

Soft X-ray tomography for monitoring fusion plasma dynamics

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INTRODUCTION

- In fusion devices, the local soft X-ray (SXR) plasma emissivity is rich in information about electron temperature and density, magnetohydrodynamic (MHD) activity and concentration of impurities that can be inferred with the help of dedicated tomographic reconstruction and synthetic diagnostic tools [1, 2].
- Nevertheless, estimating the local plasma emissivity from a sparse set of noisy line-integrated measurements is a mathematically ill-posed inverse problem, that requires an adequate regularization procedure [1].
- In this contribution, we introduce some tools aiming at validating and speeding up the X-ray tomographic inversions. The traditional approach based on Tikhonov regularization, including magnetic equilibrium constraint and parameter optimization, is presented. The advantages and drawbacks of substituting it with neural networks for fast inversions are investigated. Finally, the perspectives for plasma profiles reconstruction and validation are discussed.

Soft X-ray (SXR) emissivity in tokamak plasmas

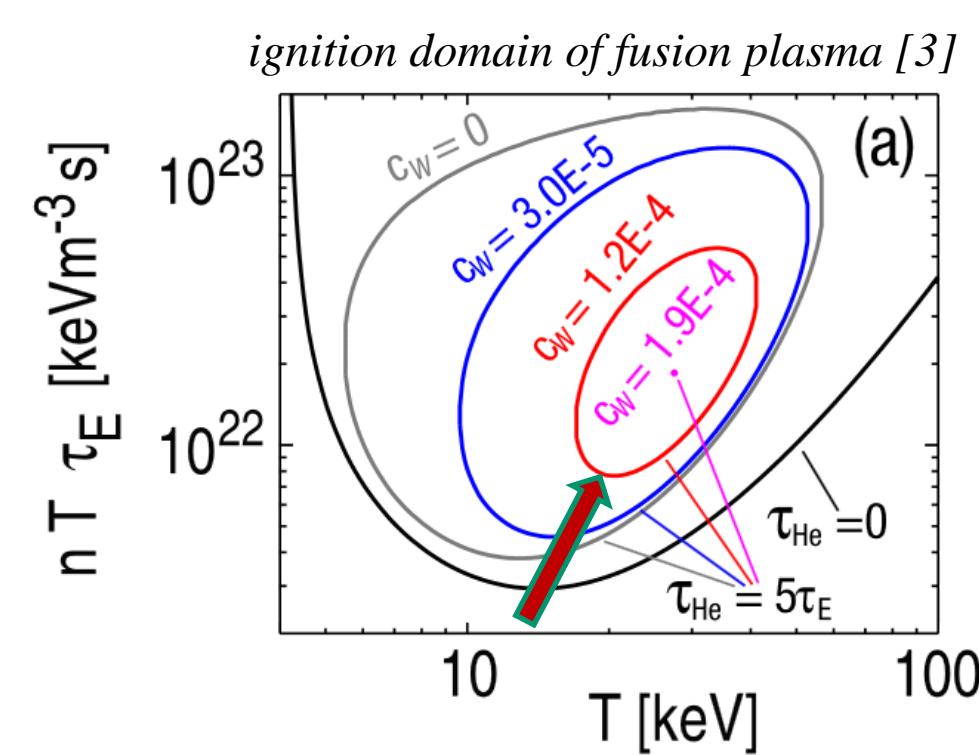
- SXR plasma emissivity for a given ion species:

$$\mathcal{E}_Z^\eta = n_e n_Z L_Z^\eta(T_e)$$

electron temperature (keV)
cooling factor (W.m⁻³)
electron density (m⁻³)
ion density of species Z (m⁻³)

With: $L_Z^\eta(T_e) = K_{Z,ff}^\eta + K_{Z,fb}^\eta + K_{Z,bb}^\eta$

Bremsstrahlung Radiative recombination Line radiation



Due to strong X-ray radiation, tungsten (W) impurity concentration must stay below 0.01% in future fusion reactors

Forward and inverse problem

- Forward problem:

$$m_i = \int_{LoS} \varepsilon^\eta(x, y) dr_i + \tilde{m}_i$$

Line-integrated measurement of i-th chord / LoS
2D emissivity field in a poloidal cross-section
perturbative noise

In matrix form: $\mathbf{m} = \mathbf{T} \cdot \boldsymbol{\varepsilon} + \tilde{\mathbf{m}}$

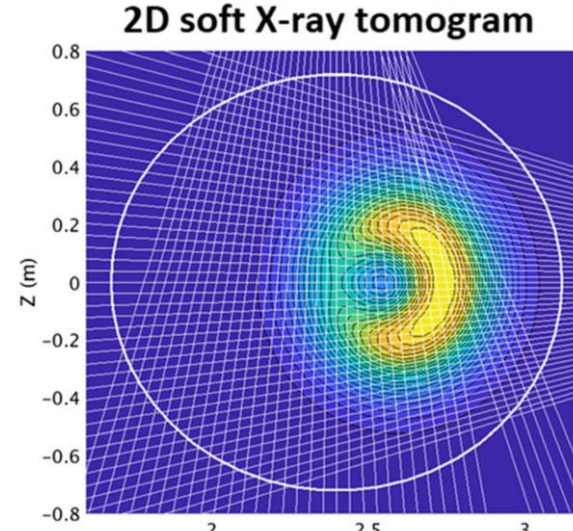
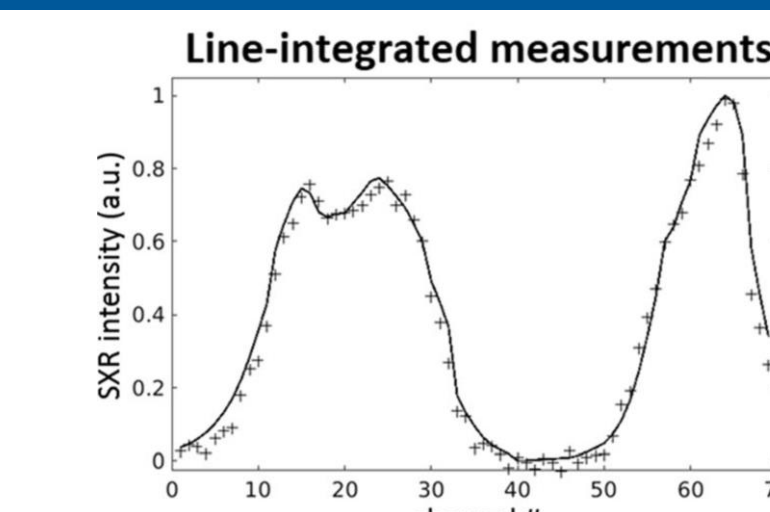
Transfer matrix

- Plasma tomography issue:

- number of lines-of-sight << number of pixels
- noisy line-integrated data
- Inverse problem is not well-posed:

$$\boldsymbol{\varepsilon} \rightarrow \mathbf{T}^{-1} \cdot \mathbf{m}$$

- Mathematically ill-posed problem → requires regularization procedure



Tikhonov Regularization

- Tikhonov regularization: minimization of an objective function

$$\boldsymbol{\varepsilon}_0 = \arg \min_{\boldsymbol{\varepsilon}} (\|\mathbf{m} - \mathbf{T} \cdot \boldsymbol{\varepsilon}\|^2 + \lambda \cdot \mathbf{T}^T \boldsymbol{\varepsilon} \cdot \mathbf{H} \cdot \boldsymbol{\varepsilon})$$

Reconstruction error χ^2
Free parameter
Regularization term (imposes smoothness on the solution)



Andrey Tikhonov

- Common method in tokamaks for the regularization operator is based on Minimum Fisher Information (MFI):

$$\mathbf{H}_{MFI} = \mathbf{T}^T \cdot \mathbf{W} \cdot \mathbf{T}$$

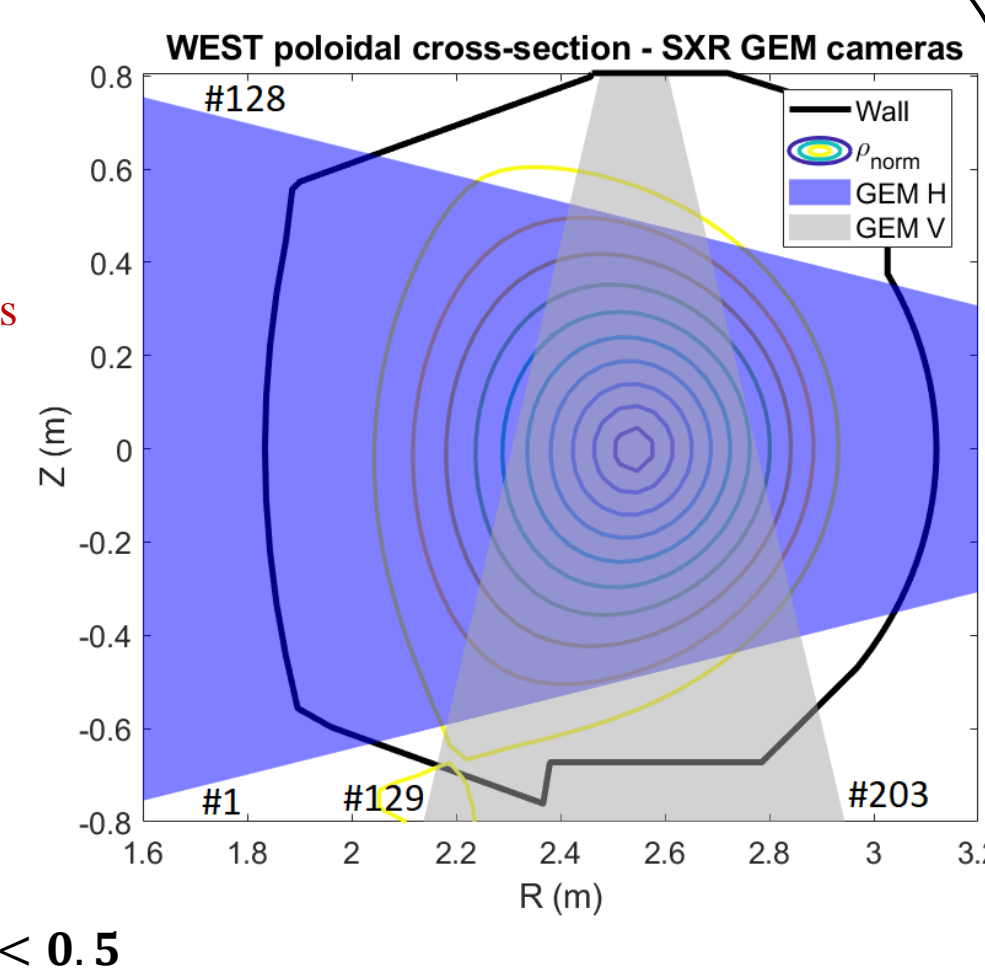
W = diag(1/ε)
∇: spatial gradient

- Anisotropy to include the constraint of magnetic equilibrium:

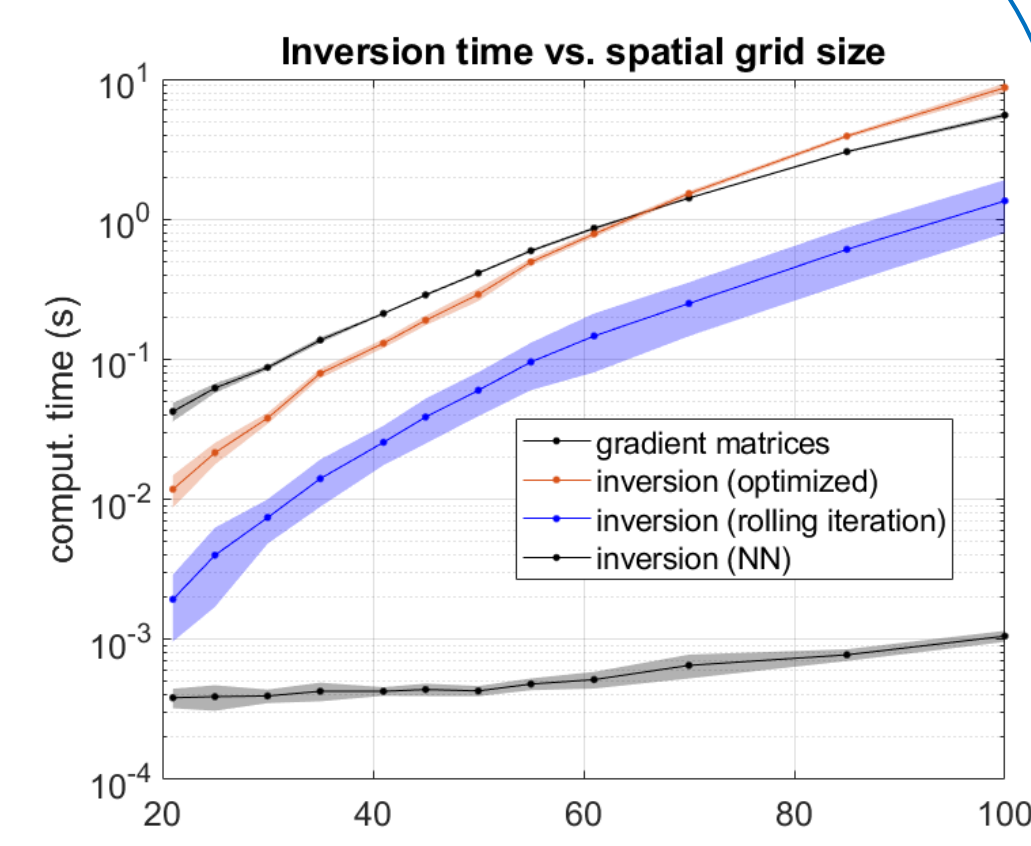
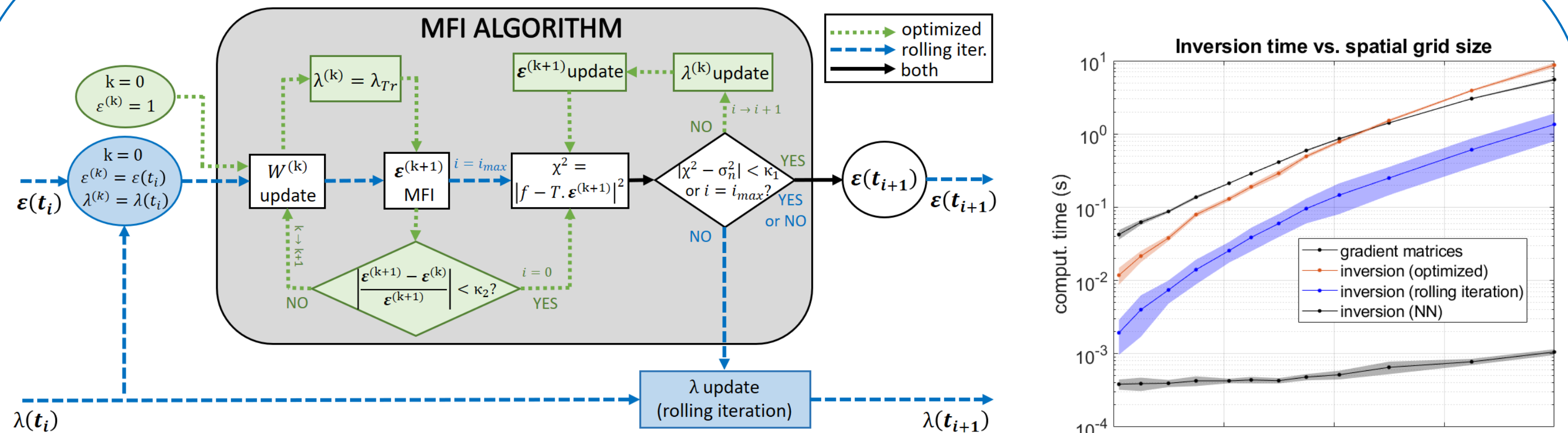
$$\mathbf{H}_{MFI,anis} = (\mathbf{1} - \boldsymbol{\tau})^T \mathbf{T}^T \cdot \mathbf{W} \cdot \mathbf{T} \cdot \boldsymbol{\tau} + \boldsymbol{\tau}^T \mathbf{T}^T \cdot \mathbf{W} \cdot \mathbf{T} \cdot \boldsymbol{\tau}$$

anisotropy factor: 0 < τ < 0.5

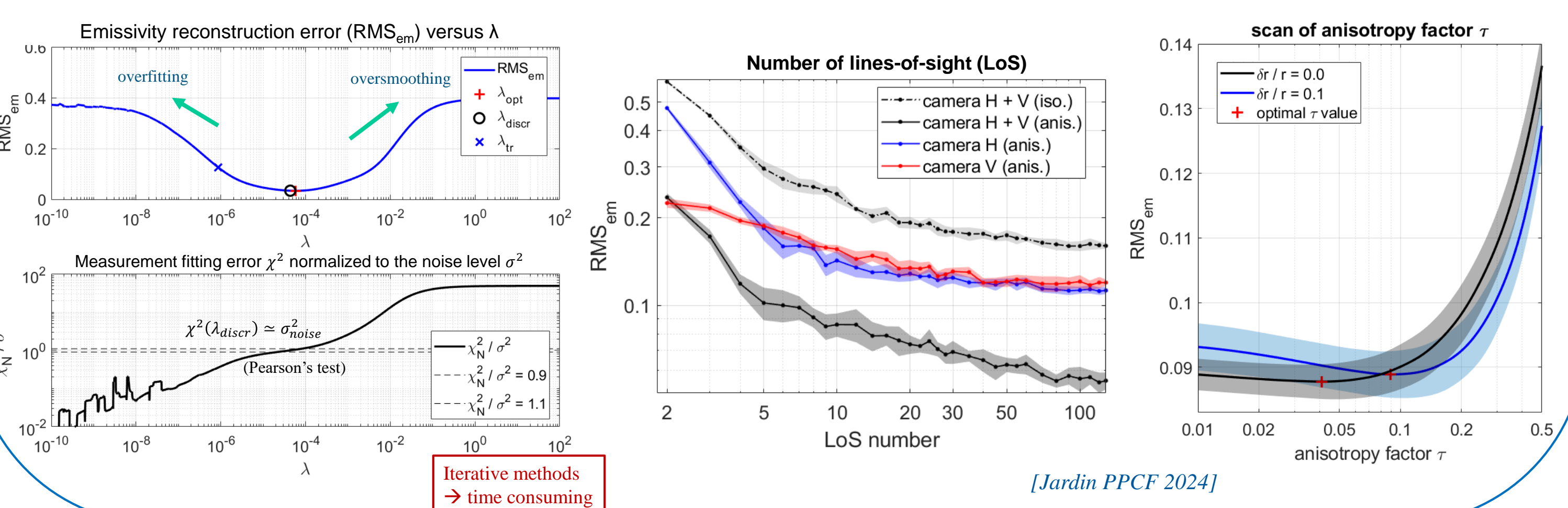
Approach used on various tokamaks: TCV, COMPASS, ASDEX-U, Tore Supra / WEST, ...



- Minimum Fisher algorithm implemented on Tore Supra / WEST:



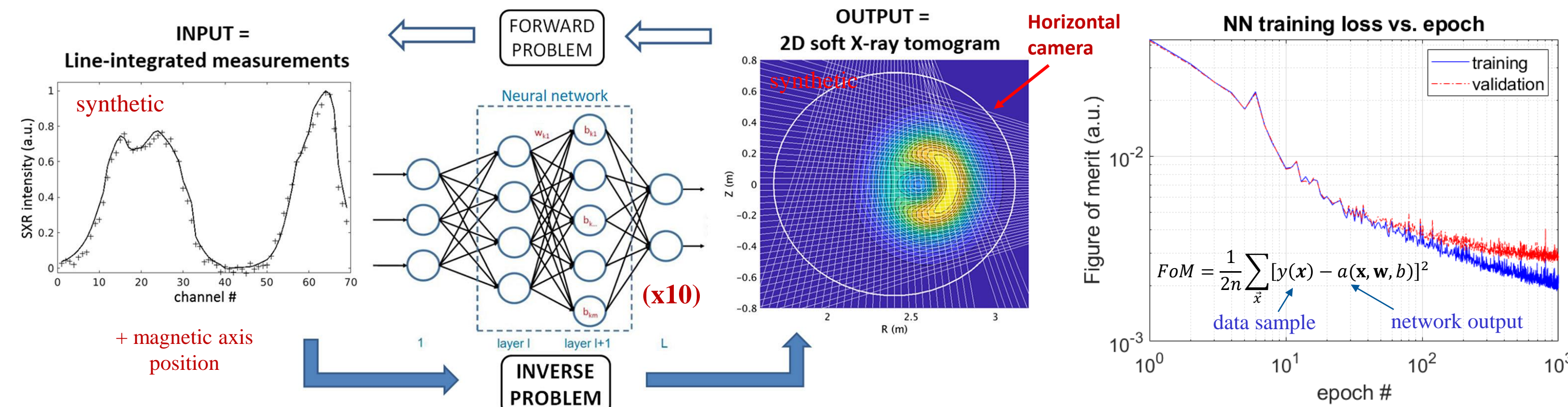
- Exploration of some parameters:



Neural Networks

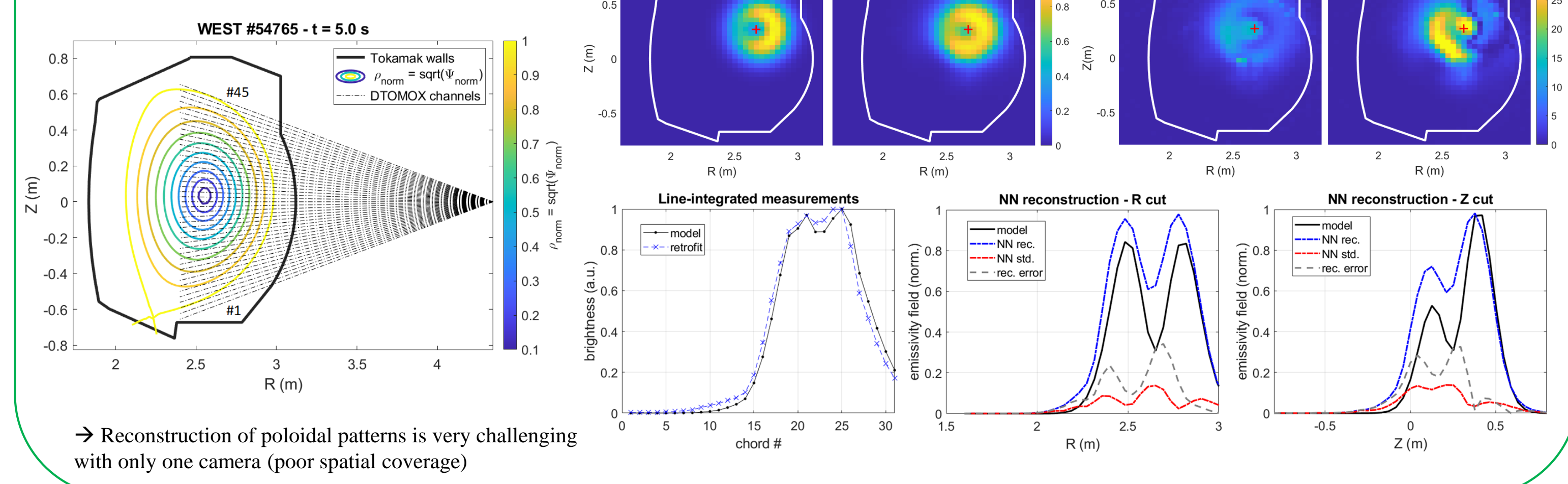
- Neural networks are a promising tool for real-time tomography applications. We applied them to the WEST SXR diagnostic geometry:

- 10 fully-connected NNs trained in parallel → reconstructions with error bars (standard deviation of solutions),
- Only the horizontal DTOMOX camera of WEST is used (vertical being replaced) → limited spatial coverage,
- Magnetic axis used as additional input of Neural Network (NN) to help with the reconstruction,
- Training database and validation made with synthetic profiles, then applied on real data and compared with MFI.

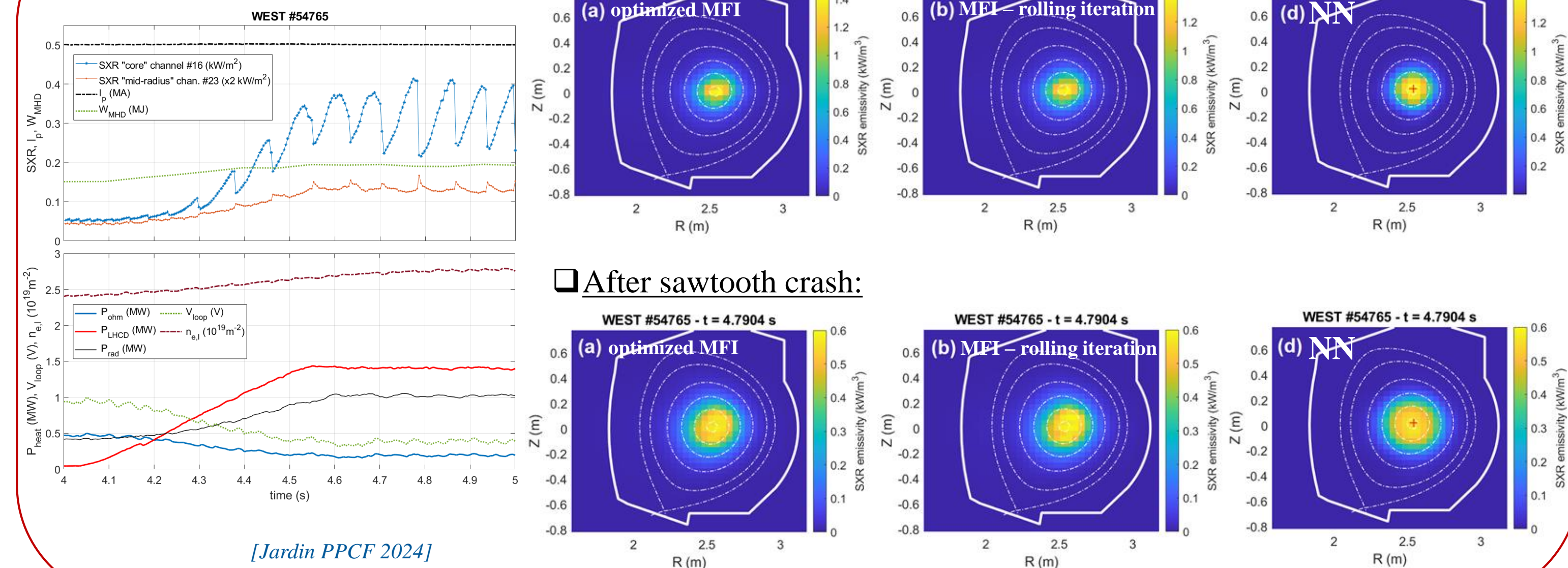


Experimental tests on WEST

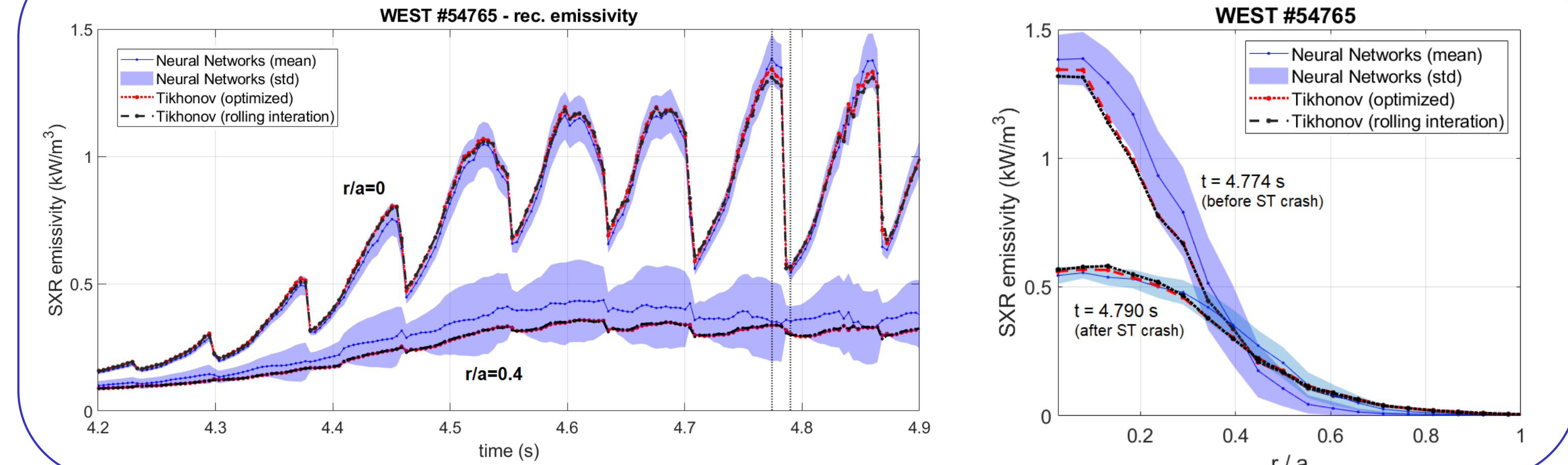
- DTOMOX radial camera:



- Test on WEST shot #54765:



- Experimental comparison on time traces and radial profiles:



Conclusion & perspectives

- NN performance satisfying, given poor geometric coverage of plasma (one camera here) and limited amount of a priori information (magnetic axis position) → good prospects for future fusion devices with limited real-time information available and reduced allocated space for cameras, like in ITER [K. Chen FED 2021] or DEMO [W. Gonzalez FED 2019].
- NN reconstructions could be improved by using convolutional neuron layers instead of fully-connected ones [F. Matos FED 2017]. Nevertheless, largest improvement can be expected by increasing number of cameras and a priori information in NN inputs, e.g. plasma volume, elongation or triangularity, that could be the subject of further work.
- NN training with synthetic profiles + application to real data → important to develop algo. ready-to-use from the start of tokamak operation, without the need to first constitute an experimental database (though, traditional methods e.g. Tikhonov regularization still crucial tool for validation purposes and off-line analysis).

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