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

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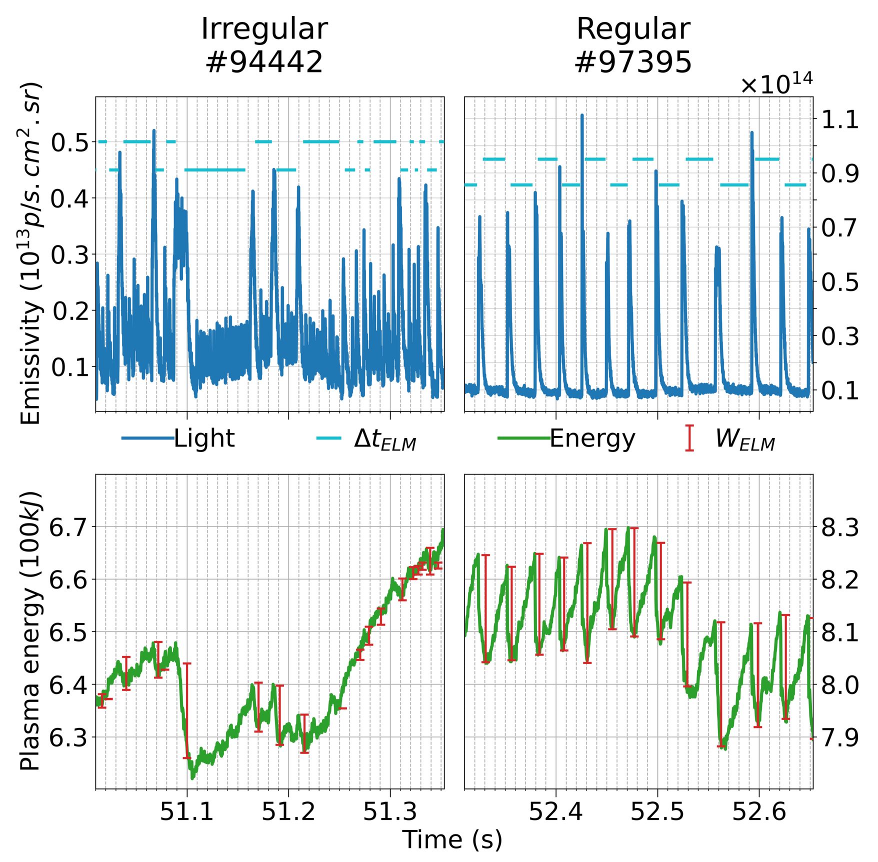
Edge-localized modes

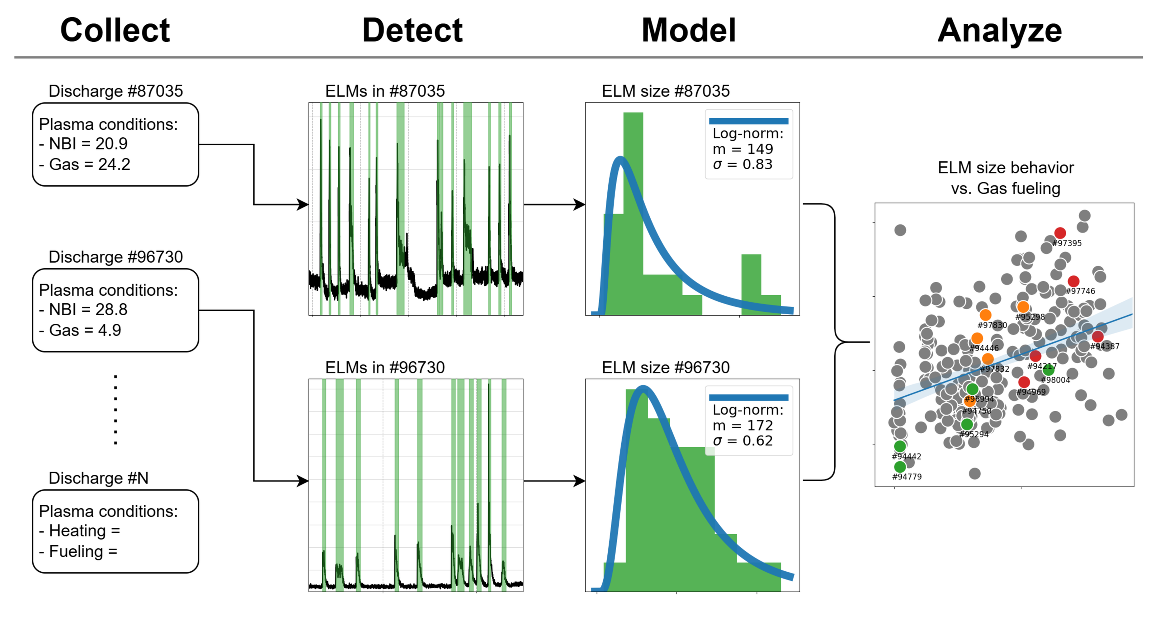
- Plasma edge MHD instability
- Quasi-periodic release of energy and particles
- Behavior (and signature) highly variable, depends on experiment conditions

Goals:

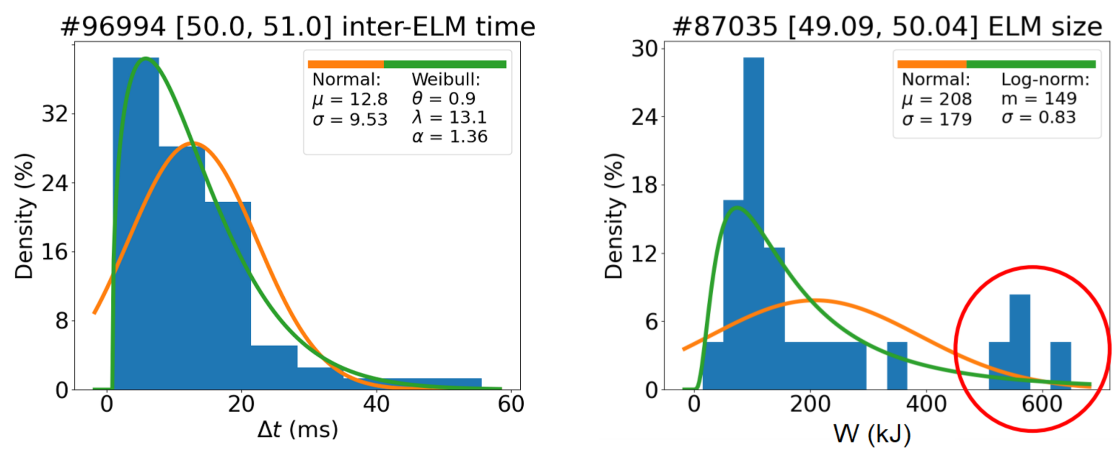
- Finding which, and how, machine and plasma conditions affect stochastic ELM properties
- Understanding the full variability of ELMs and the impact of statistical outliers



Strategy

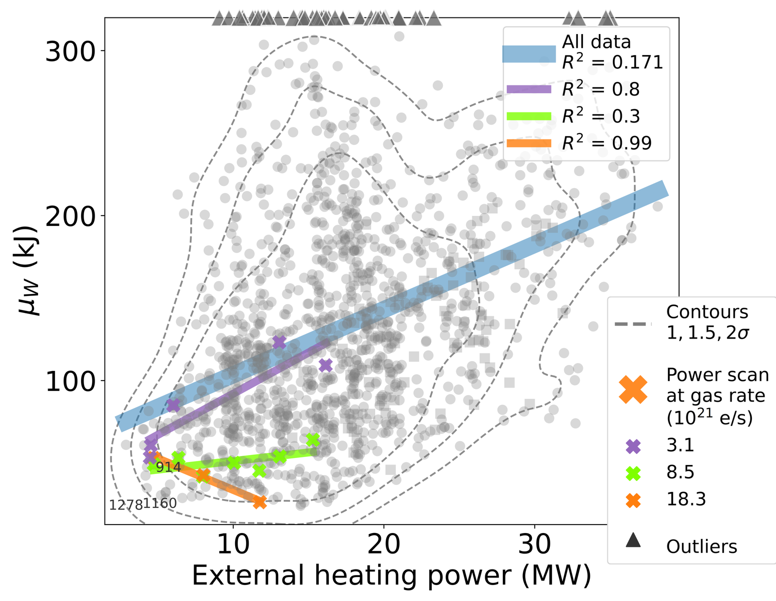


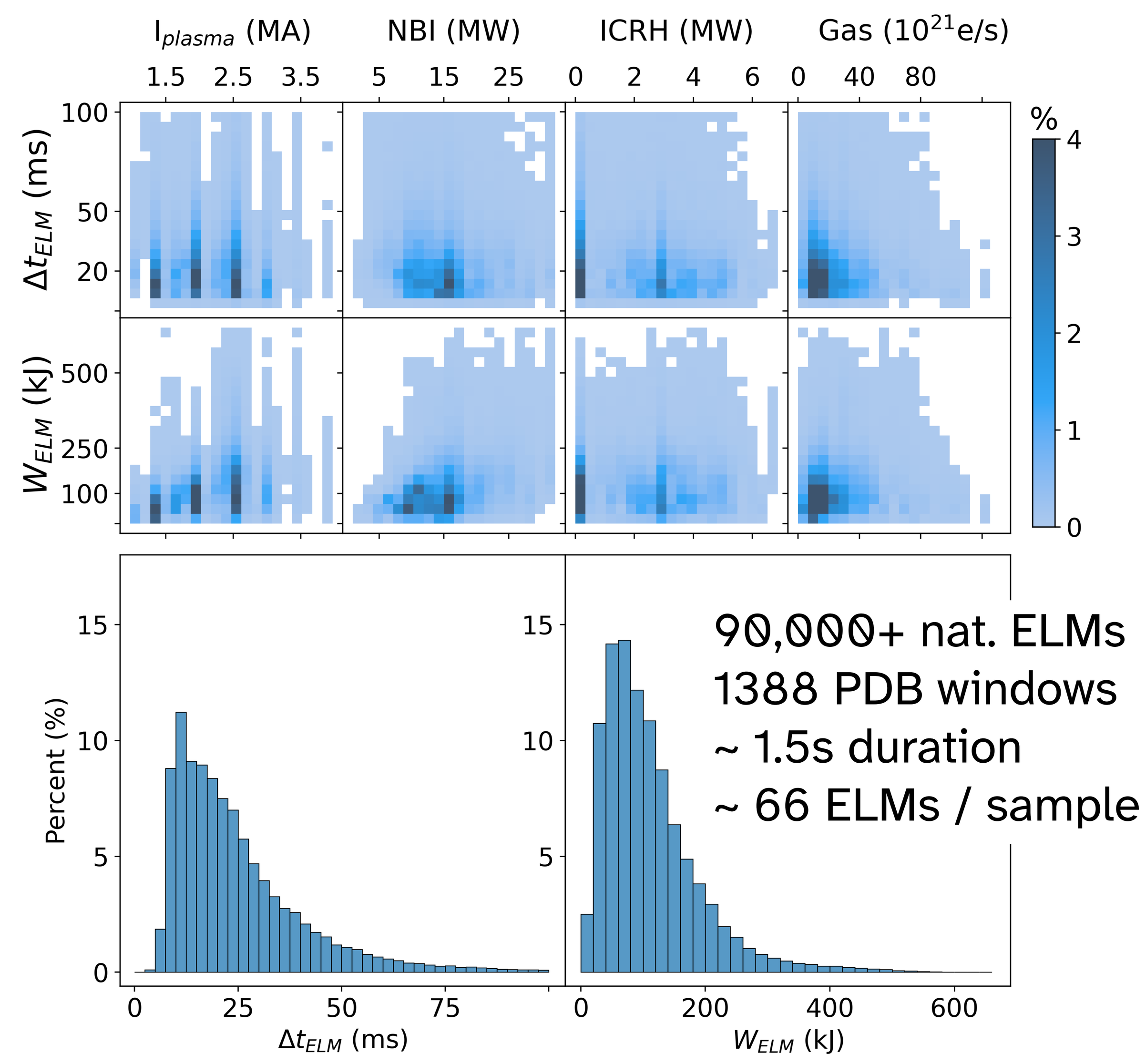
Collective ELM behavior

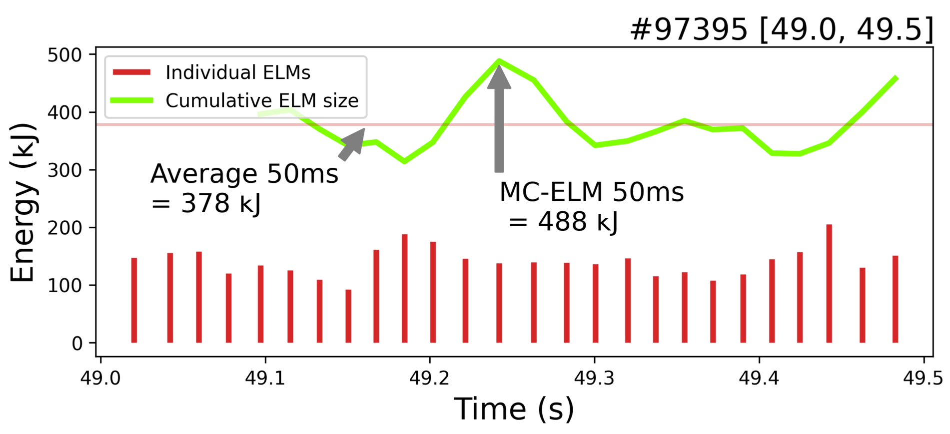


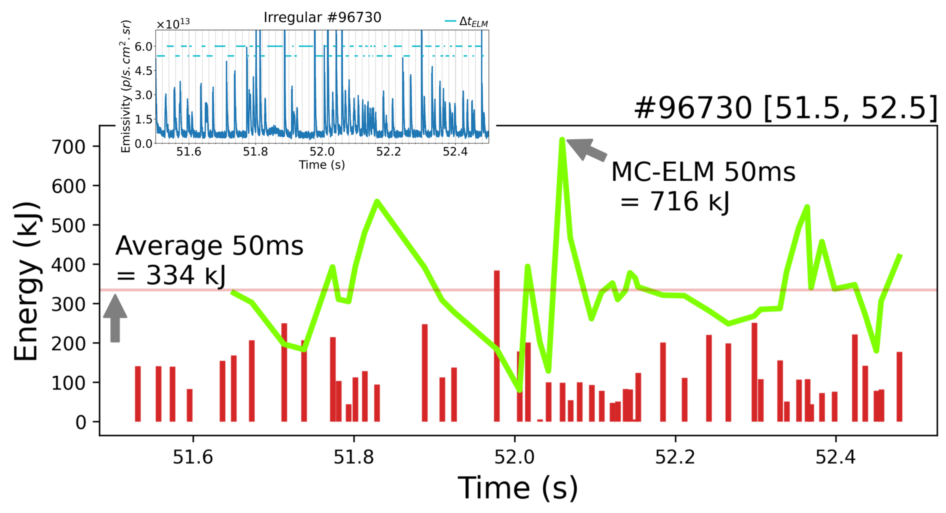
- Distributions of ELM timing and energy losses preserve information on ELM variability
- Distribution tails reveal outliers, as averages mask occasional large ELMs
- Spikes in cumulative ELM losses show the impact of a quick succession of ELM

Maps of distribution parameters show shot-averaged ELM trends









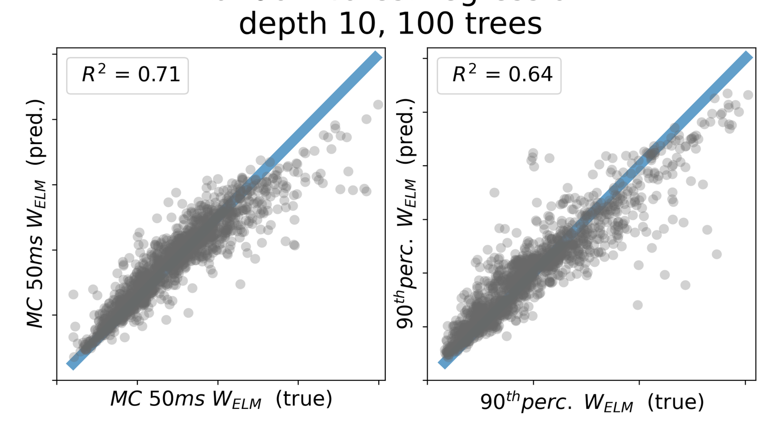
Risk analysis

Predict risk of occasional large ELMs from experiment conditions with multi-regression:

- Forward selection, 2/3 cross-validation

	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

Random forest regression
depth 10, 100 trees



Regression with natural ELMs

Measure impact of inputs with feature importance:

- Model-averaged change in R^2 and percentage error

Expanding ELM dataset with machine learning

ML training dataset: 214 shots, 270 windows, 13,825 manual marked ELMs — JET campaign 2019-2021

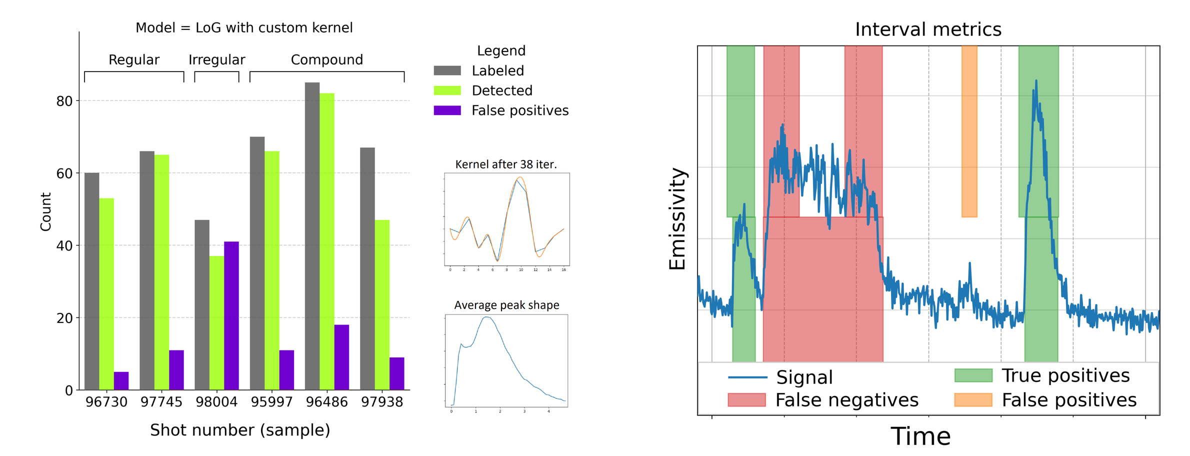
\+ Applied advanced detection: 1301 shots, 1665 windows, 120,000+ automatic ELMs — PDB-ILW* data

* L. Frassinetti et al 2021 Nucl. Fusion 61 016001

- Time-series event detection
- Scan for specific pattern: peaks, drops, sequences
- Specialized metrics for evaluation: interval overlap
- Robust performance, tested on other machines

Method Score (%)	ROT	MACD	RZS	LoG	LoG doG	LoG CK	Deconv	CNN	CNN min.	RNN 3L	RNN BN	RNN 1L
TP	34.4	87.2	90.0	86.6	80.8	83.0	78.1	80.0	73.6	91.9	85.2	70.7
FP	17.5	21.6	16.4	12.8	10.9	9.4	70.3	16.6	15.6	15.9	15.7	13.3
$F_{0.5}$	55.9	81.4	85.6	87.0	86.5	88.4	56.3	82.2	80.5	86.5	84.6	81.0

RNN: GRU 3L = 64,32,16,1; BN = 32,BN,1; 1L = 8,1



- Open source: `infusion-ugent/elm-detection.git`
  ELM annotations restricted to JET access

Conclusion

- Probabilistic view of ELM variability, and study of rare but large ELMs
- Robust event detection and outlier analysis tools at scale
- Applicable to condition monitoring and fault diagnosis