

NEURAL OPERATOR SURROGATE MODELS OF PLASMA EDGE SIMULATIONS: FEASIBILITY AND DATA EFFICIENCY

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MOTIVATION

- Plasma modelling is essential for predicting divertor and core behaviour in future fusion devices (e.g., ITER, STEP).
- High-fidelity codes like JOREK are accurate but computationally prohibitive for iterative tasks (scenario optimisation, control).
- Neural surrogates can accelerate predictions, but existing CNN surrogates lack discretisation invariance.
- Fourier Neural Operators (FNOs) generalise across discretisations and show promise for PDE surrogates.
- This work:
 - Evaluates FNOs on JOREK datasets (Electrostatic & Reduced-MHD).
 - Explores transfer learning to improve data efficiency across fidelity levels and variables.

FNOs

Neural Operators learn mappings between functions, not just between fixed grids. They can generalize across different discretizations (unlike CNNs or RNNs).

FNOs [2] use the Fourier transform to efficiently capture long-range interactions in PDEs. An FNO block consists of:

- Transform fields into frequency space.
- Learn how different frequencies evolve (with trainable weights).
- Transform back to real space for predictions.

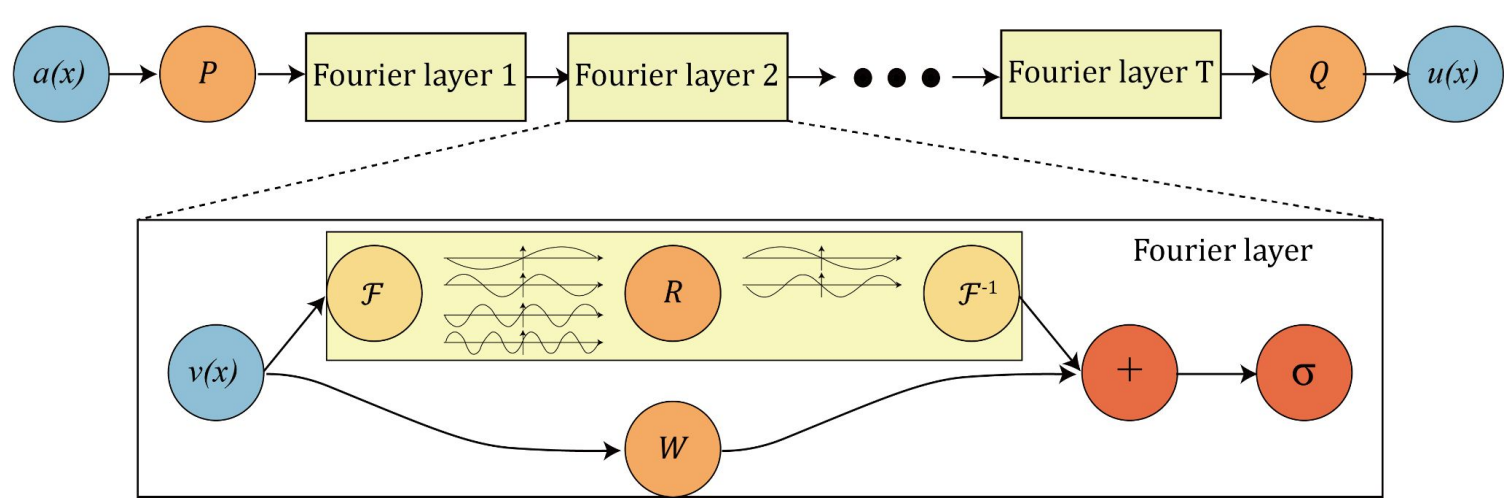


Figure 1: Fourier layer in the FNO [2]

EXPERIMENTS AND RESULTS

Baseline Performance

- FNOs reproduce short-term plasma dynamics with high accuracy.
- Long rollouts capture global structures but diverge at blob–boundary interactions.
- Errors spike at a specific point in trajectory events (e.g., wall impact).

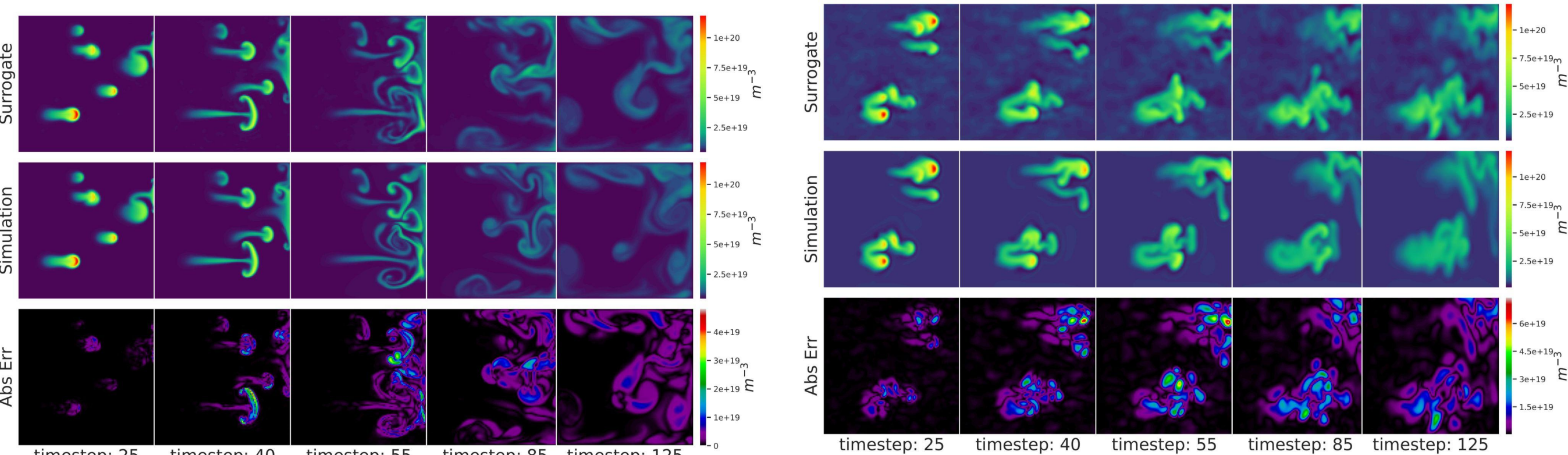


FIG. 1. Example rollout for both datasets: (LEFT) electrostatic JOREK dataset, and (RIGHT) reduced-MHD JOREK dataset.

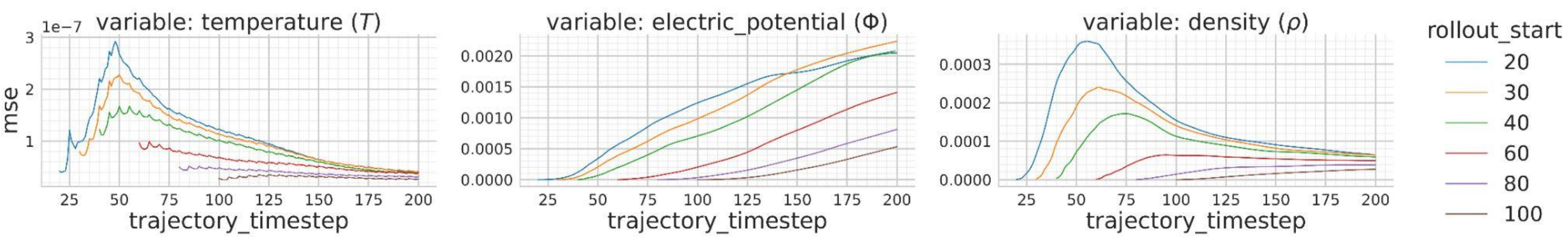
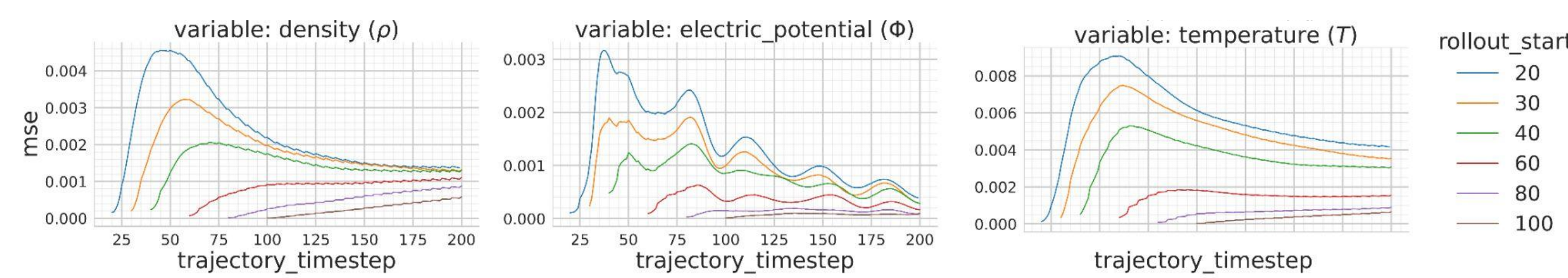


FIG. 4. Long-rollout FNO errors for (TOP) electrostatic JOREK and (BOTTOM) reduced-MHD JOREK fields: autoregressive rollouts from different start points.



Spatial Error Patterns

- Electrostatic JOREK: errors concentrated near boundaries.
- Reduced-MHD JOREK: errors arise earlier, not boundary-driven.

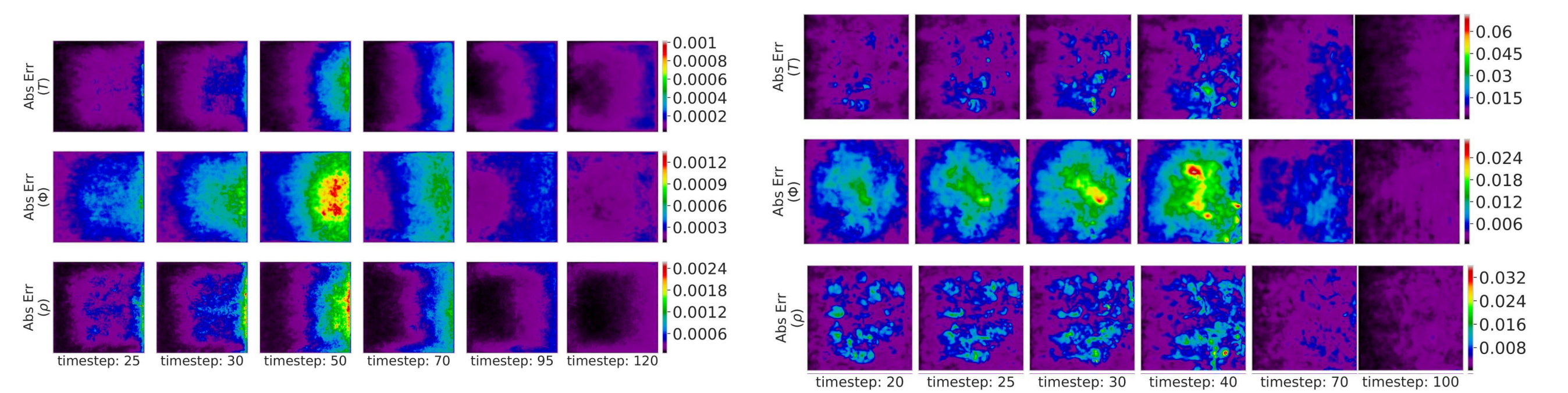


FIG. 5. This figure illustrates the pointwise model error for the (LEFT) electrostatic JOREK and (RIGHT) reduced-MHD JOREK dataset at specific time steps, averaged across the validation dataset. All errors are calculated from the rescaled fields.

DATASETS

- 2D slab-geometry JOREK [4] simulations of filamentary blob dynamics.
- Electrostatic JOREK: density, potential, temperature, vorticity.
- Reduced-MHD JOREK: adds magnetic flux & toroidal current.

TABLE 1. DATASET SIZES, VARIABLES, AND SPATIAL DIMENSIONS

Dataset	Size	Trajectory length	Variables	Dimensions
Electrostatic JOREK	2000 traj.	200 timesteps	2	100x100
Reduced-MHD JOREK	11391 slices + 20 traj.	10 per slice / 200 per traj	4	100x100

MODEL TRAINING

- FNO implemented using PDEArena [1].
- Input: sequence of timesteps, Output: next timesteps.
- Training: MSE loss, random trajectory sampling, early stopping.
- Rollouts: autoregressive prediction with error accumulation.
- Transfer learning: pre-train on large/low-fidelity dataset, fine-tune on smaller/high-fidelity dataset.

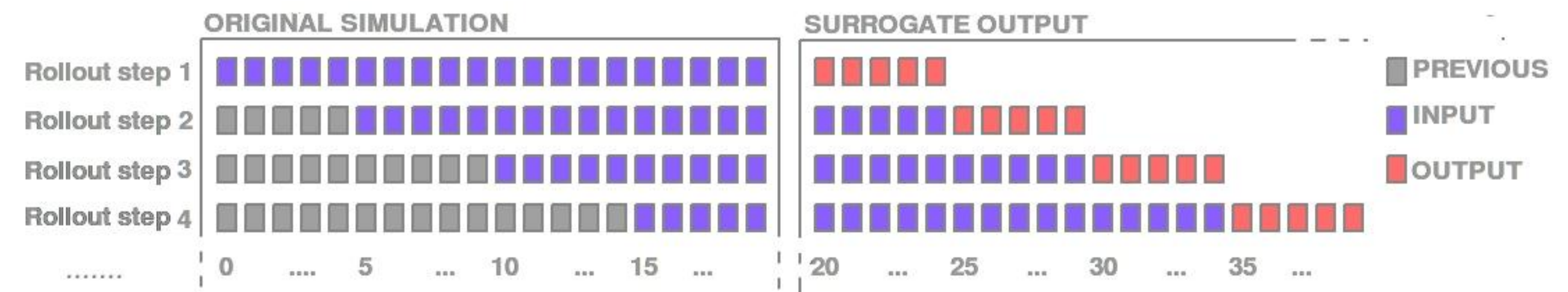


Figure 2: Model rollout example if input time steps were 4 and output time steps were 1

EXPERIMENTS AND RESULTS (TRANSFER LEARNING)

Idea: Train model weights on abundant, low-cost data -> fine-tune on scarce, expensive high fidelity data.

Boosts performance when high-fidelity simulations are limited.

Like learning to ride a bike before learning to ride a motorbike - shared skills transfer, but differences can cause problems.

- Cross-fidelity transfer: significant gains for small datasets (order-of-magnitude error reduction at short times).

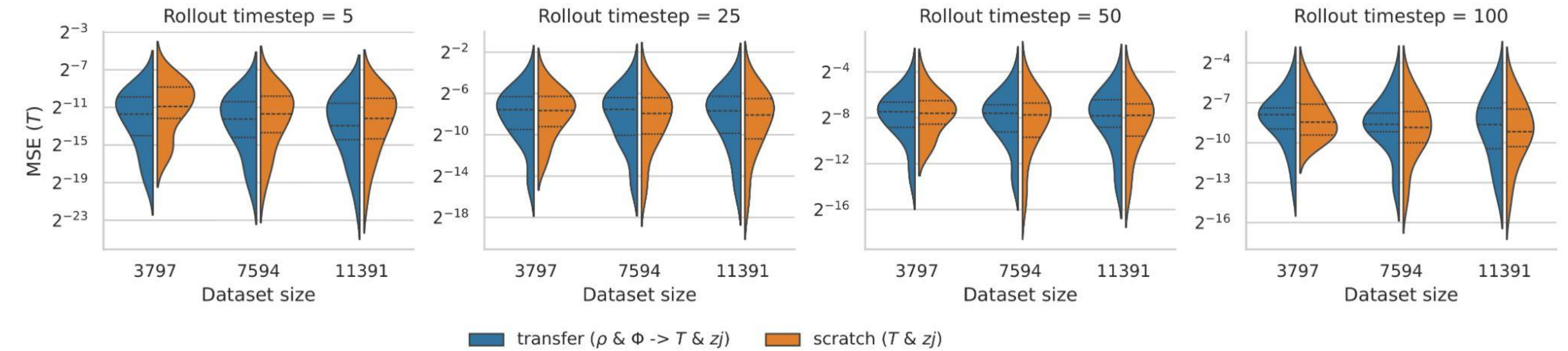


FIG. 8. Scratch and transfer model error at different timesteps and dataset sizes on reduced-MHD JOREK (density). Scratch was trained from scratch on the reduced-MHD JOREK dataset whilst transfer model was first trained on electrostatic JOREK and then finetuned on reduced-MHD JOREK.*

- Cross-variable transfer: partial improvement, but sometimes the transfer model performed worse at longer rollouts + larger dataset sizes (risk of negative transfer during long rollouts).

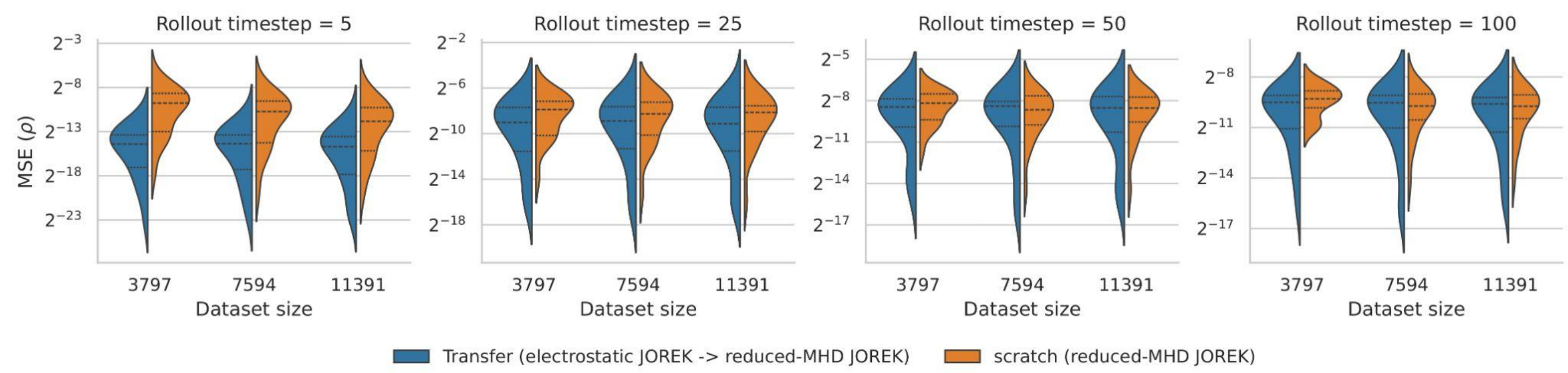


FIG. 9. Scratch and transfer model error at different timesteps and dataset sizes on reduced-MHD JOREK (temperature). Scratch model was trained directly on the corresponding variables on the dataset. Transfer x2 model was first trained on electrostatic JOREK density and electric potential, finetuned on reduced-MHD JOREK density and electric potential (similar to prior section) and the transferred to reduced-MHD JOREK temperature and current.*

*The line is the medium error and the error bars correspond to the 16th and 84th percentile.

CONCLUSION & FUTURE WORK

- FNO surrogates can approximate JOREK simulations efficiently.
- Strong in short-term predictions, but long-rollout stability remains a challenge.
- Transfer learning reduces high-fidelity data needs, especially across fidelity levels.
- Transfer to unseen variables is harder, sometimes harmful.
- No explicit physics constraints; MSE loss misses fine-scale structures.
- Future:
 - Attention architectures & physics-informed losses.
 - Active learning, domain adaptation, LoRA.
 - Scaling to higher-dimensional, multiphysics simulations.

REFERENCES:

- [1]. <https://microsoft.github.io/pdearena/>
- [2]. Li, Zong-Yi et al. "Fourier Neural Operator for Parametric Partial Differential Equations." ArXiv abs/2010.08895 (2020)
- [3]. Murtaza Dalal, Alexander C. Li, and Rohan Taori. Autoregressive models: What are they good for?, 2019.
- [4]. Hoelzl M. et al., Nucl. Fusion 61 065001