

Bayesian inference for data integration and diagnostic optimization in fusion devices

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8th International Conference on Frontiers in Diagnostic Technologies (ICFDT8)
Frascati, 19–21 October 2026



EUROfusion



This work has been carried out within the framework of the EUROfusion Consortium, funded by the European Union via the Horizon Research and Training Programme (Grant Agreement No 101019720 — 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.

1. Data integration and sensor fusion
2. Bayesian data integration at WEST
 - Equilibrium and kinetic profiles
 - Soft X-ray emissivity and tungsten concentration
3. Accelerating inference
4. Bayesian experimental design
5. Conclusions and outlook

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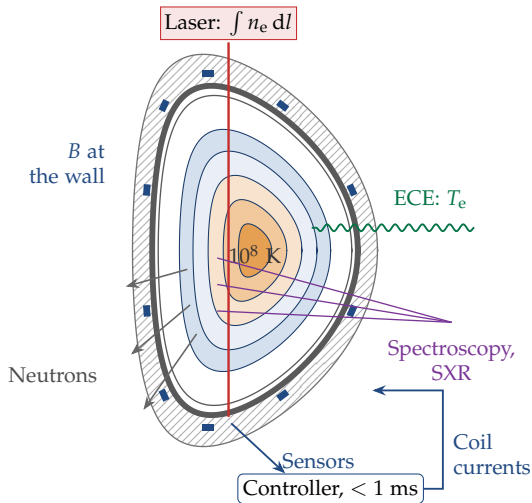
Fusion plasmas: a hard measurement problem

Indirect

Line integrals, external fields, spectra: the quantity of interest is never measured directly $\rightarrow$ inverse problems

Reactor

Thick blanket and shield (hatched), neutron damage, few ports, cost: fewer diagnostics $\rightarrow$ more must be inferred



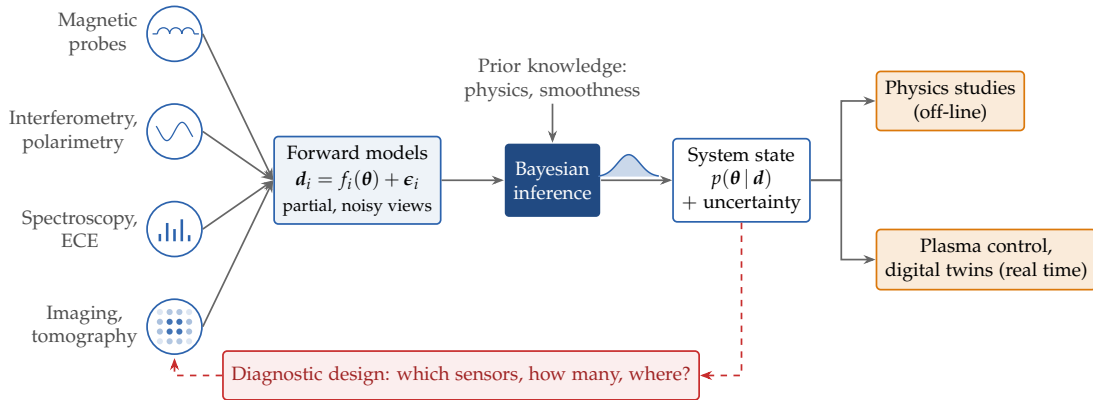
Heterogeneous

Each diagnostic sees a different, partial aspect: B , n_e , T_e , radiation, impurities

Fast

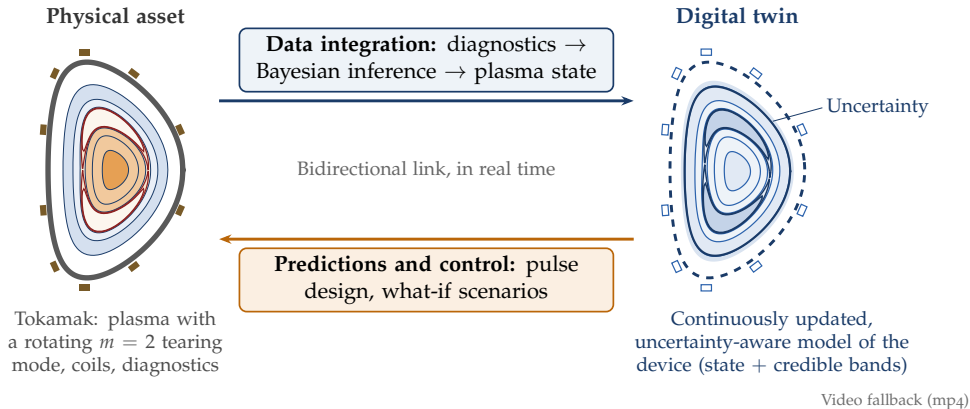
Position and shape control at kHz rates: the plasma state is needed *now*, with its uncertainty

Data integration



- *Data integration* (off-line) $\leftrightarrow$ *sensor fusion* (real time)
- Application areas: aerospace, autonomous driving, medical imaging, radio astronomy, ...

Digital twins



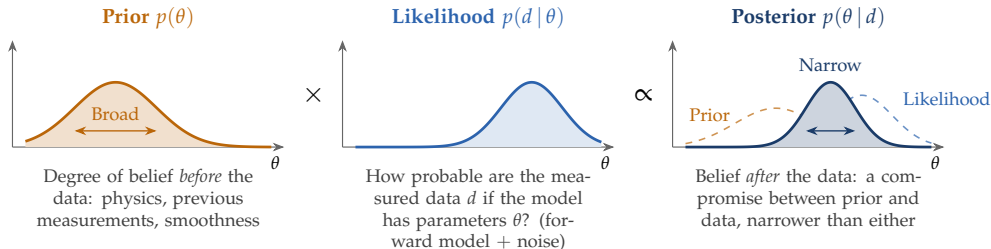
- EUROfusion DTE project: digital twin for pulse design and plasma-facing components



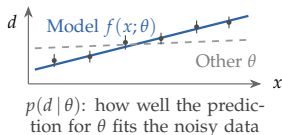
Bayesian inference: the framework

Bayes' rule: $p(\theta | d) \propto p(d | \theta) p(\theta)$ **posterior** $\propto$ **likelihood** $\times$ **prior**

Data shrink the uncertainty: broad prior $\rightarrow$ narrower posterior, pulled towards the data



Likelihood: data vs. model



Bayesian computation: getting the posterior out

Linear model, Gaussian prior:
analytic posterior, one matrix solve

Otherwise, sample it:
Markov chain Monte Carlo; exact, but slow

Or approximate it: variational inference, fast but approximate

Or learn it: neural-network surrogate, milliseconds

Gaussian process priors for spatial correlation

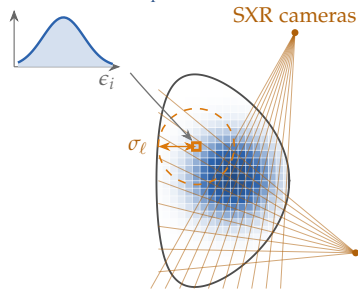
- Local quantity ϵ (emissivity, current density, $n_e, \dots$) on a grid of n pixels
- Gaussian process (GP) prior: a continuous, multivariate normal:

$$p(\epsilon) = \mathcal{N}(\mu_{\epsilon 0}, \Sigma_{\epsilon 0}),$$

$$(\Sigma_{\epsilon 0})_{ij} = k(\mathbf{r}_i, \mathbf{r}_j) = \sigma_f^2 \exp \left[-\frac{\|\mathbf{r}_i - \mathbf{r}_j\|^2}{2\sigma_\ell^2} \right]$$

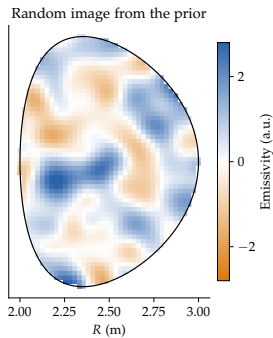
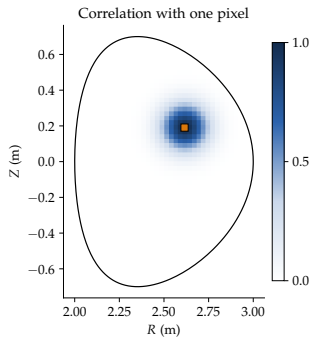
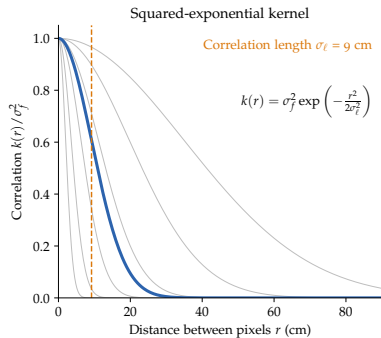
- Two hyperparameters: amplitude σ_f and correlation length σ_ℓ (smoothness)
- Linear forward model + Gaussian likelihood
→ Gaussian, *analytic* posterior:
fast tomography with uncertainties

Prior on one pixel $p(\epsilon_i)$:
mean μ_i , variance σ_f^2



Pixels i with emissivity ϵ_i ; neighbours within $\sim \sigma_\ell$ correlated through $k(\mathbf{r}_i, \mathbf{r}_j)$

Gaussian processes impose smoothness



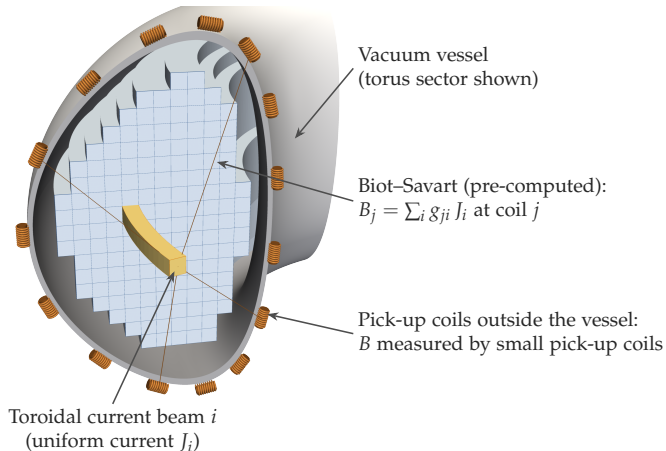
Video fallback (mp4)

- Correlation length σ_ℓ : how far a pixel 'knows' about its neighbours
- σ_ℓ, σ_f : hyperparameters to be inferred

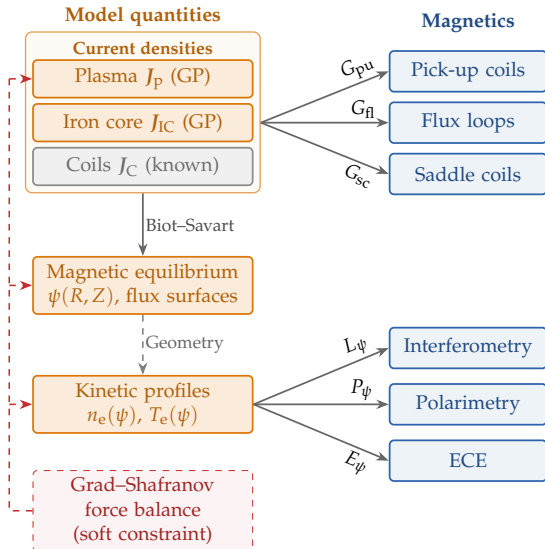
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The current-beam model

- Plasma current and poloidal field coils: grid of toroidal beams
- Each beam carries uniform current J_i
- Field and flux *linear* in beam currents (pre-computed Biot–Savart response)
- Iron core segments: free currents
- Coils: known currents



Model definition



Linear forward models

$$d_{pu} = G_{pu}^P J_p + G_{pu}^{IC} J_{IC} + G_{pu}^C J_C + \epsilon$$

$$d_{fl} = G_{fl}^P J_p + \dots + \epsilon$$

$$d_{sc} = G_{sc}^P J_p + \dots + \epsilon$$

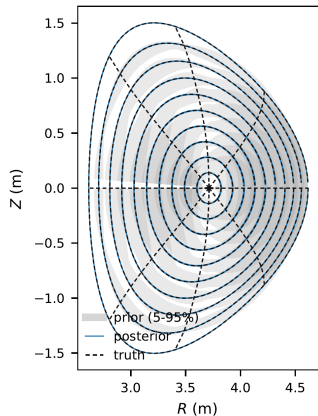
Orange: inferred; **grey:** known input
 ϵ : measurement noise

$$d_{int} = L_\psi n_e + \epsilon \quad \text{Line integrals}$$

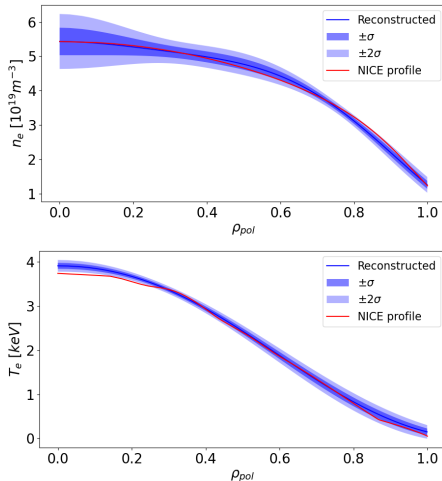
$$d_{pol} = P_\psi n_e + \epsilon \quad \int n_e B_{||} dl \text{ (Faraday)}$$

$$d_{ECE} = E_\psi T_e + \epsilon \quad \text{Resonance} \leftrightarrow B(R)$$

Equilibrium and kinetic profiles



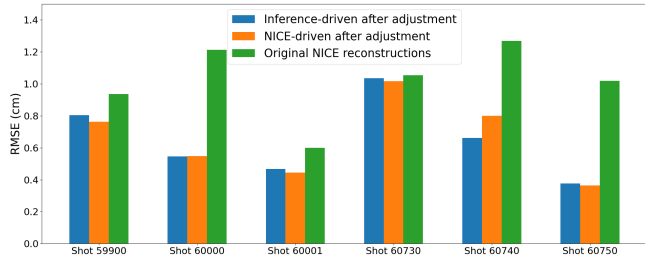
Synthetic test: flux surfaces,
prior band vs. posterior and truth



WEST pulse: n_e and T_e profiles with $\pm\sigma$, $\pm 2\sigma$ bands

Comparison with NICE and VacTH

- *NICE*: WEST's Grad-Shafranov equilibrium code
- *VacTH*: independent boundary reconstruction from toroidal harmonics
- Bayesian X-point closer to VacTH than NICE (RMSE ≈ 1 cm)



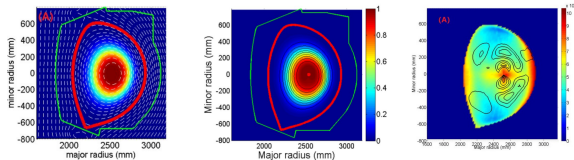
RMSE of X-point position vs. VacTH

J. De Rycke et al., J. Instrum. **21**, Co4064, 2026

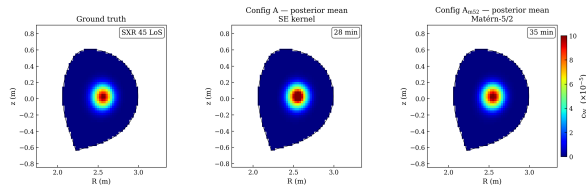
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Impurity transport: soft X-ray tomography and tungsten

- Tungsten (W) from wall radiates strongly: key quantity to monitor
- SXR tomography with GP priors: 2D emissivity + uncertainty
- + interferometry + ECE $\rightarrow$ joint posterior over (c_W, n_e, T_e) by MCMC
- Validated on synthetic and real data (WEST, HL-2A)



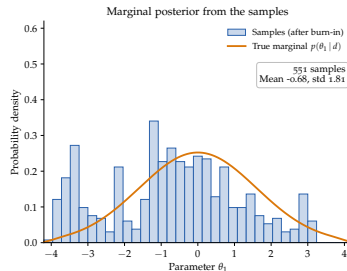
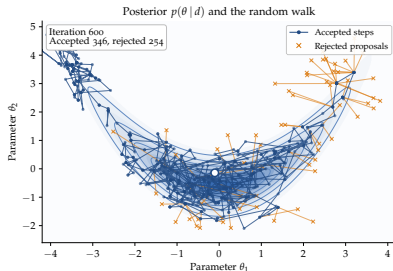
SXR emissivity: truth, posterior mean, posterior variance



Tungsten: truth and posterior mean (two GP kernels)

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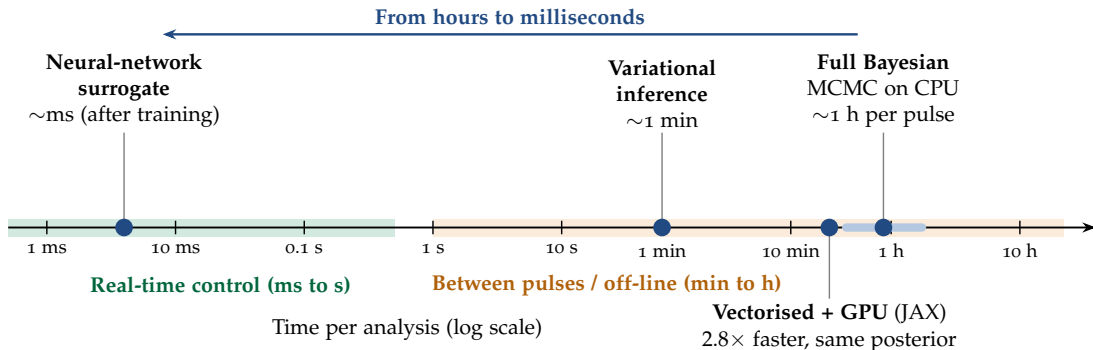
Markov chain Monte Carlo: exploring the posterior



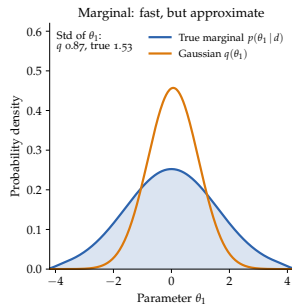
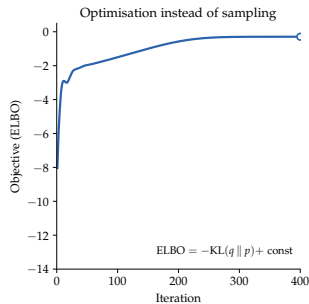
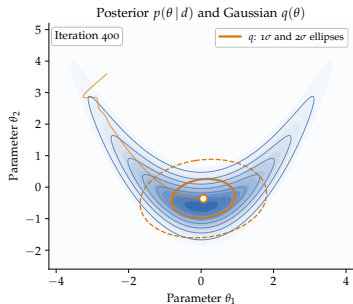
Video fallback (mp4)

- Nonlinear forward models $\rightarrow$ non-standard posterior
- Sample posterior with random walk
- 10^4 – 10^6 evaluations for a converged chain: *hours* per pulse for tomography

Routes toward real-time inference



Variational inference: optimisation instead of sampling



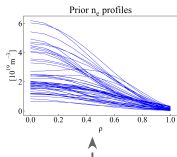
Video fallback (mp4)

- *Optimise* tractable $q(\theta)$ (e.g. Gaussian): minimize $\text{KL}(q \parallel p)$
- Gradient steps vs. random walk: minutes vs. hours

Learning the whole inference chain

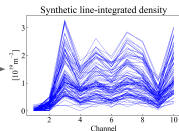
Training (off-line, once): learn the map from data to posterior profile

Samples from the prior
 $n_e(\rho)$

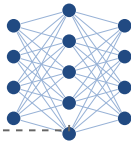


Forward model
+ noise

Synthetic measurements
(line-integrated density)



Neural network
data $\rightarrow$ profile



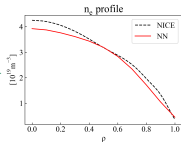
Targets: the sampled profiles (regression loss)

Deployment (real time):

Measured data
(WEST interferometer)

Trained network

$\sim$ ms



Inferred n_e profile vs. reference (NICE)

- Trained entirely on synthetic data from prior and forward model
- Replaces whole inference chain

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Which sensors do we really need?

- Design η : e.g. number and position of sensors (before measurement)
- Utility = *information gain*:

$$U_{\text{KL}}(\mathbf{x}, \eta) = \int p(\boldsymbol{\theta} | \mathbf{x}, \eta, I) \log \frac{p(\boldsymbol{\theta} | \mathbf{x}, \eta, I)}{p(\boldsymbol{\theta} | I)} d\boldsymbol{\theta}$$

- *Expected utility* = *mutual information* (MI) $\mathbf{x}$ vs. η :

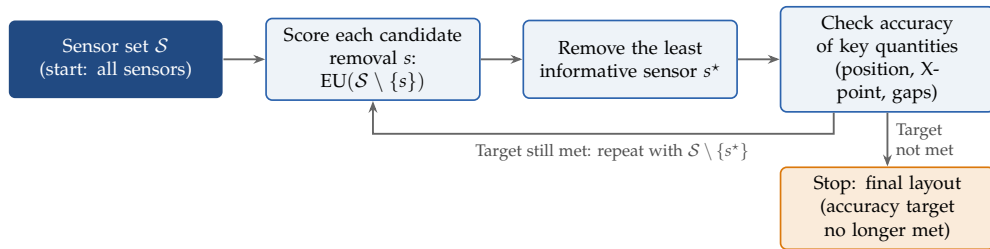
$$\text{EU}(\eta) = \int p(\mathbf{x} | \eta, I) U(\mathbf{x}, \eta) d\mathbf{x}$$

- Gaussian linear model $\rightarrow$ Bayesian D-optimality:

$$\text{EU}(\eta) = -\frac{1}{2} \log \left(\frac{|\boldsymbol{\Sigma}_{\text{post}}(\eta)|}{|\boldsymbol{\Sigma}_{\text{prior}}|} \right)$$

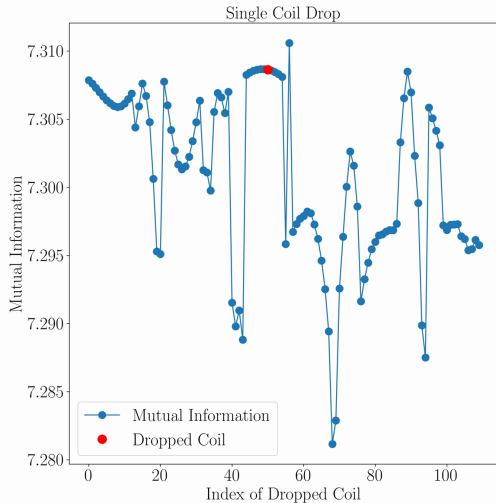
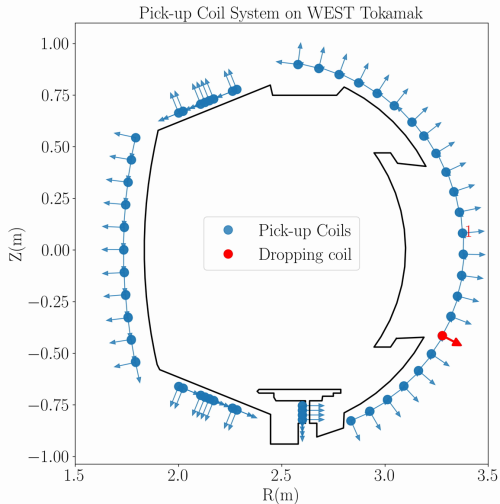
- Reconstruction quality evaluated with predictive density (NLPD) and RMSE

Greedy sensor removal



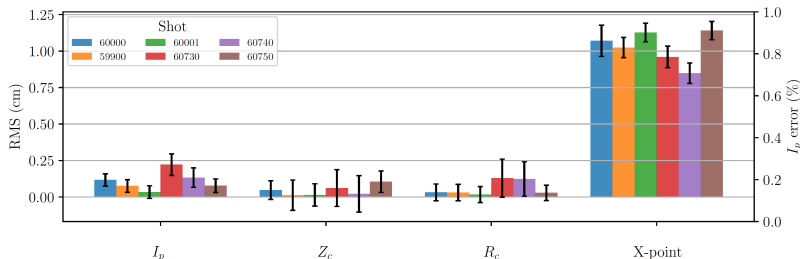
- One sensor at a time: the one whose removal costs the least information
- Control-relevant quantities (plasma current, position, X-point, gaps) monitored at each step
- Repeated over many pulses $\rightarrow$ layout robust to plasma scenario

Sequential coil removal



Click image to play (55 s)

WEST pick-up coil optimization



Error on inferred quantities after removal

- Greedy removal (similar results with genetic algorithm)
- Marginalized over 6 WEST pulses
- 1/3 of pick-up coils can go:
 - I_p within 0.5%
 - Centroid and X-point within 0.5 cm

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Take-home messages

- Bayesian data integration: one probabilistic model for all diagnostics, with uncertainty on every inferred quantity
- Gaussian processes: flexible priors, analytic posteriors for linear problems
- Validated at WEST: equilibrium, kinetic profiles, impurity concentration
- Toward real time: vectorisation and GPUs, variational inference, neural-network surrogates
- Bayesian experimental design: fewer sensors, same information
- Applications in many other scientific areas

- Open software suite for Bayesian and ML-based data integration
- Benchmarking of acceleration strategies against full posterior
- Bayesian 3D equilibrium reconstruction
- Uncertainty propagation to actuators and controllers
- Diagnostic design for next-step devices