SURROGATE MODEL FOR LASER-PLASMA INJECTOR DEVELOPMENT

K. Cassou[1], G. Kane[1], V. Kubytskyi[1], A. Beck[2], P.Drobniak[1], F. Massimo[3]

1.Université Paris-Saclay, CNRS/IN2P3, IJCLab, 91405 Orsay, France
2.Laboratoire Leprince Ringuet, CNRS/IN2P3, 91120 Palaiseau, France
3.Université Paris-Saclay, CNRS, LPGP, 91405 Orsay, France

on behalf of the PALLAS collaboration

ABSTRACT

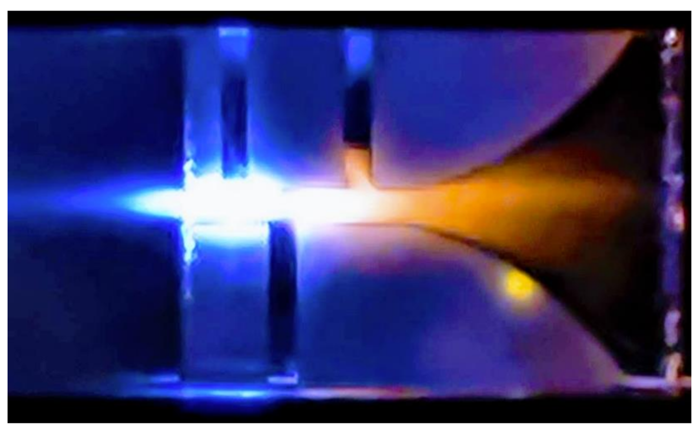
Plasma targetry design for PALLAS experiment relies on numerical PIC parametric studies, computational fluid dynamic studies and an experimental test bench equipped with plasma density profile diagnostics, density measurement and plasma species spatial distribution for target charecterisation. We discuss construction of surrogate model of PALLAS, based on 15000 simulations performed for sparsely spaced input parameters for laser-plasma injector (laser, target density profile and species distribution). Para-metric studies were performed with Smilei PIC code [1] using the azimuthal mode and envelop approximation with a low number of particles per cell [2]. Based on these simulation data we constructed ML models with K-Folds validation [3] to limit the overfitting (GP , Neuronal Network and decision trees]). The surrogate models then used to quickly probe parameter set of interest, predict the optimum and interpret relation between parameters. Goal of these studies is to assist the plasma target cell design and determined working points of the laser-plasma injector for a specified energy, charge, beam emittance and beam divergence.

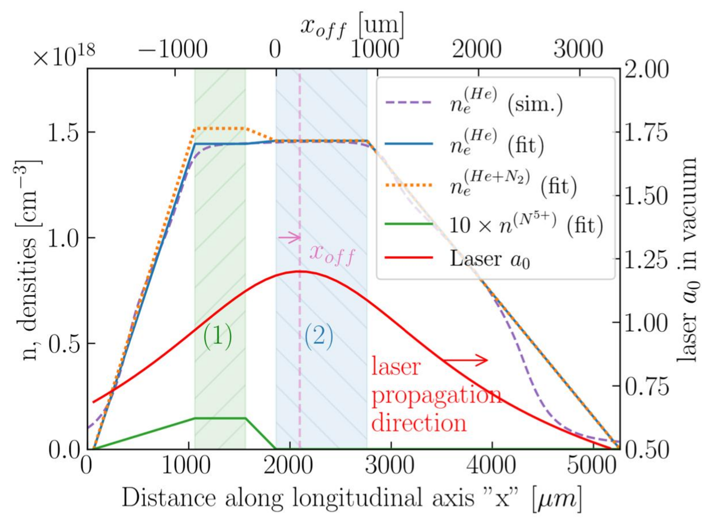
PALLAS project

Build a **laser-plasma injector** (**LPI**) prototype with **reliability** and **control** comparable to conventional **RF accelerator** standards.

- plasma cell parameters, tailored plasma density profile
- laser transport, focalization and advanced laser control
- e- beam transport, characterization

Parameters	phase 1	phase 2	phase 3	unit
energy	150	**200**	200	MeV
charge	15-30	**30**	**>30**	pC
frep	10	10	10	Hz
energy spread	<5%	**< 3%**	< 2%	rms
$\varepsilon_{n,rms}$	1	**<1**	**<1**	μm
stability	5%	**3%**	**<1%**	-
reproductibility	5%	**3%**	<3%	-





Data driven studies

Main idea: (re)use knowledge of already computed configurations (scans, BO, random search) and obtained beam parameters to construct **surrogate model of the accelerator.**

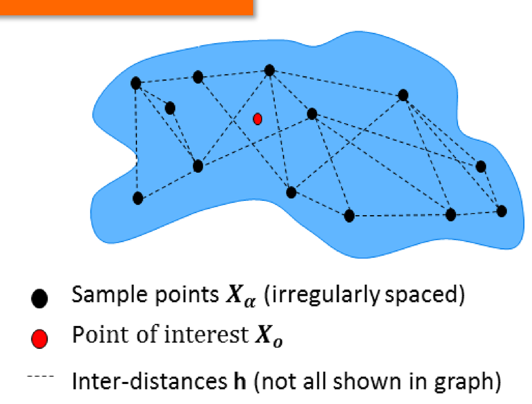
Quickly probe different configurations, perform fast **optimization** in global parameters space, estimate uncertainty. Better understand our data, relations between features.

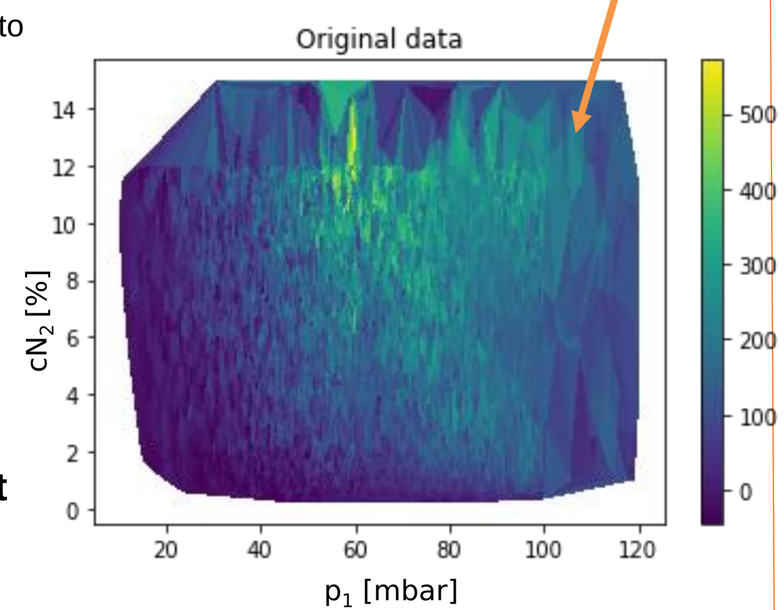
New configuration can be estimated from the surrogate model and validated with SMILEI. New refined data is then inserted in the dataset to continuously improve surrogate model.

- Inputs of our parameter space: X_{of}, a_0, C_{N2}, p_1
- Outputs: E_{med} , E_{mad} , Q , ε_y.
  Can contain more beam parameters, objective functions, etc.

E_{med} , E_{mad} , Q , $\varepsilon_y = \boldsymbol{F}(X_{of}, a_0, C_{N2}, p_1)$ **Possible**

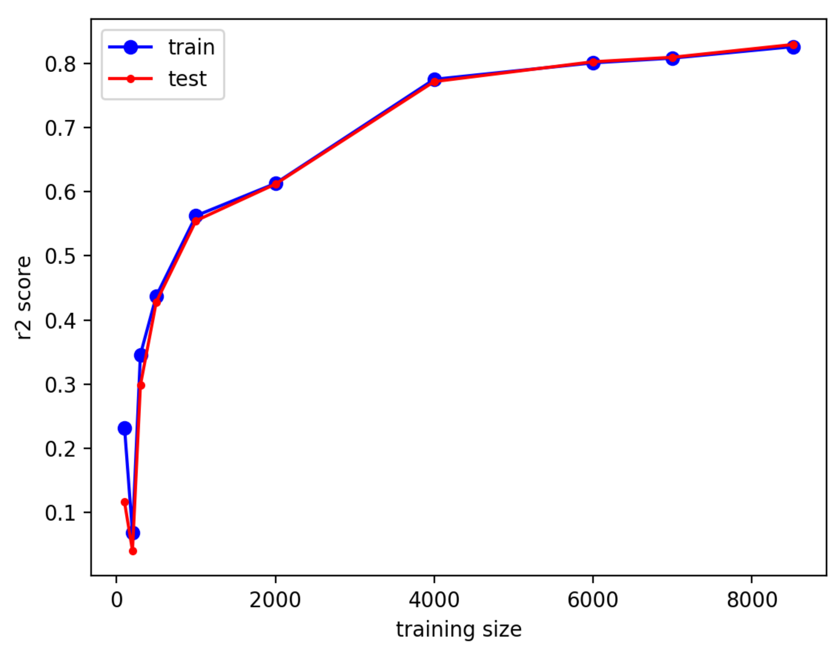
$X_{of}, a_0, C_{N2}, p_1 = \boldsymbol{F}^{-1}(E_{med}, E_{mad}, Q, \varepsilon_y.)$ **Difficult**

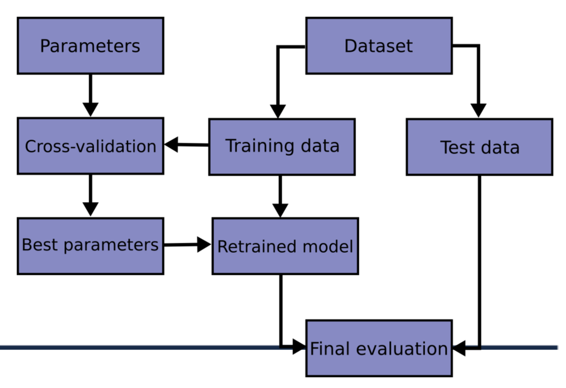




Methodology

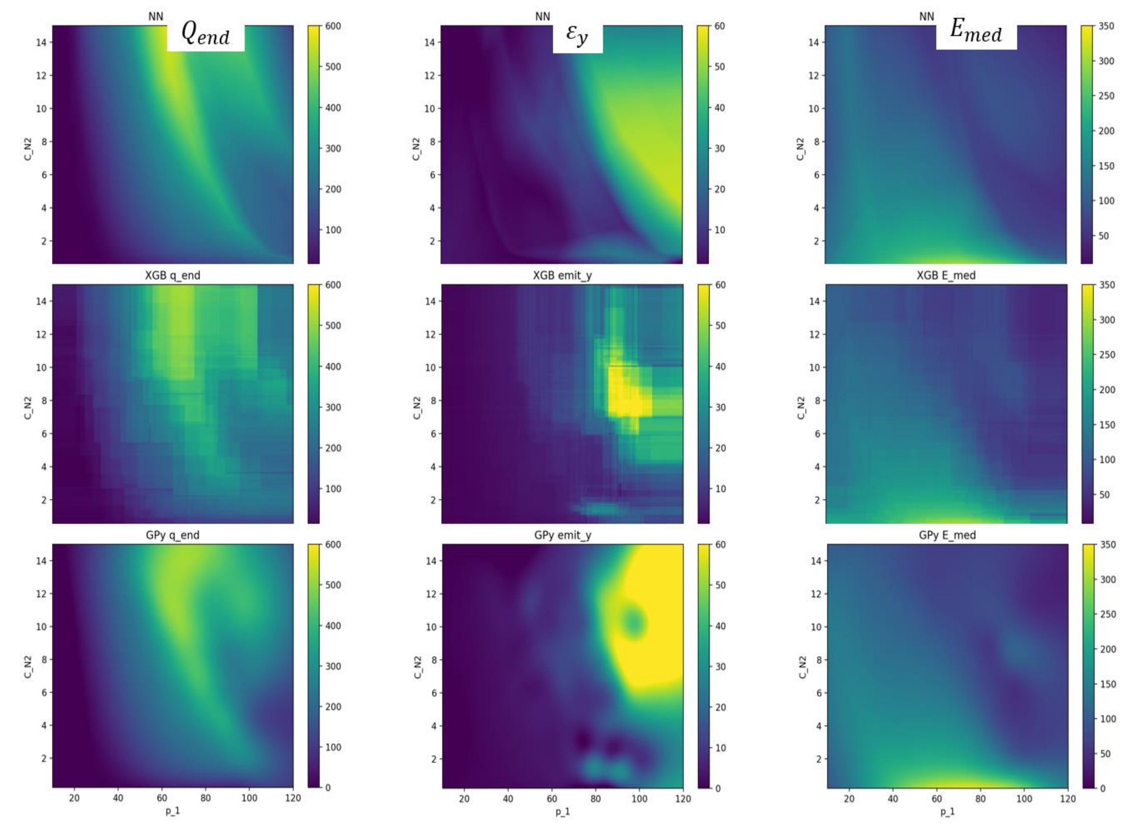
- Neural Network,Gaussian Process,Gradient boosted decision tree
- We ran **15000** thousands **simulations** in different configurations corresponding to the conditions of **PALLAS** LPI
- From those simulations we generated surrogate models with the methods cited above with **K-folds** cross validation
- We then looked for the minimum of an objective function to get the optimal working point of the LPI
- To test the robustness of the **surrogate model** we ran others simulations around the optimum of the objective function



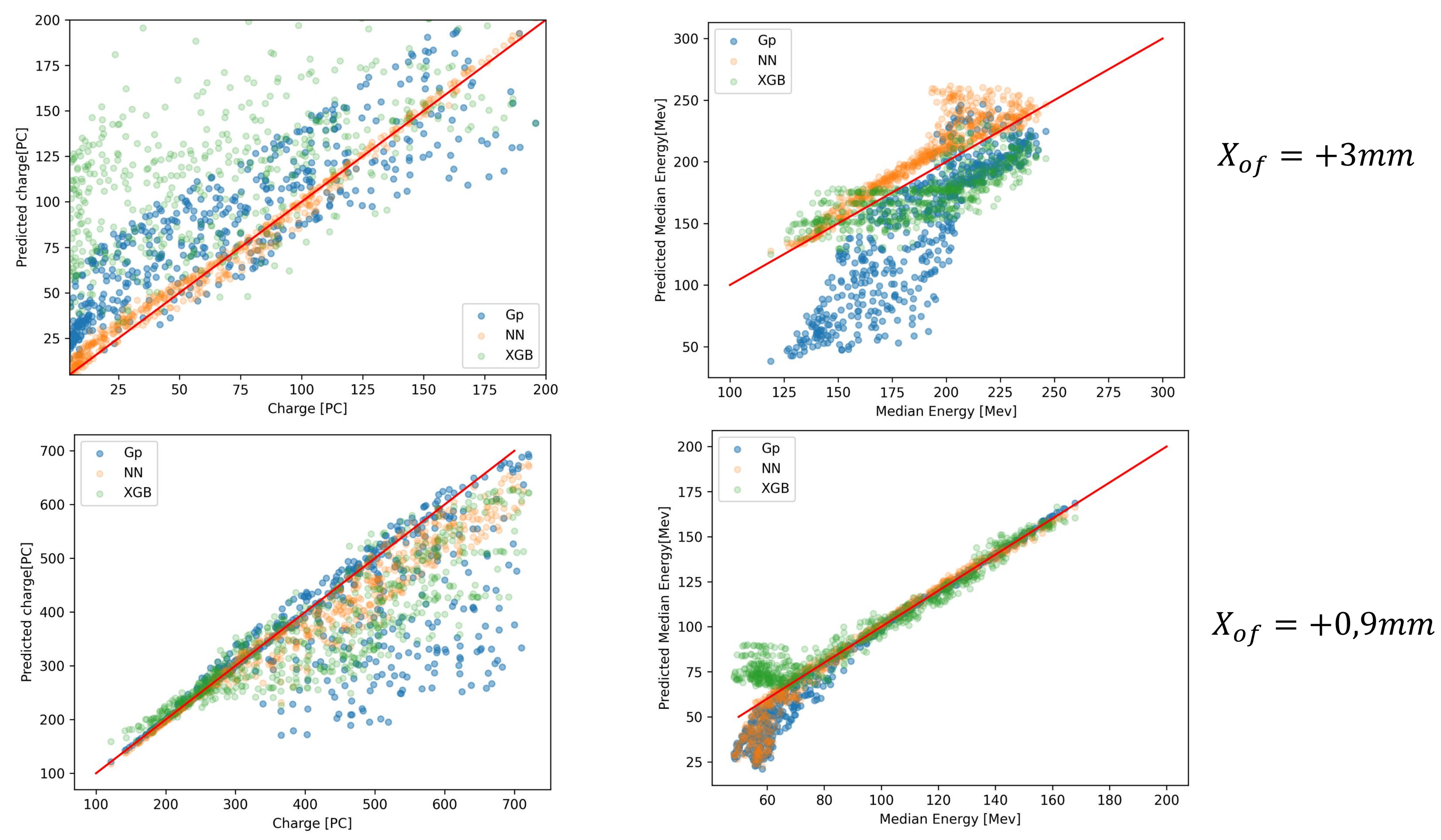


Predicted beam parameters

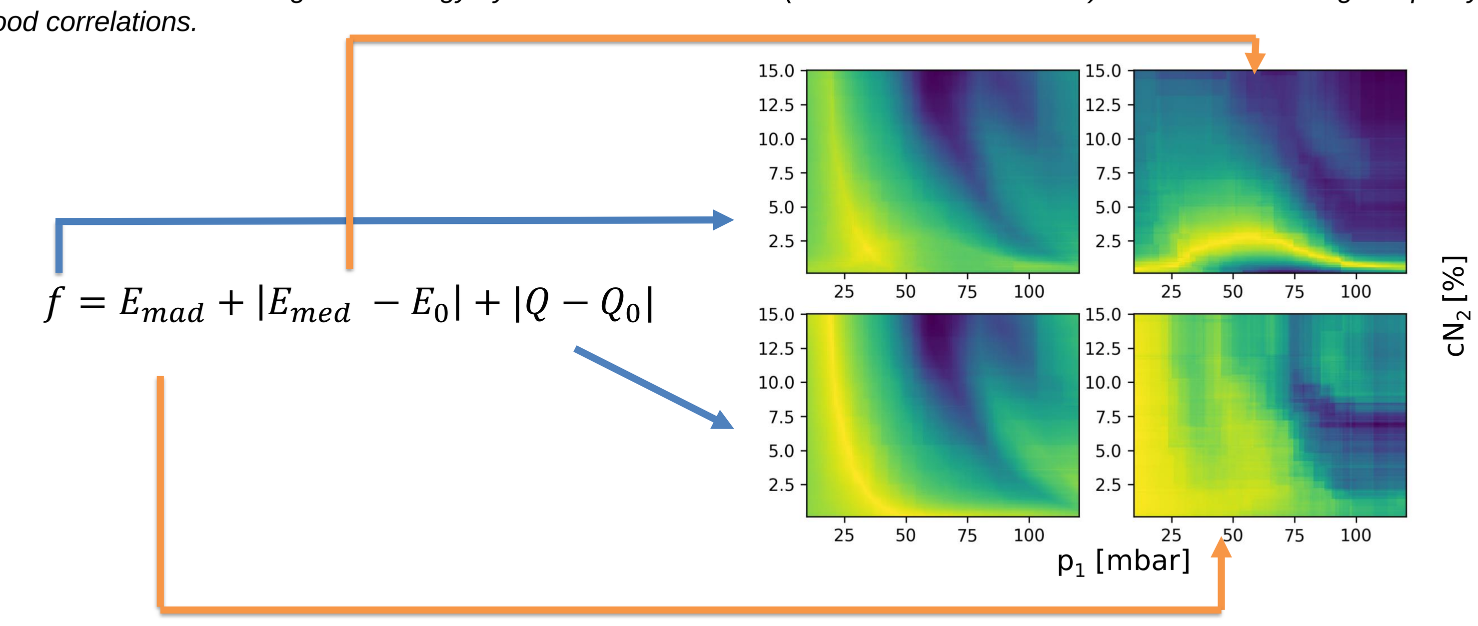
Prediction maps of trained ML models:



Comparaison of ML methods for differents oputputs features



New data: Predicted charge and energy by differents ML models (trained on initial dataset). Neural Networks gives pretty good correlations.



We minimize objective function **f** to find the input parameters that gave the optimal working point of the LPI.

SUMMARY

- Performed in-depth study with ML in context of PALLAS, better understood our data, parameters. 10 000 samples to get a converging surrogate model. All techniques have shown good performances
- Possible to use conventional optimization methods on the surrogate model.
- Allow us to get a global view of possible PALLAS beam parameters
- A similar approach will be used in our experimental studies, and will facilitate the search of the optimal working point.
- We demonstrate the ability of NN to generalize better in zones with very few training data

[1] P. Drobniak et al., arxiv 2305.09264(2023)
[2] SMILEI: smileipic.github.io/Smilei/
[3] Géron, Aurélien. Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow. " O'Reilly Media,inc.", 2022.
[4]A Dopp et al., Data-driven Science and Machine Learning Methods in Laser-Plasma Physics https://arxiv.org/pdf/2212.00026.pdf

IJCLab - Laboratoire de Physique des 2 Infinis **Irène Joliot-Curie**
Bâtiment 100 - 15 rue Georges Clémenceau - 91405 Orsay cedex - France
UMR 9012, CNRS, Université Paris-Saclay, Université Paris Cité

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