

Fusion Data Science at Ghent University

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with thanks to

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*inf*usion



EUROfusion



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Overview

1. Introduction: data science
2. Regression analysis for scaling laws
3. Probabilistic characterization of stochastic plasma phenomena
4. Sensor fusion
5. Anomaly detection and predictive maintenance
6. FUSION-EP joint master program

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What is data science?

- Activities:
 - Data processing: cleaning, filtering, visualization, ...
 - Optimization
 - Estimation, testing and prediction
 - Pattern recognition: clustering, regression analysis, dimensionality reduction
 - Methods:
 - Probability theory
 - Statistics
 - Machine learning
 - Artificial intelligence
 - Culture
 - Be
 - Tra
 - Co



Foundations matter

- Performance in complex environments
- Robustness of methods and results
- Simplicity:
 - Explainable models
 - Minimal parameter tuning
 - Adoption in data-intensive communities



vs.

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Global H-mode confinement scaling in tokamaks

- Updated ITPA global H-mode energy confinement database (DB5.2.3):
 - New data closer to ITER conditions and expanded ranges
 - New data from devices with fully metallic walls
- Issues with IPB98(y,2):

Density scaling Power degradation

$$\tau_{E,\text{th}} = 0.0562 I_p^{0.93} B_t^{0.15} \bar{n}_e^{0.41} P_{l,\text{th}}^{-0.69} R_{\text{geo}}^{1.97} (1 + \delta)^{\alpha_\delta} \kappa_a^{0.78} \epsilon^{0.58} M_{\text{eff}}^{0.19}$$

$\Omega_i \tau_{E,\text{th}} = 4.24 \times 10^{-7} \rho_*^{-2.69} \beta_t^{-0.90} \nu_*^{-0.0081} q_{\text{cyl}}^{-2.99} (1 + \delta)^{\alpha_\delta} \kappa_a^{3.29} \epsilon^{0.71} M_{\text{eff}}^{0.96}$

β degradation No collisionality scaling No δ scaling

Robust Bayesian regression

- Motivation:

- Measurement uncertainty
- Model uncertainty
- Heterogeneity: multi-machine database
- Errors in all variables
- Multicollinearity: e.g. $I_p \propto B_t$

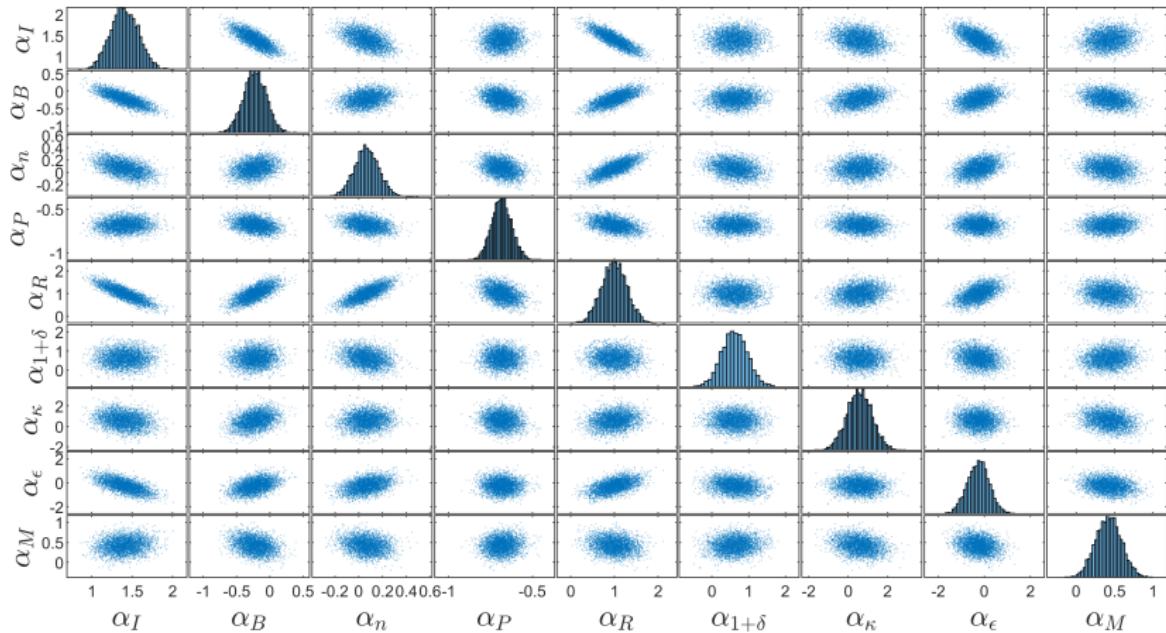
- Robust likelihood:

$$p(\{y_{i_k,k}\}, \{x_{i_k,j,k}\} | \{\alpha_0, \alpha_j\}, \{\gamma_k\}) \\ = \prod_k \prod_{i_k} \frac{1}{\sqrt{2\pi\gamma_k^2\sigma_{\text{mod},i_k,k}^2}} \exp \left[-\frac{1}{2} \frac{(y_{i_k,k} - \eta_{i_k,k})^2}{\gamma_k^2\sigma_{\text{mod},i_k,k}^2} \right]$$

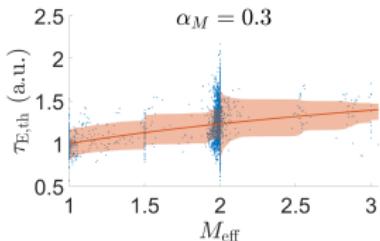
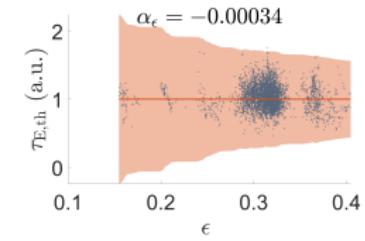
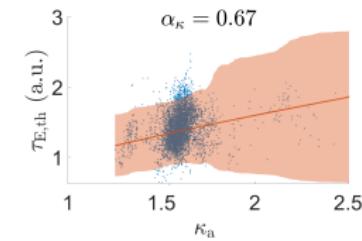
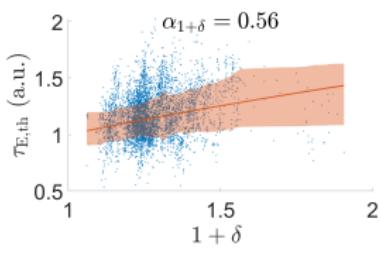
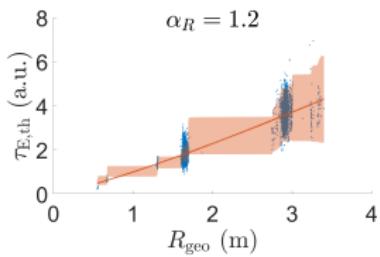
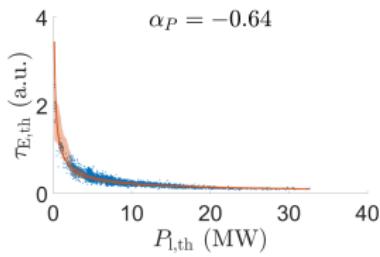
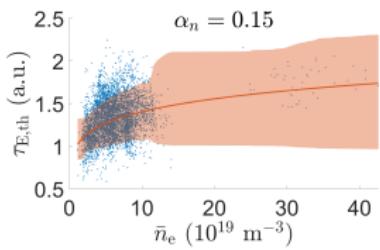
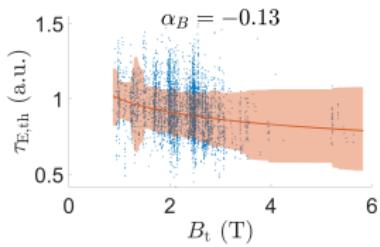
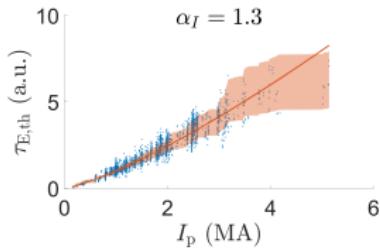
1 for each device

Practical error bars

- Model uncertainty: sensitivity analysis
- $\sim 10 \times$ larger error bars



Trends



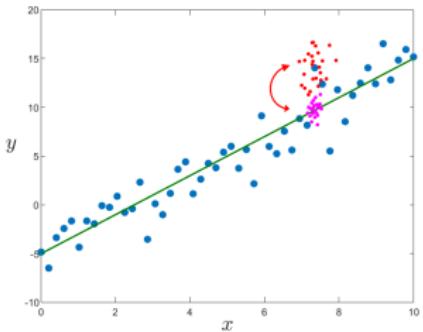
Geodesic least squares

- Geodesic least squares: *GLS*

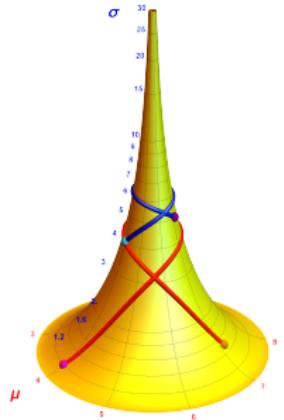
$$\prod_k \prod_{i_k} \frac{1}{\sqrt{2\pi\sigma_{\text{tot},i_k,k}^2}} \exp \left[-\frac{1}{2} \frac{(y_{i_k,k} - \eta_{i_k,k})^2}{\sigma_{\text{mod},i_k,k}^2} \right]$$

↑
Rao geodesic distance (GD)
↓

$$\frac{1}{\sqrt{2\pi} \sigma_{\text{obs}}} \exp \left[-\frac{1}{2} \frac{(y - y_i)^2}{\sigma_{\text{obs}}^2} \right]$$



G. Verdoollaeghe *et al.*, Nucl. Fusion, 55, 113019, 2015
G. Verdoollaeghe *et al.*, Entropy, 17, 4602–4626, 2015



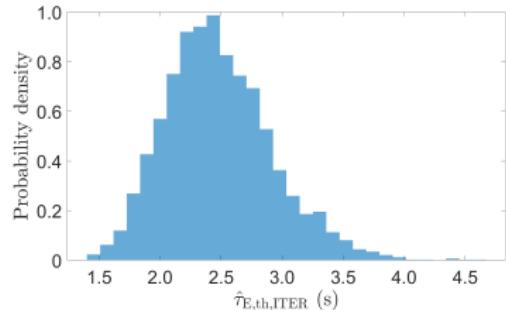
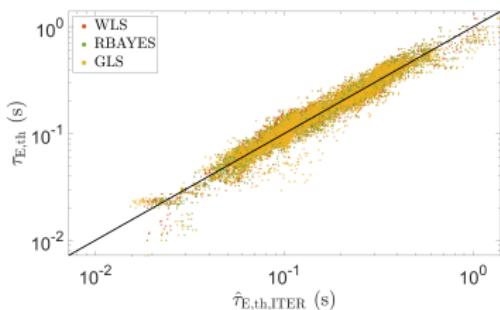
Multi-machine engineering scaling

STD5-IL ELMy H-mode (error bars from Bayesian analysis)

Engineering scaling

$$\tau_{E,\text{th}} = (0.067 \pm 0.060) I_p^{1.29 \pm 0.17} B_t^{-0.13 \pm 0.17} \bar{n}_e^{0.15 \pm 0.10} P_{l,\text{th}}^{-0.644 \pm 0.060} R_{\text{geo}}^{1.19 \pm 0.29} \\ \times (1 + \delta)^{0.56 \pm 0.35} \kappa_a^{0.67 \pm 0.65} M_{\text{eff}}^{0.30 \pm 0.17} \rightarrow \mathbf{H}_{20}$$

$$\hat{\tau}_{E,\text{th},\text{ITER}} = 2.79 \pm 0.44 \text{ s}$$



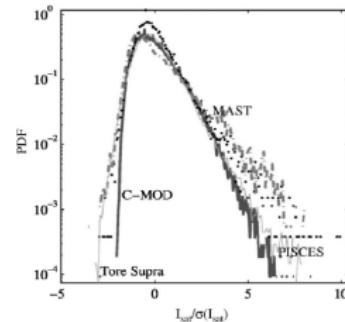
G. Verdoollaeghe *et al.*, Nucl. Fusion, **61**, 076006, 2021

Overview

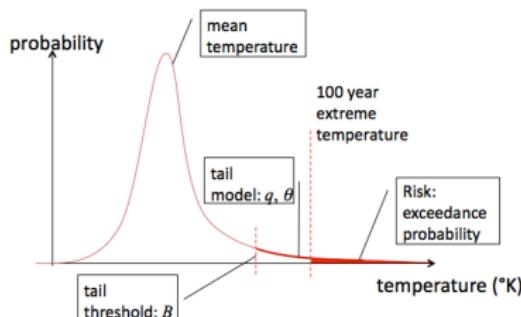
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Why a probabilistic approach?

- Quantify and compare uncertainty, variability, fluctuations
- Physical information from distributions
- Risk analysis, extreme events

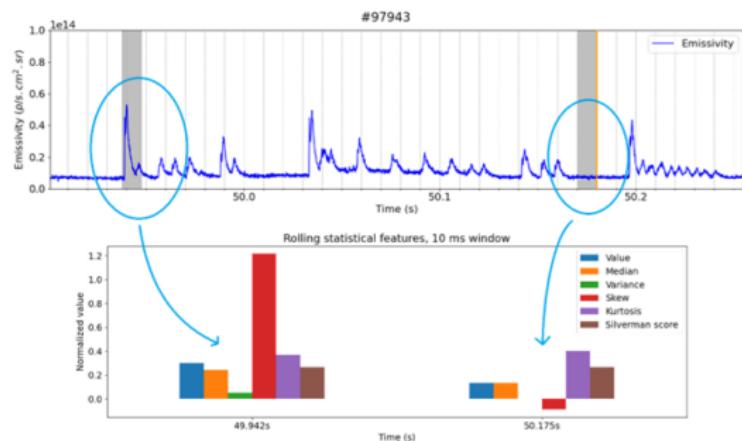


I. Sandberg *et al.*, Phys. Rev. Lett. **103**, 165001, 2009



Edge-localized modes

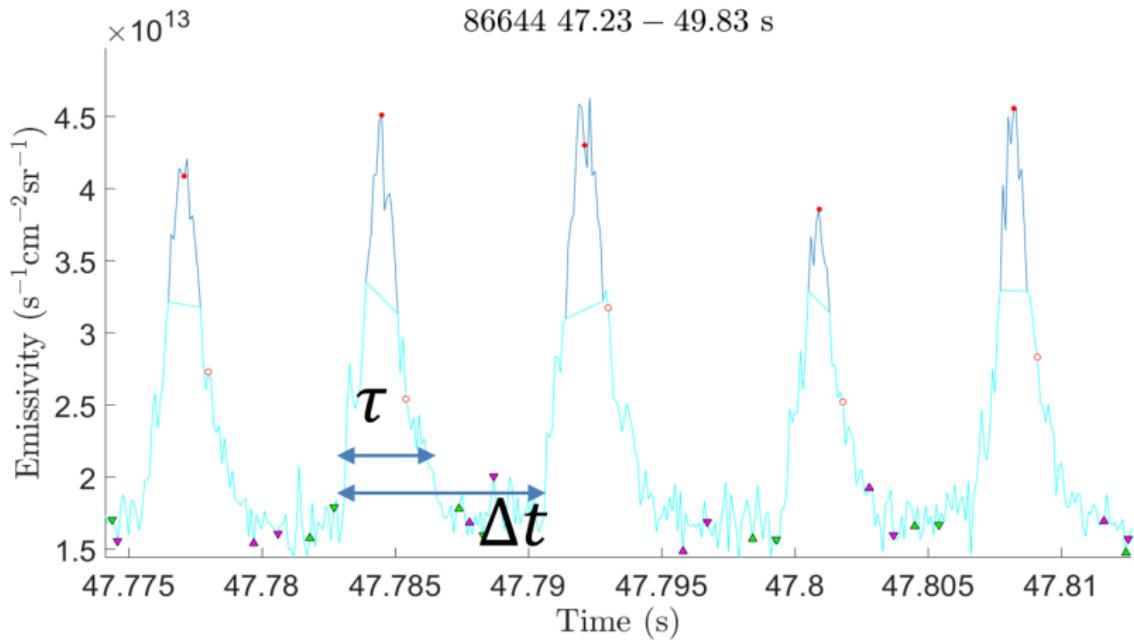
- Distributions of ELM characteristics
- Dependence of distributions on plasma conditions



Results		
TP (%)	FP (%)	
Optimal threshold	34.41	17.53
Laplacian of Gaussian	86.61	12.79
Deconvolution	78.14	70.30
Rolling z-score	89.99	16.39
Convolution NN	80.01	16.63
Recurrent NN	91.95	15.90

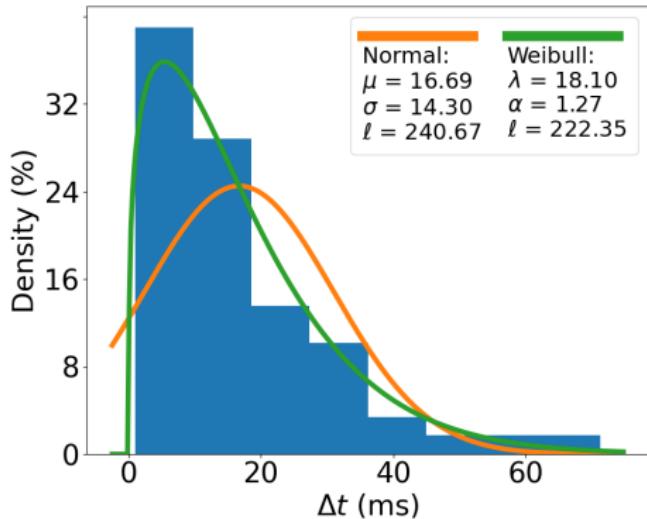
J. Alhage et al., in preparation, 2024

ELM timing

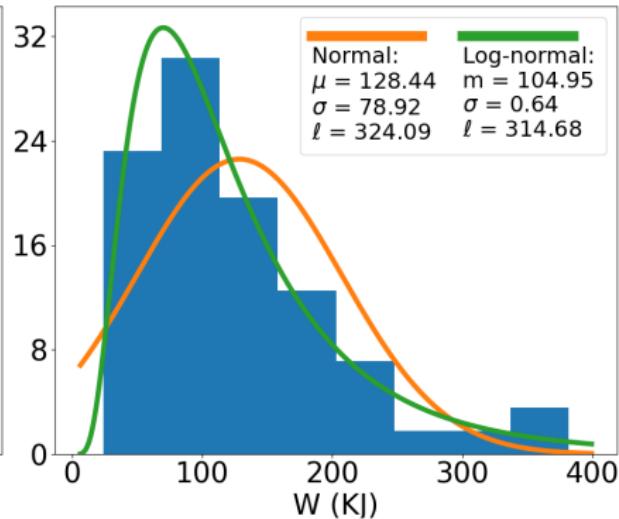


Inter-ELM time Δt

#97747 [49.0, 50.0] inter-ELM time



#96988 [50.5, 51.5] ELM size



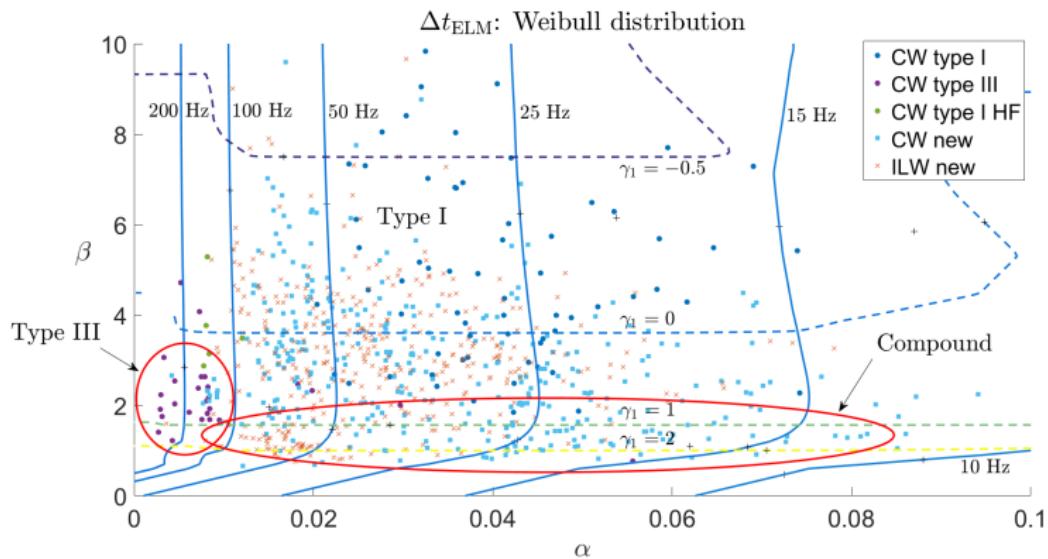
J. Alhage et al., in preparation, 2024

Shifted Weibull distribution:

$$p(t) = \frac{\beta}{\alpha} \left(\frac{t - t_m}{\alpha} \right)^{\beta-1} \exp \left[- \left(\frac{t - t_m}{\alpha} \right)^\beta \right], \quad t > t_m$$

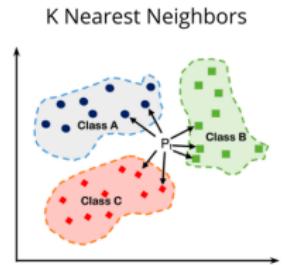
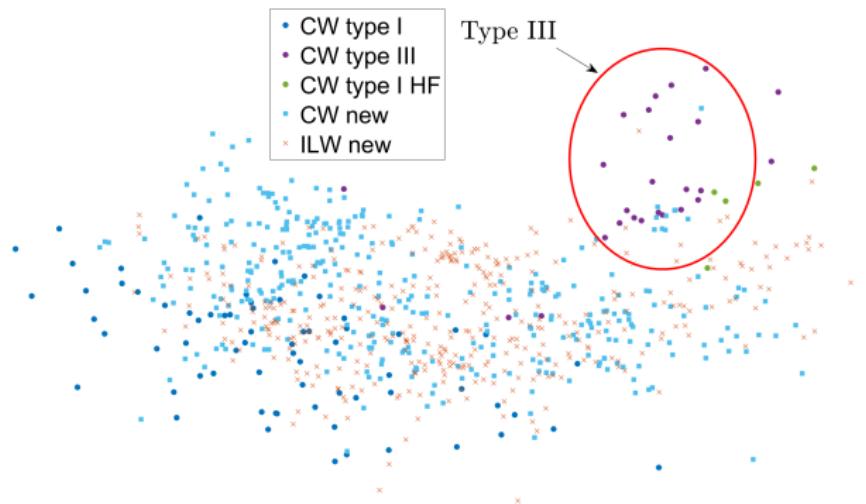
Distribution map Δt_{ELM}

- 453 plasmas from JET carbon wall
- 379 plasmas from JET ITER-like wall
- 100 reference plasmas (A. Shabbir *et al.*, Rev. Sci. Instrum. **87**, 11D404, 2016)



Projected map Δt_{ELM}

Approximately isometric projection with multidimensional scaling:

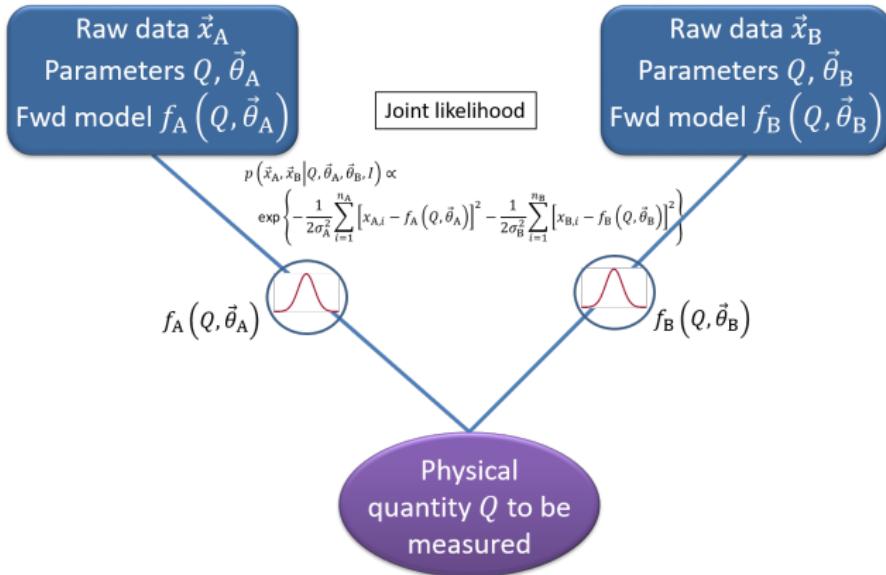


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Sensor fusion

- Sensor fusion / Data fusion / integrated data analysis (IDA)

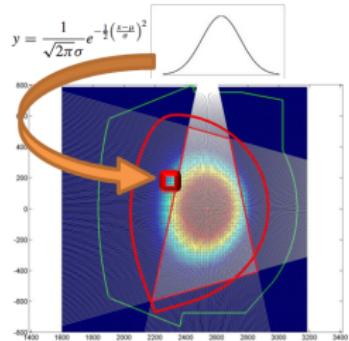


$$\underbrace{p(Q, \theta_A, \theta_B | x_A, x_B, I)}_{\text{Posterior}} \propto \underbrace{p(x_A, x_B | Q, \theta_A, \theta_B, I)}_{\text{likelihood}} \underbrace{p(Q, \theta_A, \theta_B | I)}_{\text{Prior}}$$

Gaussian process tomography

- Gaussian process prior:

$$p(\boldsymbol{\epsilon} | \boldsymbol{\mu}_{\epsilon 0}, \Sigma_{\epsilon 0}, I) = (2\pi)^{-n/2} |\Sigma_{\epsilon 0}|^{-1/2} \\ \times \exp \left[-\frac{1}{2} (\boldsymbol{\epsilon} - \boldsymbol{\mu}_{\epsilon 0})^t \Sigma_{\epsilon 0}^{-1} (\boldsymbol{\epsilon} - \boldsymbol{\mu}_{\epsilon 0}) \right],$$

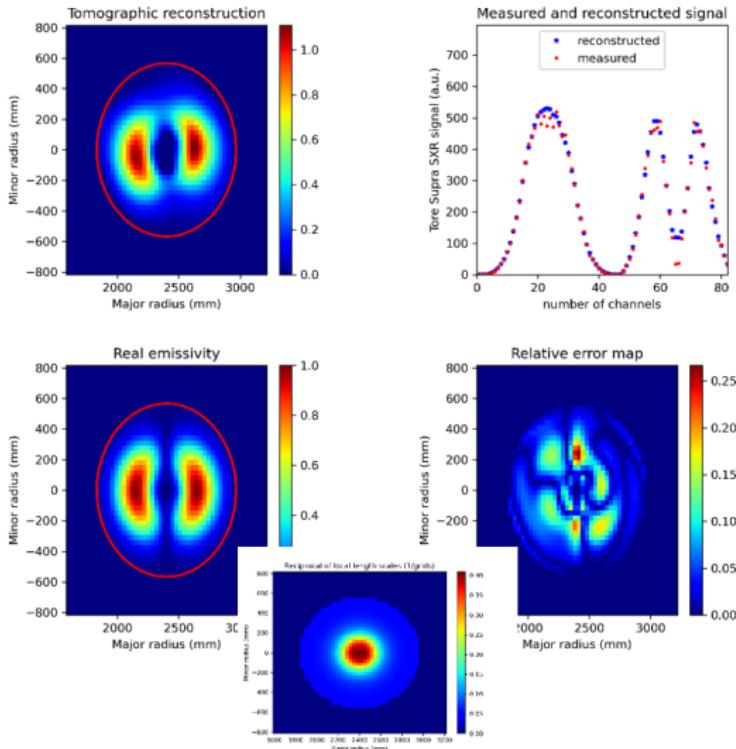


$$\Sigma_{\epsilon 0} = \begin{bmatrix} k(\mathbf{r}_1, \mathbf{r}_1) & \dots & k(\mathbf{r}_1, \mathbf{r}_n) \\ \vdots & \ddots & \vdots \\ k(\mathbf{r}_n, \mathbf{r}_1) & \dots & k(\mathbf{r}_n, \mathbf{r}_n) \end{bmatrix},$$

$$k(\mathbf{r}_i, \mathbf{r}_j) = \sigma_f^2 \exp \left[-\frac{1}{2} \left(\frac{\|\mathbf{r}_i - \mathbf{r}_j\|}{\sigma_l} \right)^2 \right]$$

J. Svensson, EFDA-JET PR (11) 24, 2011
D. Li et al., Rev. Sci. Instrum. 84, 083506, 2013

Soft X-ray emissivity reconstruction



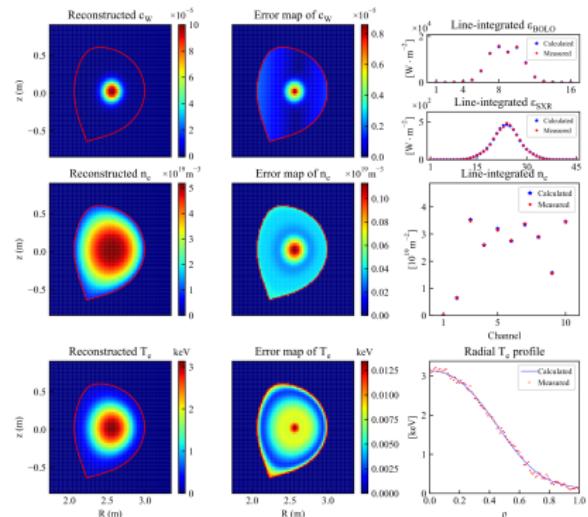
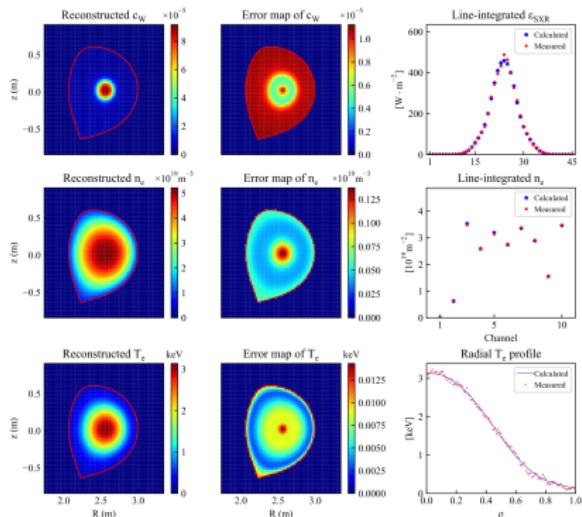
T. Wang et al., Rev. Sci. Instrum. **89**, 063505, 2018

H. Wu et al., EPS 2023

H. Wu et al., J. Fus. Energ. **43**, 9, 2024₂₃

Integrated tungsten concentration estimation

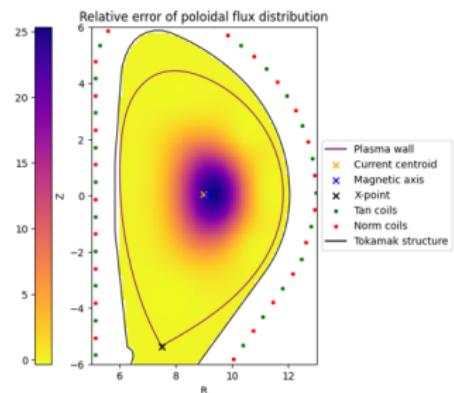
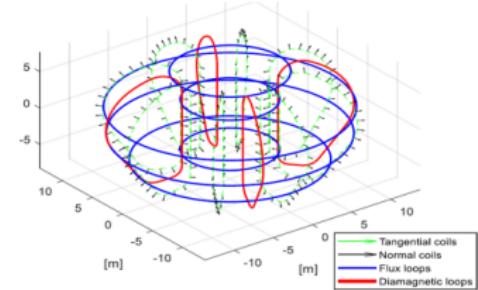
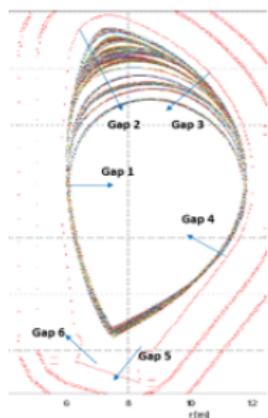
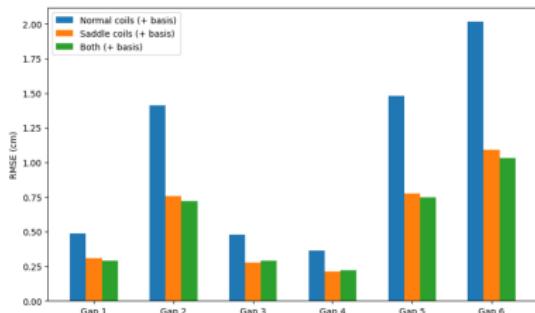
- SXR vs. SXR + bolometry:



H. Wu et al., J. Fusion Energ. 43, 9, 2024

- Real-time performance via neural network emulation

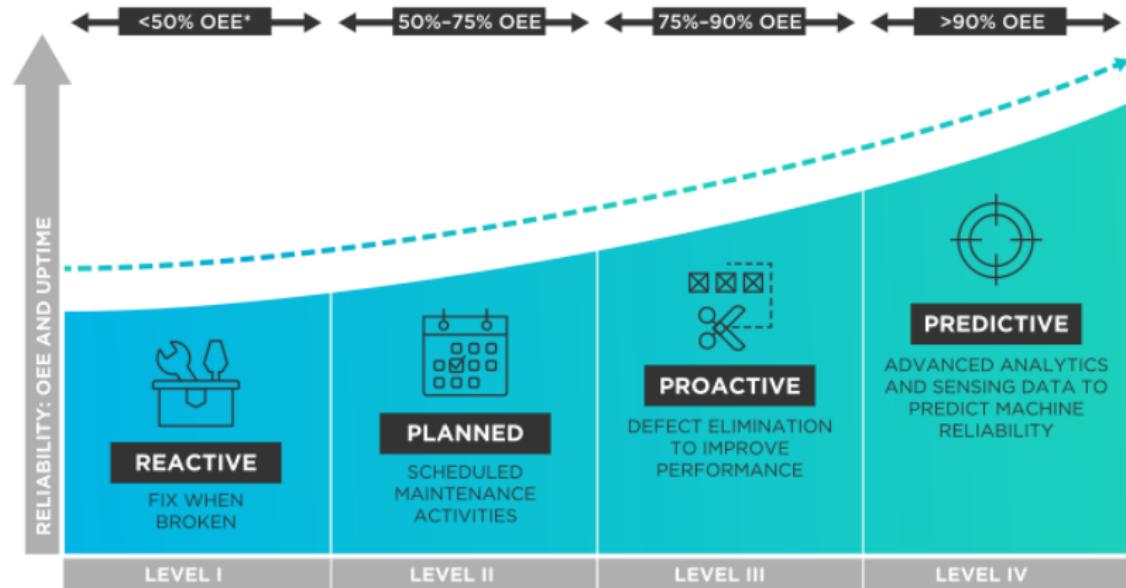
Plasma position in DEMO



Overview

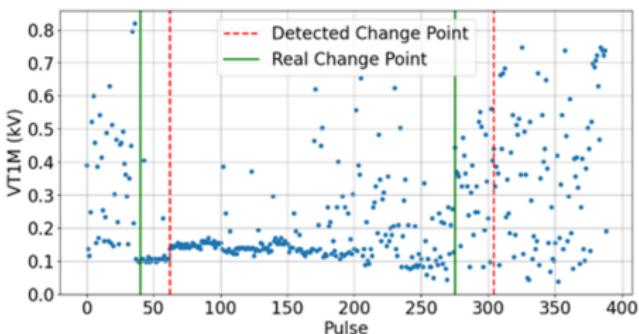
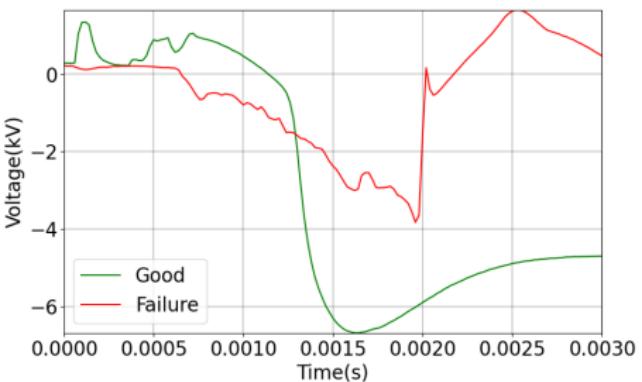
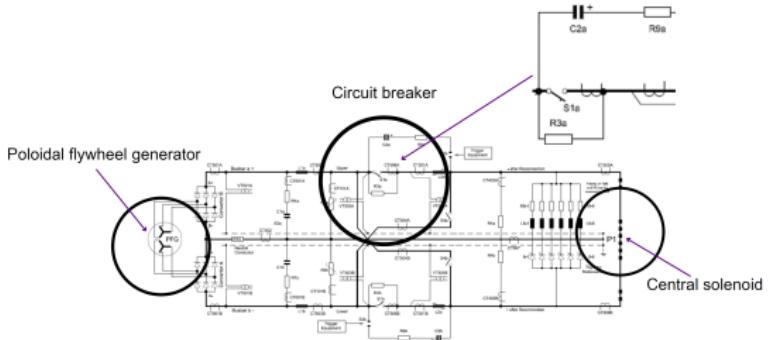
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Predictive maintenance



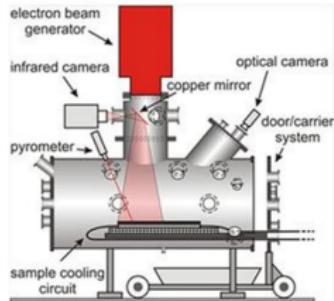
*OVERALL EQUIPMENT EFFECTIVENESS

JET Ohmic heating circuit breakers

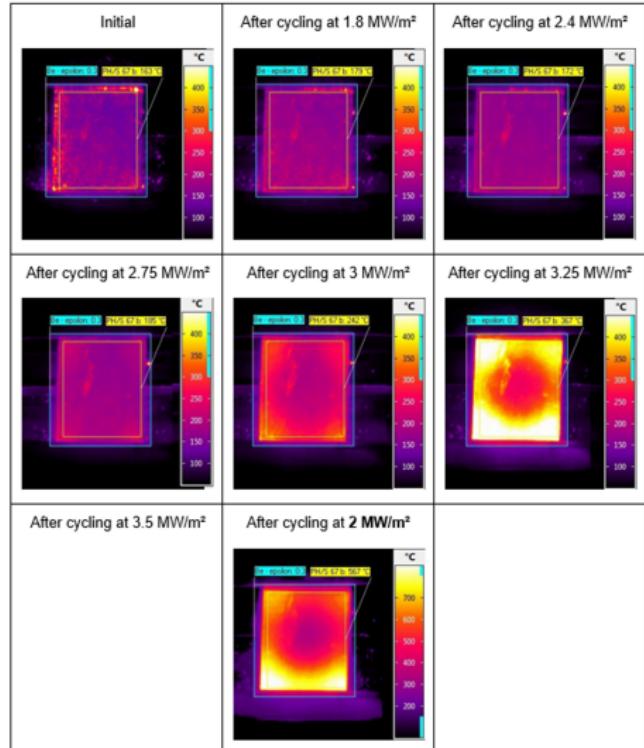


Overheating of beryllium tiles

Electron beam facility JUDITH 2



- max. power 200 kW
- acceleration voltage 30 – 60 kV
- EB diameter ≤ 5 mm FWHM
- loaded area 40×40 cm 2



Courtesy of T. Loewenhoff, FZ-Juelich

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FUSION-EP

- European Master of Science in Nuclear Fusion and Engineering Physics
- Two-year joint European master
- 8 Full Partner institutions
- 25 Associate Partners worldwide:
CEA-IRFM, CIEMAT, IPP, ITER, SWIP, ...
- Joint experimentation, Summer Event



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Universität Stuttgart



[Statement on privacy](#)



<https://fusion-ep.eu/>

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43rd International Workshop on Bayesian Inference and Maximum Entropy Methods in Science and Engineering

July 1-5, 2024
Ghent, Belgium

<https://maxent2024.ugent.be>

21st International Congress on Plasma Physics

September 8-13, 2024
Ghent, Belgium

<https://icpp2024.ugent.be>