Algorithm Development for Multi-Energy Soft-X-Ray based T_e Profile Reconstruction

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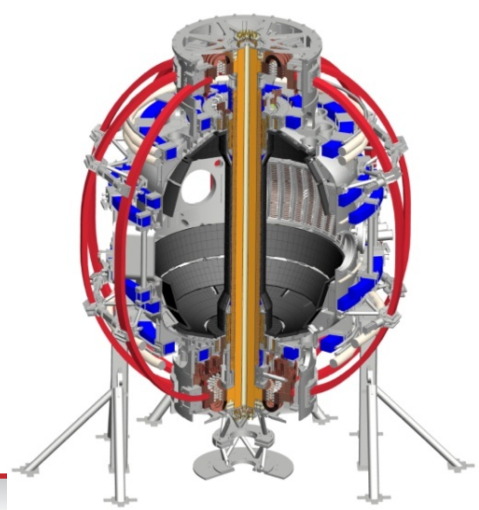

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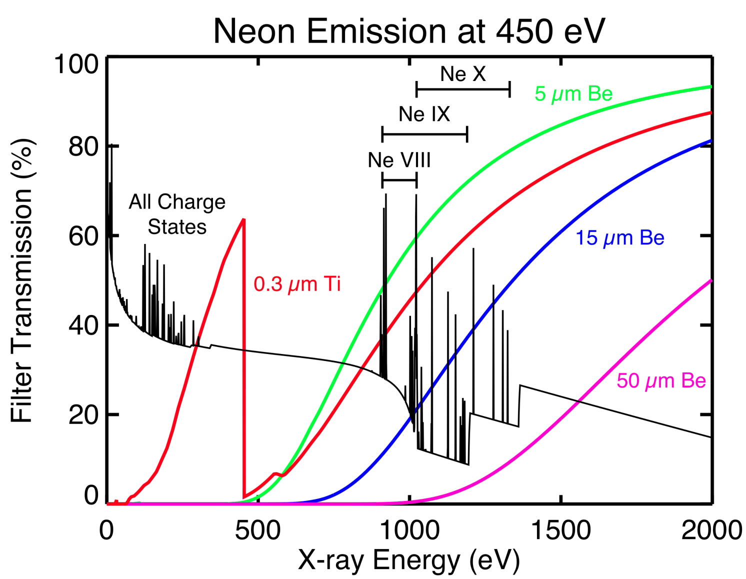
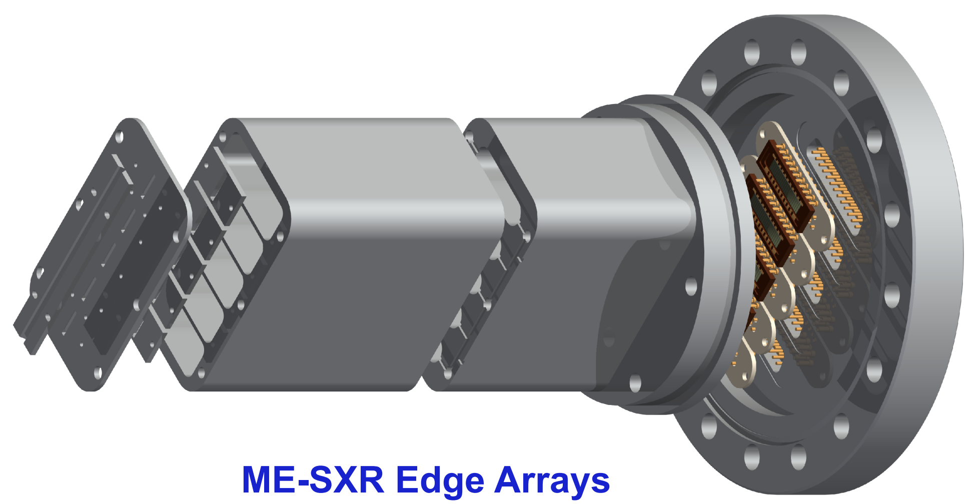
Neural Networks can be Used to Calculate Fast (>10 kHz) T_e Profiles from Multi-Energy SXR Measurements

- Thomson scattering provides 60 Hz T_e measurements
- With proper atomic and impurity transport modeling, multi-energy SXR data has been used to calculate high-resolution (~10 kHz) T_e between Thomson pulses
- Neural networks can calculate T_e without these complex models, and can be used for real-time T_e measurements
- These neural networks have been studied with synthetic x-ray data, and successfully tested with real data

Multi-Energy SXR Arrays Use High Time Resolution Diode Arrays with Different Filters for Coarse Spectral Resolution

- NSTX edge array used 5 diode arrays (0.3 μm Ti, 5, 15, and 50 μm Be, and one without a filter for bolometry)
- 20 spatial channels provided ~1 cm resolution of the plasma edge (R=127-147 cm) with a time resolution >10 kHz
- Digitally-controlled variable gain amplifiers provided excellent signal-to-noise for the low intensities measured in the edge

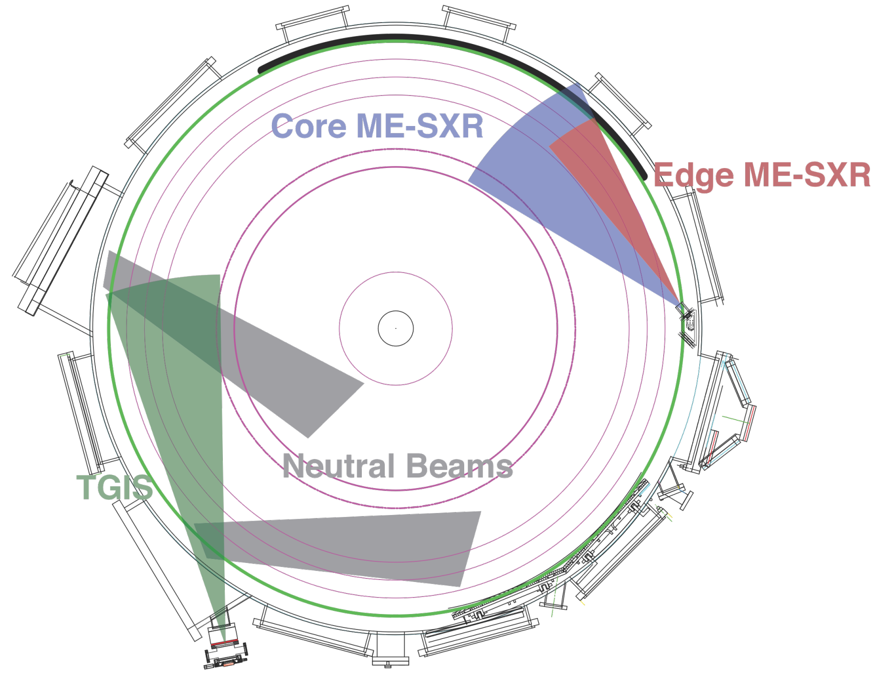


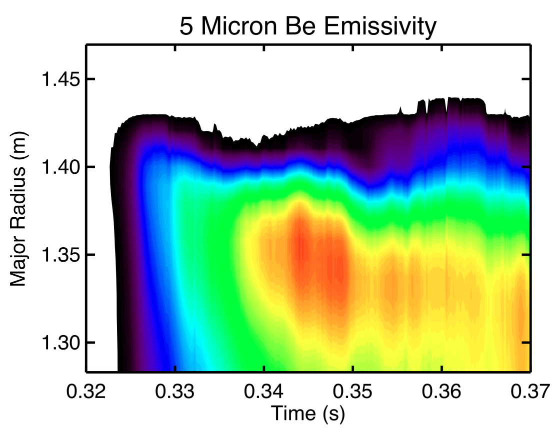


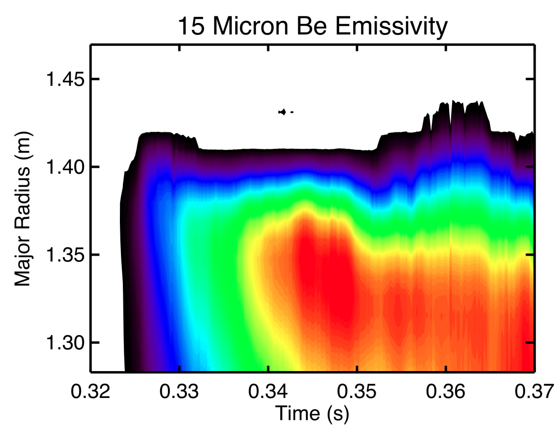
ME-SXR Edge Arrays

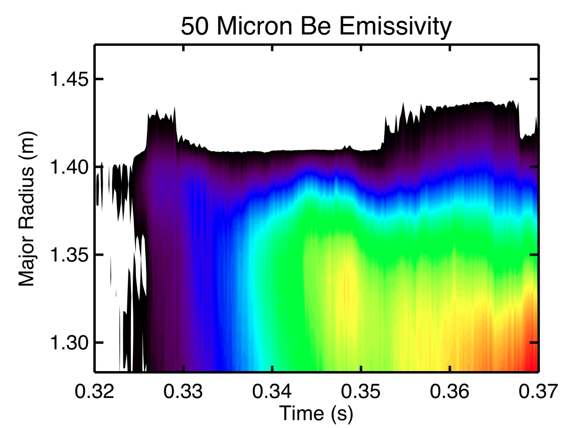
NSTX-U Will Have a New In-vessel ME-SXR Diagnostic with Core and Edge Subarrays

- Core ME-SXR for fast T_e, impurity transport, MHD measurements
- Hi-res edge ME-SXR to study edge phenomena such as ELMs
- TGIS will have same view of the original neutral beam



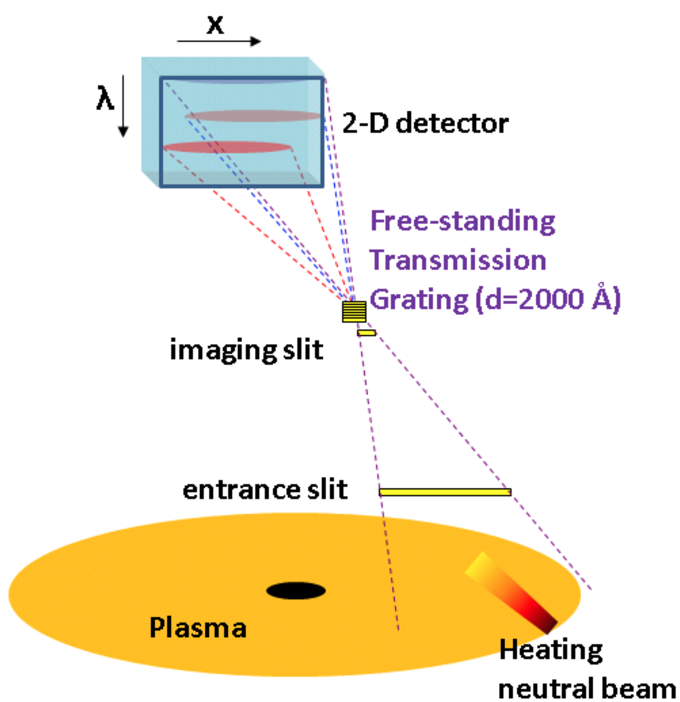


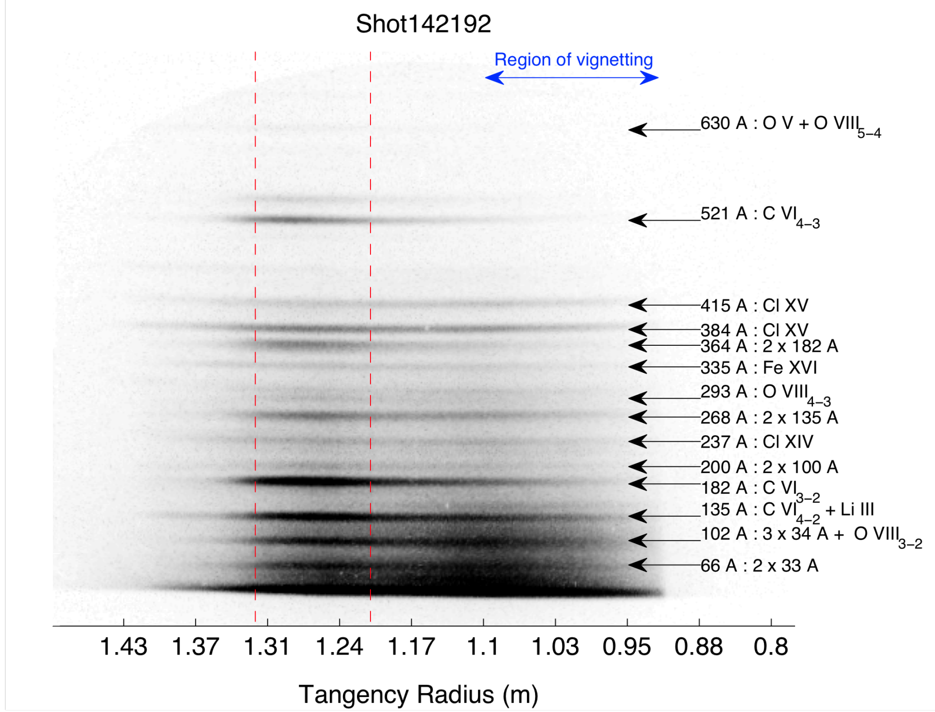




A Transmission Grating based UV Imaging Spectrometer Provides Constraints on Impurity Concentrations

- Radially resolved spectrometer operates in a survey mode covering 30 to 700 Å with spectral resolution $\delta\lambda/\lambda \sim 3\%$.
- Detector time resolution is less than for ME-SXR (400 ms will be upgraded to 10 ms for NSTX-U)





It has Previously been Shown that Electron Temperature can be Found Numerically from ME-SXR Measurements

- Linearization of elements contributing to x-ray emission allows separation of T_e, n_e, and impurity concentrations by using the differences between filtered measurements
- SXR emissivity, E_f, is a function of density and impurity response (a function of T_e) weighted by concentration

$$E_f\left(n_e, T_e, c\right) = n_e^2 \sum_i c_i R_{f,i}$$

- 2nd order expansion adds additional terms, including 'cross-term' dependence on change in temperature and density

$$\Delta E_f = \frac{\partial E_f}{\partial n_e}\Delta n_e + \frac{\partial^2 E_f}{\partial n_e^2}\frac{\Delta n_e^2}{2} + \frac{\partial E_f}{\partial T_e}\Delta T_e + \frac{\partial^2 E_f}{\partial T_e^2}\frac{T_e^2}{2} + \frac{\partial^2 E_f}{\partial n_e \partial T_e}\Delta n_e \Delta T_e$$

Emissivity Calculations Depend on Accurate Modeling of Atomic Processes and Impurity Transport

- Change in relative emissivity depends also on curvature of filtered response function $R_f(T_e)$

$$\frac{\Delta E_f}{E_f} = \boxed{\frac{2\Delta n_e}{n_e}} + \boxed{\frac{\Delta n_e^2}{n_e^2}} + \boxed{\frac{\sum_i c_i R'_{f,i}}{\sum_i c_i R_{f,i}} \Delta T_e} + \boxed{\frac{\sum_i c_i R''_{f,i}}{\sum_i c_i R_{f,i}} \frac{\Delta T_e^2}{2}} + \boxed{\frac{2}{n_e} \frac{\sum_i c_i R'_{f,i}}{\sum_i c_i R_{f,i}} \Delta n_e \Delta T_e}$$

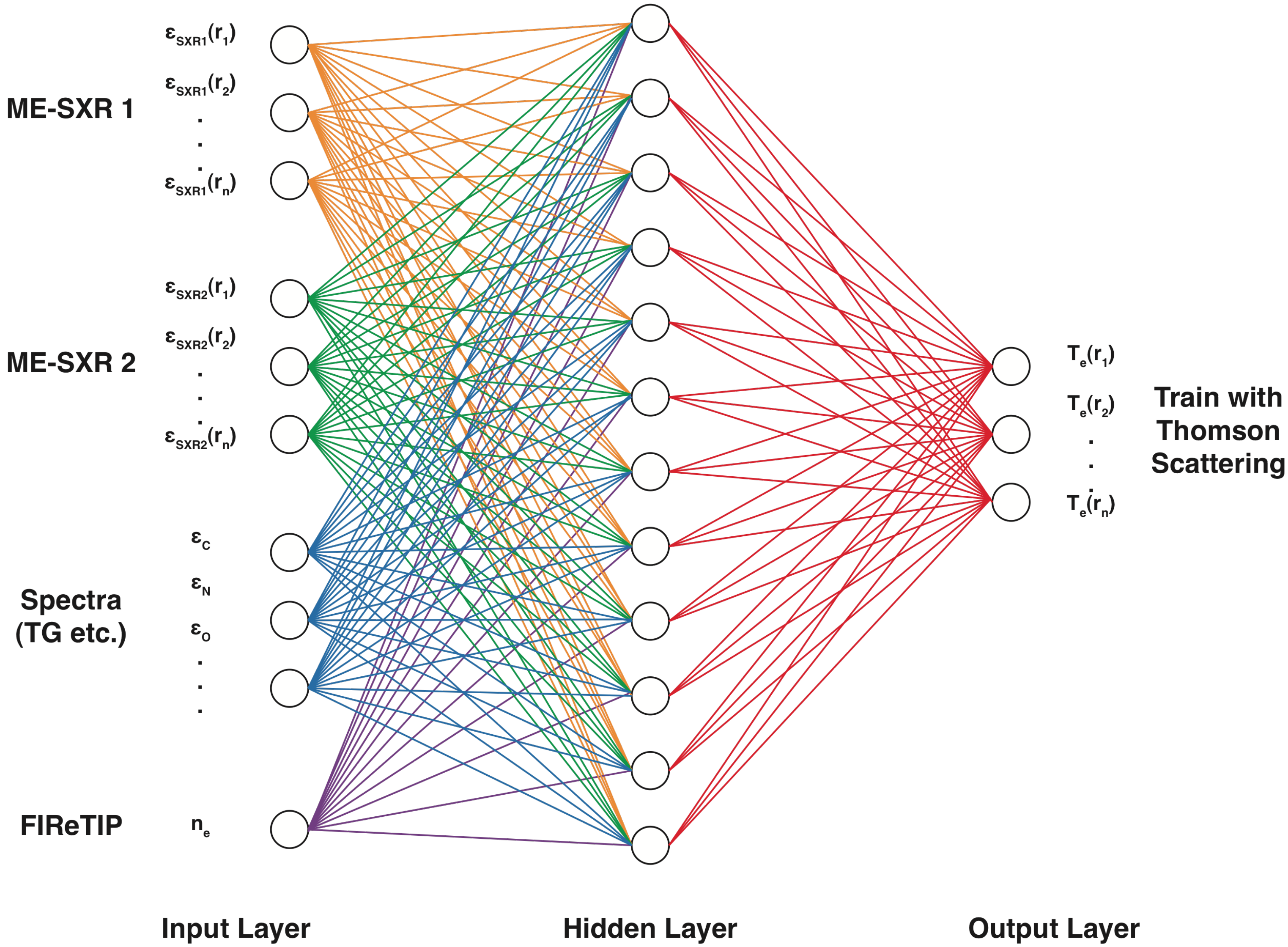
- Difference of relative emissivities removes 1st and 2nd order terms, but leaves dependence on density from 'cross-term,' solve for T_e using quadratic equation

$$\frac{\Delta E_{f1}}{E_{f1}} - \frac{\Delta E_{f2}}{E_{f2}} = \boxed{\left(\frac{\sum_i c_i R'_{f1,i}}{\sum_i c_i R_{f1,i}} - \frac{\sum_i c_i R'_{f2,i}}{\sum_i c_i R_{f2,i}} \right)} \left(1 + \boxed{\frac{2\Delta n_e}{n_e}} \right) \Delta T_e + \boxed{\left(\frac{\sum_i c_i R''_{f1,i}}{\sum_i c_i R_{f1,i}} - \frac{\sum_i c_i R''_{f2,i}}{\sum_i c_i R_{f2,i}} \right) \frac{\Delta T_e^2}{2}}$$

A Simple Feedforward Neural Network Was Tested on Synthetic X-ray Data as an Alternative to Finding T_e

- PyBrain, a modular machine learning library for Python, was utilized to create the neural network
- A three-layer feedforward network was used
  - Input layer with up to 461 nodes (20 for each ME-SXR array, 400 for the TGIS, 1 for FIReTIP)
  - The number of nodes in the hidden layer was optimized
    - Unless otherwise stated, 40 hidden nodes were used
  - Output layer had 20 nodes, for temperature profiles with the same radial resolution as the ME-SXR arrays
  - The layers were fully connected
- The Rprop- learning algorithm [Igel and Hüsken, Neuro-computing 50 (2003) 105-123] is used for supervised training of the neural network
  - All input and outputs are scaled to the range of 0 to 1 for best results

A Fully-Connected Three-Layer Neural Network Inputs X-ray and Spectroscopic Data, Outputs Temperature Profiles

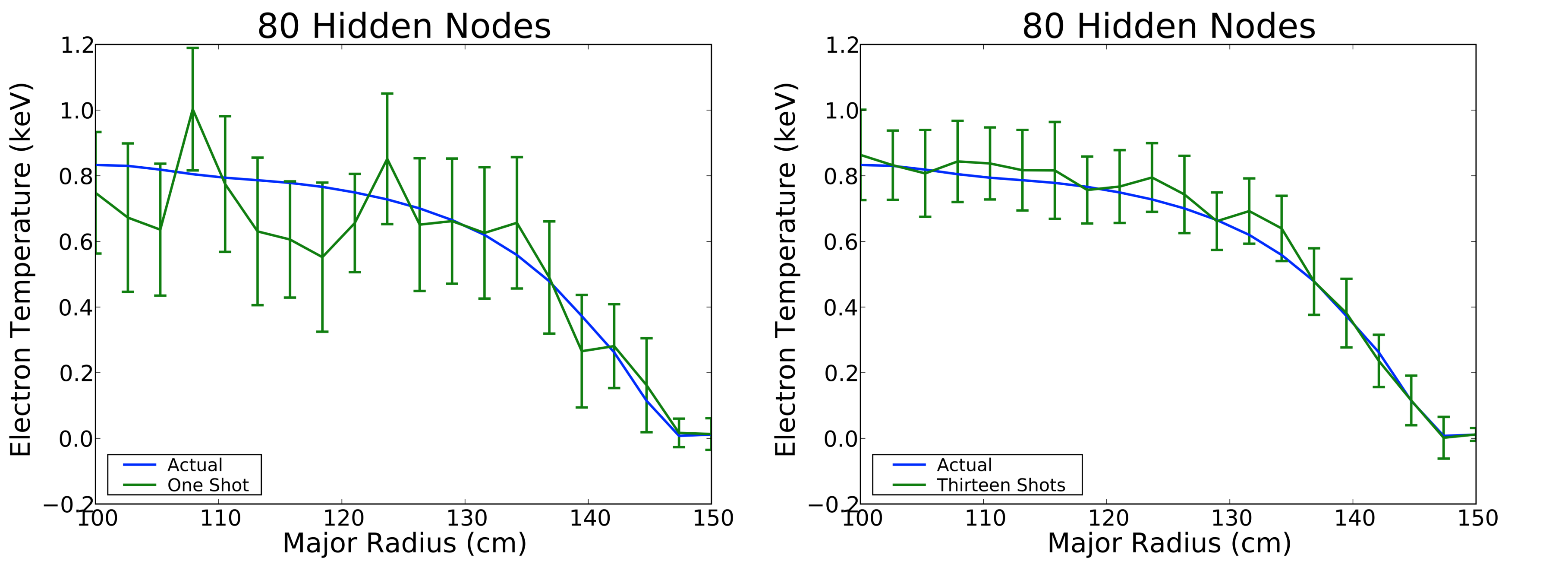


Synthetic X-Ray Data were Generated using Real Thomson Data and Emissivity Coefficients from Atomic Models

- Electron temperature and density were obtained from Thomson scattering, carbon density from CHERS
- Additional impurities were assumed to have the same density profile as carbon (O 20% of C, N 10%, Fe 0.1%)
- Impurities were assumed to be in coronal equilibrium
- CHIANTI atomic database was used to calculate line and continuum emission from each impurity
- Synthetic ME-SXR, TGIS, and FIReTIP diagnostics were used to calculate expected signals
- Gaussian noise was added to each signal
- To account for slow TGIS time response (relative to the ME-SXR), an additional, correlated noise was added to each channel of the diagnostic

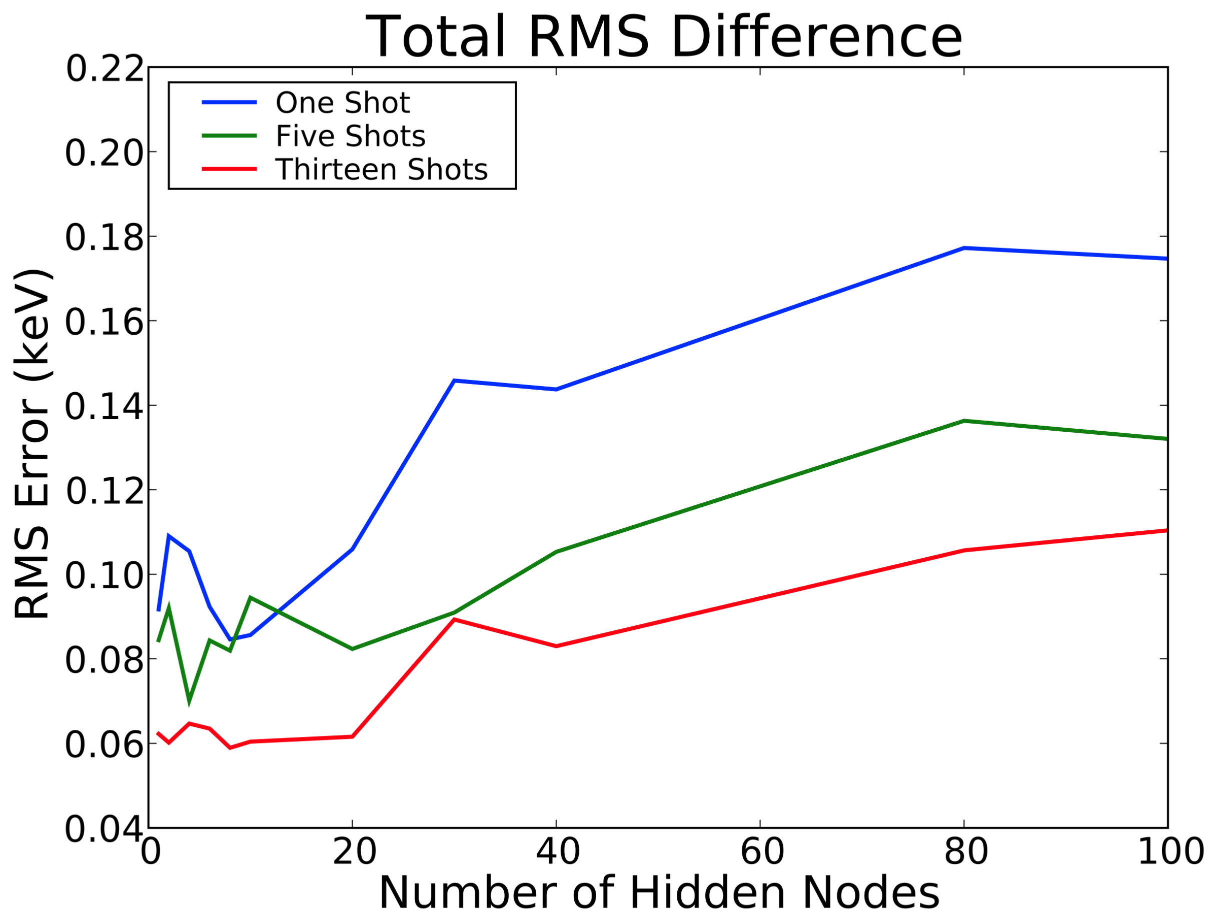
Neural Network Performance Improves as the Training Dataset Grows

- Each discharge provides ~30-50 Thomson measurements for training (only times with peak T_e > 200 eV were used)
- Test case was tried on a NN trained with one shot, then on a NN trained with 13 shots covering B_T and I_P scans
- Error bars represent total RMS error throughout a discharge



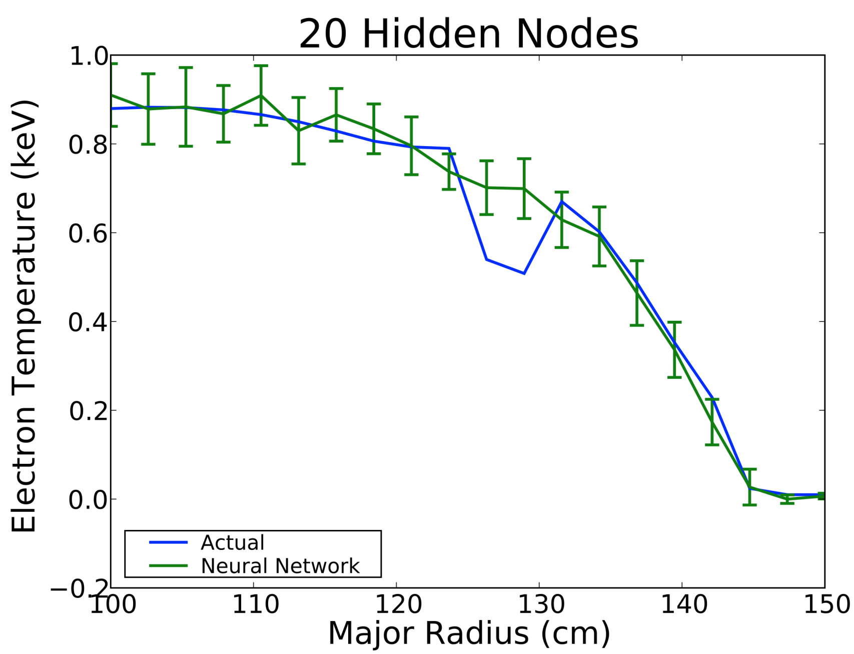
Fewer Hidden Nodes Generated Fits with Smaller RMS Error

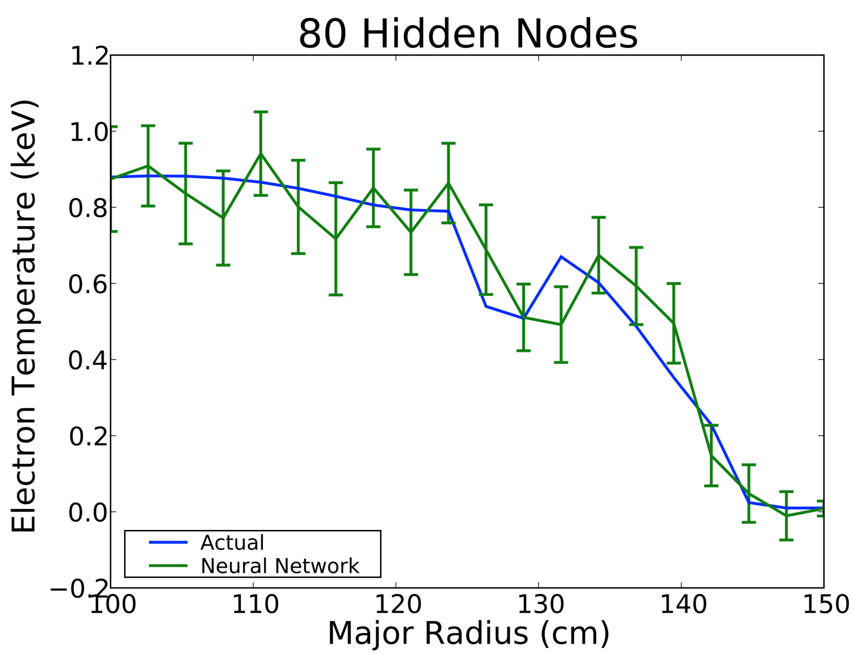
- A large dataset and small number of hidden nodes provides a neural network with the smallest error



Reducing the Number of Hidden Nodes Smooths Out the Temperature Profile, which can Miss Radial Structures

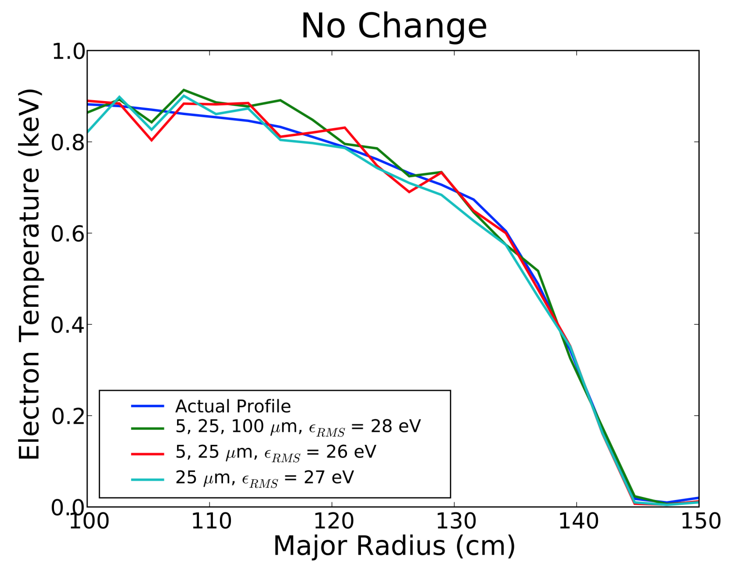
- A narrow band of depressed temperature (a “cold pulse”) was added to the synthetic data
- With 20 Hidden nodes, the total RMS error was small, but the pulse was not picked up
- With 80 hidden nodes, the network recognizes the pulse

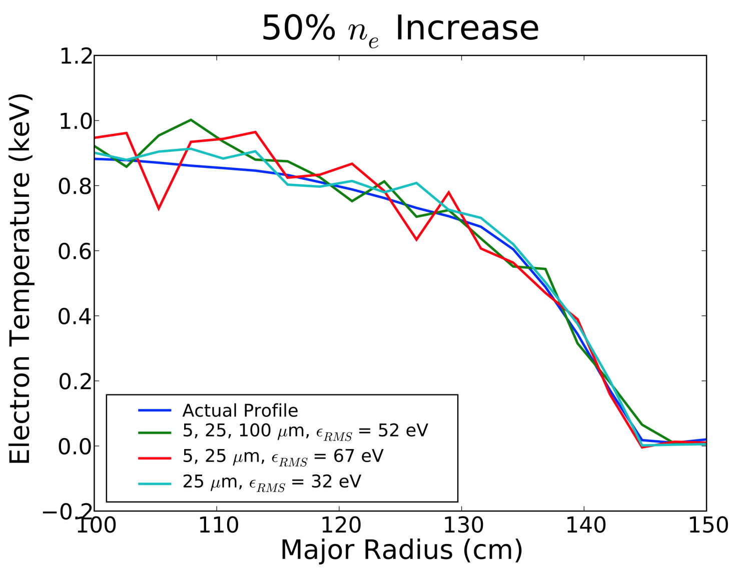


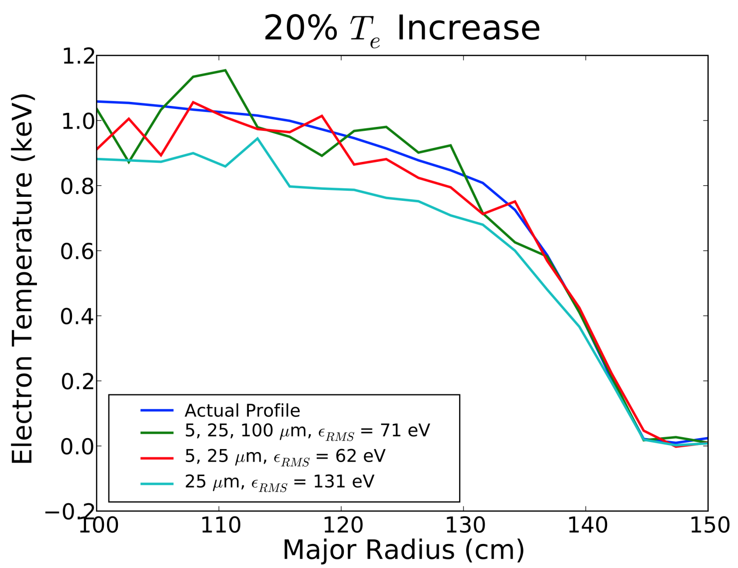


Multiple ME-SXR Arrays are Needed to Distinguish Changing Temperatures from Densities and Impurity Concentrations

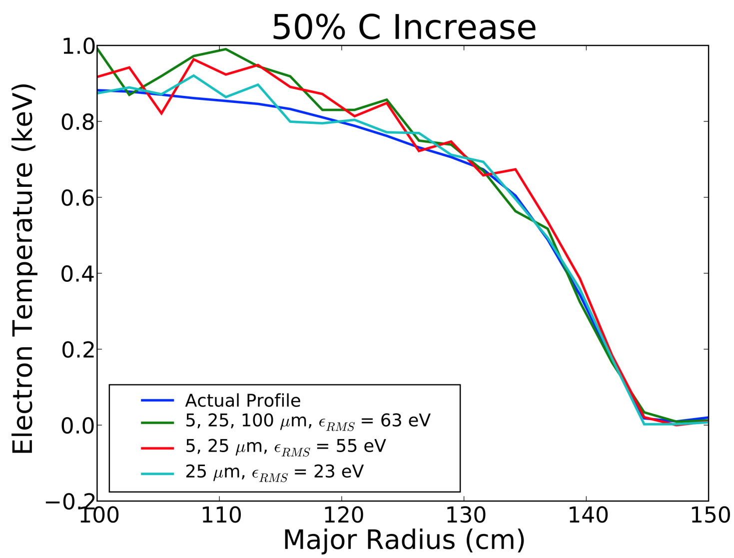
- When trained on one array, network is unresponsive to changes in one parameter
- A third (or more) arrays may be beneficial when several parameters vary independently

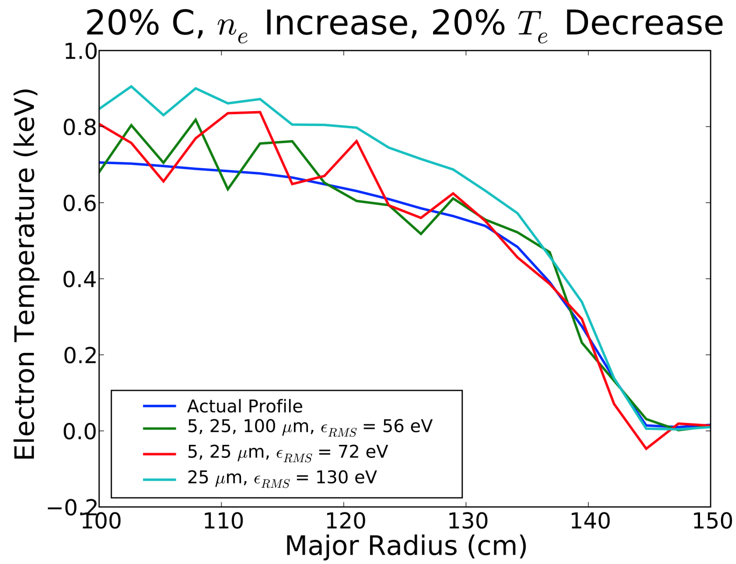


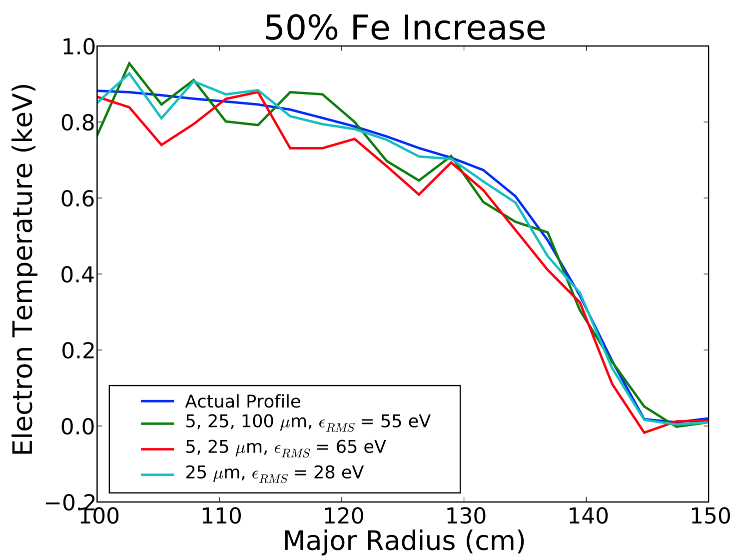


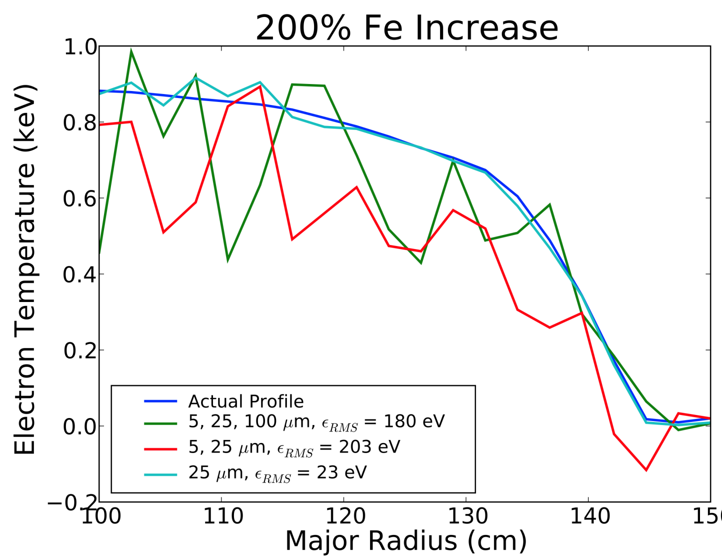


Network Works for Small Changes in Impurity Concentration, but not for Large Influxes that are not Included in Training



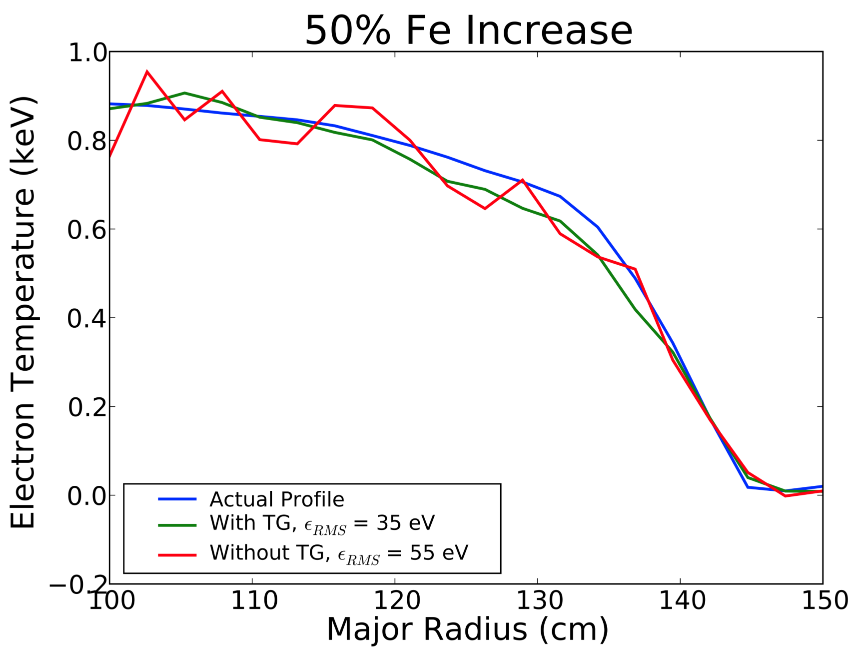


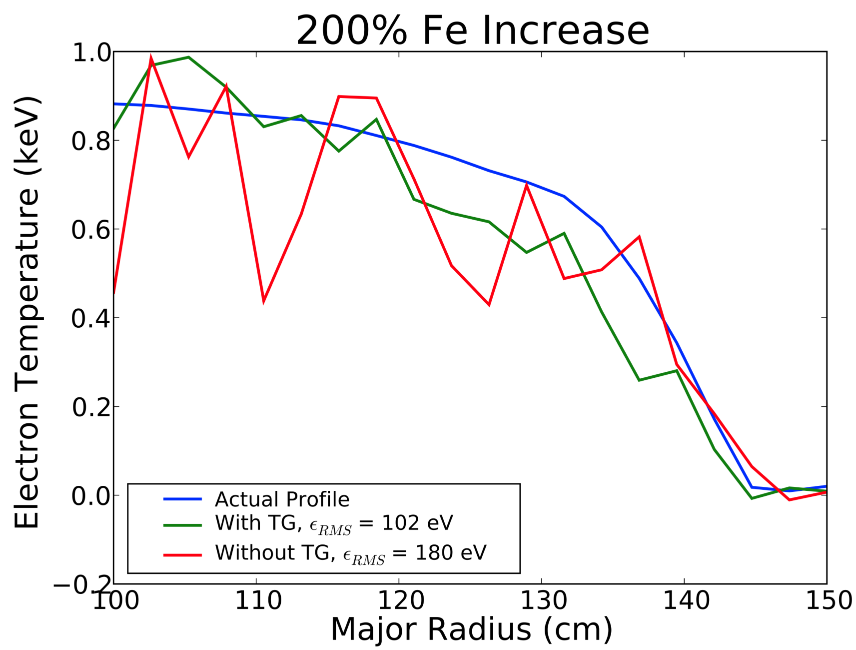




Unexpected Impurity Influx can be Accounted for with TGIS or Other Spectroscopy Data

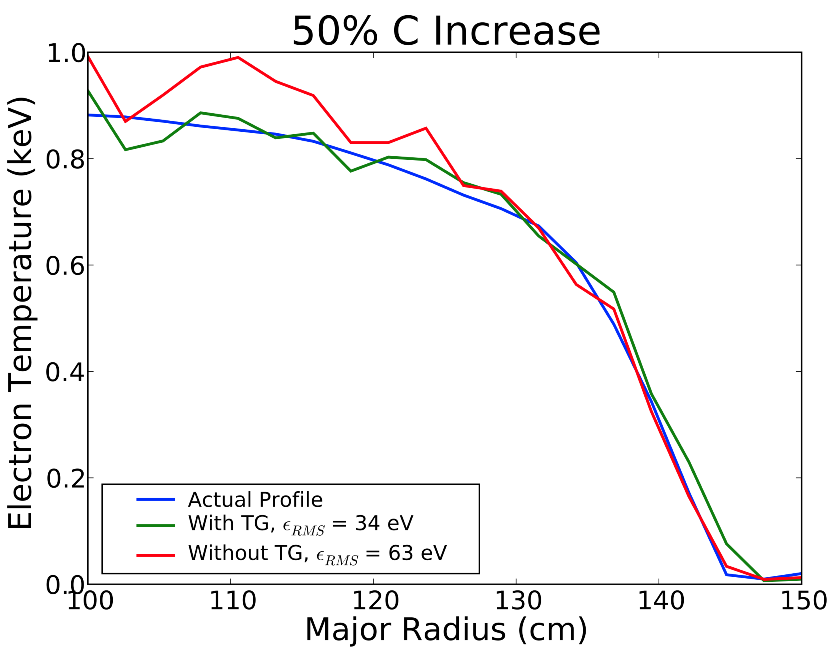
- TGIS data does an excellent job correcting small errors from changes in impurity concentrations, and also does a reasonable job correcting for very large influxes of impurities
- Other spectrometers, while not providing the spatial resolution of the TGIS, might contribute additional constraints, or could possibly be used in real-time

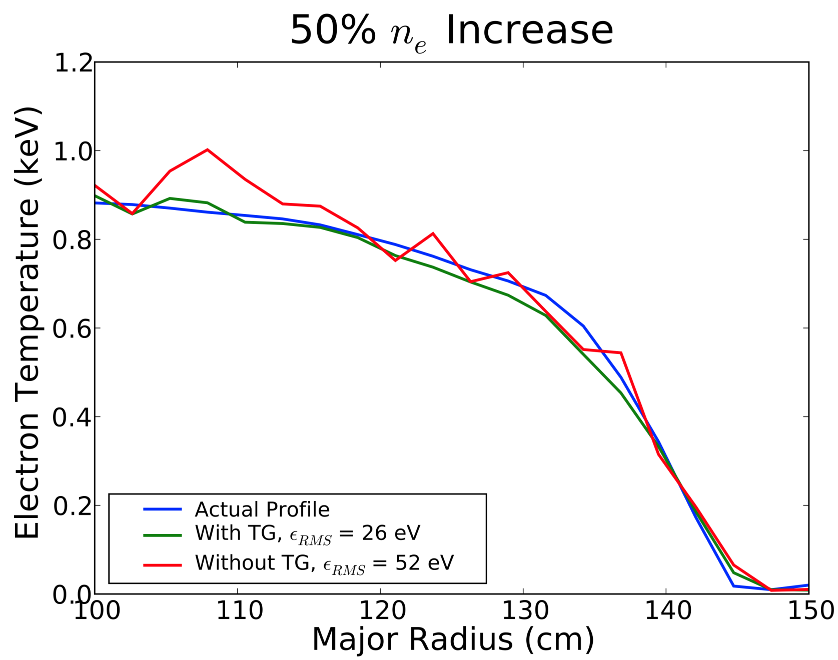




Additionally, the TGIS Improves Neural Network Performance with Density Fluctuations

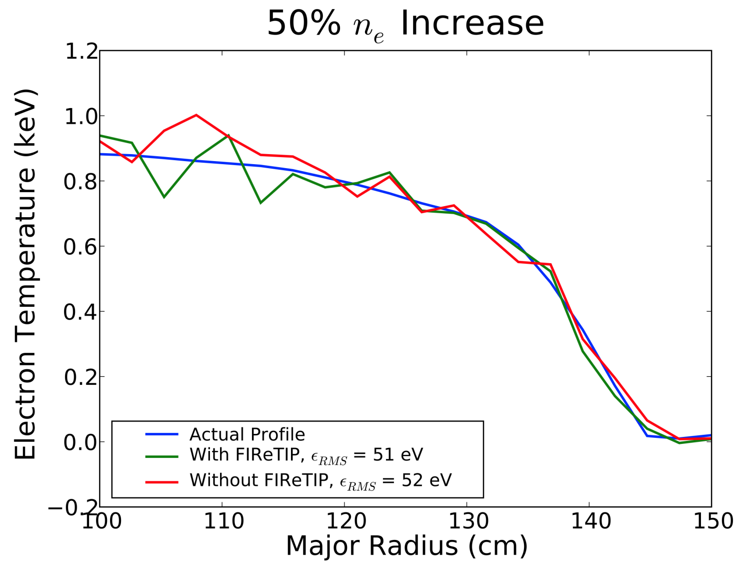
- Emissivity is proportional to the electron density times impurity density, TGIS can help identify which is changing
- With TGIS, the network might be able to determine n_e, Z in addition to T_e (future work)

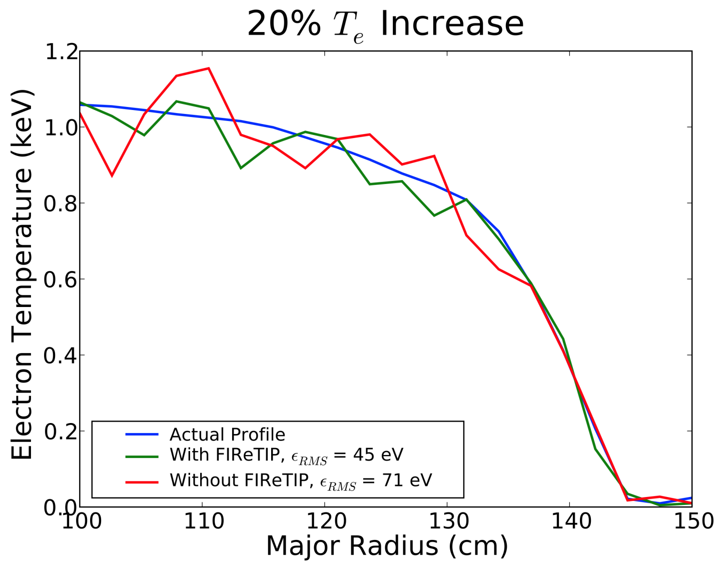


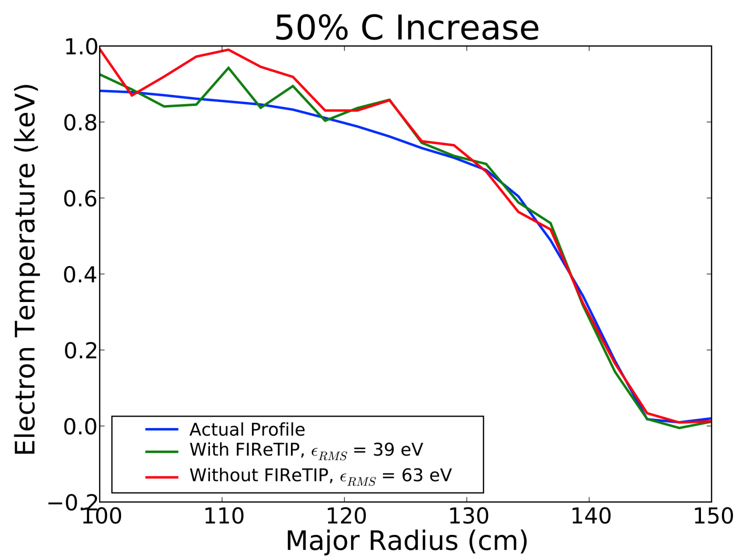


Adding Additional Diagnostics to the Network can Further Enhance Performance

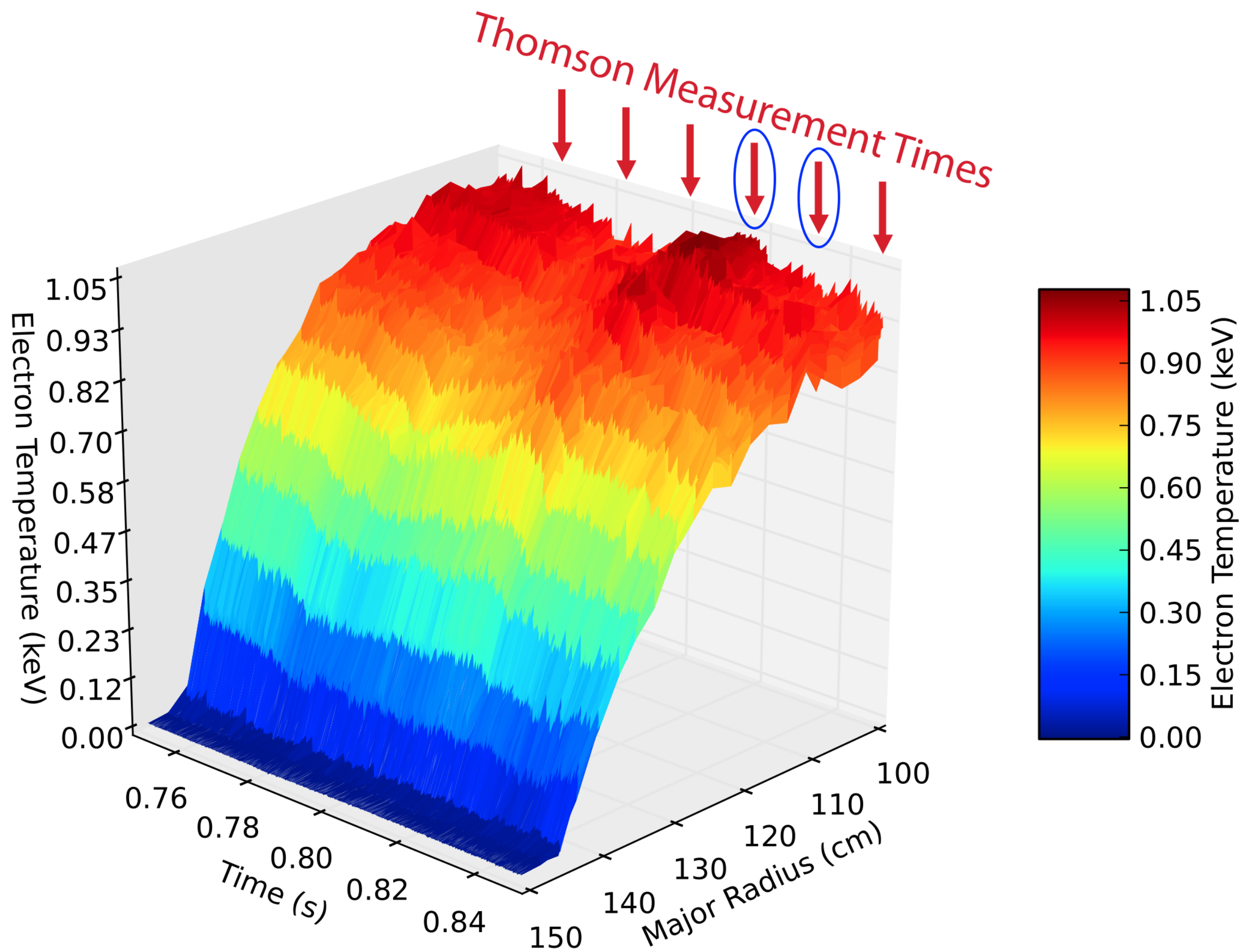
- Adding line-averaged density from the FIReTIP diagnostic improves performance by ~50% in some simulations
- This might be available for a real-time diagnostic



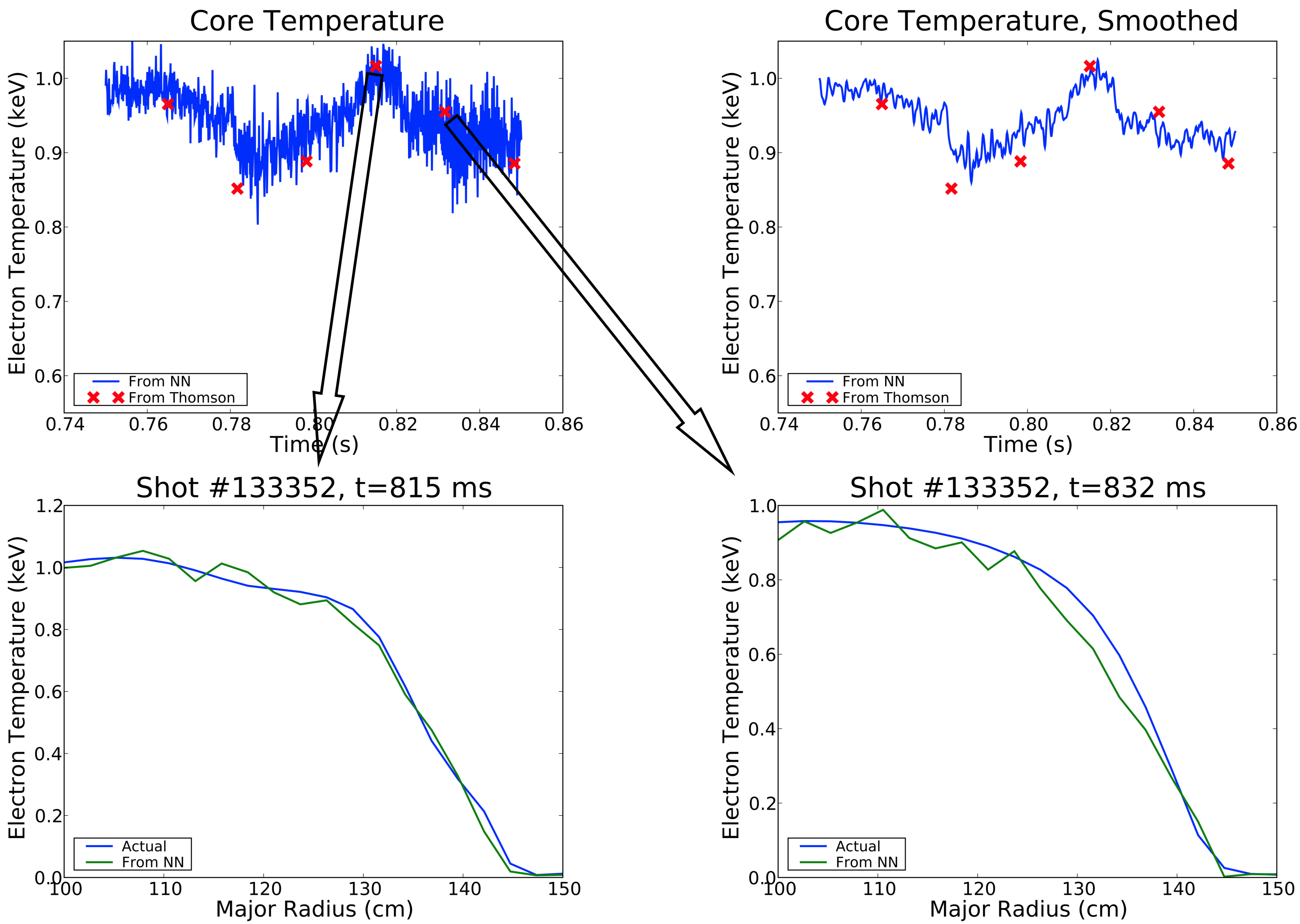




First Test on Experimental Data Used Raw, Uncalibrated Data from Previous-Generation, Three-Array, Optical SXR Array



Trained on 32 Discharges, this Neural Network Produces Fast T_e Profiles in Agreement with Thomson Scattering



Neural Networks have Proven Useful for Fast T_e Measurements and will be Further Investigated and Applied

- It has been demonstrated that neural networks can be used to calculate T_e from ME-SXR measurements
  - Training with larger datasets greatly improves results, and the number hidden nodes must be optimized for the highest accuracy without smoothing over radial features
  - One ME-SXR array is insufficient, though two arrays are adequate
  - Adding additional data to the network, such as TGIS and FIReTIP, further improve the accuracy of the results

- Future studies will include:
  - Tests to see if n_e and Z can also be found with additional arrays
  - Physics studies using real data