Neural-network models for pedestal & transport, and their possible inclusion in TRANSP

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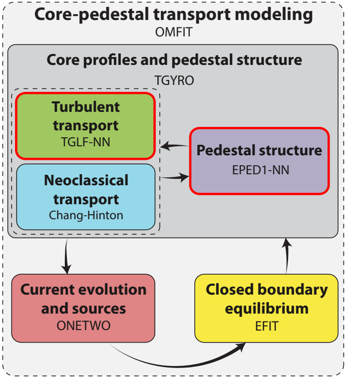

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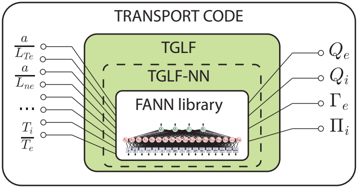
Princeton NJ

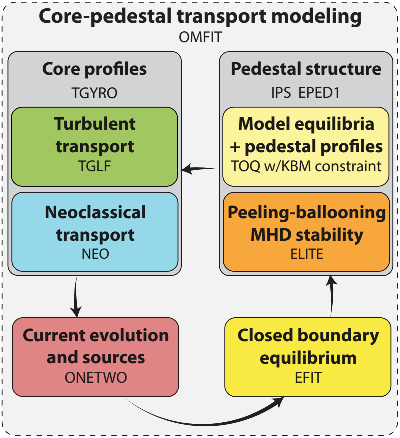
4-5 May 2017



GENERAL ATOMICS

DIII-D NATIONAL FUSION FACILITY

First principles iterative workflow robustly finds the self-consistent steady-state coupled solution



Iterate to convergence:

- **EPED1** provides pedestal boundary condition
  - Find highest pedestal based on PB and KBM stability conditions
- **TGYRO** is a flux-driven transport code
  - Given geometry, sources and sinks efficiently finds stationary profiles solution for density, temperature and momentum

Computationally expensive:

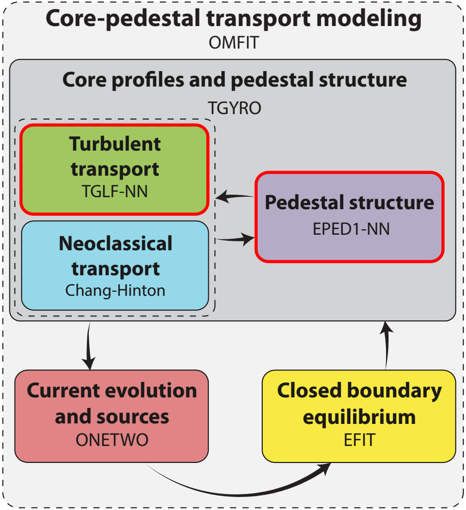
- Requires access to HPC and takes of order 1 day per simulation!

Neural network models accelerate the most time consuming aspects of core-pedestal simulation

Iterations nesting:

1. tight coupling in **TGYRO**: flux matching & pedestal
2. loose coupling in **OMFIT**: sources & equilibrium

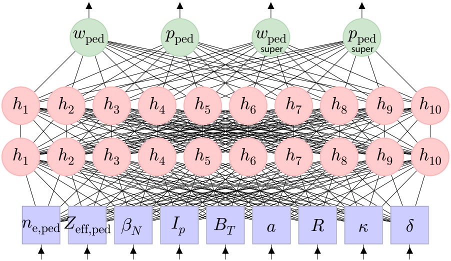
TGYRO simulations with coupled core-pedestal NN models run in few seconds

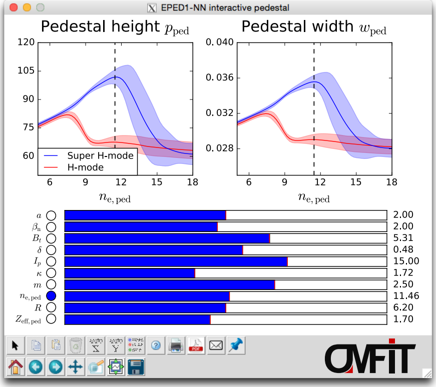


NN captures both H-mode and Super H-mode pedestal roots of EPED1 model

10 EPED input parameters to predict p_{ped}, w_{ped} and $p_{\mathrm{ped,super}}$, $w_{\mathrm{ped,super}}$

1. **normal H-mode** solution
2. **super H-mode** solution





The two sets of outputs are set to be equal when there is only one pedestal root

EPED1-NN model closely reproduces EPED1 predictions Trained across input parameter range of multiple devices

Built database of ~20,000 EPED1 runs (2 million CPU hours)

DIII-D: 3,000 runs

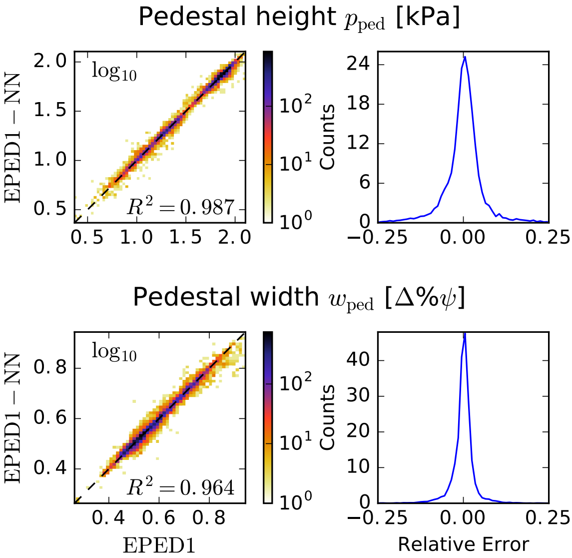
KSTAR: 700 runs

JET: 200 runs

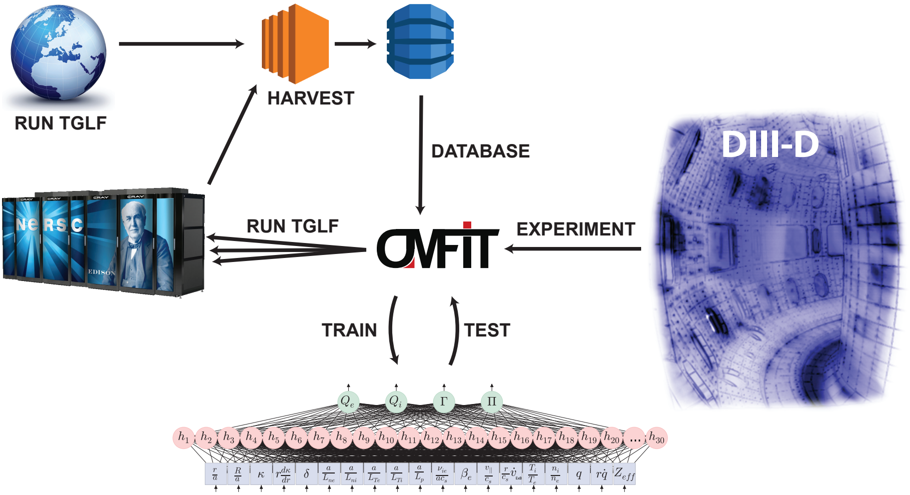
ITER: 15,000 runs

CFETR: 1,200 runs

$\times 10^9$ **speedup**

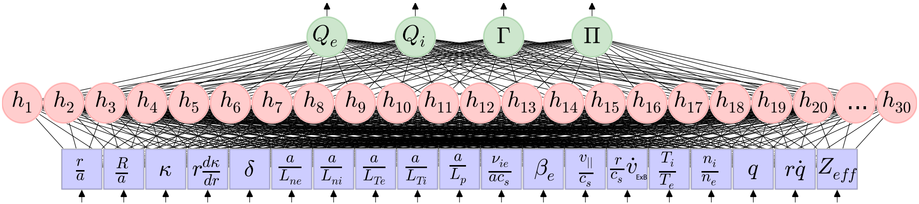


Leveraged OMFIT framework for experimental data access, spawn of simulations, database handling, and NN training



Infrastructure shared with other projects require handling databases

TGLF-NN neural network topology is more complex



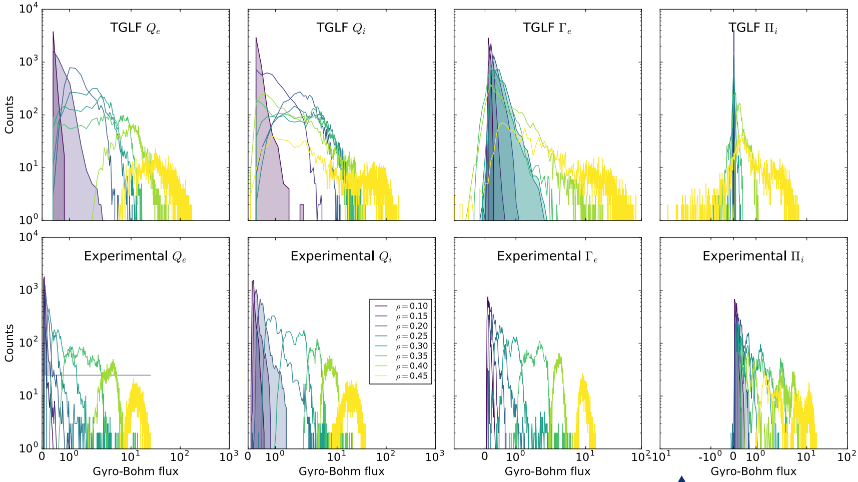
23 dimensionless input parameters (for D,C plasma)
to predict gyro-Bohm fluxes $Q_e, Q_i, \Gamma_e, \Pi_i$

r/a	Normalized minor radius
R/a	Normalized major radius
κ	Elongation
$r\frac{\partial \kappa}{\partial r}$	Elongation shear
δ	Triangularity
$\frac{\partial R}{\partial r}$	Shafranov shift
q	Safety factor
$\frac{q^2 a^2}{r^2} \frac{\partial q}{\partial r}$	Safety factor shear
β_e	Kinetic to magnetic pressure ratio
ν_{ie}/ac_s	Collision frequency
T_i/T_e	Ion to electron temperature ratio
n_D/n_e	Deuterium to electron density ratio
n_C/n_e	Carbon to electron density ratio
Z_{eff}	Effective ion charge

a/L_{Te}	Electron temperature scale length
a/L_{Ti}	Ion temperature scale length
a/L_{ne}	Electron density scale length
a/L_{nD}	Deuterium density scale length
a/L_{nC}	Carbon density scale length
$\frac{qa^2}{rB^2_{\text{unit}}} \frac{\partial p}{\partial r}$	Total pressure gradient
$\text{sign}(I_\text{p}) R\omega_{\text{tor}} \frac{a}{c_\text{s}}$	Parallel velocity
$-\text{sign}(I_\text{p}) R \frac{\partial \omega_{\text{tor}}}{\partial r} \frac{a}{c_\text{s}}$	Parallel velocity gradient
$-\text{sign}(I_\text{p}) \frac{r}{q} \frac{\partial \frac{V_{E\times B}}{R}}{\partial r} \frac{a}{c_\text{s}}$	$E \times B$ velocity shear

Trained on 32,000 TGLF runs based on 24 DIII-D discharges probing ion energy transport (power and torque scans)

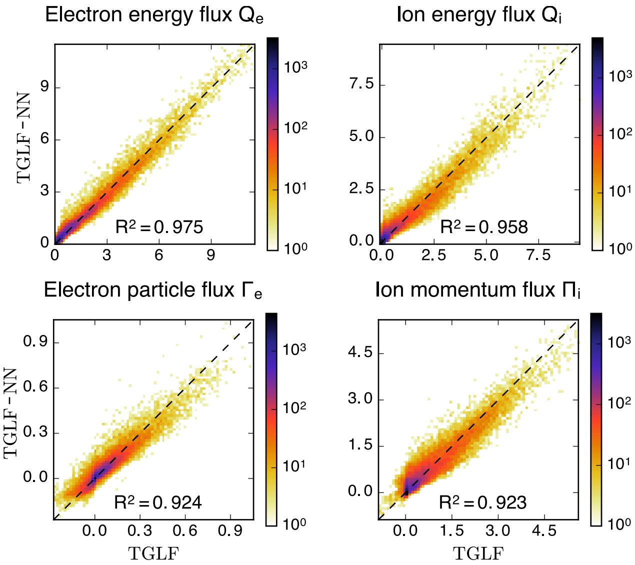
Raw TGLF fluxes are in qualitative good agreement with experimental power/particle/momentum balance fluxes



GENERAL ATOMICS

TGLF-NN model closely reproduces TGLF predictions

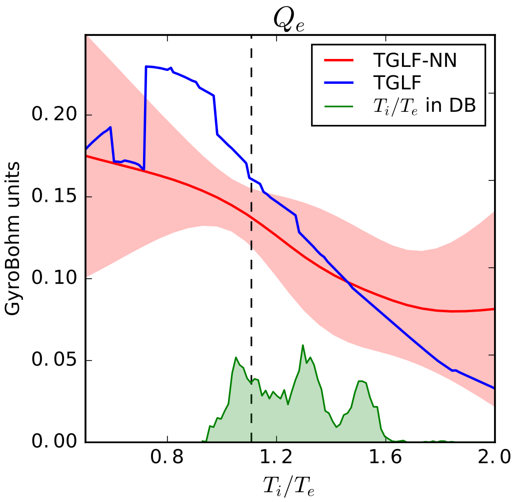
$\times 10^6$ **speedup**



GENERAL ATOMICS

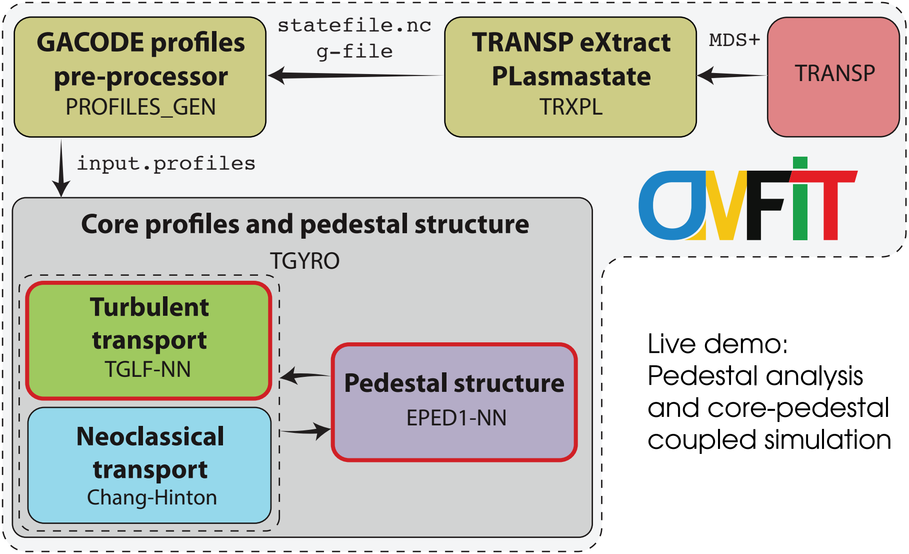
TGLF-NN regularization smooths out discontinuities in the original TGLF solution

Smoothness of fluxes affects convergence of transport solvers



GENERAL ATOMICS

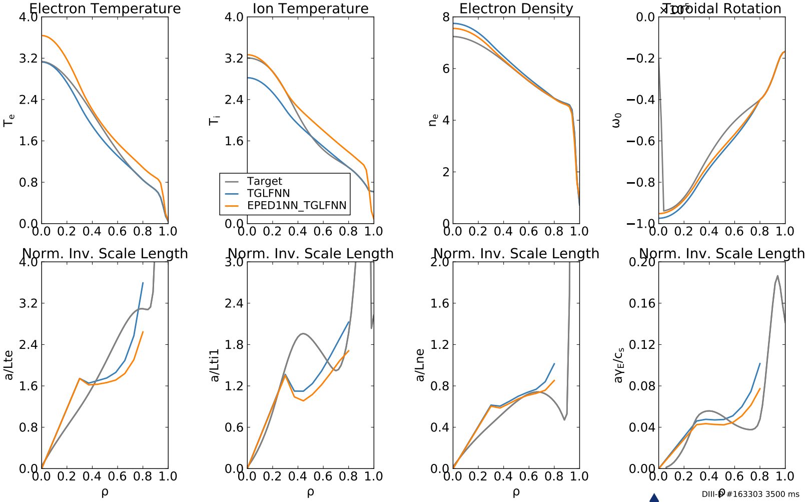
Effort towards enabling routine/streamlined DIII-D core-pedestal simulations capabilities (predict-first initiative)



Live demo:
Pedestal analysis
and core-pedestal
coupled simulation

TGYRO simulations with EPED1-NN and TGLF-NN allow routine stationary core-pedestal predictive simulations

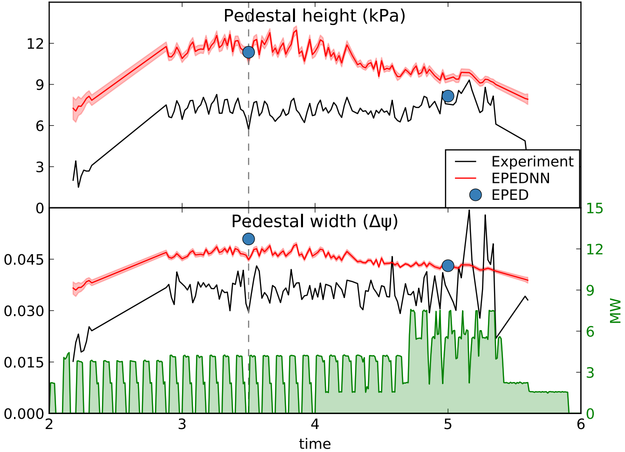
Coupled core-pedestal predictions show relatively good agreement with the experiment



GENERAL ATOMICS

Spot-check with full EPED1 simulations shows that NN reproduces original model with high degree of accuracy

EPED1-NN calculation allows routine (indirect) validation of EPED model with experiment



GENERAL ATOMICS

We have established a pipeline for the development of a fidelity hierarchy of GA pedestal and transport models

First Principles Models →	Reduced Models →	Machine Learning
Standalone →	Loose Coupling Integration →	Tight Coupling Integration
Days/Hours →	Minutes/Seconds →	Milliseconds
One of a Kind →	Supervised →	Automatic
Physics Validation →	Planning & Engineering →	Control

GENERAL ATOMICS

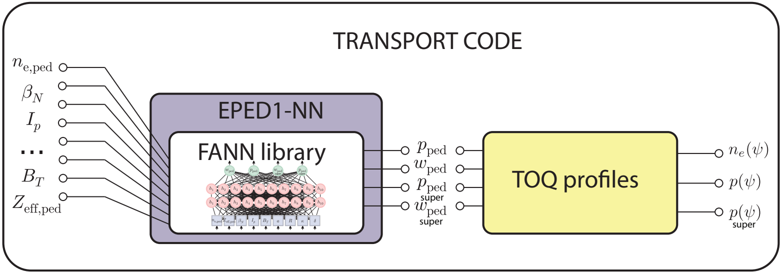
PEDESTAL:

`EPED` → `EPED1-NN`

TRANSPORT:

`(C)GYRO` → `TGLF` → `TGLF-NN`

EPED1-NN with TOQ profiles routine to generate pressure and density profiles consistent with full EPED1 model



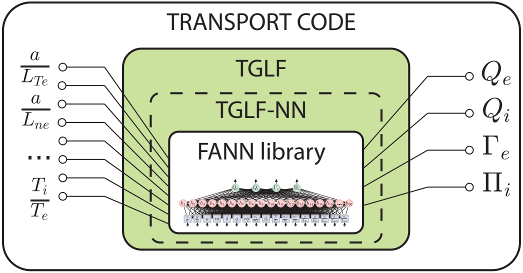
TOQ profiles routine

- Translates pedestal width/height predictions to full density and pressure profiles like the ones that are used in the full EPED1 model

Both EPED1-NN and TGLF-NN have APIs for Python, FORTRAN, C to support:

- OMFIT
- Transport codes
- Control systems

TGLF-NN can be easily used in codes that already use TGLF



Being part of TGLF facilitates

- Integration
- Validation & Verification

Start using TGLF-NN is easy:

1. Update TGLF to latest version
2. Build (with link to FANN library)
3. Switch TGLF_NN_MAX_ERROR>0

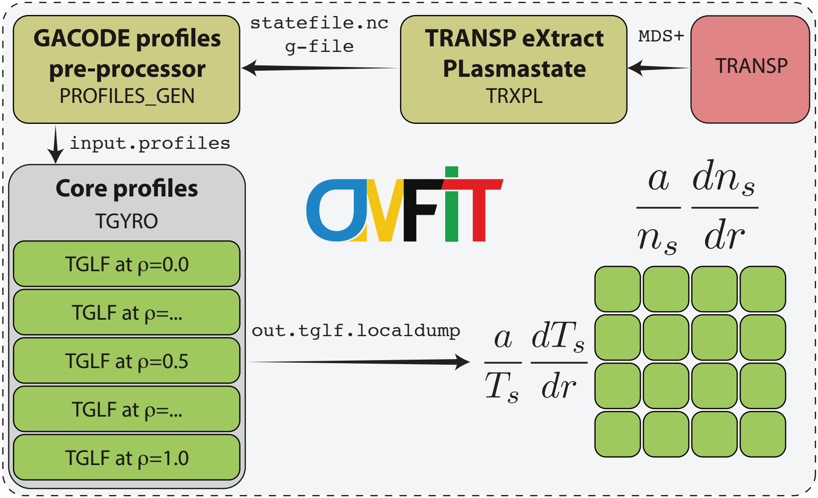
GENERAL ATOMICS

EPED1-NN and TGLF-NN models enable routine predictive core-pedestal predictive transport simulations

- EPED1-NN and TGLF-NN models have been developed
- Verified that they produce accurate results within training range
  - Models are being extended for wider parameters range
  - Arsene Tema master thesis at GA on these topics
- Demonstrated that within TGYRO routine core-pedestal coupled simulations are possible by leveraging speed of neural network models
- NN models have been designed to be easily included in other transport codes
- Source code and NN models available on GitHub upon request

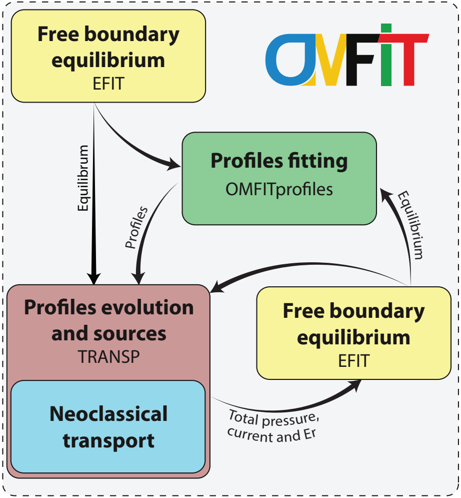
In addition to running TRANSP, synergy with OMFIT enables important cross-devices analyses/predictive capabilities

e.g. Multidimensional sensitivity and spectral flux analyses



In addition to running TRANSP, synergy with OMFIT enables important cross-devices analyses/predictive capabilities

e.g. Time-dependent kinetic equilibrium reconstructions



GENERAL ATOMICS

Open invitation to TRANSP developer to join the 3rd OMFIT code-camp: Aug 21st to 25st

A focused opportunity for developers to self-organize into small working groups to address outstanding issues and quickly bring new ideas to life

- Serious coding
- Fun environment