Sixth IAEA Technical Meeting on Fusion Data Processing, Validation and Analysis

The Potential of Physics-Informed Neural Networks to Analyse Tokamak Diagnostic Measurements

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on behalf of JET Contributors and
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Outline

(*) See presentation by Novella Rutigliano "Physics-Informed Neural Networks for Multi-Diagnostic Reconstruction in Tokamaks"

Introduction

Diagnostics in fusion reactors play a key role in both scientific (physics understanding, modelling, optimisation) and technological challenges (e.g. plasma control).

Extracting accurate and reliable information from diagnostics is not straightforward because:

- **Plasma is among the most complex systems**
  (It is characterised by many variables, multi-physics and multi-scale phenomena, non-linearities, etc.)

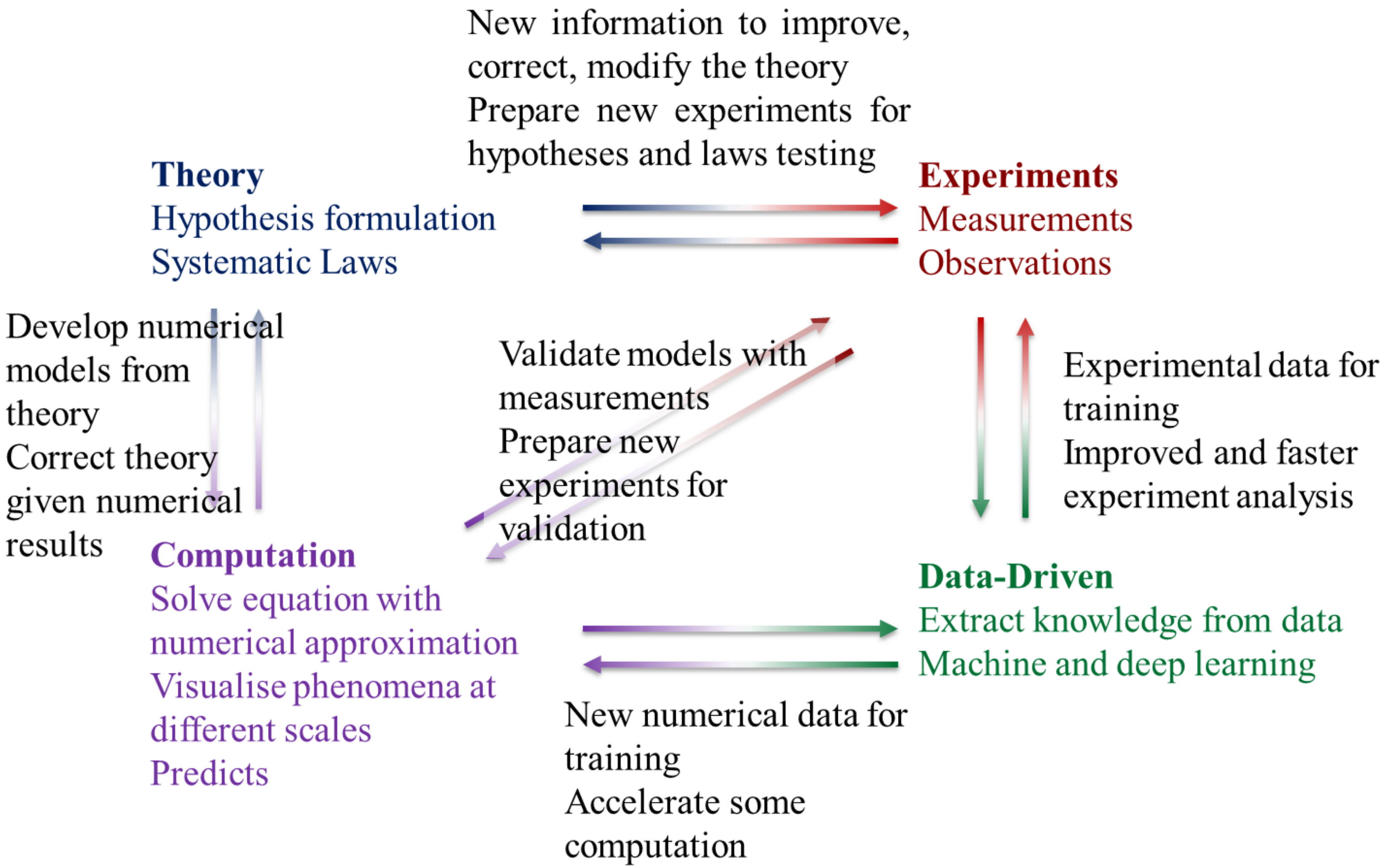
- **Diagnostic capabilities are limited**
  (They are external, line-integrated, often non-linear, etc.)

Introduction

Such a complex environment requires an **integrated approach** involving **theory**, **experiment**, **computation**, and **artificial intelligence**.

However, this integration is only partial, since there is typically a **lack of synergy** among these four methodologies.

In recent years, **Physics-Informed Machine Learning** (PIML) has been gaining attention because of its many unique features.



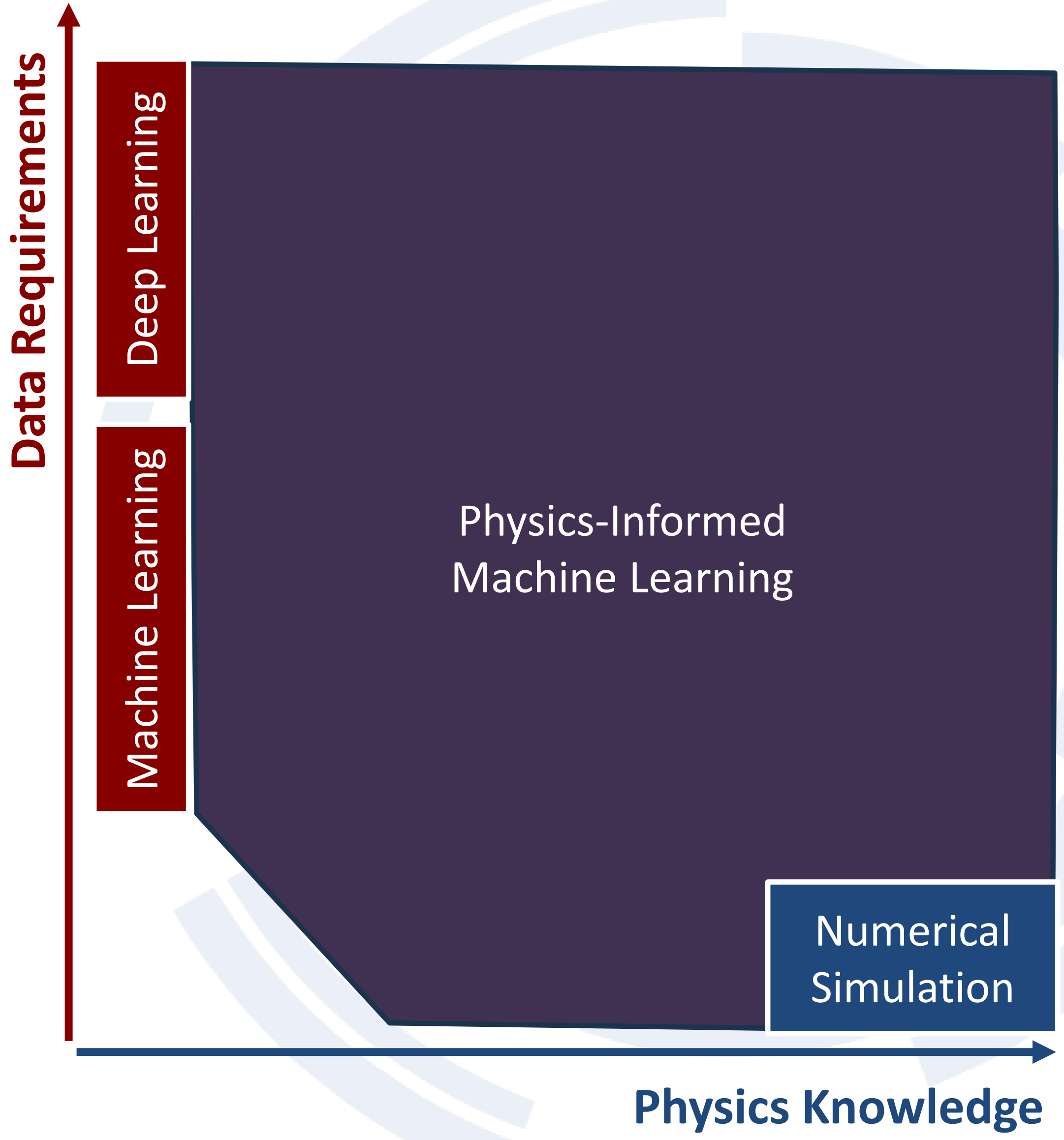
Hey A J G . 2009 The fourth paradigm : data-intensive scientific discovery (Microsoft Research)

Karniadakis, G.E., Kevrekidis, I.G., Lu, L. et al. Physics-informed machine learning. Nat Rev Phys **3**, 422–440 (2021). https://doi.org/10.1038/s42254-021-00314-5

Physics-Informed Machine Learning

Physics-Informed Machine Learning (**PIML**) offers the possibility to develop methodologies that synergistically combine theory, experiment, computation, and data-driven approaches.

In fact, PIML methods are AI-based techniques trained to minimise a loss function that incorporates physical equations (of various types, such as Partial Differential Equations), as well as **data** from both **theoretical considerations** (e.g., boundary conditions) and **experimental measurements**.



Experiments

Theory

PIMLs: Hybrid Computation/Data-driven Method → **Results/Output**

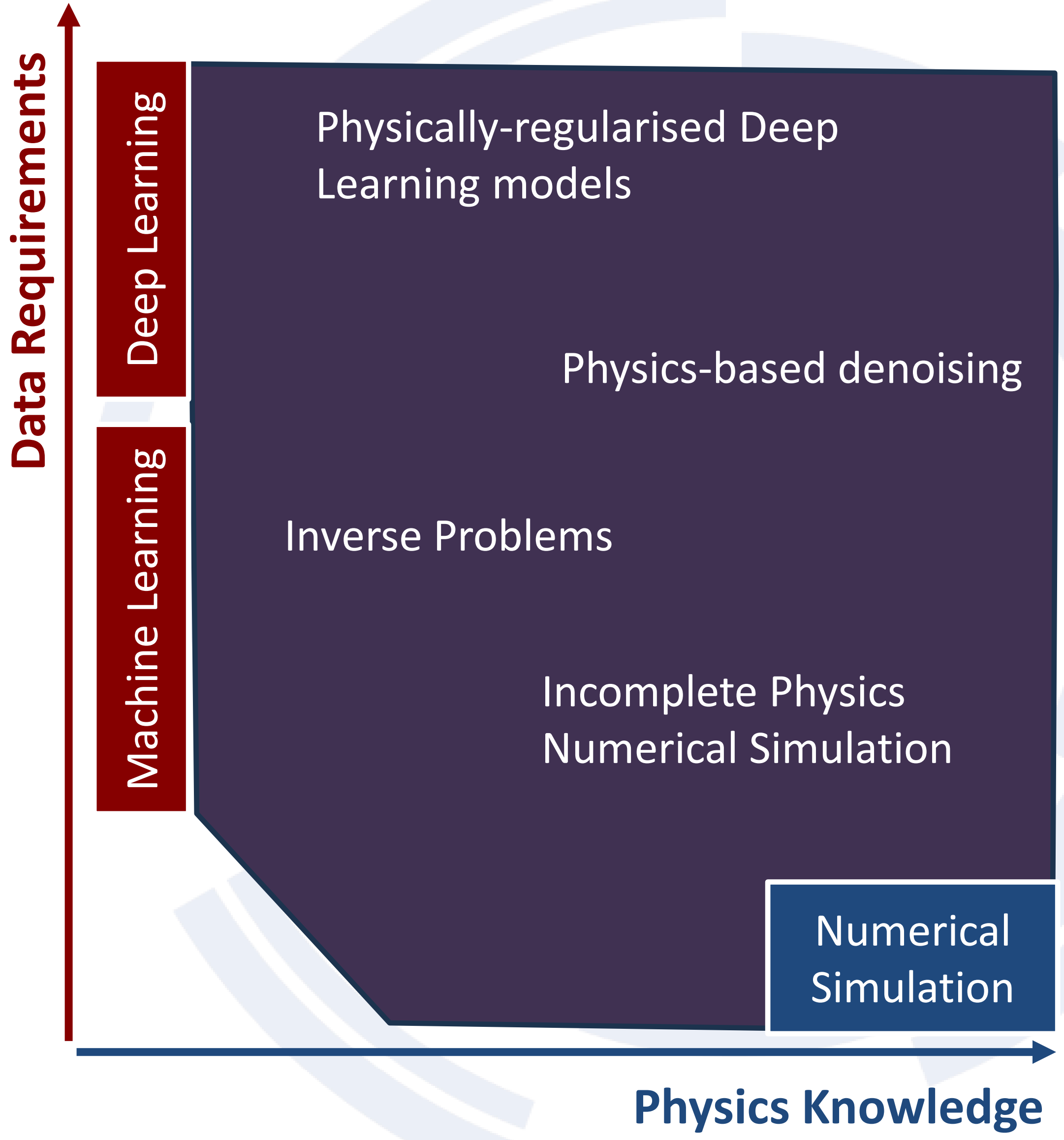
Physics-Informed Neural Networks

Among the various Physics-Informed Machine Learning tools, **Physics-Informed Neural Networks** (**PINNs**) offer unique opportunities.

Thanks to their flexibility, PINNs can be applied to various purposes, such as:

- Numerical simulations (with advantages such as a meshless approach)
- Inverse problems
- Modelling
- Missing data reconstruction
- And more

This presentation focuses on the applications of **PINNs to diagnostics** in nuclear fusion.



M. Raissi et al. Journal of Computational Physics, 378, 2019 https://doi.org/10.1016/j.jcp.2018.10.045

Why PINNs for diagnostics processing?

Inverse problems

Innovative regularisation equations which may take into account multi-diagnostics, multi-physics, non-linear, and multi-scale features.

Data-Integrated Analysis

Can easily integrate different diagnostics, how they are weighted in the learning processes, modelling also complex behaviours like non-linearities

Noise, Outliers, Faults detection and Cross-Calibration

Mixing data and physics can help in smoothing out noise and outliers, which typically do not obey the physical equations. Moreover, multi-diagnostics approach can be used for cross-calibration purposes.

Direct Modelling

In modelling, experiments and diagnostics are used to validate numerical/theoretical models. Now, data can be implemented in the simulation process, guiding the models and allow for direct discovery of the parameters.

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1. Introduction

2. Physics-Informed Neural Networks (PINNs)

2.1 General Methodology

2.2 Applications to diagnostics

2.2.1. Time-resolved tomography

2.2.2. Multi-diagnostic profile reconstruction

2.2.3. Physics-enhanced denoising

2.2.4. Multi-diagnostic equilibrium(*)

3. Conclusions

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Deep Neural Networks

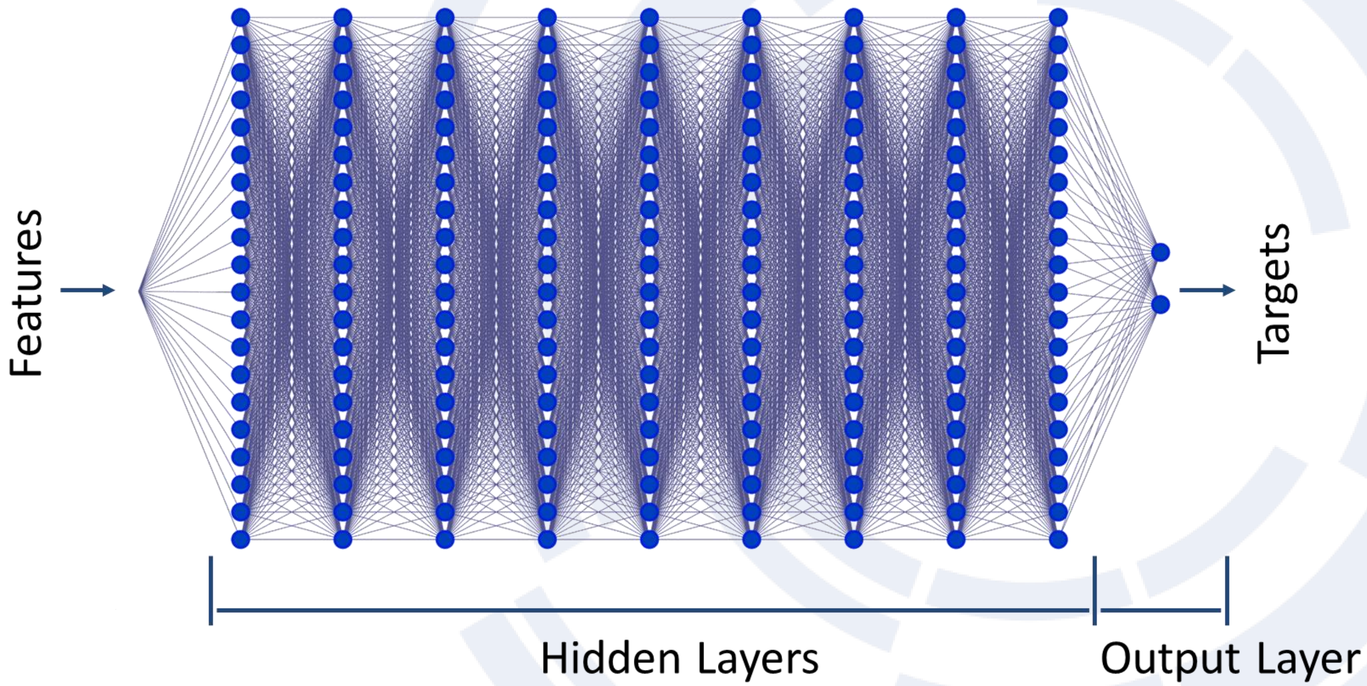
A neural network is a **mathematical model** $\boldsymbol{f}$ defined by several **parameters** $\boldsymbol{\theta}$ that given the **features (or inputs)** $\boldsymbol{X}$ returns the **targets (or outputs)** $\boldsymbol{Y}$:

$$\boldsymbol{Y} = \boldsymbol{f}(\boldsymbol{\theta}, \boldsymbol{X})$$

From the **universal approximation theorem**, we can assert that:

"a sufficiently deep neural network can approximate any function"

The process to tune the parameters θ is known as **training**



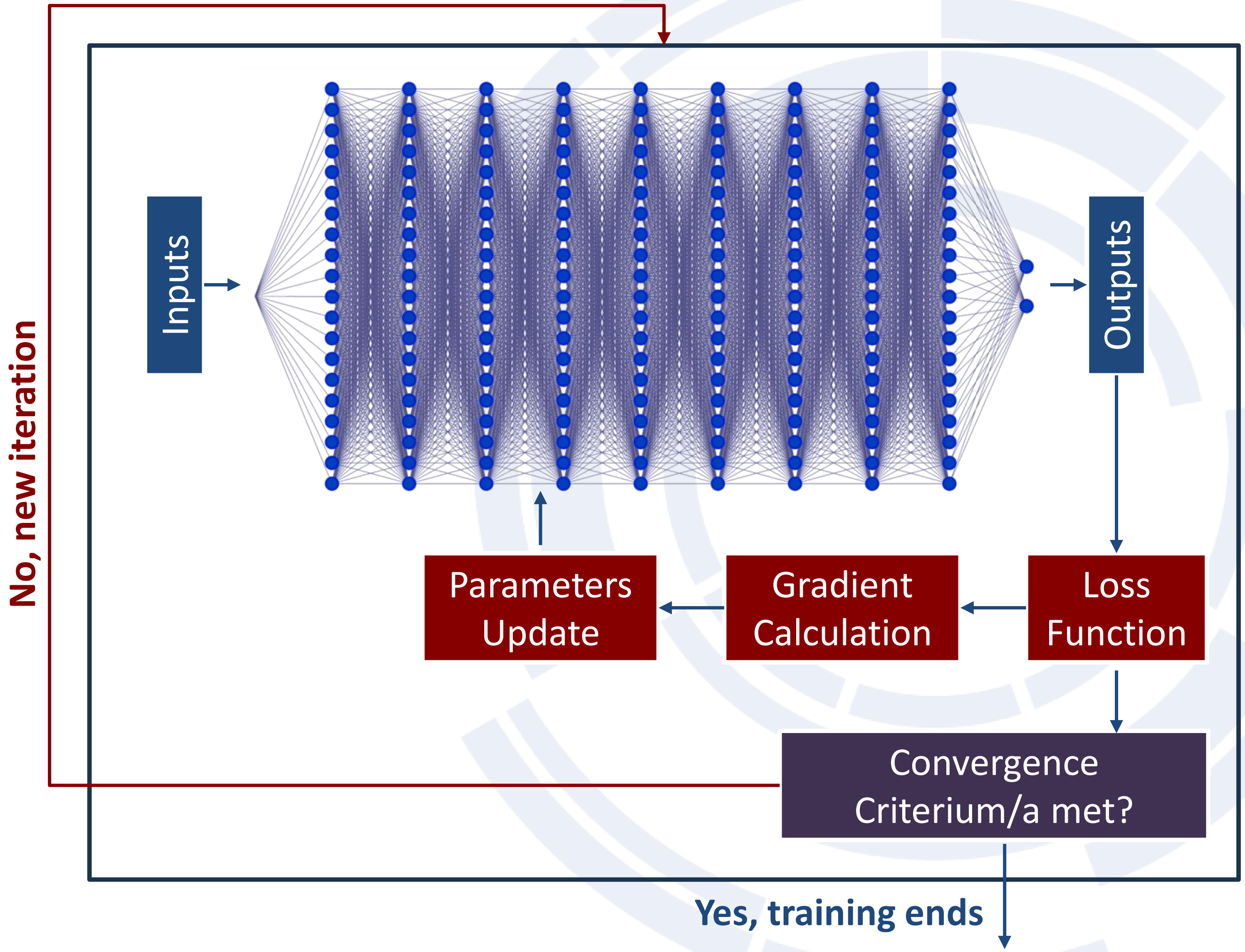
Good Fellow et al. "Deep Learning" MIT Press, (2016)

Training a Deep Neural Network

Training steps:

- Neural network parameters are randomly initialized.
- The neural network is tested with these parameters, and the outputs are used to compute a loss function.
- The gradient of the loss function with respect to the parameters is calculated.
- The parameters are updated.
- Steps 2–4 are repeated until a convergence criterion is reached.

Good Fellow et al. "Deep Learning" MIT Press, (2016)

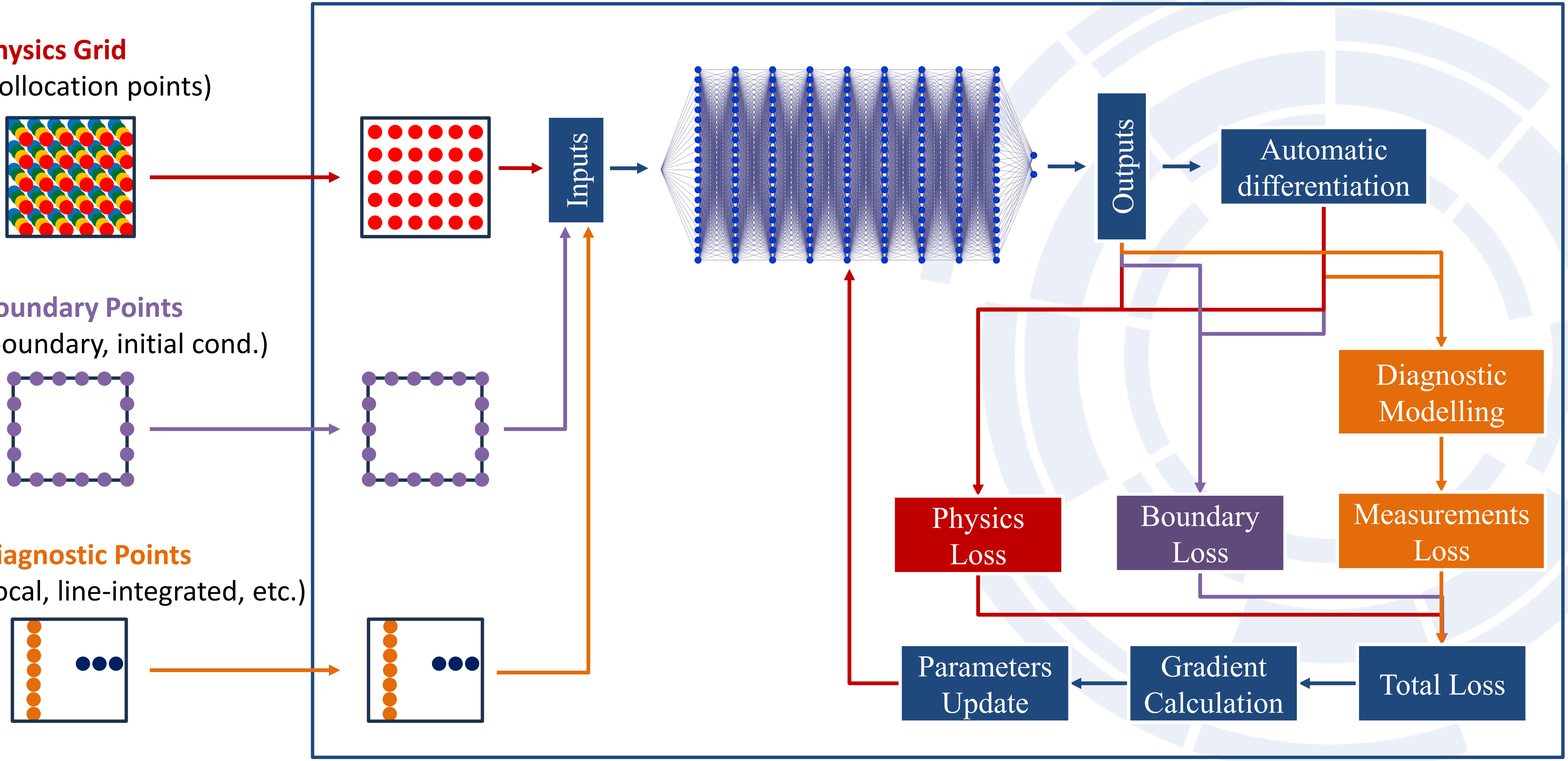


Training a Physics-Informed Neural Network

Physics Grid
(collocation points)

Boundary Points
(boundary, initial cond.)

Diagnostic Points
(local, line-integrated, etc.)



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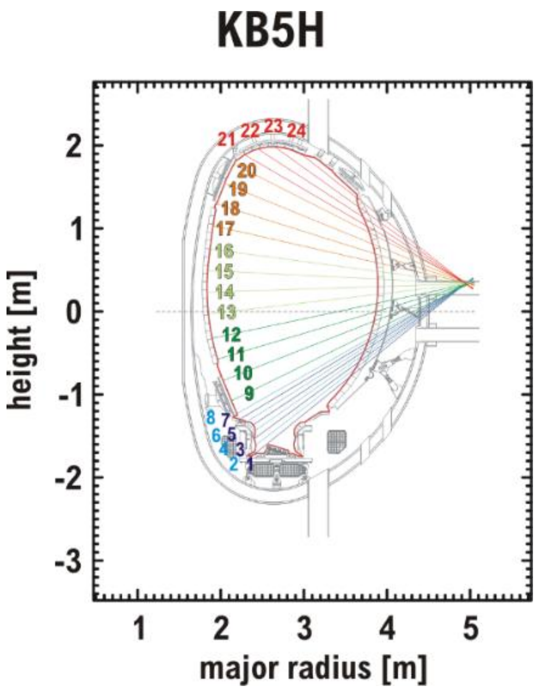
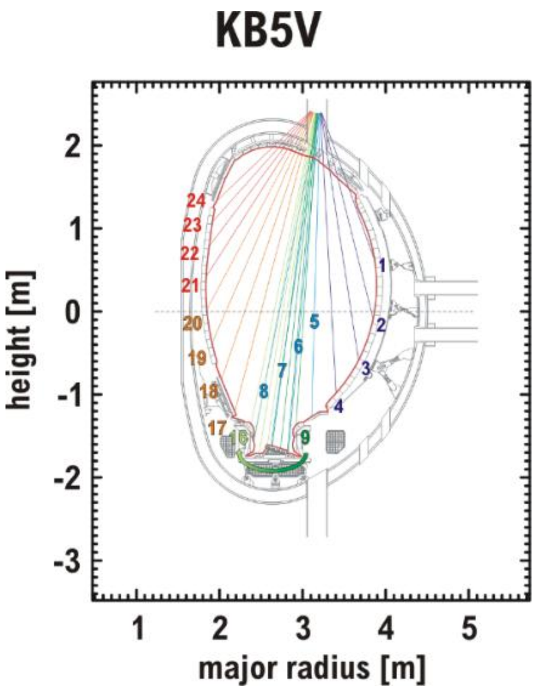
Time-Resolved Tomography

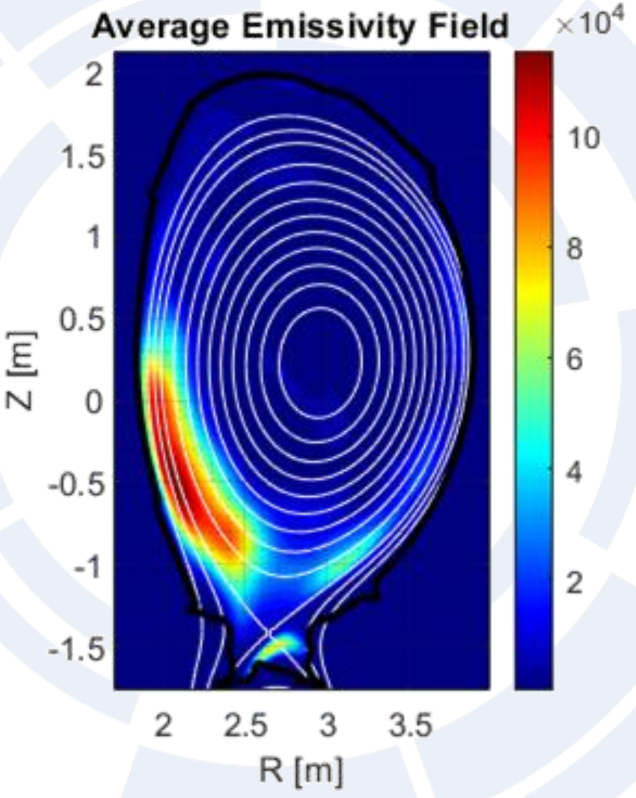
Line-Integrated Radiation is measured by bolometric cameras (at JET, 24 channels horizontal and 24 vertical)





Inversion algorithm

Reconstructed Emissivity



48 measurements
1089 unknowns (for a 33x33 pixel image)

ill-posed problem

Regularisation

Time-Resolved Tomography

Regularization is typically based on the **spatial smoothness of emissivity**, with smoother fields expected along magnetic surfaces.

$$Reg.Equation = \left(\alpha_{\parallel} \nabla_{\parallel}\varepsilon\right)^2 + \left(\alpha_{\perp}\nabla_{\perp}\varepsilon\right)^2$$

⇩

We also aim to enforce **temporal smoothness** by using a diffusion equation:

$$Reg.Term = \left(\frac{\partial\varepsilon}{\partial t} - D_{\parallel}\Delta_{\parallel}\varepsilon - D_{\perp}\Delta_{\perp}\varepsilon\right)^2$$

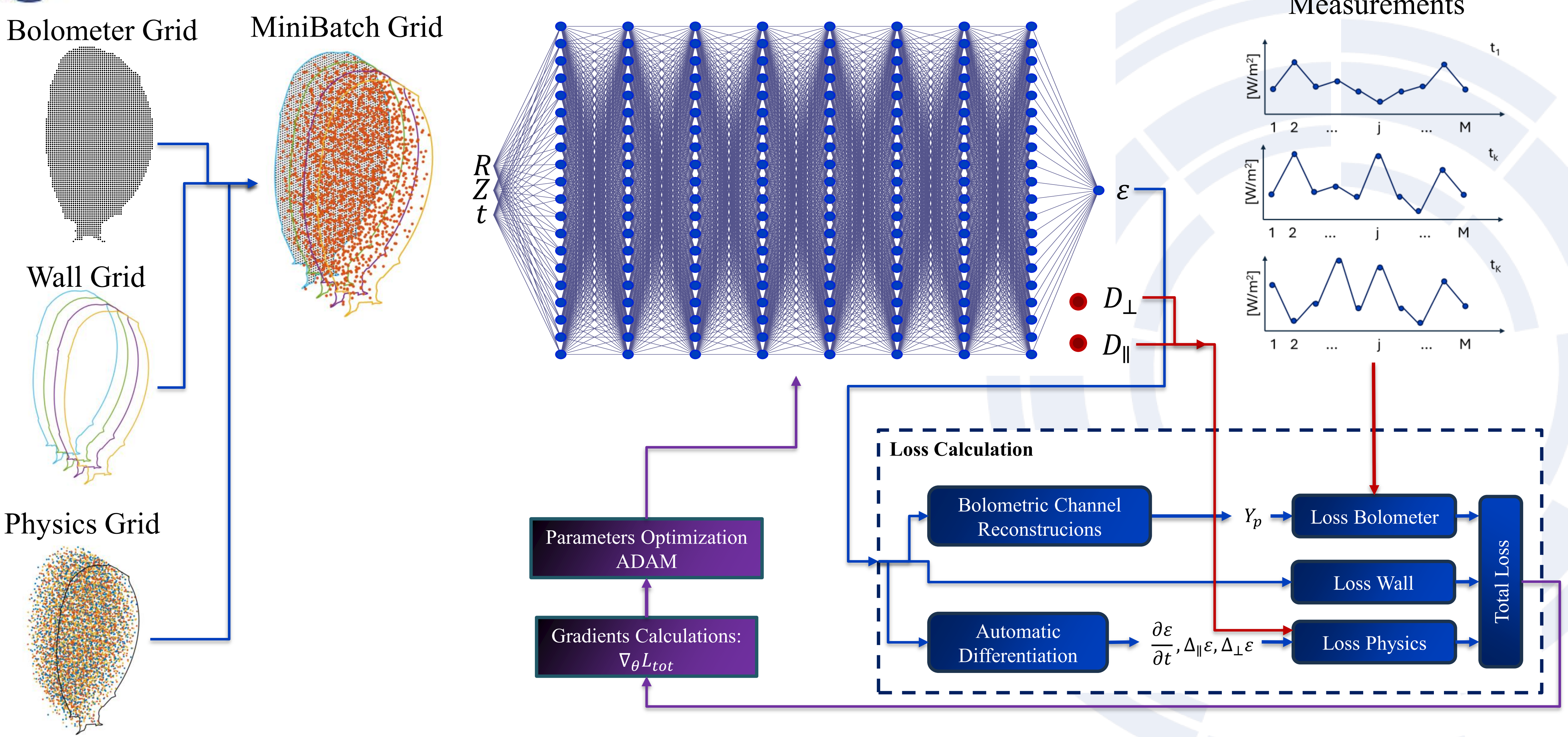
The choice of the **hyperparameters** plays a crucial role in the quality of the reconstruction.

⇩

Physics-Informed Neural Networks (PINNs) can incorporate **incomplete physics** equations, with parameters (such as diffusion coefficients) automatically inferred by the model.

See presentation by Ivan Wyss "Latest Developments of the Maximum Likelihood Approach to Tomography for both Offline and Real Time Investigation of the Total Emission of Radiation"

Time-Resolved Tomography

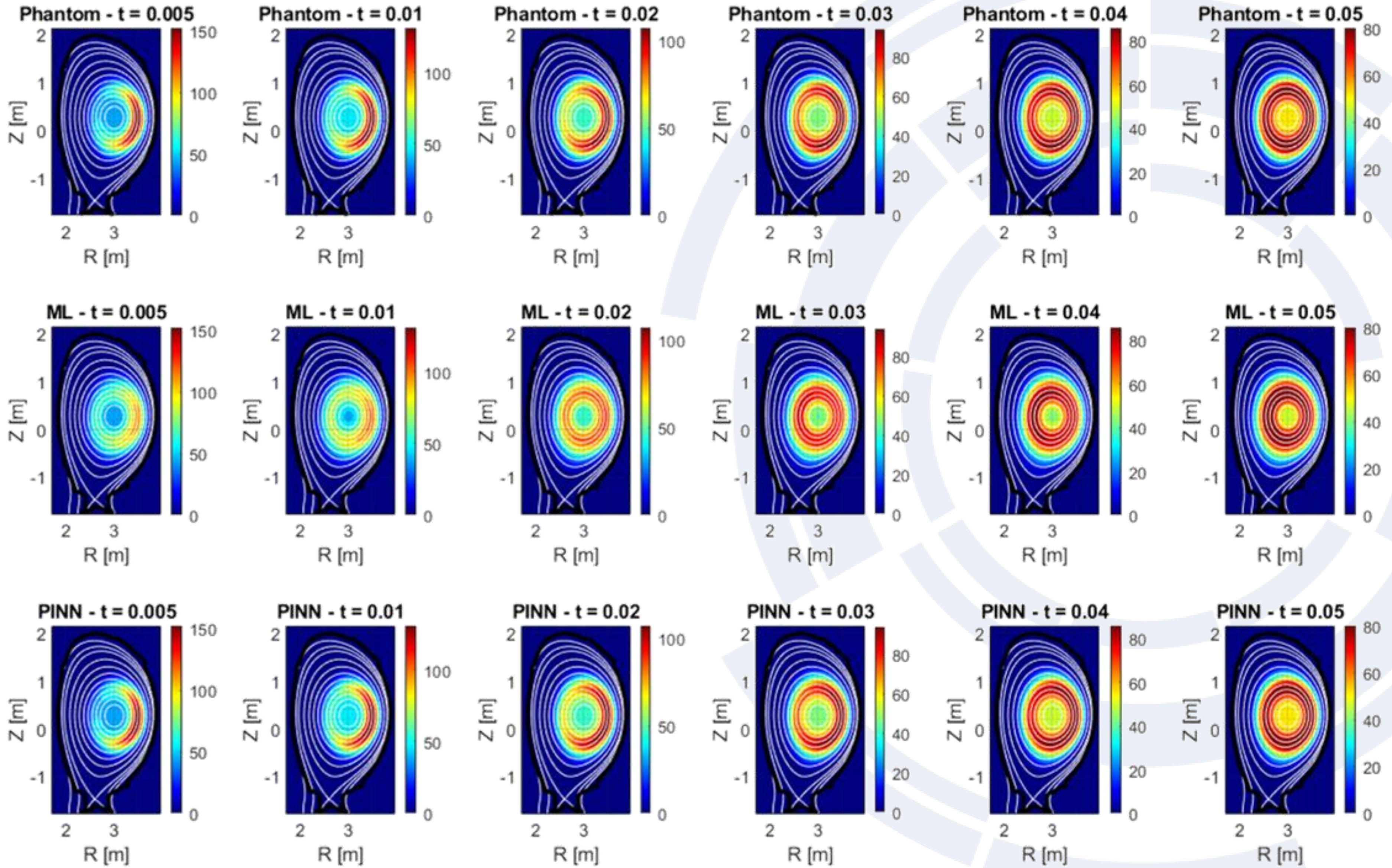


Time-Resolved Tomography

Target

Standard Method

PINN

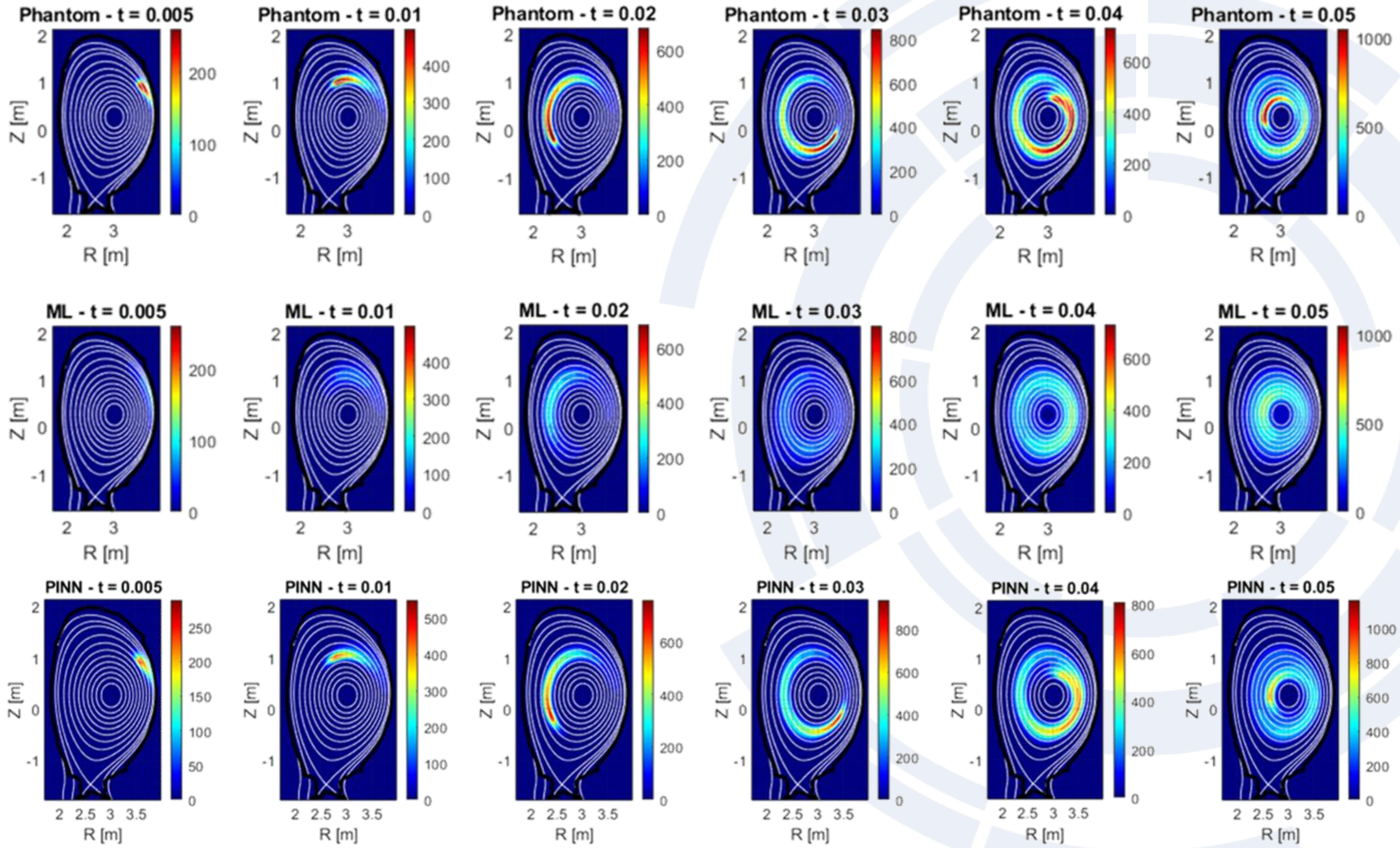


Time-Resolved Tomography

Target

Standard Method

PINN

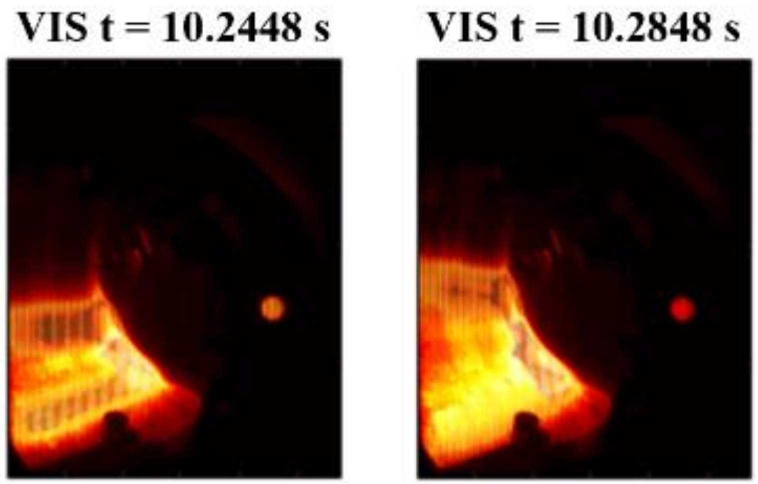


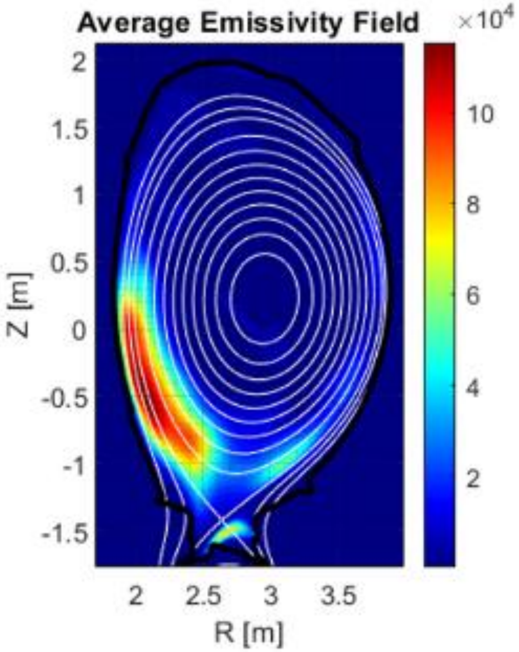
Time-Resolved Tomography

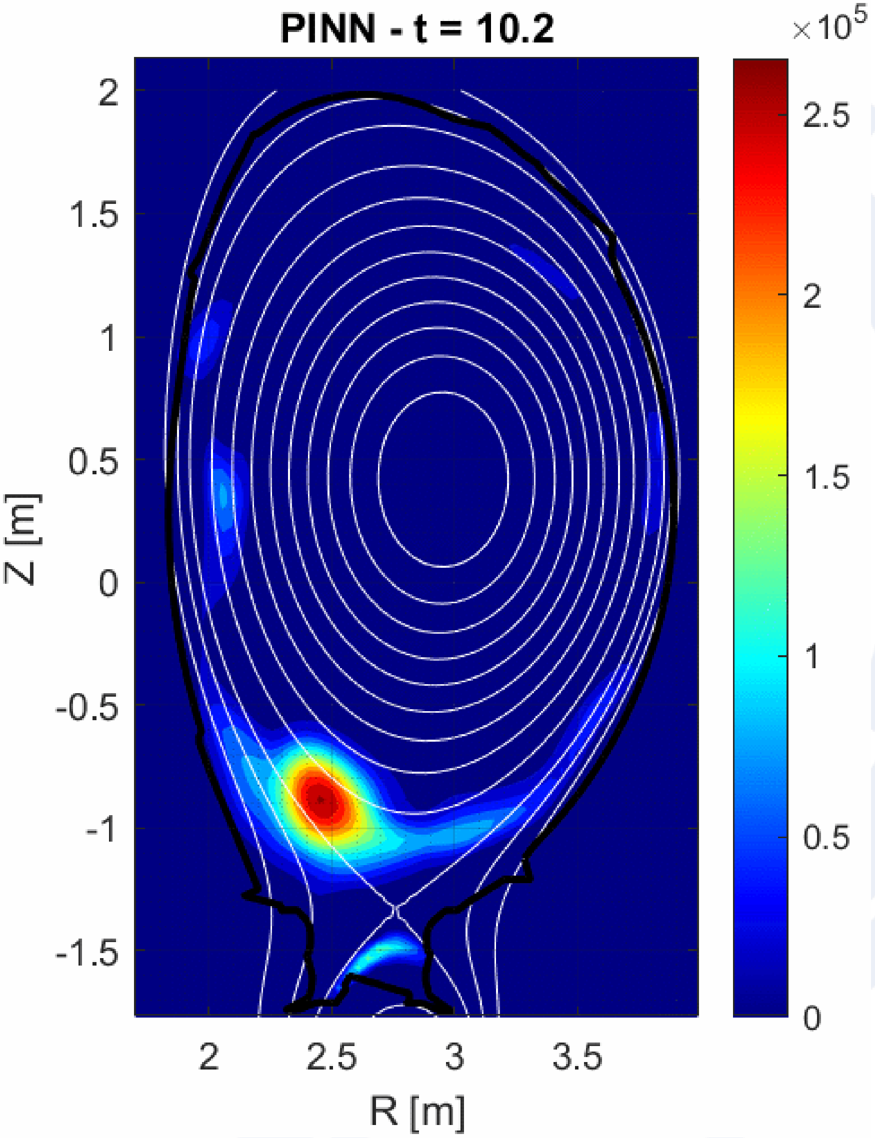
Test performed on various types of radiations:

- MARFE
- Edge-Localised Modes
- Impurity Accumulations

MARFE – Visibile Camera







R. Rossi *et al* 2025 *Nucl. Fusion* **65** 036030
https://iopscience.iop.org/article/10.1088/1741-4326/adb3bc

Outline

(*) See presentation by Novella Rutigliano "Physics-Informed Neural Networks for Multi-Diagnostic Reconstruction in Tokamaks"

Multi-Diagnostic Inversion

Different diagnostics are used to measure the same quantity in different regions and in different ways. How to combine them?

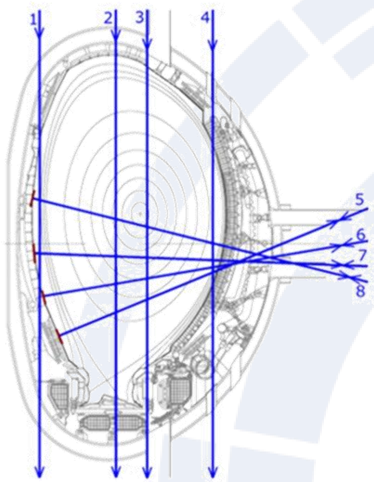
Electron density at JET is measured by:

Interferometer:
Line-integrated density, 8 line of sight

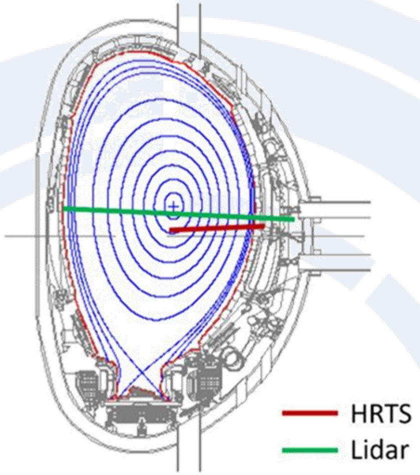
High Resolution Thomson Scattering (HRTS)
Local measurements limited to low field side and midplane

Lidar
Local measurements, low resolution, mid plane

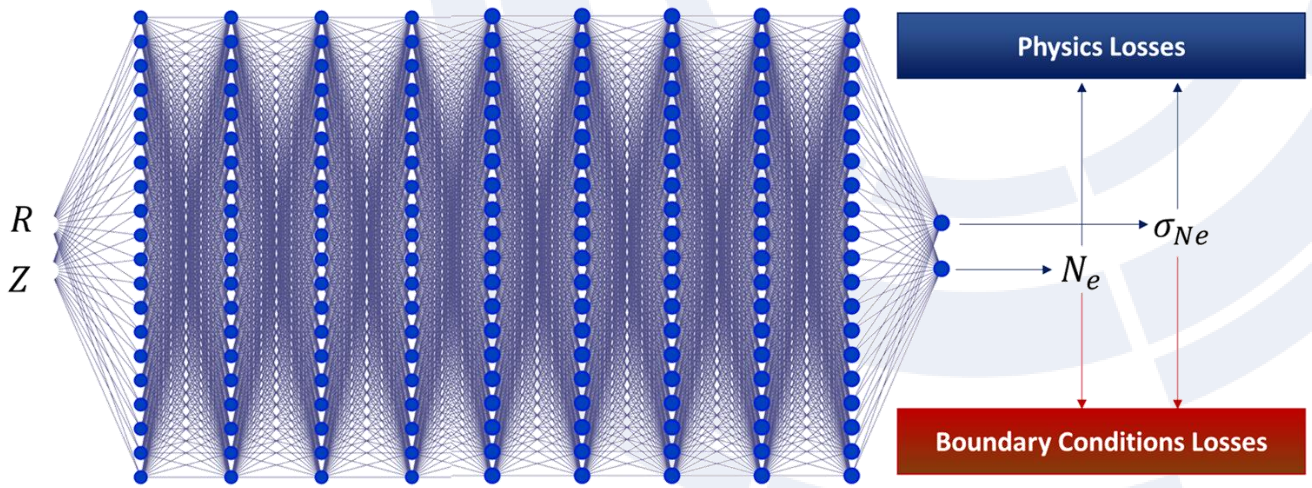
Interferometer



HRTS and Lidar



MLTOMOnet



Multi-Diagnostic Inversion

$$\mathcal{L} = \alpha\mathcal{L}_p + \mathcal{L}_{ML,LID} + \mathcal{L}_{ML,N_e} + \mathcal{L}_{wall}$$

$$\mathcal{L}_{ML,LID} = \frac{1}{M_{ch}}\frac{1}{M_k}\sum_{ch}\sum_{k}\left(\log\left(\sqrt{2\pi}\sigma_{LID,ch}\right) + \frac{\left(LID_{ch,k} - LID^b_{ch,k}\right)^2}{2\sigma^2_{LID,ch}}\right)$$

$$\mathcal{L}_{ML,N_e} = \frac{1}{M_b}\frac{1}{M_k}\sum_{i_b}\sum_{k}\left(\log\left(\sqrt{2\pi}\sigma_{N_{e,i_b,k}}\right) + \frac{\left(N_{e,i_b,k} - N^b_{e,i_b,k}\right)^2}{2\sigma^2_{N_{e,i_b,k}}}\right)$$

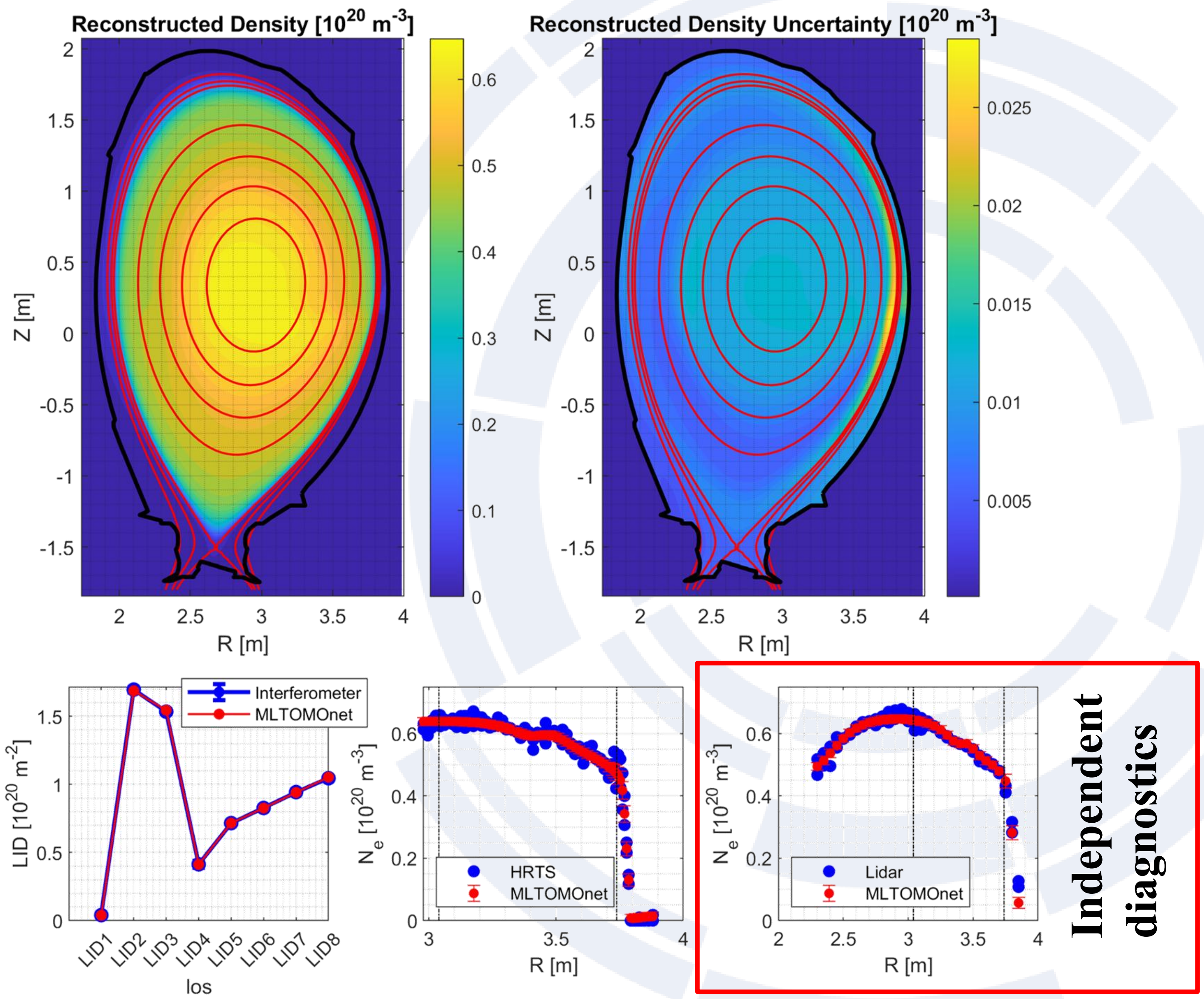
$$\mathcal{L}_{p,N_e} = \frac{1}{M_p}\frac{1}{C_\parallel^2}\sum_{i_p=1}^{M_p}\left(\nabla_\parallel N_e\left(R_{i_p}, Z_{i_p}\right)\right)^2 + \frac{1}{M_p}\frac{1}{C_\perp^2}\sum_{i_p=1}^{M_p}\left(\nabla_\perp N_e\left(R_{i_p}, Z_{i_p}\right)\right)^2$$

$$\mathcal{L}_{p,\sigma_{Ne}} = \frac{1}{M_p}\frac{1}{C_\parallel^2}\sum_{i_p=1}^{M_p}\left(\nabla_\parallel \sigma_{Ne}\left(R_{i_p}, Z_{i_p}\right)\right)^2 + \frac{1}{M_p}\frac{1}{C_\perp^2}\sum_{i_p=1}^{M_p}\left(\nabla_\perp \sigma_{Ne}\left(R_{i_p}, Z_{i_p}\right)\right)^2$$

Multi-Diagnostic Inversion

A unique reconstructed profile that considers both HRTS and interferometric measurements (LIDAR is used for test)

Uncertainty prediction highlights regions where different diagnostics say different things: useful for fault diagnostic detection.



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Direct Modelling and Denoising

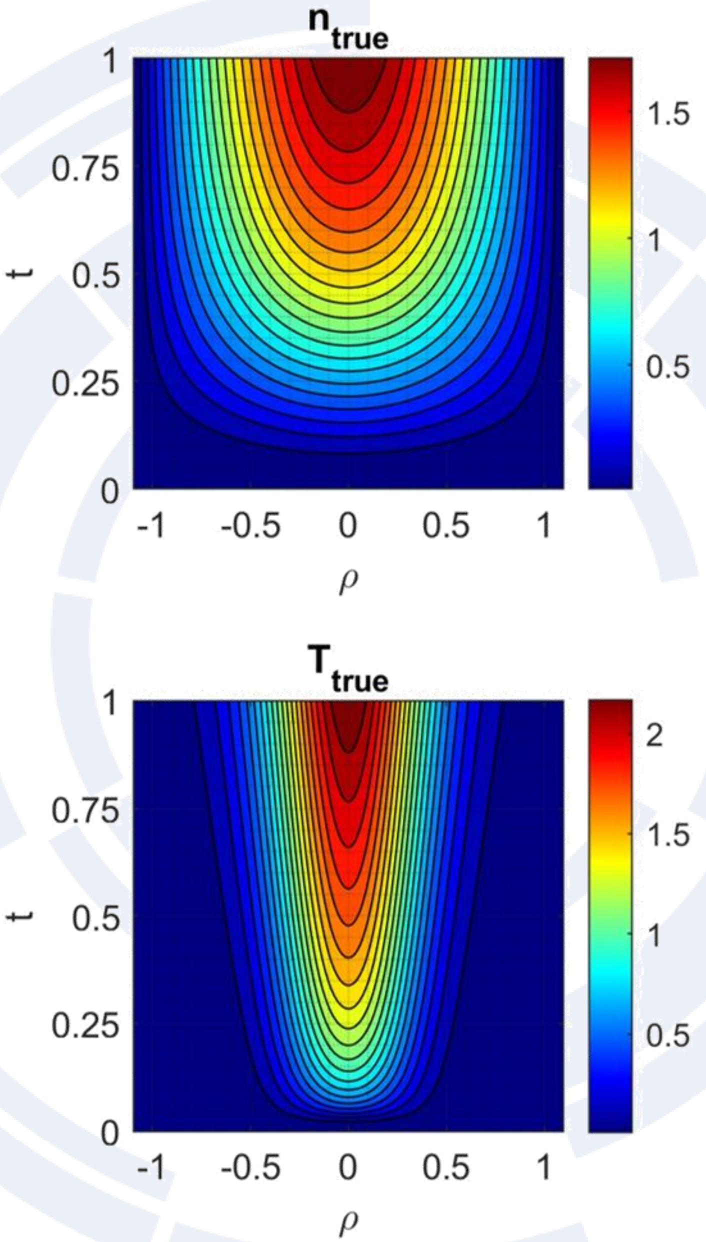
(Numerical) Case Study

By using 1.5D transport equations, the evolution of density and temperature is simulated

1. **Variable transport coefficients**, where the transport coefficient depends on density and temperature ($\mathrm{D}(\mathrm{n},\mathrm{T}), \chi(n,T)$)

Once derived the two fields, **synthetic diagnostics** are used to simulate tokamak-like measurements.

1. **Thomson scattering** (local measurement of electron density and temperature)
2. **Interferometer** (line-integrated measurement of density)



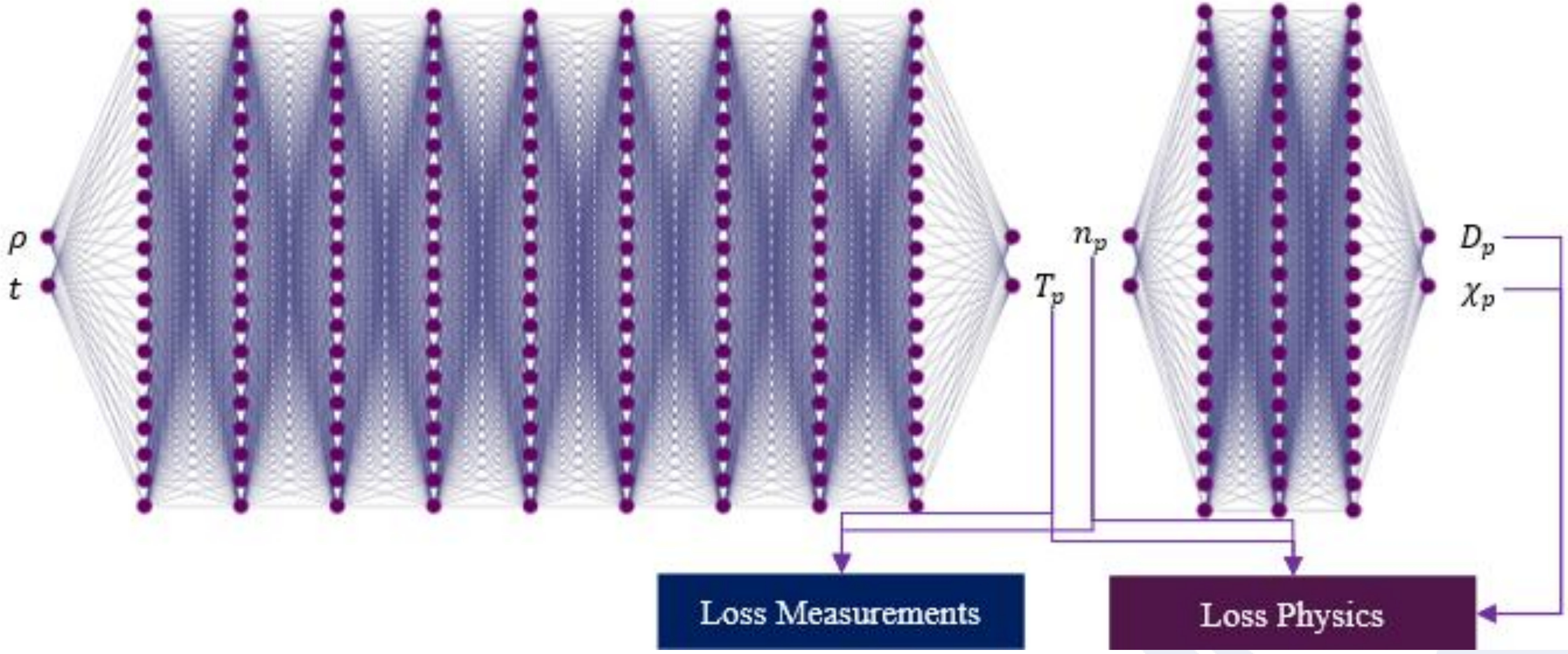
1.5D transport equations for plasma

$$\frac{1}{V'}\left(\frac{\partial}{\partial t}-\frac{\dot{\Phi}}{2\Phi}\frac{\partial}{\partial\rho}\rho\right)(V'n)+\frac{1}{V'}\frac{\partial}{\partial\rho}\Gamma-\mathrm{S}=0$$

$$\frac{3}{2}\frac{1}{V'^{5/3}}\left(\frac{\partial}{\partial t}-\frac{\dot{\Phi}}{2\Phi}\frac{\partial}{\partial\rho}\rho\right)\left(V'^{5/3}nT\right)+\frac{1}{V'}\frac{\partial}{\partial\rho}\left(q+\frac{5}{2}\Gamma\,\mathrm{T}\right)-\mathrm{P}=0$$

$$\Gamma=-DV'\langle(\nabla\rho)^2\rangle\frac{\partial n}{\partial\rho}\qquad q=-\chi\,V'\langle(\nabla\rho)^2\rangle n\frac{\partial T}{\partial\rho}$$

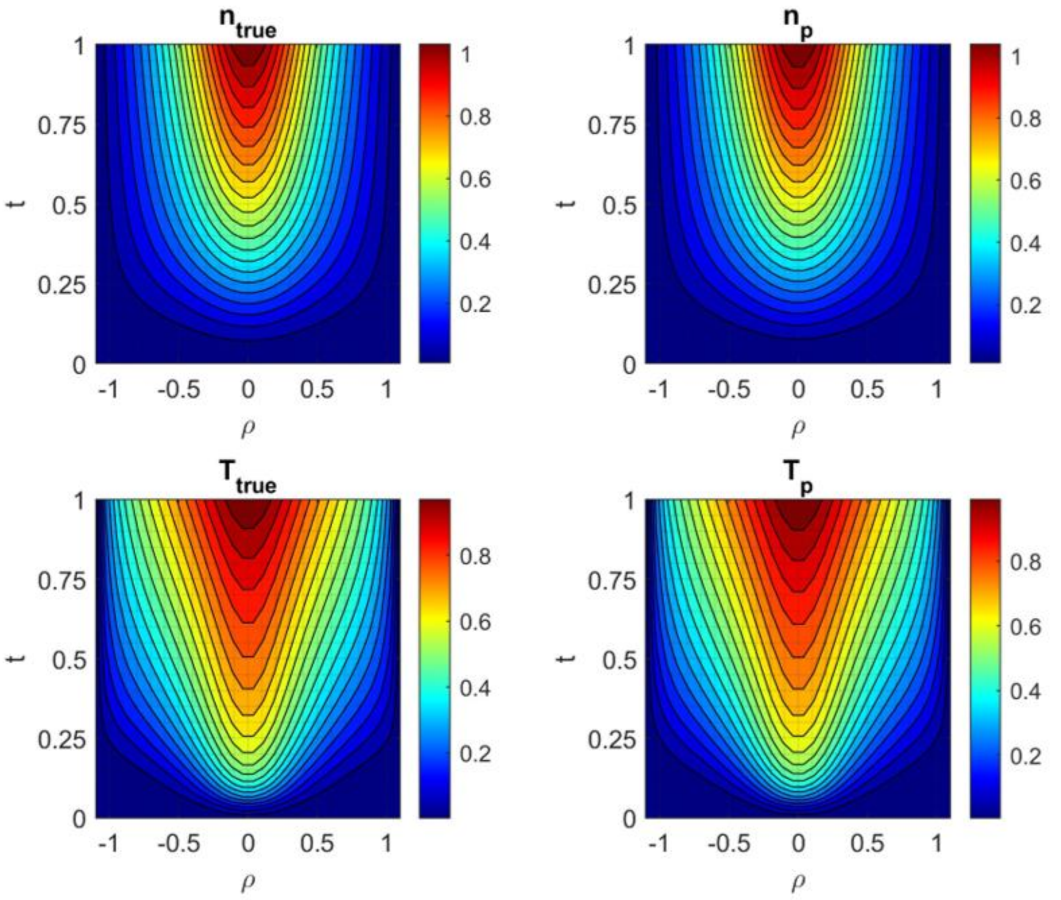
Modelling-based denoising

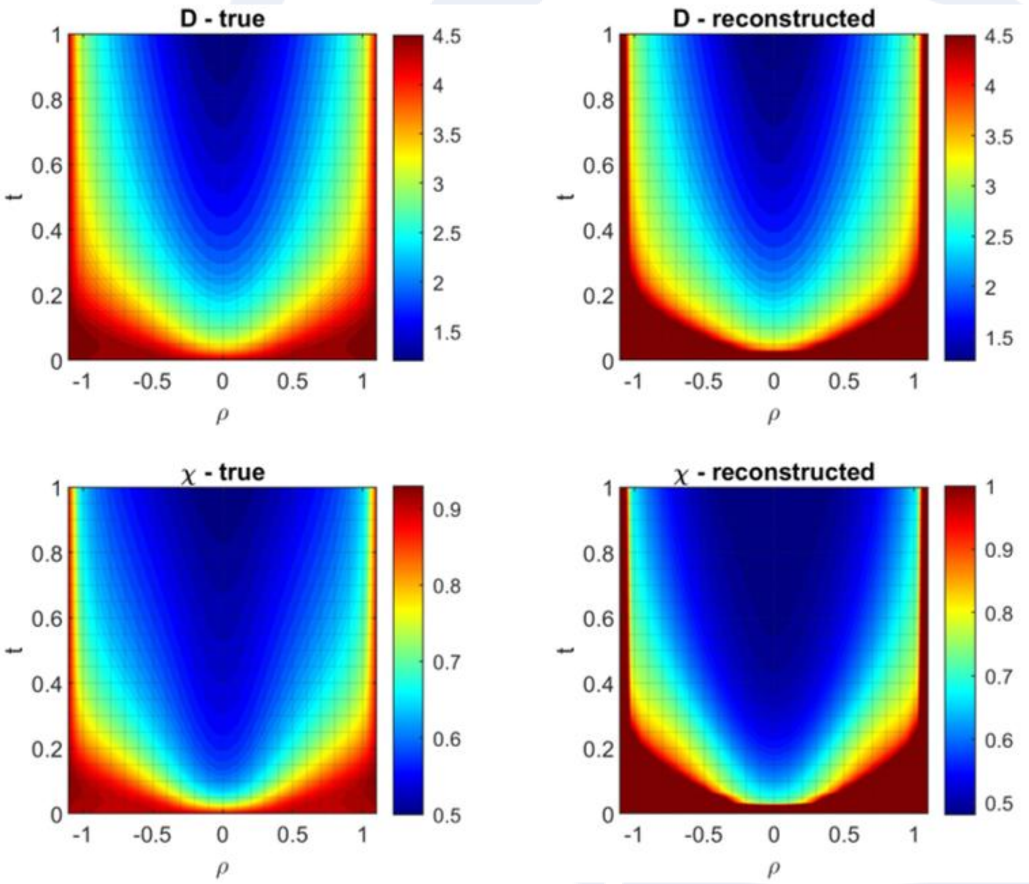


Multi-Diagnostic Inversion

Both the fields and the transport coefficients are reconstructed with high accuracy by combining the physics equations and the data from synthetic diagnostics.

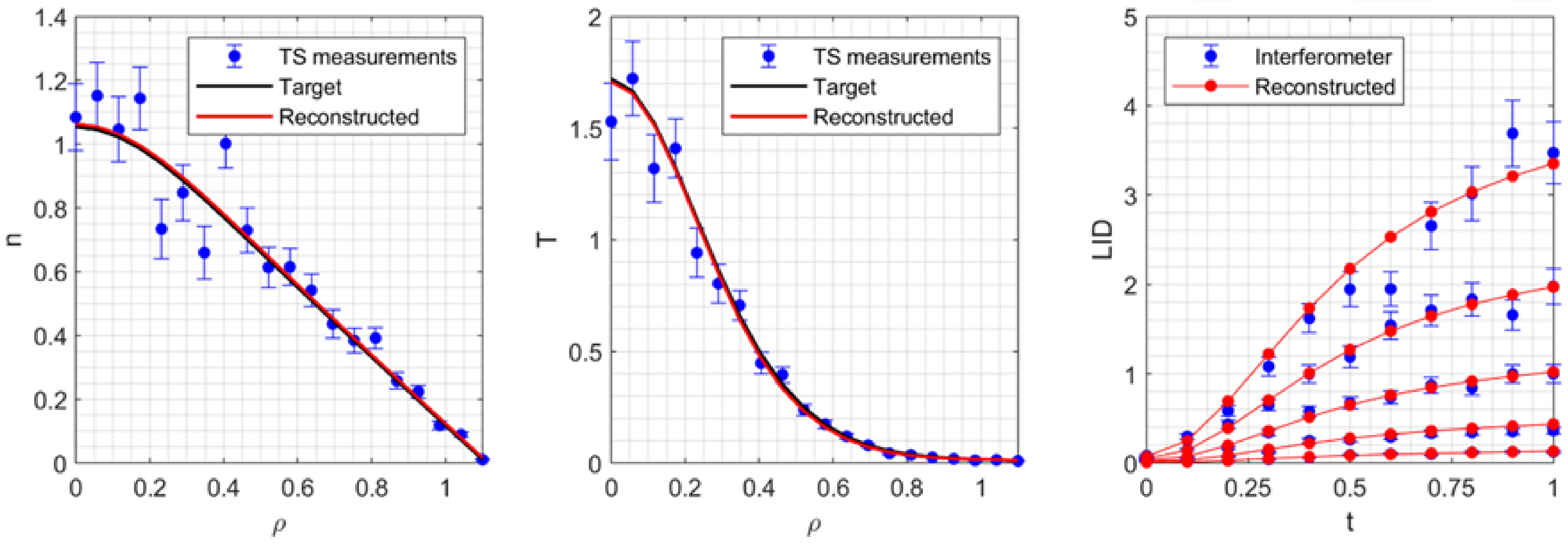
Riccardo Rossi et al. “Direct-Modelling in Nuclear Fusion by Combining Data-Integration and Physics-Informed Neural Networks”, *Proceedings of International Joint Conference of Neural Networks (IJCNN2025)* Rome, Italy, 2025





Modelling-based denoising

The diagnostics, affected by noise, are reconstructed by the PINN without the noise and are very close to the ideal measurements, implying that the PINN can be used also for **denoising**. This feature is ensured by using the physical term in the loss, which smooths out unphysical phenomena like noise.



Riccardo Rossi et al. “Direct-Modelling in Nuclear Fusion by Combining Data-Integration and Physics-Informed Neural Networks”, Proceedings of International Joint Conference of Neural Networks (IJCNN2025) Rome, Italy, 2025

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Conclusions

Physics-Informed Neural Networks (PINNs) combine physics and data-driven methods in a synergistic way, enabling a **wide range of applications.**

They provide efficient methods for **data denoising** and **enhanced inverse problem** solving by **integrating multiple diagnostics** with both **data-driven** and **physics-guided approaches**.

Overall, PINNs represent a highly promising framework for **bridging computational and experimental physics**.

However, unleashing **their full potential still requires significant progress on multiple fronts**, including **AI-related aspects** (e.g., training strategies, architectures, hyperparameter optimisation), **physical considerations** (e.g., equation formulation), and **diagnostic challenges** (e.g., uncertainty handling).

Physics-Informed Neural Networks for Diagnostics

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