Application of Neural Ordinary Differential Equations for ITER Burning Plasma Dynamics

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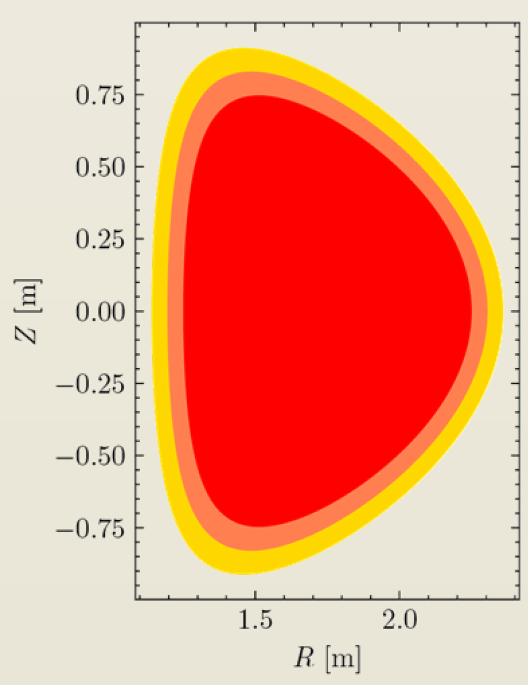
Introduction

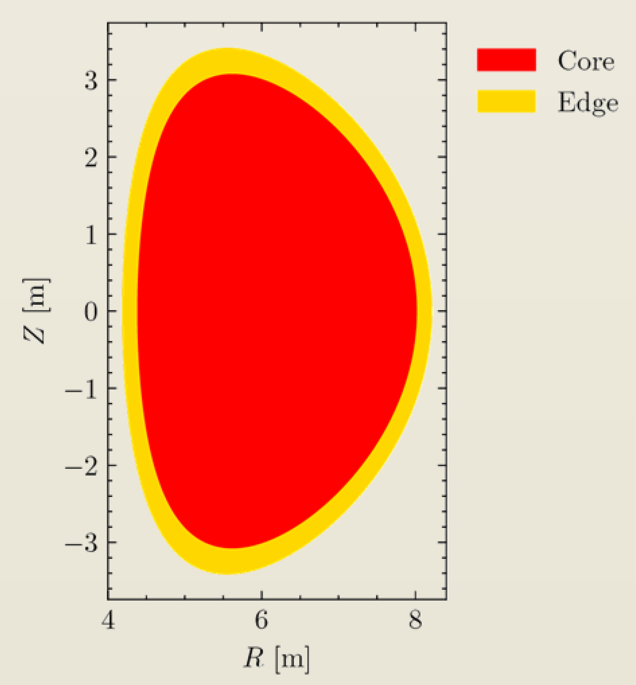
- Understanding **burning plasma dynamics** in **ITER** is essential for advancing **controlled thermonuclear fusion**.
- Accurately modeling **multi-region, multi-timescale energy transfer** is key to predicting **plasma thermal stability**.
- **NeuralPlasmaODE** leverages **machine learning** to enhance **burning plasma simulations**.

Burning Plasma Dynamics Model

- **Geometry:** The tokamak plasma is divided into **core, edge, scrape-off layer (SOL), and divertor** regions, each treated as a separate node.



DIII-D Cross Section



ITER Cross Section

- **Particle Balance:** Tracks densities influenced by external sources, fusion reactions, particle transport, and ion orbit loss (IOL).

$$\frac{dn_\sigma^{\text{node}}}{dt} = S_{\sigma,\text{ext}}^{\text{node}} + S_{\sigma,\text{fus}}^{\text{node}} + S_{\sigma,\text{tran}}^{\text{node}} + S_{\sigma,\text{IOL}}^{\text{node}}$$

- **Energy Balance:** Captures energy transfer from fusion power, auxiliary heating, transport mechanisms, and radiation losses.

$$\frac{dU_\sigma^{\text{node}}}{dt} = P_{\sigma,\text{aux}}^{\text{node}} + P_{\sigma,\text{fus}}^{\text{node}} + Q_\sigma^{\text{node}} + P_{\sigma,\text{tran}}^{\text{node}} + P_{\sigma,\text{IOL}}^{\text{node}}$$

$$\frac{dU_e^{\text{node}}}{dt} = P_\Omega^{\text{node}} + P_{e,\text{aux}}^{\text{node}} + P_{e,\text{fus}}^{\text{node}} - P_{\text{rad}}^{\text{node}} + Q_e^{\text{node}} + P_{\sigma,\text{tran}}^{\text{node}}$$

Parametric Diffusivity Model

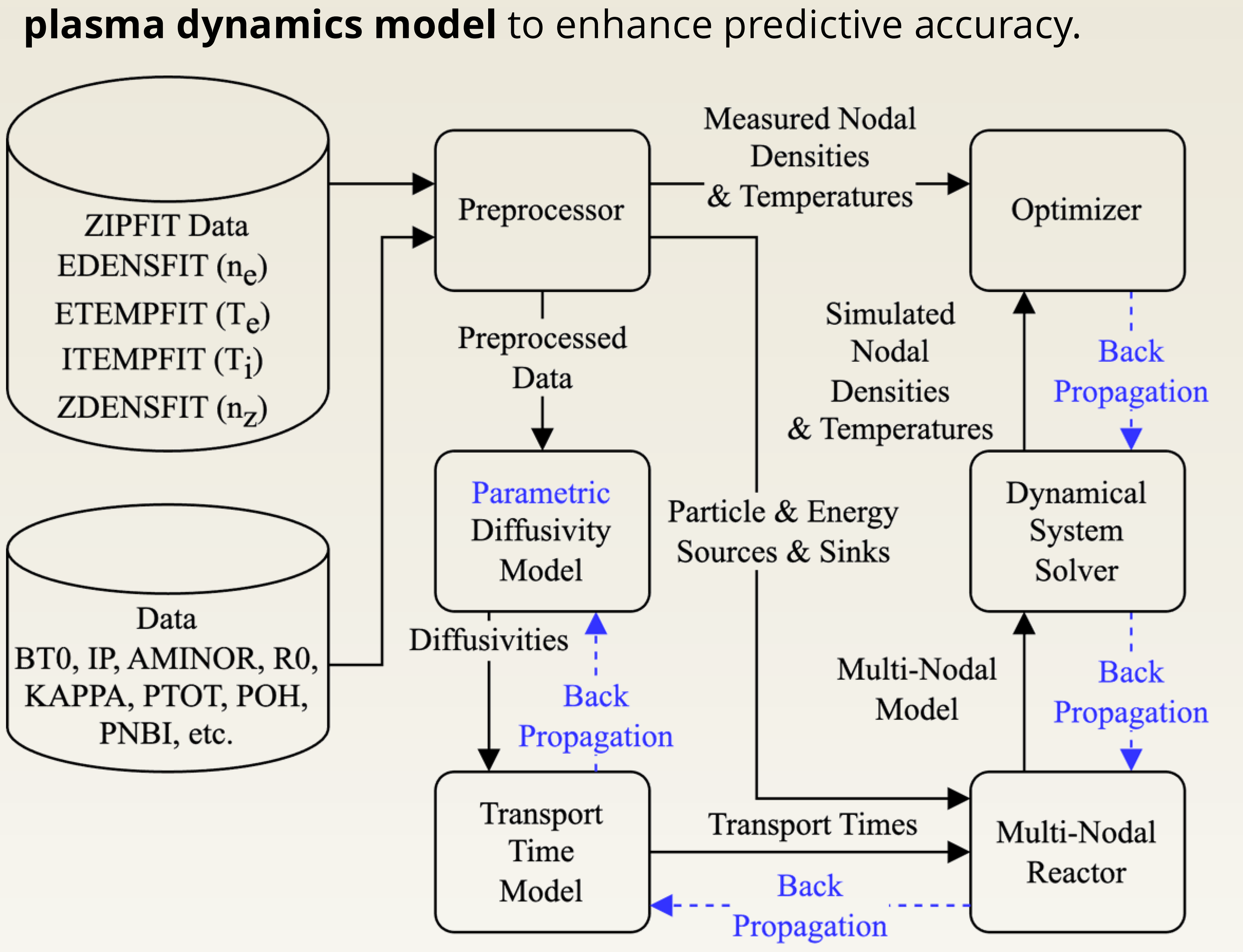
- **NeuralPlasmaODE** uses a **data-driven approach** to optimize diffusivity parameters:

$$\frac{\chi(\rho)}{1\text{m}^2/\text{s}} = \alpha_H \left(\frac{B_T}{1\text{T}}\right)^{\alpha_B} \left(\frac{n_e}{10^{19}\text{m}^{-3}}\right)^{\alpha_n} \left(\frac{T_e}{1\text{keV}}\right)^{\alpha_T} \left(\frac{|\nabla T_e|}{1\text{keV/m}}\right)^{\alpha_{\nabla T}} \cdot q^{\alpha_q} \kappa^{\alpha_\kappa} \left(\frac{M}{1\text{amu}}\right)^{\alpha_M} \left(\frac{R}{1\text{m}}\right)^{\alpha_R} \left(\frac{a}{1\text{m}}\right)^{\alpha_a}$$

- Parameters optimized from **DIII-D experimental data** are **transferred** to **ITER simulations** and **fine-tuned**.

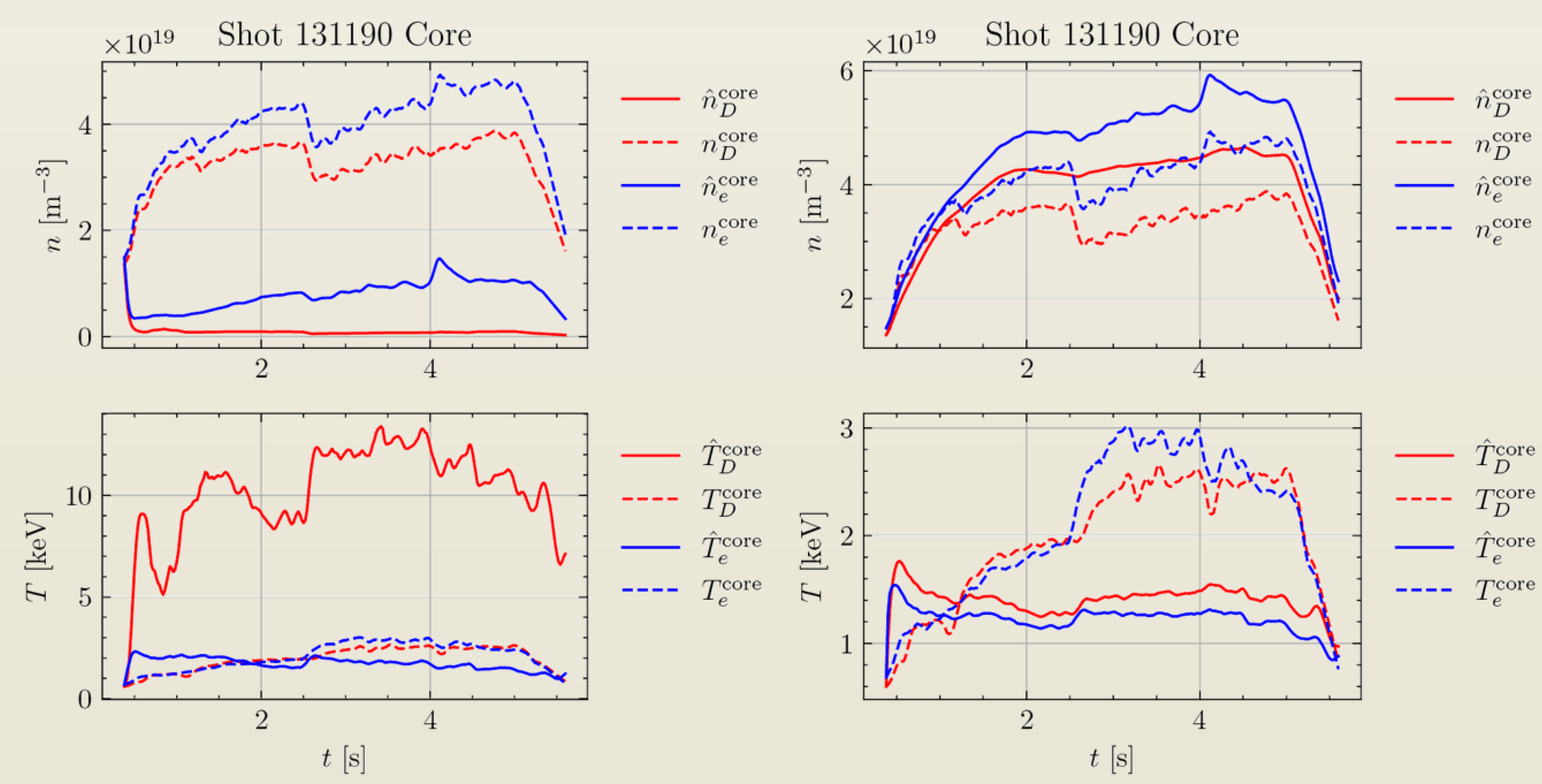
Computational Framework

- **NeuralPlasmaODE** combines **Neural ODEs** with the **burning plasma dynamics model** to enhance predictive accuracy.



DIII-D Simulation Results

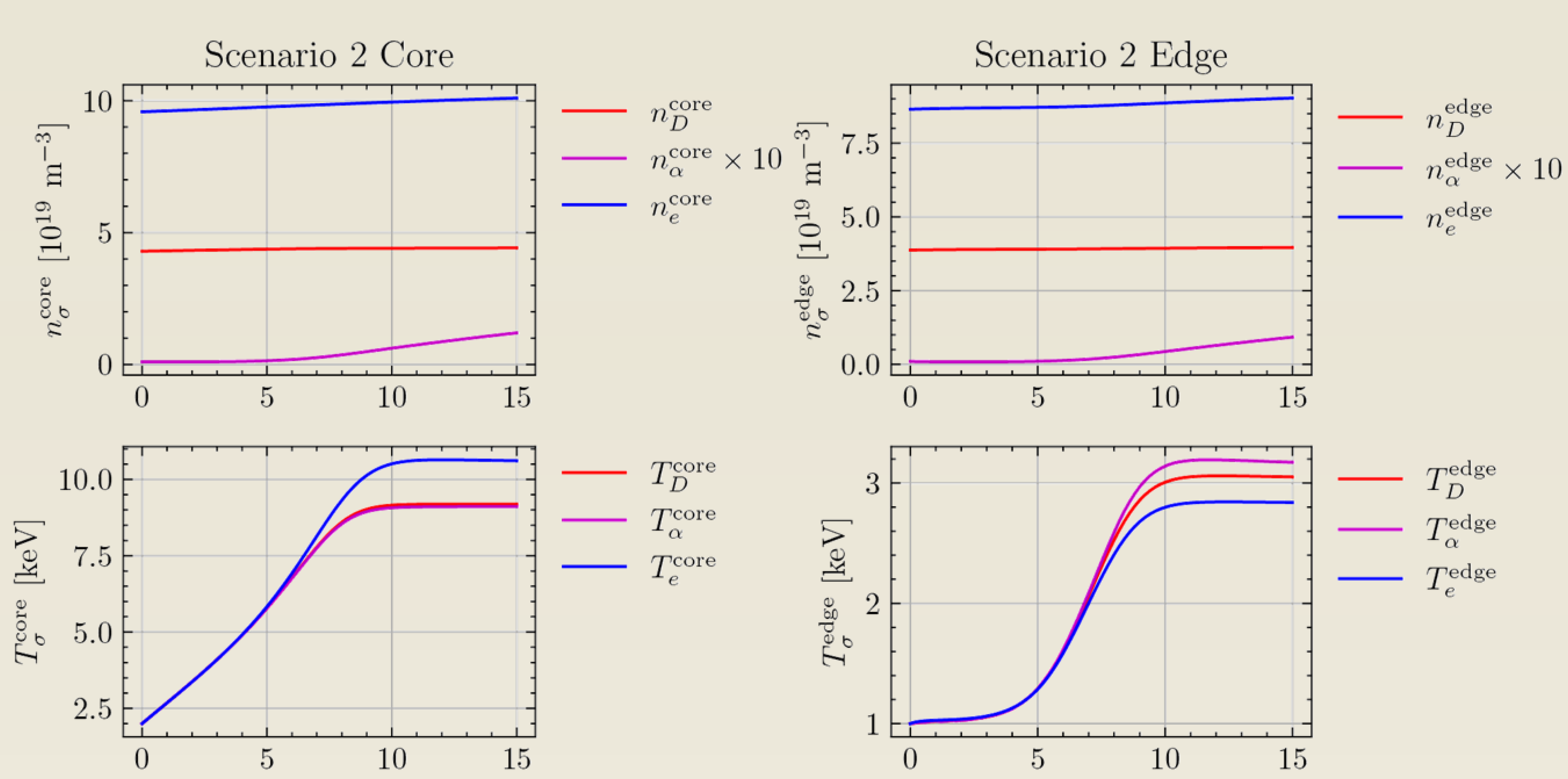
- **Optimized diffusivity parameters** reduce **mean squared error (MSE)** by **over 98%** compared to the empirical model, demonstrating significant improvement.
- The model accurately predicts **core and edge densities and temperatures**, demonstrating better agreement with DIII-D experimental data.
- The model **generalizes well across test shots**, confirming its reliability for modeling diverse plasma conditions.



Empirical Model **NeuralPlasmaODE**

ITER Simulation Results

- **Inductive Scenario:** Core electrons lose energy through **radiation and energy transport processes**, leading to stable plasma conditions without uncontrolled temperature rise.
- **Hybrid Scenario:** Increased auxiliary heating and fusion heating raise core temperatures, but **enhanced transport and radiation losses** balance energy outflow, preventing power excursions.
- **Non-Inductive Scenario:** Higher core temperatures and steeper temperature gradients drive **strong energy transport to the edge**, maintaining equilibrium without instability.



Inductive Scenario (Core) **Inductive Scenario (Edge)**

Conclusion

- **NeuralPlasmaODE** successfully models **ITER plasma transport** using **Neural ODEs** and **transfer learning** from **DIII-D data**.
- The model accurately captures **multi-region, multi-timescale energy transfer**, providing insights into plasma thermal dynamics.
- Simulations for various scenarios confirm the role of **radiation and transport processes** in regulating plasma energy balance.

References

Stacey, Weston M. "A Nodal Model for Tokamak Burning Plasma Space-Time Dynamics." *Fusion Science and Technology* 77.2 (2021): 109-118.
Liu, Zefang, and Stacey, Weston M. "Application of Neural Ordinary Differential Equations for Tokamak Plasma Dynamics Analysis." *ICLR 2024 Workshop on AI4DifferentialEquations In Science.*
Acknowledgment: This material is based upon work supported by the U.S. Department of Energy, Office of Science, Office of Fusion Energy Sciences, using the DIII-D National Fusion Facility, a DOE Office of Science user facility, under Award(s) DE-FC02-04ER54698.

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