# Real-time machine learning modeling of pressure and density profiles on NSTX

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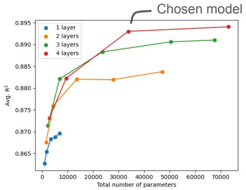
## Motivation & overview

- Control systems for fusion reactors would greatly benefit from real-time density and pressure profile data (i.e. cross-sections of plasma) during operation.
- Existing code (e.g. TRANSP) can produce these profiles but is far too slow to be run in real time.
- We offer a much faster alternative by using neural networks to produce NSTX profiles in real time.

## Inputs, outputs, and model topology

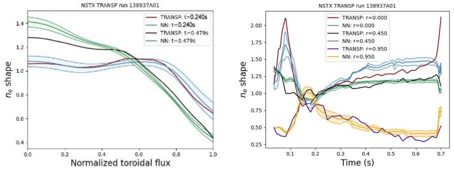
| Inputs | | Outputs | |
|---|---|---|---|
| Symbol | Name | Symbol | Name |
| $R_0$ | Major radius | $n_e$ | Electron density profile |
| $a$ | Minor radius | $n_eT_e$ | Electron pressure profile |
| $B_{\phi,v}R$ | Vacuum toroidal field | | |
| $\kappa$ | Elongation | | |
| $I_p$ | Plasma current | | |
| $\delta_u$ | Upper triangularity | | |
| $\delta_l$ | Lower triangularity | | |
| $\langle n_e \rangle$ | Volume average electron density | | |
| $\langle n_eT_e \rangle$ | Volume average electron pressure | | |




- $R^2$ used to measure model accuracy.
- Architecture: 4 hidden layers of 100 nodes each.

## Dataset

- 1837 NSTX shots, with a total of ~995,000 time slices.
- Per time slice: 9 scalars and 2 post processed profiles (with 20 points each).
- Inputs scaled to mean 0, variance 1 before training/testing.




Examples of a radial profile at a single time (left) and three fixed radial points tracked through time (right). Colored areas are neural net prediction ± one standard deviation. This shot had an average $R^2$ of 0.87, indicating relatively good agreement across both profiles.

## Previous work (NSTX-U)

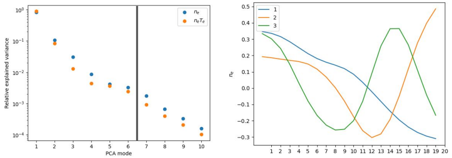
- Approach was first applied to NSTX-U data by M. Boyer with promising results.
- Goal of this research: further validate the approach on NSTX. NSTX has a much larger dataset with a wider range of experimental conditions.

## Data preprocessing

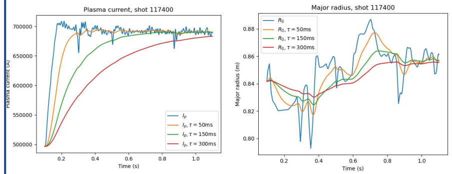
- Principal component analysis used to reduce dimensionality of profile data. Neural net output is the weight of each PCA mode that was kept.
- Added low-pass filtered versions of scalar inputs to incorporate time history.
- Filter described by

$$x_{n+1} = \frac{u_n - x_n}{\tau}(t_{n+1} - t_n)$$

where $x$ are filtered values, $u$ is real value and $\tau$ is the time constant of the filter.



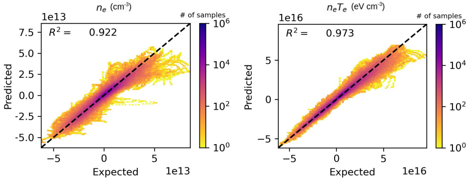

Left: relative variance in profiles explained by each PCA mode. The first 6 were kept, explaining 99.7% of the variance in profiles. Right: the first 3 density PCA modes, explaining 98% of variance.



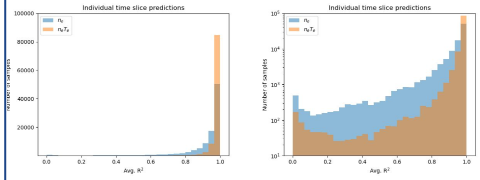

Two examples of low-pass filtered scalar inputs with a set of time constants.

## Results

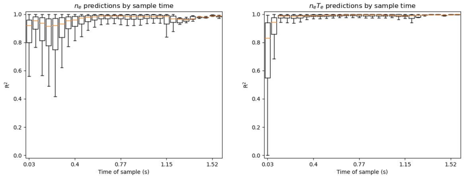
- Results are very promising overall. Data seems well suited to prediction by neural networks.
- Pressure appears easier to predict than density.
- Most poor predictions are concentrated at the start of shots.




Comparison between actual and predicted values for each radial point of each time slice in the testing dataset (note the log scale).



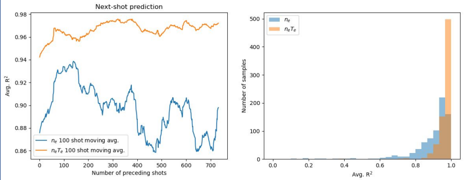

Distribution of $R^2$ values for each time slice on linear scale (left) and logarithmic scale (right). Need to investigate source of very low ($R^2 < 0.2$) predictions.




Distribution of $R^2$ values for different times across all samples. Clearly, the net struggles most with very early times, especially for pressure (right).

## Example: next-shot prediction

- In an actual application, we will only have data from the shots that have already been run at the time.
- More realistic test: predict each shot by only looking at previous data.
- Results: Good overall. Predictions are accurate even with small training datasets. Still some low-$R^2$ outliers.




$R^2$ results for predicting each shot based only on available data at the time. Pressure is generally very well predicted. Drops in density prediction may be due to changing reactor conditions or changing experimental goals.

## Conclusions

- Overall, a neural network can reliably reproduce TRANSP profile predictions with high accuracy.
- Approach was effective on both NSTX and NSTX-U, showing promise for use in other reactors as well.
- Most poor predictions are at early times in the shots.
- Model can predict shots outside of training space reasonably well.

## Future work

- Improve estimation of volume-averaged density and pressure, potentially with a second neural network.
- Determine necessary steps to improve density prediction (potentially need new input quantities).
- Improve measures of model uncertainty (Monte Carlo dropout, training parameter space analysis, etc.)
- Apply technique to other fusion reactors (e.g. DIII-D).

This work was made possible by funding from the Department of Energy for the Summer Undergraduate Laboratory Internship (SULI) program. This work is supported by the US DOE Contract No. DE-AC02-09CH11466.