

J Alhage et al.

# **Detection of ELMs at JET and analysis of ELM variability and risk**

Preprint of paper submitted for publication in Special Issue of  
“52nd EPS Conference on Plasma Physics (EPS 2026), Edinburgh, Scotland”



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.

This is a preprint. For all inquiries regarding copyright and licensing, please contact:  
Publications Officer, EUROfusion Programme Management Unit, Boltzmannstr. 2,  
85748 Garching, Germany, or e-mail [publications.officer@euro-fusion.org](mailto:publications.officer@euro-fusion.org).

# Detection of ELMs at JET and analysis of ELM variability and risk

J. Alhage<sup>1</sup>, C. Haems<sup>1</sup>, M. Van Damme<sup>1</sup>, Y. Zhang<sup>1</sup>, D. Van Eester<sup>2</sup>,  
D. Frigione<sup>3</sup>, L. Garzotti<sup>4</sup>, D. Keeling<sup>4</sup>, F. Rimini<sup>4</sup>, V.K. Zotta<sup>5</sup>, G. Verdoolaege<sup>1</sup>,  
JET Contributors<sup>6</sup>, and the EUROfusion Tokamak Exploitation Team<sup>7</sup>

<sup>1</sup> *Department of Applied Physics, Ghent University, 9000 Ghent, Belgium  
orcid.org/0009-0003-5702-939X    jerome.alhage@ugent.be*

<sup>2</sup> *Laboratory for Plasma Physics LPP-ERM/KMS, B-1000 Brussels, Belgium*

<sup>3</sup> *Università di Roma Tor Vergata, Via del Politecnico 1, Roma, Italy*

<sup>4</sup> *United Kingdom Atomic Energy Authority, Culham, Abingdon, Oxon OX14 3DB, United Kingdom*

<sup>5</sup> *Dipartimento di Ingegneria (DIAEE), SAPIENZA Università di Roma, 00184 Roma, Italy*

<sup>6</sup> *See the author list of C.F. Maggi et al., Nucl. Fusion 64, 112012, 2024*

<sup>7</sup> *See the author list of N. Vianello et al, Nucl. Fusion 66, 116010, 2026*

In order to ensure safe and efficient operation of fusion reactors, it is essential to prevent or mitigate off-normal events by monitoring the plasma and machine components. We here consider detection and risk analysis for edge-localized modes, or ELMs. These quasi-periodic plasma instabilities lead to the expulsion of heat and particles, potentially causing damage to plasma-facing components [1, 2]. Detecting ELMs and characterizing their behavior is crucial for understanding the conditions which lead to their onset [3, 4]. The stochastic nature of ELMs complicates this task, as both the signature of ELMs and their impact are highly variable, requiring sufficiently general analysis methods. In this work, highly robust event detection methods were developed using machine learning, and their performance was compared. The algorithms were then used to process discharges from the EUROfusion pedestal database (PDB) [5], producing more than 100,000 individual ELM events, on top of nearly 14,000 events labeled by hand. We investigated the factors influencing ELM timing and size, from a statistical point of view. Probabilistic reasoning was used for risk assessment of rare events, as within shots where small ELMs are expected, occasional large ELMs may appear.

**ELM detection algorithms** Automatic detection of ELMs is commonly required by various analysis tasks, and it is a first step toward the statistical analysis of ELM properties [6–10]. Improving these detection techniques turned out to be necessary in plasma regimes with relatively small or compound ELMs, such as those observed and characterizing the JET baseline scenario [11] shown as test cases in this contribution. We implemented several general peak detection methods, based on robust thresholding, filters for time series, novelty detection, one-dimensional neural networks, and object detection methods exploiting feature invariance. Then, we tuned these algorithms to identify a specific shape or sequence of ELMs. Finally, we com-

pared their performance quantitatively over an unseen portion of the dataset, using specialized *interval-overlap*  $F_\beta$  metrics. The Laplacian of Gaussian (LoG) method, a smoothed edge detection filter that is notable for its simplicity, reached 86% in sensitivity, and the addition of a specialized kernel reduced false positives to below 10%. The recurrent neural network (RNN) model, however, yielded the highest test accuracy at 92%, and holds the most potential.

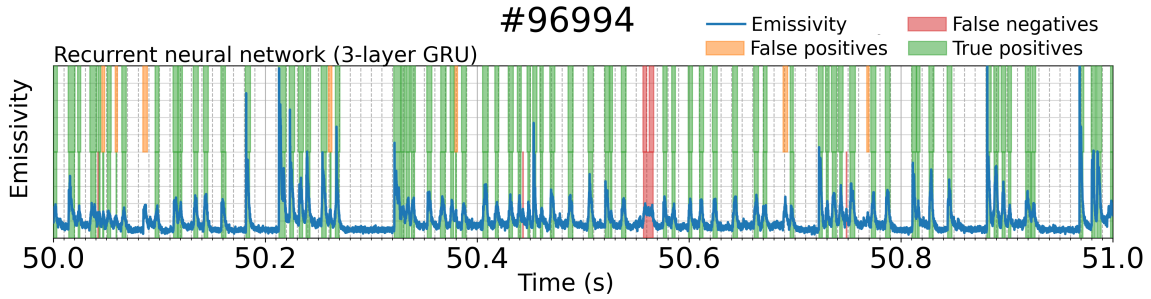


Figure 1: Output of the RNN detection model in JET discharge #96994. The plotting area shows both the ground truth (bottom-half) and predicted labels (top-half), over the input BeII emissivity signal (blue line). When the span of a peak is sufficiently covered by a prediction, the region is marked as true positive in green, or otherwise a false negative in red. A false positive in orange is a predicted peak which does not match any label. This method is highly robust in cases such as this one, containing a mix of small and large ELMs.

**Data analysis techniques** Having established robust ELM detection, we proceeded by analyzing time windows in JET pulses under stationary plasma conditions, each covering a series of ELMs. In each window, ELM behavior is characterized using the parameters of probability distributions fitted to their timing and released energies (with drops in  $W_{MHD}$  as a proxy). This probabilistic approach extends beyond mere averages of ELM properties, important considering the stochasticity in the data [12–14]. The tail heaviness of the distributions is a measure of the risk of the occurrence of rare, but large ELMs, whereas averages mask the extremes.

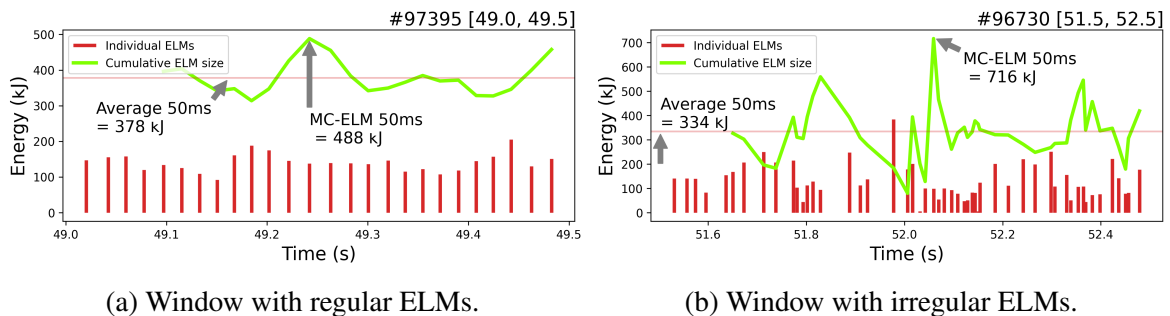


Figure 2: Modeling of the impact of a sequence of ELMs, using the maximum cumulative ELM losses in an interval of 50 ms. In shots with regular ELMs (2a), this quantity tracks the average ELM size. In the case of irregular ELMs (2b), however, consecutive ELMs may cause a considerably larger spike in the accumulated energy.

Furthermore, the impact of a series of large, but irregularly timed ELMs is quantified using the accumulation of energies as shown in figure 2. In a next step, the effect of plasma conditions on these descriptors of ELM behavior is studied using distribution maps in figure 4, and regression analysis and feature importance in table 1.

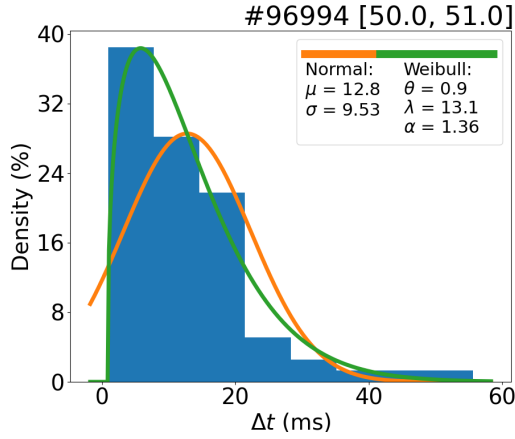


Figure 3: The inter-ELM time distribution in JET discharge #96994 is skewed. The shifted Weibull distribution provides a better fit than the normal PDF, making use of the extra shape parameter  $\alpha$ .

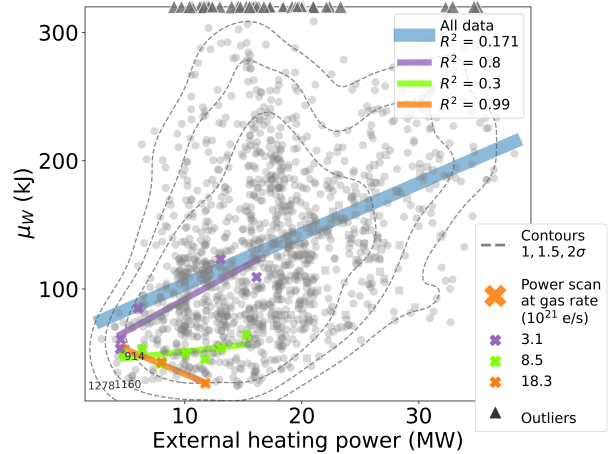


Figure 4: Shot-averaged ELM size versus the total external heating power [15]. At low (purple) and high (orange) gas fueling, heating power and ELM size are highly correlated, but not at intermediate gas rates (green).

ELMs in nearly 2000 PDB windows are laid-out in figure 5, originating from 2012-2020 JET shots. In this dataset, we see that long-tailed ELMs can be observed regardless of ELM frequency or average size. Excluding shots with pellet-triggered ELMs, lowering the total heating power can reduce the likelihood of rare large ELMs. However, the choice of heating system has no effect, and the role of gas injection depends on subsets. The maximum cumulative ELM energy, representing a proxy to ELM heat loads at the most stressful moment during the pulse, is mostly governed by input heating power, followed by plasma current.

	Plasma current	Safety factor q95	NBI+ICRH heat. power	ICRH power proportion	Gas fuel. throughput	Upper triangularity
ELM size MC 50ms	0.33	0.05	0.56	0	0.01	0.07
ELM size top 10%	0.48	0.03	0.02	0.02	0.08	0.24
ELM size mean	0.45	0.01	0.07	0.02	0.09	0.25
ELM size std. dev.	0.47	0.04	0.04	0.01	0.07	0.24

Table 1: Breakdown of the importance of input plasma or machine parameters on ELM size, characterized by statistical features that describe both the average behavior and extreme events, such as long-tailed ELMs and a quick succession of energetic ELMs.

**Conclusion and future work** We developed several techniques to robustly detect ELMs, quantify their variability, and assess the risk of occasional large ELMs. In doing so, we provided tools for machine operators to make risk-informed decisions with regards to ELM behavior, capabilities that advance further as the operational space is explored. Moreover, the techniques for event identification and modeling can also be applied for fault diagnosis across plant systems, such as the electrical and mechanical systems that need monitoring, where the scale and variety of sensor data requires automated condition monitoring.

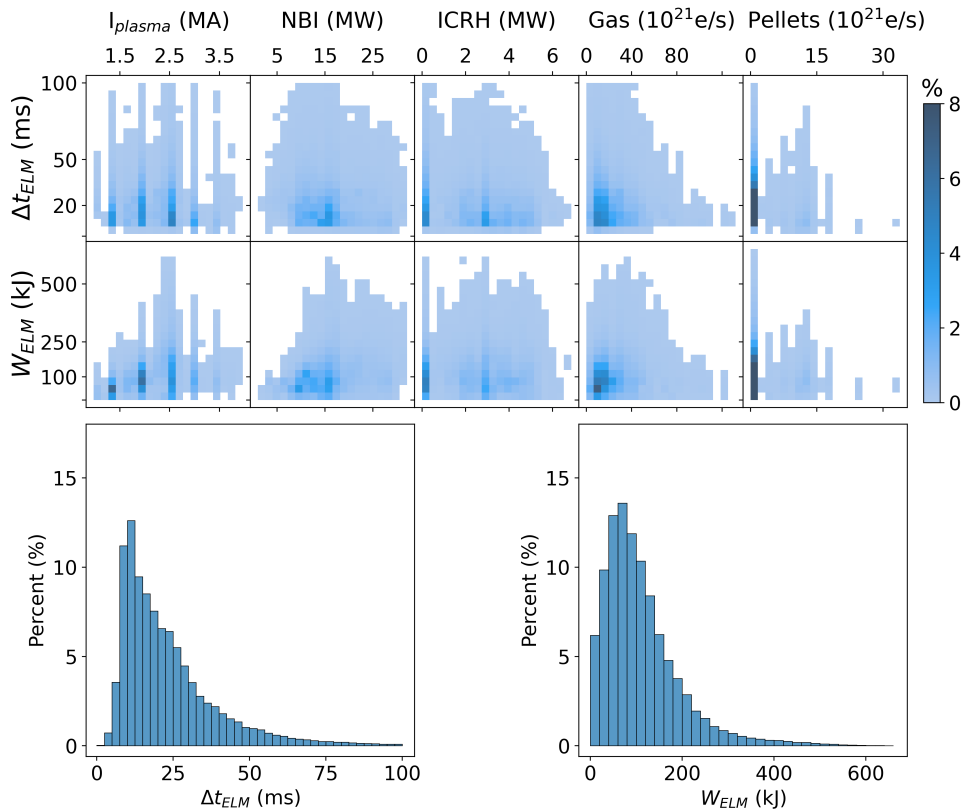


Figure 5: Summary of ELM and plasma parameters in the ELM analysis dataset, which is based on stationary time windows from the EUROfusion pedestal database.

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. (Please mind the addendum 2019-2020). The authors acknowledge Lorenzo Frassinetti, JET Contributors, and the EUROfusion Tokamak Exploitation Team for their support.

## References

- [1] H. Zohm, PPCF **38**, 105 (1996).
- [2] J. W. Connor et al., AIP Proc. **1013**, 174 (2008).
- [3] T. Eich et al., Nuc. Mat. Ener. **12**, 84 (2017).
- [4] J. Garcia et al., Phys. Plas. **29**, 032505 (2022).
- [5] L. Frassinetti et al., NF **61**, 016001 (2020).
- [6] N. Teo et al., R. Sci. Inst. **95**, 073528 (2024).
- [7] M. Berta et al., Fus. Eng. Des. **123**, 950 (2017).
- [8] A. Jalalvand et al., Nature Com. **16**, 8506 (2025).
- [9] J. Adamek et al., NF **63**, 086009 (2023).
- [10] A. Shabbir et al., NF **57**, 036026 (2017).
- [11] L. Garzotti et al., PPCF **67**, 075011 (2025).
- [12] G. Verdoolaege et al., EPS 45 proc., 813 (2018).
- [13] A. Shabbir et al., R. Sci. Inst. **87**, 11D404 (2016).
- [14] A. Murari et al., PPCF **56**, 114007 (2014).
- [15] A. R. Field et al., PPCF **62**, 055010 (2020).