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# Detection of plasma confinement states in the TCV tokamak

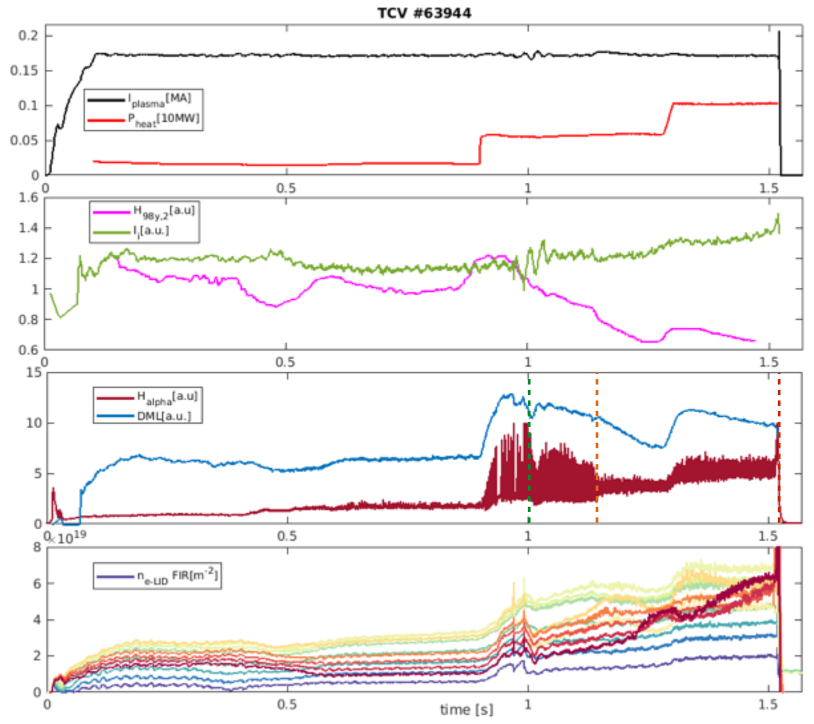

**G. Marceca[1], F. Matos[2], A. Pau[1], F. Felici[1], V. Menkovski[3], the TCV Team[a] and the EUROfusion MST1 Team[b]**

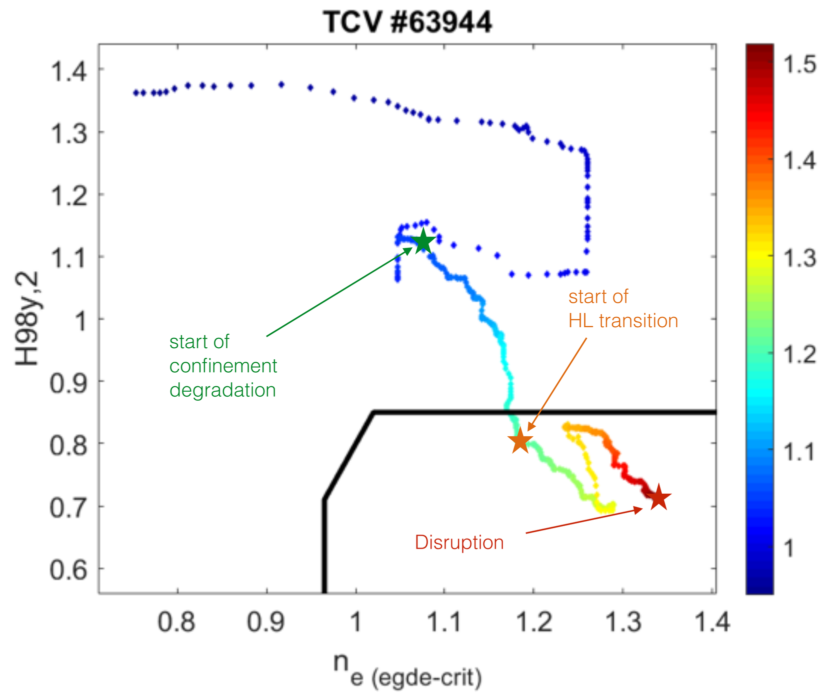
[1] Ecole Polytechnique Fédérale de Lausanne (EPFL), Swiss Plasma Center (SPC), CH-1015 Lausanne, Switzerland; [2] Max-Planck-Institut für Plasmaphysik, D-85748 Garching, Germany; [3] Eindhoven University of Technology, 5612 AZ Eindhoven, Netherlands;
[a] See author list of "S. Coda et al 2019 Nucl. Fusion 59 112023"; [b] See author list of "B. Labit et al 2019 Nucl. Fusion 59 086020"

First author e-mail: gino.marceca@epfl.ch

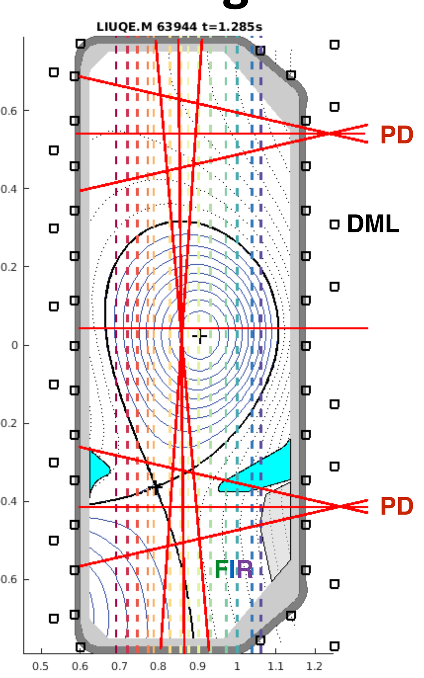

## Introduction

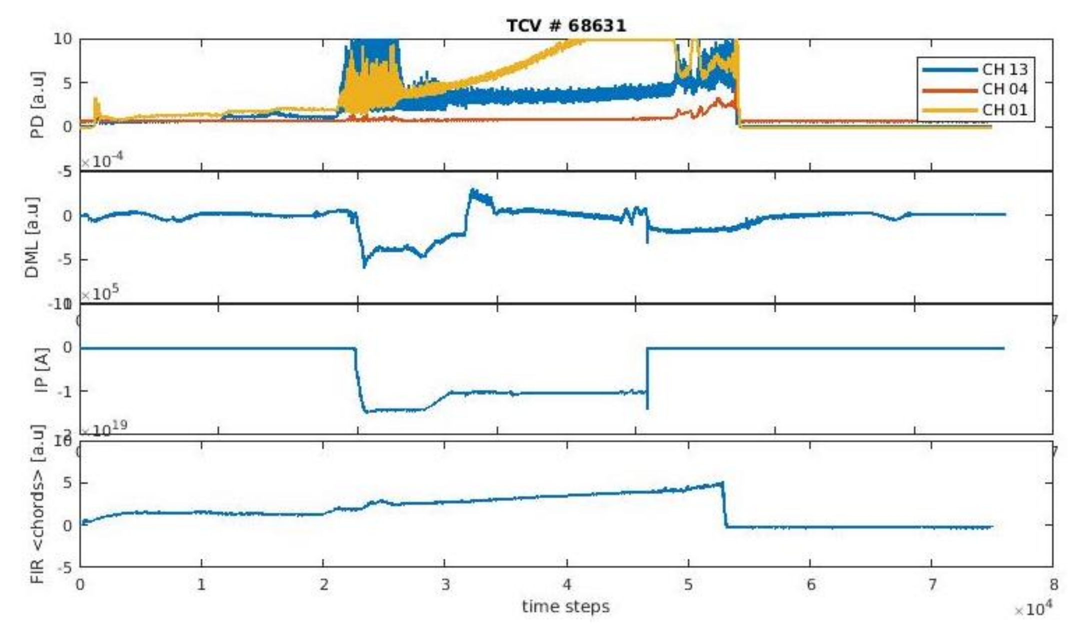
- **Tokamak plasmas** can be described as being in three **confinement states:** Low (L), Dithering (D) and High (H) modes.
- Accessing and maintaining the plasma regime in H mode is a key aspect to optimize the **energy confinement** that large scale fusion reactors such as ITER and DEMO are foreseen to operate.
- Importance of early detection of **confinement degradation**, typically found in high density limit scenarios, which can potentially lead to a **disruption**, the highest concern for next-step fusion devices based on the tokamak principle.
- Need to inform the control system when the H-L transition occurs, since it can destabilize the plasma and cause disruptions.




## Real time signals measured by TCV diagnostics



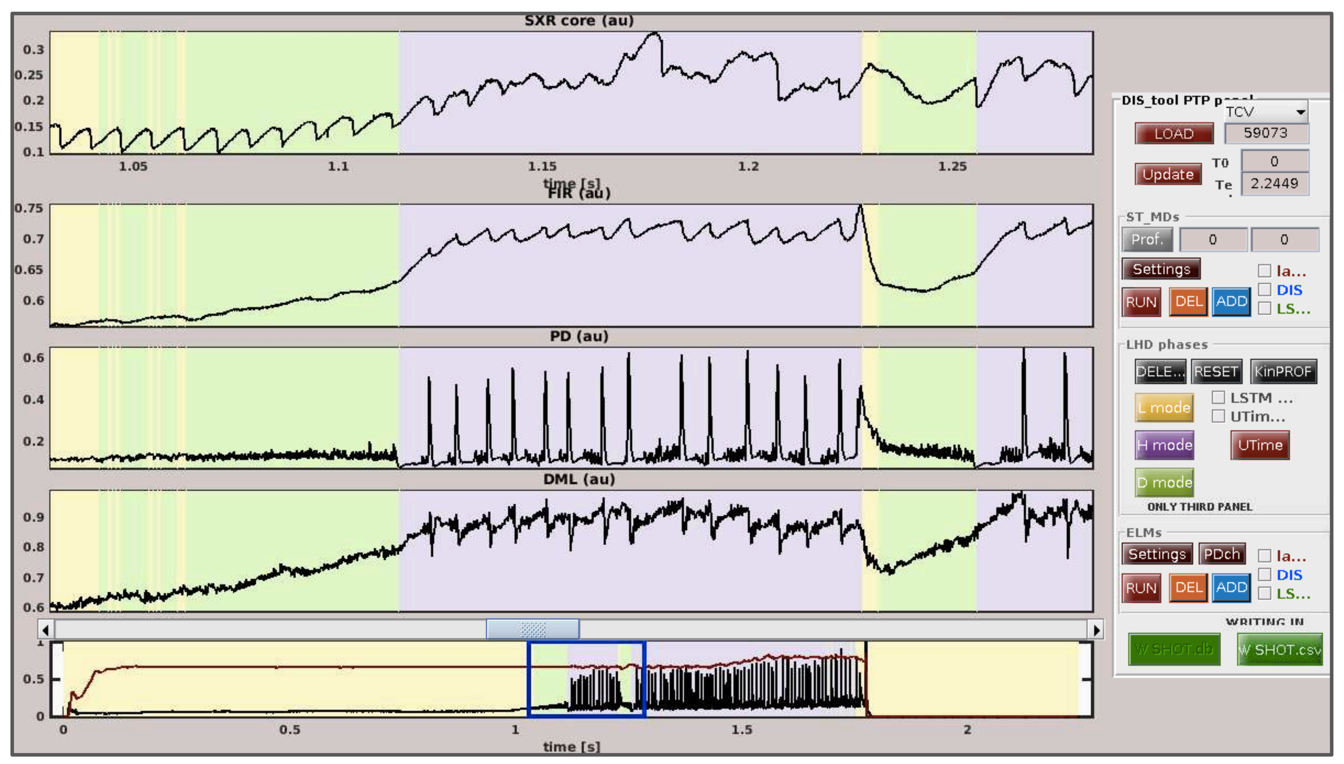

**Signal processing**

- Resampling (50 kHz → 10 kHz)
- PD channel selection
- FIR chords averaging
- IP > 20 kA

Signal validation

## Validation of signals from expert knowledge using the DIS tool

- The validation and construction of the database is done using the *DIS_tool* interface which allows domain experts to easily label each time step of a discharge as being in L, D or H mode.
- Labelling is a time consuming process which requires many iterations and consensus across different experts, where disagreement (in particular for the D modes) is typical.
- Accurate ML models can automatize this process and help in the production of large and consistent DBs across different existing Tokamaks.

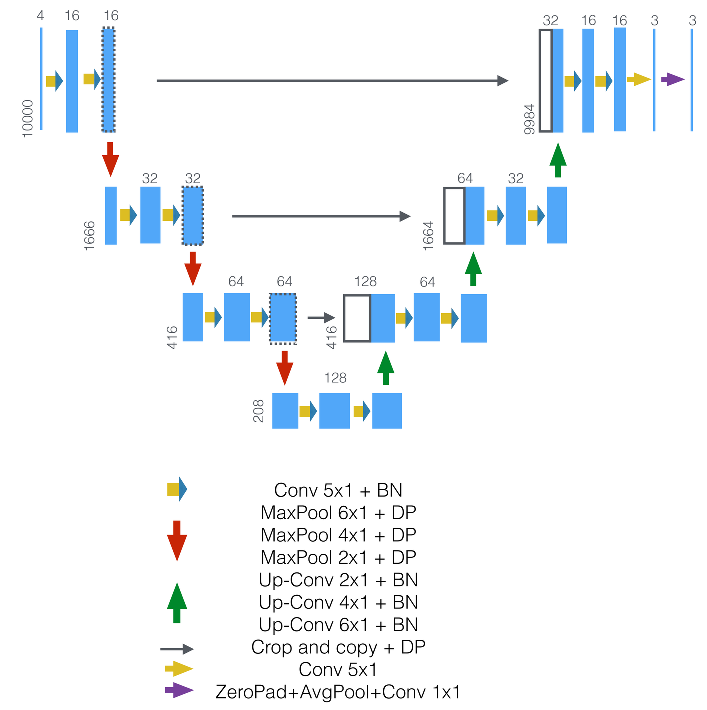


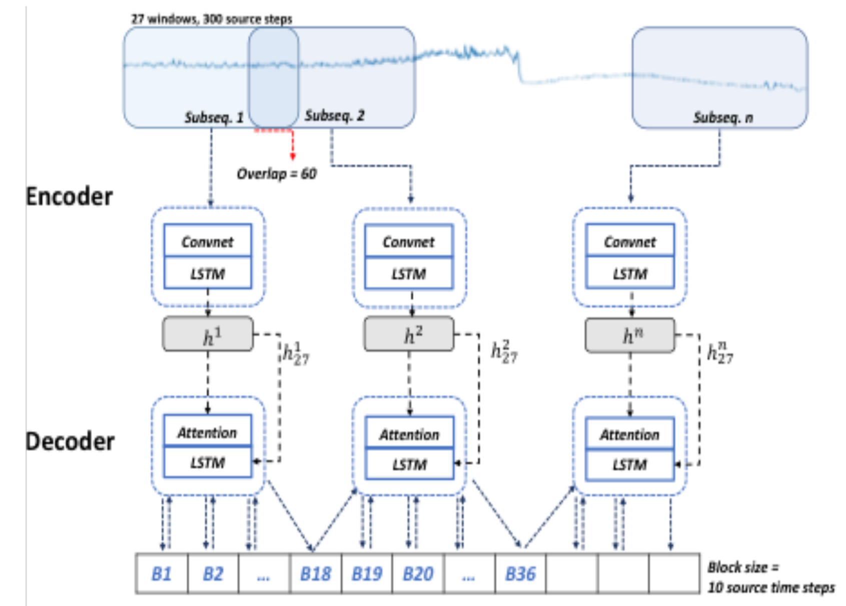

[A. Pau FED 2017]

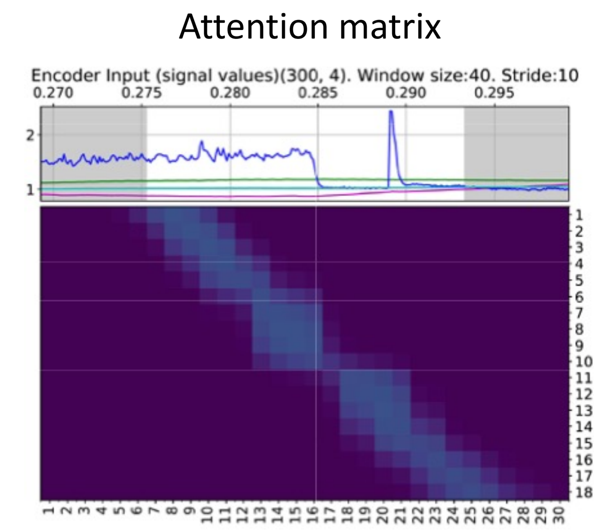
## Encoder-Decoder neural networks to detect plasma confinement states

Two encoder-decoder networks proposed: a 1D UNet architecture (UTime) and a seq2seq model with attention.

- The multi-scale convolutional structure of **UTime** allows to capture patterns at different scales present in the plasma.
- UTime processes the whole signal at once (offline) with the ability to see at large context. It is a good candidate model to help with the time consuming lavelling process.
- **Seq2seq** overcomes two limitations of previous studies based on a CNN-LSTM architecture [1]: it can produce decisions over sequence of outputs and is not constrained to have same source/target resolutions.
- It can run in RT, with a delay determined by the length of the encoder.
- The decoder was extended with an attention layer to capture larger context of long input sequences.





[1] F. Matos et al NF 2020


## Results in TCV

**Evaluation metric:** Cohen's Kappa-statistic ($\kappa$) measures the agreement between two sets of categorical data (ground truth vs model predictions).

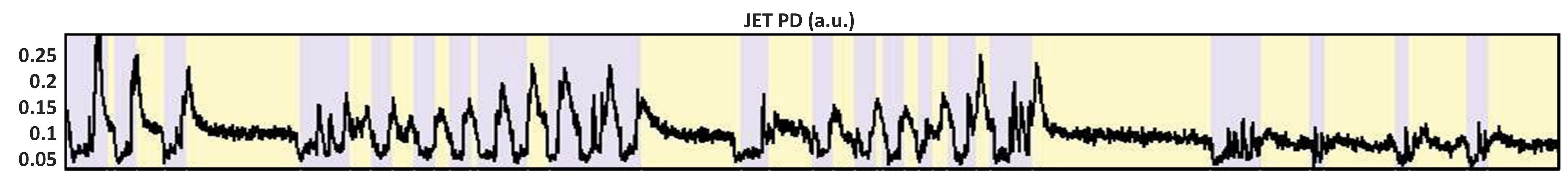
$$\kappa = \frac{p_o - p_e}{1 - p_e}, \quad p_e = \frac{1}{N^2}\sum_{k=1}^{3} n_{k1} n_{k2} = \text{prob of random agreement}$$

$$p_0 = accuracy, \quad n_{ki} = \text{\#times set } i \text{ predicted category } k$$

| $\kappa$ scores | | L | D | H | Mean |
|---|---|---|---|---|---|
| CNN-LSTM (dataset [1]) | Train | 0.96 | 0.89 | 0.97 | 0.96 |
| | Test | 0.82 | 0.77 | 0.85 | 0.83 |
| CNN-LSTM | Train | 0.98 | 0.91 | 0.98 | 0.98 |
| | Test | 0.92 | 0.78 | 0.91 | 0.90 |
| seq2seq | Train | 0.99 | 0.99 | 0.99 | 0.99 |
| | 5-CV | $0.97 \pm 0.01$ | $0.89 \pm 0.03$ | $0.98 \pm 0.01$ | $0.97 \pm 0.01$ |
| | **Test** | **0.94** | **0.86** | **0.96** | **0.94** |
| UTime | Train | 0.99 | 0.98 | 0.99 | 0.99 |
| | 5-CV | $0.97 \pm 0.01$ | $0.88 \pm 0.04$ | $0.97 \pm 0.01$ | $0.97 \pm 0.01$ |
| | **Test** | **0.94** | **0.89** | **0.96** | **0.95** |

## Transfer Learning: TCV → JET (preliminary)

- TL with UTime from TCV to JET requires only few shots and iterations for convergence, demonstrating the model ability to adapt quickly to different domains.
- The model can well recognize the « dithering cycles », a typical phenomena present in JET.




## Conclusions and next steps

- Two models based on an encoder-decoder architecture were developed to detect plasma confinement states in TCV.
- The existing TCV database of plasma states was highly extended and refined based on a consensus of expert knowledge.
- Thanks to both, the new database and the models, results surpassed by ~10% previous ones based on an CNN-LSTM model.
- As next steps we will rely on TL to deliver extensive and consistent databases for other machines. We will also implement the seq2seq model in the real-time control system and predict the confinement degradation as a disruption precursor.

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