Optimizing Laser-Plasma Accelerators through Machine Learning

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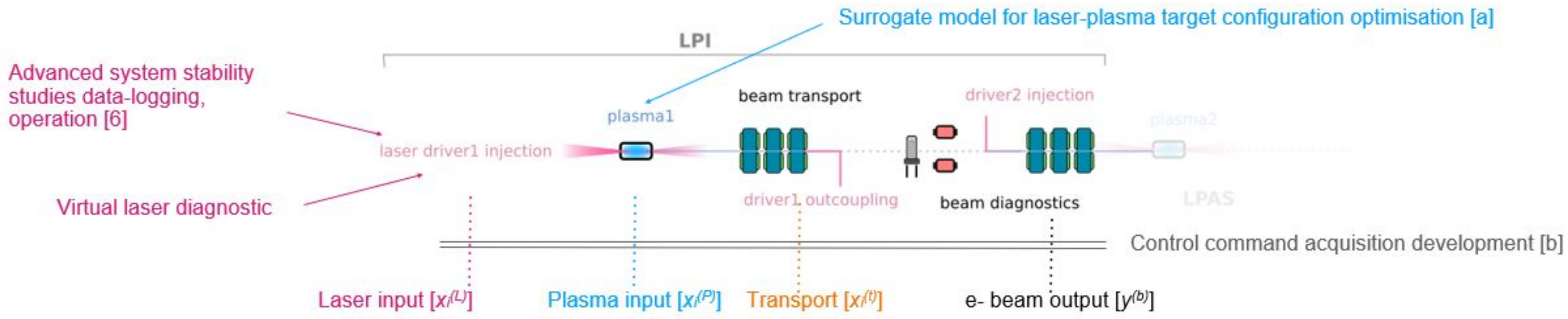
M. Fuchs - KIT

PALLAS project

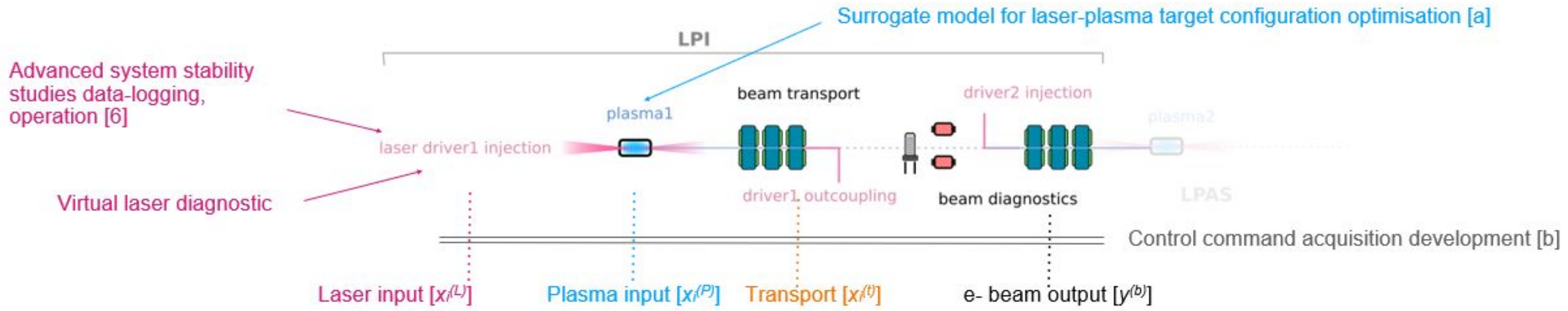
Test facility for laser-plasma injector optimisation towards RF control reliability



In the context of advanced accelerator high quality beam laser plasma injector (LPI) for EuPRAXIA [1] preparatory technical design phase and future high gradient accelerator R&D at IJClab [2]: 10 Hz **200MeV** LPI test facility to improve quality and stability of e- beam generated by laser-plasma accelerator.

[1] Assmann, R. W. et al. EuPRAXIA Conceptual Design Report. Eur. Phys. J. Spec. Top. 229, 3675–4284 (2020).
[2] pallas.ijclab.in2p3.fr

PALLAS project



Research and development lines :

- advanced laser control
- development of plasma targetry => plasma cell
- electron beam control and transport

For these we need modern data and control system.

To achieve it we do sophisticated modeling of target, PIC, and electron beam transport.

Context for French - German plasma acceleration:

Several common interest in laser-plasma accelerator development between German and French IN2P3 groups:

- IJClab DESY/KIT: **laser-plasma injector development**
  - KIT: 50 MeV laser-plasma injector @10 Hz for cSTART[1]
  - PETRA-IV: laser-plasma injector prototype [2]
- DESY - lasy library, LASY also advance laser control

In 2024 CNRS International PhD grant application (MITI2024) between IJClab and KIT (Pr. M. Fuchs) with the support of the DMlab : "*Optimising laser-plasma accelerators through Machine Learning*" … granted ✅

… and here i'm starting my PhD 🚀

[1] : N. Ray et al. Laser-plasma injector for an electron storage ring, IPAC24 (2024) DOI:10.18429/JACoW-IPAC2024-MOPR44
[2]: S. Antipov et al., Design of a prototype laser-plasma injector for an electron synchrotron, PRAB, 24, 11 (2024)

Laser-plasma acceleration

- Electron acceleration using plasma Wakefield
- 1000 times higher acceleration field than in conventional accelerators

- Laser-plasma acceleration consists of many nonlinear processes

- Main challenges:
  - Shot-to-shot stability
  - Beam quality at all aspects at the same time

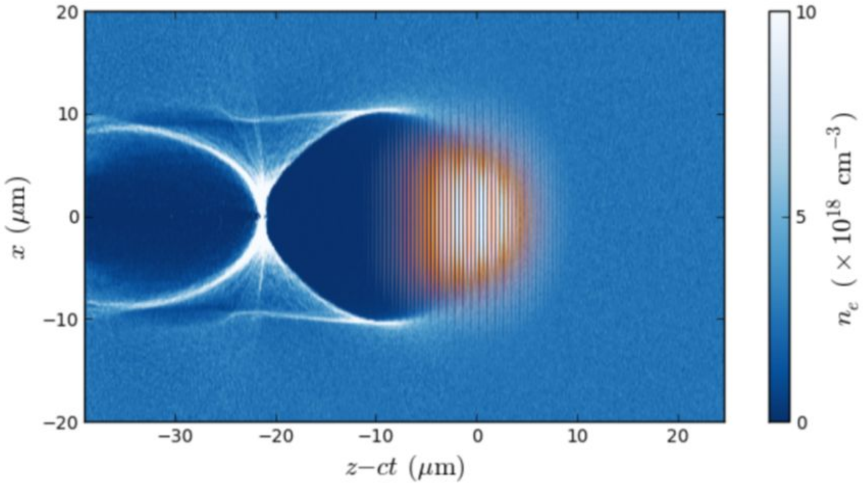
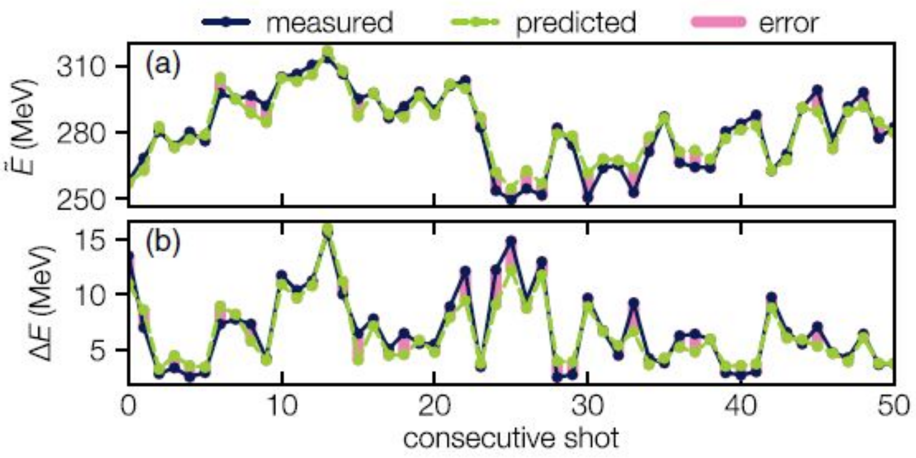
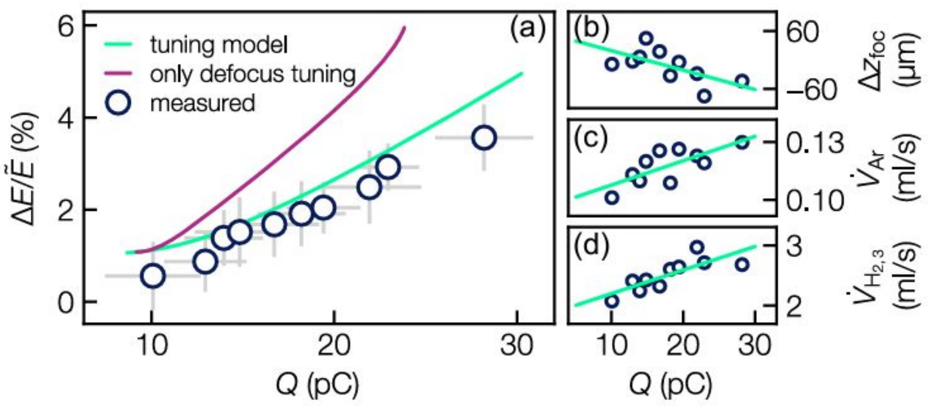


Image taken from R. Lehe PhD Thesis
https://pastel.hal.science/tel-01088398v1

ML optimization in Laser-plasma





Neural Network Model prediction of beam quality

Prediction accuracy is around 80%

M. Kirchen et al. 2021

https://doi.org/10.1103/PhysRevLett.126.174801

Beam charge tuning curve at 250 MeV

S. Jalas et al. 2023

https://doi.org/10.1103/PhysRevAccelBeams.26.071302

ML optimization in Laser-plasma

PALLAS

PHYSICAL REVIEW ACCELERATORS AND BEAMS **26,** 084601 (2023)

Bayesian optimization of laser-plasma accelerators assisted by reduced physical models

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REVIEW

Data-driven science and machine learning methods in laser–plasma physics

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(Received 30 November 2022; revised 30 March 2023; accepted 24 May 2023)

Usage of Bayesian optimization to decrease computing time

Detailed review on ML methods in laser-plasma physics

A. Ferran Pousa et al. 2023

https://doi.org/10.1103/PhysRevAccelBeams.26.084601

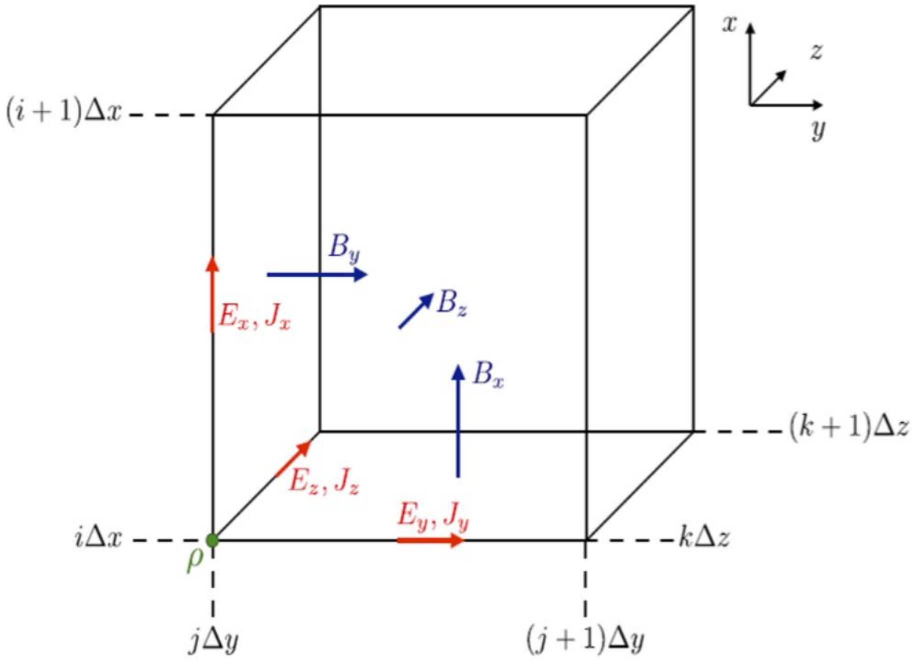
A. Döpp. et al. 2022

http://dx.doi.org/10.1017/hpl.2023.47

Particle-in-Cell(PIC) simulations

- Maxwell-Vlasov set of equations are calculated during laser propagation
- In PALLAS PIC simulations are performed with **Smilei** code

Simplified low-fidelity simulation takes 30 minutes on 240 cores. High-fidelity simulation can take a week.



J. Derouillat et al. Comput. Phys. Commun. 222, 351-373 (2018)

PALLAS simulation parameters

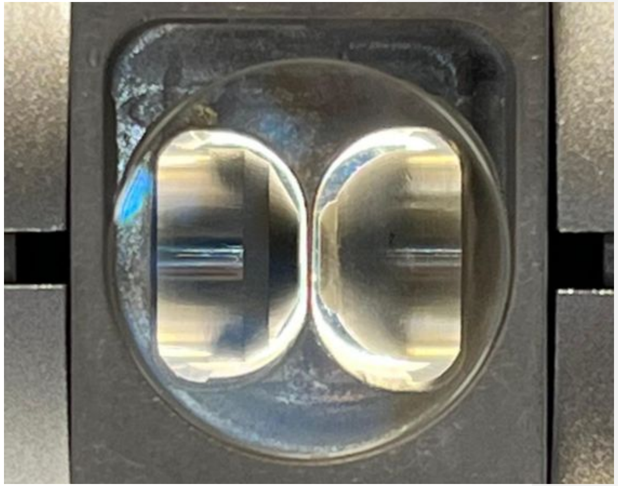
Simulation inputs:

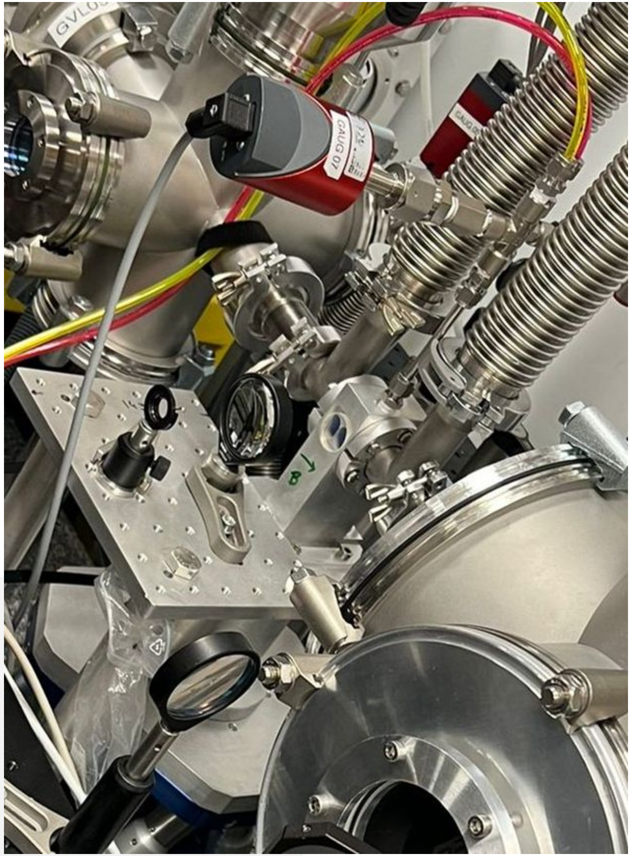
Laser focal position (x_of) [-400, 1700] µm

Normalized vector potential (a_0) - laser intensity [1.1, 1.8]

Dopant percentage (c_N2) [0.2, 11]%

Gas pressure (p_1) [11, 100] mbar





Optimisation in PALLAS

- Using PIC simulations, we generated a large dataset of approximately **12,000 simulations**
- Simulation data is used to train ML models that predict key electron bunch characteristics (e.g., energy spread, emittance)
- We employ also Bayesian Optimization (Xopt library[1]) directly with simulations to test different target profiles
- For the electron beam propagation simulations we use RF-Track[2]

PHYSICAL REVIEW ACCELERATORS AND BEAMS **26,** 091302 (2023)

Random scan optimization of a laser-plasma electron injector based on fast particle-in-cell simulations

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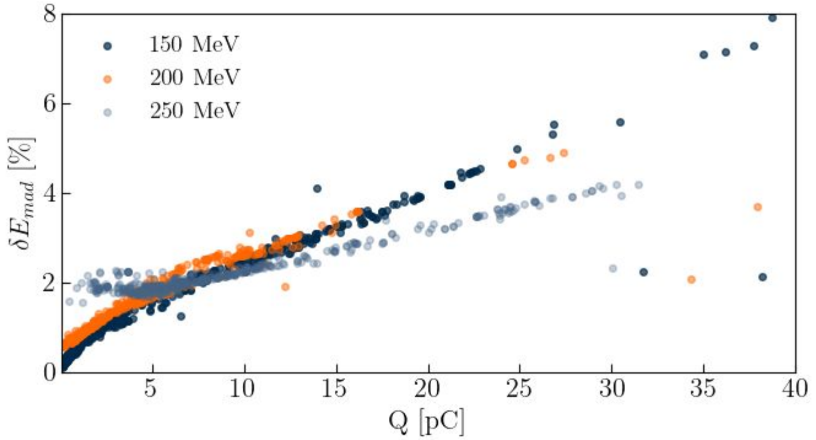
Drobniak, P. et al. Phys. Rev. Accel. Beams 26, 091302 (2023)

[1] R. Roussel et al. https://doi.org/10.18429/JACoW-IPAC2023-THPL164
[2] Andrea Latina, CERN

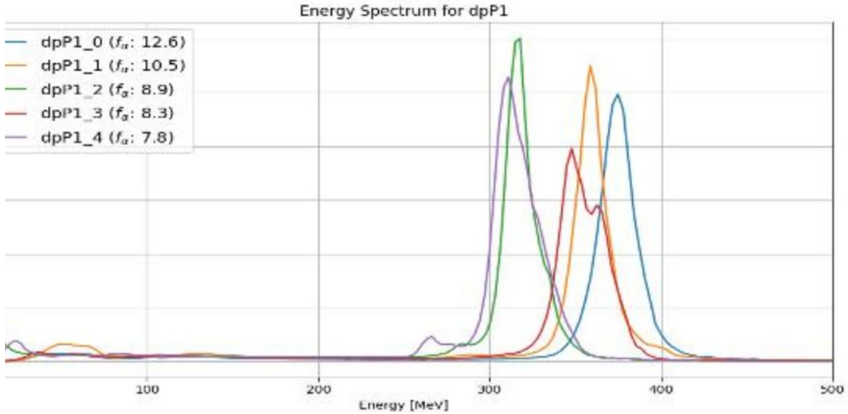
Optimisation in PALLAS



Pareto Front as the result of MOBO search for 3 different energies 150, 200 and 250 MeV within a ± 10 MeV

G. Kane, PhD student PALLAS

https://doi.org/10.48550/arXiv.2408.15845



5 Best energy spectra after single objective Bayesian optimization for optimized target profile

J. Serhal, PhD student PALLAS

Inverse problem

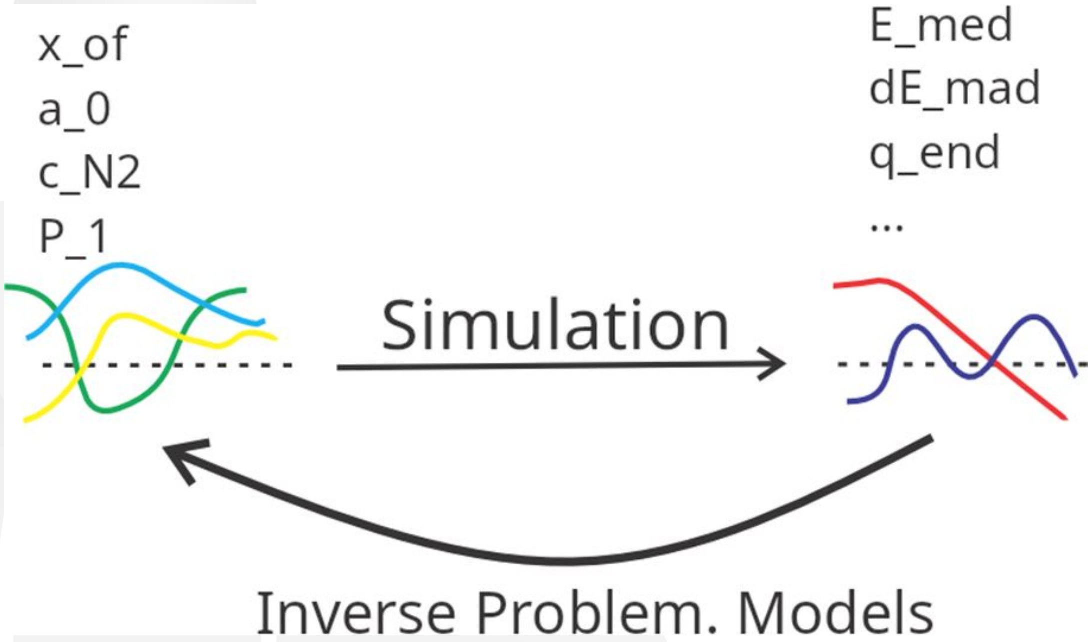
The inverse model was trained using Neural Networks

Input Parameters:

- Focal position x_of
- Bunch characteristics

Outputs:

- Simulation inputs except x_of

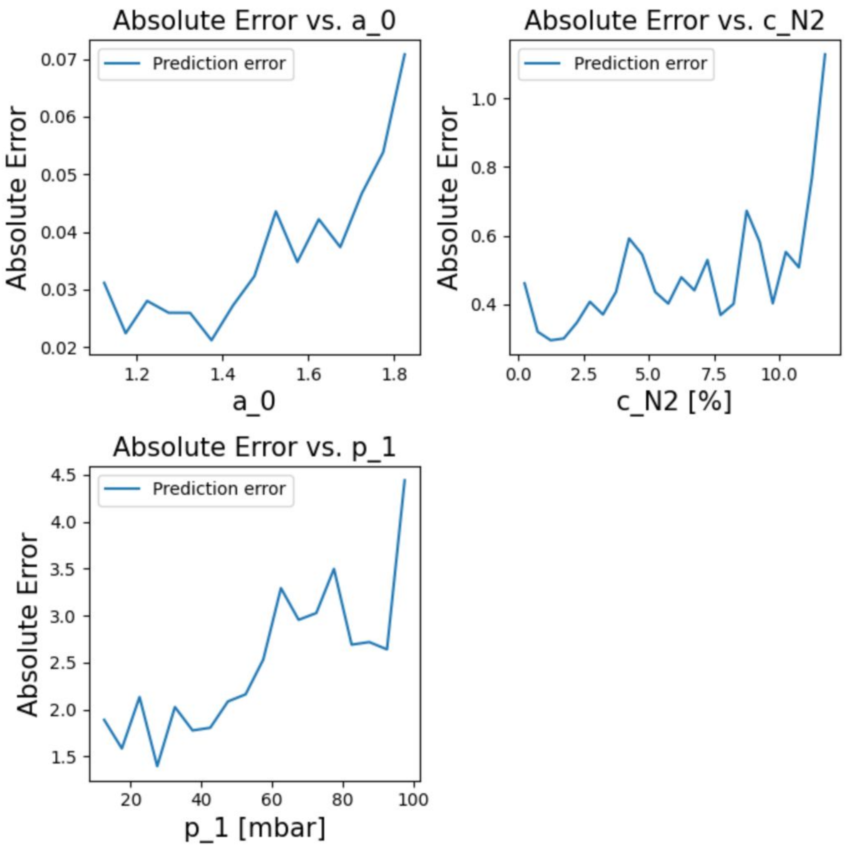


Inverse problem

- Focal position causes non-unique solutions problem

- In the case of a big amount of inputs, accuracy can reach **99%**

- With 4 inputs and focal position as scan parameter:
  - Accuracy **89.4%**
  - Validation for the bunch energy
  - Can not be validated below 10pC



PALLAS optimisation plan

The aim is to optimize laser-plasma acceleration process with these steps:

- Surrogate models improvement on the simulation data : Extend models to phase-space distribution (seed for start to end simulations)
- Surrogate model training on the experimental data
- Inverse model improvement
- On-fly experiment optimization with Bayesian optimisation
- Beam transport optimization for electron beam characterisation

Additionally we work with Geant4 colleagues on introducing our ML model as a source in Geant4 simulation.

Thank you for attention!