Surrogate modelling of ray-tracing and radiation transport code for faster real-time plasma profile inference in a magnetic confinement device

FSD Science Coordination Meeting / KoM AI&ML projects

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project devised in collaboration with

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Background

- Infer plasma parameters, e.g. electron temperature, density
- Complex relation between spectral intensity of the ECE radiation and, e.g., the desired parameters, the magnetic fields, the mixing of radiation polarisations upon reflections off the vacuum vessel walls
- TRAcing VISualized (TRAVIS) code: radiation transport code solving accounting for wave absorption and emission
- Applied Bayesian inference is computationally expensive
- Example: inferring the $T_{\rm e}$ profile for a single steady state discharge of 10 seconds duration with 1 kHz sampling can take days



Iterative Bayesian Inference

Background

- Infer plasma parameters, e.g. electron temperature, density
- Complex relation between spectral intensity of the ECE radiation What can we try to achieve with AIIML based approaches? and, e.g., the desired parameters, the magnetic fields, the mixing radiation polarisations upon reflections off the vacuum vessel

Parameters

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- TRAcing VISualized (TRAVIS) code: radiation transport ca accounting for wave absorption and emission
- Applied Bayesian inference is computationally
- Example: inferring the $T_{\rm e}$ profile for a single of 10 seconds duration with 1 kHz san



Project

Approach

• Replace iterative Bayesian inference with surrogate AI models to provide fast inverse mappings



Non-Iterative, Direct Inverse Mapping with ML Surrogate Models

- Application to plasma parameter inference from diagnostics
- Target real-time application in the control room (min or even ms scale)
- Expect general applicability of resulting models & knowledge

Partners

- MPI for Plasma Physics in Greifswald (IPP)
- University of Southern Denmark (SDU) as associated 3rd party via the Technical University of Denmark (DTU)

Iterative Bayesian Inference

Project

Methods

- ANNs as generic function approximators
- Direct inverse mapping has huge potential
- Complexity analysis:
 - Trade off speed vs accuracy
 - Requirements per application
- Focus on estimation of error and uncertainty due to requirements for plasma operation
- Investigate Physics Informed Neural Networks (PiNNs), Kolmogorov-Arnold Networks, and especially for stages 2 & 3 Bayesian Networks (also as PiNN variants) and ANNs/PiNNs with Bayesian last layer; architectures...
- Optimisation: sampling strategy for training, using, e.g., ridge regression, Sobolev-type regularisation



Non-Iterative, Direct Inverse Mapping with ML Surrogate Models

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Team – Backgrounds & Roles

SDU

- Henrik Bindslev Fusion, Collective Thomson Scattering, modelling mm-waves in plasmas
- Esmaeil Nadimi AI/ML in energy and health care applications
- Jan-Matthias Braun AI/ML in biosignal analysis and adaptive control
- Collaboration with DTU on Collective Thomson Scattering
 IPP
- Daniel Böckenhoff AI/ML applications for fusion
- Neha Chaudhary Experiment design & execution
- Pavel Aleynikov & Nikolai Marushchenko TRAVIS

Outline

Development of surrogate models in three stages

- Stage 1: Surrogate forward model (Dec. 2024)
- Stage 2: Full inverse model for the TRAVIS node (July 2025)
- Stage 3: Full inverse model for combined diagnostics (Dec. 2025)

Further Outcomes

- Integration into the MINERVA framework (June 2025)
- Documentation towards the use of AI models (Dec. 2025)

