Machine Learning-based Data Analysis and Surrogate Modeling For COXINEL Experiment

A. Willmann[1], A. Ghaith[1], Y. Chang[1], A. Debus[1], M. LaBerge[1], M. Labat[4], P. Ufer[1,2], S. Schoebel[1,2], N. Hoffmann[1], M. Bussmann[1,3], M.-E. Couprie[4], U. Schramm[1,2], and A. Irman[1]

[1] Helmholtz-Zentrum Dresden-Rossendorf, Germany, [2] Technische Universität Dresden, Germany,
[3] Center for Advanced Systems Understanding, Görlitz, Germany, [4] Synchrotron SOLEIL, Saint-Aubin, France

EUROPEAN NETWORK FOR NOVEL ACCELERATORS EuroNNAc4 NPACT supported by EU via I-FAST

iFAST

HZDR HELMHOLTZ ZENTRUM DRESDEN ROSSENDORF

SOLEIL SYNCHROTRON

CASUS CENTER FOR ADVANCED SYSTEMS UNDERSTANDING

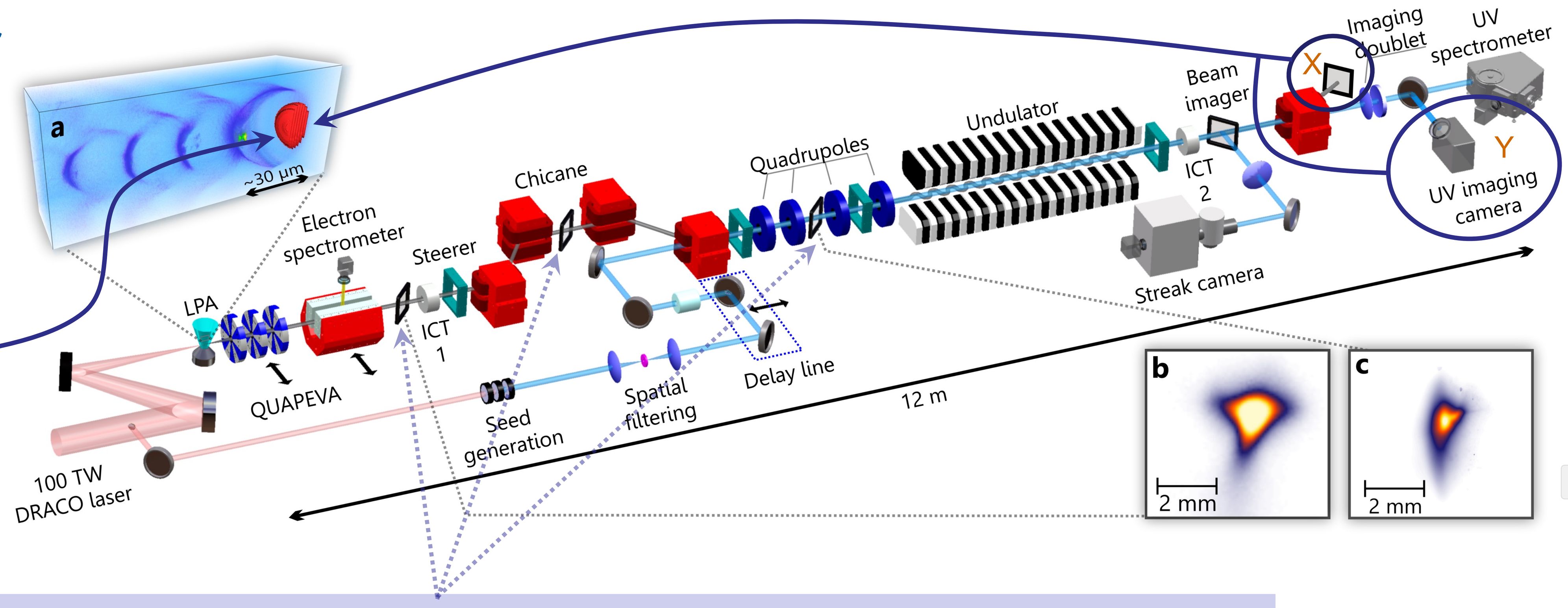
TECHNISCHE UNIVERSITÄT DRESDEN

Control and Optimization of a laser-driven Free Electron Laser

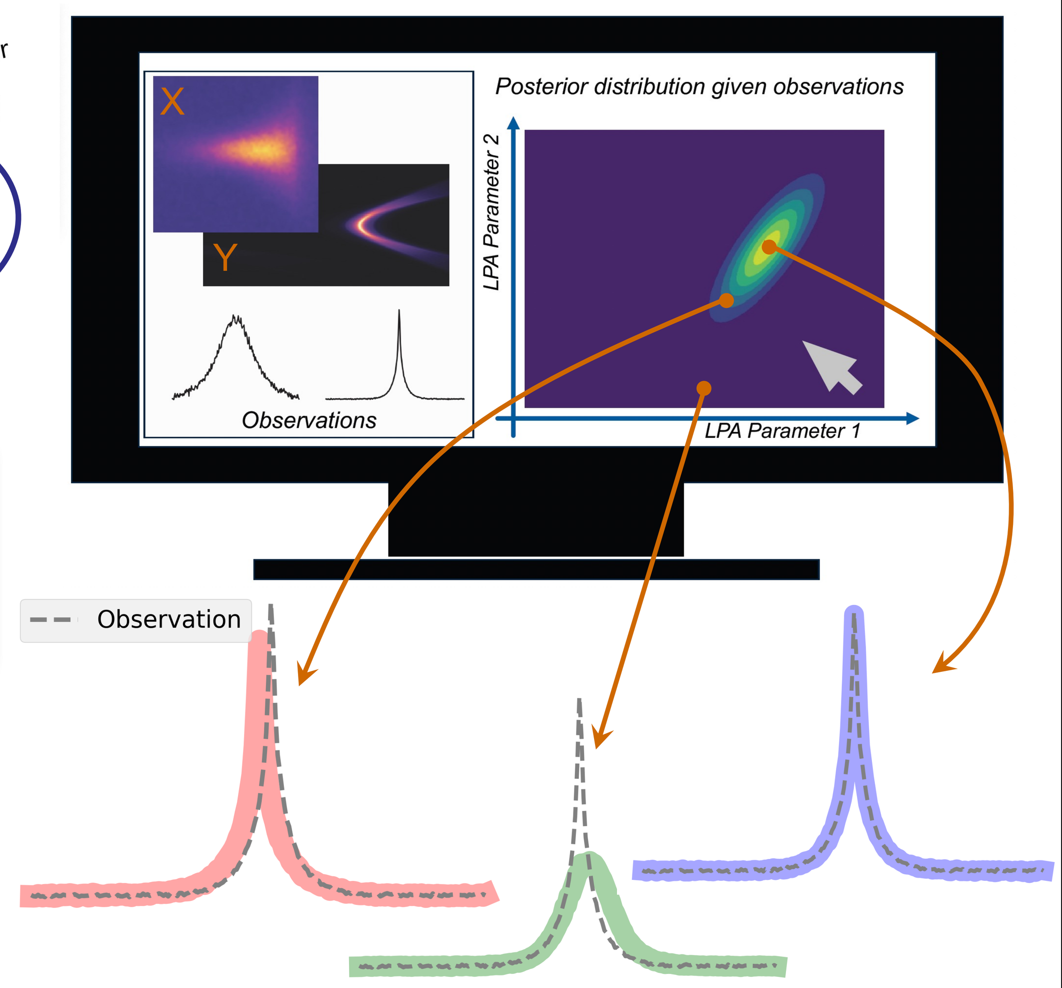
COXINEL[1]:
COherent **X**-ray source **IN**ferred from **E**lectrons accelerated **L**aser

Automatic inversion of experimental measurements from the last imager and UV imaging camera to beam parameters at the source

LPA parameters:
- Energy spread
- Divergence
- Size



The ill-posed inverse problem has no unique solution and is resolved up to a posterior distribution (probability of LPA parameters given observations).



Virtual diagnostics provide data from all imagers in a digital form with access to the phase space of the beam in the beamline

1. Labat, M. et al. (2023). Seeded free-electron laser driven by a compact laser plasma accelerator. Nat. Photon. 17, 150–156.

Method: Simulation-based Inference

Sample LPA parameters and pass them into the simulator

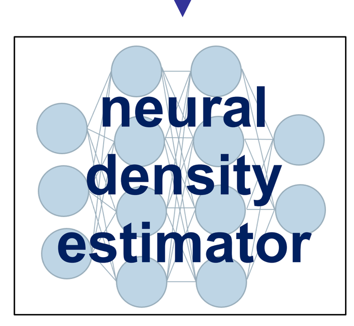
1

Prior distribiution of LPA parameters: **uniform** if no assumptions are given

Simulator
Beam propagation: `APS elegant`[3]
Undulator radiation: `SRW`[4]

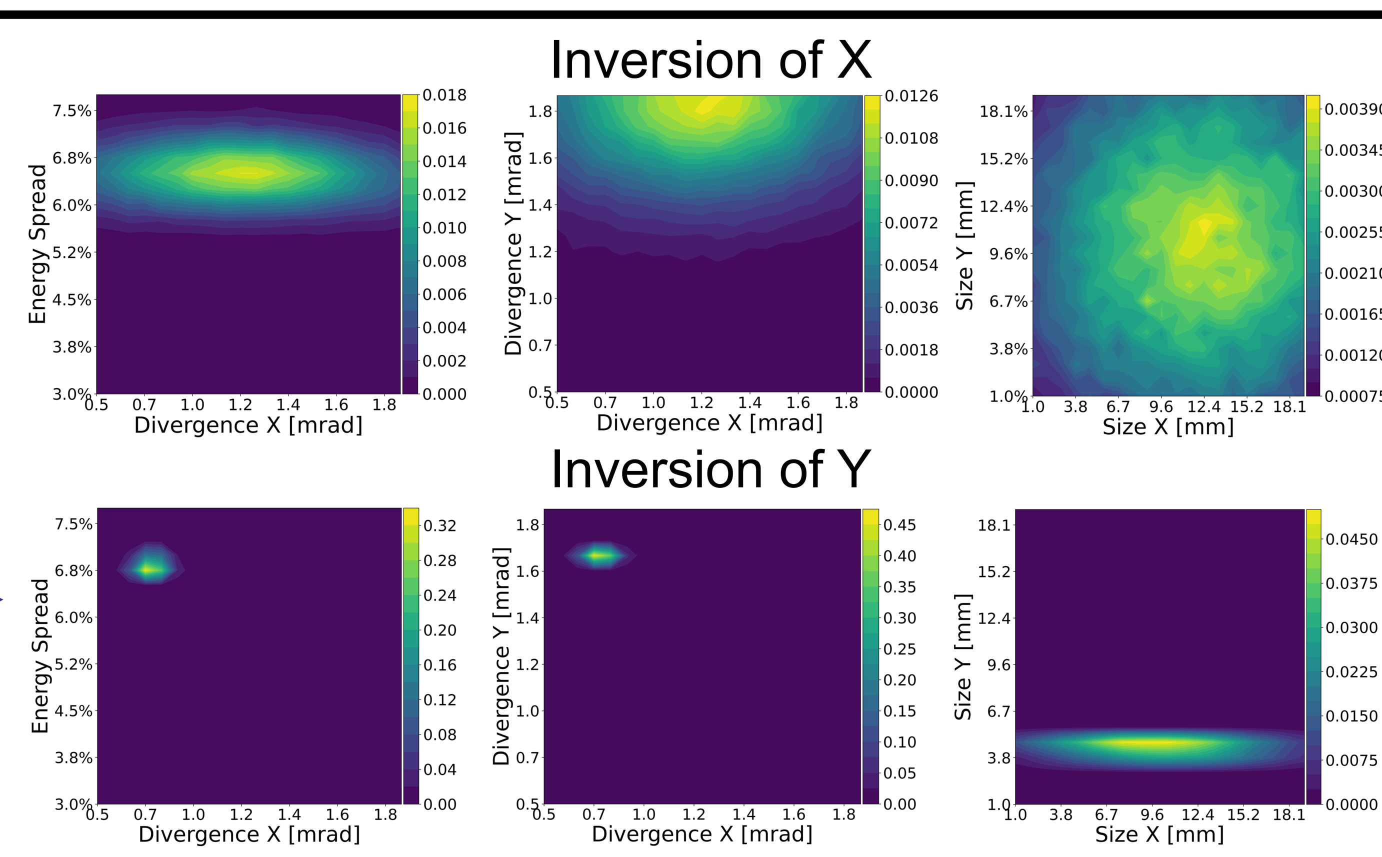
2

Observation X or Y



3

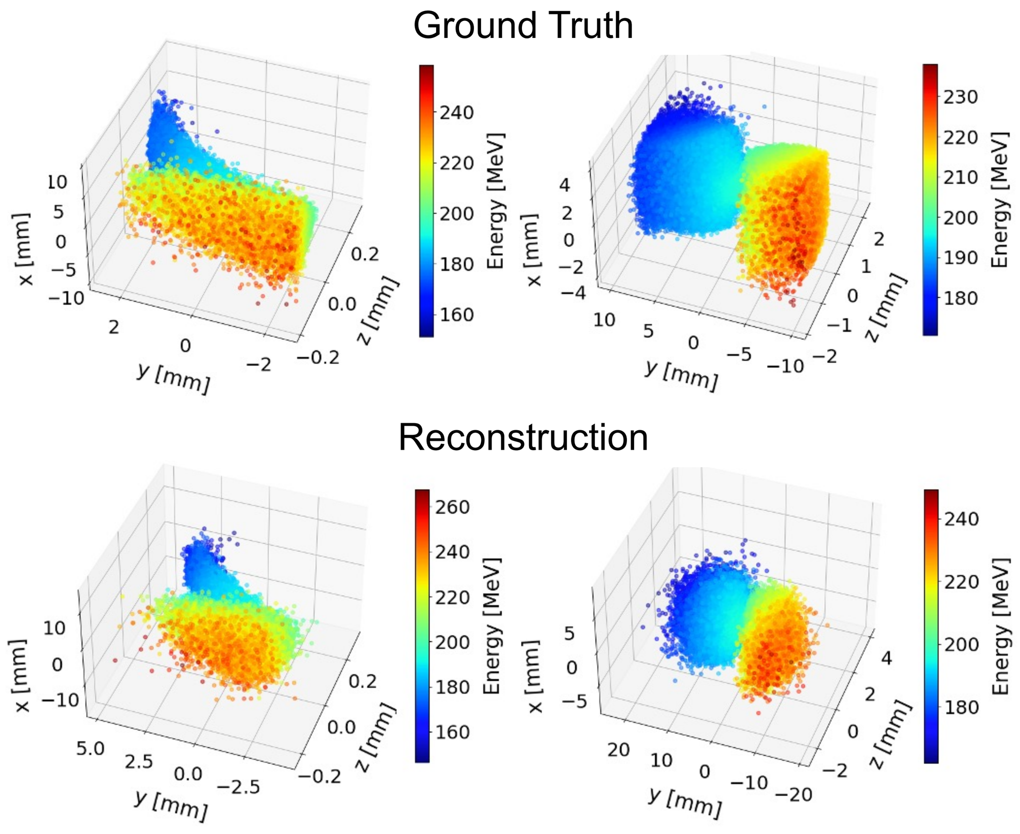
Compute simulations of a corresponding measurement (X or Y) for sampled parameters



Surrogate models replace the numerical code to decrease computational costs and sample simulations fast.

Surrogate model of the beam transport[3]

Stated problem: reconstruct expected distributions of electrons at imagers in the beamline for the given LPA parameters (*c*: number of an imager and LPA parameters).

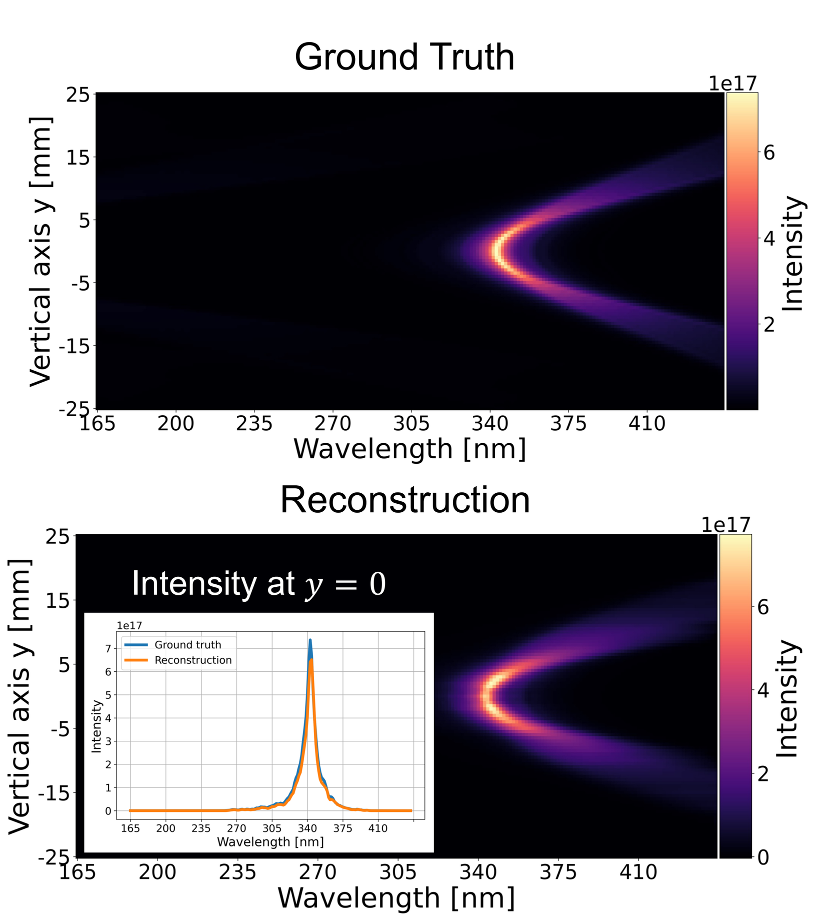


Data: each electron in a bunch is given by 6 coordinates in phase space. Training/Validation data was simulated by `APS elegant`[3] for varying LPA parameters.

Acceleration of computations: 10x faster than simulation.

Surrogate model of undulator radiation

Stated Problem:
Reconstruct undulator radiation by a given electron bunch at the entrance of the undulator.



Data: spatio-spectral distribution of undulator radiation simulated by `SRW code`[4].

Acceleration of computations: 390x faster than simulation.

2. Tejero-Cantero, A. et al. (2020). sbi: A toolkit for simulation-based inference. Journal of Open Source Software, 5(52), 2505.
3. Borland, M. (2000). A flexible sdds-compliant code for accelerator simulation. ANL, Argonne, IL, 60439.
4. Chubar, O., and Elleaume, P. (2013). Synchrotron Radiation Workshop (SRW). No. SRW; 002835MLTPL00. Brookhaven National Lab.(BNL), Upton, NY (United States).
5. Willmann, A. et al. (2023). Learning Electron Bunch Distribution along a FEL Beamline by Normalising Flows. arXiv preprint arXiv:2303.00657 (2023).

Summary

- Virtual diagnostics in experiments help to exploit correlations among all experimental data
- Decrease of performance detection and its characterizations available in the beamline
- Identification of well-behaved operating states
- Surrogate models are decreasing requirements to hardware and time consumption of data analysis

ACKNOWLEDGEMENT This poster presentation has received support from the European Union's Horizon 2020 Research and Innovation programme under Grant Agreement No 101004730.

Anna Willmann | Institute of Radiation Physics | Laser Particle Acceleration | HelmholtzAI | a.willmann@hzdr.de | www.hzdr.de