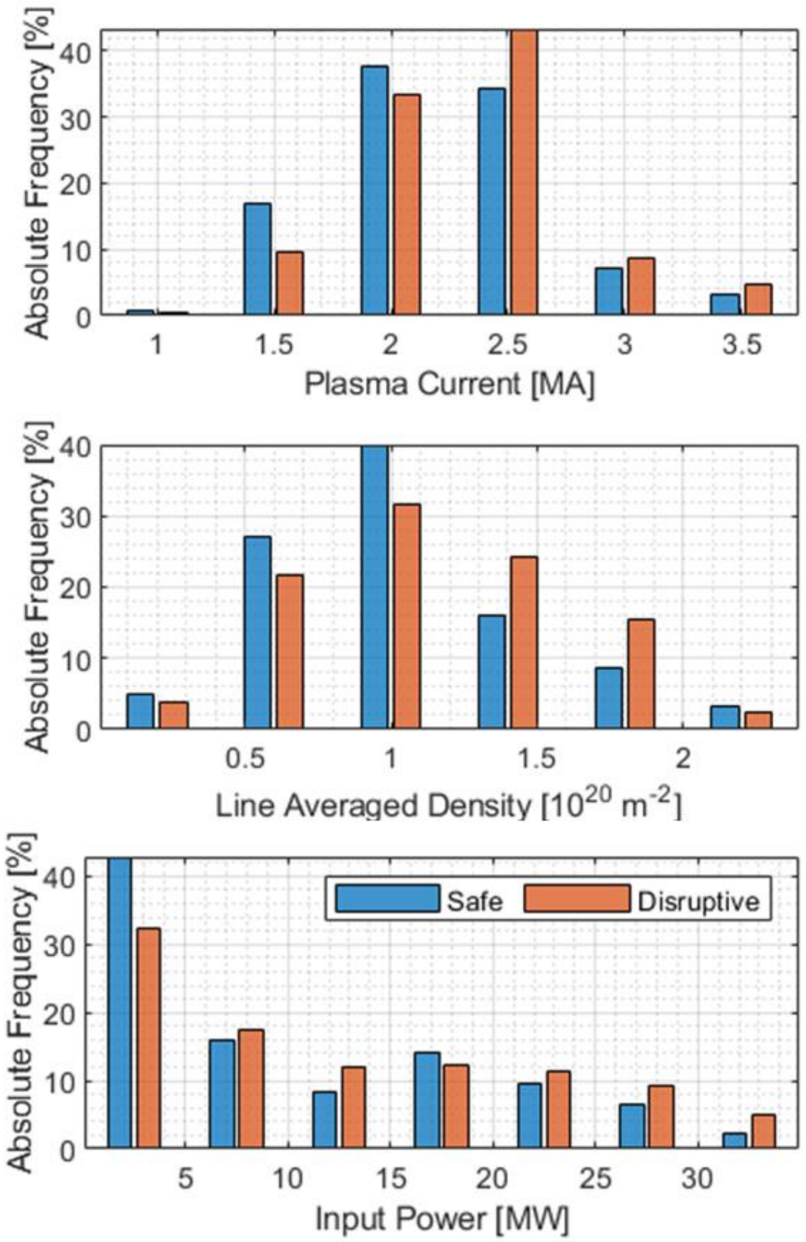
Database

The database consists of 1683 JET pulses, spanning from the high-power DD campaign to the full tritium and DT campaign (C38, C39, C40, C41). The DB includes 1141 not disruptive pulses and 542 disruptive.

	C38	C39	C40	C41	Total
Total	907	168	310	298	1683
Safe	653	133	184	171	1141
Disruptive	254	35	126	127	542
Ramp Up Disruptions	0	0	0	0	0
Flat Top Disruptions	62	23	33	33	151
Ramp Down Disruptions	192	12	93	94	391



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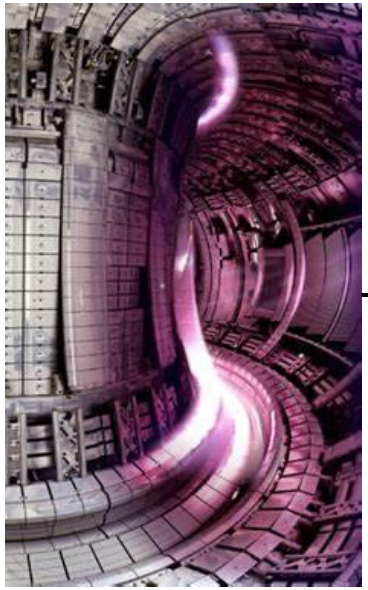
System Architecture

Tokamak (plasma)



Diagnostics

Mode Locked Amplitude
Internal Inductance
Plasma Current

Thomson Scattering (HRTS)

Bolometer cameras

Detectors and Classifiers Ensemble

MHD anomaly detector

Electron temperature anomaly detector and classifier

Radiative anomaly detector and classifier

Alarm classification system

Control System

Disruption Mitigation System

- Only real-time compatible signals have been used
- All algorithms have computational times compatible with real-time

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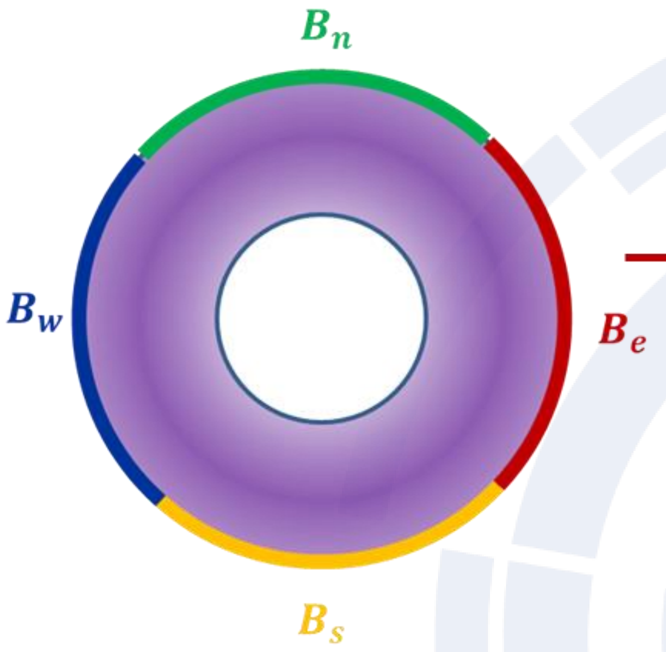
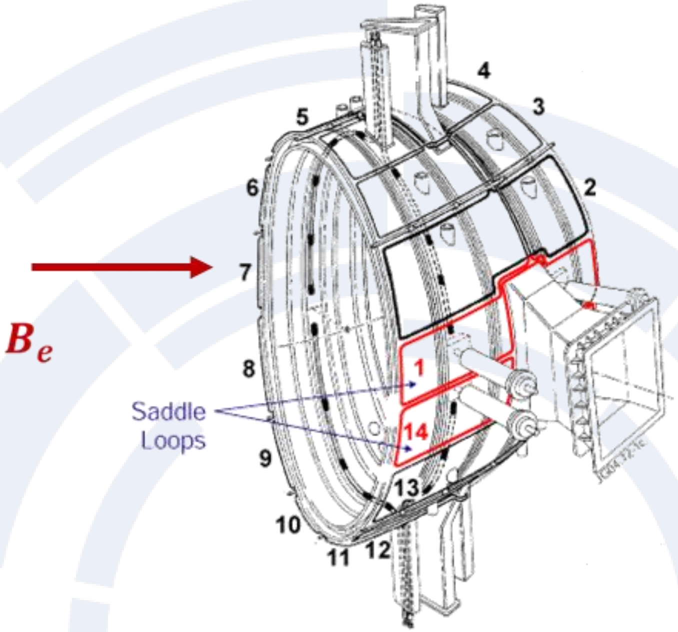
Magnetic anomalies

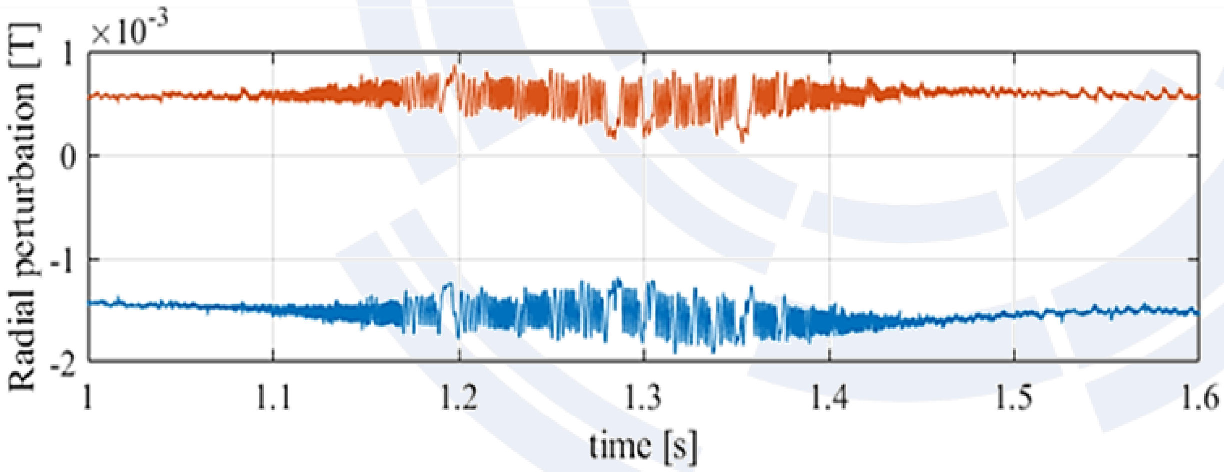
Before disruptions, in most discharges, a big MHD mode (usually a 2,1) increases in amplitude and decreases in frequency still it "locks" to the wall.

By specific magnetic coils it is possible to monitor both the frequency and the magnitude of the modes.

Combining the mode lock amplitude with other plasma quantities (such as the internal inductance) it is possible to improve prediction accuracy.





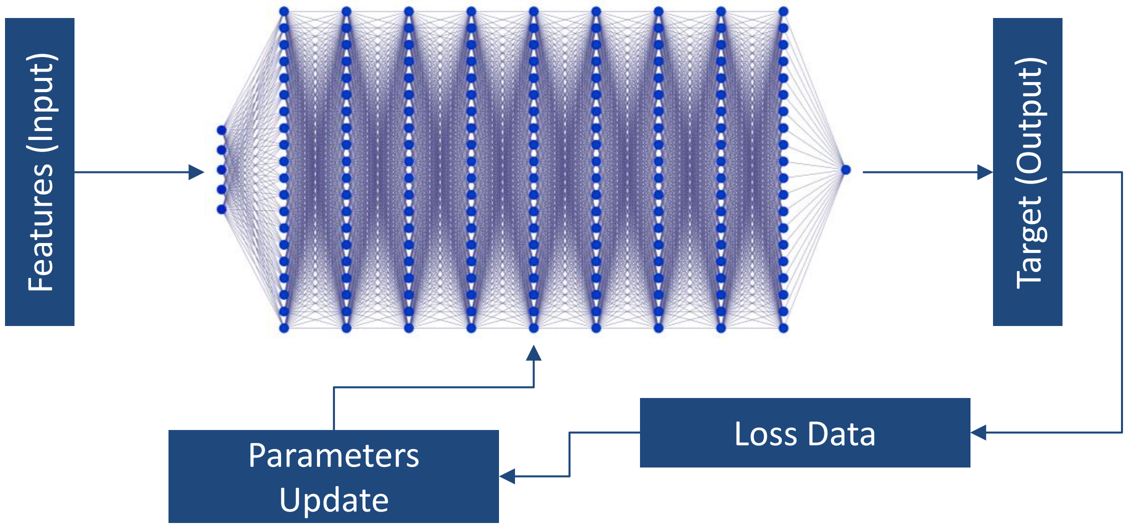


Peluso E., Rossi R., et al. "Alternative Detection of n = 1 Modes Slowing Down on ASDEX Upgrade", Applied Sciences 10 (21), 2020

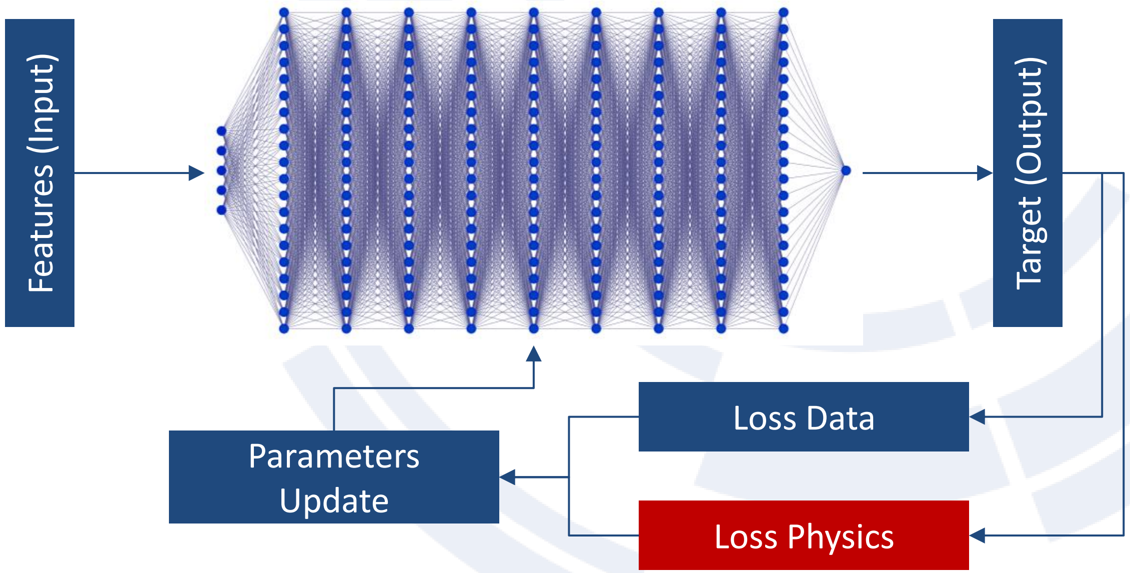
Physics-Informed Neural Networks (PINNs)

A machine/deep learning algorithm can be described as a function $f(\theta, X)$ where X are the features (inputs) and θ are the parameters to be tuned.

In supervised learning, θ are tuned with "example", i.e. data already labelled (in our case, for binary prediction, disruptive and safe previous pulses).



In Physics-Informed Learning, θ can be tuned minimising a loss function that takes into account both typical supervised loss and a physics-based loss function.

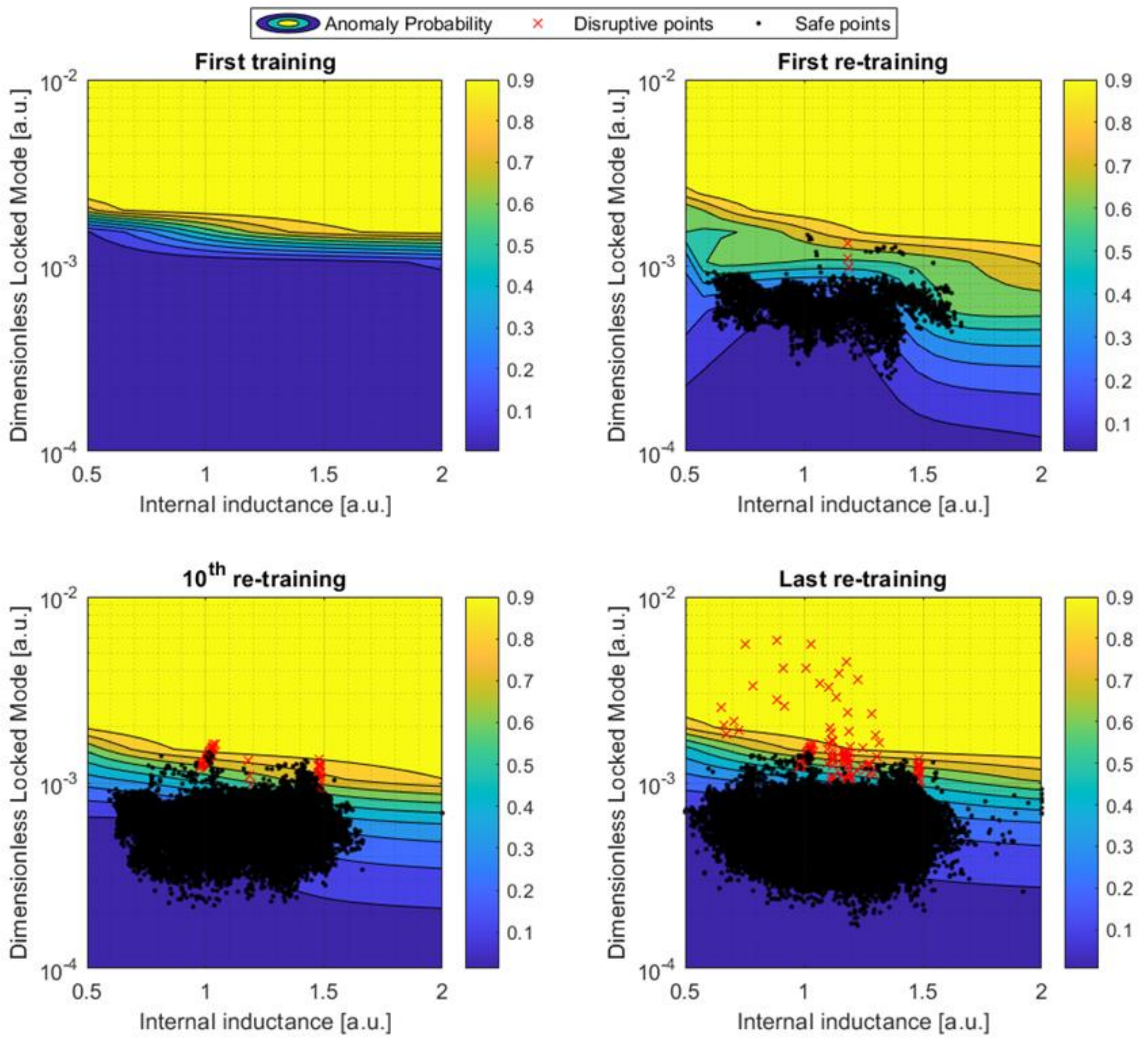


Rossi R. et al. "On the potential of physics-informed neural networks to solve inverse problems in tokamaks", Nuclear Fusion, 2023

PINN classification of Mode Locking

At the beginning, **no data** is present. **The predictor is trained with physics.**

Pulse-by-pulse, data populates the training set and the PINN is updated. However, physics is still used for regions in presence of **data scarcity** and for **extrapolation** (allowing also for **physics-informed transfer learning**).



Rossi R., et al. "A hybrid physics/data-driven logic to detect, classify, and predict anomalies and disruptions in tokamak plasmas" Nuclear Fusion, 2024

Outline

Electron Temperature Hollowness

The electron temperature profile is expected to have the maximum value on the magnetic axis (plasma core).

Electron temperature hollowness may occur, leading to destabilisation of magnetic configuration (MHD modes triggering).

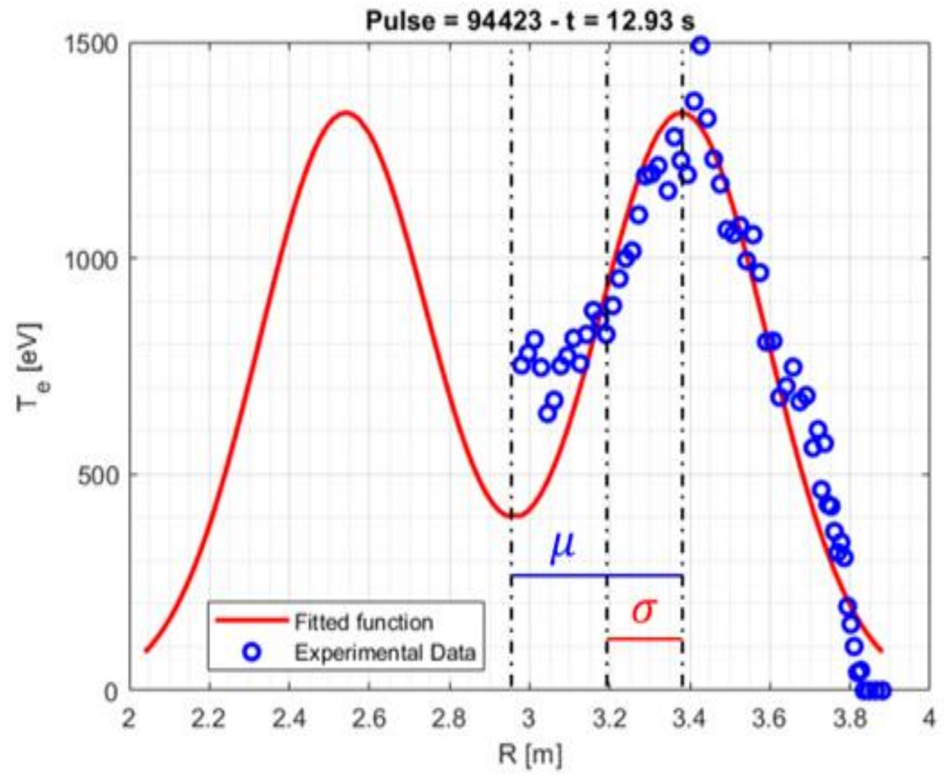
Detection and classification of electron temperature hollowness has been based on a simple statistical indicator that is **stable**, **universal**, **accurate** and **specific**.

No training is needed.

$$G(r)_{bimodal} = Ae^{-\frac{(r-\mu)^2}{2\sigma^2}}\left(1 + e^{-\frac{2\mu r}{\sigma^2}}\right)$$

$$\Downarrow$$

$$GFH = \frac{\mu}{\sigma} = \sqrt{2D_B}$$



Warning time [s]	Sensitivity	1-Specifity	Accuracy
1.09	97.09%	0.00%	99.56%

Rossi R. et al. "Development of robust indicators for the identification of electron temperature profile anomalies on JET", PPCF 2022

Electron Temperature Edge Cooling

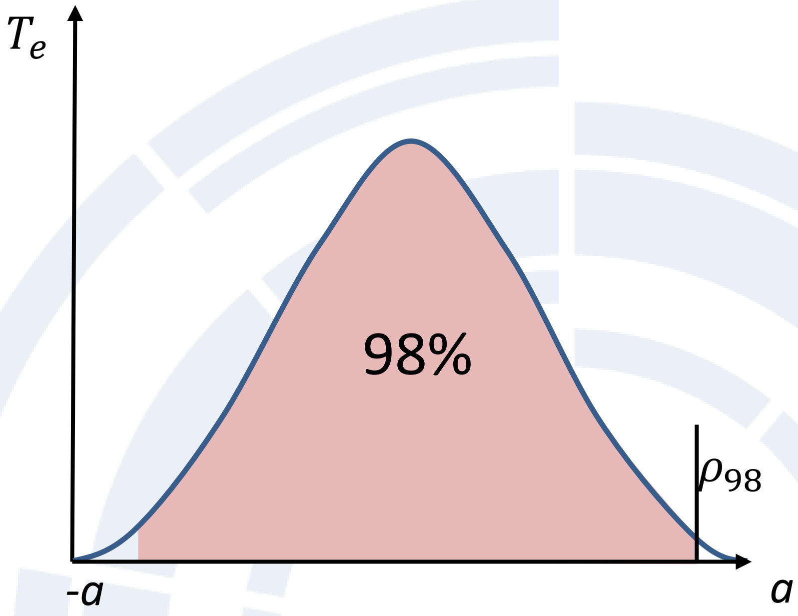
Enough hot plasma is expected inside the separatrix.

If edge electron temperature is too low (**Edge Cooling**), resistivity dominates and MHD modes may be triggered.

Detection and classification of electron temperature edge cooling has been based on another statistical indicator that is **stable**, **universal**, **accurate** and **specific**.

No training is needed.

It aims at measuring the magnetic radius at which 98% of temperature is contained.



$$CDF_T(r) = \frac{\int_{-a}^{\rho_{98}} T_e dr}{\int_{-a}^{a} T_e dr} = 0.98$$

$$\Downarrow$$

$$CBC = 1/\rho_{98}$$

Warning time [s]	Sensitivity	1-Specifity	Accuracy
0.320	99.90%	0.00%	99.98%

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Radiative Anomalies

Radiation is a loss of energy.

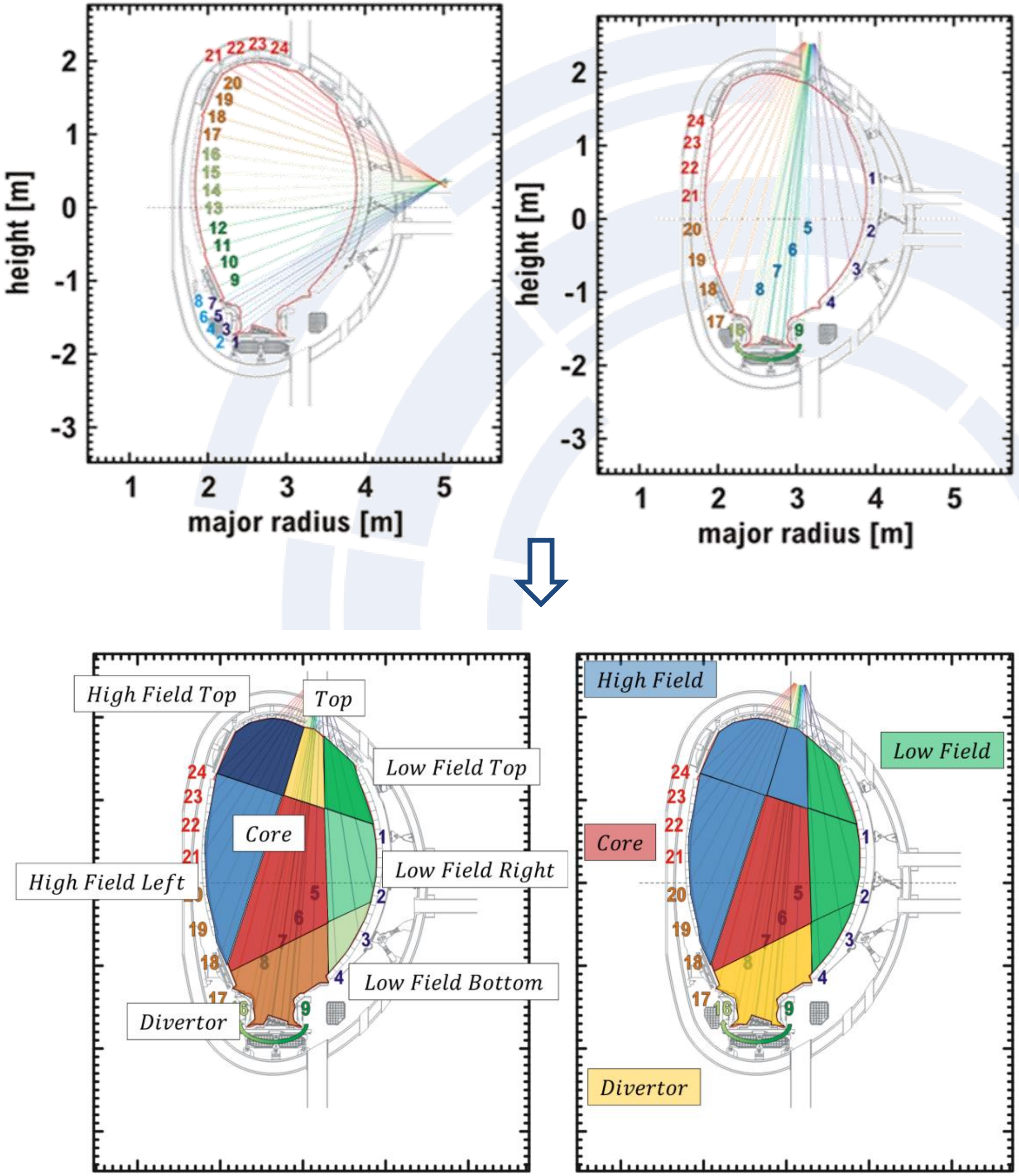
Too **high local radiation** leads to **local cooling**:

1. **Core Radiation**: Electron Temperauture Hollowness
2. **MARFE Radiation**: Edge Cooling
3. **Low Field Side Radiation**: Edge Cooling
4. **Anomalous Divertor Radiation**: Edge Cooling

Measuring local radiation is fundamental.

In tokamaks, we have bolometers (or diodes), which measure the line-integrated emissivity.

We need **fast inversion techniques**. A simple low spatial fast inversion inversion has been developed to evaluate the radiation in specific regions of the tokamak.



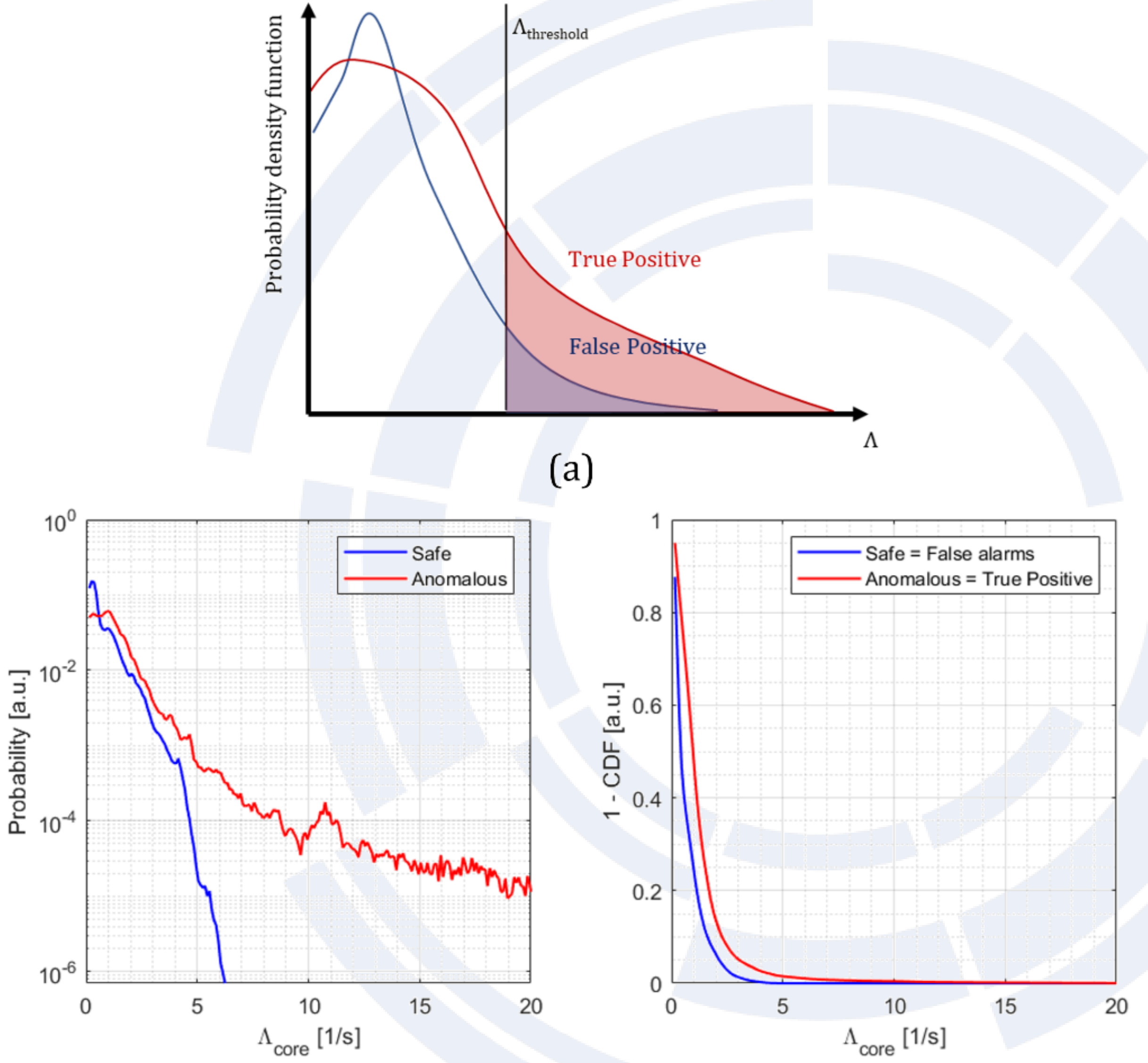
Radiative Anomalies Detection and Classification

A simple low-spatial resolution fast-time inversion has been developed to monitor the emitted power in specific region of the plasma.

Computational time is acceptable for real-time applications (10 to 100 μs).

Anomaly indicators have been calculated as the inverse of local radiative cooling times:

$$\frac{1}{\tau_{rad,i}} = \Lambda_i = \frac{P_{rad.i}}{W_p}$$



(a)
(b)

Rossi R. et al. *"A systematic investigation of radiation collapse for disruption avoidance and prevention on JET tokamak", Matter and Radiation at Extremes, 2023*

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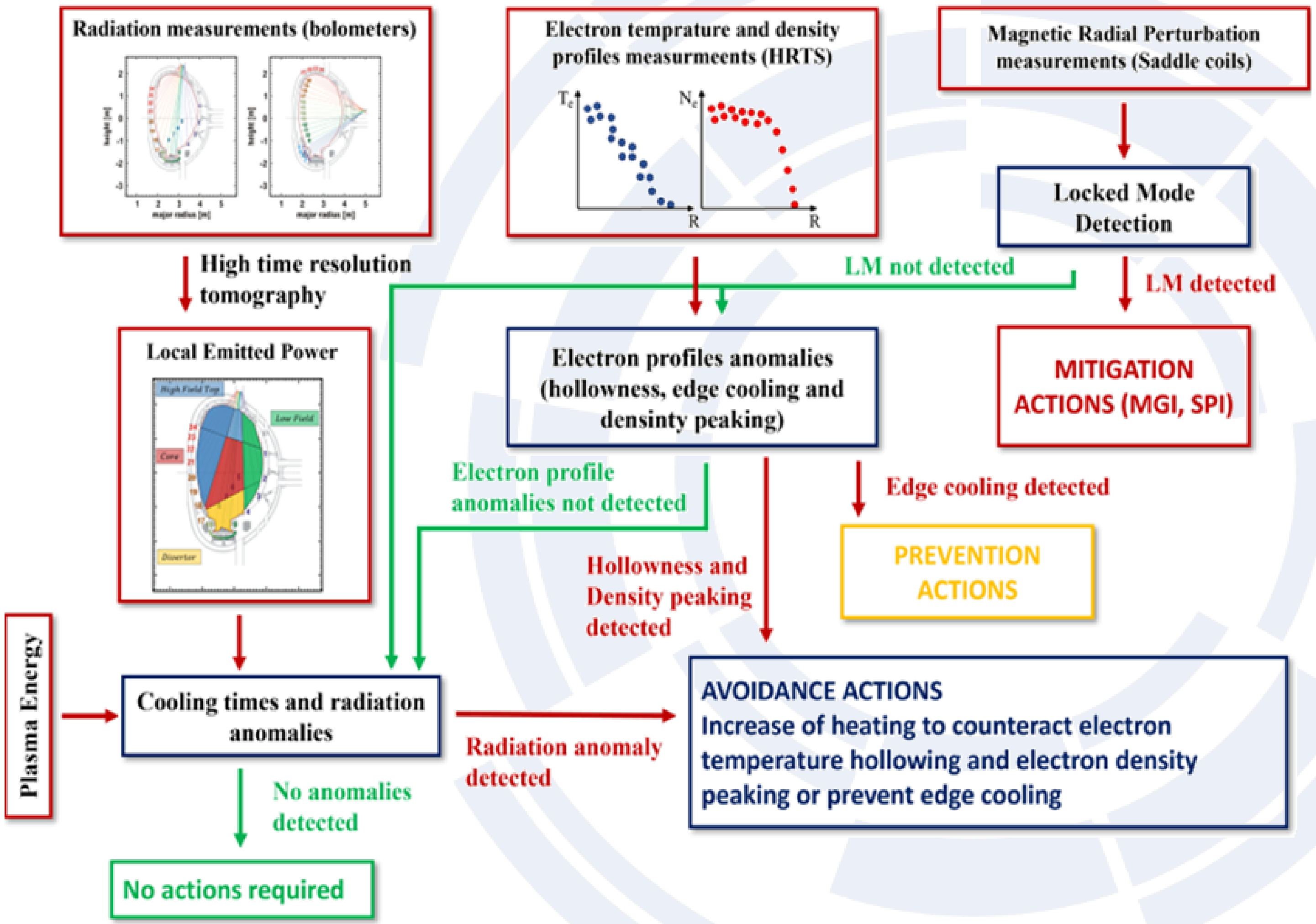
Alarm and mitigation/prevention/avoidance control logic

Given the paths to disruptions and the typical time scales of the various phenomena, one can propose a control and mitigation schemes which:

1. **Radiation anomalies** trigger **control schemes** to counteract local cooling (both edge and core)
2. **Hollowness** trigger control schemes to sustain **core heating**
3. **Edge Cooling** trigger **early termination** of the plasma (Prevention)
4. **MHD anomaly** trigger **mitigation** actions



Murari A., Rossi R., et al. "A control oriented strategy of disruption prediction to avoid the configuration collapse of tokamak reactors", Nature Communications, 2024

Outline

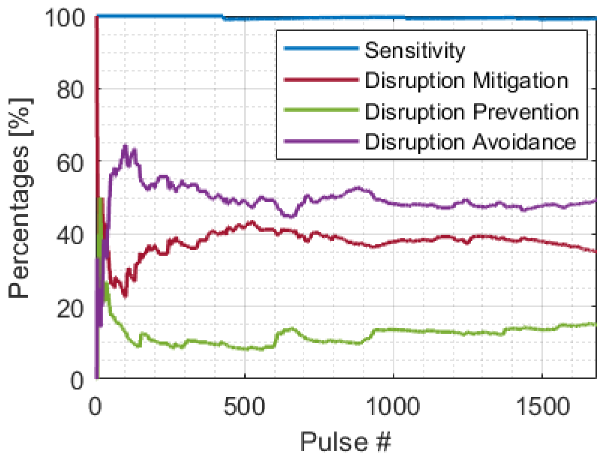
Results – Statistical analysis

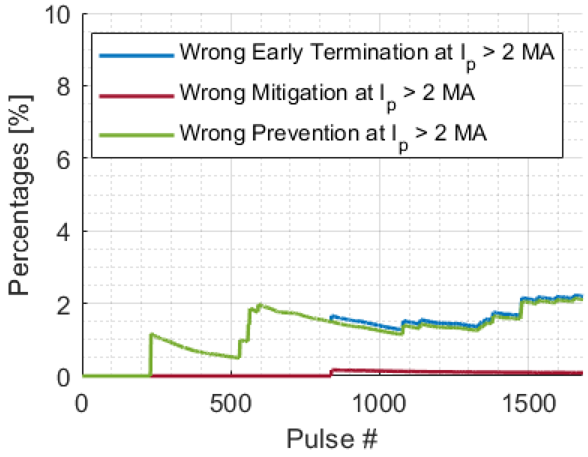
Hypotising a minimum time for successful avoidance (200 ms), prevention (100 ms) and mitigation (10 ms), expected statistics on the database has been evaluated.

These results have been obtained starting with no data in the training set (only physics guided at the beginning) and the predictors have been retrained with new data pulse-by-pulse (adaptive learning).

Wrong early terminations at high plasma current (> 2 MA) are very low (2%).

Some safe pulses have alarms in radiation patterns and electron temperature profile, but these are not false alarms (anomaly present but not disruptive). Important to be detected for control and not mitigation!





	Total	Mitigation	Prevention	Avoidance
Disruptive JET DMV	36	3	5	28
Disruptive JET JTT	19	1	0	18
Disruptive JET no actions	20	5	4	11
Safe JET JTT	33	7	0	10
Safe JET no actions	178	0	0	0

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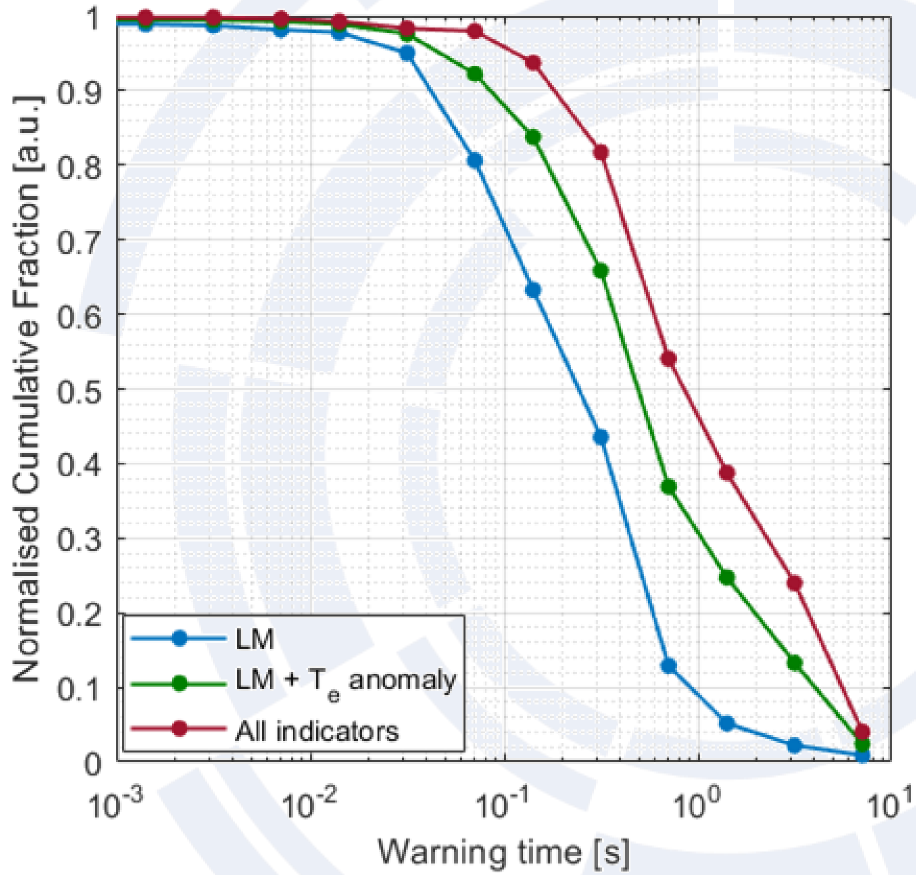
Results – Warning times statistics

Warning times are extremely improved using eletron temperature and radiation anomaly indicators, going from a median value of 200 ms for a MHD-based detector to 900 ms combining MHD, electron temperature and radiation anomalies.

High warning times from radiation and electron temperature are important since they allows for control schemes to recover from the instability and avoid disruptions.

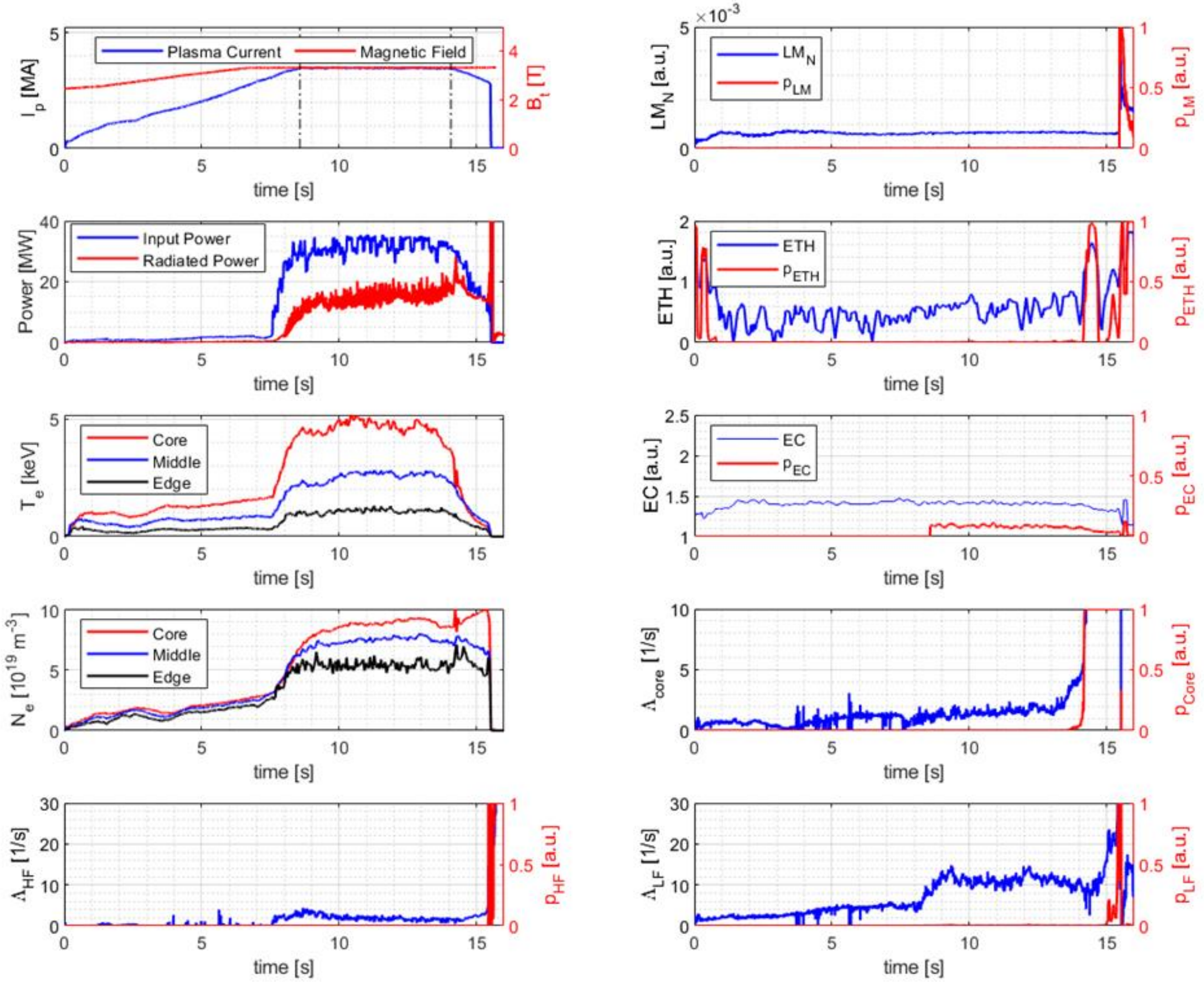
Disruptive Time vs DMV	Mitigation	Prevention	Avoidance
Mean [ms]	481	135	1115
Median [ms]	165	118	689
Min [ms]	25	80	135

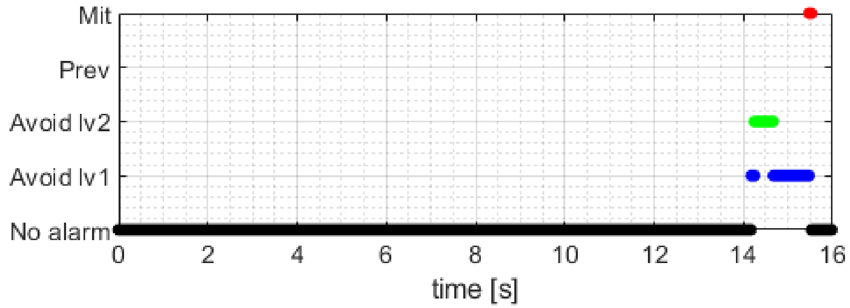


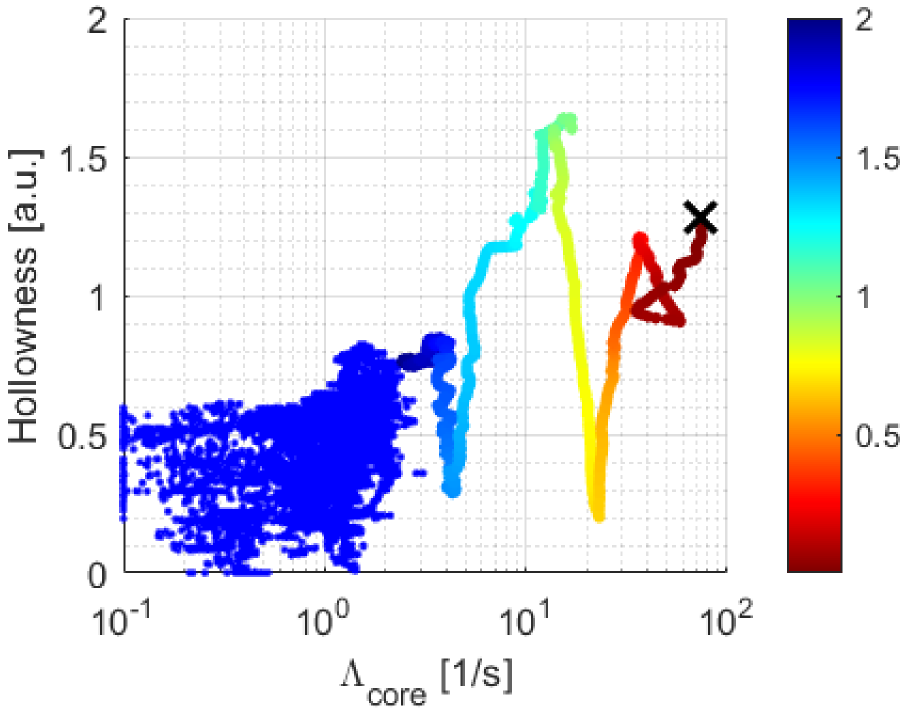
Murari A., Rossi R., et al. "A control oriented strategy of disruption prediction to avoid the configuration collapse of tokamak reactors", Nature Communications, 2024

Results – Example 1 – Pulse 96486

(core-hollowness-mode locking- disruption)



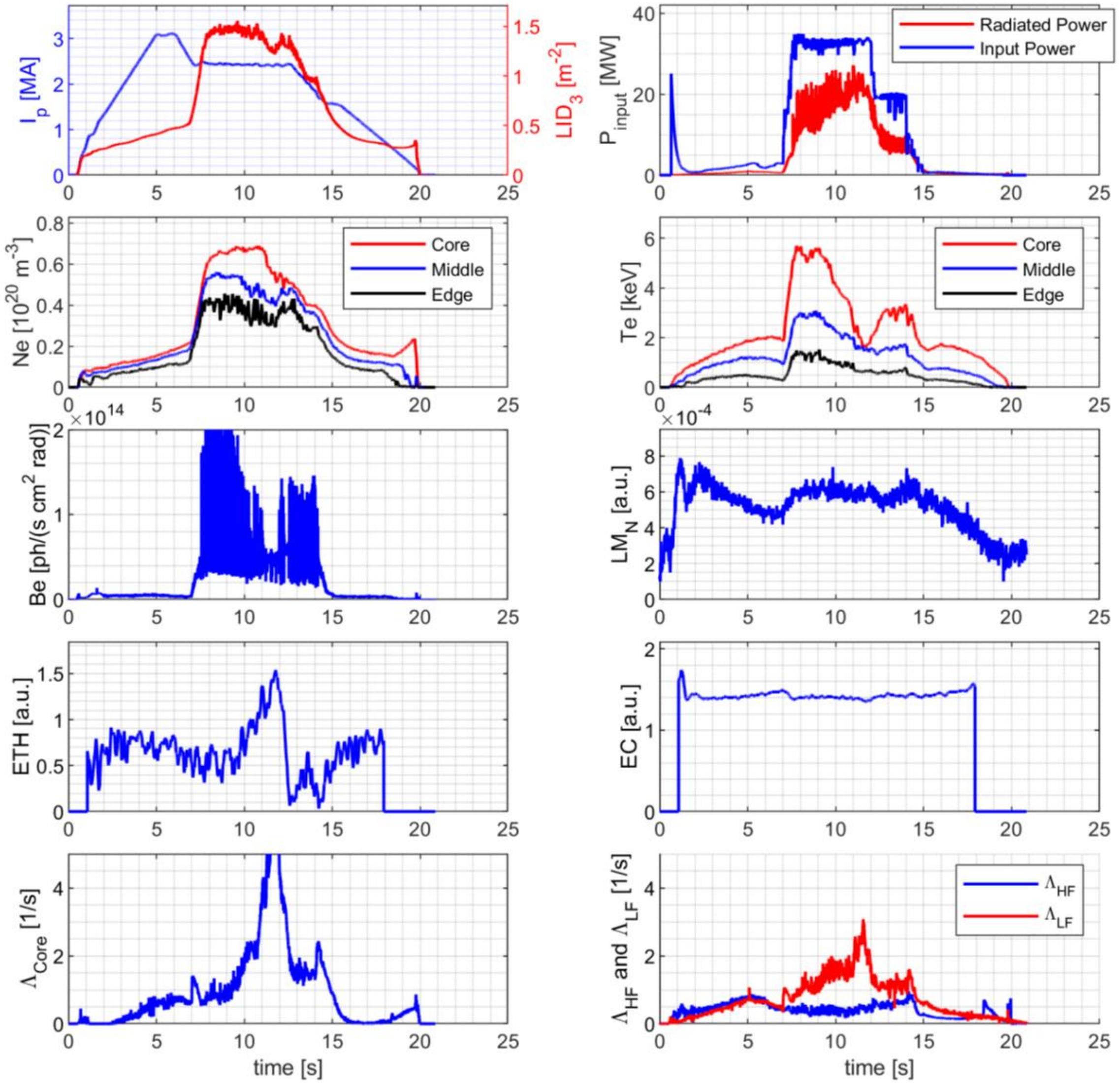


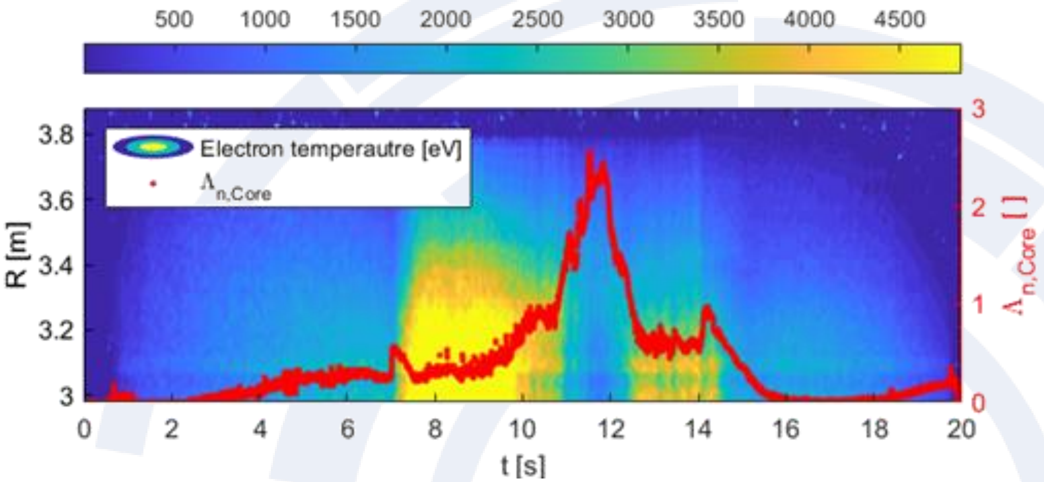


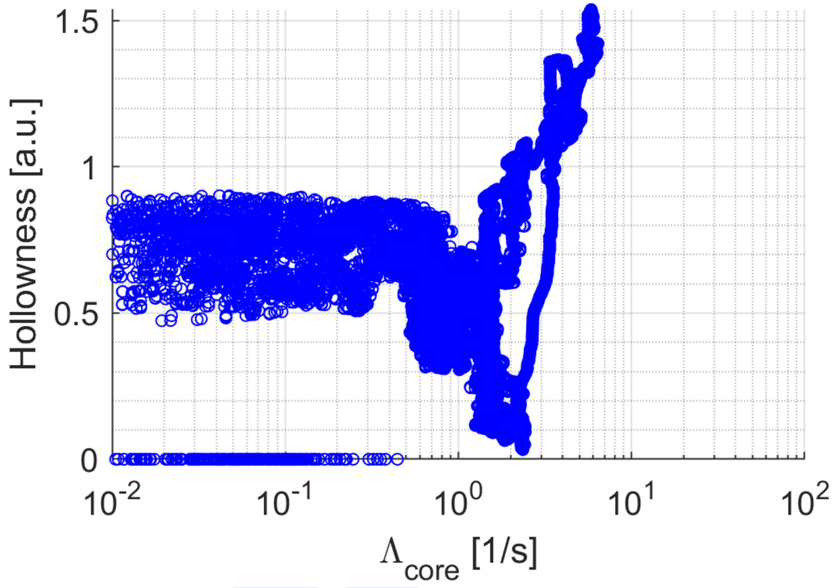
Murari A., Rossi R., et al. "A control oriented strategy of disruption prediction to avoid the configuration collapse of tokamak reactors", Nature Communications, 2024

Results – Example 2 – Pulse 96491

(core-hollowness-recovering)







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Conclusions

A new disruption predictor has been developed combining physics and data driven indicators and machine learning.

The predictor is able to **detect and classify MHD, electron temperature and radiative anomalies**, allowing the control system to take the proper countermeasures.

Several “Simulations” of prediction in four JET campaigns have been performed, starting from **no previous training set** (simulating the beginning of the operation of a new tokamak, like ITER)

Performances are very high in terms of accuracy, sensitivity, specificity, and warning times, suggesting that this hybrid methodology implemented with adaptive learning is a good candidate for ITER and other new reactors.

Future Developments

- Implementation of new anomalies (e.g. density limits)
- Implementation of the predictor to other tokamaks to gather experience for ITER.

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Adaptive Training Logic

A **realistic adaptive training logic** has been implemented, starting from zero training pulses (everything based on physics and statistical indicators).

MHD training

Physics + Data.

Data labelled following these rules:

No Alarm No disruptions:
Stable time slices

Disurption occurred:
last 100 ms are anomalous time slices

Temperature anomalies training

No Training is Needed

Radiation anomalies training

Physics + Data.

Data labelled following these rules:

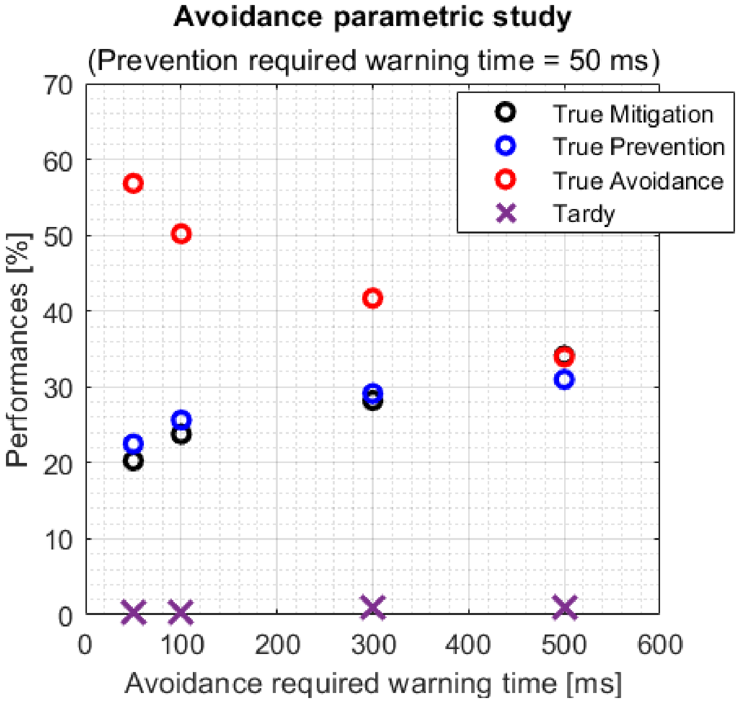
No Alarm No disruptions:
Stable time slices

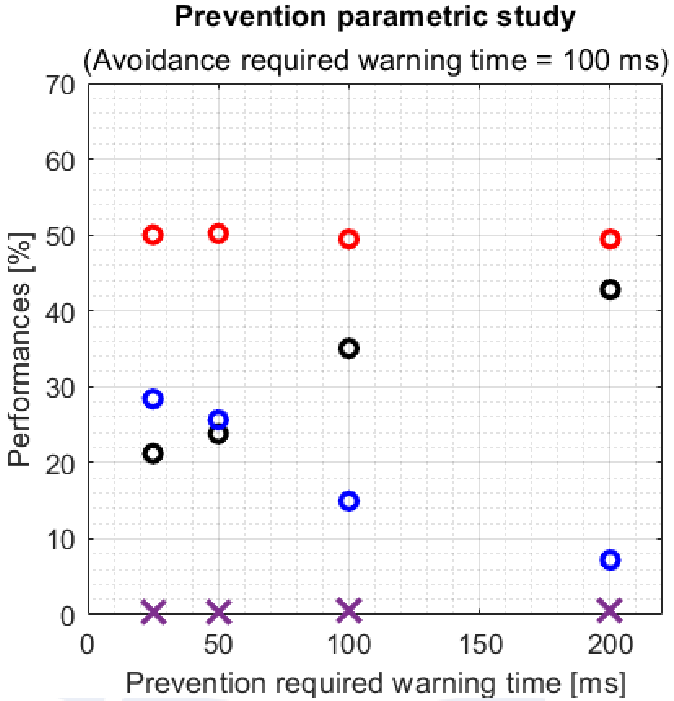
Disurption occurred or MHD/Eletron Temperature detected:
last 2000 ms are anomalous time slices

Results – Sensitivity analysis

Control strategies are under development and improvements. Of course, the quality of the predictor is a function of time required by the control system to perform mitigation, prevention, and avoidance.

We performed a **sensitivity analysis** of our algorithm varying avoidance and prevention times.





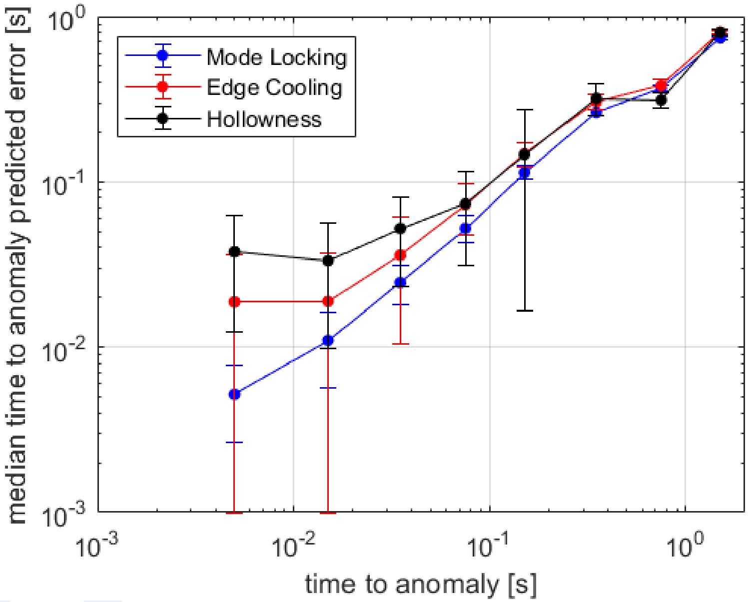
Rossi R., et al. "A hybrid physics/data-driven logic to detect, classify, and predict anomalies and disruptions in tokamak plasmas" Nuclear Fusion, 2024

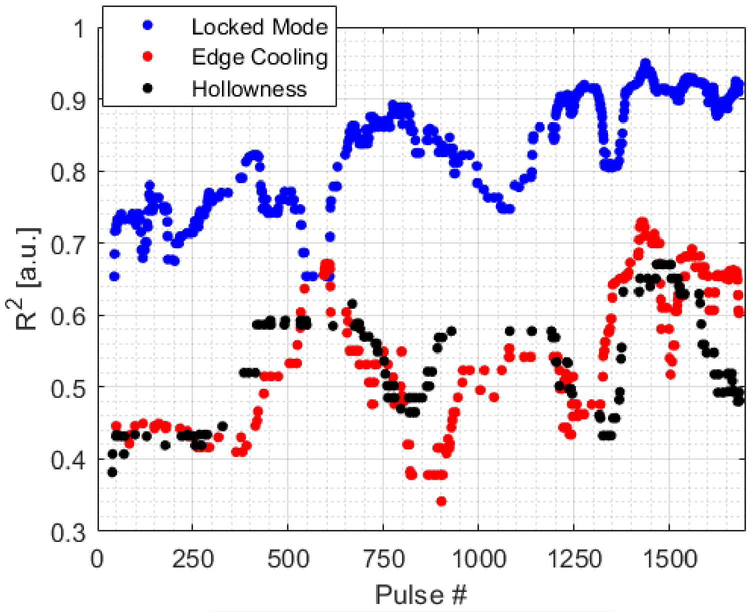
Results – Time To Anomaly Prediction

A **time to anomaly predictor** has been developed based on neural networks.

Prediction of MHD anomalies is good, since their a usually preceed by other anomalies.

Probably, it may have sense to predict an **anomaly proximity indicator** and not a time-to-anomaly, being it depedent also to the control system.





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Results – Comparison with JET Control System

We compare our results with JET disruption detection and control system.

Results validate the goodness of the predictor
(larger warning times and predictions in line with JET control system)

	Total	Mitigation	Prevention	Avoidance
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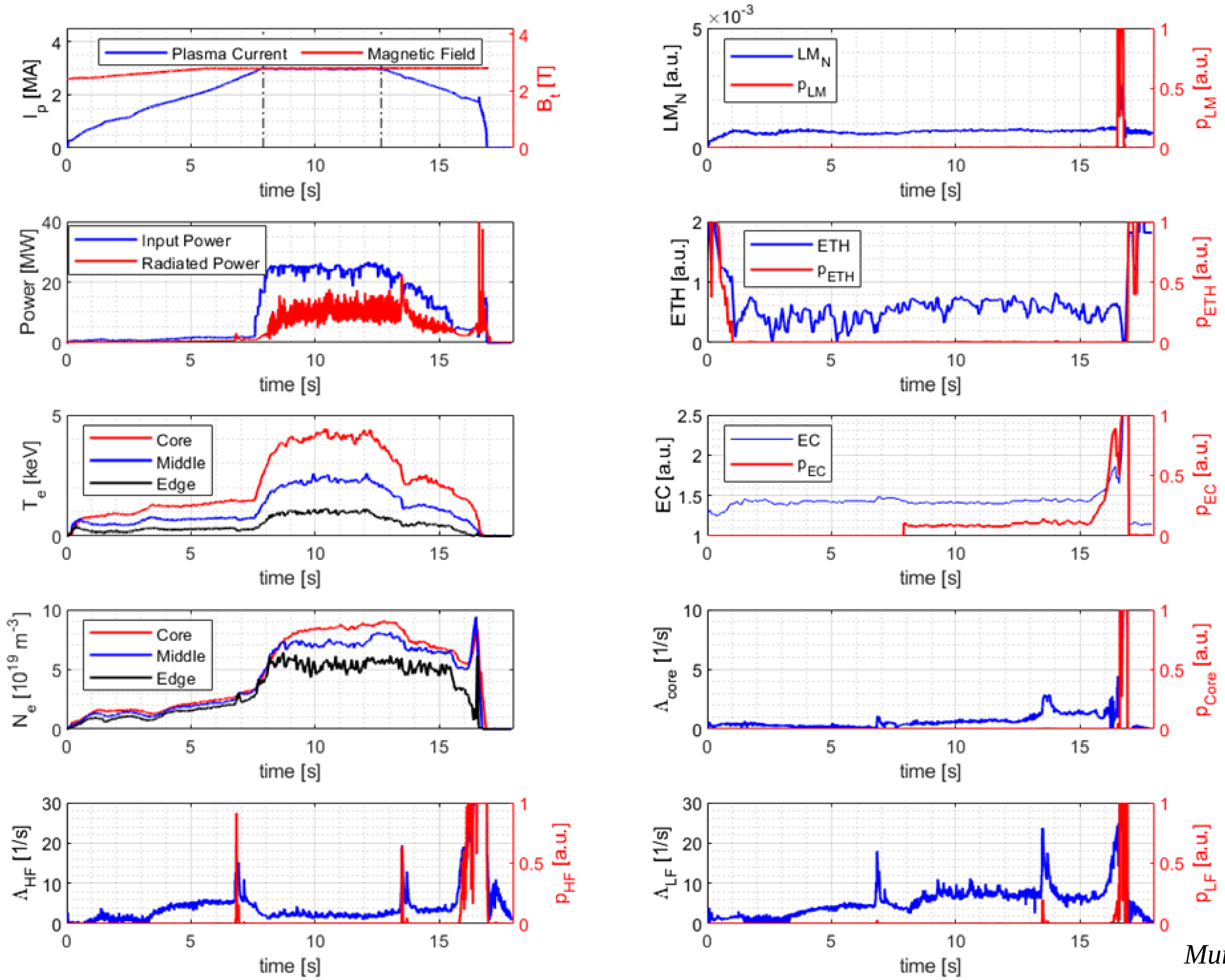
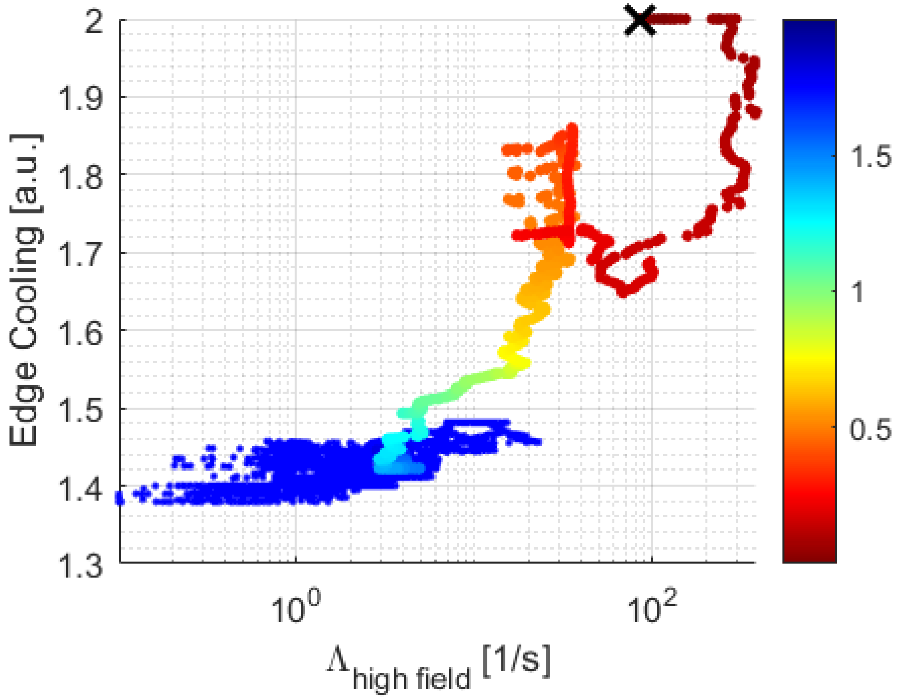
Median [ms]	165	118	689	
Min [ms]	25	80	135	

Murari A., Rossi R., et al. "A control oriented strategy of disruption prediction to avoid the configuration collapse of tokamak reactors", Nature Communications, 2024

Results – Example 2 – Pulse 94650





Murari A., Rossi R., et al. "A control oriented strategy of disruption prediction to avoid the configuration collapse of tokamak reactors", Nature Communications, 2024