AI for Fusion: Old Challenges, New Tools

AI for Science Symposium

4th September 2025 - Stockholm

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UKAEA Data Science
UCL SML

Who are we?

UK Atomic Energy Authority

Data Science and Viz Team,
UK Atomic Energy Authority

Sustainability and Machine Learning Group,
University College London

Why do we care?

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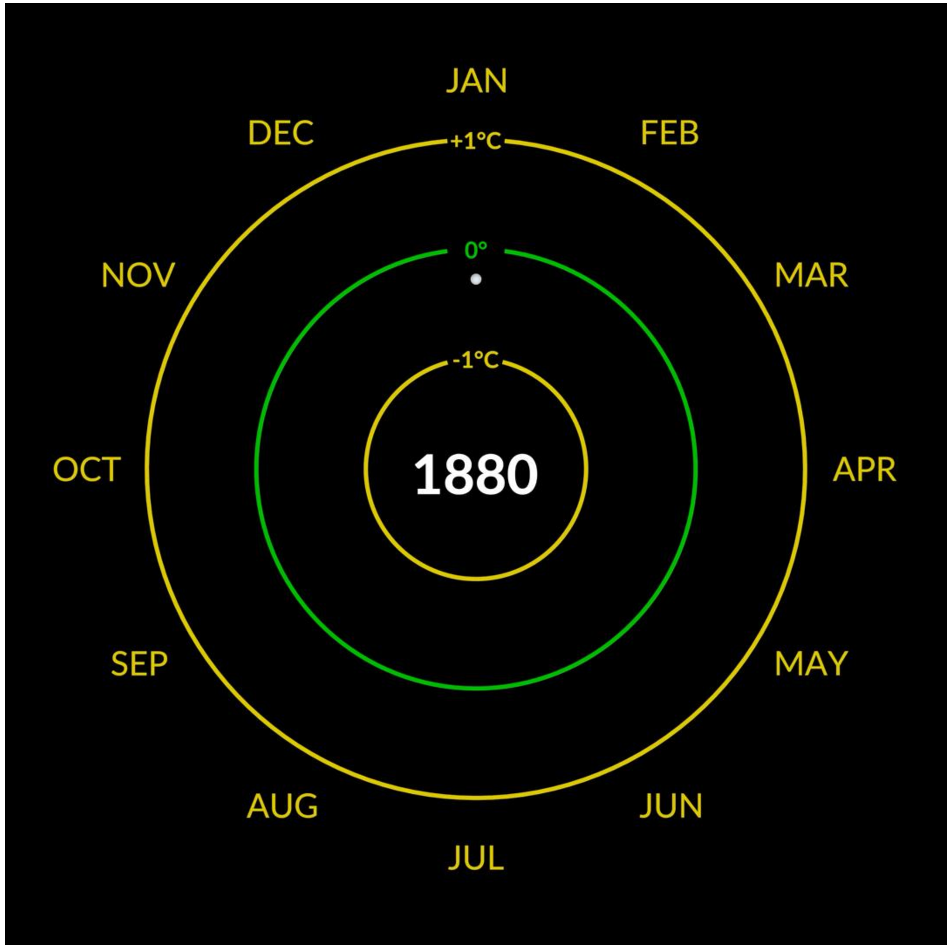
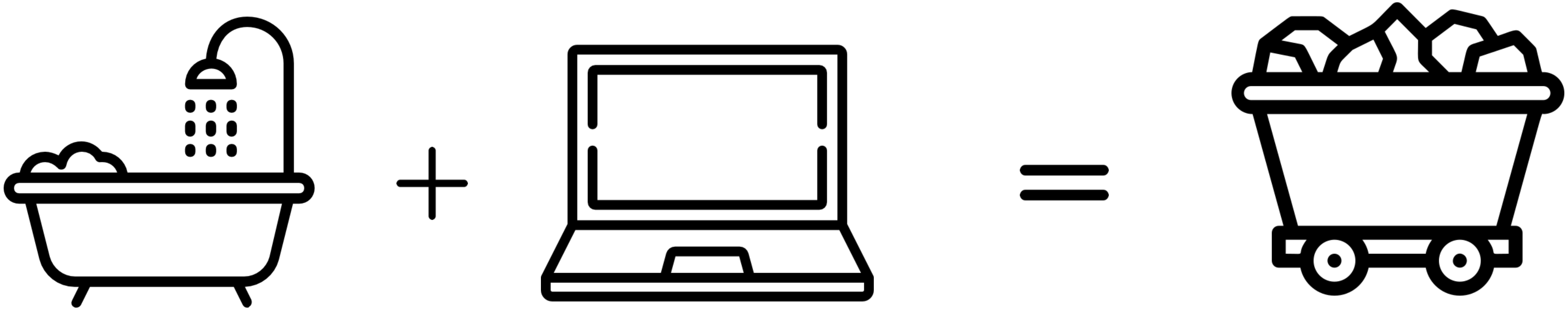


Source: NASA

Why Fusion exactly?

Because of it’s high yield and virtual inexhaustibility

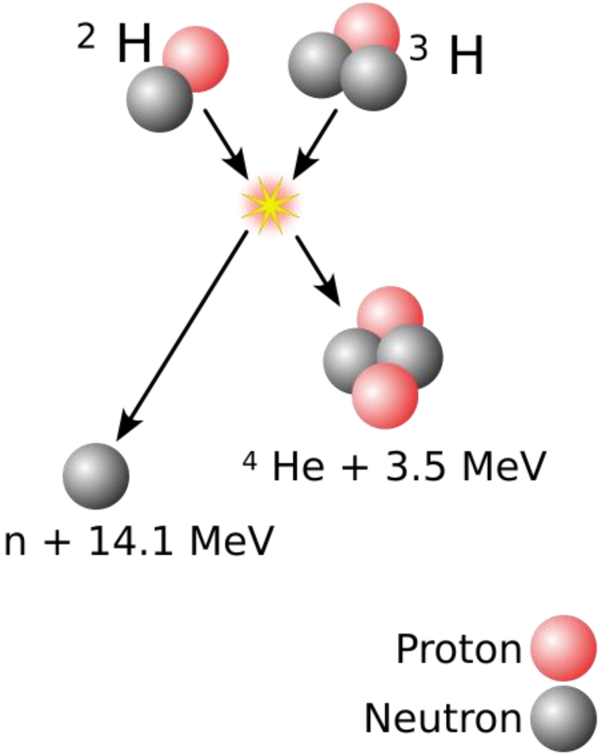


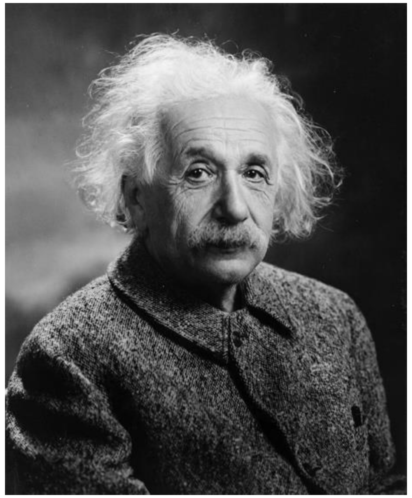
1 bathtub of water (Hydrogen) + 2 laptop batteries (Lithium) = 16,000 wheelbarrows of coal

Which is the equivalent of 1 person's energy usage for 60 years.

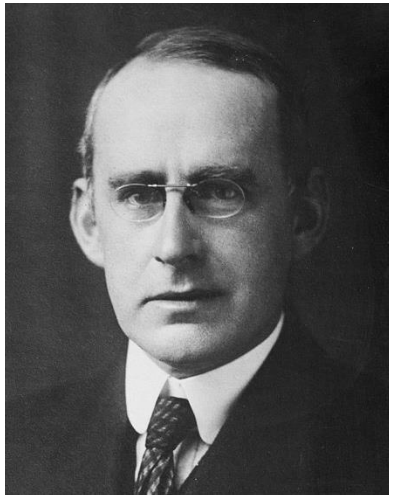
Image Source: Flaticon

What is Fusion?





Albert Einstein



Arthur Eddington

Fusing of the nuclei of two lighter elements to form the nuclei of a heavier element.
The difference in mass between the reactants is manifested as energy according to $\boldsymbol{E = mc^2}$

Image Source: Wikipedia

Nearest "sustainable Fusion reactor"

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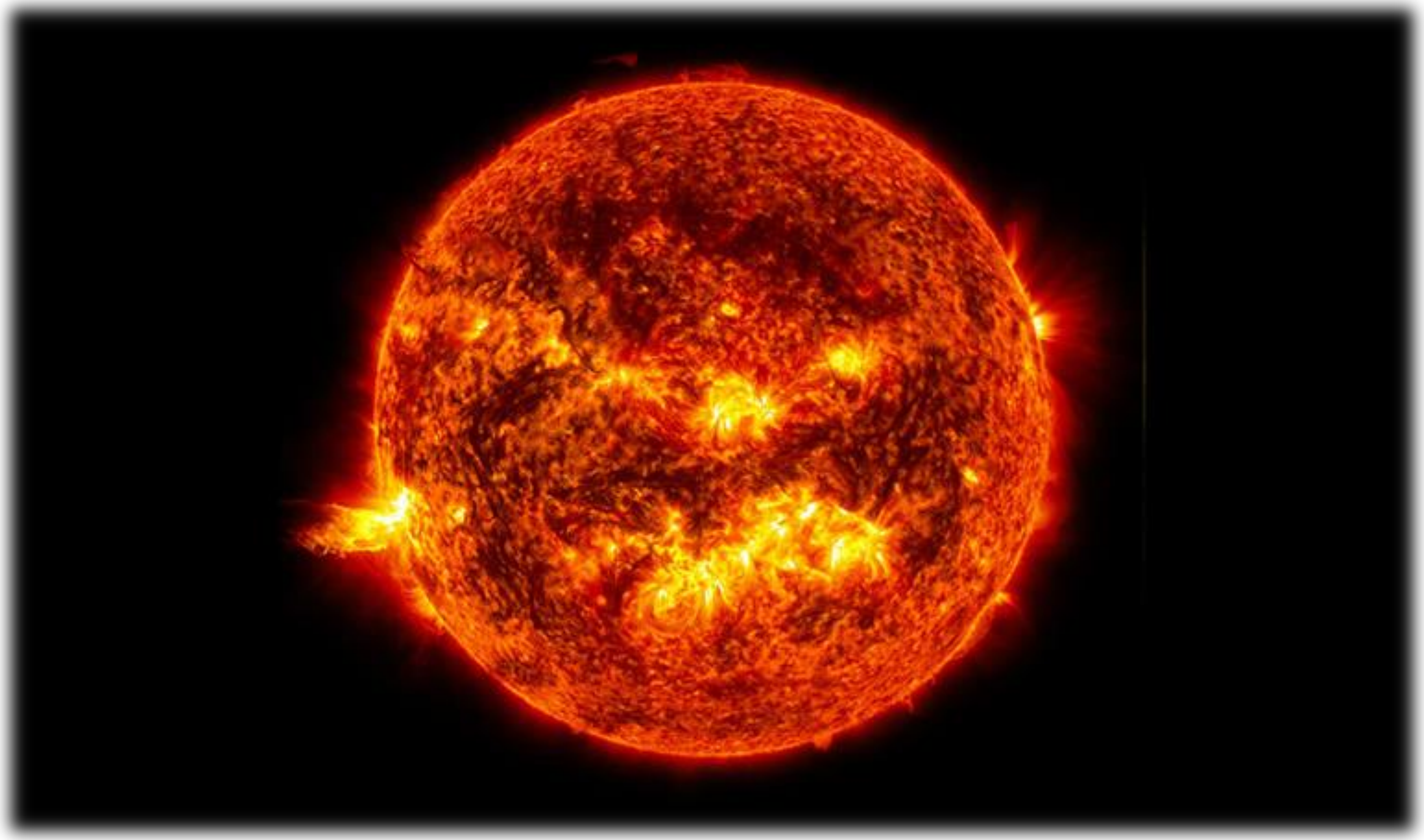

Our Sun

Image Source: NASA

What's really the challenge?

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Fusion occurs due to the strong nuclear force, which has an extremely short interaction range.

Since nuclei carry positive charges that push them apart, they must be forced close enough together to feel the attractive pull of the strong nuclear force.

What's the challenge?

Fusion occurs due to the strong nuclear force, which has an extremely short interaction range.

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My three-year-old nephew's reaction to this.

What's the challenge?

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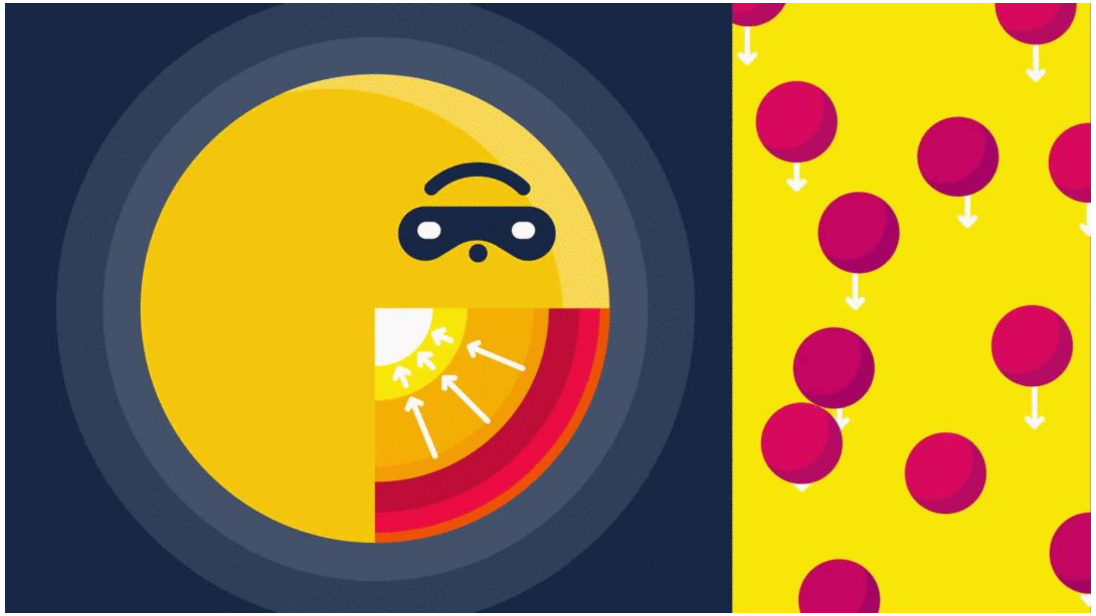
Fusion occurs due to the strong nuclear force, which has an extremely short interaction range.

Since nuclei carry positive charges that push them apart, they must be forced close enough together to feel the attractive pull of the strong nuclear force.



Sun has a cheeky little trick for this: Gravity

Video Source: Kurzgesagt

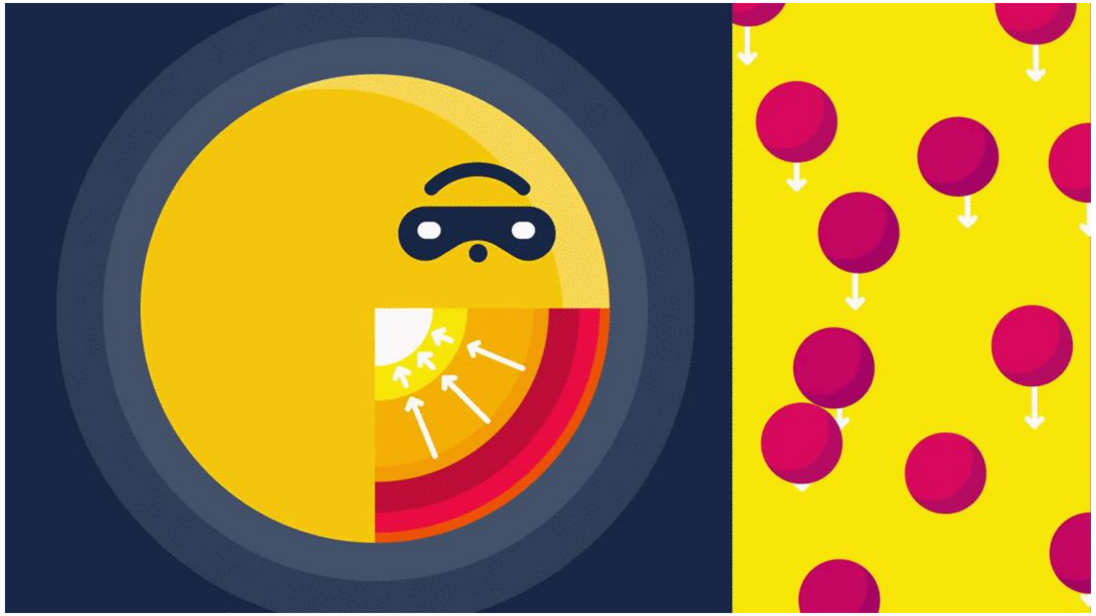
What's the challenge?

UK Atomic Energy Authority

Fusion occurs due to the strong nuclear force, which has an extremely short interaction range.

Since nuclei carry positive charges that push them apart, they must be forced close enough together to feel the attractive pull of the strong nuclear force.

We can't replicate this pressure and resort to cranking up the temperature



Sun has a cheeky little trick for this: Gravity

Fusion Triple Product = *density x temperature x confinement time*

Video Source: Kurzgesagt

Challenges are often opportunities!

At such high temperatures, the gas takes the form of plasma, a hot ionised gas that an electromagnetic field can control.

Tokamak: Magnetic Confinement

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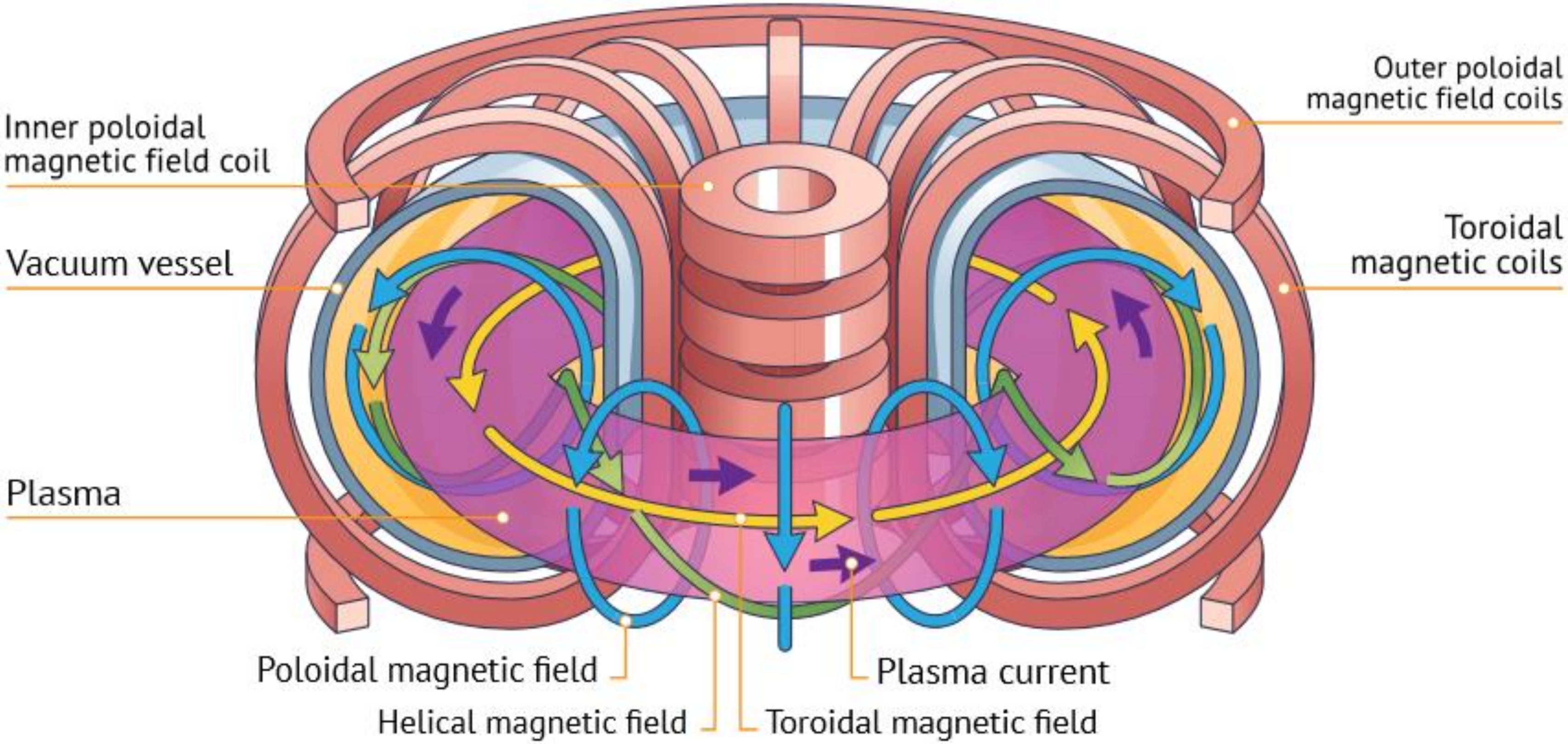
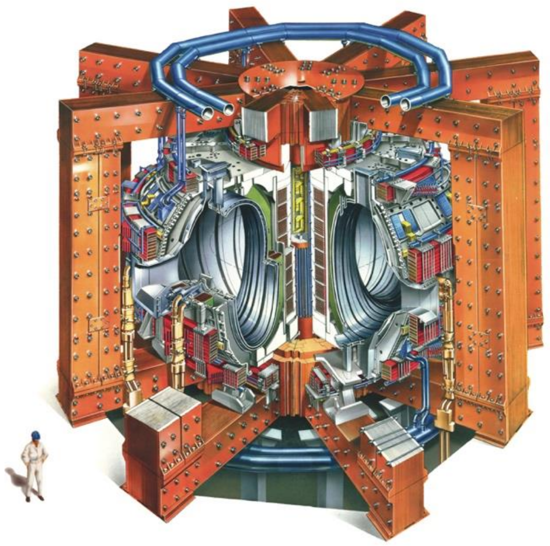
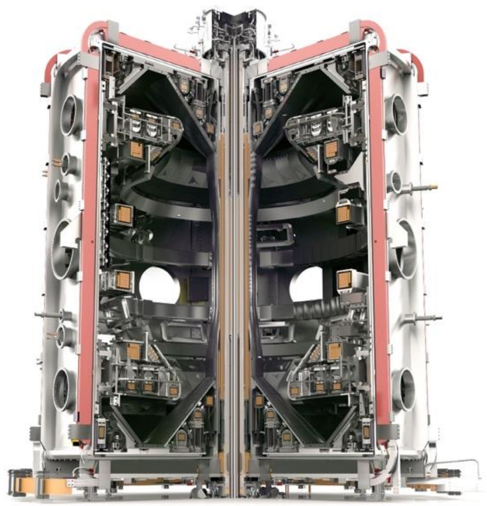


Image Source: Energy Encyclopedia

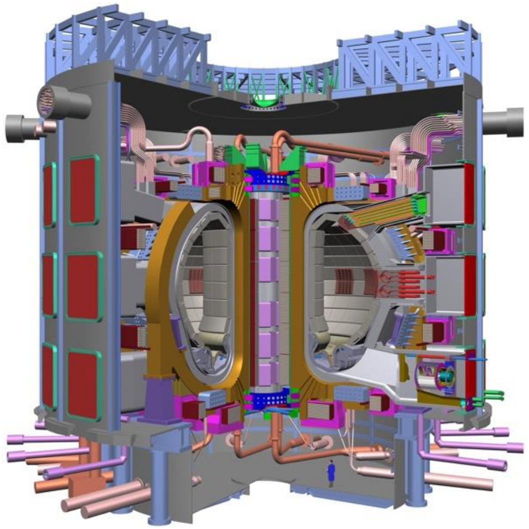
Tokamaks in practice



JET

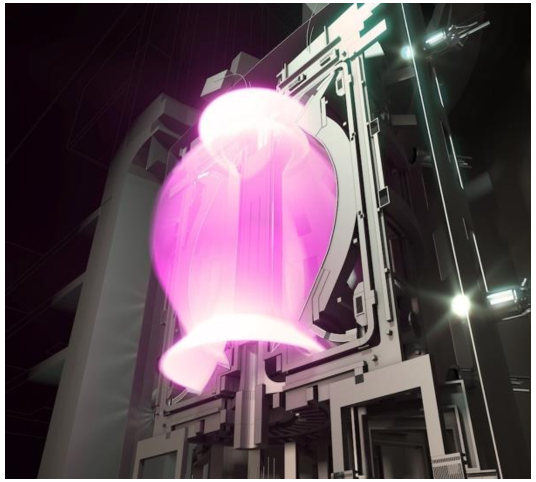


MAST – U



ITER

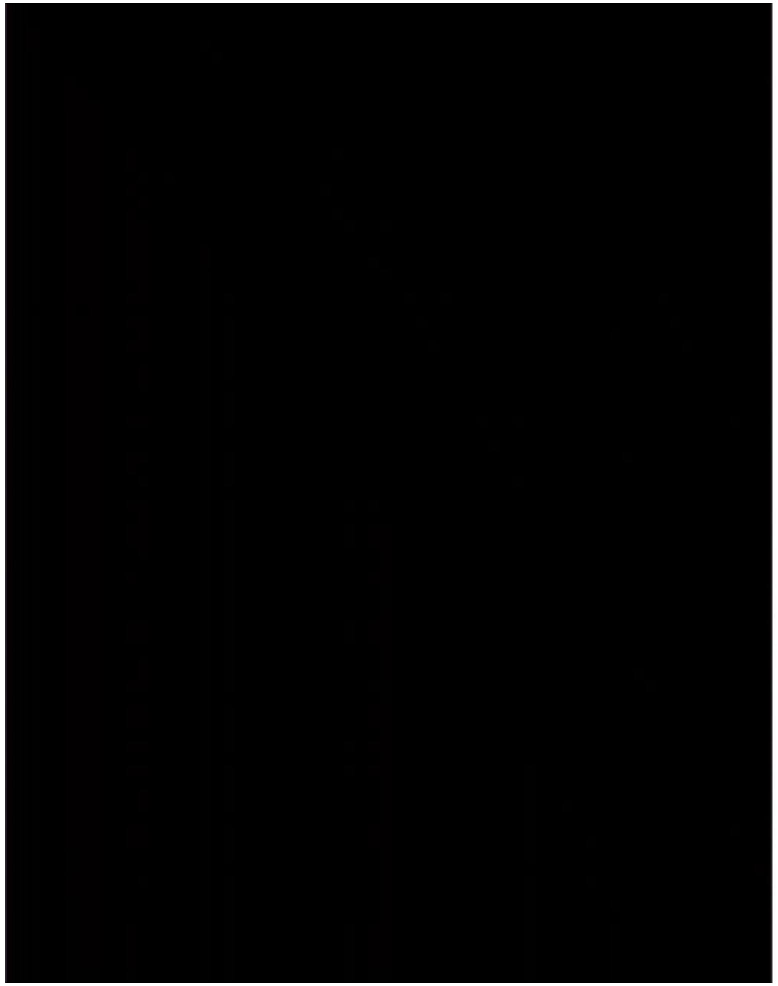
CFS ARC



STEP

Image Source: Eurofusion, CFS, ITER, UKAEA

Just because its complex does not mean its impossible.

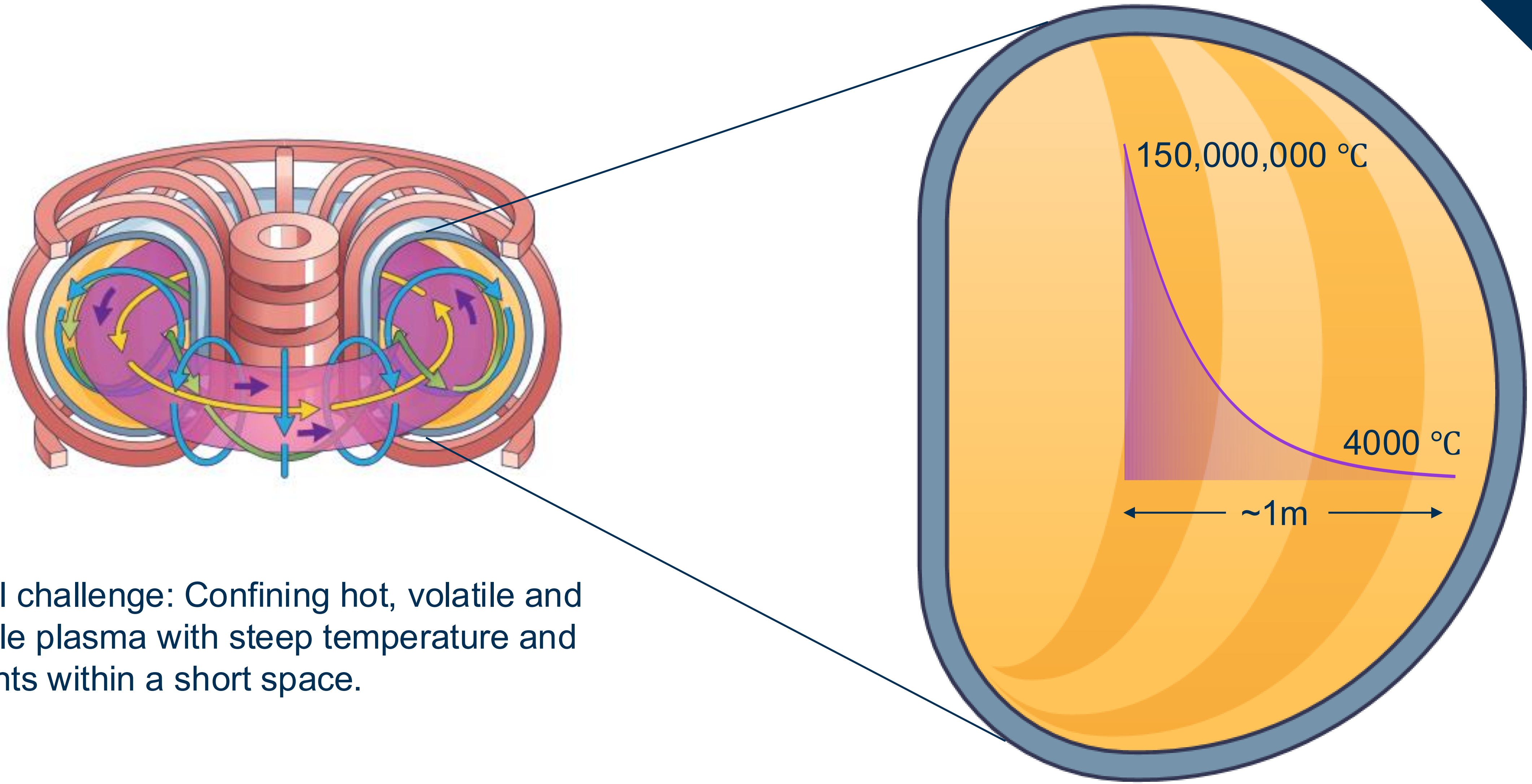


World Record Plasma:

In 2023, JET set the world record by generating 69 megajoules using a mere 0.2 milligrams of fuel.

But it only lasted for 5 seconds.

What makes Fusion so hard for us?

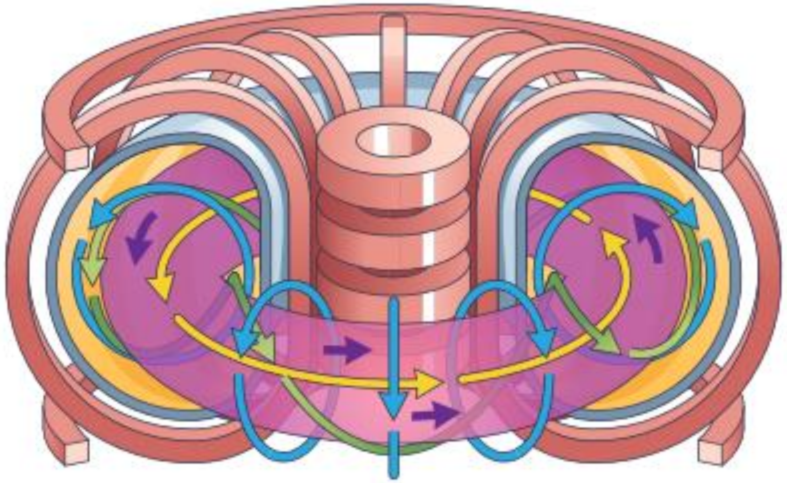


Central challenge: Confining hot, volatile and unstable plasma with steep temperature and gradients within a short space.

The gradient steepens further given the superconducting magnets' near-absolute-zero cooling

Image Source: Energy Encyclopedia

What makes Fusion so hard for us?



Materials

- Excessive Heat Load on Plasma Facing Components
- Breeding Blankets for D-T Fuel Cycle

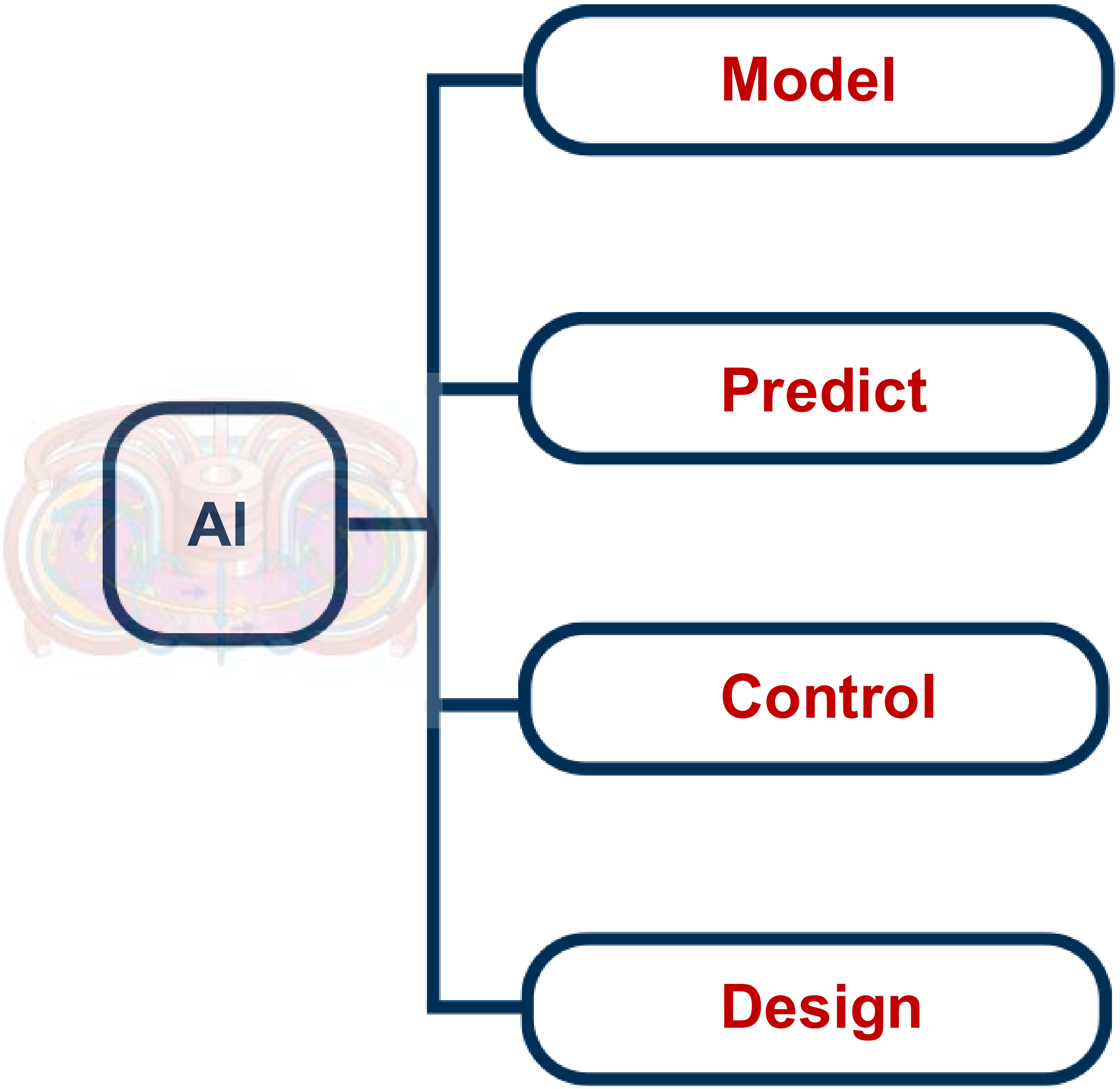
Instabilities

- Complex Multi-Scale Multi-Physics leading to wildly chaotic behaviour
- Nonlinear turbulent regimes

Confinement

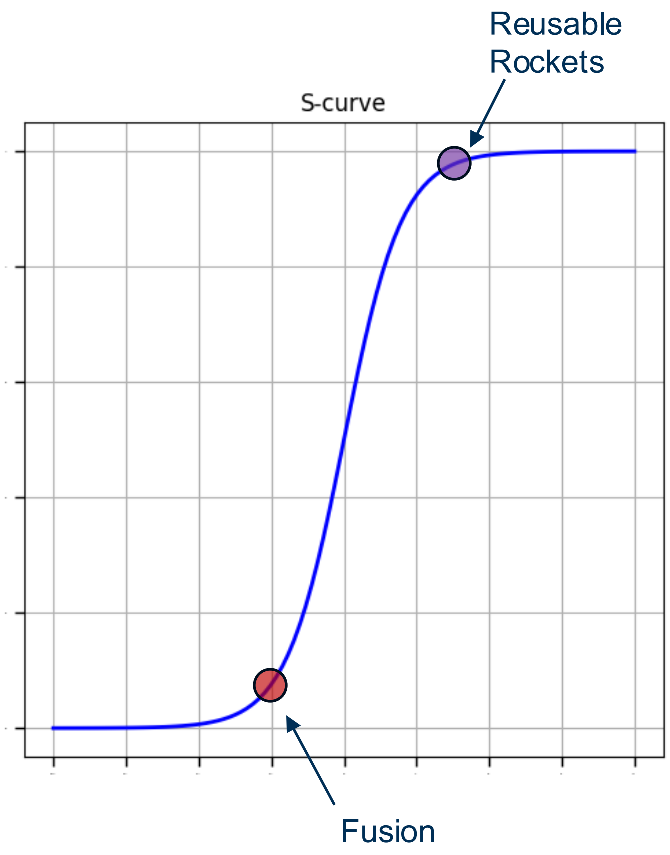
- Sharp Temperature and Pressure gradients
- Exhausts to remove impurities

What can AI do to help?



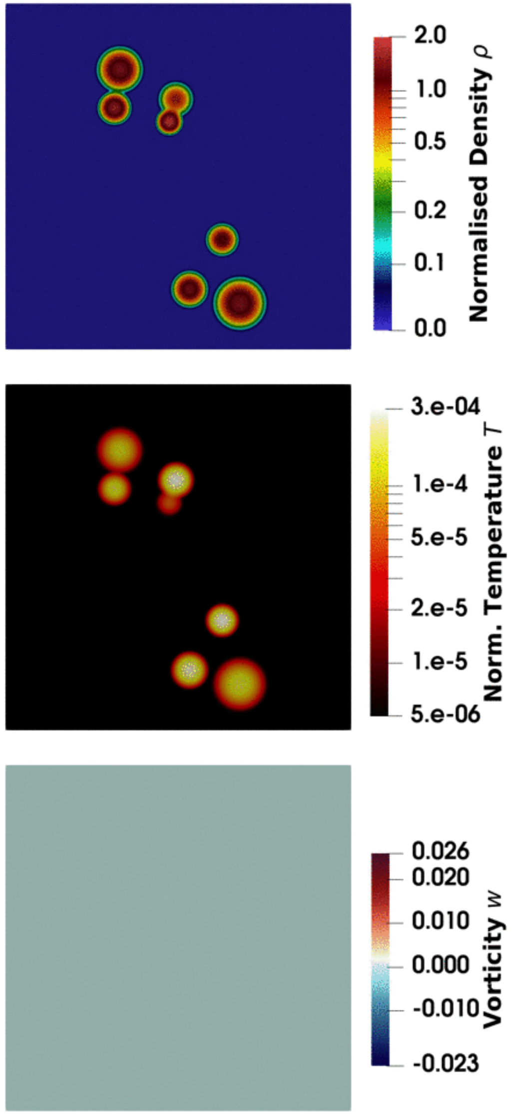
What can AI do to help?

State of Fusion Research



- Too costly to use a design-build-test-iterate model
- Cannot experimentally observe reactor-grade burning plasma in current devices.
- Will have to climb further up the engineering S-curve by going in-silico.

In-silico research: Simulations



We need ***robust digital twins:***

Accurate, actionable **simulations** which can be used to optimise designs under uncertainty.

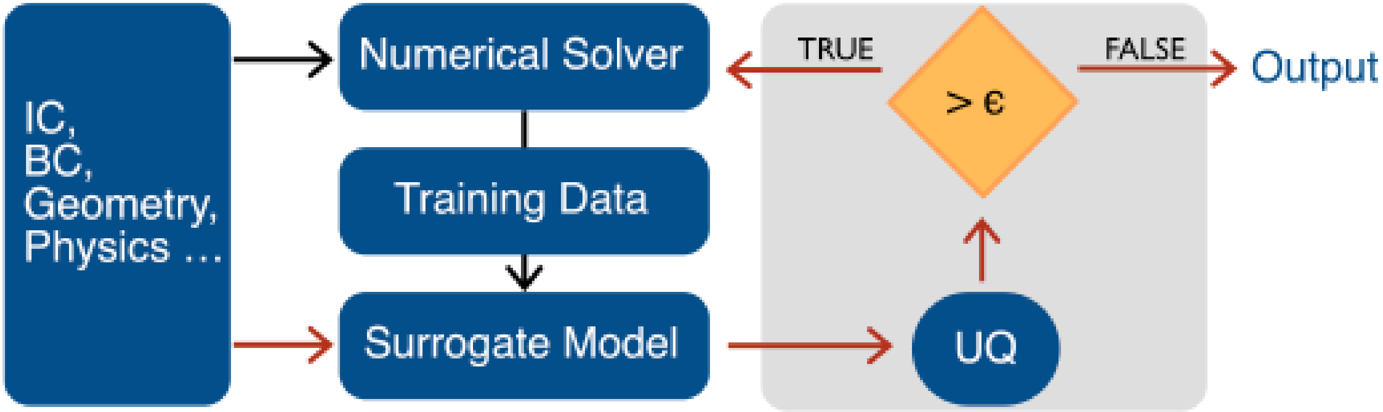
Very hard due to the wealth of different physics operating on different scales.

Requires extensive computing resources.

Source: Pamela et al. 2025. Neural-Parareal

Surrogate Modelling

Computationally intensive, complex, Multiphysics simulations can be *approximated* with AI-driven surrogate models.



Usually, surrogate models are taken as operator-based models such as Gaussian Processes and Neural Operators that learn to generalise around the domain physics.

Source: Gopakumar et al. 2025. Calibrated Physics-Informed Uncertainty Quantification

Surrogate Modelling: MHD

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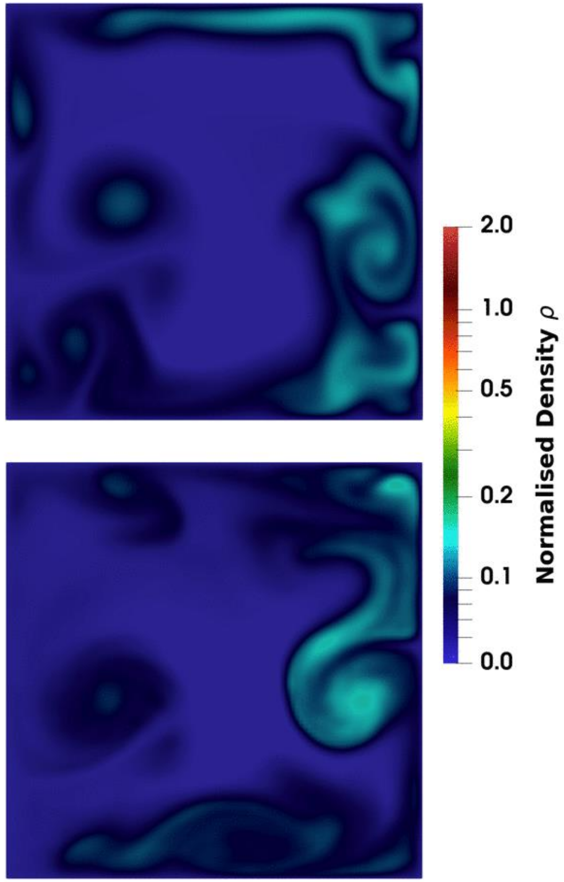
Numerical PDE Solver

Neural-PDE Solver

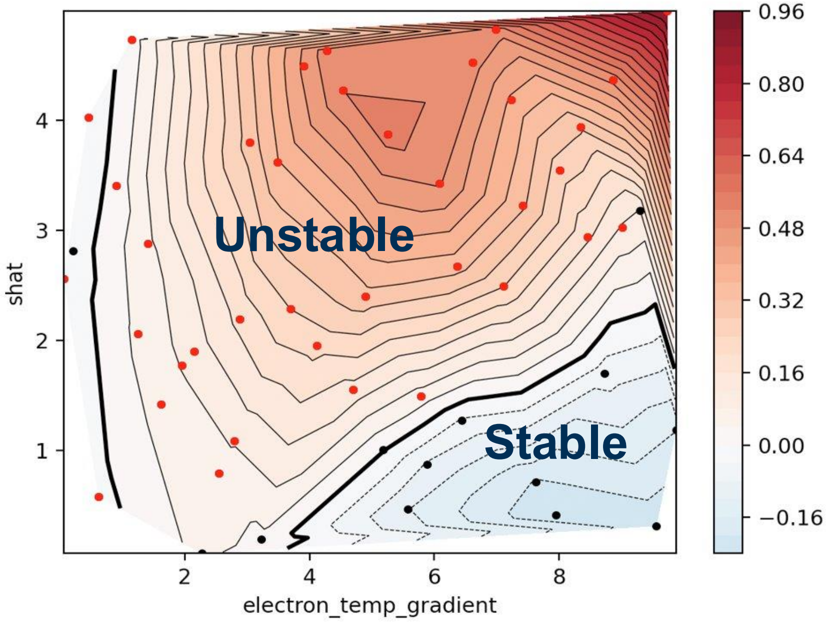


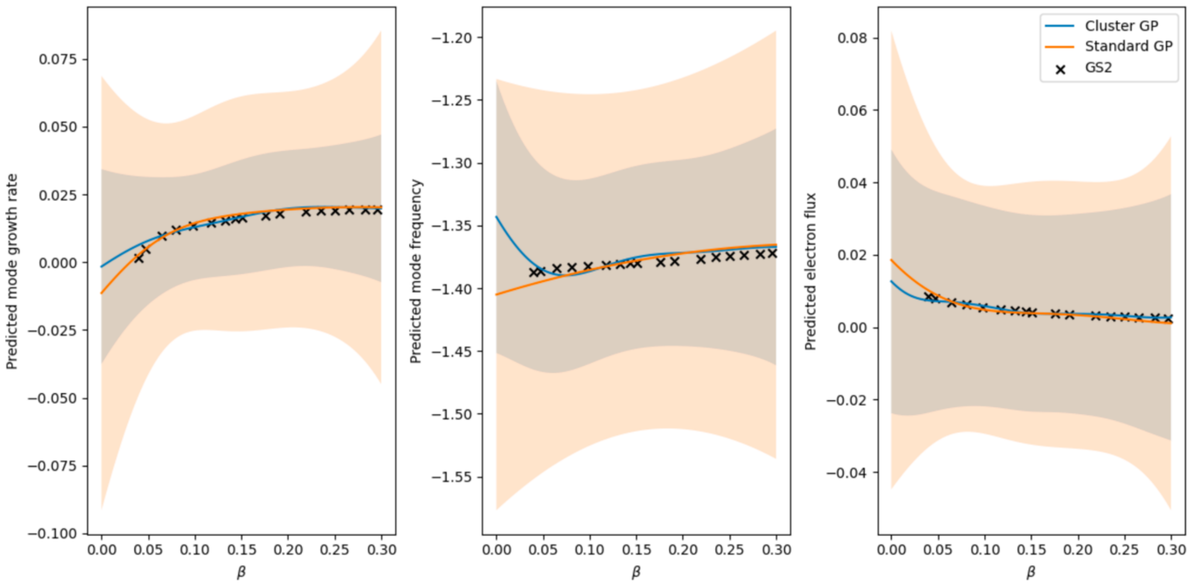
Neural-PDE solvers, such as a Fourier Neural Operators, can approximate Magnetohydrodynamic behaviour 1 million times faster than a traditional numerical solver.

It took approximately 350 core hours for each simulation datapoint to converge, while the model's training took slightly more than 10 hours on a single GPU.

Source: Carey et al. 2025. Data Efficiency of neural operator surrogate models for edge plasma simulations.

Surrogate Modelling: Gyrokinetics



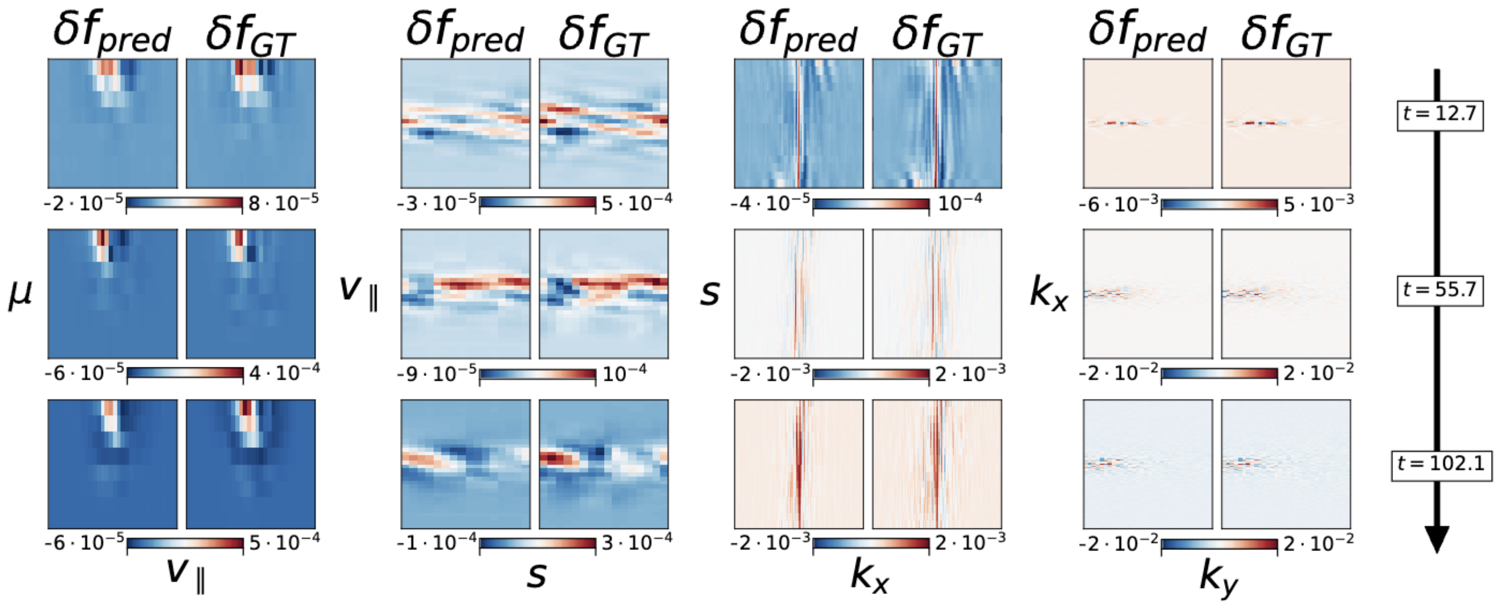


Operator methods such as Gaussian Processes are inherently probabilistic, enabling us to learn across turbulent operational regimes and predict gyrokinetic behaviour in tokamaks

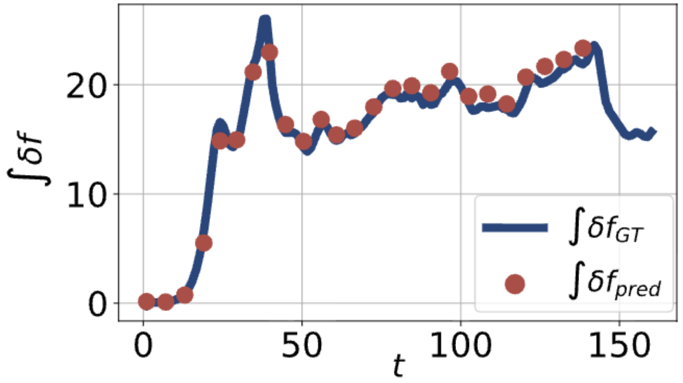
Reducing the modelling time from 100s to 0.001s

Source: Hornsby et al. 2024. GP surrogate models for the properties of micro-tearing modes in spherical tokamaks

Surrogate Modelling: Gyrokinetics



5D Swin-UNet can accurately predict the distribution function in five dimensions. One-step model predictions of the distribution function, δf_{pred}, versus ground truth, δf_{GT}, over time are reported.



Heat flux time trace comparing the ground truth with the prediction for the holdout trajectory.

Source: Galetti at al. 2025. 5D Neural Surrogates for Nonlinear Gyrokinetic Simulations of Plasma Turbulence

Surrogate Modelling: Active Learning

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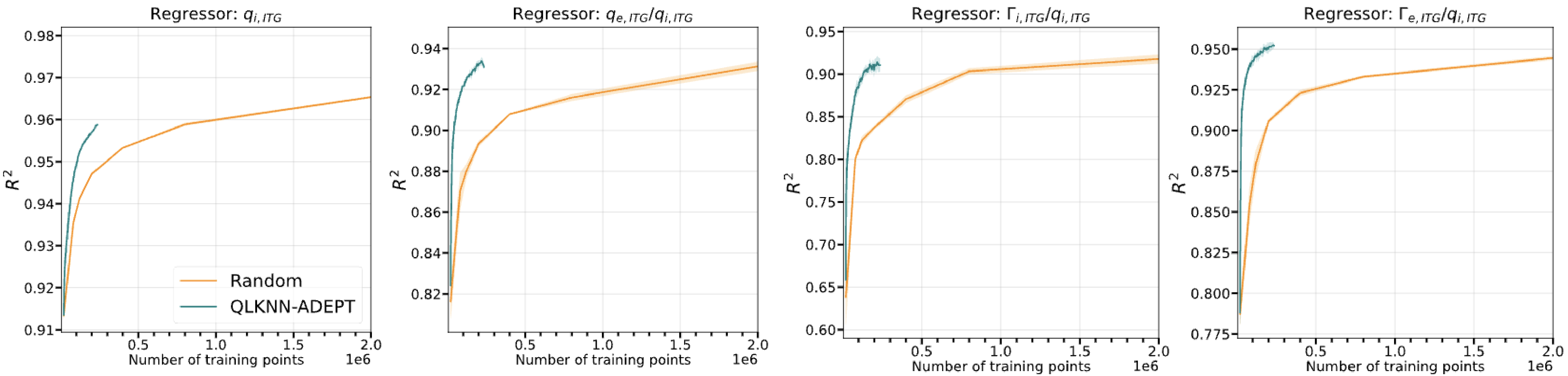
Models are data hungry. Simulations are expensive. By using Active Learning, We can reduce the data required for model training by a factor of 20.



Source: Zanisi et al. 2024. Efficient training sets for surrogate models of tokamak turbulence with Active Deep Ensembles

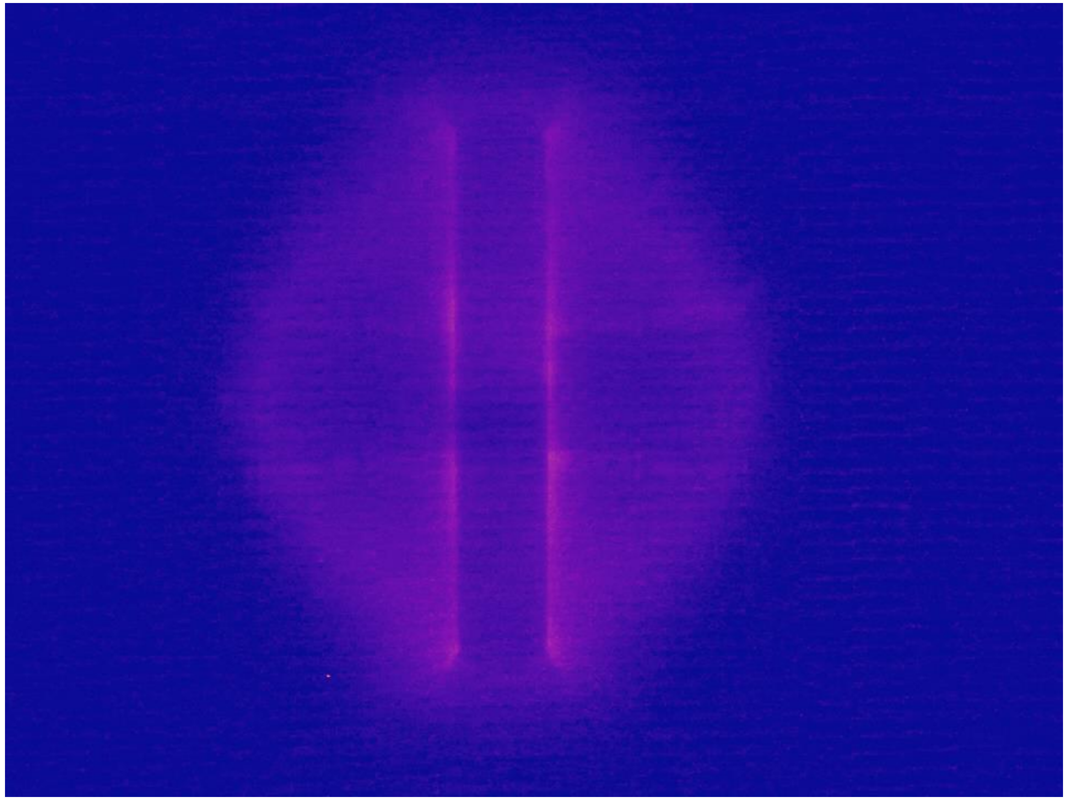
Digital Twins for **Predictions**

Visualising the plasma within MAST-U using Nvidia Omniverse

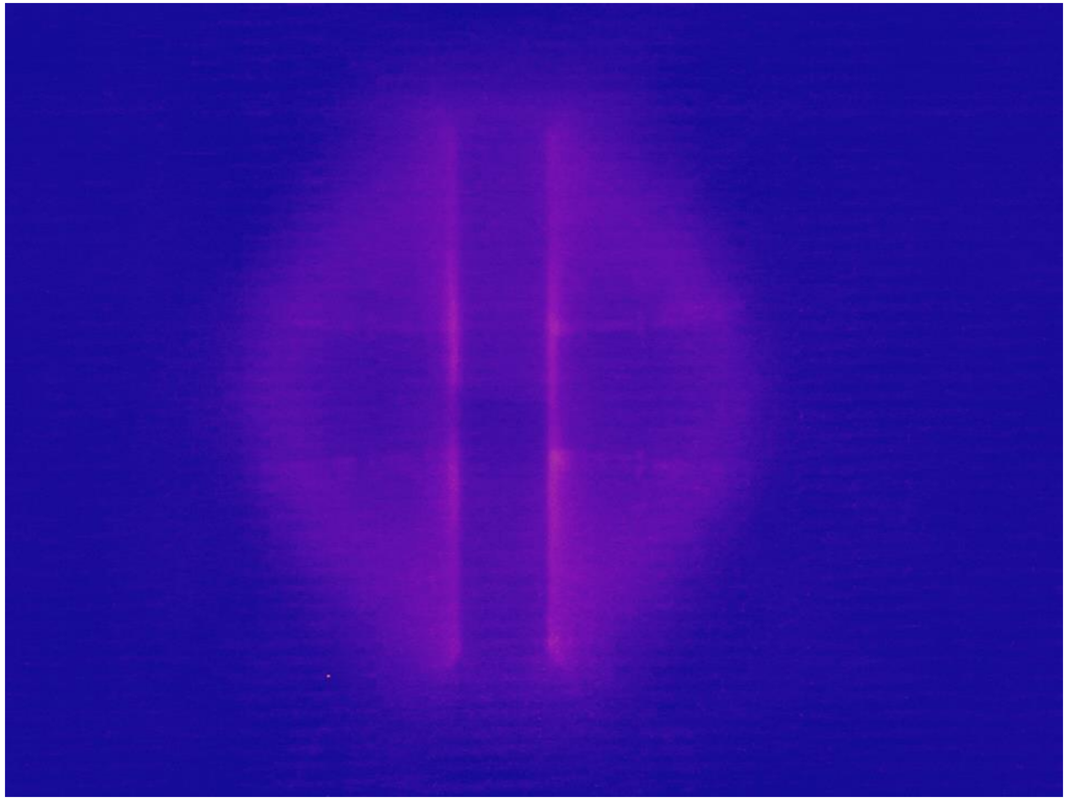
- Simulations might not be representative of the experiment
- **Sim2Real Gap**
- Experimental data might be noisy and sparse.

Source: Bhatia et al. 2025. Visualising digital twins of fusion power plants using Nvidia Omniverse

Digital Twins for Predictions (faster than real-time)



Camera



Model

Source: *Gopakumar et al. 2024. FNO for Plasma Modelling*

Digital Twins for real-time Predictions

Helps to forecast in real-time plasma events such as:

PAPER • OPEN ACCESS

Identifying L-H transition in HL-2A through deep learning

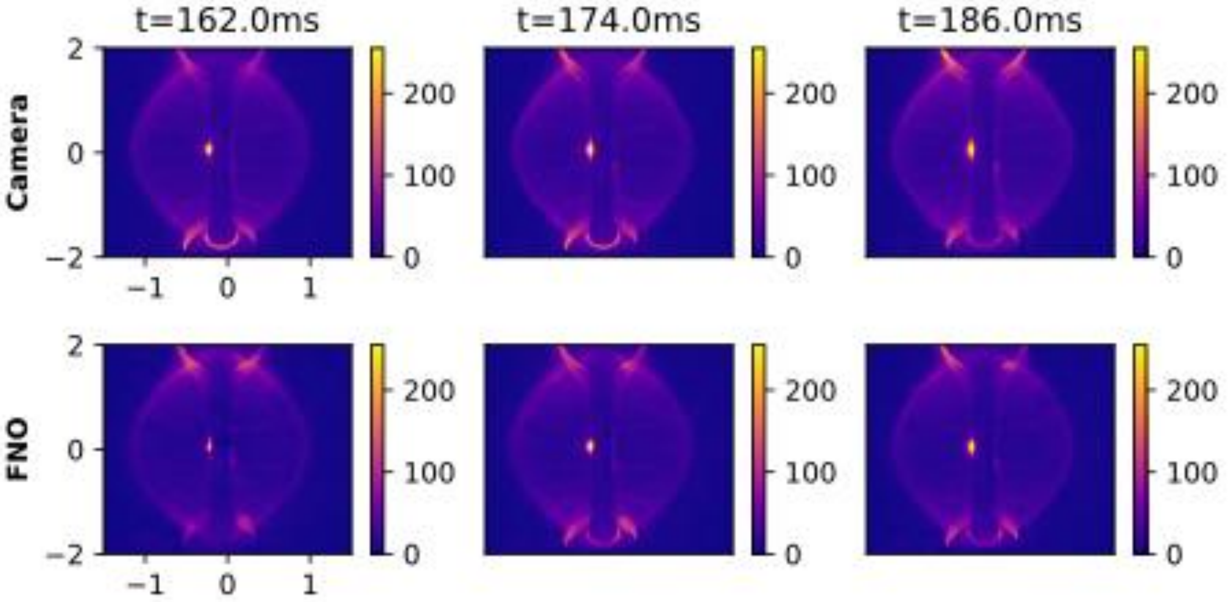
Meihuizi He, Zongyu Yang*, Songfen Liu*, Fan Xia and Wulyu Zhong

Published 11 September 2024 • © 2024 The Author(s). Published by IOP Publishing Ltd
Plasma Physics and Controlled Fusion, Volume 66, Number 10
Citation Meihuizi He *et al* 2024 *Plasma Phys. Control. Fusion* **66** 105019
DOI 10.1088/1361-6587/ad75b7

ELSEVIER
Fusion Engineering and Design
Volume 157, August 2020, 111634

Real-time classification of L-H transition and ELM in KSTAR

Giwook Shin, J.-W. Juhn, G.I. Kwon, S.-H. Hahn



LH Transitions

Source: Gopakumar et al. 2024. FNO for Plasma Modelling

Digital Twins for real-time Predictions

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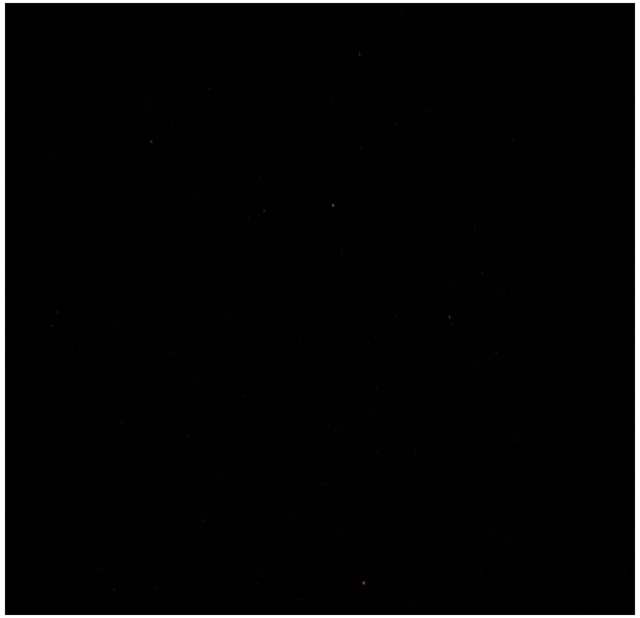
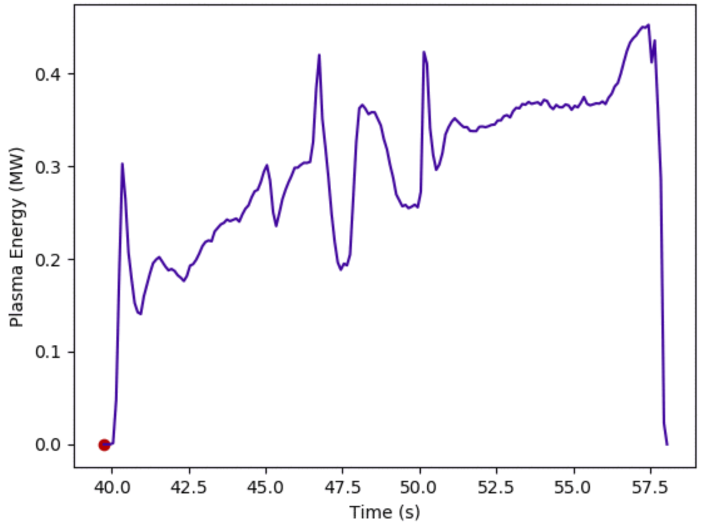
Helps to forecast in real-time plasma events such as:





Disruptions

nature

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nature › letters › article

Letter | Published: 17 April 2019

Predicting disruptive instabilities in controlled fusion plasmas through deep learning

Julian Kates-Harbeck, Alexey Svyatkovskiy & William Tang

Nature **568**, 526–531 (2019) | Cite this article

18k Accesses | **320** Citations | **348** Altmetric | Metrics

RESEARCH ARTICLE | FEBRUARY 03 2020

Machine learning control for disruption and tearing mode avoidance

Special Collection: Invited Papers from the 2nd International Conference on Data-Driven Plasma Science

Yichen Fu; David Eldon; Keith Erickson; Kornee Kleijwegt; Leonard Lupin-Jimenez; Mark D. Boyer; Nick Eidietis; Nathaniel Barbour; Olivier Izacard; Egemen Kolemen

A real-time machine learning-based disruption predictor in DIII-D

C. Rea, K.J. Montes, K.G. Erickson, R.S. Granetz and R.A. Tinguely

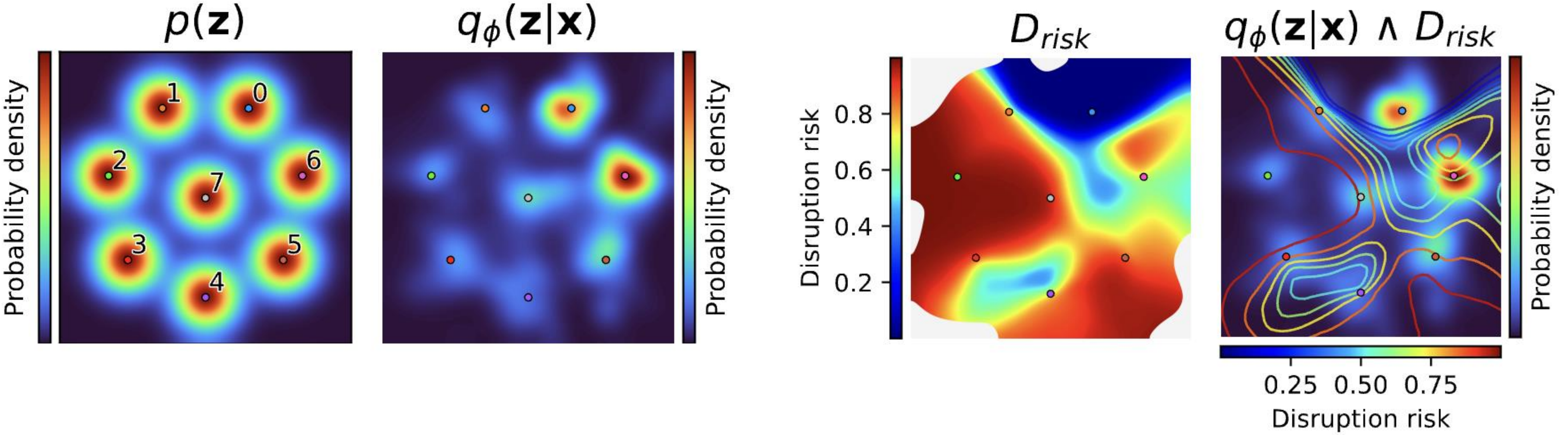
Published 23 July 2019 • © 2019 IAEA, Vienna

Nuclear Fusion, Volume 59, Number 9

Citation C. Rea *et al* 2019 *Nucl. Fusion* **59** 096016

DOI 10.1088/1741-4326/ab28bf

Scientific Discovery from Digital Twins

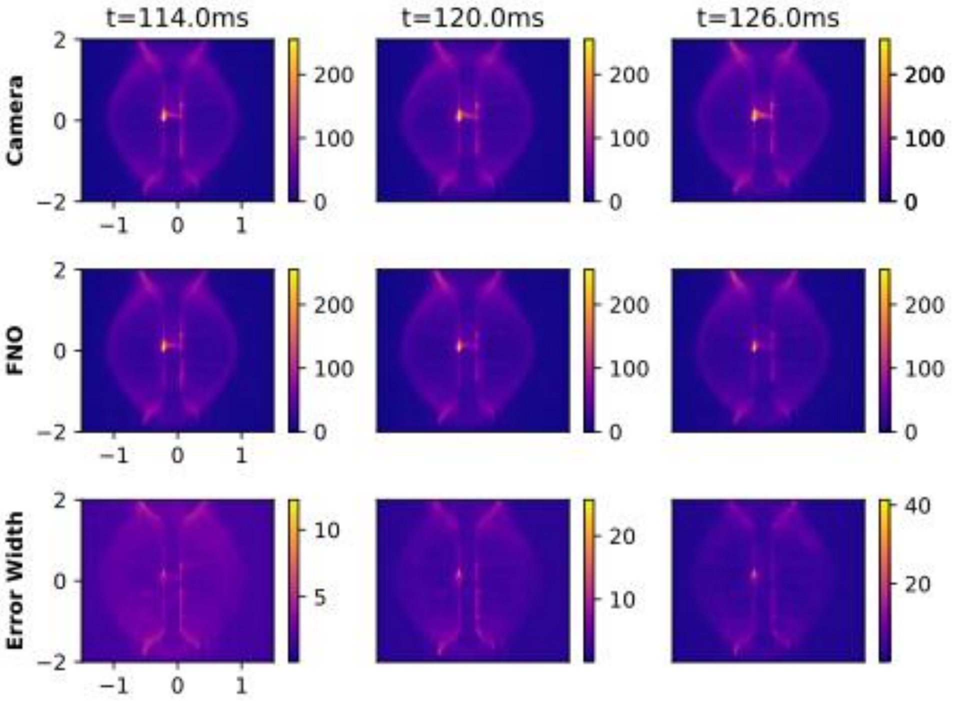


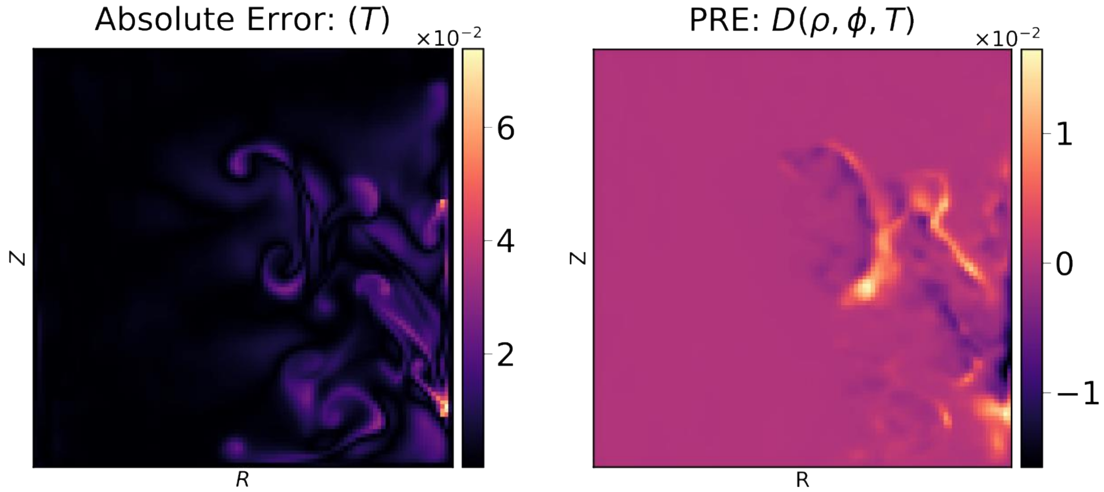
Multimodal VAE trained to learn characteristics of the plasma shot distribution in the TCV device, allowing us to identify shot conditions that are more prone to disruption. This helps us gain an interpretable representation of the plasma state leading to a disruption.

Source: Poels et al. 2025. Plasma State Monitoring and Disruption Characterisation using Multimodal VAEs

Uncertainty Quantification

“All models are wrong, but some are useful”. In safety-critical scenarios such as Fusion, the only way to make them useful is to equip them with *valid* uncertainty quantification





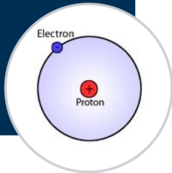
Bayesian, frequentist, and verified methods allow these models to express confidence bounds, making these models “actionable”

Source: Gopakumar et al. 2025. UQ for surrogate models using conformal prediction. Calibrated physics-informed UQ.

AI for Plasma Control

Magnetics 

Heating 

Fuel 

Exhaust 

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Control 1000s of parameters that influence the confinement of plasma.

All the while dealing with instabilities and avoiding disruptions

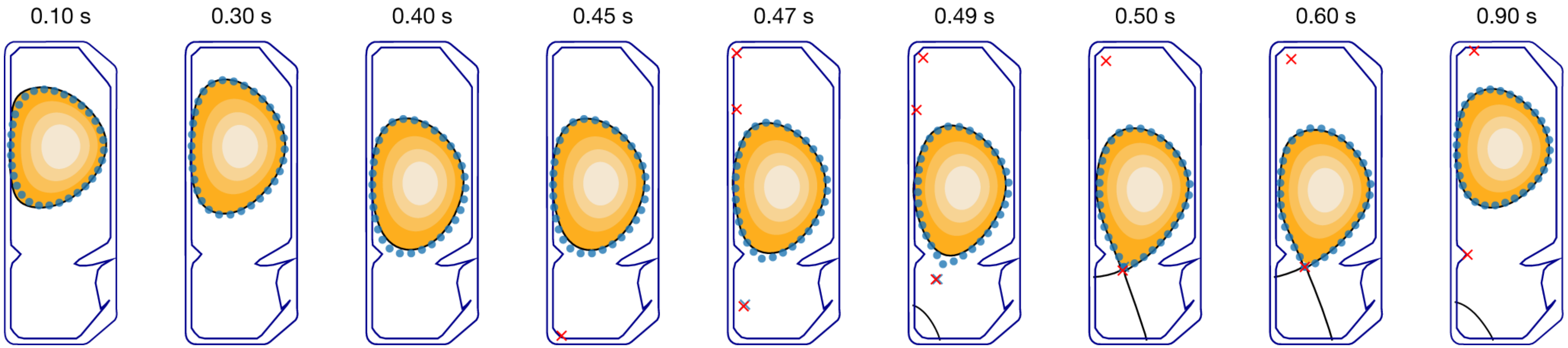
Extended stable plasma control requires a predictive knowledge of how the Plasma would evolve in time.

Control is fertile soil for AI

AI for Plasma **Control**

Work done by Google DeepMind with EPFL.

Trained a reinforcement learning algorithm to control the plasma equilibrium in real-time.



The RL model learned to autonomously control the voltages of magnetic coils to achieve complex plasma configurations, simultaneously optimising plasma current, boundary shape, and spatial position, while maintaining stability.

Source: Degrave et al. 2022. Magnetic control of tokamak plasmas through deep reinforcement learning.

AI for Plasma Control

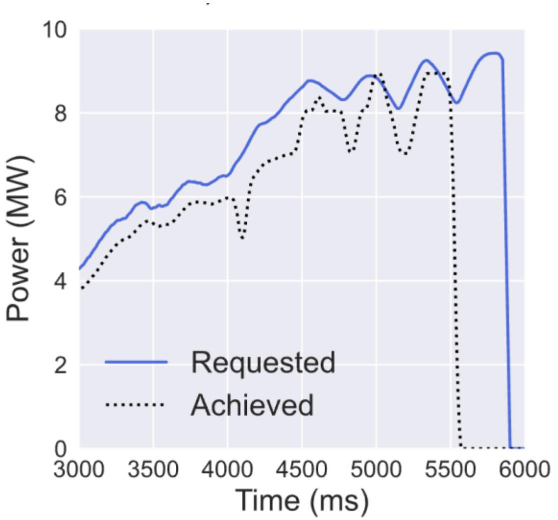
FreeGSNKE: Free and open source evolutive equilibrium code. Finite difference, fully Python, **ML/AI friendly**.

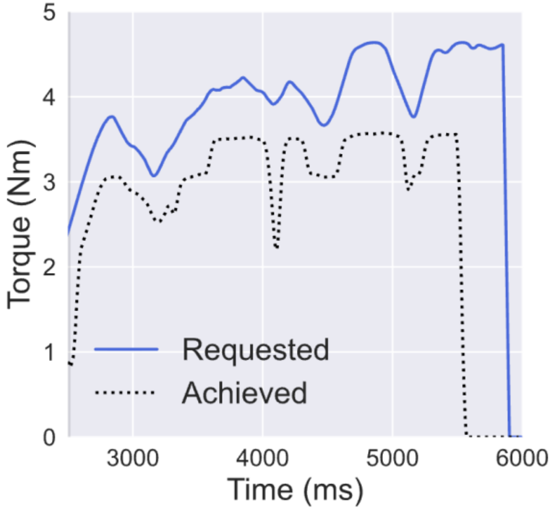
UK Atomic Energy Authority

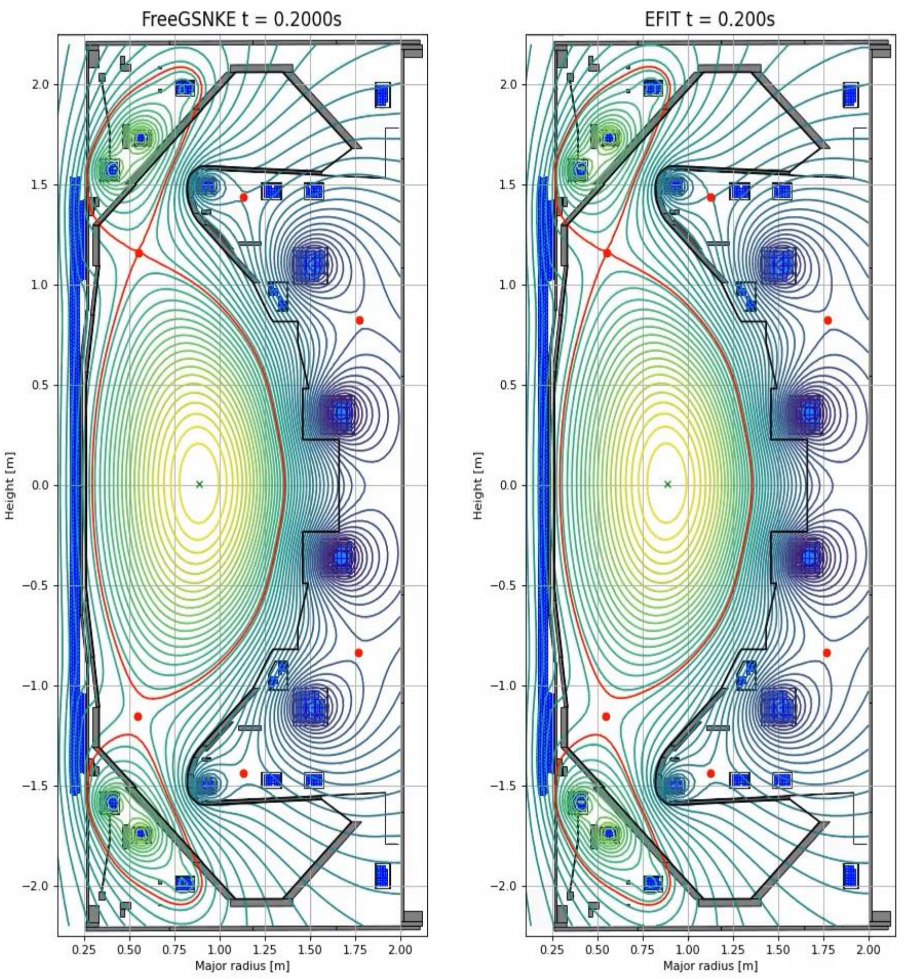
Offline Model-Based Reinforcement Learning for Tokamak Control

Ian Char[1], Joseph Abbate[2], László Bardóczi[3], Mark D. Boyer[2], Youngseog Chung[1], Rory Conlin[4], Keith Erickson[2], Viraj Mehta[5], Nathan Richner[6], Egemen Kolemen[2,4], and Jeff Schneider[1,5]

[1]Machine Learning Department, Carnegie Mellon University
[2]Princeton Plasma Physics Laboratory
[3]General Atomics
[4]Department of Mechanical and Aerospace Engineering, Princeton University
[5]Robotics Institute, Carnegie Mellon University
[6]Oak Ridge Associated Universities







https://github.com/FusionComputingLab/freegsnke

Source: Char et al 2023. Offline Model-Based Reinforcement Learning for Tokamak Control

AI for Plasma **Control**

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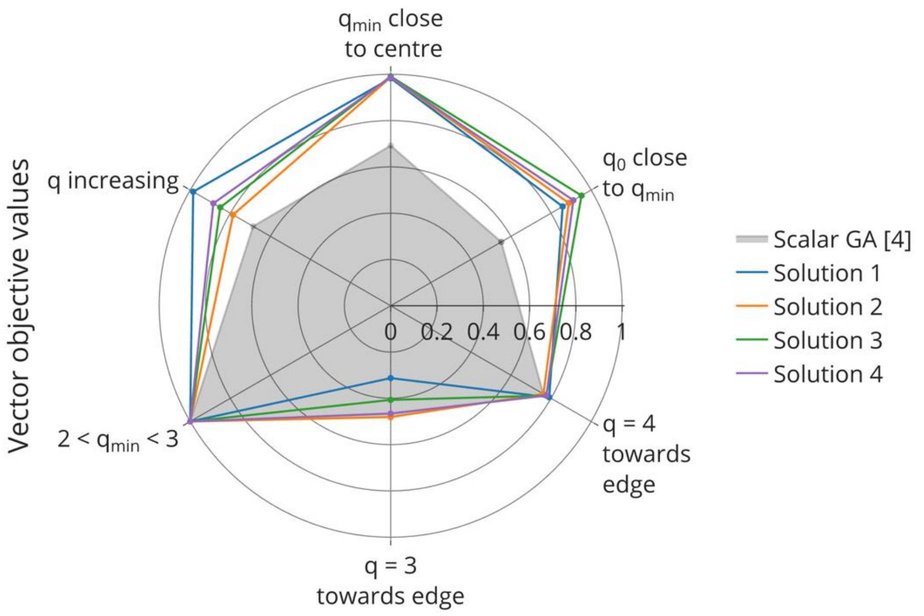
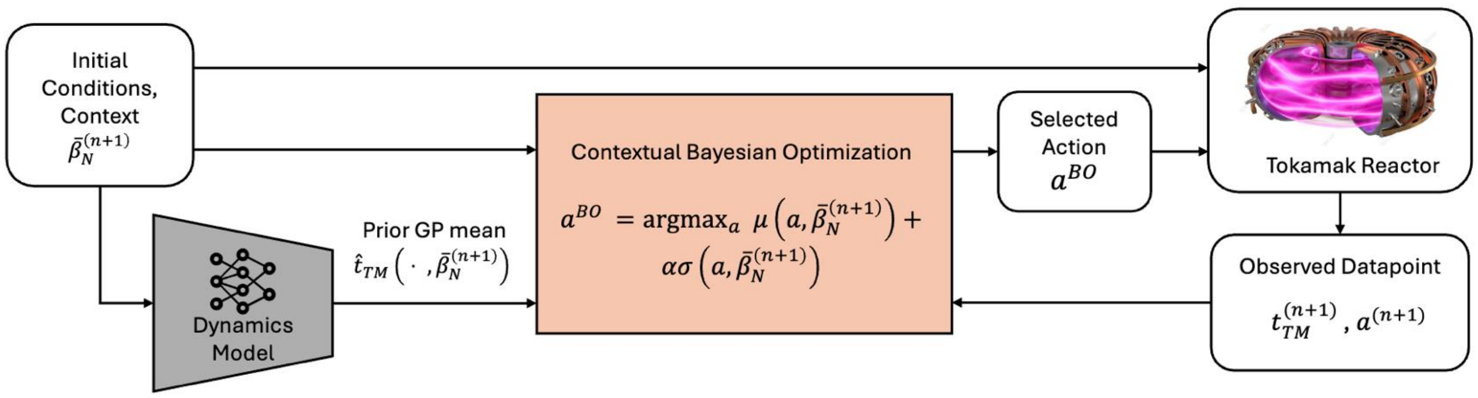
Multi-objective Bayesian Optimisation over heating parameters to identify a Pareto front of solutions within a pulsed plasma.





Source: Brown et al. 2024. Multi-Objective Bayesian Optimization for Design of Pareto-Optimal Current Drive Profiles in STEP
Sonker et al. 2025. Multi-Timescale Dynamics Model Bayesian Optimization for Plasma Stabilization in Tokamaks

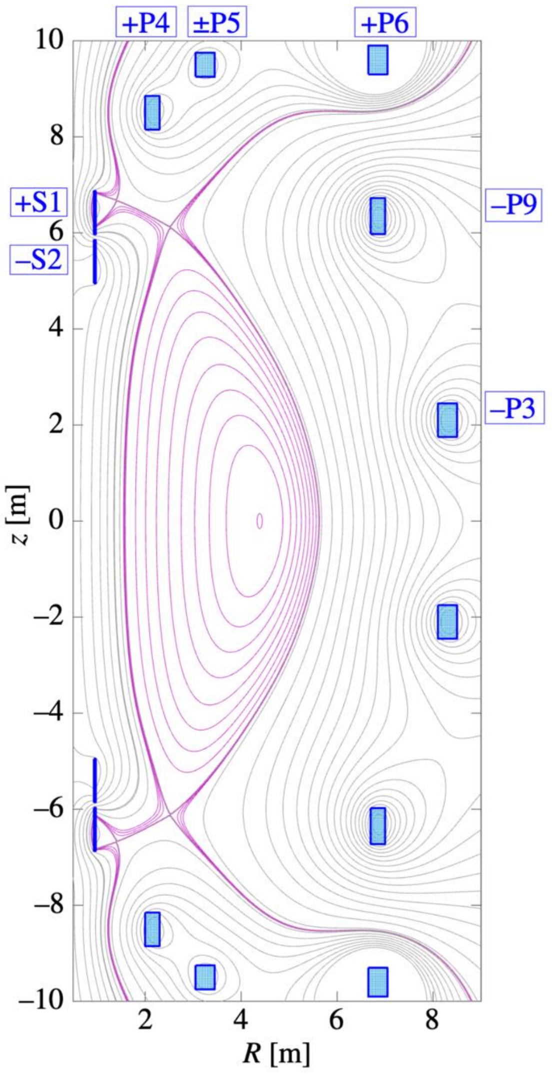
AI for Reactor **Design**

Currently in the process of designing the Spherical Tokamak for Energy Production (STEP).

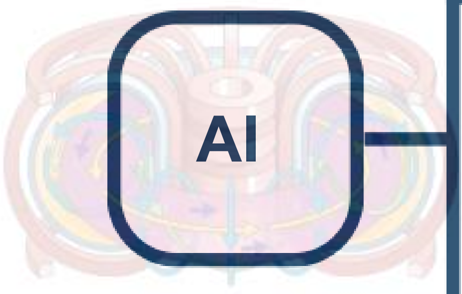
Design space is high-dimensional with multiple competing objectives to be met under several constraints.

Informed sampling across the evaluation space helps reduce the computational burden by 50%

Multi-objective Bayesian Optimisation over the shape and location of magnetic field coils to obtain an ideal plasma equilibrium.



Source: Nunn et al. 2024. Bayesian optimisation of poloidal field coil positions in tokamaks



AI

Model

Surrogate modelling to help accelerate simulations. Bridging the sim2real gap across simulations and experiments.

Predict

Digital twinning of experiments with real-time prediction of plasma behaviour.

Control

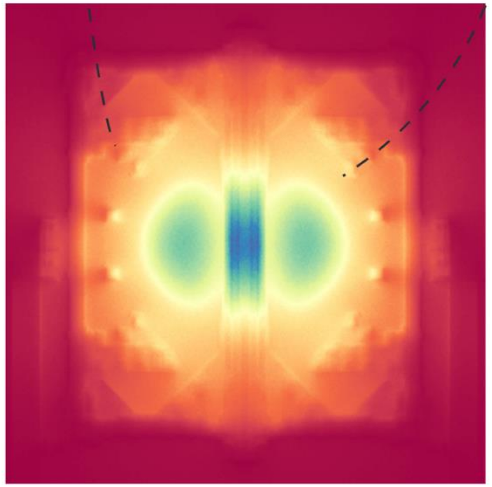
Agentic control over plasma actuators for long-term confinement.

Design

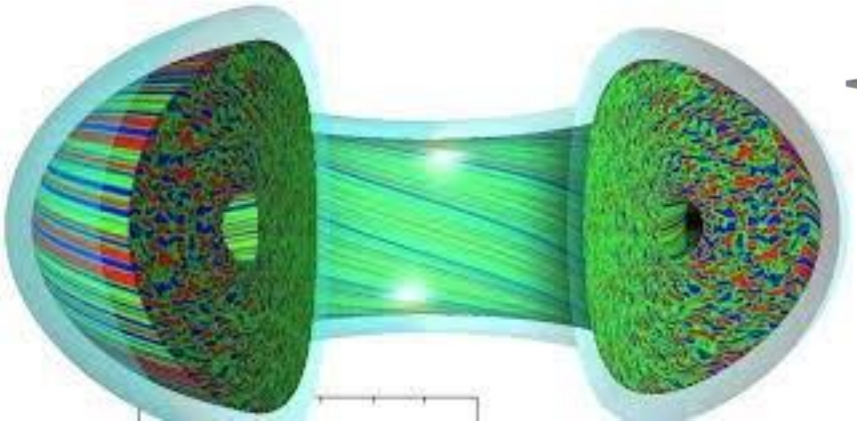
Efficient exploration of high-dimensional, multi-objective design space of a Tokamak.

Next Steps: Universal Physics Engine for Integrated Modelling

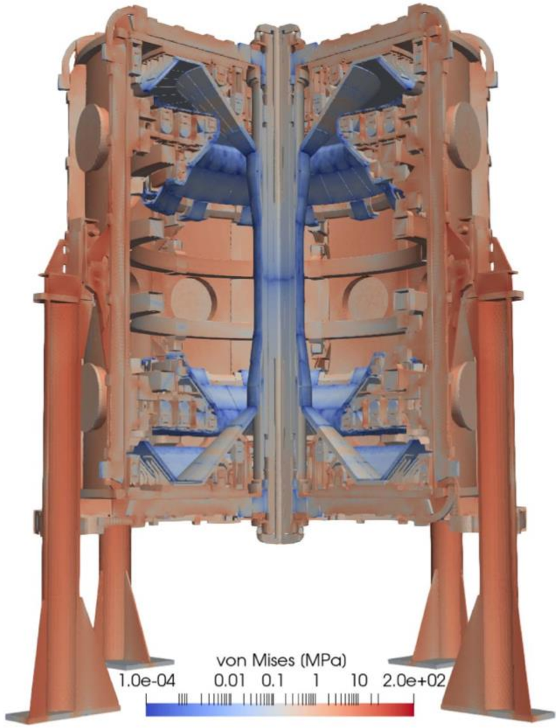
Surrogate models for multi-scale plasma interactions across the tokamak core and edge, including structural thermohydraulic stress and irradiation damage.



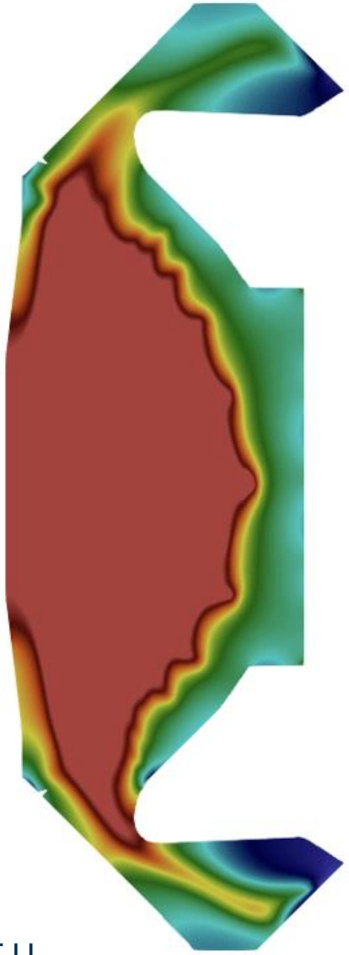
Modelling Neutron Flux Field.
Reali et al. 2025.



Plasma Turbulence at the Core. PPPL.



Mechanical Stress over MAST-U due to gravitational forces.
Ellis et al. 2025



ELM instabilities in MAST-U.
Smith et al. 2020.

Next Steps:
Foundation Models for Tokamaks

Full-scale digital Twin capable of predicting plasma evolution across the diagnostic paradigms.

Multimodal Timeseries Foundation Model

Cross-Machine Translation

Press release

IBM, STFC and UKAEA collaborate on fusion energy design

UKAEA, STFC's Hartree Centre and IBM have partnered to collaborate on designing future experimental fusion powerplants.

From: UK Atomic Energy Authority

Published 12 December 2024

Last updated 18 December 2024 — See all updates

Rob Akers (UKAEA), Kate Royse (STFC Hartree Centre) and Juan Bernabe-Moreno (IBM) at signing of partnership agreement for fusion collaboration

It’s often joked that Fusion is always 30 years away.

But with the help of AI it just might be.

UK Atomic Energy Authority

Appendix

Benefits of fusion

UK Atomic Energy Authority

1 **LOW CARBON**
Fusion is low carbon, with low land usage

2 **SAFE**
The fusion process is readily and safely controllable

3 **RELIABLE**
Fusion energy will be baseload and does not depend on seasonal variation, the sun, or the wind

4 **SUSTAINABLE**
Fusion fuel is potentially abundant in our seas and the Earth's crust

5 **ENERGY EFFICIENCY**
Fusion provides the most power-dense process available on Earth