

Learning Gaussian-Like Deposition to Reduce PIC Noise in HEXAPIC at Scale

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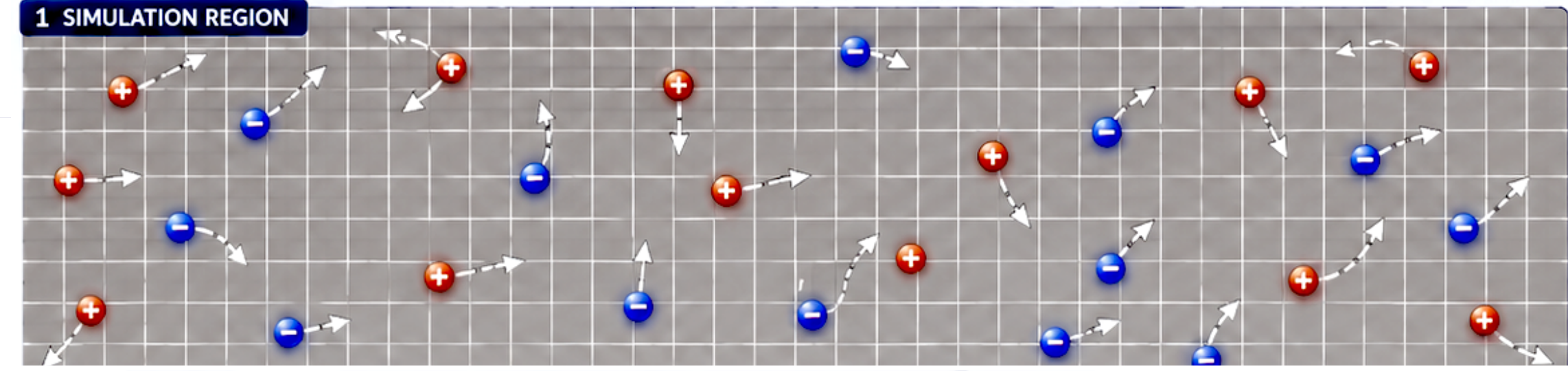
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Background

Particle-in-Cell (PIC) simulations are widely used for modeling fusion edge physics, electric propulsion, and space plasmas, but large PIC runs are expensive, often limited by memory and across nodes, not just by raw compute. A common source of error is numerical noise because we represent a huge number of real particles with a finite number of sample particles, which can introduce fluctuations that hide weak physical signals and reduce diagnostic quality. Using smoother, higher-order deposition can reduce this noise, but it usually increases memory traffic and scalability. In this work, we explore a ML approach that learns a smooth, Gaussian-like deposition behavior to reduce high-frequency noise with multicore CPU and single-GPU implementation, and training is performed using a data-parallel approach in PyTorch.



Motivation and Goals

Motivation

- Large PIC studies are expensive, and at scale the main limits are often memory and node-to-node communication, not just compute speed.
- The standard cloud-in-cell (CIC) particle-grid coupling is fast and scalable, but its noise can reduce diagnostic quality and hide weak physical signals¹.

Goals

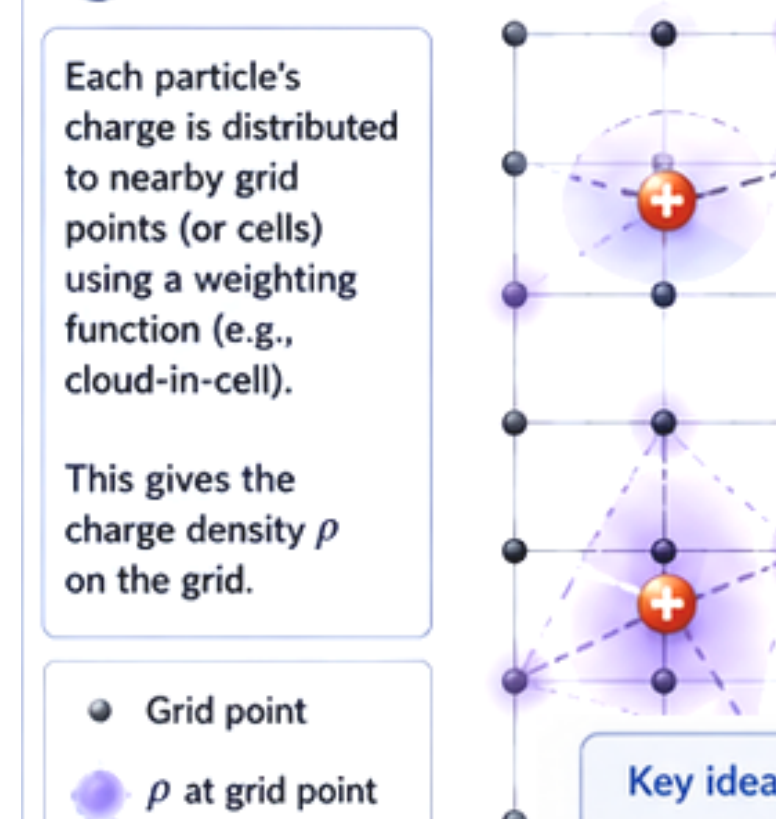
- Reduce high-frequency noise introduced during particle-to-grid deposition while keeping the PIC loop unchanged in its main structure.
- Integrate a Machine Learning (ML)-based, Gaussian-like smooth deposition approach into the Heterogeneous Exascale PIC (HEXAPIC) workflow.
- Support scalable training and testing using distributed PyTorch (data parallelism, and model parallelism using multicore CPUs and a single GPU.)

We used the AMD EPYC Rome CPU and NVIDIA A100 GPU for training on the MeluXina HPC machine.

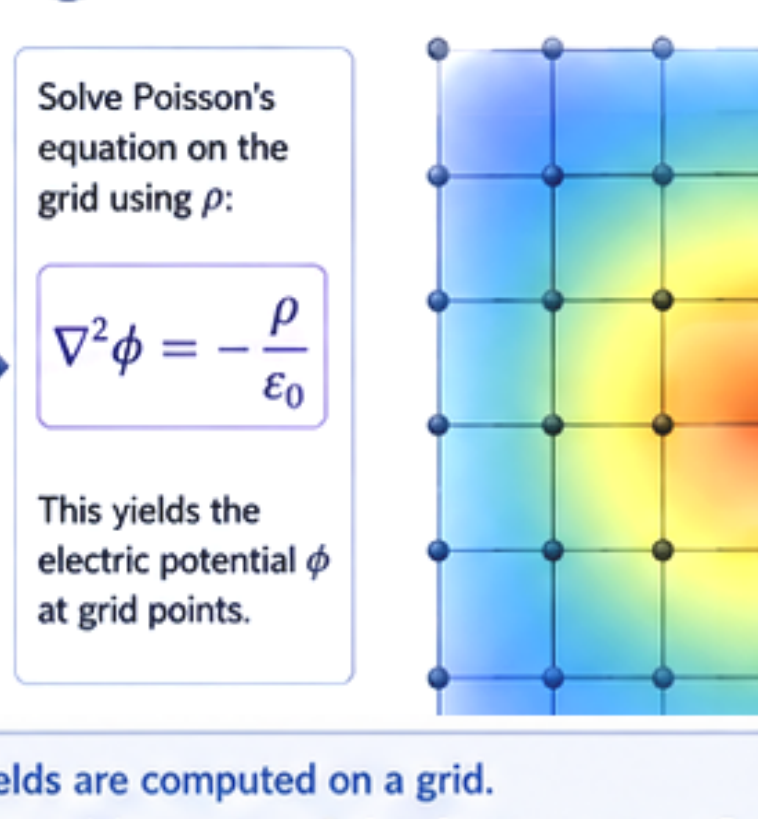
Results

- Qualitative agreement:** For an exemplary case, the predicted Gaussian-deposited field closely matches the true Gaussian deposition. The difference map (pred – true) remains near zero, with small residuals localized around the charge peaks.
- Accuracy:** MAE = 7.53×10^{-4} . Mean abs. charge error: 1.246913×10^{-2} .

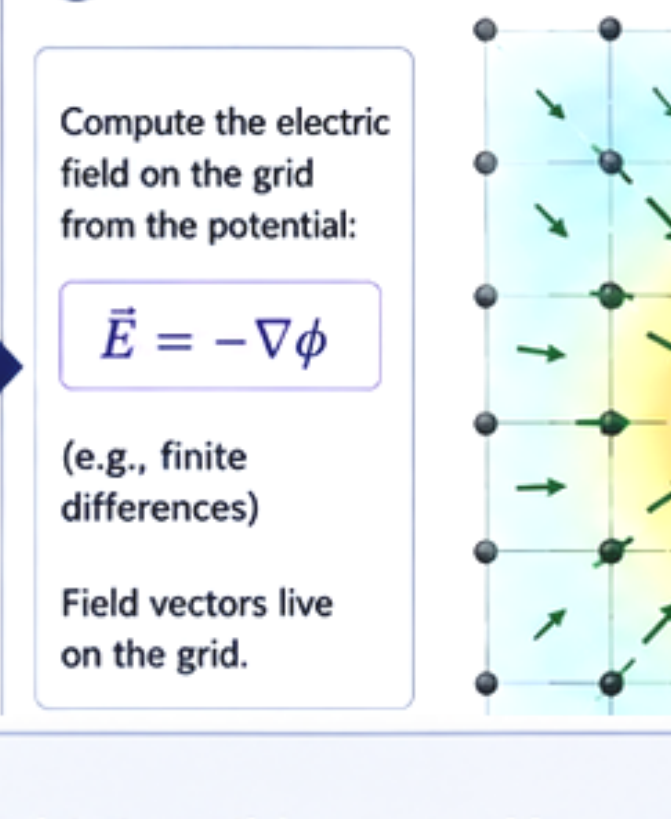
2 CHARGE DEPOSITION ON GRID



3 ELECTRIC POTENTIAL ON GRID



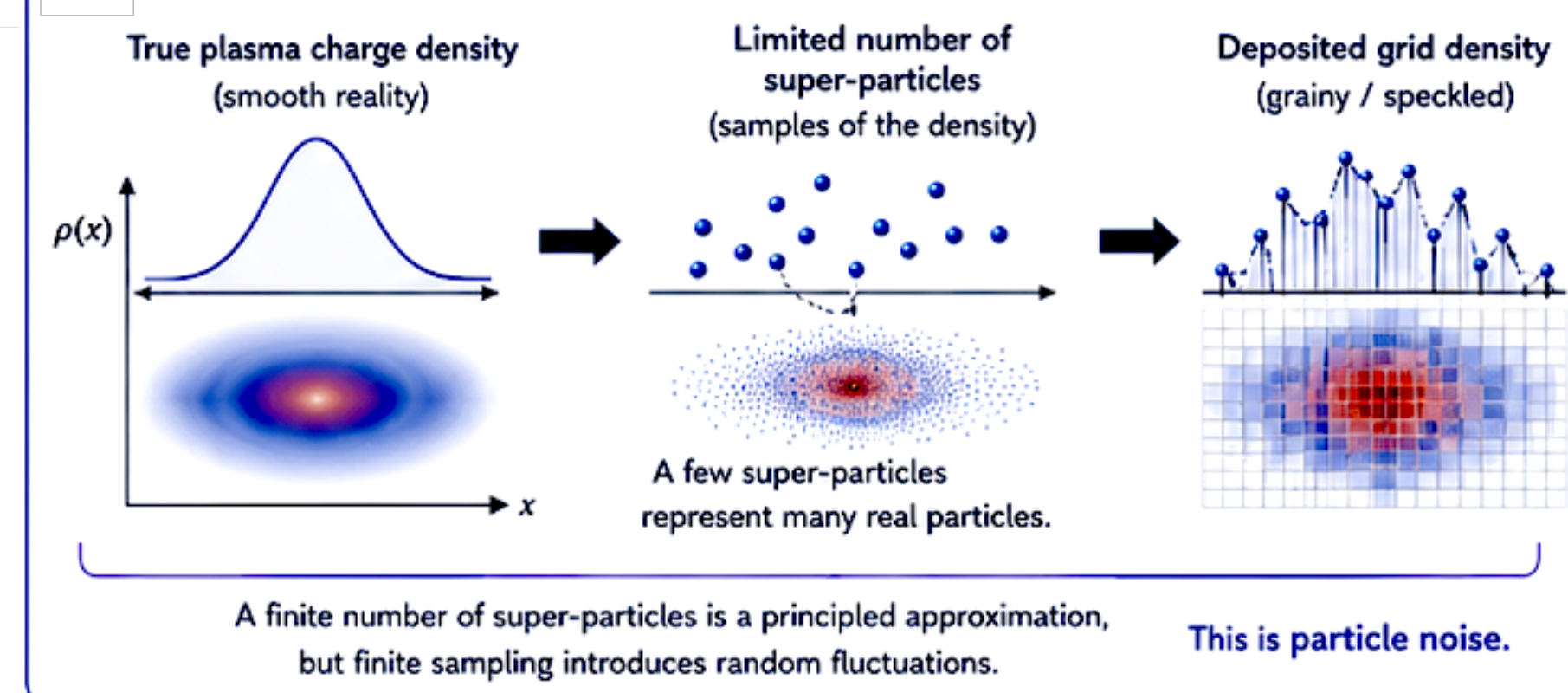
4 ELECTRIC FIELD ON GRID



Key idea: particles are continuous, but fields are computed on a grid.

Particles → Deposit charge (ρ) → Solve for φ → Compute E → Interpolate to particles → Move particles

Where noise comes from

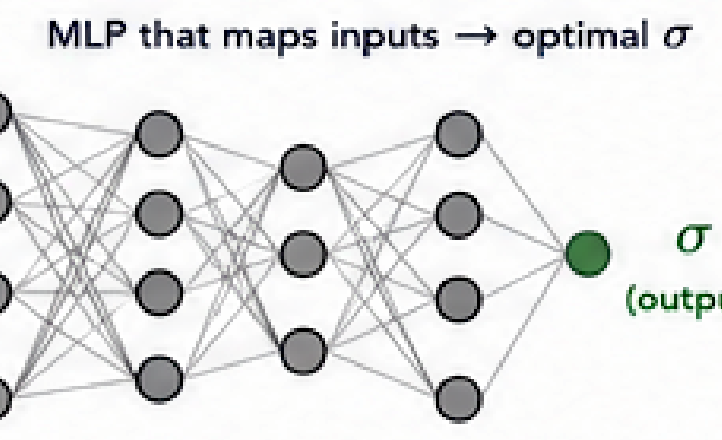


4.1 Inputs

- $k\Delta x$ (mode resolvedness)
- Drift / flow speed $v_0/\omega_{pe}\lambda_D$
- Thermal speed $v_{th}/\omega_{pe}\lambda_D$
- Debye length resolution $\Delta x/\lambda_D$
- Particles-per-cell (ppc-equivalent)
- Optional: gradients / local features (for σ -field extension)

Goal: generalize across problems and regimes.

4.2 Model (baseline: global σ)



Choose σ to reduce noise (low MISE) while preserving the physically important mode's growth rate γ and real frequency ω_r .

$$L = L_{MISE} + \lambda_\gamma \left(\frac{\gamma_\sigma - \gamma_0}{\gamma_0} \right)^2 + \lambda_\omega \left(\frac{\omega_{r,\sigma} - \omega_{r,0}}{\omega_{r,0}} \right)^2$$

Density error
(reduce noise)

Growth-rate fidelity
(preserve γ)

Frequency fidelity
(preserve ω_r)

4.3 Training data

- Analytic surrogate (cheap, bulk of data)
- Sample wide grid in parameter space
- For each sample and many σ values:
 - Compute T_{eff}^2
 - Solve dispersion → $\gamma_\sigma, \omega_{r,\sigma}$
 - Compute MISE(σ) (analytic shot-noise model)
- Provides dense, labeled training set

- Sparse PIC validation (expensive, small set)
- Run full PIC for selected points (warm / kinetic)
- Measure true γ and ω_r
- Check surrogate accuracy and calibrate if needed

4.4 Loss and physical knob

Minimize dynamics-constrained loss L .

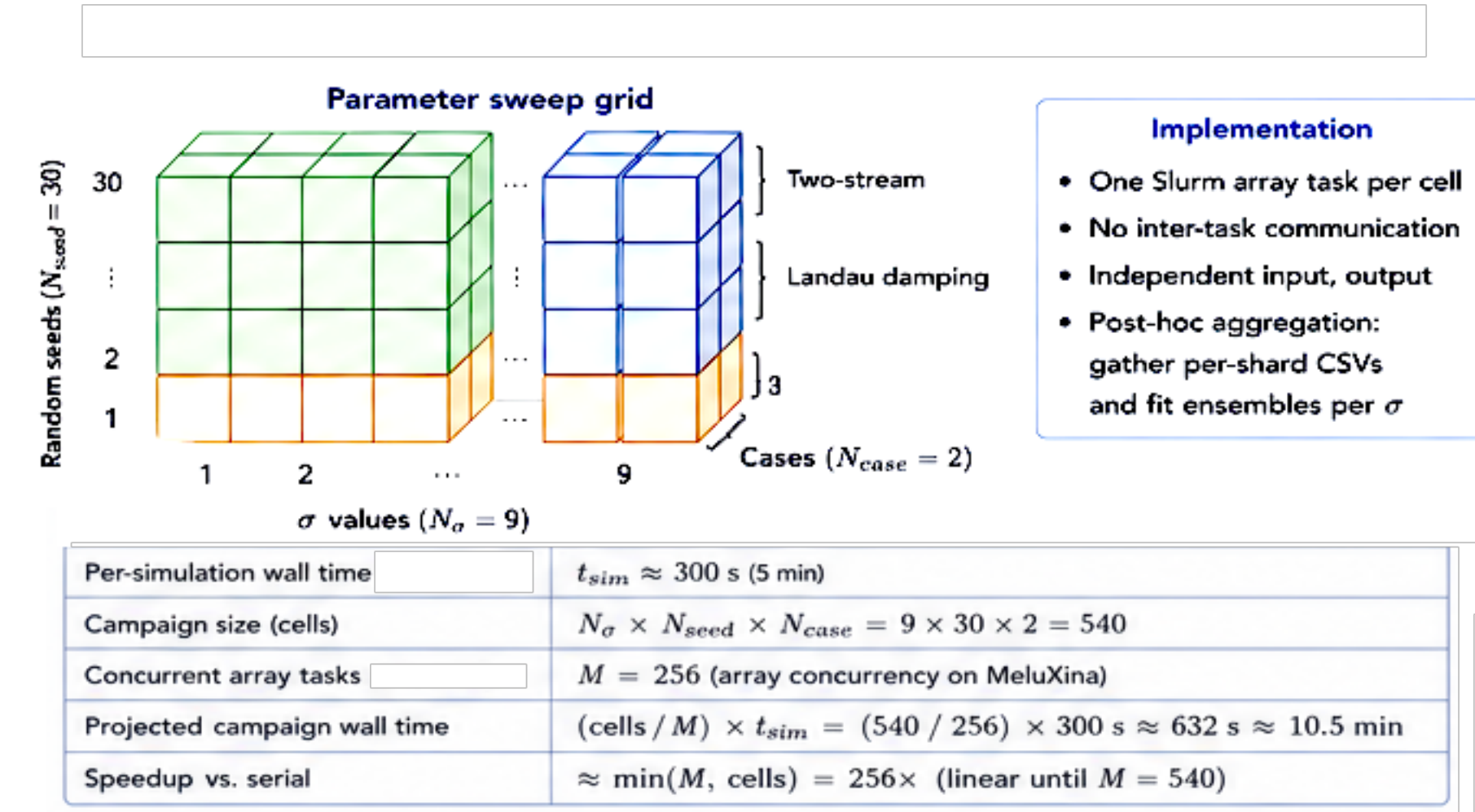
Expose one physical knob to user:

Allowed relative growth-rate error ϵ_γ (e.g., 5%)

Map ϵ_γ → loss weights (principled): Increase λ_γ until $|(\gamma_\sigma - \gamma_0)/\gamma_0| \leq \epsilon_\gamma$ holds at the predicted σ .

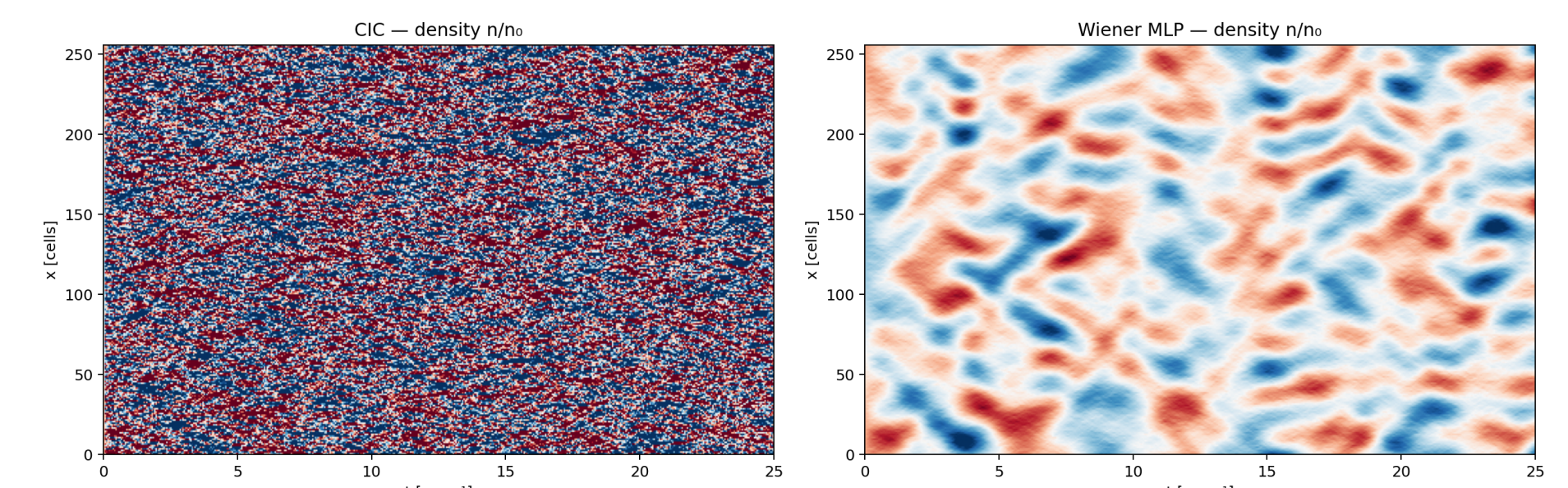
λ_ω set to keep $|(\omega_{r,\sigma} - \omega_{r,0})/\omega_{r,0}|$ within a small tolerance (e.g., 2%).

1. Simulation parameter sweep — throughput (task) parallelism



Measured variance reduction (Landau damping growth rate)

δf fraction α	Variance reduction (vs full-f)	Equivalent particle count increase ($\approx V$)	α^2 -scaling ratio (measured)
$\alpha = 1.0$ (full-f)	1×	1×	—
$\alpha = 0.1$	119×	$\sim 119\times$	11.9 (theory = 10)
$\alpha = 0.01$	1,916×	$\sim 1,916\times$	191.6 (theory = 100)
$\alpha = 0.001$	11,957×	$\sim 11,957\times$	1,195.7 (theory = 1000)



References

- Touati *et al.*, *Plasma Phys. Control. Fusion* **64**, 115014 (2022)
- Krishnasamy *et al.*, “Large-Scale Deep Learning Medical Image Methodology and Applications Using Multiple GPUs,” in *ICABME* (2023).