# EUROfusion

# Studying pedestal dynamics using high-temporal-resolution density profiles predicted via machine learning

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## Background

Measurement of electron density profiles at JET is performed with different diagnostics:

- Thomson scattering (HRTS) provides good spatial accuracy (≈1 cm) but low sampling rate (≈20 Hz) [1];
- Reflectometry (KG10) provides high temporal resolution (≈1-10 kHz) but occasionally suffers from issues related to radial position accuracy [2].

To study high temporal resolution phenomena, such as pedestal dynamics in Edge Localized Mode (ELM) cycles, time consuming methods such as ELM synchronisation of HRTS profiles has previously been used [3].

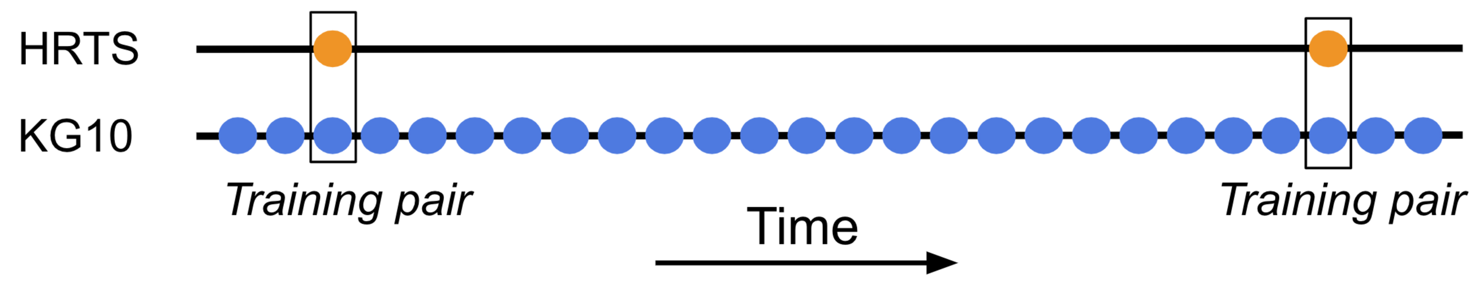
## Mission

In this work we show a fast automated approach to predict high-temporal-resolution HRTS density profiles from KG10 data using machine learning.

We demonstrate the utility by studying pedestal dynamics in the ELM cycle.

## Strategy

1. Create a training set with HRTS data and pair each entry with the KG10 data that is nearest in time;
2. Train neural network to predict HRTS data from KG10 data;
3. After training, the model is able to predict HRTS profiles for time instances where only KG10 data is available.



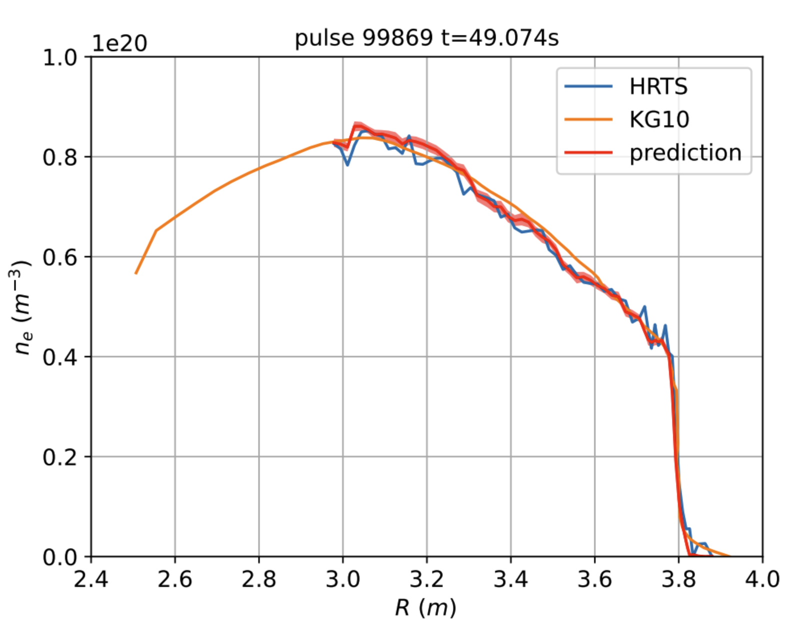

*This is an illustration. In reality, there are approximately 50-500 KG10 samples in between the HRTS samples*

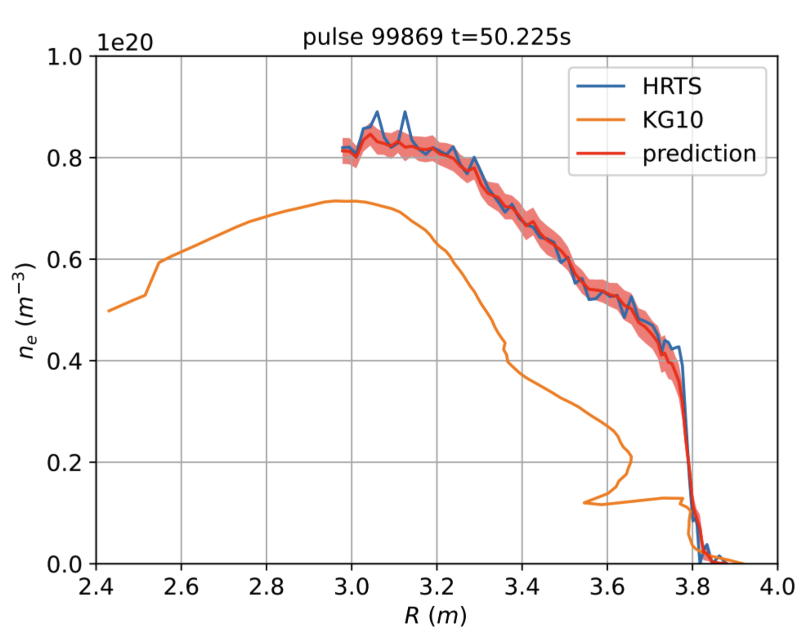
## Data set

- Training set: 43 531 pairs from 170 pulses in the JET C40 and C41 campaigns (98794-99953);
- Demonstration: DTE2 record pulse no. 99869. (2.3MA / 3.45T, high $\beta$, medium fueling: $1.4 \cdot 10^{22}$e/s) [4].

## Model & Prediction performance

- Architecture: 4-hidden-layer dense neural network with input dimension: 100 (KG10), output dimension: 63 (HRTS), nodes in each layer: 1024, activation function: ReLU;
- Training time: 5 min on single GPU;
- Mean validation set error $\approx 0.021 \cdot 10^{20}[m^{-3}]$;
- Mean test pulse (99869) error $\approx 0.021 \cdot 10^{20}[m^{-3}]$;
- Two examples are shown below. The model has learned to predict accurately both for cases where the diagnostics agree (left) and for cases where there are spatial accuracy issues with KG10 (right).

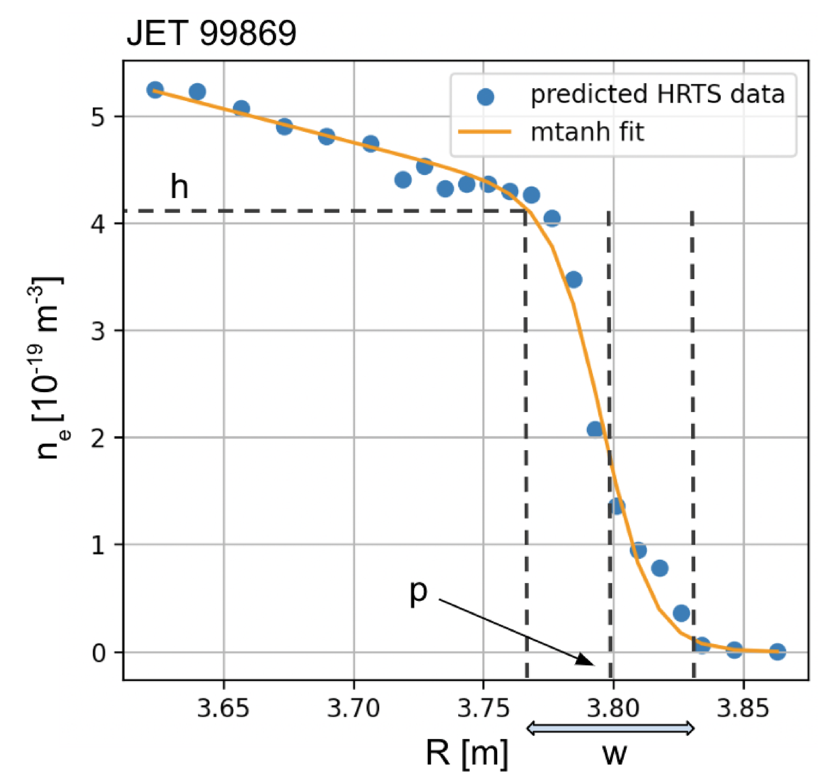



## Pedestal parameters

By fitting a modified hyperbolic tangent (mtanh) at the edge of each predicted HRTS profile, we obtain pedestal parameters for each time instance.

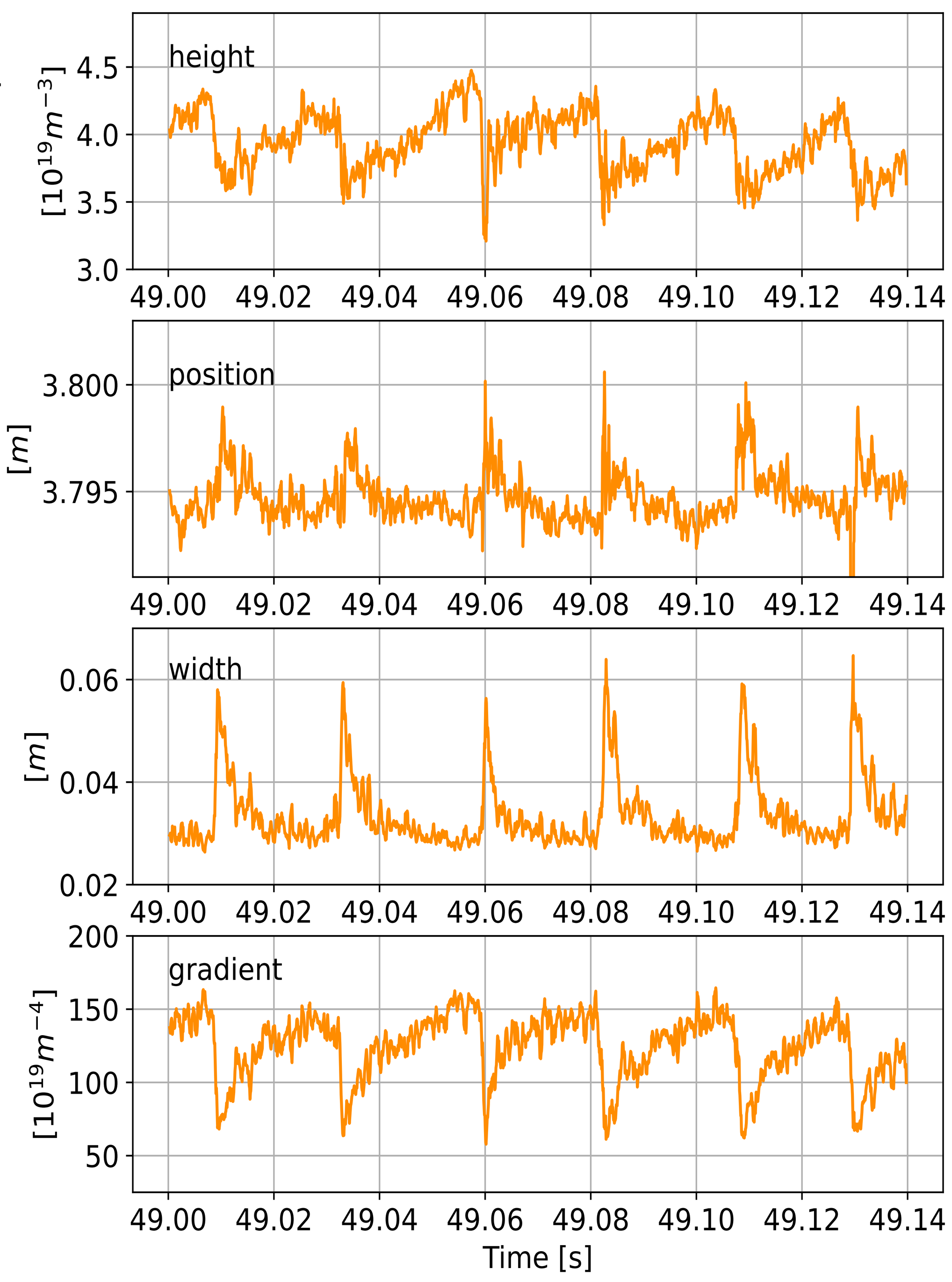
- One time frame is shown on the right;
- h - pedestal height;
- w - pedestal width;
- p - pedestal position;
- Pedestal gradient ≈ *h* / *w*;
- mtanh fitting is parameterised also by slope of core and offset.




## Pedestal dynamics (density)

We study the evolution of pedestal parameters obtained with mtanh fitting. Here, we look at a time window of approximately six ELM cycles for pulse 99869.
*Moving averages are shown (window size: 7 samples).*

- The pedestal height increases before an ELM crash occurs. For the majority of the buildup, the increase follows a linear trend.
- The pedestal position shifts inwards during the buildup of the pedestal before it rapidly shifts outwards during each ELM crash.
- The pedestal width narrows as the pedestal height increases, and each ELM crash widens the pedestal. This pattern is less linear compared to the height.
- The combined pattern of the height and width results in a pedestal gradient that increases during the buildup before each ELM crash occurs.




## Conclusions

- The model mitigates occasional spatial accuracy issues with KG10;
- Predicted HRTS profiles provides interpretable pedestal related signals at a high temporal resolution;
- In this work the HRTS and KG10 data are of equal importance. Without pairs of HRTS and KG10 data, there is no training. Without KG10 data for a particular pulse, there are no high-temporal-resolution predictions for that pulse.

## References

[1] R. Pasqualotto et al Rev Sci Instrum **75**: 3891–3893 (2004)
[2] Sirinelli et al Rev Sci Instrum **81**: 10D939 (2010)
[3] M. J. Leyland et al Rev Sci Instrum **87**: 013507 (2016)
[4] J. Garcia 2022 6th Asia-Pacific Conference on Plasma Physics (2022)

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This work has been carried out within the framework of the EUROfusion Consortium, funded by the European Union via the Euratom Research and Training Programme (Grant Agreement No 101052200 — EUROfusion). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the European Commission can be held responsible for them.