U.S. DEPARTMENT OF ENERGY | Office of Science

NSTX-U

Advanced Plasma Diagnostic Analysis using Neural Networks

K. Tritz[1], M.L. Reinke[2]

[1] *Johns Hopkins University*

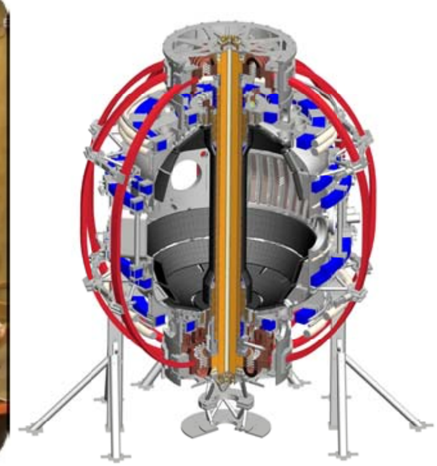
[2] *Oak Ridge National Laboratory*

58th Annual APS-DPP Conference

San Jose, CA

November 3rd, 2016

JOHNS HOPKINS UNIVERSITY



PPPL

ABSTRACT

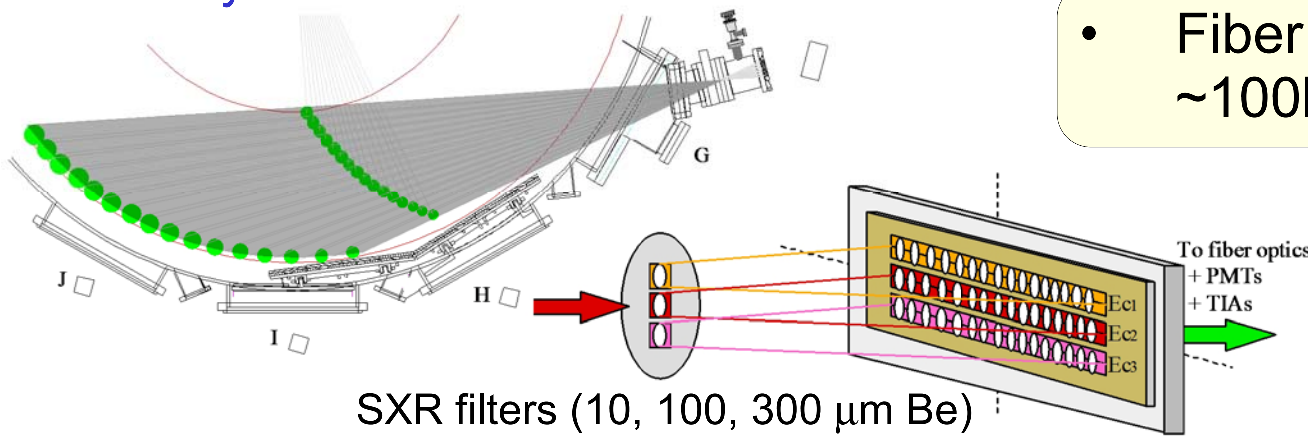
Neural networks (NN) are generally well suited to the type of problem with slow, or intermittent measurements of a particular quantity, and other measurements with higher time or spatial resolution, which are related to the intermittent measurements in some complex fashion. NN analysis is used in this manner to extract T_e profiles from multi-foil Soft X-ray measurements. Additionally, the radiated power (P_{rad}) determined using resistive foil bolometers is related to similar measurements using AXUV diode arrays through a complex and slowly time-evolving quantum efficiency curve in the VUV spectral region. First results from a NN trained using Alcator C-Mod resistive foil bolometry and AXUV diodes are presented, working towards hybrid P_{rad} measurements with the quantitative accuracy of resistive foil bolometers and with the enhanced temporal and spatial resolution of the unfiltered AXUV diode arrays.

*Work supported by the United States DoE contract number DE-FG02-09ER55012

Multi-energy tOSXR used to extract T_e profile from Soft X-ray spectral measurements

L F Delgado-Aparicio et al 2007 Plasma Phys. Control. Fusion 49 1245

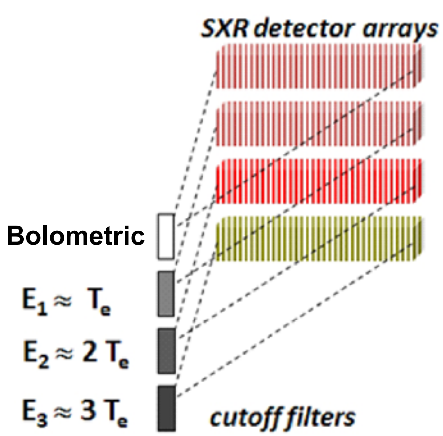
Multi-Energy Tangential Optical Soft X-ray Array



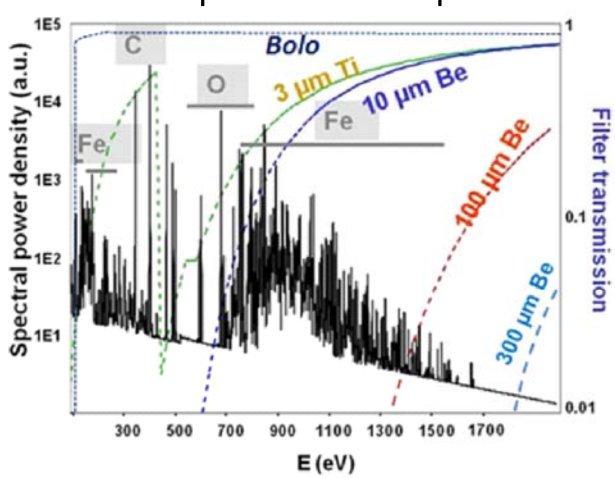
SXR filters (10, 100, 300 μm Be)

$\text{Energy}_{\text{cutoff}}$ (0.6, 1.6, 2.4 keV)

- Fiber coupled to PMTs with ~100kHz time response



Modeled plasma SXR spectrum



- ME-SXR arrays view same plasma volume through filters with different E_{cutoff}
- Division of SXR spectrum isolates T_e, n_z contribution

Neural Networks can calculate $T_e(R,t)$ without relying on accurate atomic physics modeling

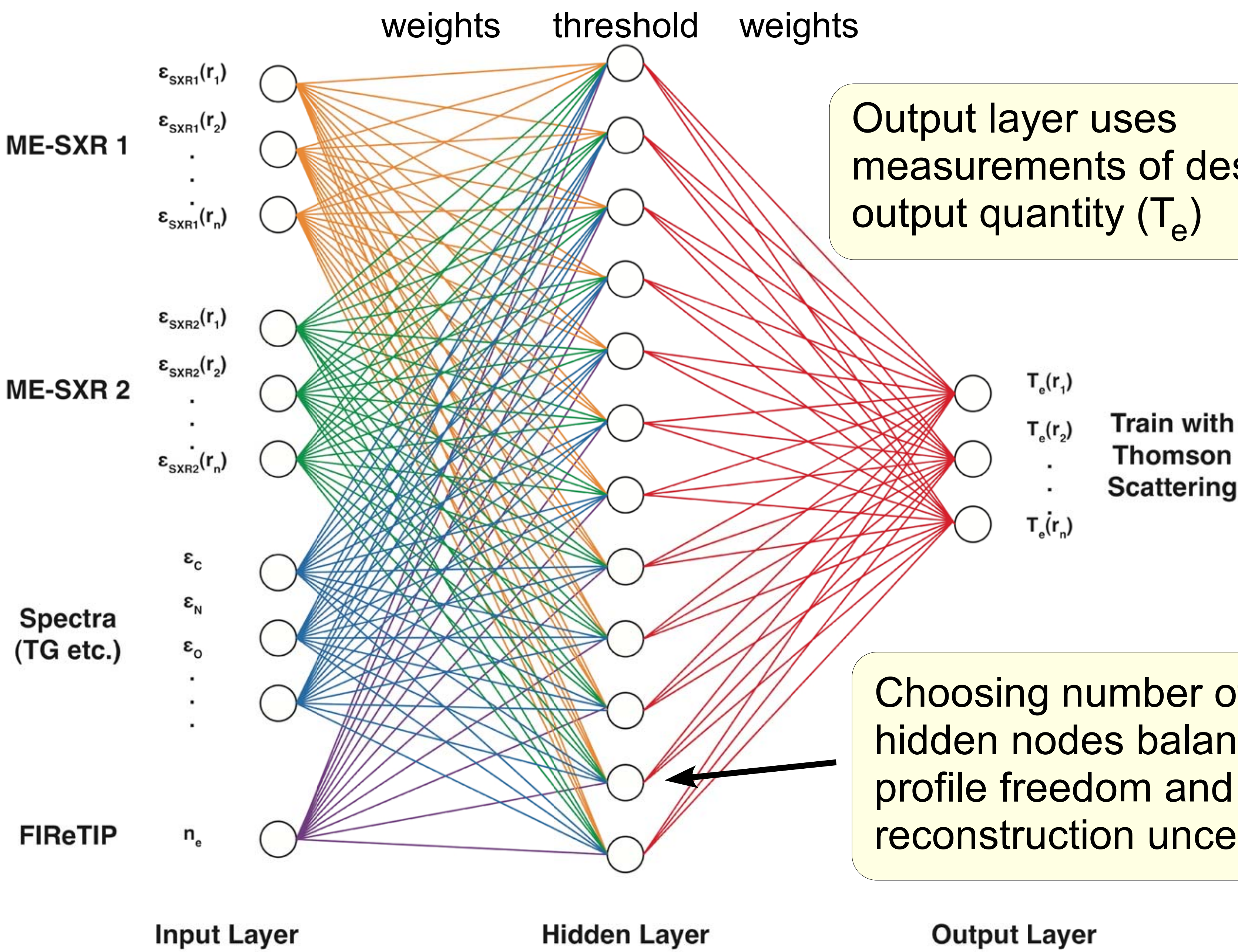
T_e from multi-energy analytic ΔE_f

- MPTS profiles $T_e(R)$ with a 60Hz repetition rate
- Accurate atomic physics modeling of filtered SXR response allows high time resolution >10kHz T_e(R) between Thomson measurements
- Large transport, non-coronal charge state distributions, atomic modeling of high-Z impurity emissivity challenges analysis

T_e from Neural Networks

- Neural networks trained with MPTS data and raw ME-SXR data
  - no atomic modeling required (or even calibrations!)
- Neural networks studied with synthetic SXR data, and successfully used with experimental ME-SXR data
- Improved results with additional diagnostics, real time $T_e(R)$ possible

A fully-connected three-layer Neural Network uses SXR and spectroscopy inputs, outputs $T_e(R)$



Output layer uses measurements of desired output quantity (T_e)

Choosing number of hidden nodes balances profile freedom and reconstruction uncertainty

Feedforward Neural Network initially tested with synthetic data to test $T_e(R)$ sensitivity and accuracy

D J Clayton et al 2013 Plasma Phys. Control. Fusion 55 095015

- PyBrain, a Python modular machine learning library used for NN

- 3-layer feedforward network used

  - number of hidden layer nodes optimized using 5x cross-validation
    40 hidden nodes generally a good choice for this study

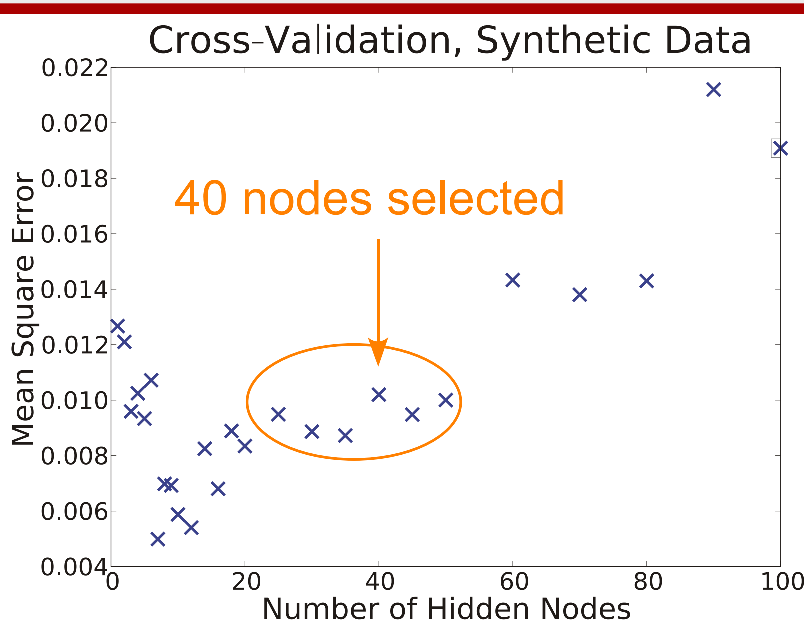
- Rprop-learning algorithm [Igel and Hüsken, Neurocomputing 50 (2003)] used for supervised training of NN using MPTS data

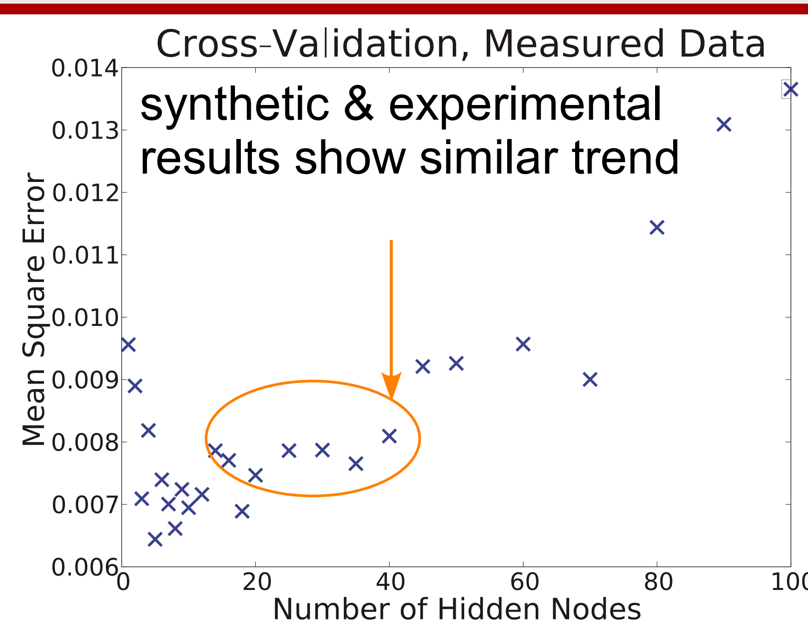
  - All inputs/outputs scaled to range from 0 to 1 for improved performance using NN sigmoid threshold function

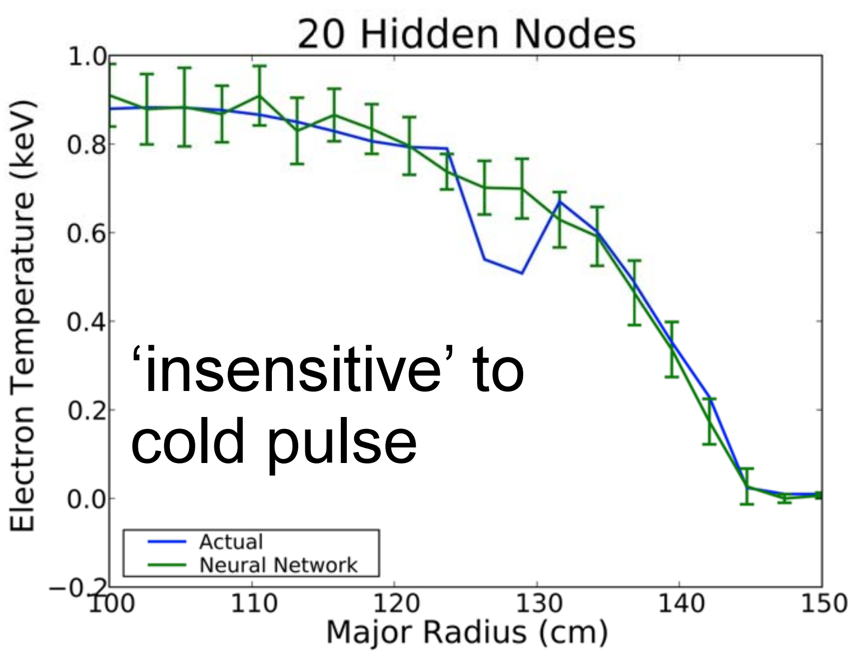
- Synthetic data for testing used real plasma profiles and SXR emissivity modeled using CHIANTI and ADAS spectrum codes

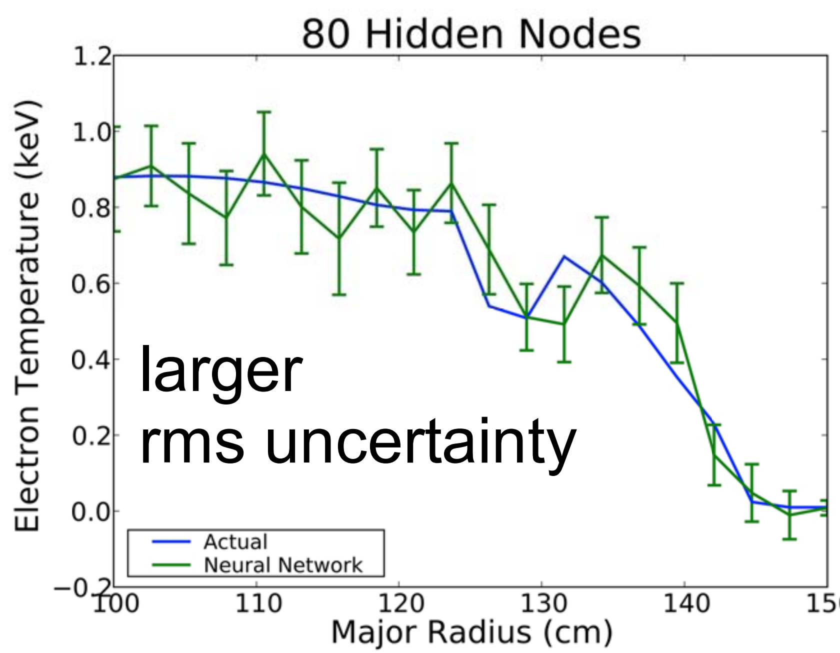
  - atomic modeling only for synthetic testing, not needed for NN $T_e(R)$

Neural Network cross-validation testing illustrates relationship between hidden nodes and T_e reconstruction error

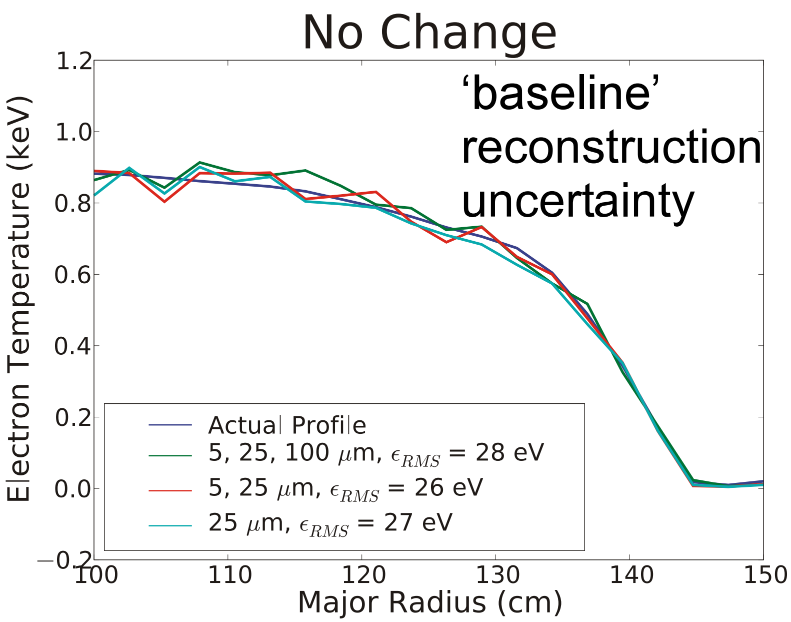


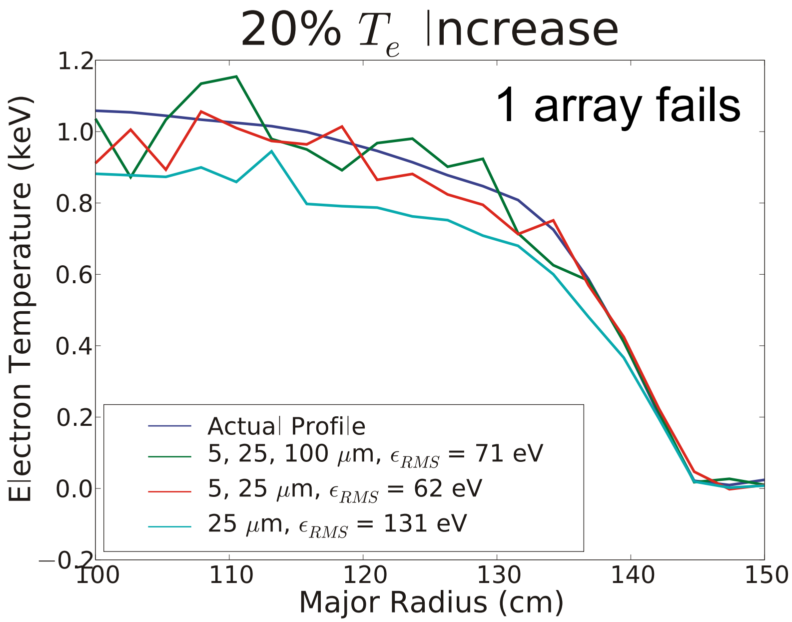


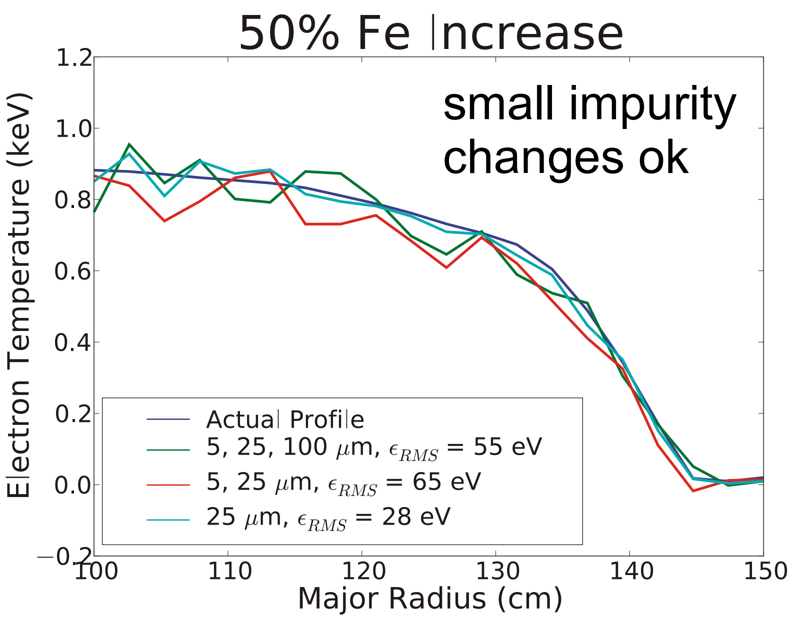


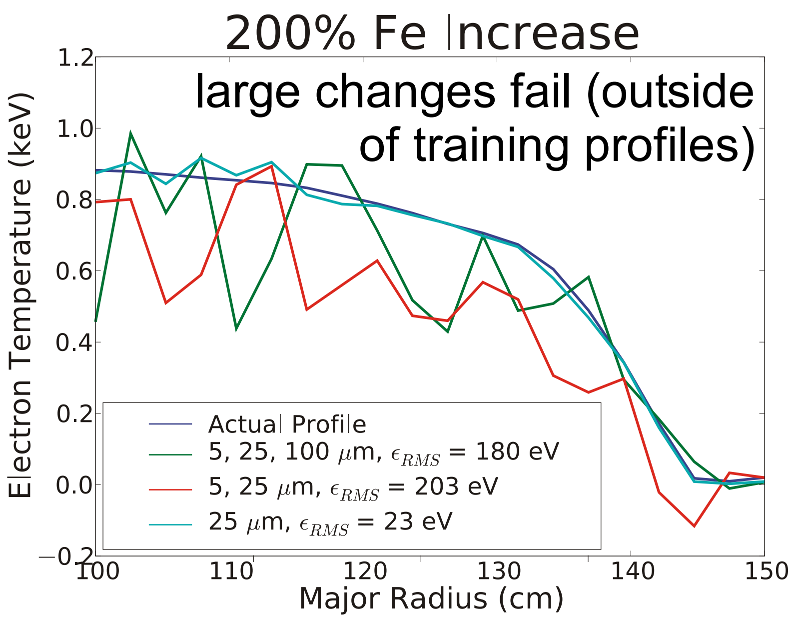


Multiple ME-SXR arrays necessary to discriminate changes in $T_e(R)$ from n_e and impurity changes

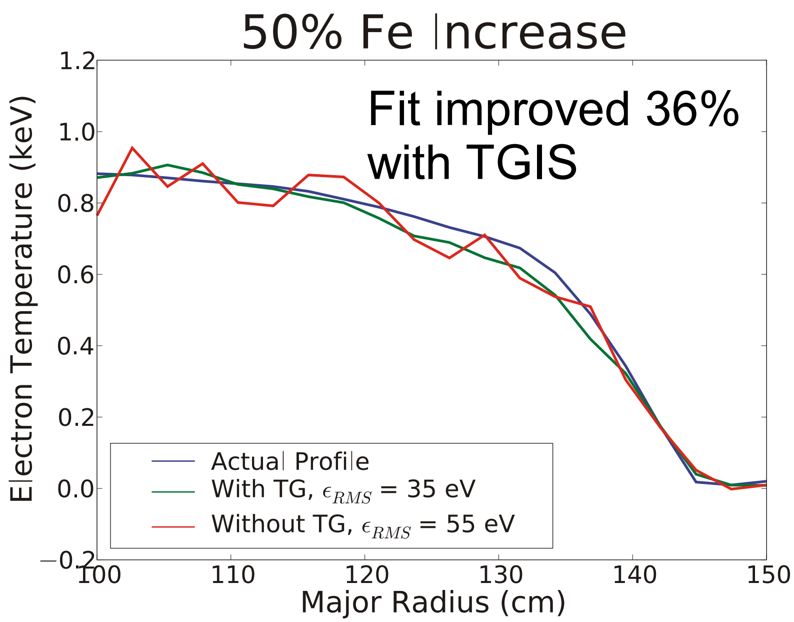


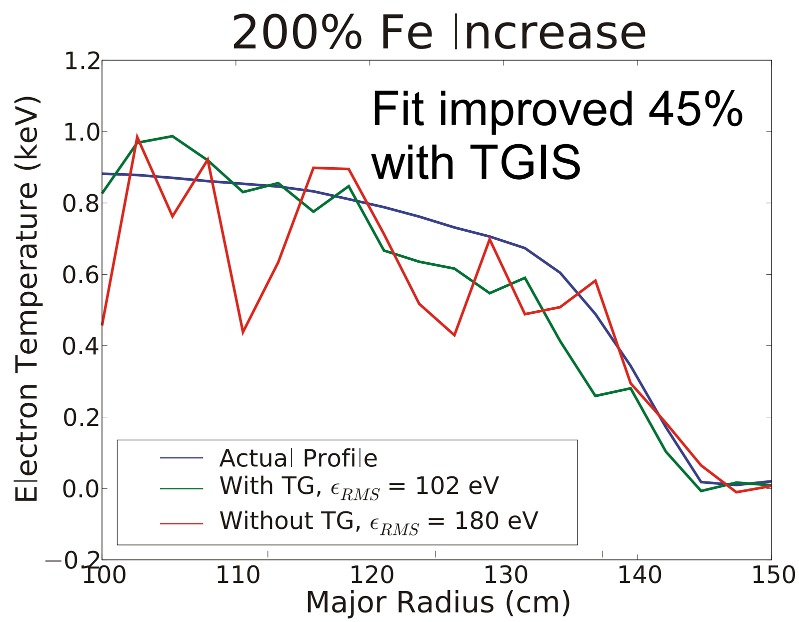


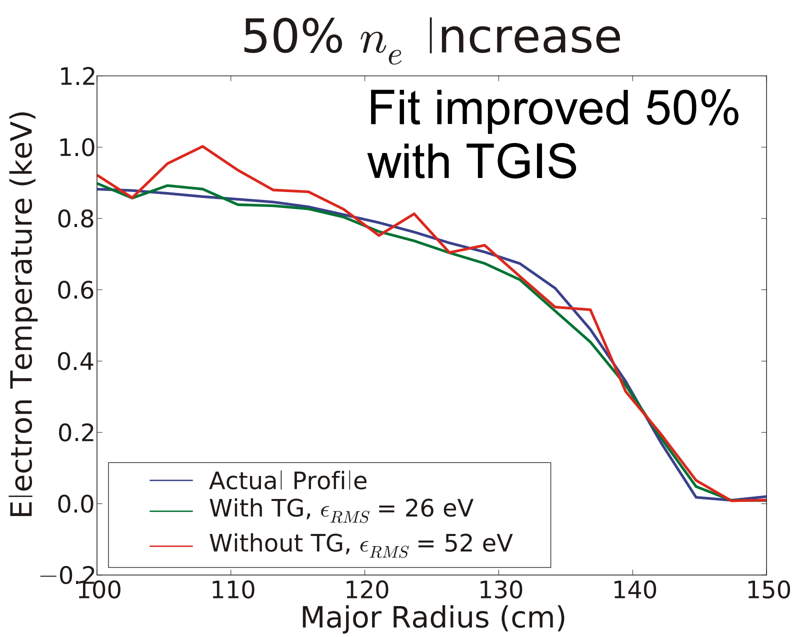


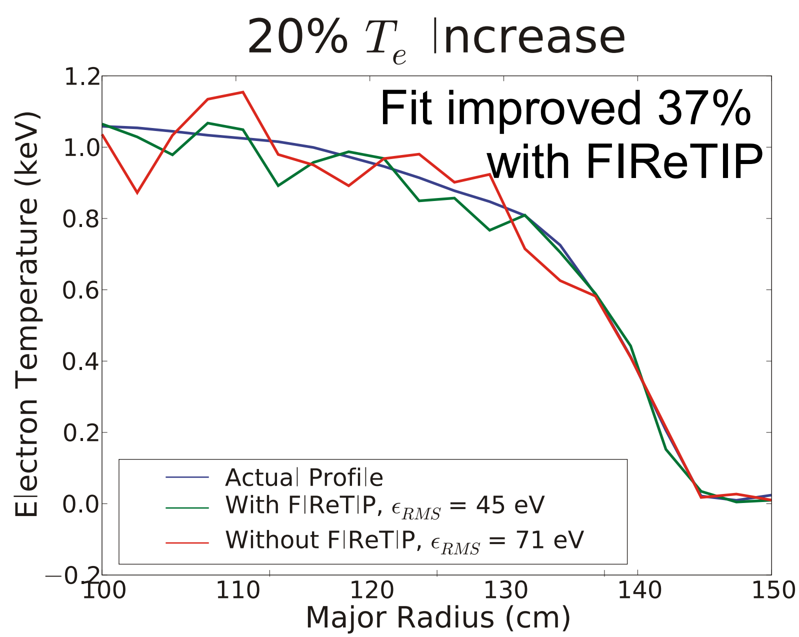


TGIS, FIReTIP diagnostics can significantly improve $T_e(R)$ Neural Network reconstruction



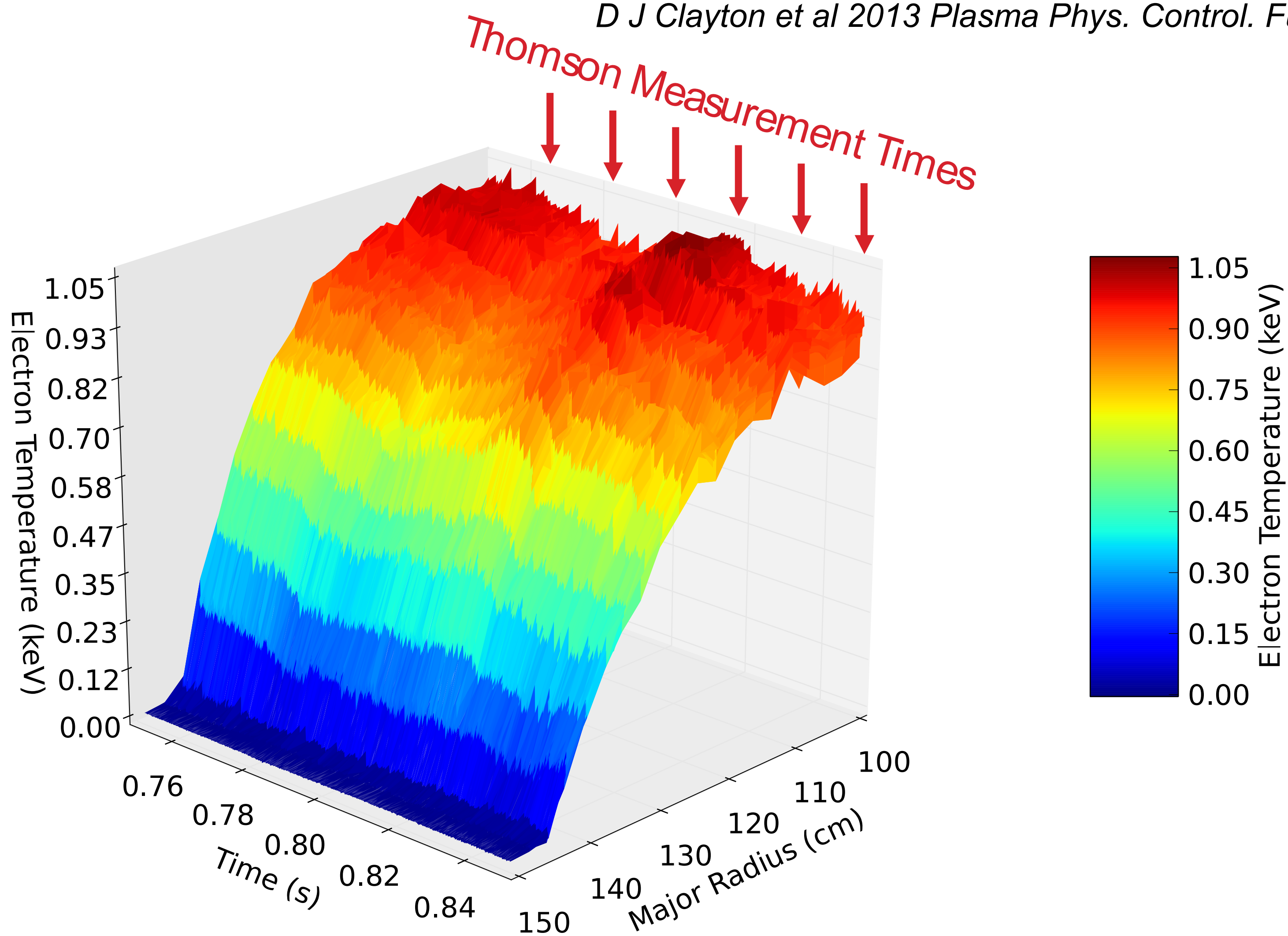






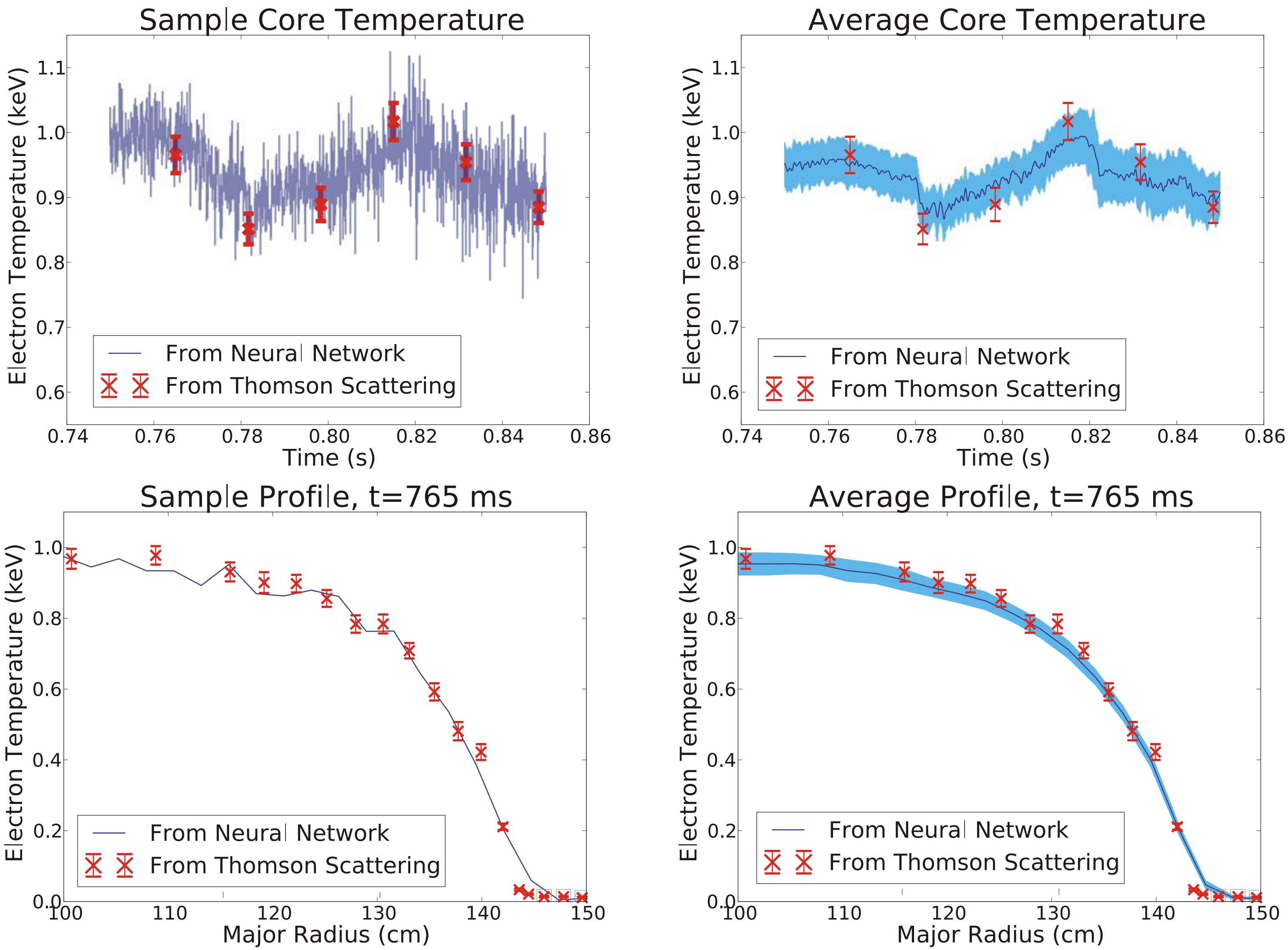
NN $T_e(R,t)$ successfully reconstructed with raw, uncalibrated data from optical ME-SXR

D J Clayton et al 2013 Plasma Phys. Control. Fusion 55 095015



- NN trained on 30 discharges (half with Ne puffs) >1800 MPTS times
  - 48 input (3 arrays x 16 channels), 40 hidden, 16 output nodes

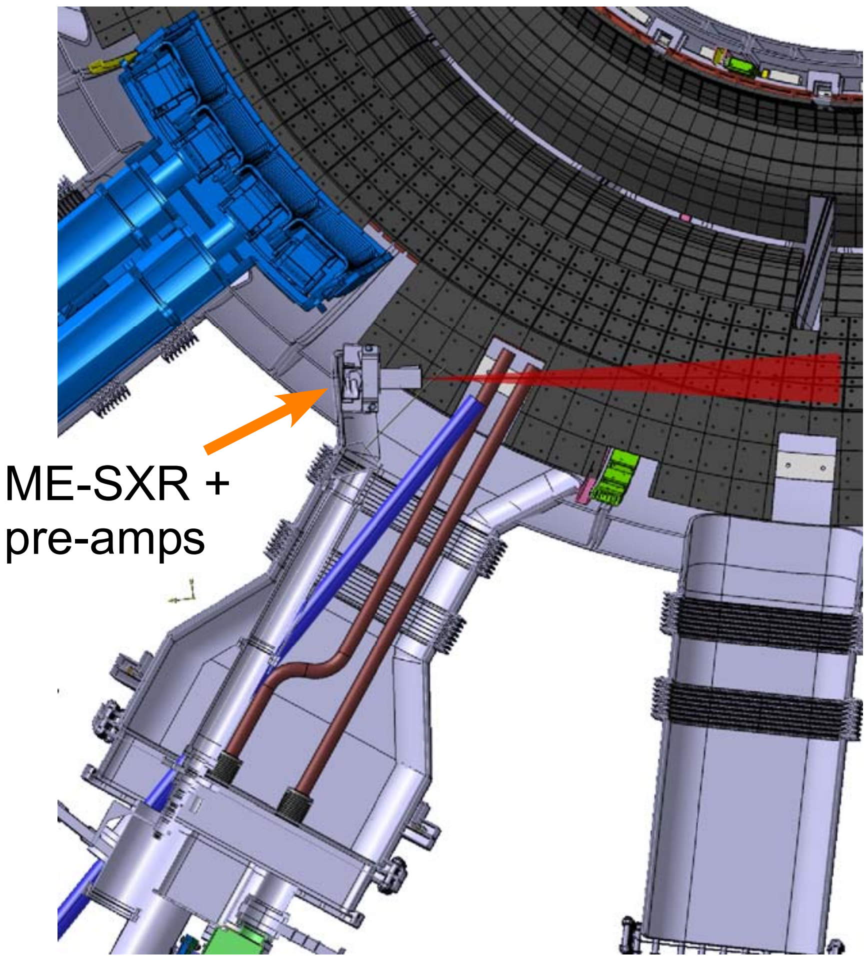
Fast NN $T_e(R,t)$ reconstruction highlights ability to measure changes missed by 60Hz MPTS system

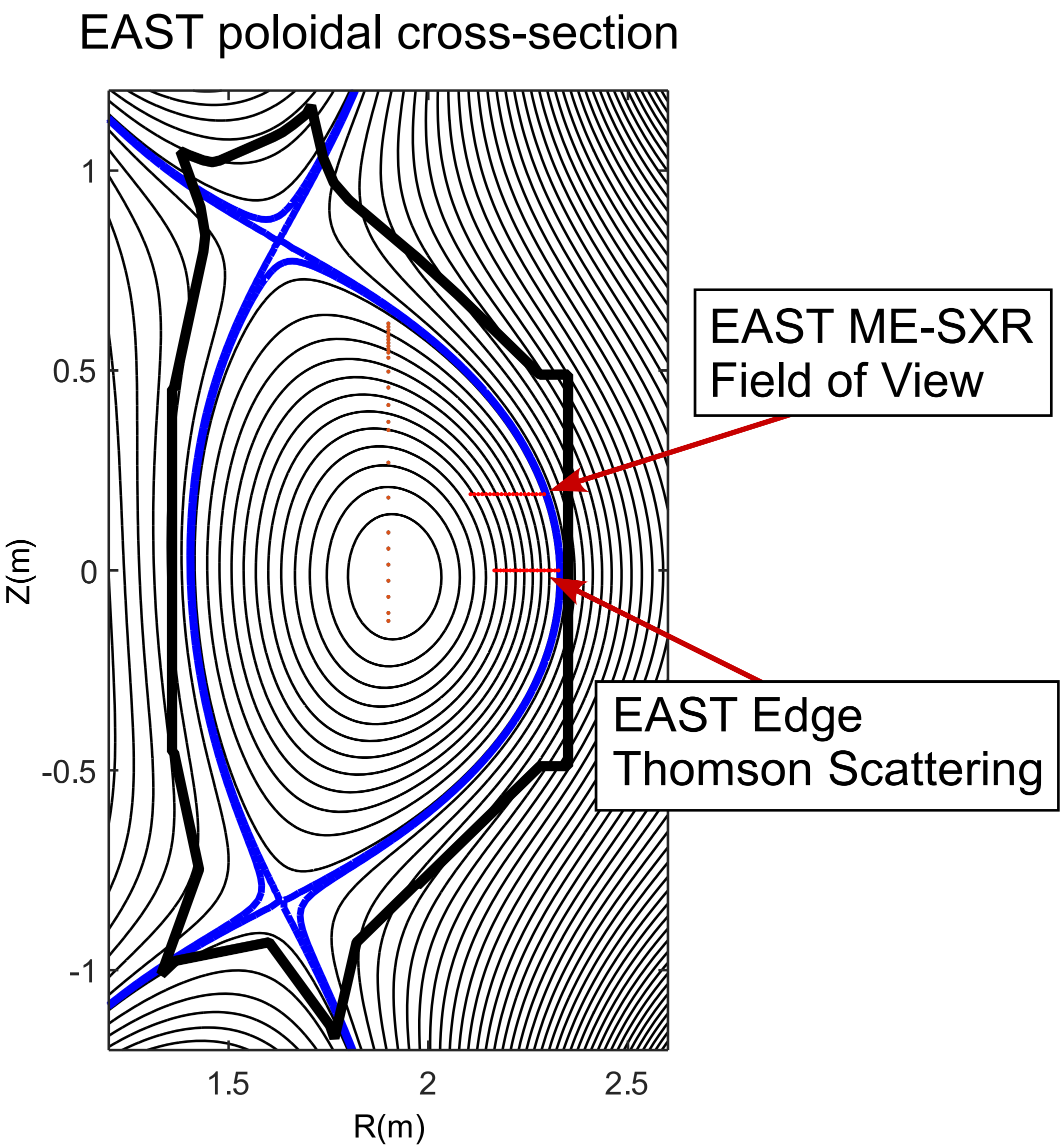


- Average profiles w/ stddev derived using ensemble fits from retraining and initializing NN 100 times with different starting connection weights

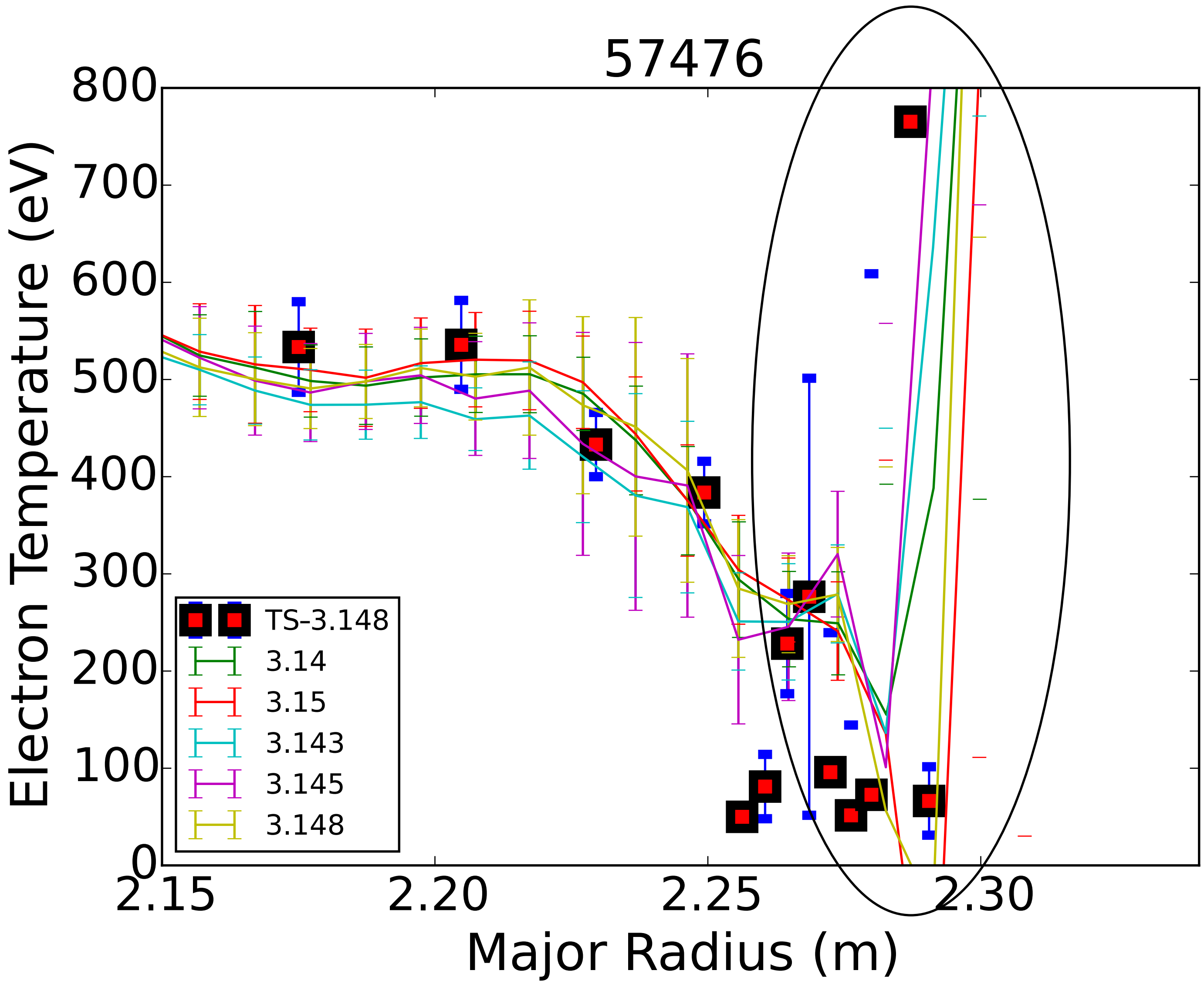
NN reconstruction can accommodate spatial mapping of diagnostic views

- Edge ME-SXR for EAST
  - re-entrant design
  - tangential view off-midplane



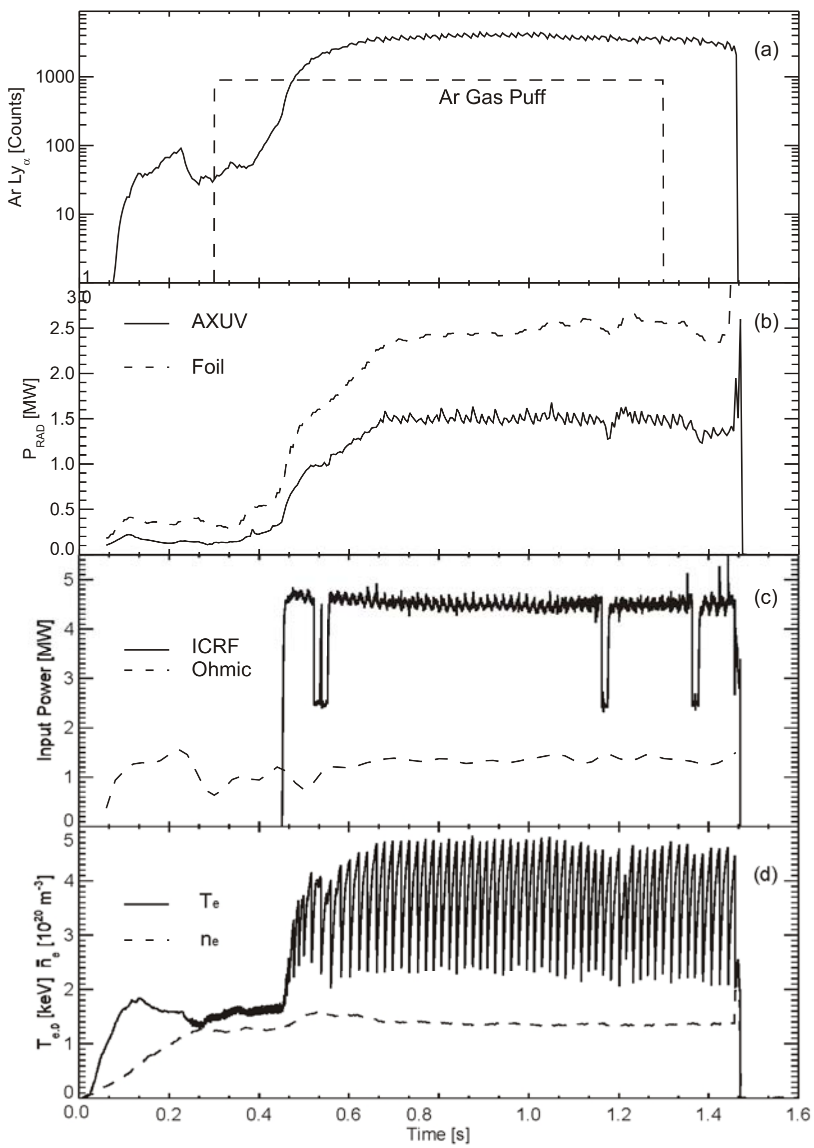


Quality of EAST Neural Network T_e reconstruction constrained by Thomson Scattering uncertainty



Neural Network analysis can be used to analyze other complex relationships: AXUV vs. foil P_{rad}

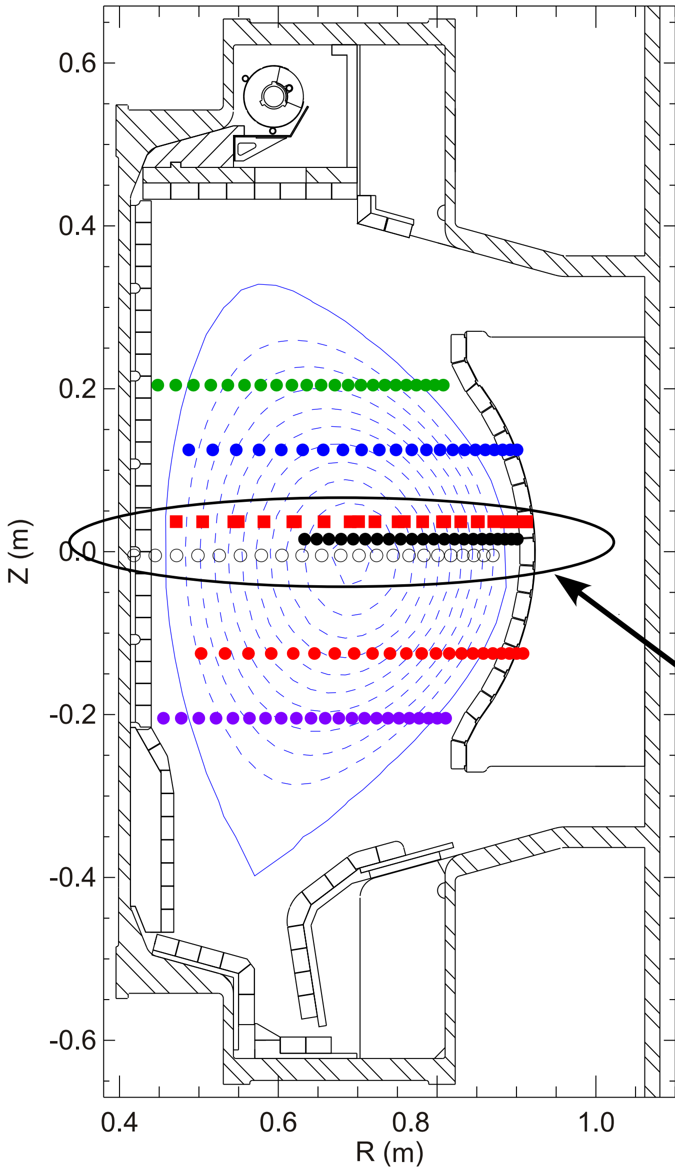
Alcator C-Mod L-mode discharge



- Foil bolometers provide industry standard P_{rad}
  - constant sensitivity over wide energy range
  - expensive, fragile, slow
- AXUV diodes can provide ‘pseudo’ P_{rad} measurements
  - fast time response, inexpensive
  - variable sensitivity at low photon energies: ~ 1-300eV
- AXUV P_{rad} underestimated in plasmas with strong impurity emission at low energy

Data from C-Mod well suited to study relationship between AXUV and foil based P_{rad}

Alcator C-Mod diagnostic layout

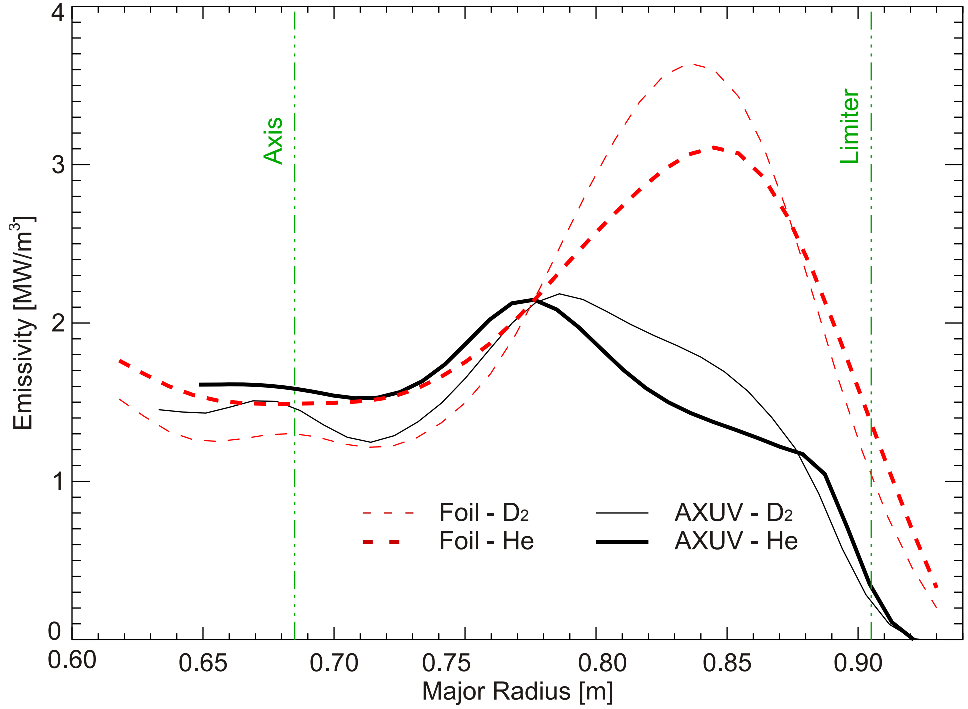


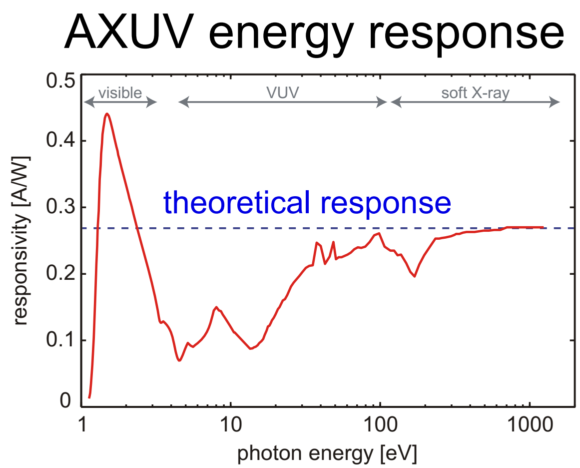
AXUV diode arrays (circles)

Foil bolometer array (squares)

- Midplane AXUV array chosen to reduce mapping uncertanties

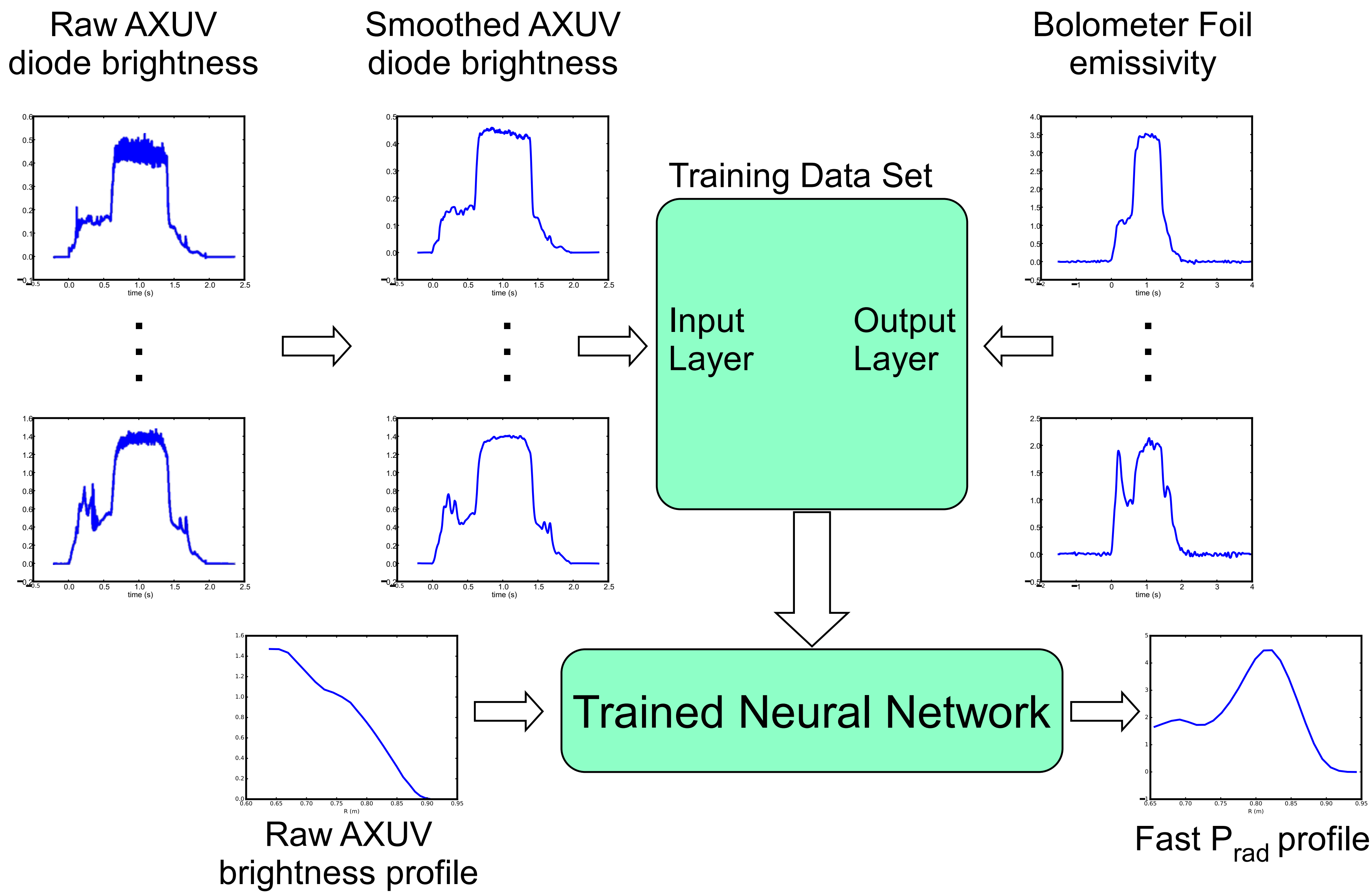
AXUV/Foil P_{rad} discrepancy can vary across plasma radius



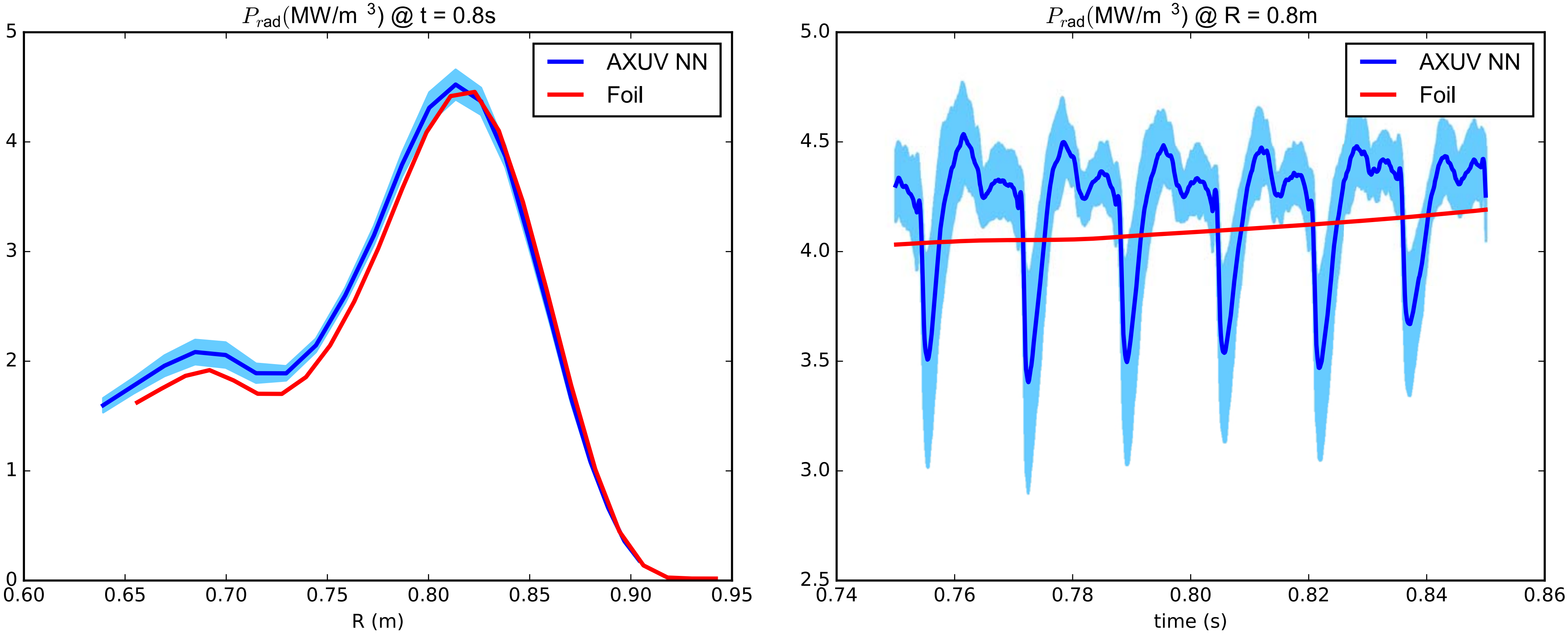


- AXUV P_{rad} underestimated in outer half of plasma minor radius
- Higher core T_e weights emission towards AXUV constant sensitivity energy range

P_{rad} Neural Network trained using smoothed AXUV brightness and Foil emissivity

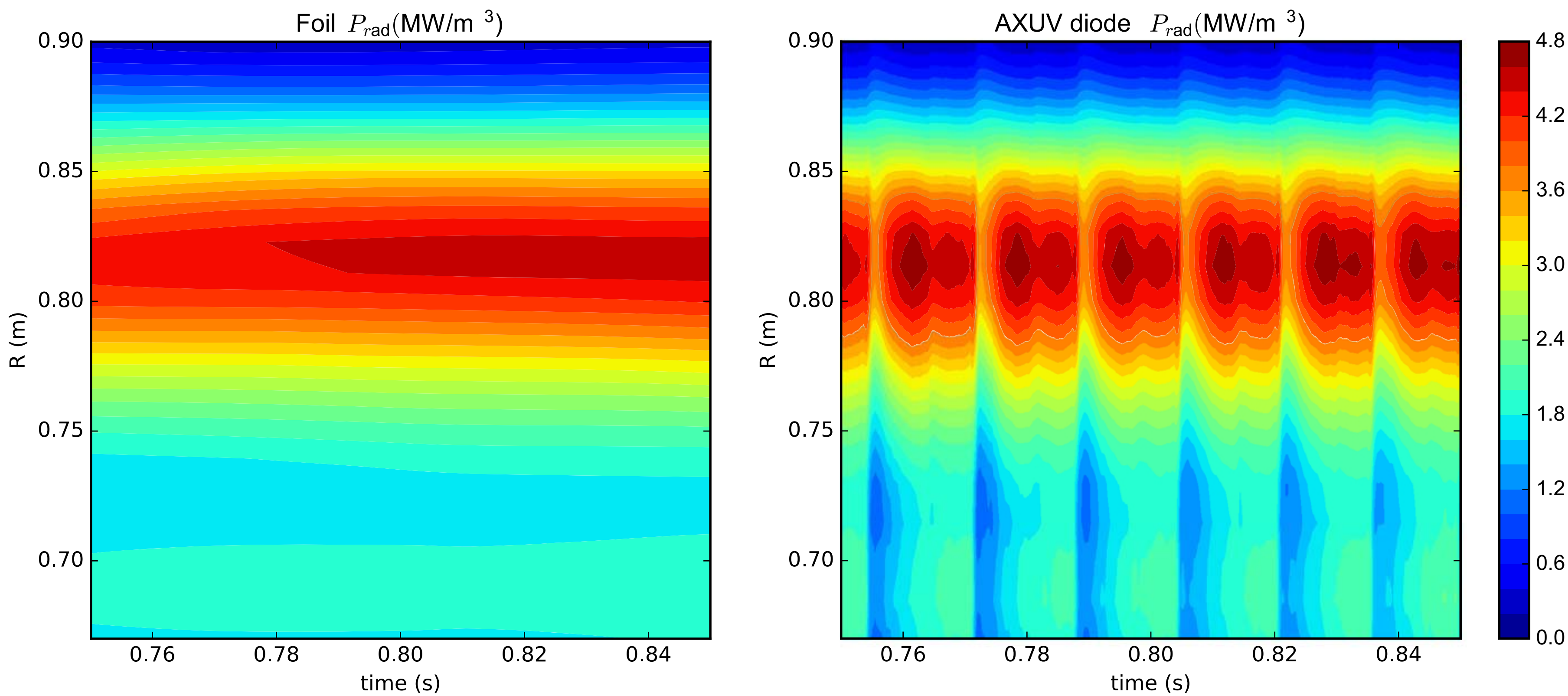


Neural Network can reconstruct high time resolution, accurate P_{rad} using AXUV measurements



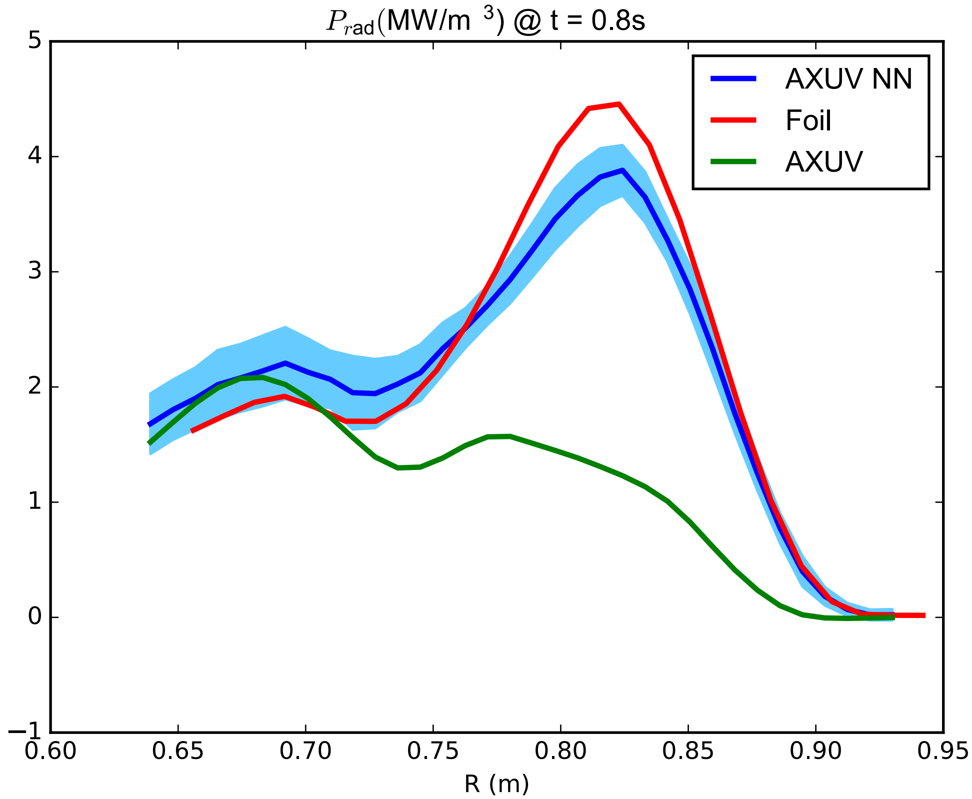
- 'Monte-Carlo' NN statistics provide estimate of error inherent in reconstructions (standard deviation shaded blue)
- Unsmoothed AXUV brightness allows reconstruction of fast P_{rad}
- Example of single-shot NN training (poor extrapolation)

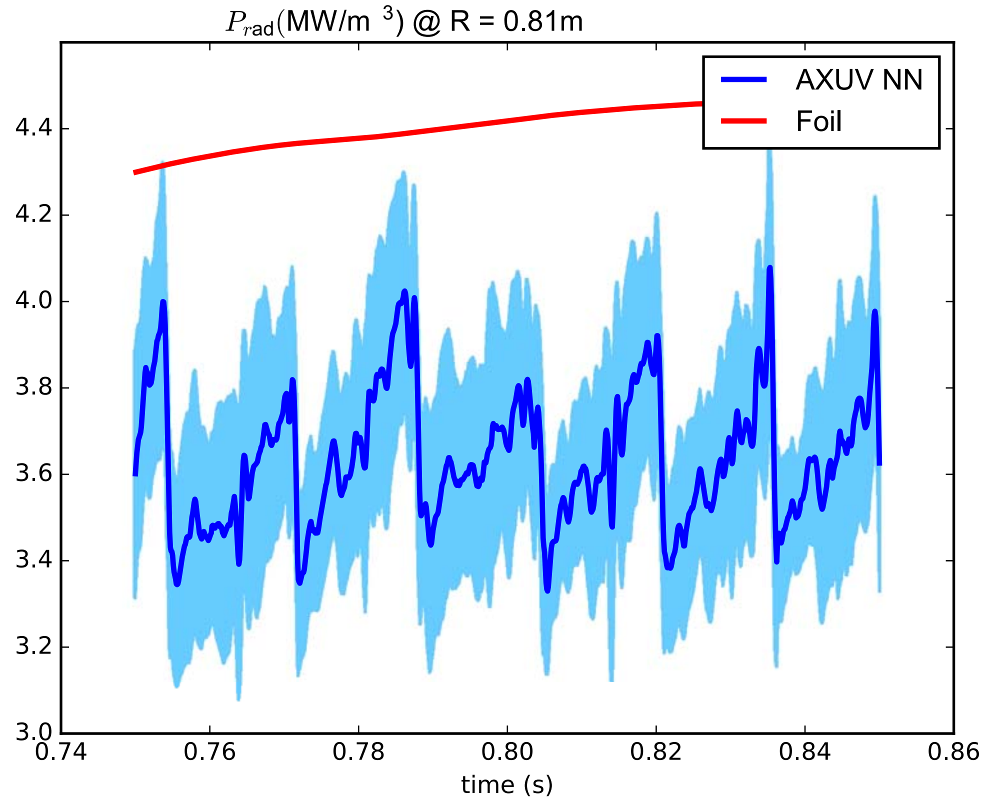
NN reconstructions using AXUV can provide P_{rad} during fast events (sawteeth, ELMs, ...)



- Foil-based P_{rad} integrates over sawtooth cycle
- AXUV P_{rad} shows dynamics of radiated power profile from core to edge

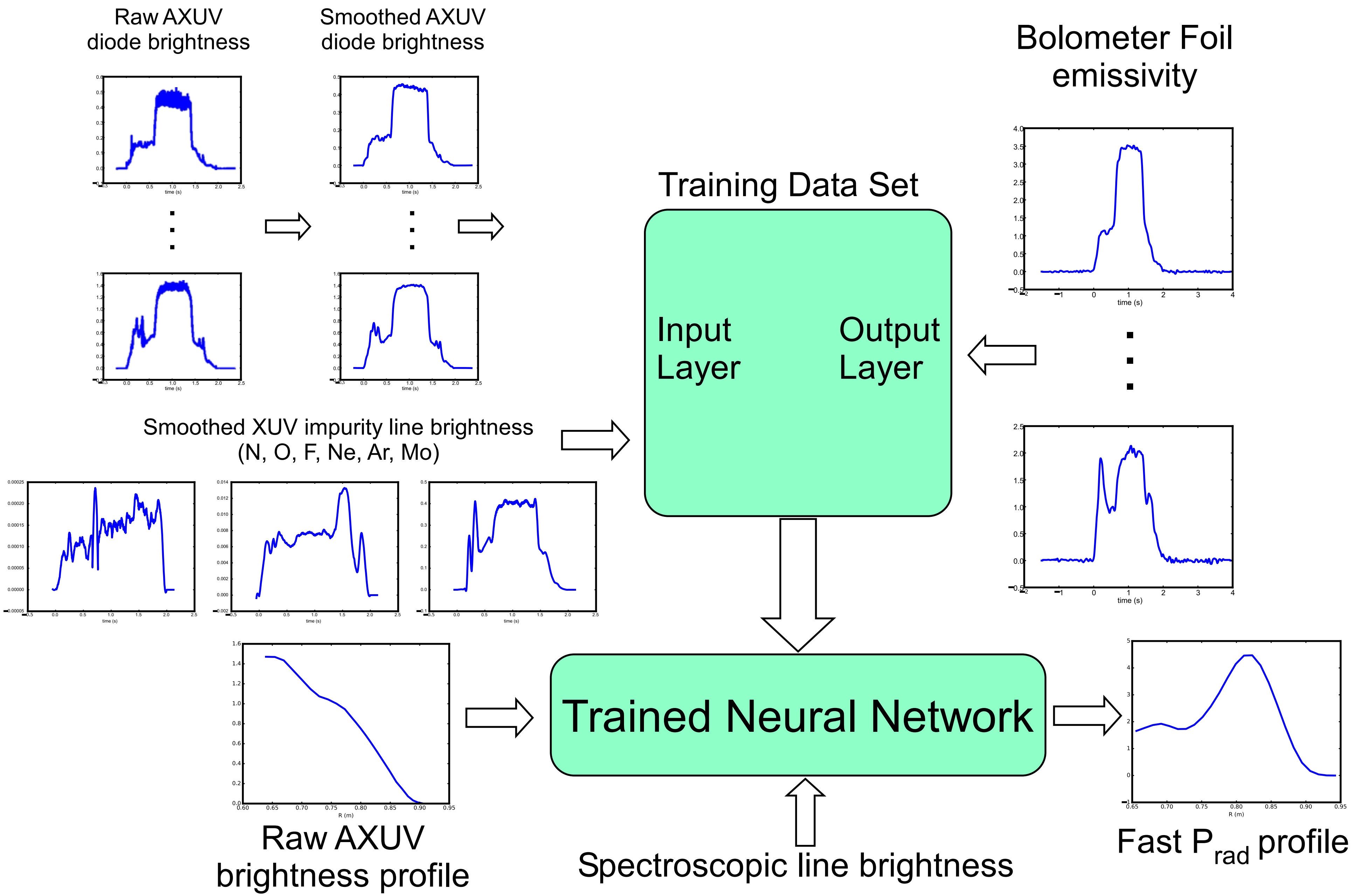
Training with additional shots improves generalization at expense of single-shot accuracy



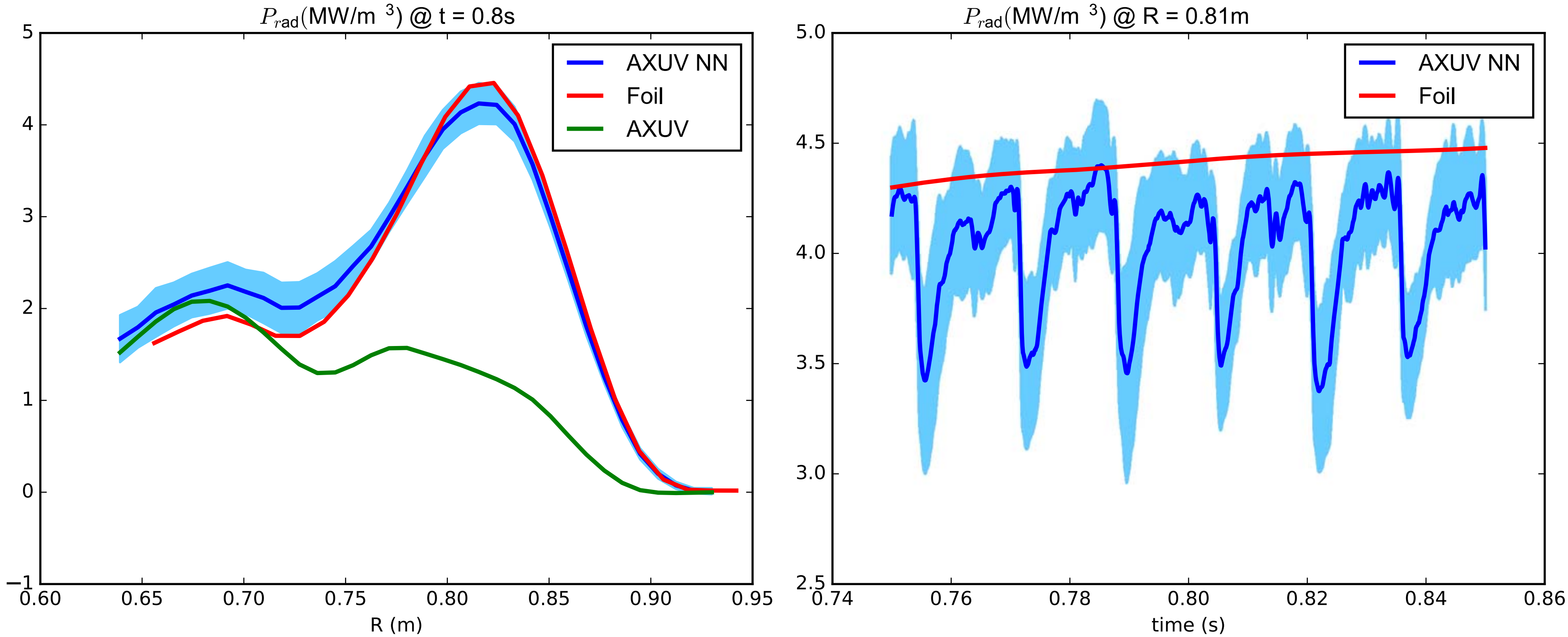


- Trained with 10 shots, varying conditions (H/L-mode, impurities)
  - 500 total time slice training sets
- Neural network reconstruction ~15% below foil P_{rad}
- Improved time-dynamics of sawtooth cycle

Addition of spectroscopic data to Neural Network training can improve reconstruction accuracy



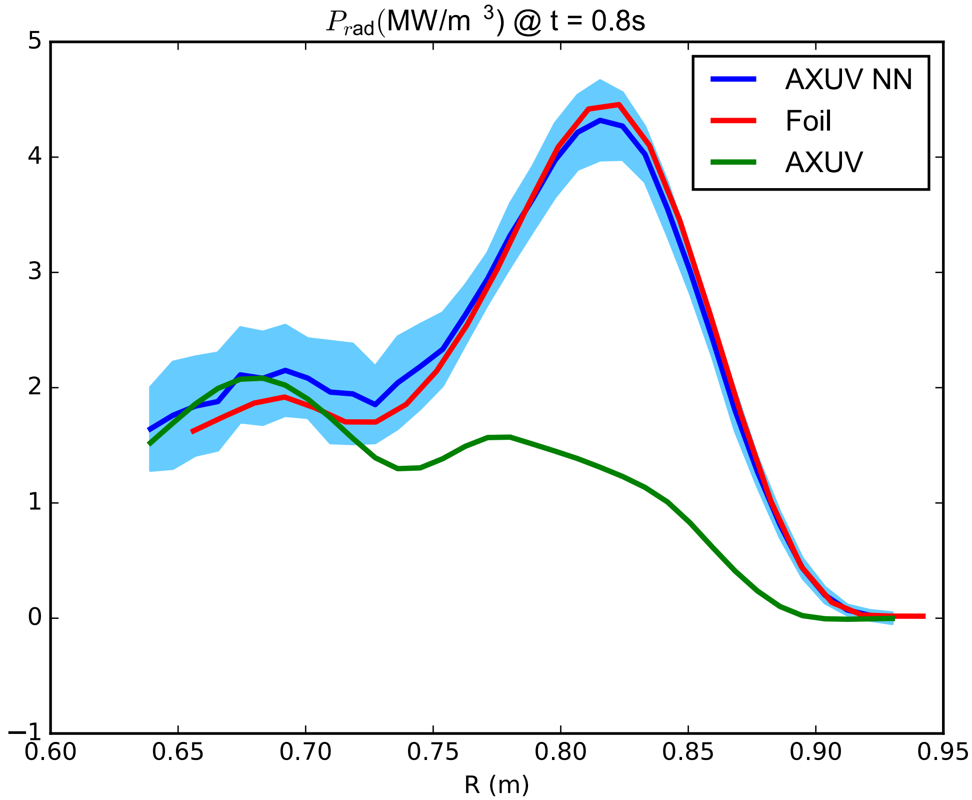
Adding spectroscopy to training set improves both generalization and accuracy

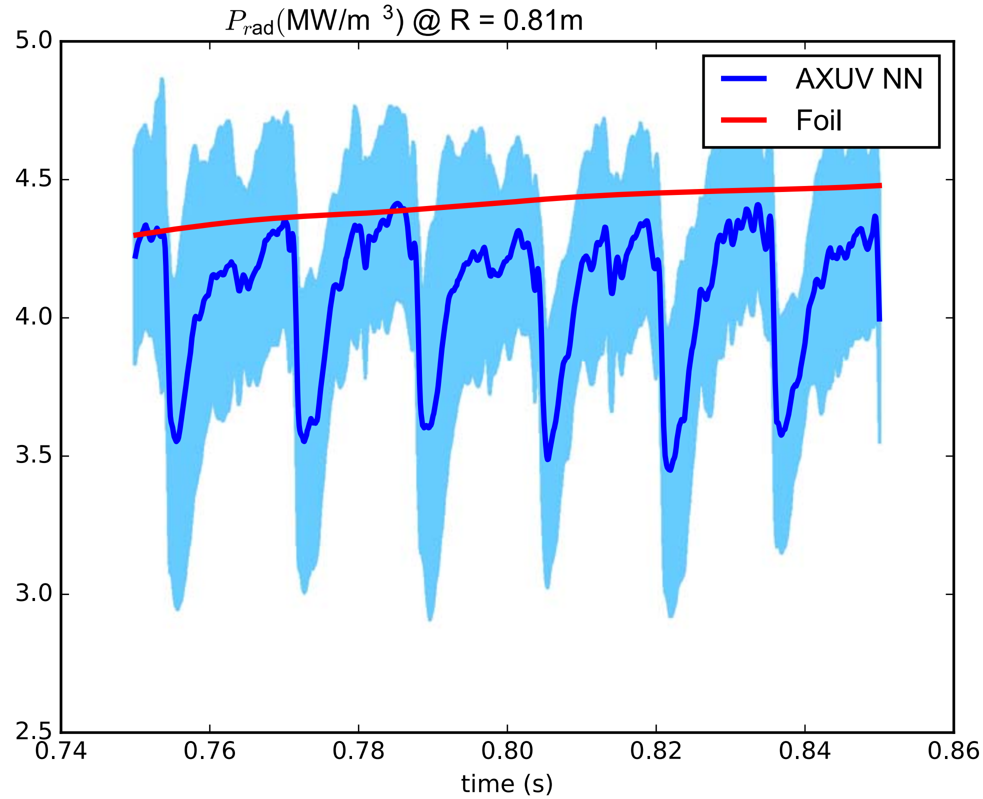


- Uses line-integrated brightness from XUV spectrometer
  - N, O, F, Ne, Ar, Mo

- Spectrometer absolute calibration unnecessary
  - but must have consistency among training shots
  - all training shots from single run campaign

Increasing Neural Network hidden nodes can improve accuracy but with higher reconstruction variability





- Optimal # of hidden nodes can be determined by GCV
- Additional training constraints can further improve accuracy
  - any fast measurement related to P_{rad}
  - visual Brehmmstrahlung, interferometry, ECE, ...

Neural Networks are a useful tool to estimate complex diagnostic relationships

- The ME-SXR array diagnostic coupled with Neural Network analysis provides a robust measurement of $T_e(R,t)$ on fast time scales

- Neural Network analysis can accommodate diagnostic mapping, but relies on reliable input training data

- Foil P_{rad} data can be used to train and reconstruct fast P_{rad} profiles from AXUV measurements, spectroscopy helps!

- Reconstruction from trained Neural Networks is fast enough for real-time feedback control