



# Building a parsimonious disruption mitigation trigger

J. Vega, G. A. Rattá, D. Gadariya

Laboratorio Nacional de Fusión – CIEMAT, Madrid, Spain



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- **Objective for 2022**
  - Matlab code applied to JET data
  - Decision making capabilities after each discharge analysis to decide on retrain needs
    - Missed alarms and false alarms
- **Parsimonious**
  - Use of a minimal number of assumptions, steps or conjectures
  - Adaptive predictor from scratch
- **Mitigation**
  - Alarms: the closer to the disruption the better
- **Software characteristics**
  - Straightforward real-time implementation
    - Any real-time environment
  - Easy and fast retraining to be carried out between discharges



- **Constraint**
  - Restricted number of diagnostics in the beginning of operation
- **The mode lock signal shows good prediction capabilities**
  - Signal increases when
    - The rotation of an MHD mode slows down and can be locked
    - The MHD mode amplitude grows
  - Signal decreases when
    - The MHD mode amplitude drops
    - The MHD mode unlocks and the rotation speeds up
- **High amplitudes in the ML do not necessarily identify a disruptive behaviour**
  - Smooth variations between consecutive samples are typical of non-disruptive conditions
- **Small amplitudes in the ML do not necessarily identify a non-disruptive behaviour**
  - Sudden variations between consecutive samples are typical of disruptive conditions
- **Predictor parameter space**
  - Two-dimensional space whose points are the amplitudes of consecutive samples

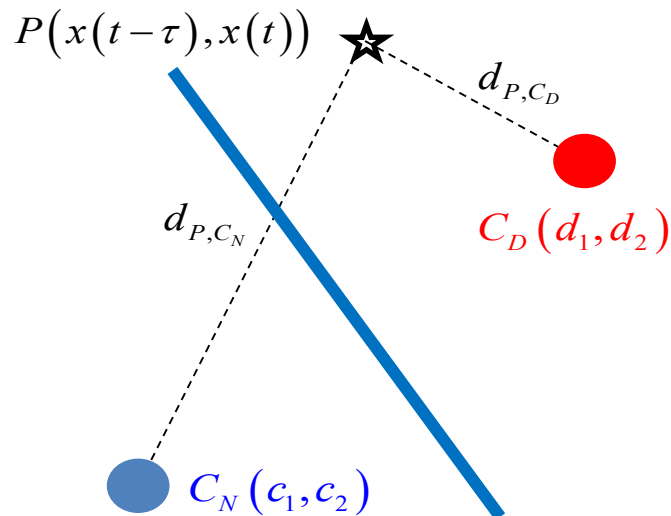
J. Vega et al. Nucl. Fusion 60 (2020) 026001 (13 pp)



- An important difference with previous adaptive predictors from scratch is the objective of not to need a first disruption to start the training
- In a first phase, the predictor only needs non-disruptive discharges and can detect a first disruption by means of anomaly detection
- After the first detected disruption, disruptive and non-disruptive information can be used



- Using anomaly detection with non-disruptive discharges to predict a first disruption
  - The predictor has to learn from non-disruptive discharges how a non-disruptive behaviour is
- After the first disruption, two centroids (disruptive and non-disruptive) summarise the disruptive and non-disruptive behaviours



Linear frontier

$$x(t) = -\frac{d_1 - c_1}{d_2 - c_2} x(t - \tau) + \frac{d_1^2 + d_2^2 - c_1^2 - c_2^2}{2(d_2 - c_2)}$$

- After missed alarms or false alarms, the centroids can be re-computed (predictor retraining) and, therefore, the two centroids condense in two points all the past history about disruptive and non-disruptive behaviours

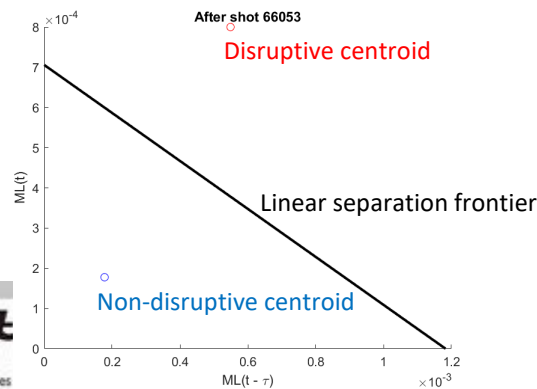
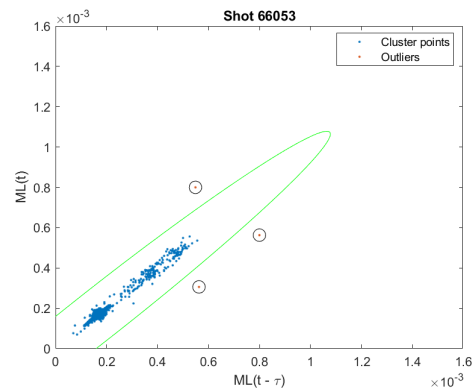
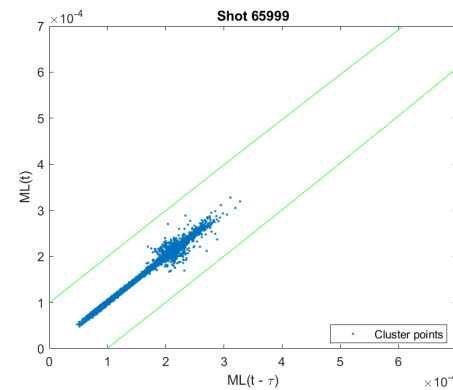
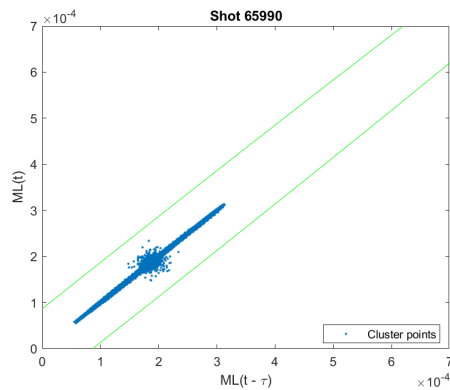
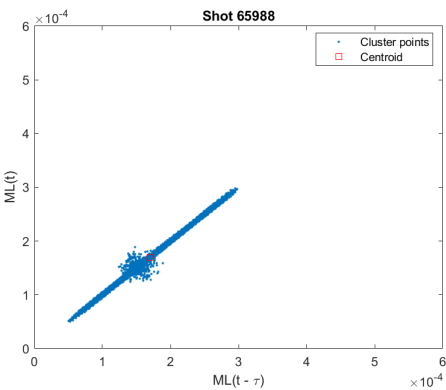


- JET C-wall data with  $I_p \geq 2$  MA
- 1886 discharges in the range 65988 – 73126
  - 124 disruptive shots
  - 1762 non-disruptive shots

# Anomaly detection to recognise a first disruptive behaviour



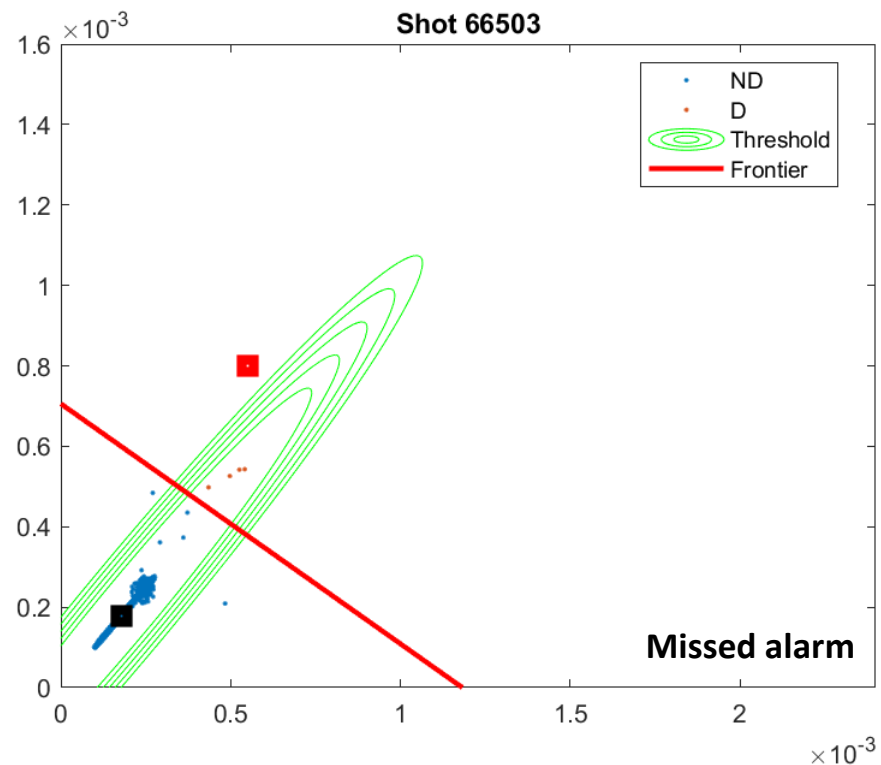
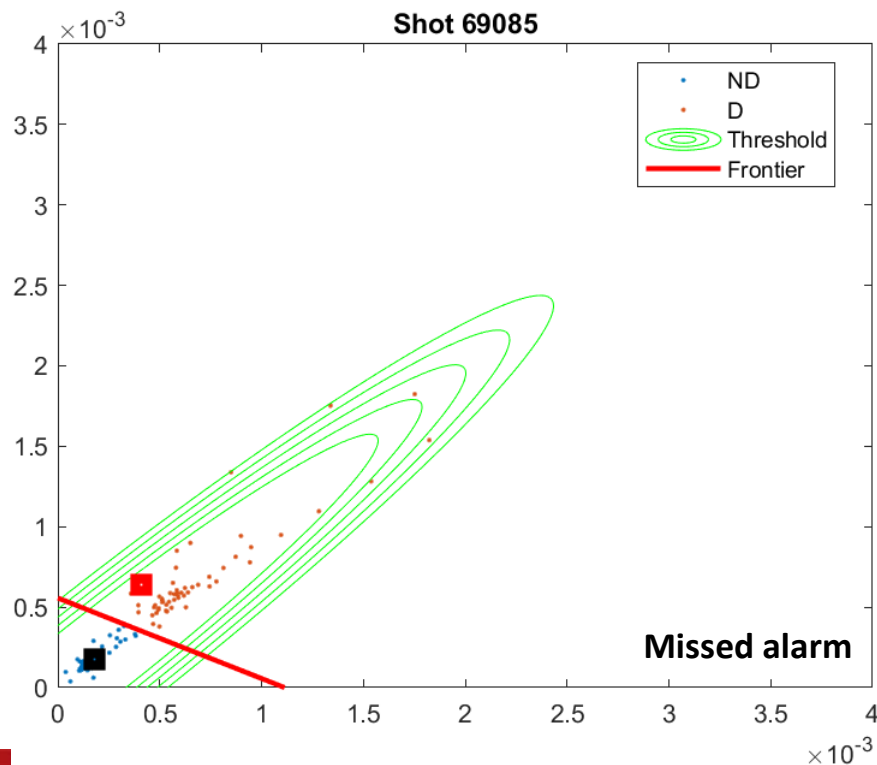
- In the two-dimensional parameter space, non-disruptive behaviours show a compact cluster of points
- A point '**far enough**' from the cluster identifies a disruptive behaviour
- To take into account the data covariance, the Mahalanobis distance is used
  - Isocontours are ellipses



# Adaptive prediction



- Two parameters can be optimised
  - Mahalanobis distance threshold to recognise disruptive behaviours when points are in the disruptive zone
  - Re-computation of centroids with information of past discharges

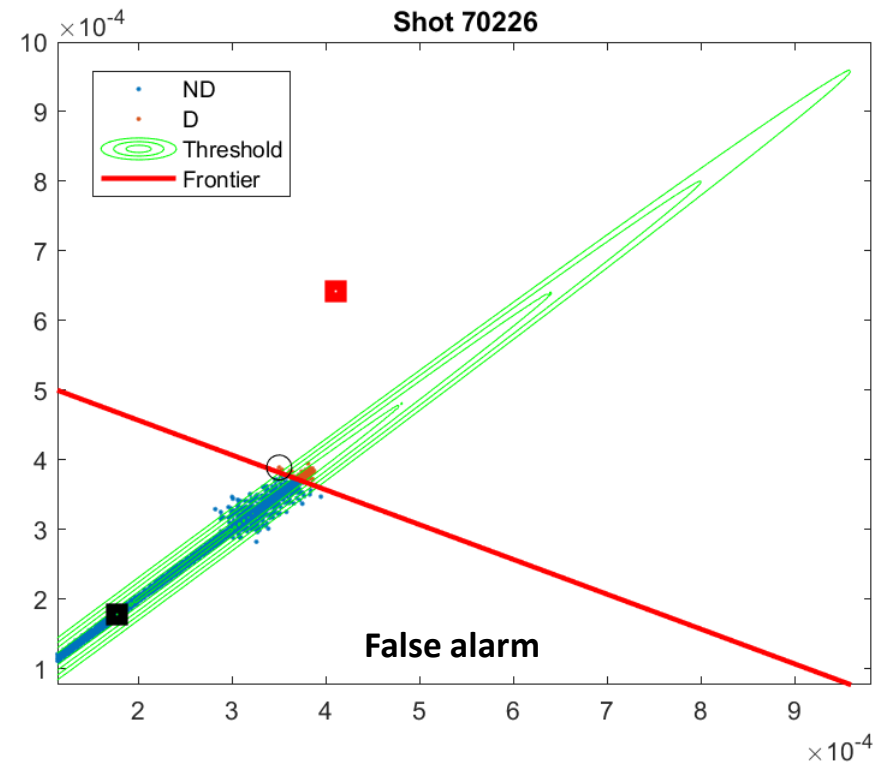
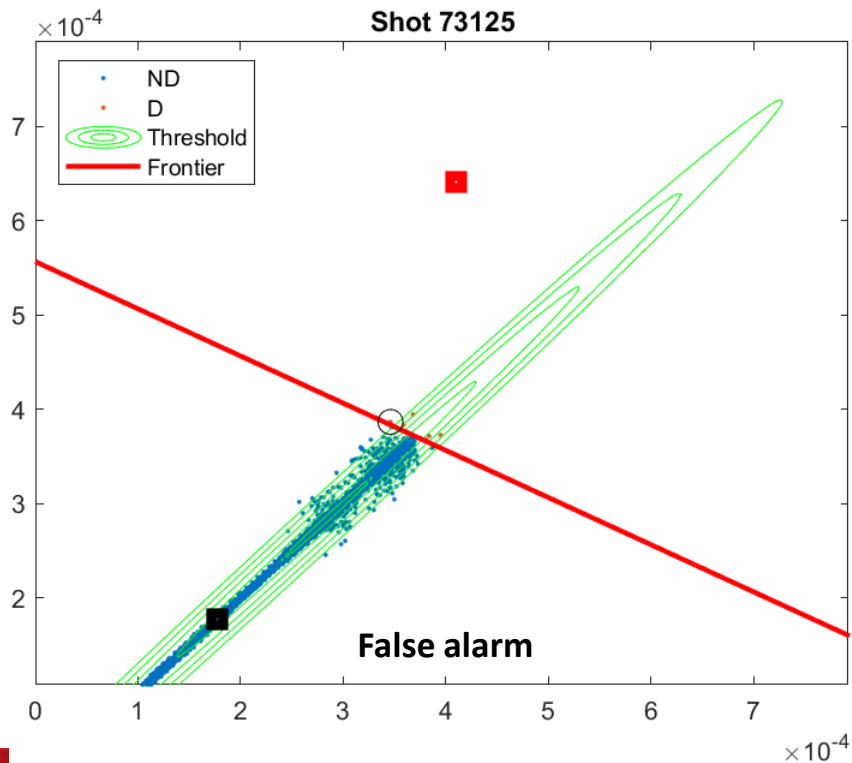




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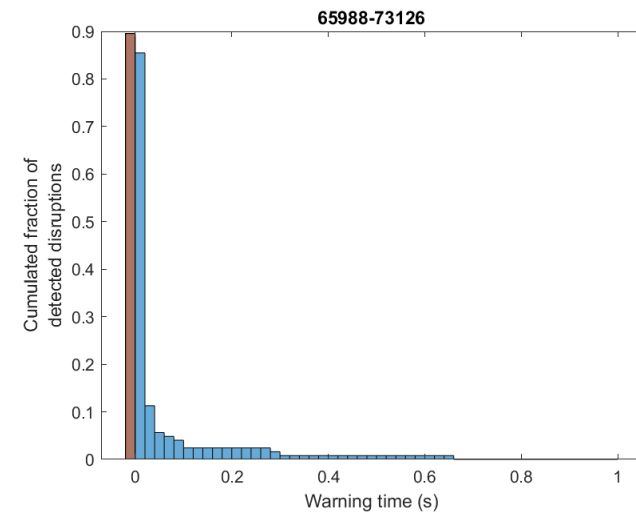
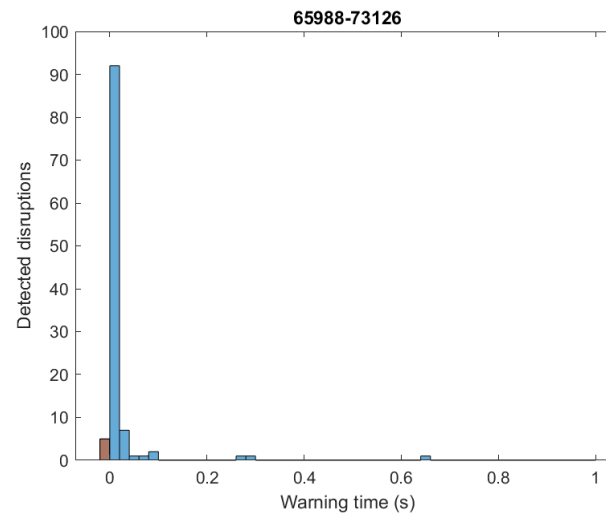
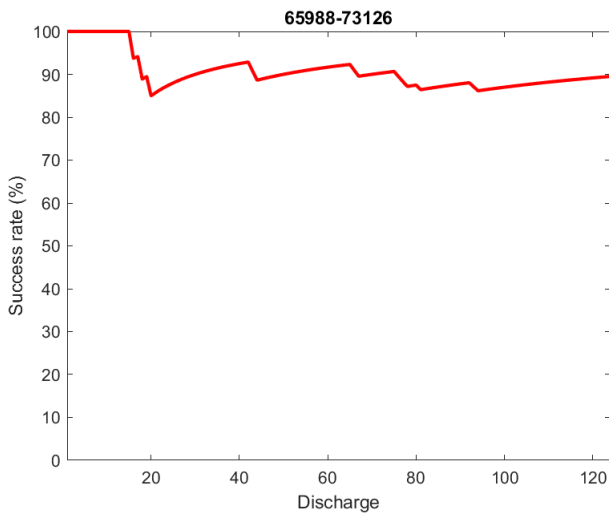
- Parameter optimisation applies to posterior discharges after the optimisation process

# Results (1/3)



- No retraining after the first computation of centroids

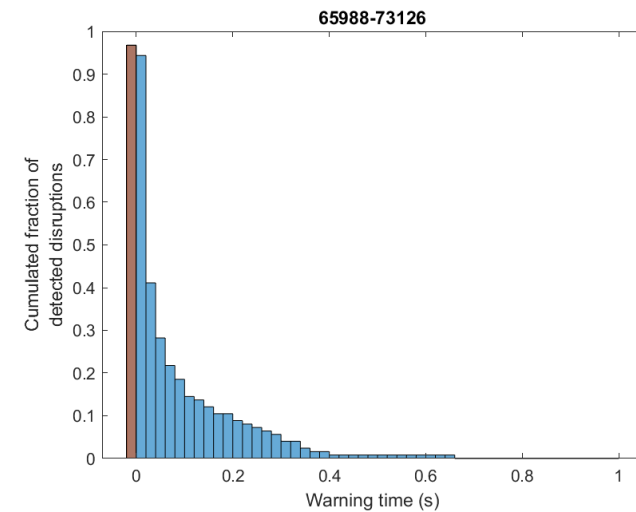
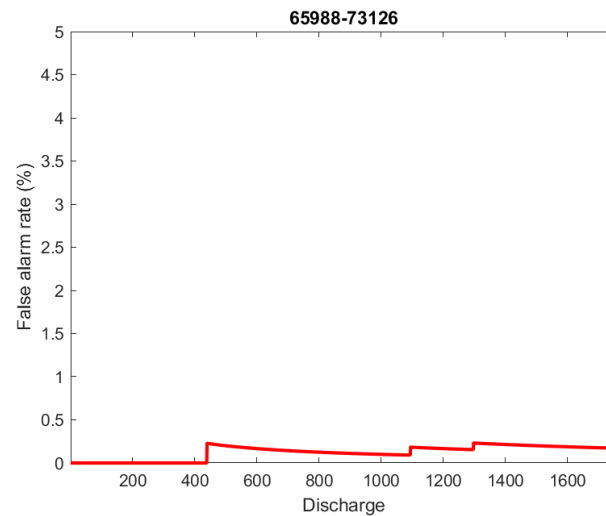
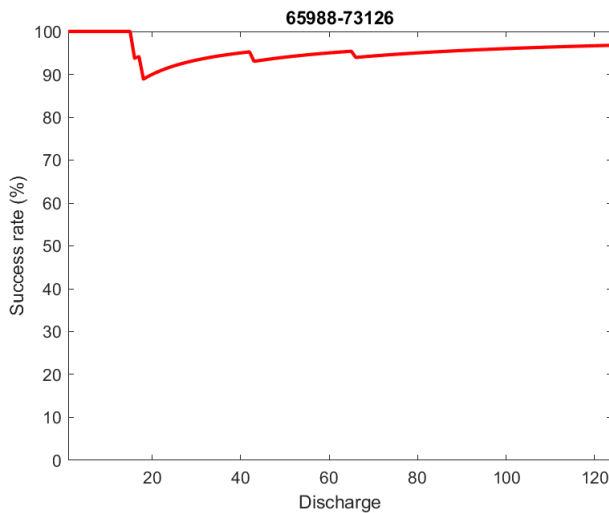
Case	Success rate (%)	False alarms (%)
1	89.52 (111/124)	0 (0/1762)





- Adaptive training after missed alarms and false alarms

Case	Success rate (%)	False alarms (%)
1	89.52 (111/124)	0 (0/1762)
2	<b>96.77 (120/124)</b>	<b>0.28 (5/1762)</b>

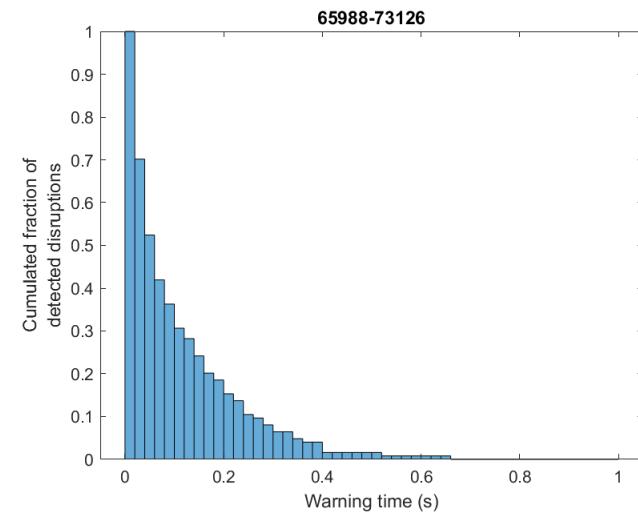
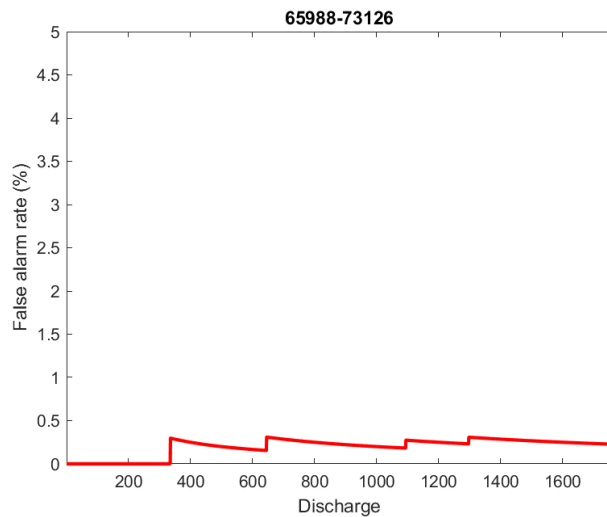


# Results (3/3)



- Application of the optimised predictor (case 2) to the whole dataset

Case	Success rate (%)	False alarms (%)
1	89.52 (111/124)	0 (0/1762)
2	96.77 (120/124)	0.28 (5/1762)
3	<b>100 (124/124)</b>	<b>0.34 (6/1762)</b>





- **Conclusions**
  - Straightforward and flexible method that only requires the ML signal and very simple computations
    - Real-time capabilities
  - Good results with JET C-wall data
  
- **Conferences and publications**
  - 2<sup>nd</sup> TM on Plasma Disruptions and their mitigation
  - NF/PPCF