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Plasma Surrogate Modelling using Fourier Neural Operators

IAEA Workshop on AI for Accelerating Fusion and Plasma Science

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Why do we need surrogate modelling ?

Computational Complexity

Latency

Unknown unknowns

What does surrogate modelling offer ?

Neighbourhood Approximations

Uncertainty Quantification

Speed

Why are we using surrogate modelling now ?

Models

Big Data

Hardware

API

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Neural Operators: Operator Learning using Neural Networks

Traditional Neural Networks (MLPs, CNNs, RNNs …) map from the **input vector space** to the **output vector space**, **learning the function** that performs the required transformation.

Vector Space

$$NN : H_\theta : A \rightarrow U$$

Neural Operators map the **input function space** to the **output function space, learning the operator** that performs the function transformation.

Function Space

$$NO : G_\theta : A \rightarrow U$$

Neural Operators: Operator Learning using Neural Networks

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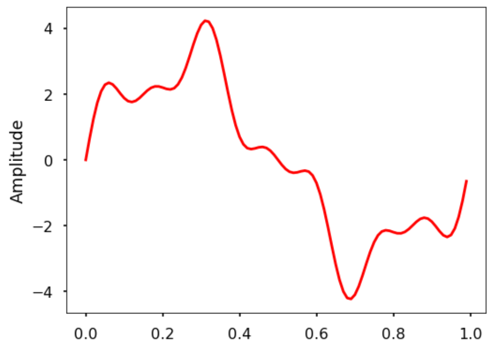
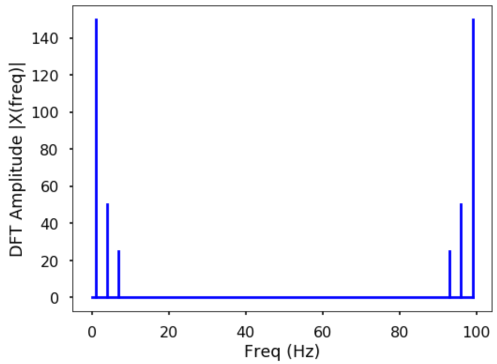
But learning in the function space means learning the continuous operators ?
How does one do that numerically ?

Basis Functions



Change of Basis →



Network is composed of Kernels that learn within the basis decomposition and point-wise operations allowing us to learn continuous representations on arbitrary discretised inputs and outputs.

Neural Operators for PDEs

Differential Operator in Space

$$\frac{\partial u}{\partial t} = D(u, X)$$

$$\frac{\partial u}{\partial t} = G_\theta(u, X)$$

Neural Operator in Space

Point-wise

Kernel Operator

$$\nu_{t+1} = \sigma\left(W \, \nu_t(x) + \kappa(a;\phi) \, \nu_t(x) \right)$$

Output

Input

Choose your Basis

Wavelet Decomposition	→	Wavelet Neural Operator[1]
Laplace Transform	→	Laplace Neural Operator [2]
Complex Transform	→	Complex Neural Operator [3]
Polynomial Basis	→	DeepONet [4]
Fourier Decomposition	→	Fourier Neural Operator [5]

[1] Tripura et al. – Wavelet neural operator: a neural operator for parametric partial differential equations
[2] Cao et al. – LNO: Laplace Neural Operator for Solving Differential Equations
[3] Tiwari et al. – CoNO: Complex Neural Operator for Continuous Dynamical Systems
[4] Lu et al. – DeepONet: Learning nonlinear operators for identifying differential equations based on the universal approximation theorem of operators
[5] Li et al. – Fourier Neural Operator for Parametric Partial Differential Equations

Choose your Basis

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Fourier Neural Operator

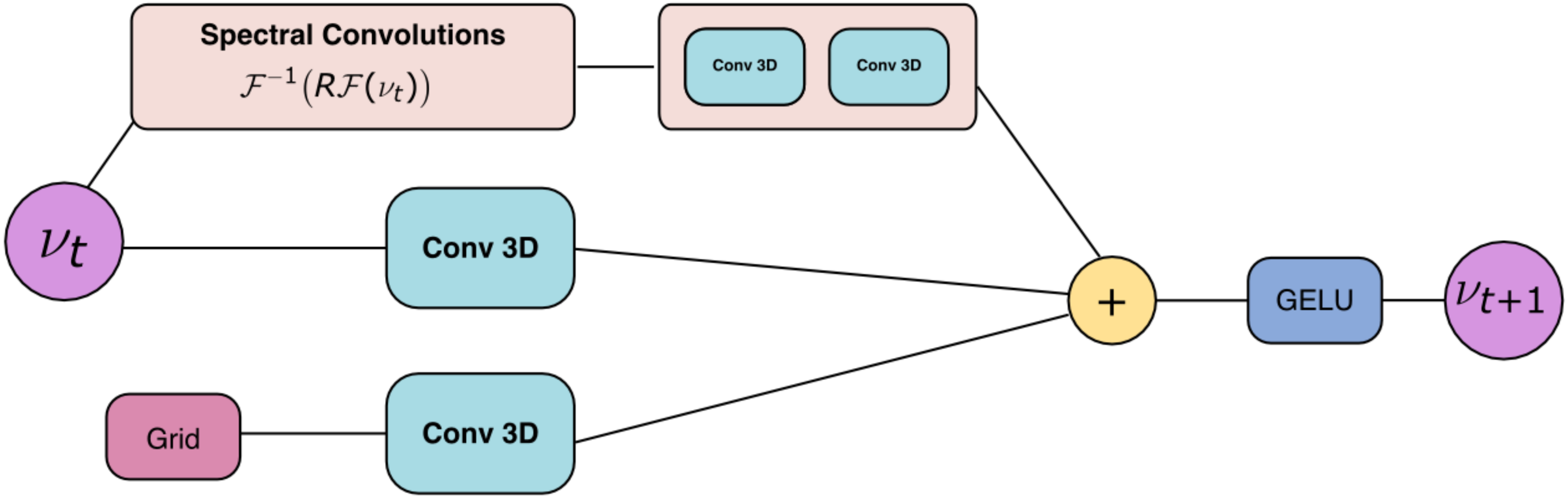
General Neural Operator Framework:

$$\underbrace{\nu_{t+1}}_{\text{Output}} = \sigma\left(\overbrace{W}^{\text{Point-wise}} \underbrace{\nu_t(x)}_{\text{Input}} + \overbrace{\kappa(a;\phi)}^{\text{Kernel Operator}} \underbrace{\nu_t(x)}_{\text{Input}}\right)$$

Fourier Neural Operator Framework:

$$\underbrace{\nu_{t+1}}_{\text{Output}} = \sigma\left(\overbrace{W}^{\text{Point-wise}} \underbrace{\nu_t(x)}_{\text{Input}} + \overbrace{\mathcal{F}^{-1}\left(R\mathcal{F}\right.}^{\text{Kernel Operator}} \left(\underbrace{\nu_t(x)}_{\text{Input}}\right)\left.\right)\right)$$

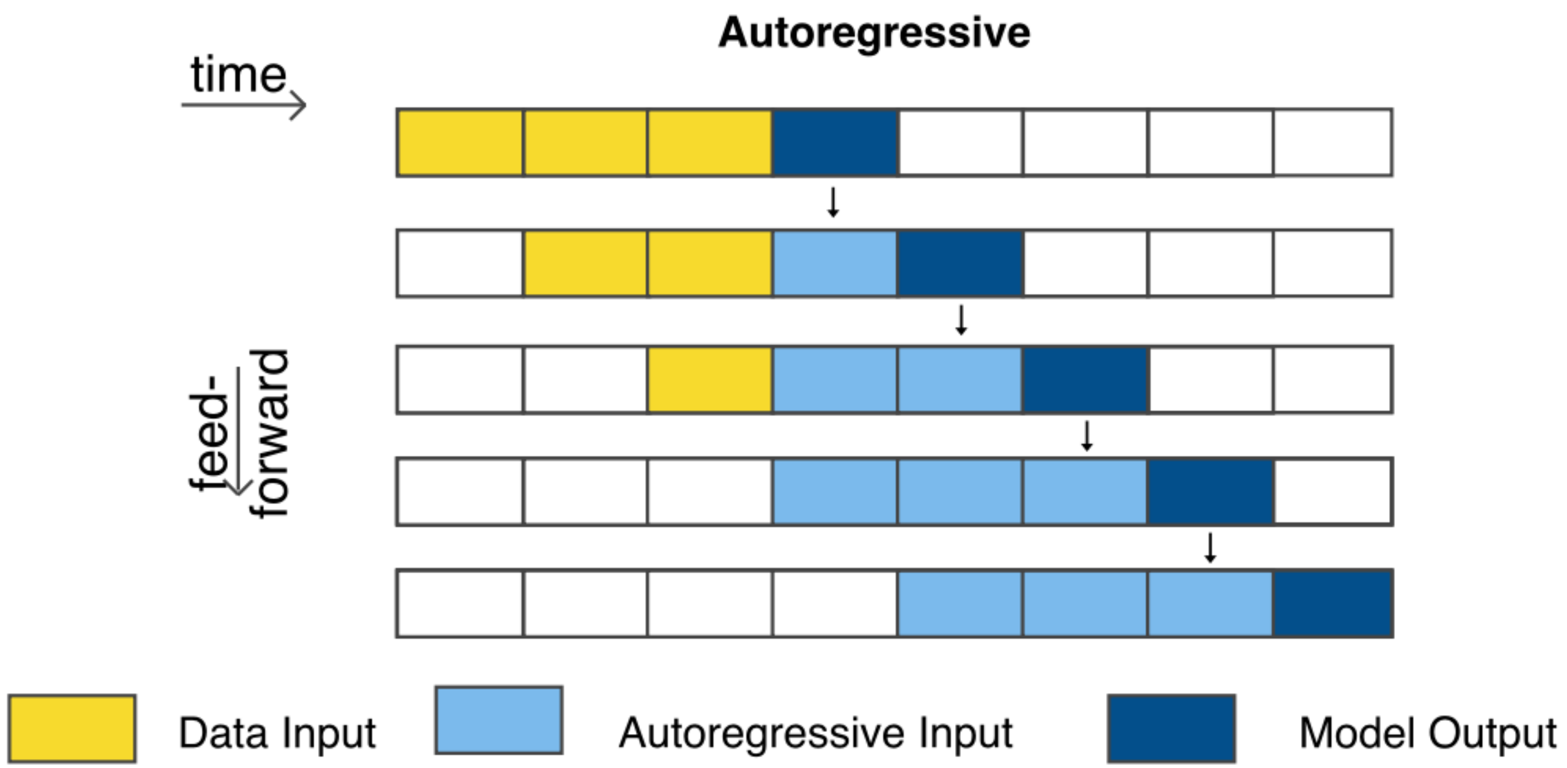
Fourier Layer



Our Contribution:

Multi-variable FNO : FNO modified with additional channel to accommodate multiple variables associated with a family of PDEs.

Now that we have a model, how do we train ?

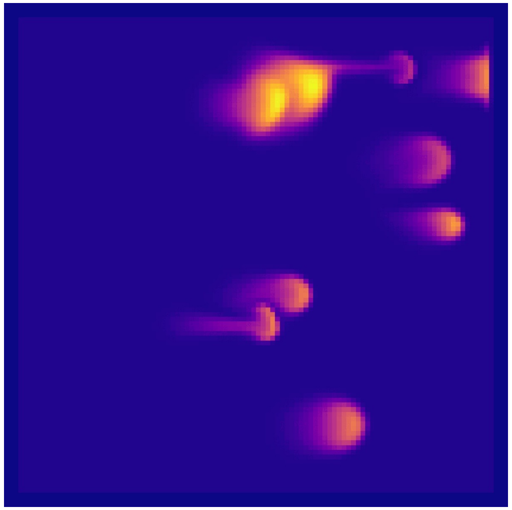


$T_{in} = 3$ **Step = 1** $T_{out} = 5$

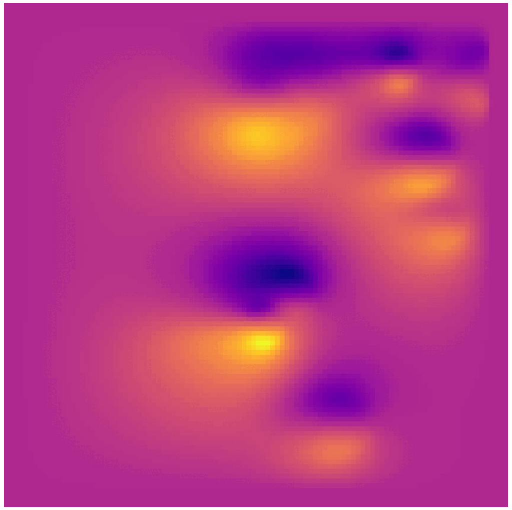
Reduced-MHD

Radial Convection of plasma blobs in toroidal geometry using JOREK

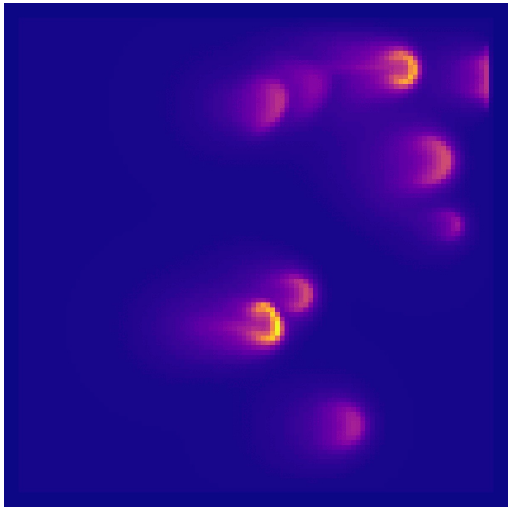
Absence of a plasma current equilibrium generates a buoyancy effect, causing the blob to move outwards towards the edge.



Density



Electric Potential

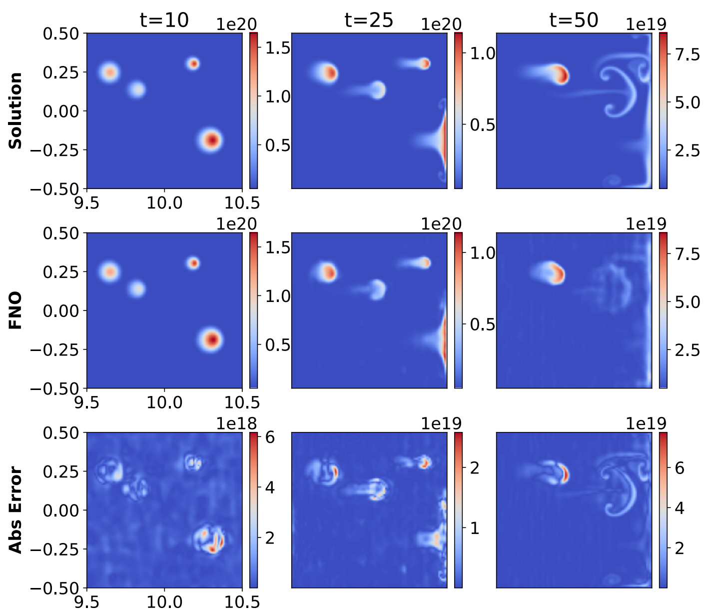


Temperature

2000 simulations built by varying the initial conditions of the plasma blobs: number, position, width and amplitude

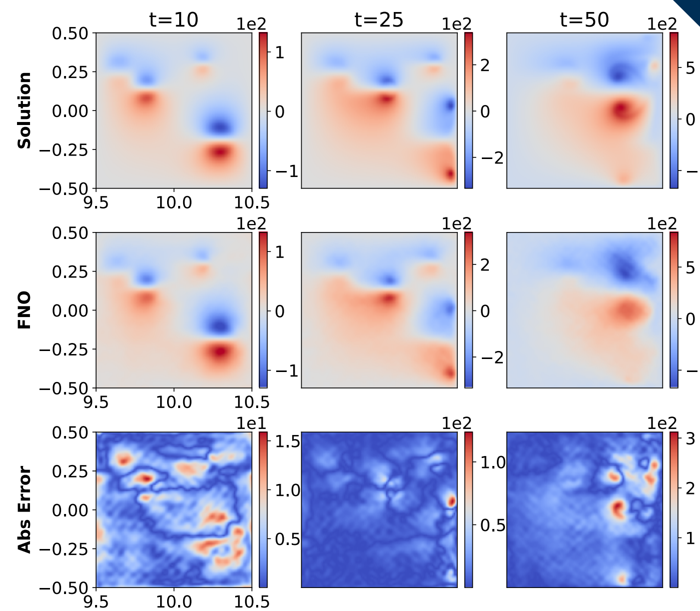
FNO over MHD

FNO: 6 orders of magnitude faster than JOREK

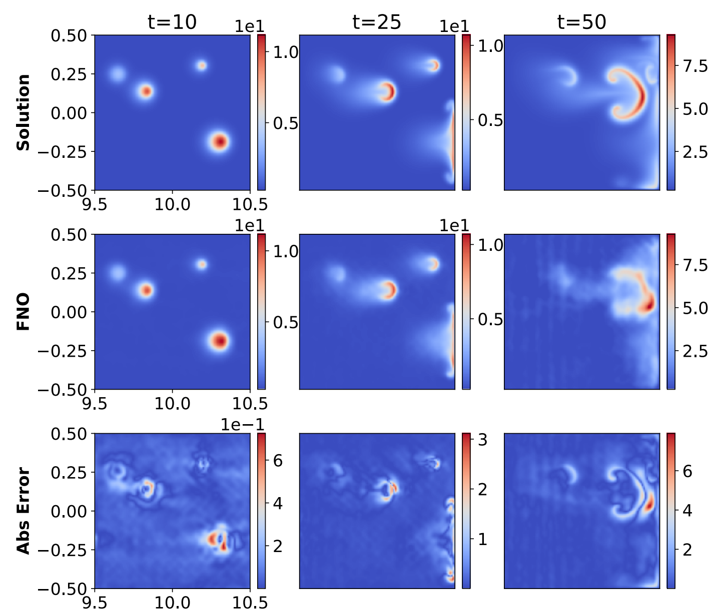


Density

T_{in} = 10
Step = 5
T_{out} = 40



Electric Potential



Temperature

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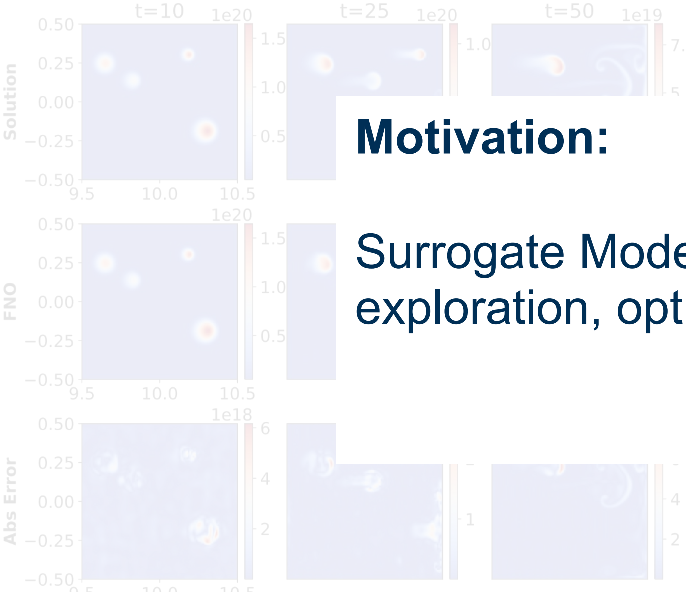


Density

$T_{in} = 10$
$Step = 5$
$T_{out} = 40$

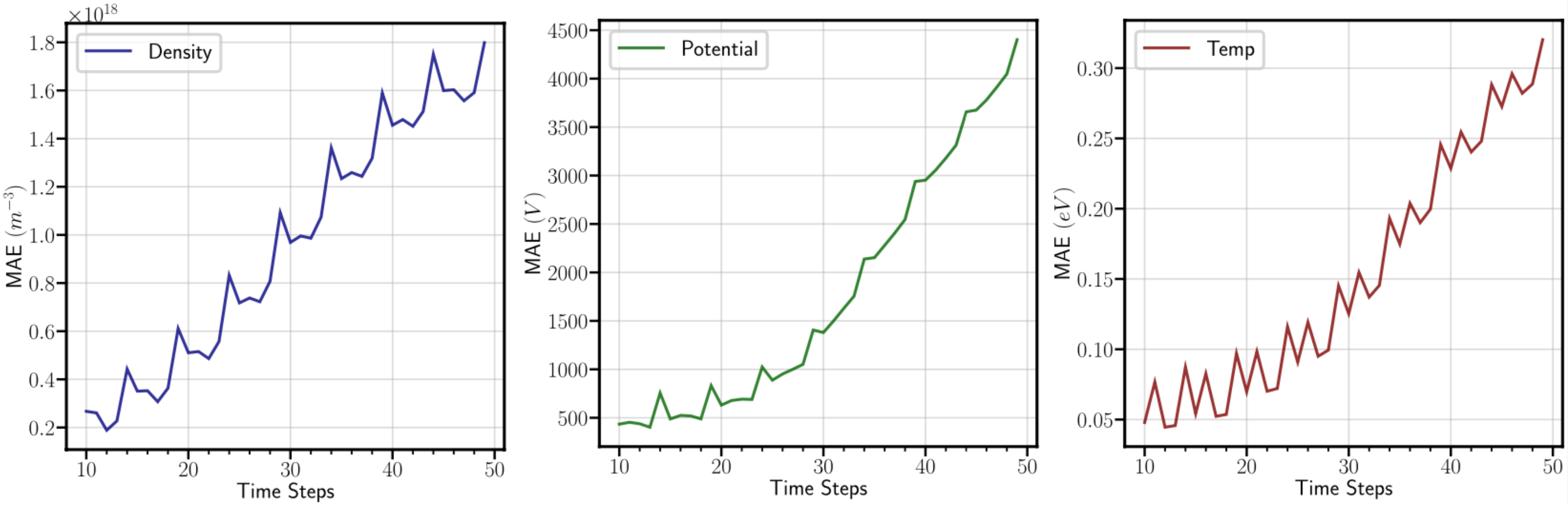
lectric Potential

Temperature

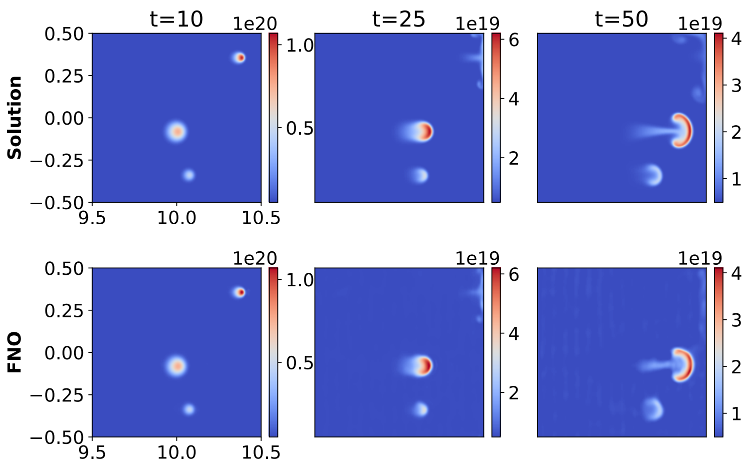
Motivation:

Surrogate Modelling for quick, iterative scenario exploration, optimisation and design of experiments.

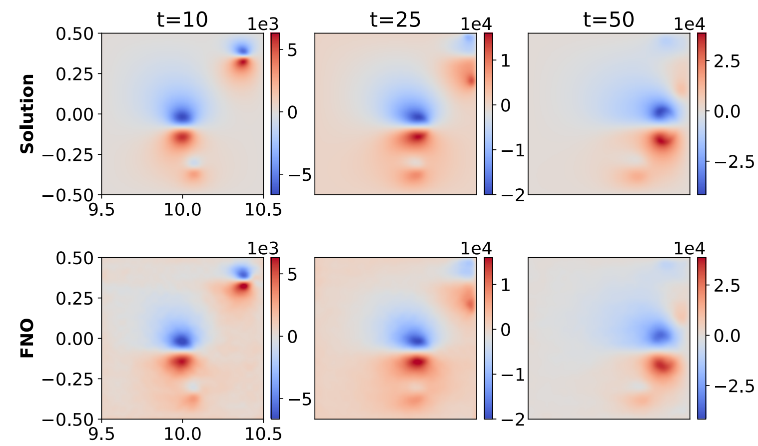
Error Growth



Super-Resolution

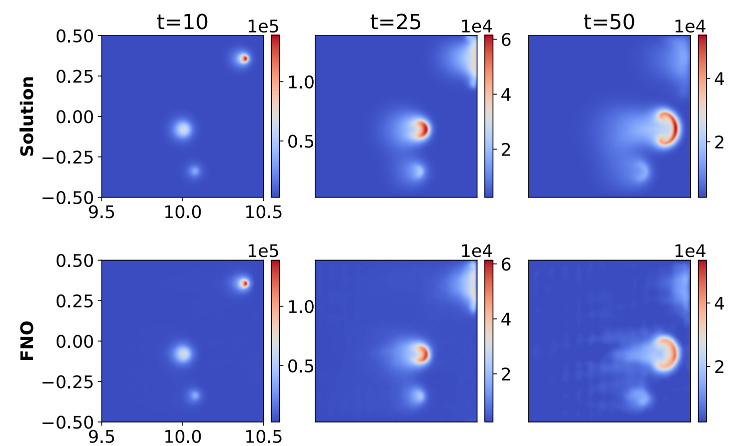


Density



Potential

Being discretisation-invariant,
FNO trained on coarser grids *(100x100)*,
can be deployed for finer grids *(500x500)*.

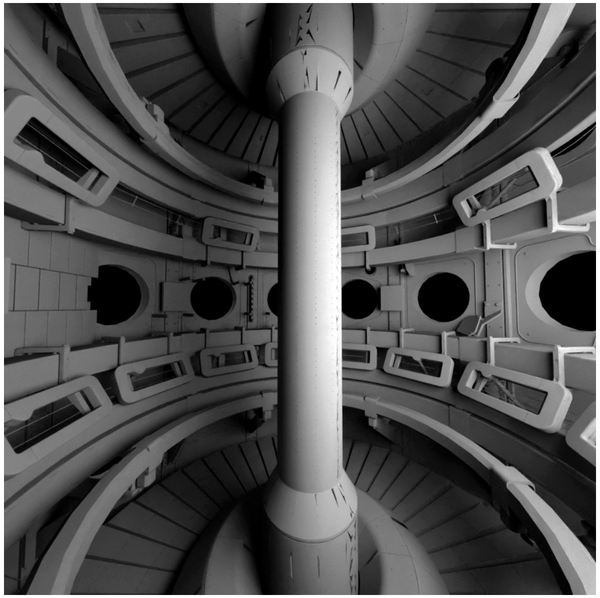


Temperature

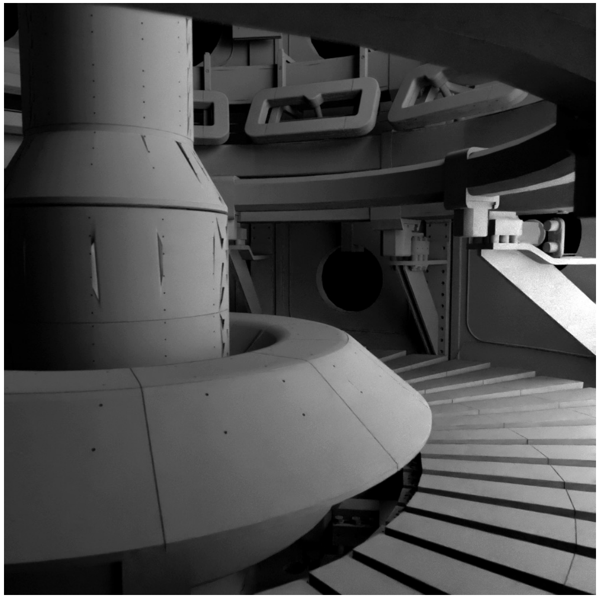
FNO Over Camera

Modelling the plasma as diagnostically captured by the Fast Cameras on MAST

Modelled over the entire shot duration of 55 shots from the last campaign on MAST (M9)



Camera viewing the central solenoid (rbb)[1]



Camera viewing the divertor (rba) [1]

[1] Synthetic renders of the camera views created using the CAD model of MAST and Nvidia Omniverse.

FNO Over Camera

Modelling the plasma as diagnostically captured by the Fast Cameras on MAST

Modelled over the entire shot duration of 55 shots from the last campaign on MAST (M9)

Motivation:

Real-time forecasting of fast camera images to track

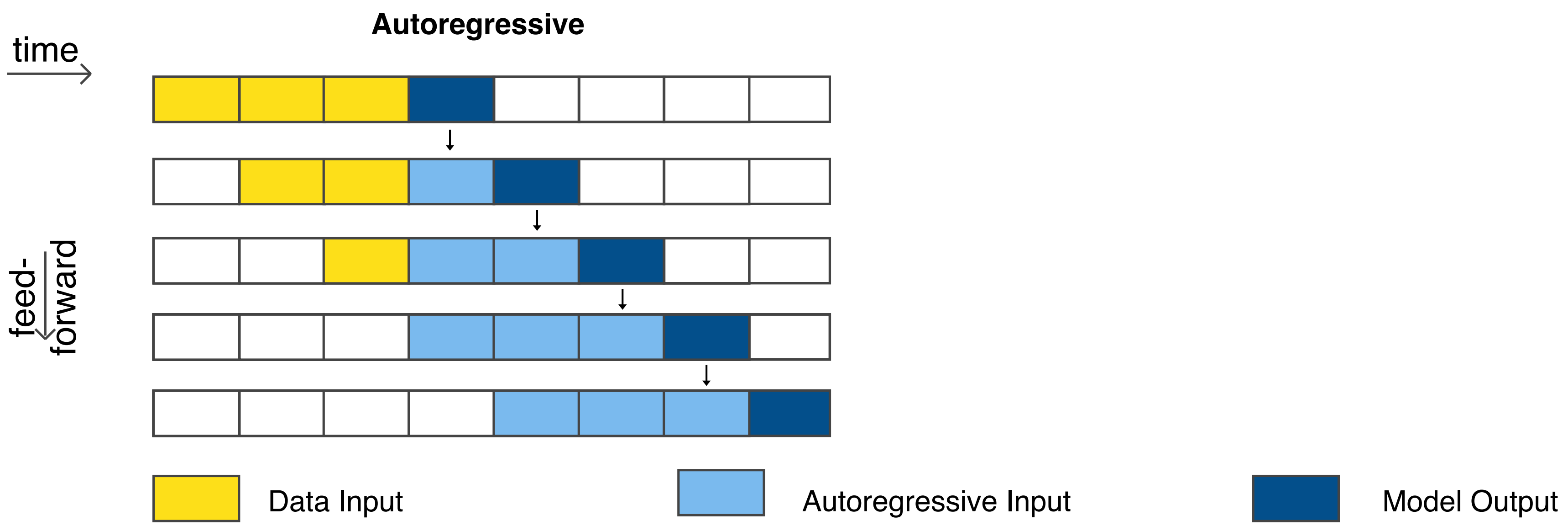
- plasma evolution,
- predict L-H transition,
- build further unto disruption prediction.
- data assimilation (Sim2Real)

Camera viewing the central solenoid (rbb)[1]

Camera viewing the divertor (rba) [1]

[1] Synthetic renders of the camera views created using the CAD model of MAST and Nvidia Omniverse.

Time Window Pipeline



Time Window Pipeline

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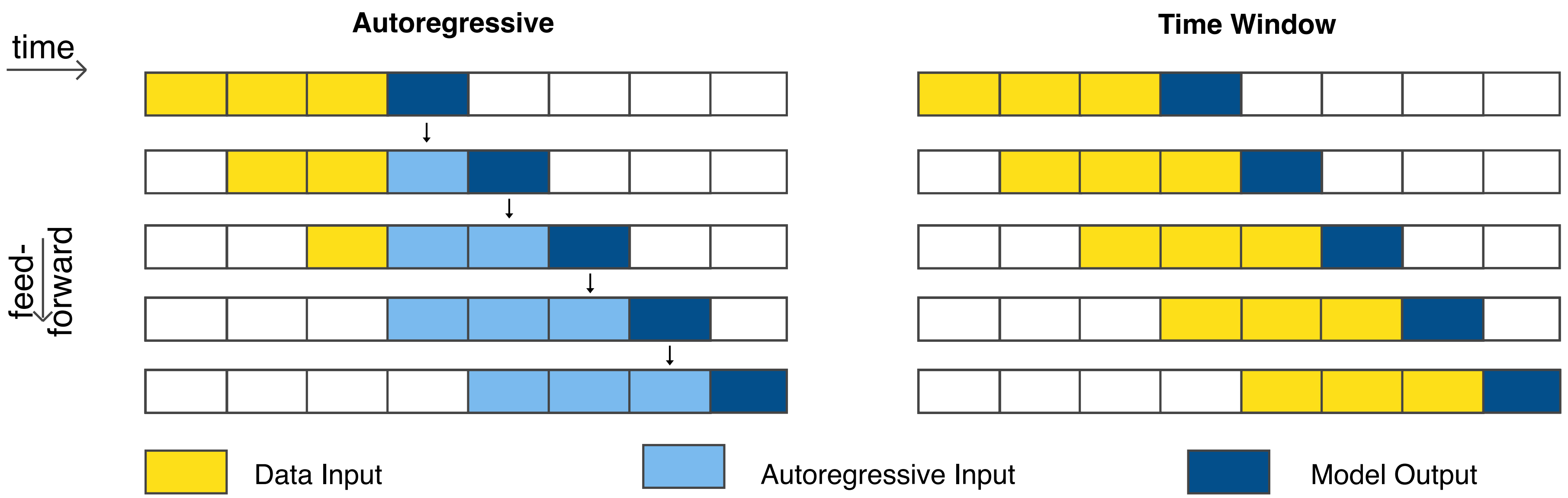
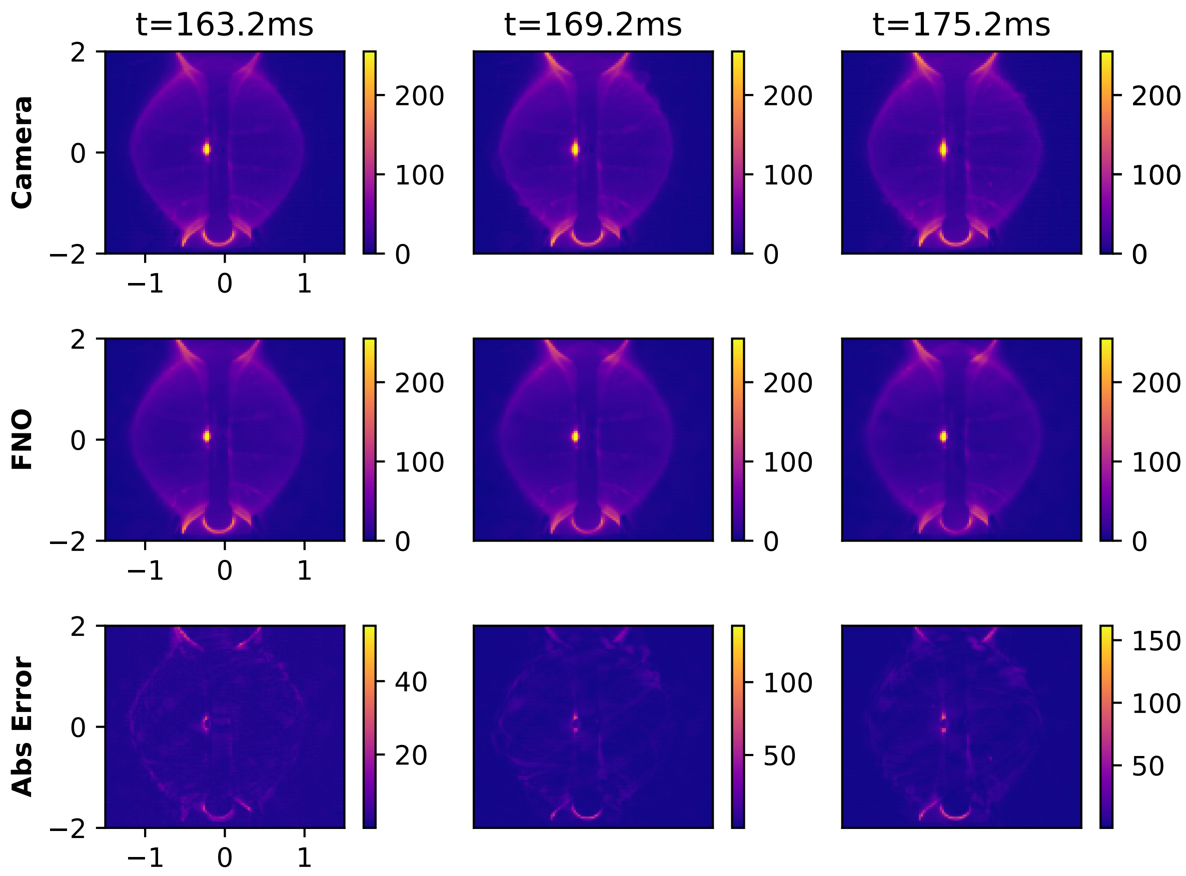
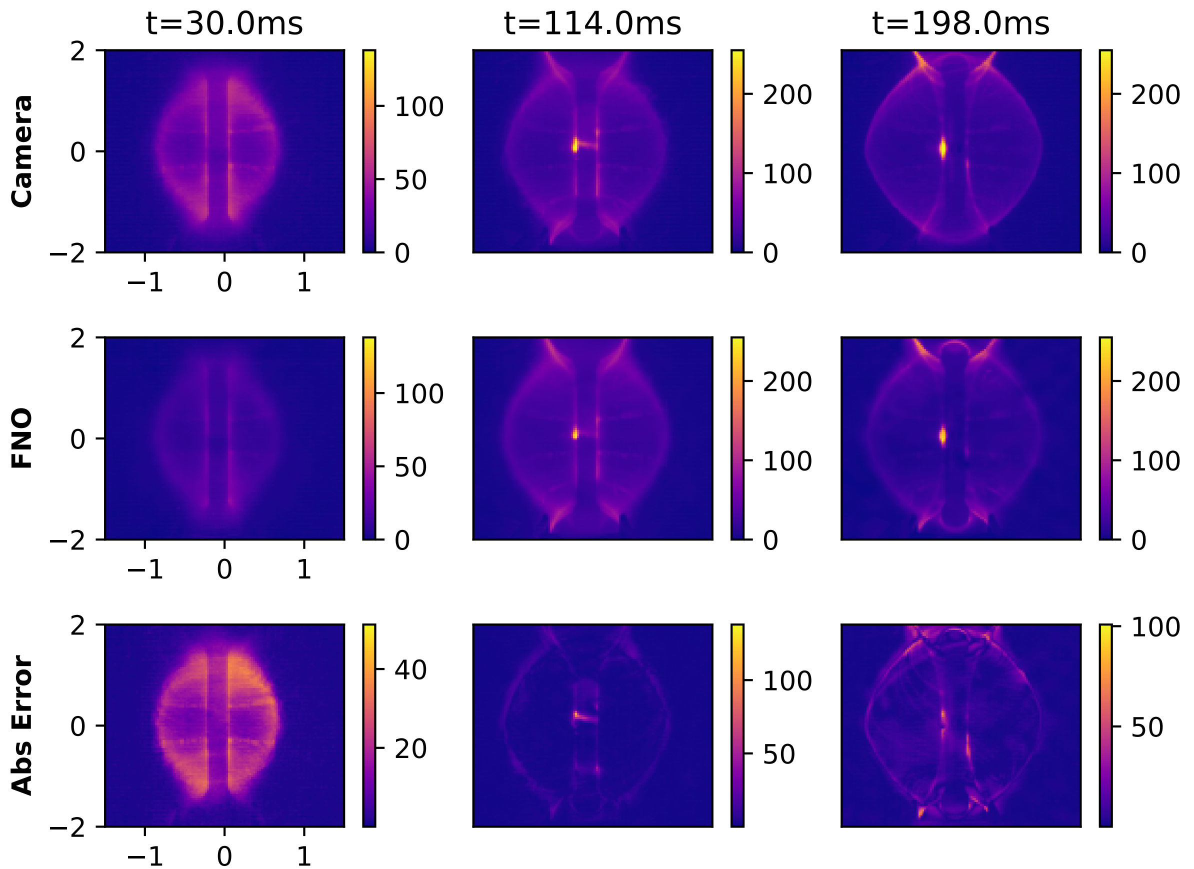


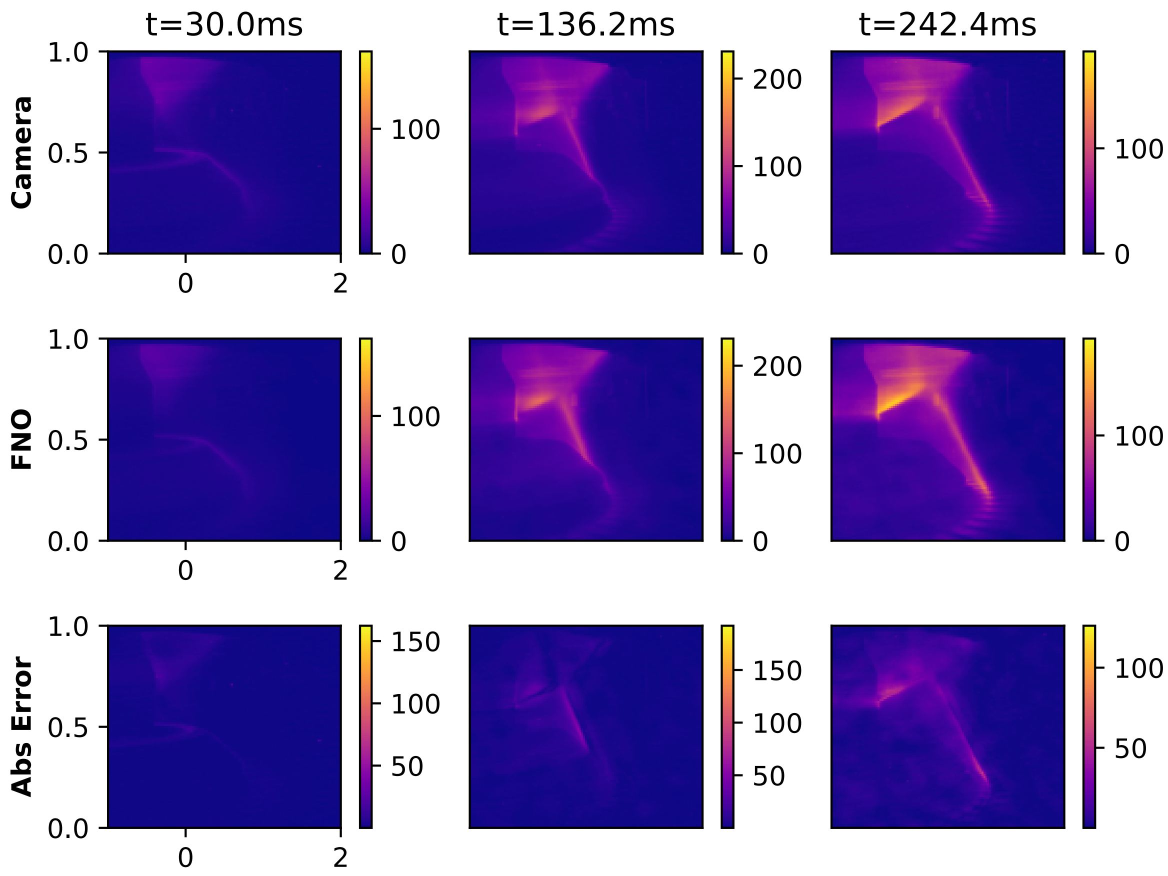
Camera viewing the central solenoid (rbb)



FNO predicting across both L and H-modes of Confinement.



Camera at the Divertor (rba)



Paper

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Plasma Surrogate Modelling using Fourier Neural Operators

- Vignesh Gopakumar, Stanislas Pamela, Lorenzo Zanisi, Zongyi Li, Ander Gray, Daniel Brennand, Nitesh Bhatia, Gregory Stathopoulos, Matt Kusner, Marc Peter Deisenroth, Anima Anandkumar, JOREK Team, MAST Team

Submitted to Nuclear Fusion

QR code to ArXiv preprint

Supplementary Slides

Impact of Training Data

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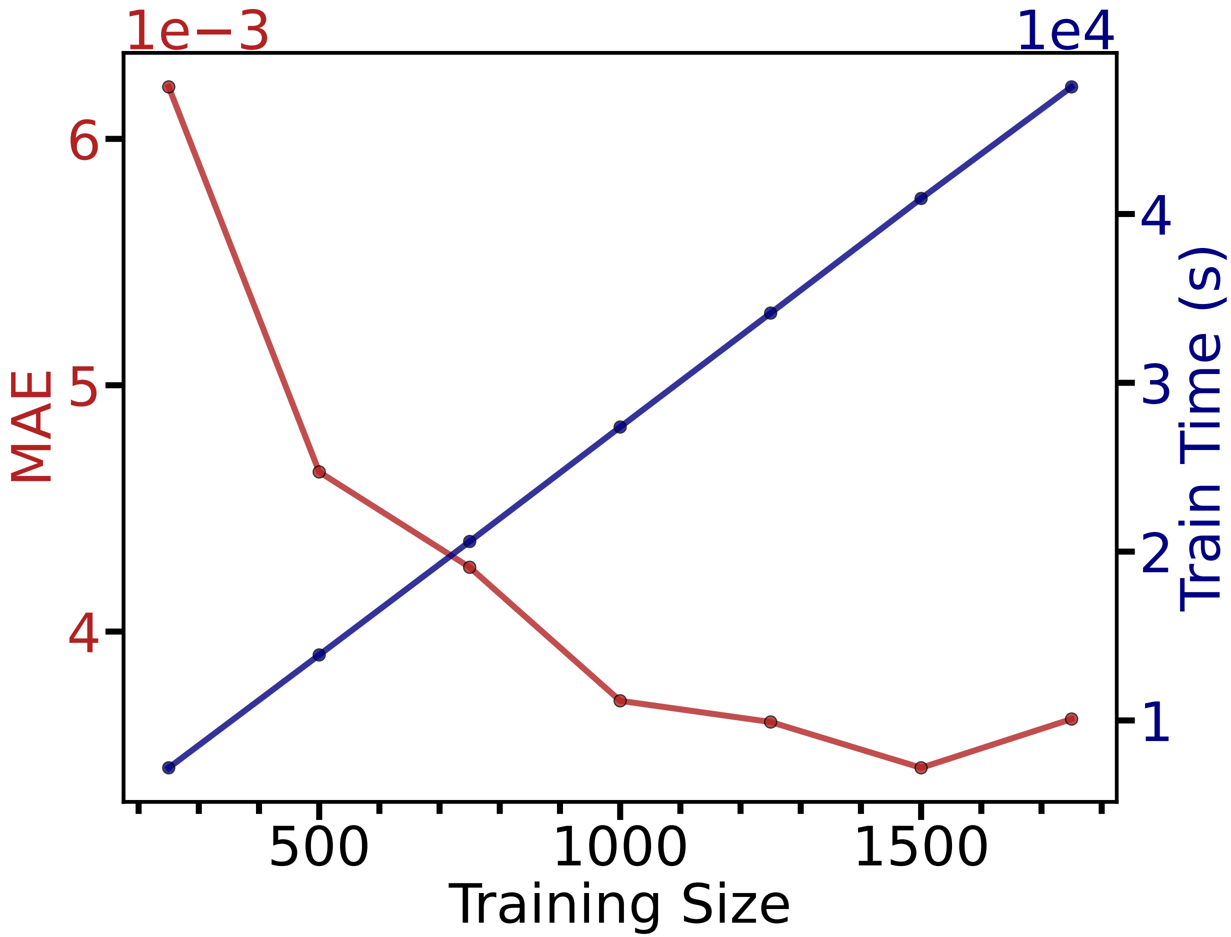
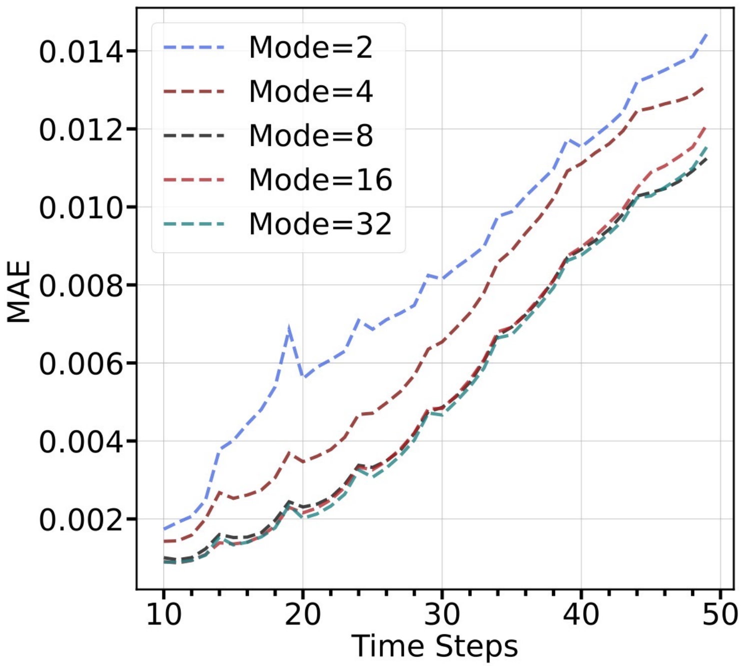
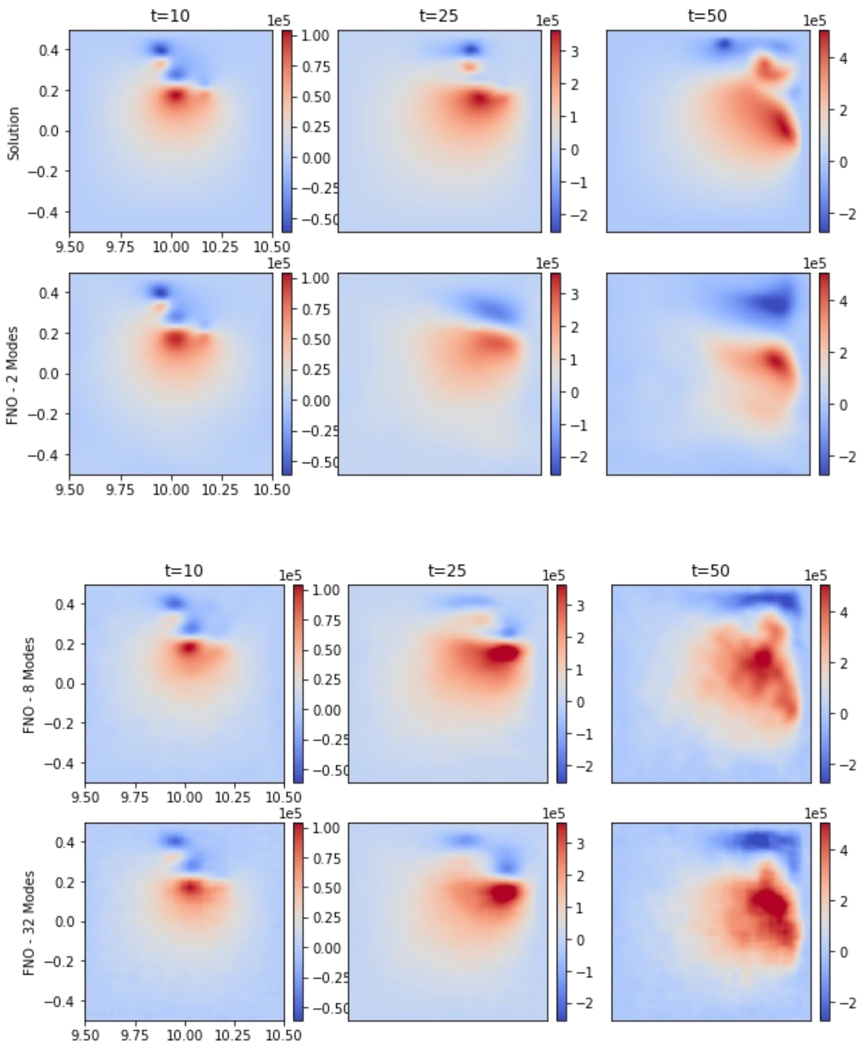
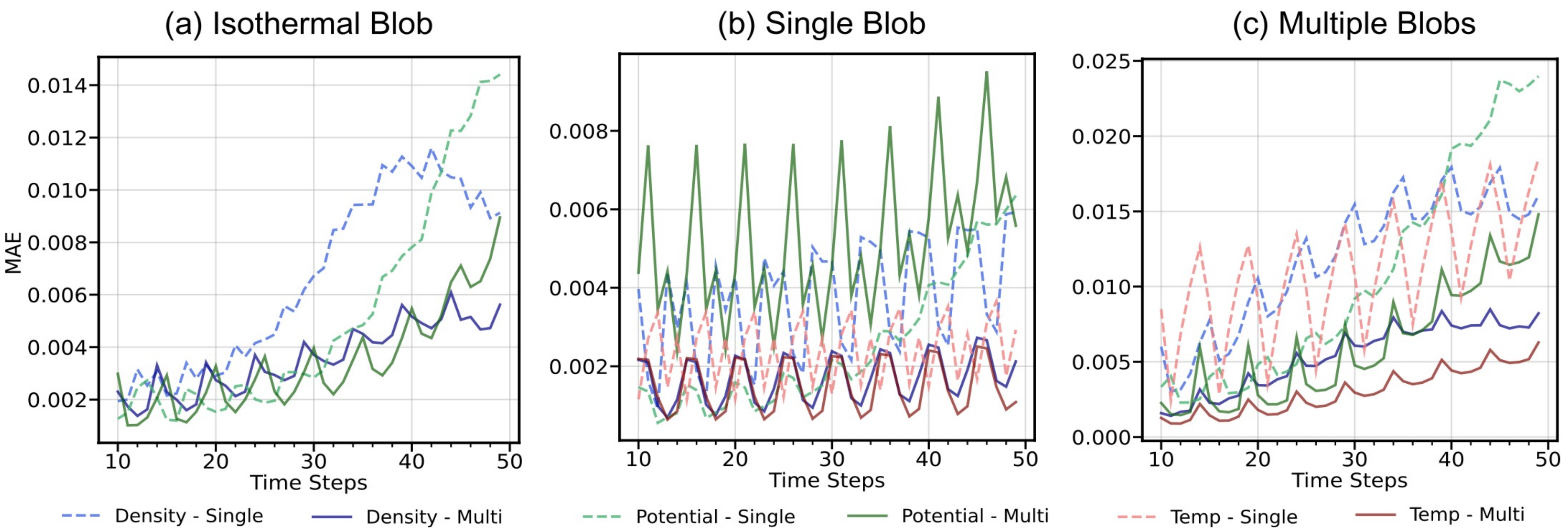


Mode Ablation Study

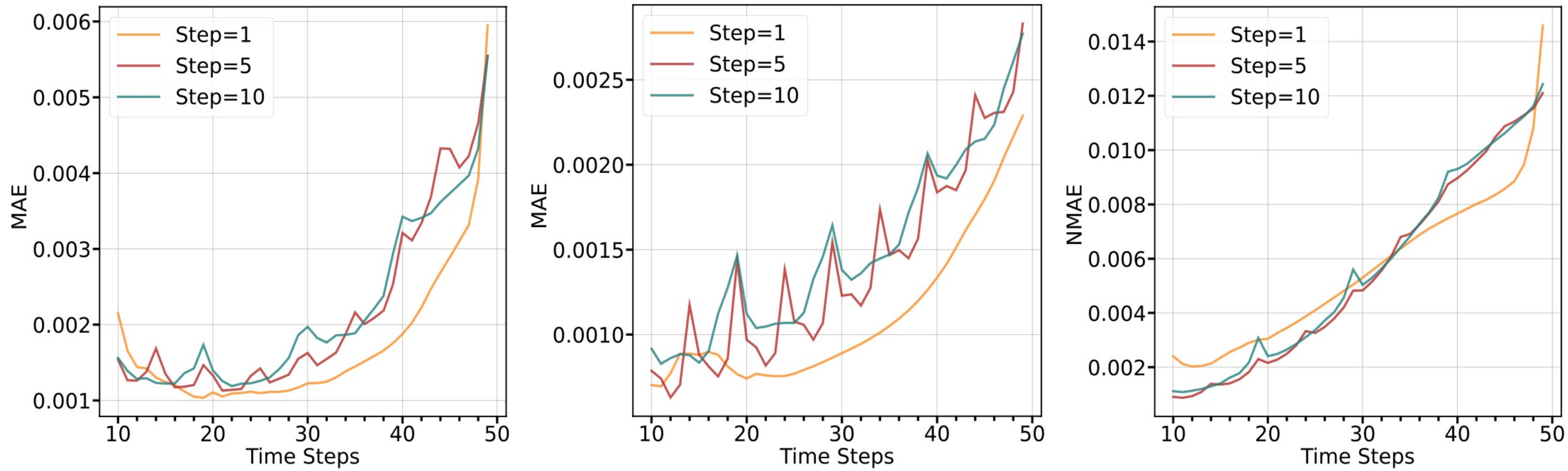




Individual FNO vs Multi-variable FNO



Impact of Step Size



(a) Isothermal Blob (b) Single Blob (c) Multi-blobs