AI in LWFA simulation

Francesco Massimo

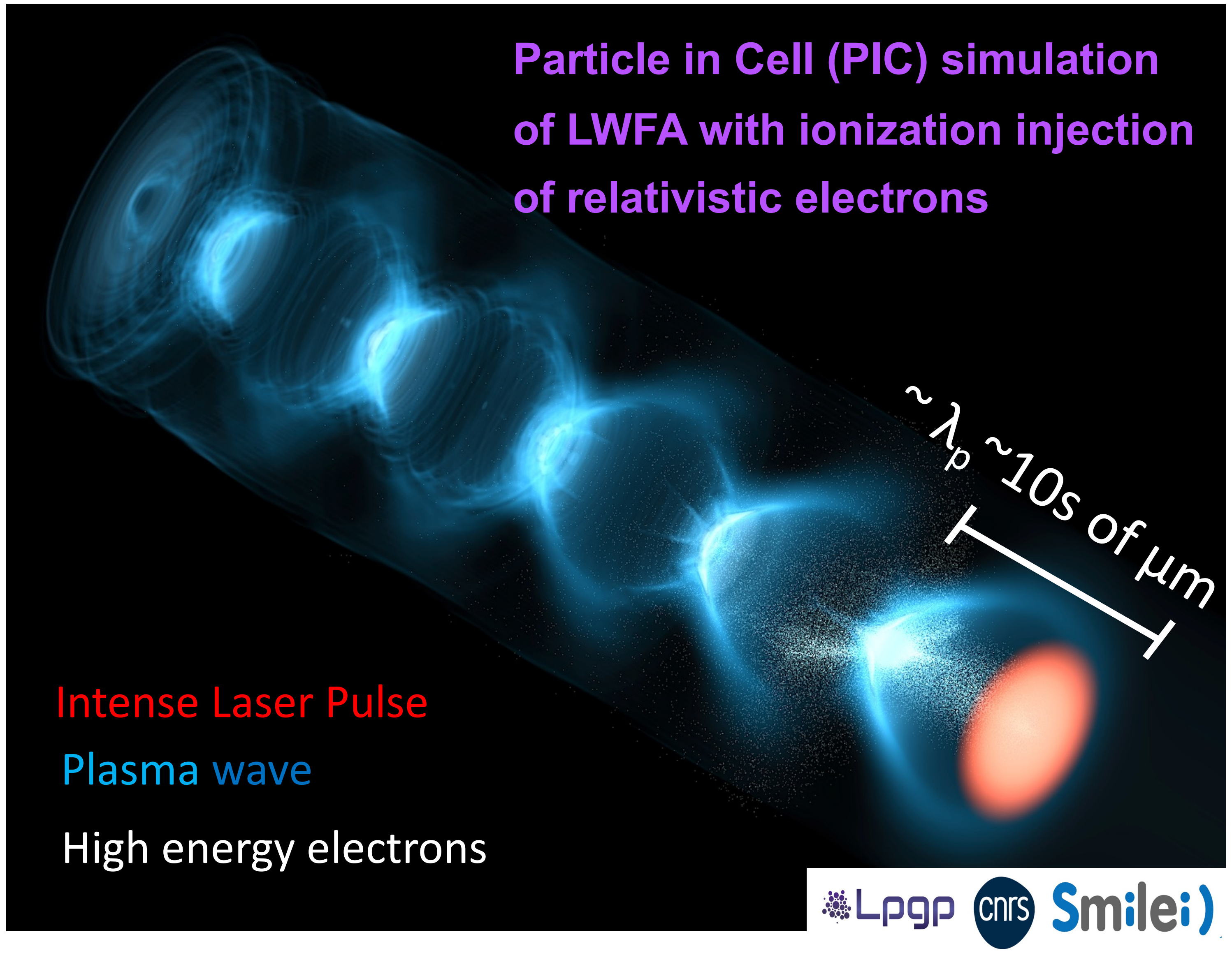
M4CAST Annual meeting,

6 nov 2024, IJClab

Plan

- Laser Wakefield Acceleration (LWFA) and its simulation
- Examples of AI applied to LWFA
- Ideas from other plasma acceleration techniques
- Conclusions

Laser Wakefield Acceleration (LWFA): a path to more compact electron accelerators

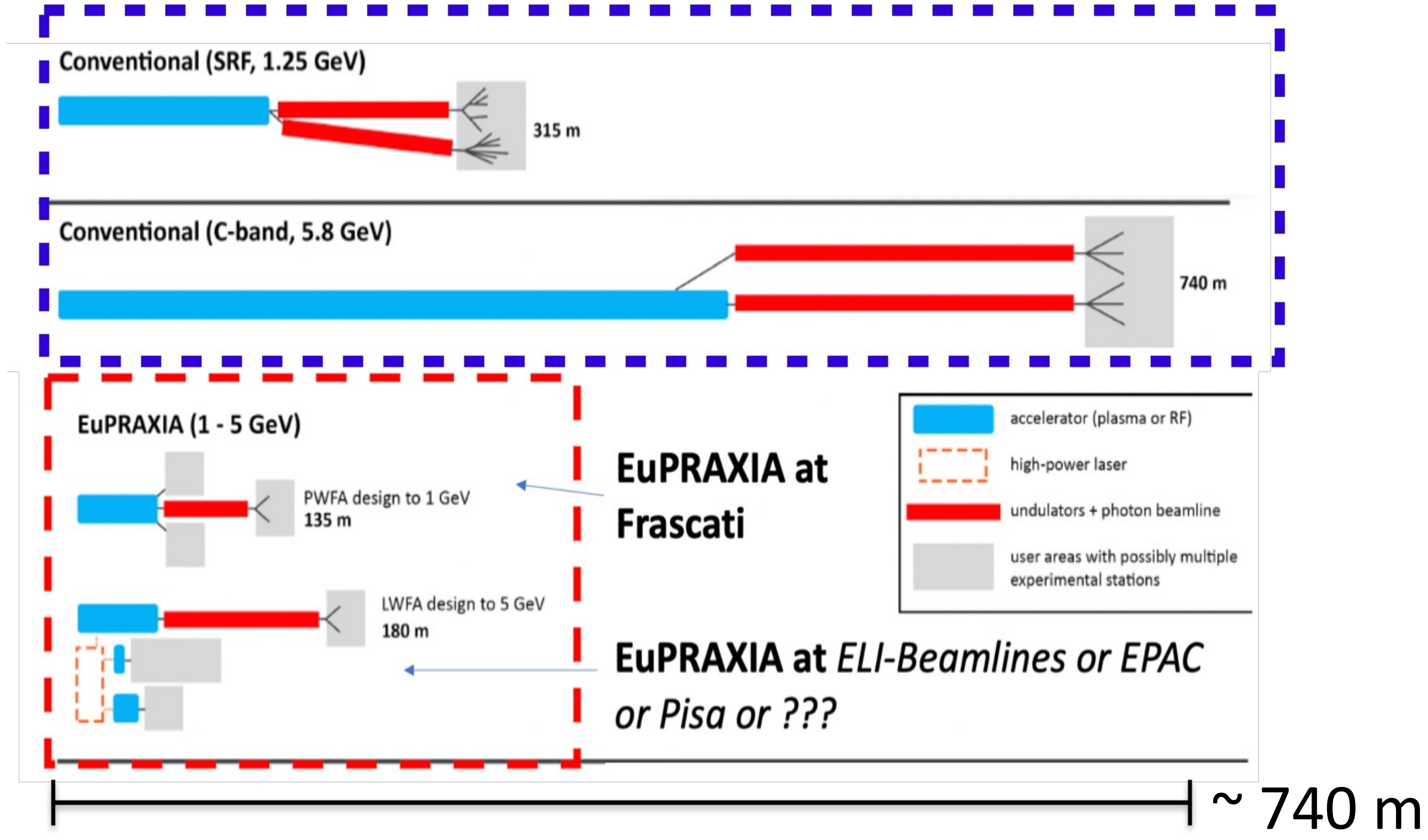


Example of large-scale plasma acceleration project: EuPRAXIA

Conventional Acceleration (Max ~100 MV/m)

Plasma Acceleration (Max ~100 GV/m)

Scientific challenge: Obtain beam qualities suited for applications



Objective: build a European, large scale, distributed plasma acceleration facility for users

R. Assmann, EuPRAXIA Preparatory Phase kick-off meeting (Nov 2022)

Plasma acceleration → Large scale projects and R&D strategy

Project EuPRAXIA:
https://www.eupraxia-facility.org/projects

Project AWAKE at CERN:
https://home.cern/science/accelerators/awake

Study group ALEGRO:
https://indico.cern.ch/event/1193719/

ALEGRO 2023

“European Strategy for Particle Physics (ESPP)”:
https://arxiv.org/abs/2201.07895

Laser Wakefield Acceleration: synergy between investigation techniques

dataset generation

dataset generation

AI

Experiment
design and analysis

Experiments

Numerical Modeling

data to analyse,
inputs for more
realistic simulations

Laser Wakefield Acceleration and AI for experiments: some examples (see next talk!)

AI

Experiments

Numerical Modeling

- Automatic control of laser and plasma parameters

  R. J. Shalloo et al., *Nature Communications* 11, 6355 (2020)
  S. Jalas et al., Phys. Rev. Lett. 126, 104801 (2021)
  F. Irshad et al., Phys. Rev. Research 5, 013063 (2023)

- Understanding dependence of beam quality on laser fluctuations

  A. R. Maier et al., Phys. Rev. X 10, 031039 (2020)

See also:

A. Döpp et al, Data-driven science and machine learning methods in laser–plasma physics. *High Power Laser Science and Engineering, 11*, E55

Laser Wakefield Acceleration and AI for experiments: some examples (see next talk!)

AI

Experiments

Numerical Modeling

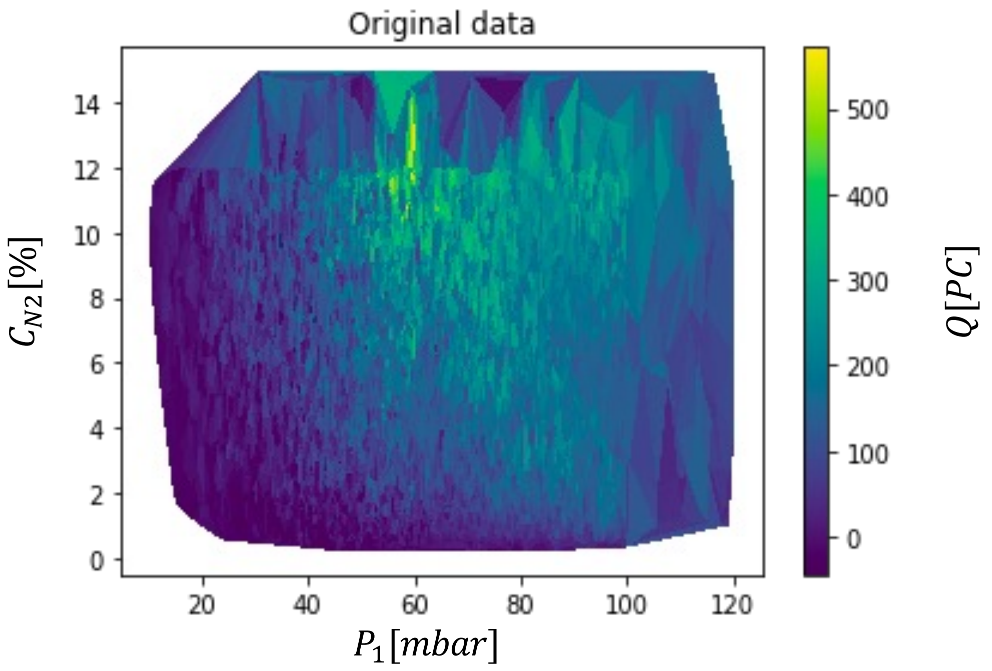
- Experiment design through Single-Objective Bayesian Optimization
  S. Jalas et al., Phys. Rev. Lett. 126, 104801 (2021)
- Quicker Bayesian Optimization by coupling simulations with different accuracy
  A. Ferran Pousa, Phys. Rev. Accel. Beams **26**, 084601 (2023)
- Experimental design through Multi-Objective, Multi-fidelity Bayesian Optimization
  F. Irshad et al., Physical Review Research 5, 013063 (2023)

See also:

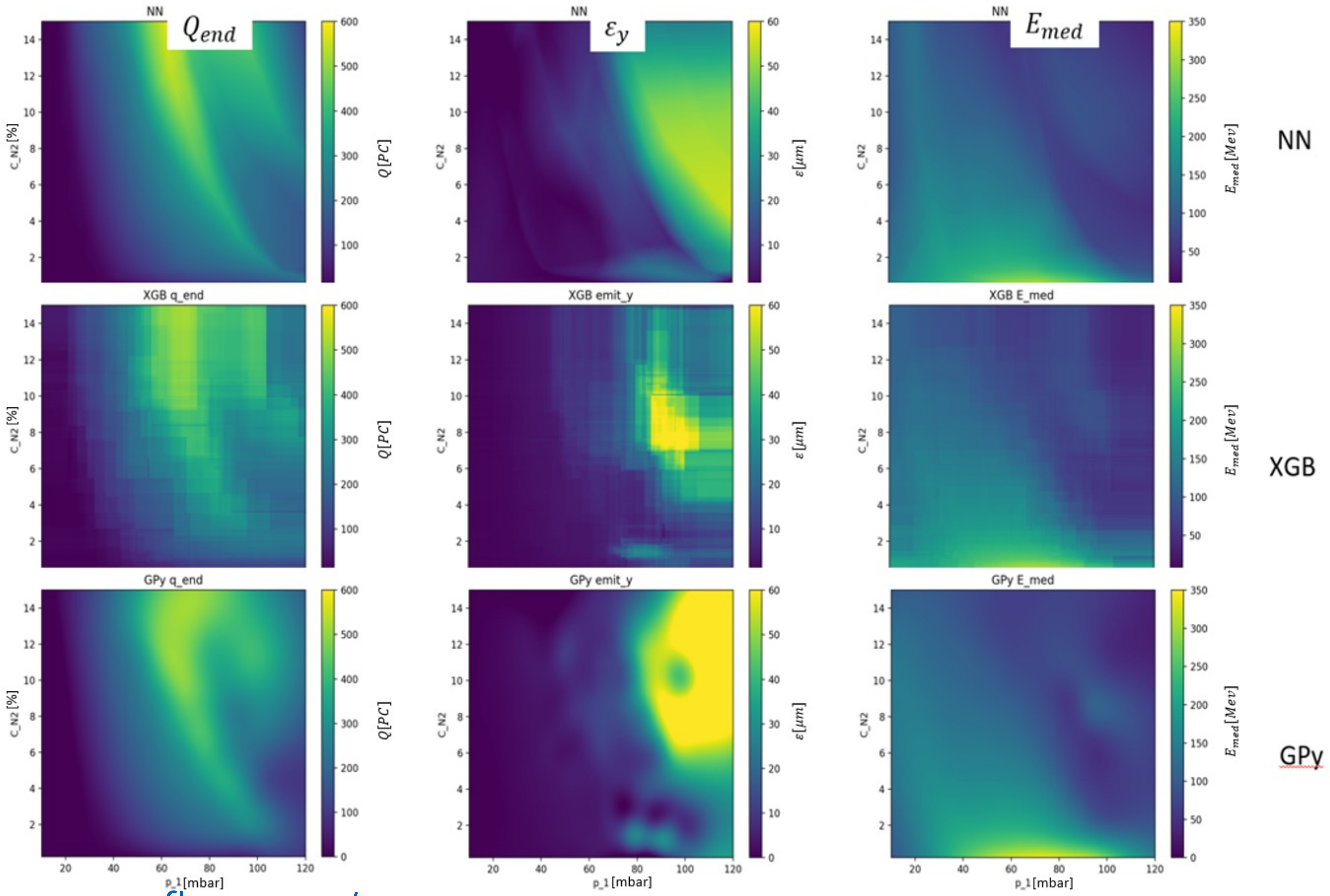
A. Döpp et al, Data-driven science and machine learning methods in laser–plasma physics. *High Power Laser Science and Engineering*, *11*, E55

Surrogate model of PALLAS

- Neural Networks [1]
- XGBoost [2]
- Gaussian Process (Gpy) [3]



Predicted beam parameters



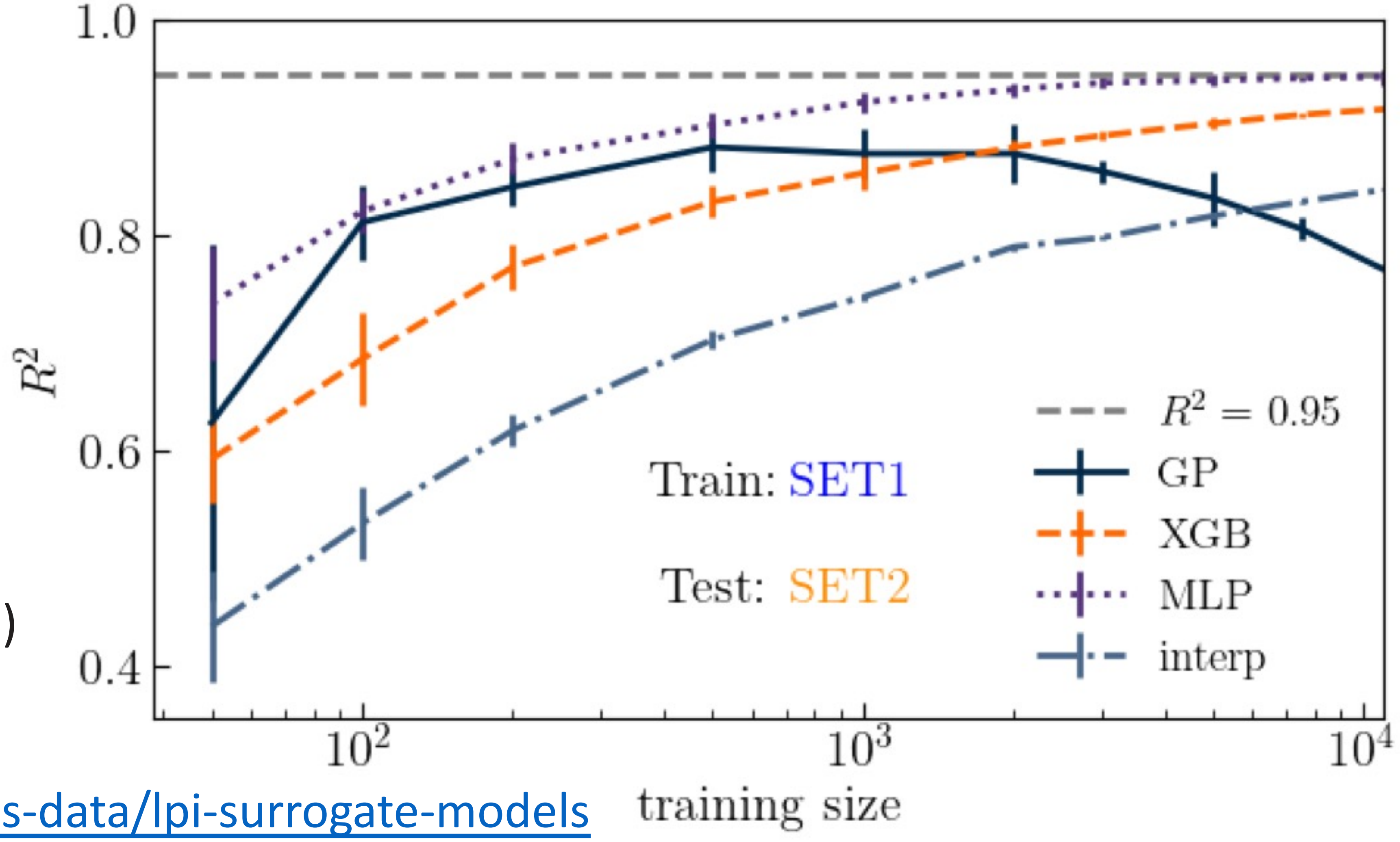
[1] Tensorflow/keras: https://www.tensorflow.org/
[2] Extreme gradient boosting : https://github.com/dmlc/xgboost
[3] A gaussian process framework in Python https://github.com/SheffieldML/GPy

V. Kubytsky, Artifact Preparation Workshop, 28 nov 2023

Surrogate model of PALLAS

- Neural Networks [1]
- XGBoost [2]
- Gaussian Process (Gpy) [3]

Dataset size required by the prediction model



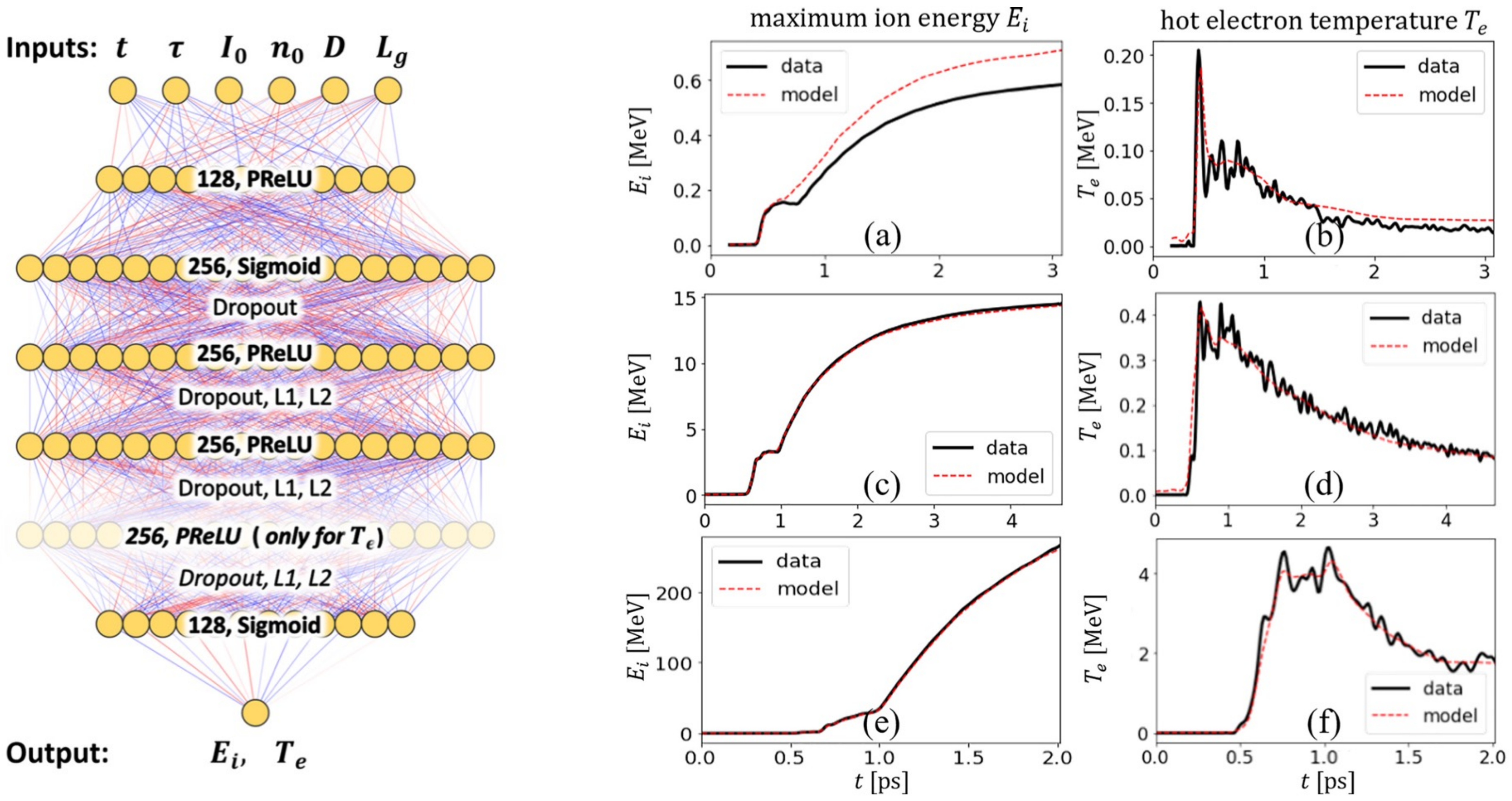
Simulations from:
P. Drobniak et al, PRAB 26, 091302 (2023)

Dataset:
https://gitlab.in2p3.fr/lpa-pic-simulations-data/lpi-surrogate-models

[1] Tensorflow/keras: https://www.tensorflow.org/
[2] Extreme gradient boosting : https://github.com/dmlc/xgboost
[3] A gaussian process framework in Python https://github.com/SheffieldML/GPy

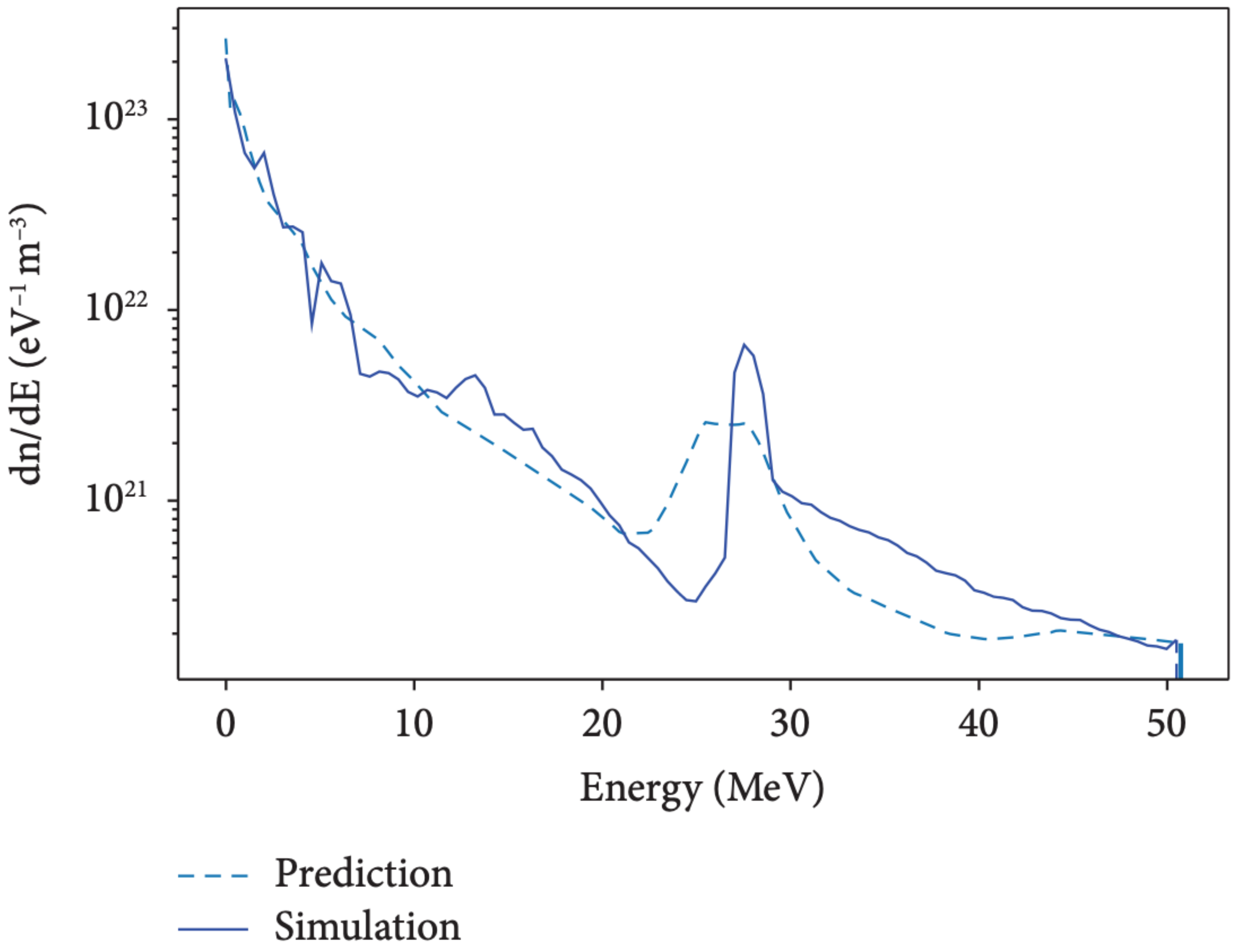
G. Kane et al, **https://arxiv.org/abs/2408.15845 (2024)**

Ideas from other plasma acceleration techniques: predicting time evolution of scalar quantities



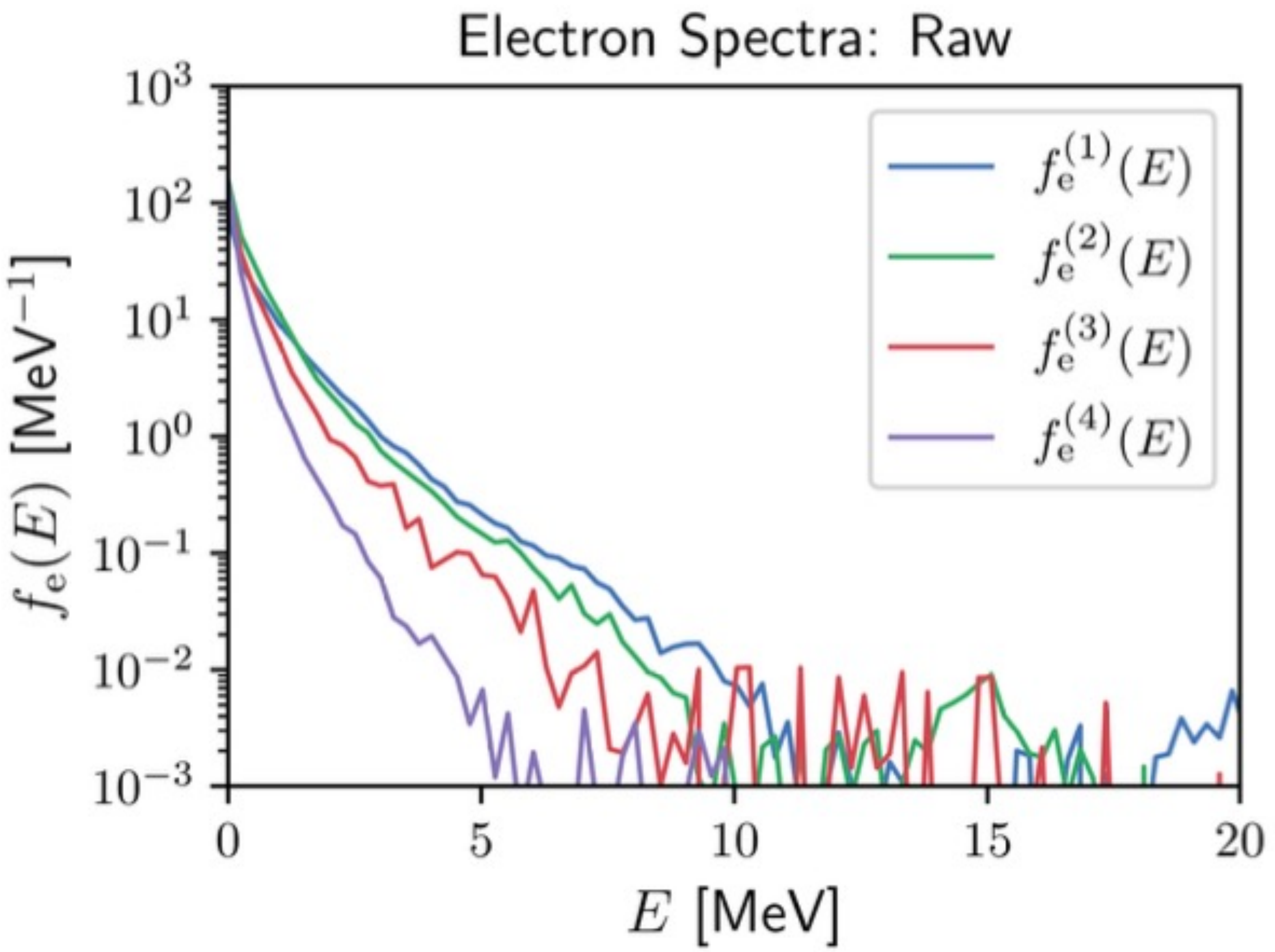
B. Schmitz et al., "Modeling of a Liquid Leaf Target TNSA Experiment Using Particle-In-Cell Simulations and Deep Learning", Laser and Particle Beams 2023

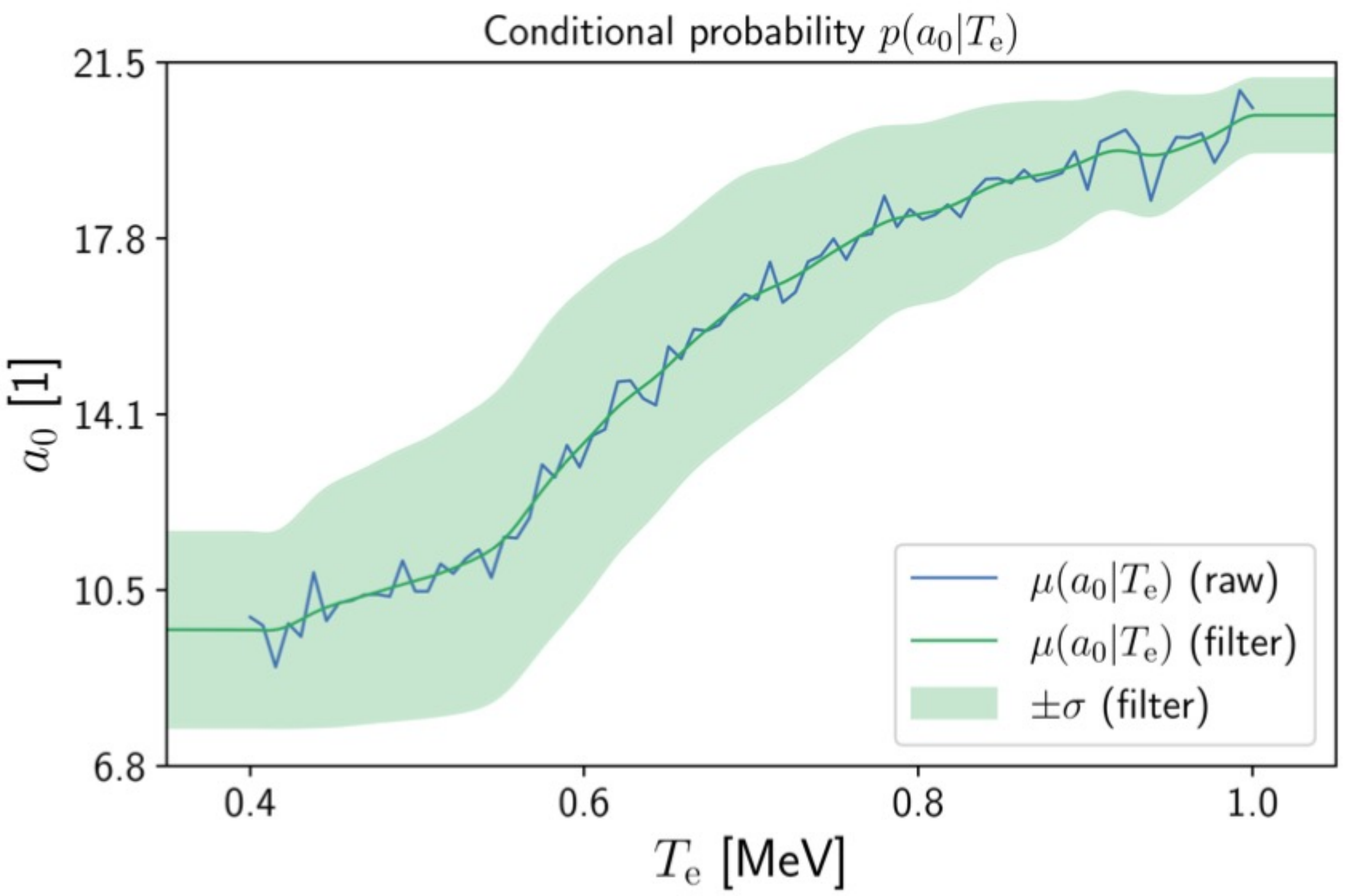
Ideas from other plasma acceleration techniques: predicting the full spectrum with deep learning



B. Djordjević, A. Kemp, J. Kim et al.,
"Modeling laser-driven ion acceleration with deep learning,"
Physics of Plasmas, 28, no. 4, 2021

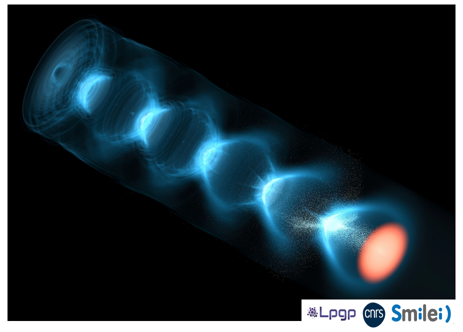
Ideas from other plasma acceleration techniques: Invertible neural network

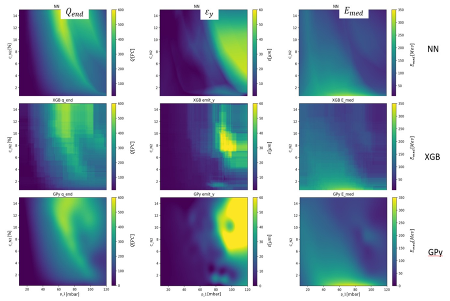


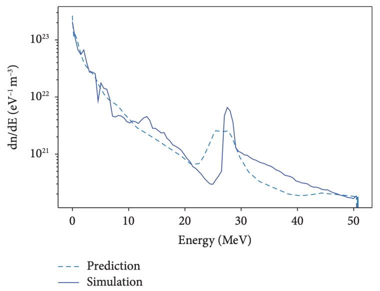


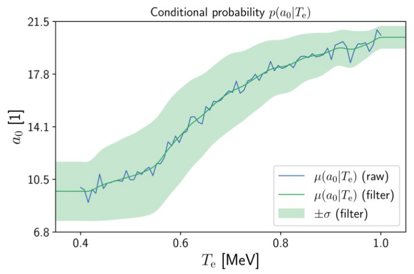
T. Miethlinger et al, "Acceptance Rates of Invertible Neural Networks on Electron Spectra from Near-Critical Laser-Plasmas: A Comparison", Parallel Processing and Applied Mathematics (2023)

Conclusions and Perspectives



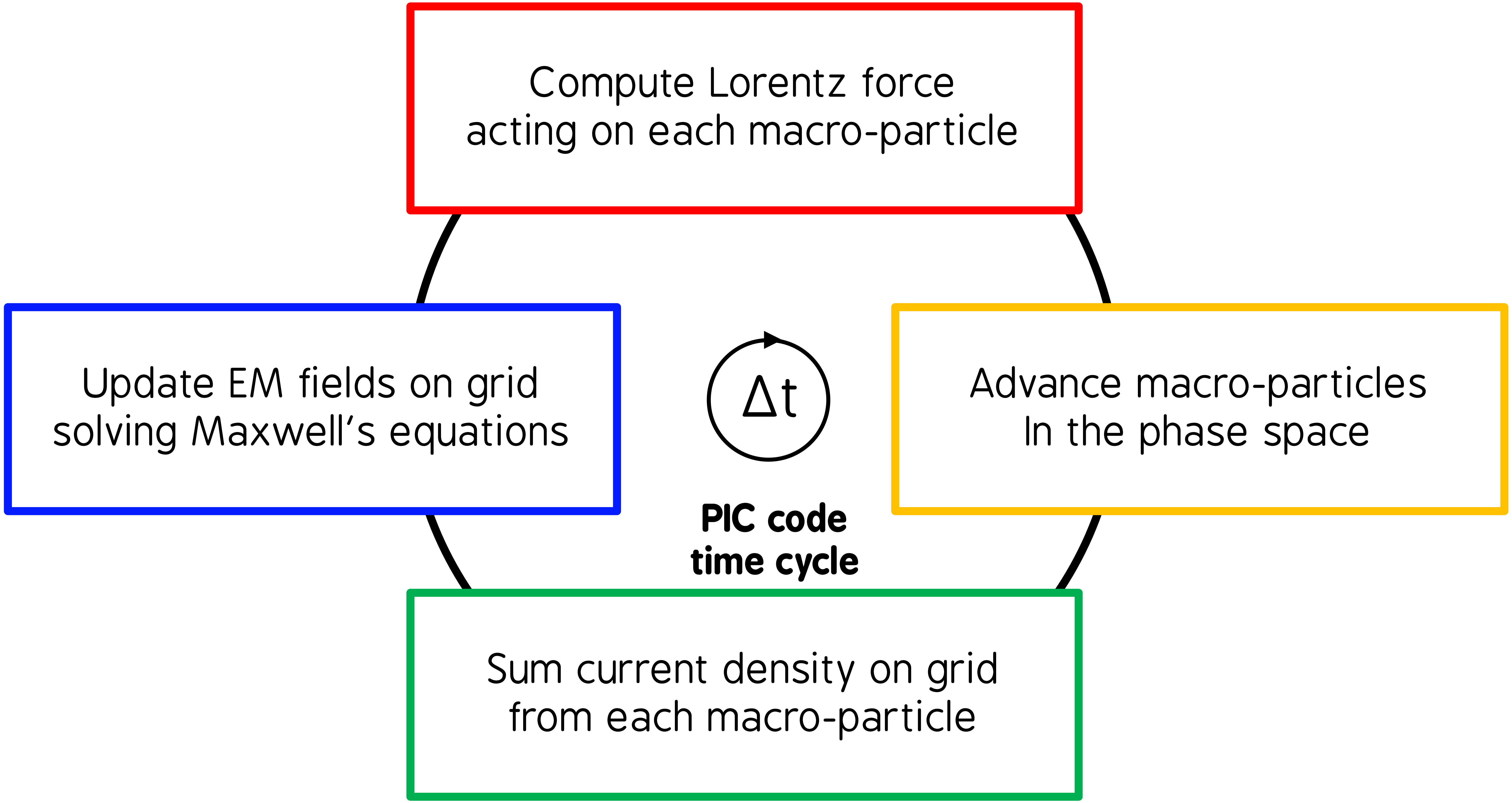






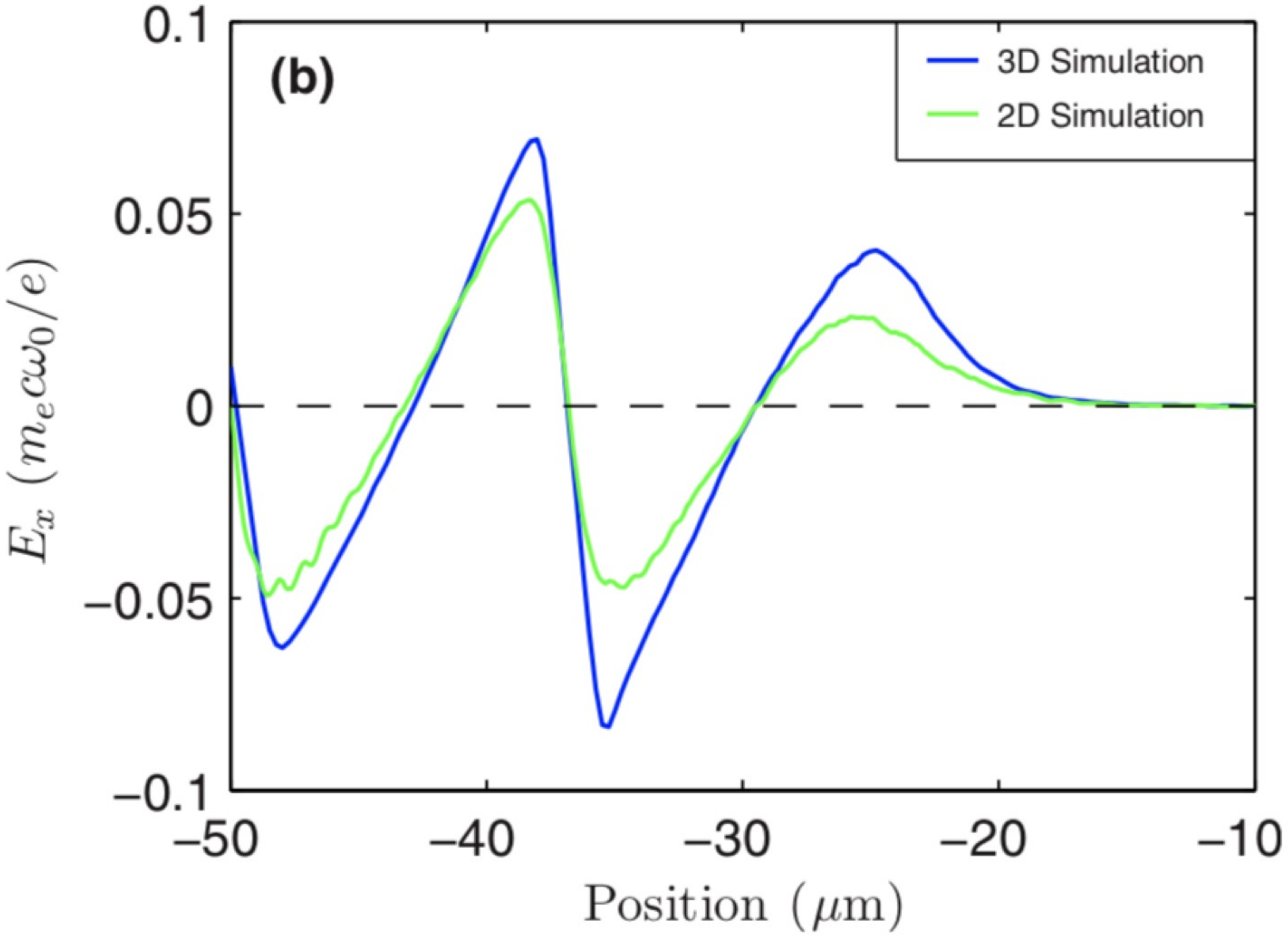
- Laser Wakefield Acceleration is a high-gradient acceleration technique with the potential to realize more compact and accessible high energy accelerators
- Experiments, Numerical Modeling and AI can work in synergy to improve beam quality in Laser Wakefield Acceleration and build plasma accelerators
- The parameter space available to LWFA experiment is vast and its numerical exploration requires considerable resources
- The LWFA community is exploring the potential of single-objective, multi-objective, multi-fidelity optimization for data-driven experiment design that navigates this parameter space
- The potential and limits of surrogate model training on large datasets is being explored as well
- Other plasma acceleration techniques can give ideas for future application of AI trained on LWFA simulations

Particle in Cell (PIC) simulation loop for LWFA



The LWFA 3D PIC simulation problem is enormous

2D cartesian simulations: Not accurate enough



X. Davoine et al., Phys. Plasmas 15, 113102 (2008)

Example of 3D simulation scale with "classic" electromagnetic PIC loop and "classic" numerical schemes

- Laser wavelength λ_0=0.8 µm -> 0.016 µm , Δx=0.016 µm, cΔt=0.99Δx
- Laser duration: 30 fs -> Window size Lx = 40 µm = 2500 * Δx
- w_0=12 µm -> Δy=Δz=0.5µm , Window size Ly = Lz = 125 µm = 192 * Δy
- Acceleration length = 1 mm ~ 60000 c* Δt
- 8 macro-particles per cell -> ~2500*250*250*8 =

10^9 macro-particles, pushed for 60k timesteps!

Exemple of full 3D simulation:
1 Mh-cpu/cmon Jean-Zay Cascadelake 2019
(ask Arnaud Beck!)