Poster ID: #352

Machine Learning techniques for diagnostics design and real-time data analysis

D. MAZON[1], J. BIELECKI[2], A. JARDIN[2], Y. SAVOYE-PEYSSON[1], M. SCHOLZ[2], AND THE WEST TEAM[#]

[1]CEA, IRFM, F-13108, Saint-Paul-les-Durance Cedex, France
[2]Institute of Nuclear Physics Polish Academy of Sciences (IFJ PAN), PL-31-342, Krakow, Poland
[#]See http://west.cea.fr/WESTteam
[*]Email: Didier.Mazon@cea.fr

Introduction

- Fast and reliable reconstruction of X-ray and neutron emissivity of fusion plasmas can enable real-time monitoring of essential parameters: electron and ion temperature, impurity concentration, fuel ion ratio, etc.
- Machine learning methods - in particular evolutionary algorithms (e.g. genetic algorithms, GA) and artificial neural networks (NNs) – are valuable for this purpose.
- This contribution highlights the following recent efforts and results:
  (1) Combining GA with custom Monte-Carlo (MC) code to optimize the design and performance of diagnostic systems for tokamak plasmas;
  (2) Employing fully-connected NNs to automate reconstruction of tungsten impurity concentration and distribution in the WEST plasma core (a crucial information to control the radiated power), using a large experimental training set from multiple diagnostics;
  (3) Applying convolutional NNs to solve the inverse problem for X-ray tomographic reconstruction of the tokamak plasma emissivity field – essential to monitor impurity distribution and asymmetries.

Diagnostic Design Optimization with Genetic Algorithm (GA)

Motivation

- Combined Genetic Algorithm (GA) and customized Monte-Carlo (MC) code were used to optimize design and performance of tokamak diagnostic systems. The study focuses on a thin-foil proton-recoil (TPR) system for neutron spectroscopy, involving intensive computations in the GA-MC framework and its validation with GEANT4 toolkit.
- GA-MC approach well-adapted to multi-dimensional optimization problem and to quantify trade-off between geometrical parameters (e.g. converter thickness, detector dimensions) to optimize both detection efficiency and energy resolution.

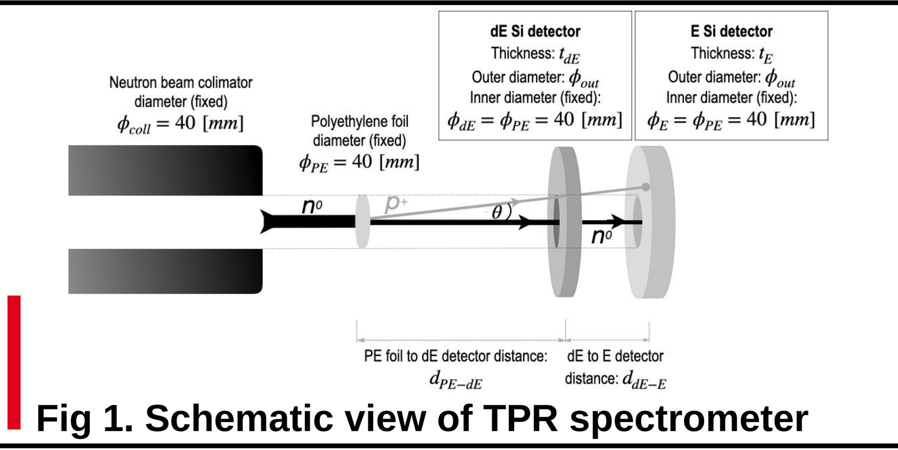


Fig 1. Schematic view of TPR spectrometer

Thin-foil proton-recoil (TPR) spectrometer design:
- Thin, hydrogen-rich polyethylene (PE) foil to convert incident neutrons into recoiled protons by elastic scattering,
- Collimated 14 MeV neutron beam, incident on PE foil,
- Charged particle detectors at a defined scattering angle. Here two annular Si detectors in dE-E configuration is assumed. Thin dE detector registers specific energy loss (dE/dx). Total recoil proton energy estimated from the sum of dE and E detector outputs.

GA-MC Workflow and first results

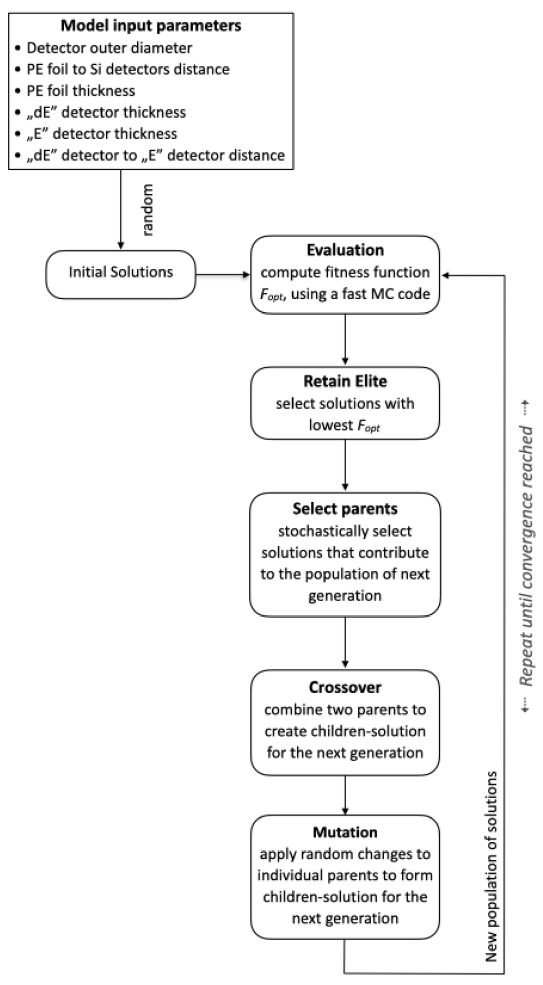


Fig 2. General workflow of the GA-MC algorithm

$$F_{opt} = \left(\frac{1}{\varepsilon} + \frac{\Delta E}{E} C\right)\left(1 + H(r - r_0)\right)$$

Fitness function F_{opt} to be minimized:
- ε = detection efficiency [p/sn]
- $\Delta E/E$ = energy resolution (FWHM) [%]
- r = event rejection rate [%]
- C = trade-off parameter

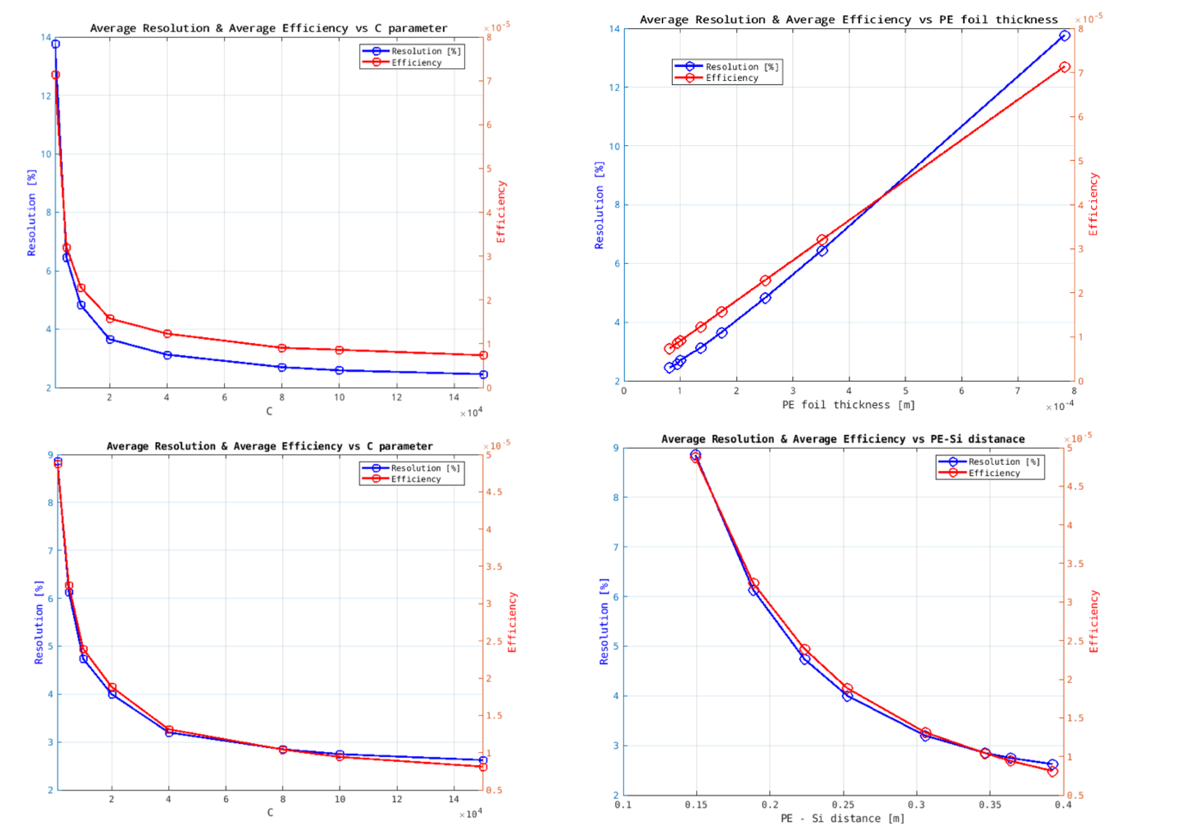


Figure 3. Examples of TPR optimization trade-off (ablation studies): TPR energy resolution and detection efficiency as a function of C parameter, for cases when only PE foil thickness (left) or PE-Si distance (right) was optimized by GA-MC, while rest of TPR parameters remained fixed (ablation study).

→ See J. Bielecki EPS Poster #170 for more details [1]

X-ray tomography with convolutional neural networks (CNN)

Previous results (FC-NN)

Successful use of Fully-Connected NN (FC-NN) already proven for SXR tomography on WEST:

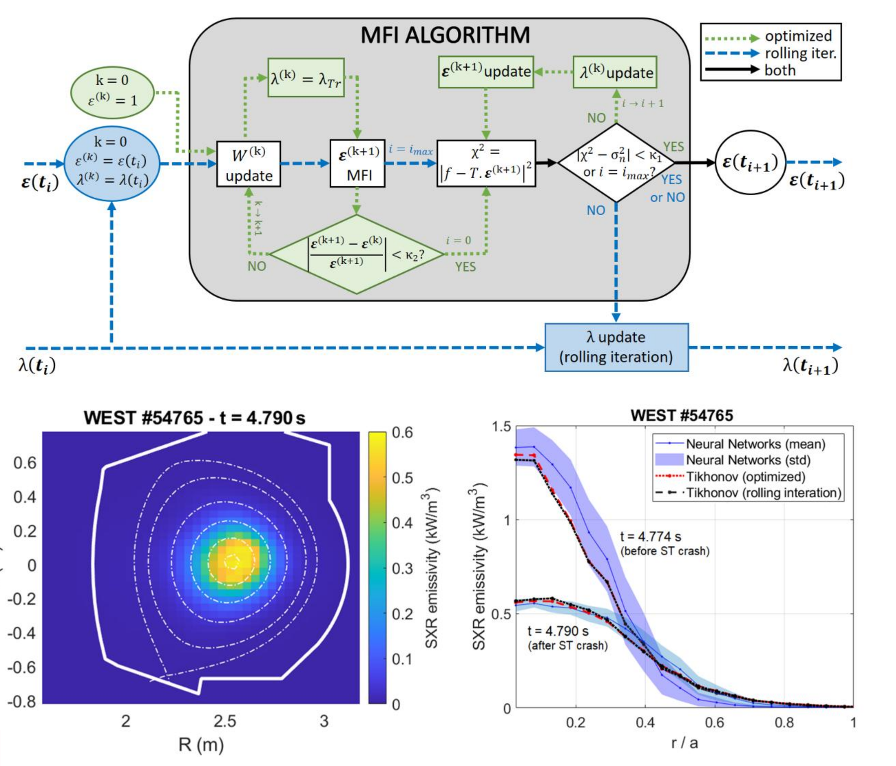
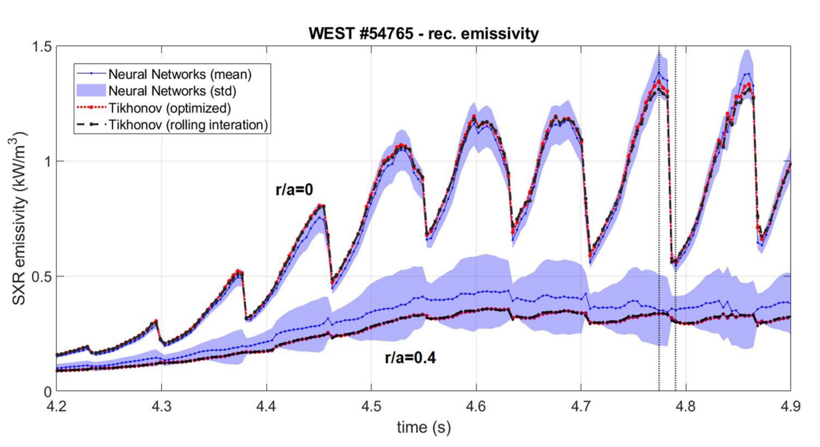


Fig 4. Workflow for Minimum Fisher Information (MFI) algorithm for SXR tomography & comparison with FC-NN.

[A. Jardin, D. Mazon et al, PPCF 66 (2024) 085010]



→ Reliable tomograms, but with significant uncertainty and limitations in terms of achievable resolution.

No improvement above 40 x 40 spatial grid, and even failure of network training at higher spatial resolutions.

Can we do better? → convolutional networks (CNN)

Tomography attempts with convolutional networks (CNN)

- We investigate CNN to solve the inverse problem for X-ray tomographic reconstruction of plasma emissivity.
- Since convolutional layers are adapted to image processing, such architecture has been implemented for the SXR tomographic system and compared with traditional Tikhonov regularization and FC-NN.
- Very promising results were obtained, in particular lower reconstruction error and higher spatial resolution than FC-NN with a computing time still several order of magnitude lower than Tikhonov regularization.

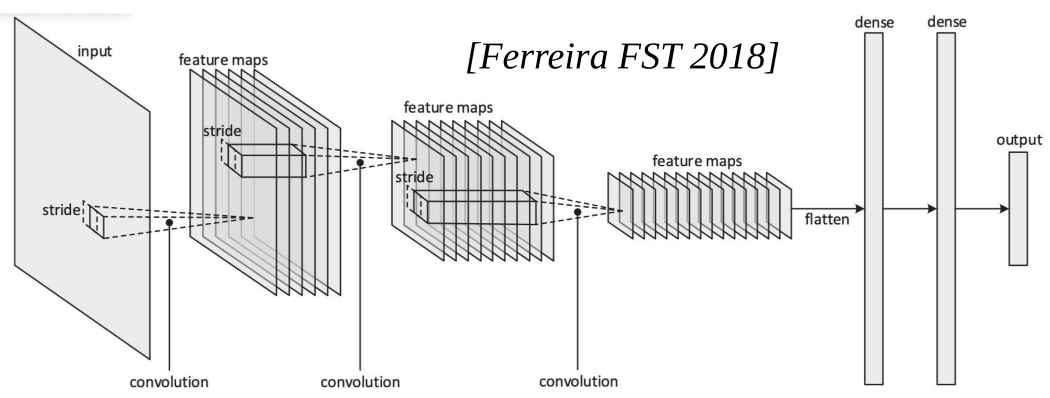


Fig 5. Structure of Convolutional Neural Network (CNN)

Our network architecture (PyTorch):
- **Input layer:** 1 node per line-integrated measurement;
- **Fully connected layers:** two dense layers of size 2535: output reshaped to 3D tensor of shape 15×13×13 (15 feature maps of size 13x13);
- **Transposed convolutions:** 2 layers, upsampled to 26×26, then 52×52;
- **Final convolution:** produces 50×50 reconstructed emissivity map.

- Training performed with hundreds of synthetic phantoms (gaussian, hollow, peaked, asymmetric, banana shapes, etc.)

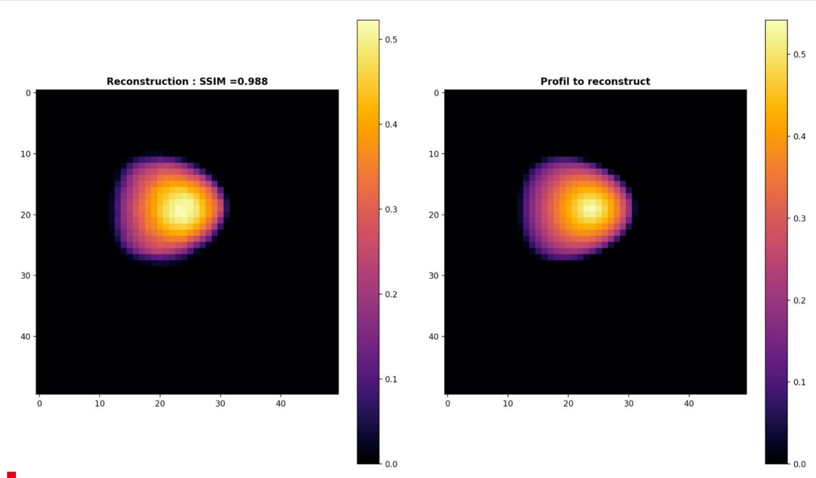


Fig 6. CNN tomography test with symmetric synthetic emissivity profile

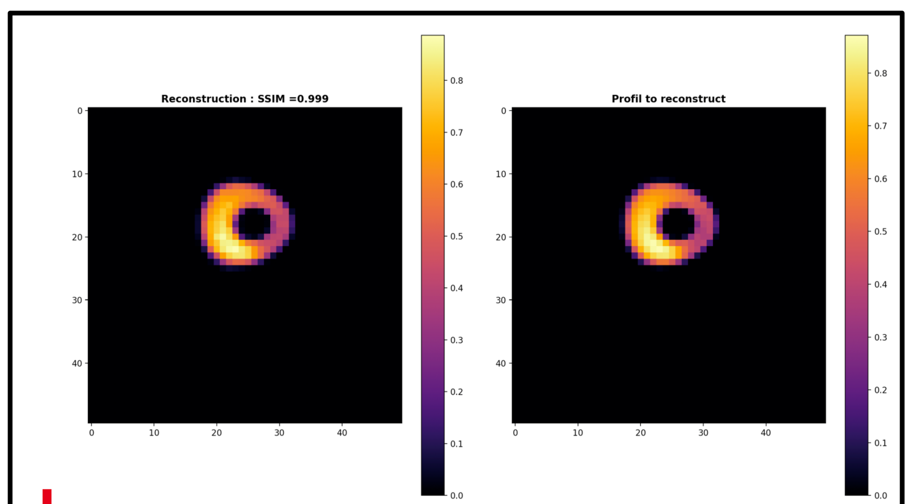


Fig 7. CNN tomography test with asymmetric synthetic emissivity profile

- Preliminary results: Significant improvement of image structural similarity (SSIM) vs previous methods without additional computation cost vs. FC-NN.

Method	Tikhonov (MFI)	Fully-connected NN	Convolutional NN
SSIM	0.9 – 0.95	0.9 – 0.95	≥ 0.99
Computing time	0.1 – 1.0 s	0.1 – 1.0 ms	0.1 – 1.0 ms

Direct W SXR reconstruction with NN

Motivation

- Fully-connected NNs were used to automate reconstruction of tungsten impurity concentration c_W and distribution in WEST plasma core, using large experimental training database from multiple diagnostics.
- Parametrization of W profile has been introduced in the analysis, and NN approach validated for several WEST discharges based on forward modelling.
- It showed good consistency and reduction of computing time by orders of magnitude.

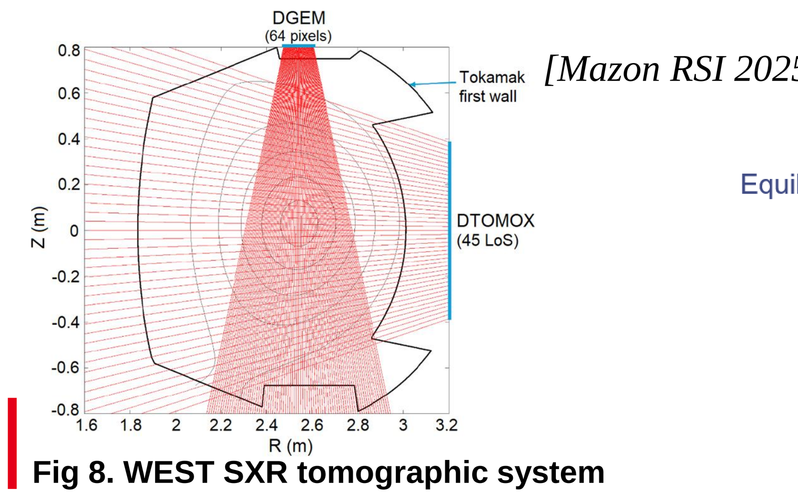
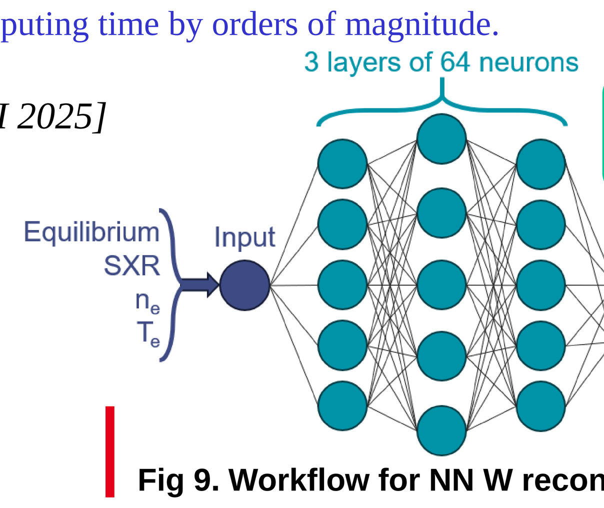


Fig 8. WEST SXR tomographic system



Hypothesis on c_W profile: $c_W = c_W^0\left[1 + \alpha\left(1 - \cos\left(\rho\frac{\pi}{2}\right)\right)\right]$

Fig 9. Workflow for NN W reconstructions.

Results

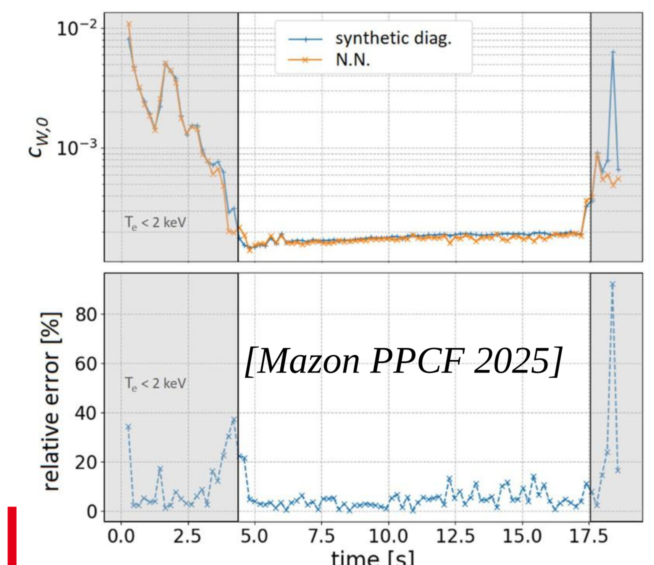


Fig 10. $c_{W,0}$ NN reconstruction for WEST #59095

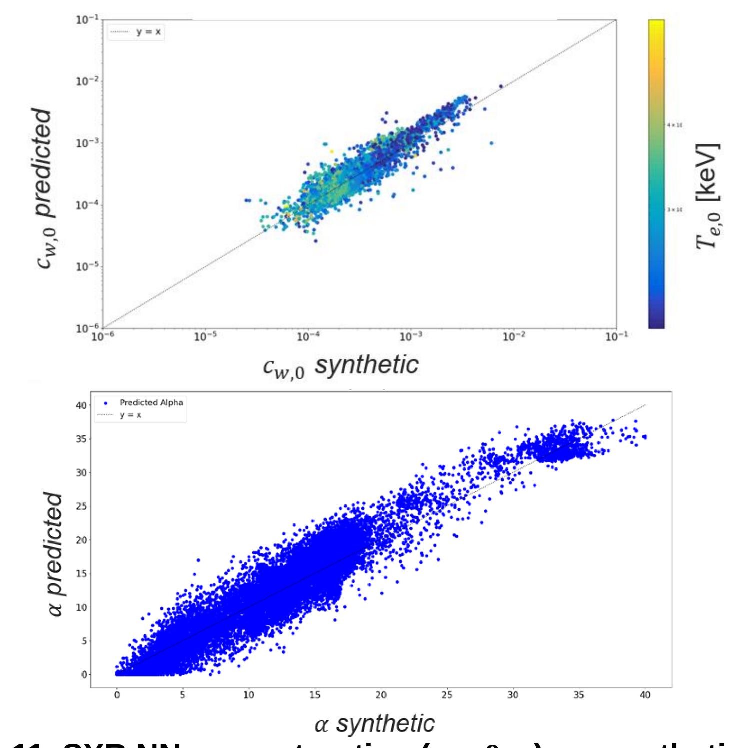


Fig 11. SXR NN reconstruction ($c_{W,0}$ & α) vs. synthetic diagnostic.

Conclusions

- The proposed GA-MC methodology is generic and may be applied in future work to the design optimization of other radiation diagnostic systems (e.g. neutron, X-ray) resilient to neutron flux in the ITER environment.
- The NN SXR results open the door to significantly enhanced capabilities for reconstructing plasma parameters, particularly to study ionization, transport and radiation properties of heavy impurities in tokamaks such as WEST or ITER with a substantial suprathermal electron population.

References

[1] J. Bielecki et al., *"On a hybrid Genetic Algorithm - Monte Carlo framework for tokamak diagnostic design optimization, applied to a neutron spectrometer"*, poster #170 at this EPS 2026 conference.
[2] D. Mazon et al, *"X-ray tomographic measurement and modeling for inferring tungsten impurity distribution in WEST plasmas: A review"*, Rev. Sci. Instrum. 96, 063509 (2025). https://doi.org/10.1063/5.0261113
[3] D. Mazon et al, *"Reconstruction of tungsten concentration in WEST plasma core with Machine Learning"*, Plasma Phys. Control. Fusion 67 075012 (2025). DOI 10.1088/1361-6587/ade62a
[4] A. Jardin, D. Mazon et al, *"Validating and speeding up x-ray tomographic inversions in tokamak plasmas"*, Plasma Phys. Control. Fusion 66 085010 (2024). DOI 10.1088/1361-6587/ad5b85
[5] D. Ferreira et al., *"Full-Pulse Tomographic Reconstruction with Deep Neural Networks"*, Fusion Science and Technology, 74(1–2), 47–56 (2018). https://doi.org/10.1080/15361055.2017.1390386

Acknowledgements. *The project is co-financed by the Polish National Agency for Academic Exchange (POLONIUM programme, contract no. BPN/BFR/2024/1/00002/U/00001). We gratefully acknowledge Polish high-performance computing infrastructure PLGrid (HPC Centers: ACK Cyfronet AGH, CI TASK, WCSS) for providing computer facilities and support within computational grants no. PLG/2025/017971 and no. PLG/2026/019127. This work has been carried out as part of the research project no. 2025/57/B/ST2/04168 financed by the National Science Centre, Poland (NCN).*