Karlsruhe Institute of Technology

Highlights & news from KIT

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ACCLAIM Meeting 03/02/2023

NEWS FROM KIT

New members

Stephan Robert Kötter
Postdoc

Orbit correction

Photoinjector laser manipulation with ML

NEWS FROM KIT

Publications

- "Bayesian Optimization of the Beam Injection Process into a Storage Ring", **C. Xu** et al., e-Print: 2211.09504 [physics.acc-ph] (submitted to PRAB)
- "Surrogate Modelling of the FLUTE Low-Energy Section", **C. Xu** et al., IPAC'22 TUPOPT070
- "Optimization Studies of Simulated THz Radiation at FLUTE", **C. Xu** et al., IPAC'22 WEPOMS023
- "KINGFISHER: a framework for fast machine learning inference for autonomous accelerator systems**", L. Scomparin** et al., IBIC'22 MOP42

NEWS FROM KIT

Outreach & collaboration

Machine Learning workshop of the MT ARD ST3 annual meeting: https://github.com/ansantam/2022-MT-ARD-ST3-ML-workshop

Keynote: reinforcement learning in the research field of accelerators, Conceptual Advances in Deep Learning for Research on Universe and Matter, A. Santamaria Garcia, September 2022, https://indico.scc.kit.edu/event/2853/contributions/11041/

Machine learning for tuning, prediction, and control at the KIT electron accelerators, 3rd ICFA Beam Dynamics Mini-Workshop on Machine Learning Applications for Particle Accelerators, A. Santamaria Garcia, November 2022, https://indico.bnl.gov/event/16158/contributions/69582/

1st collaboration workshop on Reinforcement Learning for Autonomous Accelerators (RL4AA'23)

20-21 February 2023
Institute of Beam Physics and Technology (KIT)
Europe/Berlin timezone

Karlsruhe Institute of Technology

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Reinforcement learning (RL) is a powerful learning paradigm of machine learning (ML). It is particularly suited to tackle control problems in large environments, can learn from experience without the need of a model of the dynamics, and can deal with delayed consequences.

Capturing your control problem as a meaningful Markov Decision Process (MDP) is not trivial. Additional challenges arise in the training in terms of stability and evaluation. Other practical aspects include reproducibility, efficiency, implementation, deployment in hardware, or choosing the most suitable algorithm for your problem.

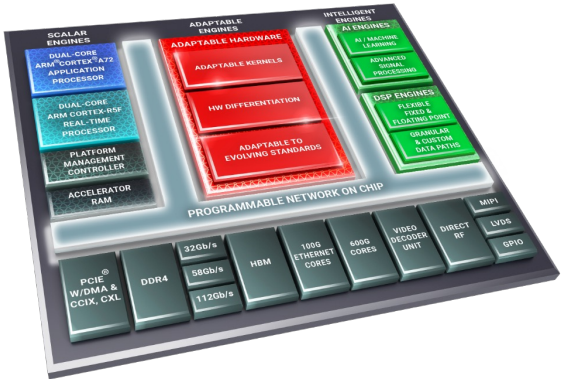
RL applications in particle accelerators are very promising, but have been deployed in real machines only a handful of times. This workshop aims at lowering the barrier in applying RL and making it a more widely used tool.

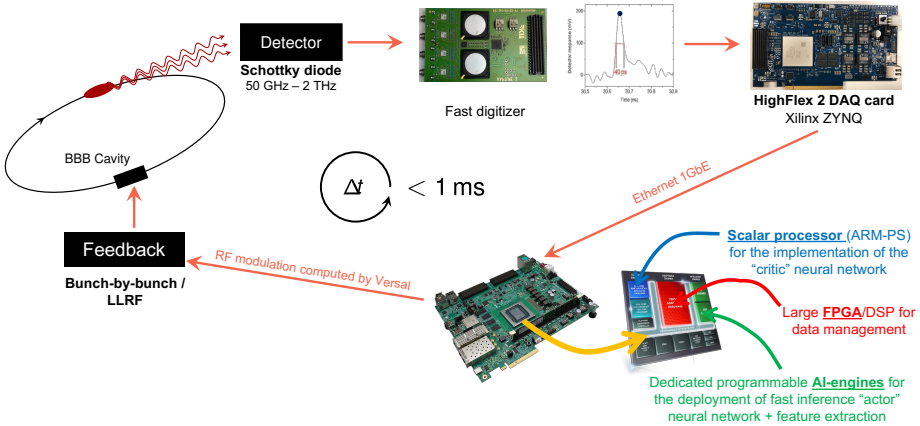
We will take time for valuable discussions on the topic of RL applied to particle accelerators and to improve our common knowledge. We will also exchange ideas about promising future avenues and help consolidate a community to advance in this area of research in accelerator controls.

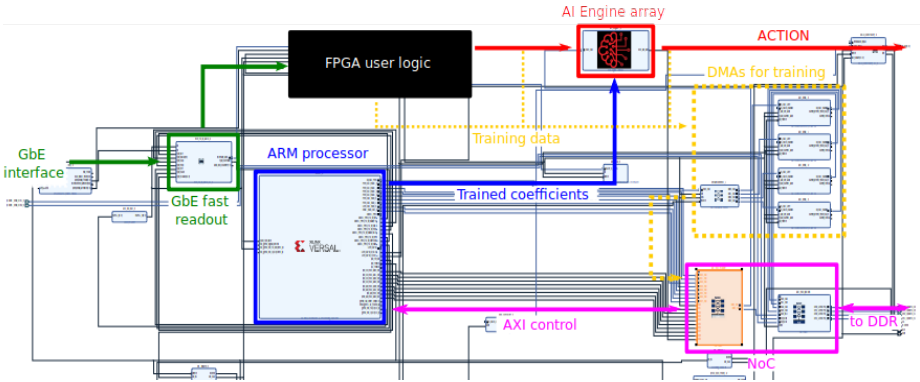
https://indico.scc.kit.edu/event/3280/

RL @KARA

- Ongoing development of RL feedback system based on Xilinx Versal platform
- Target of low loop latency (tens of µs) and long distance between detector and action necessary, plus integration with KAPTURE and KALYPSO







Courtesy of M. Caselle & L. Scomparin

Trying Bayesian optimization at the European XFEL

Cheran Xu, Sergey Tomin, Andrea Santamaria Garcia

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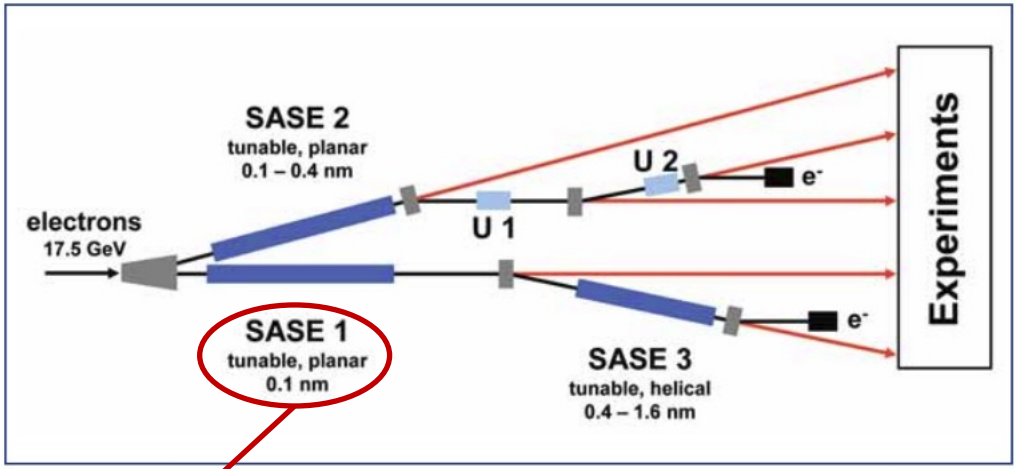
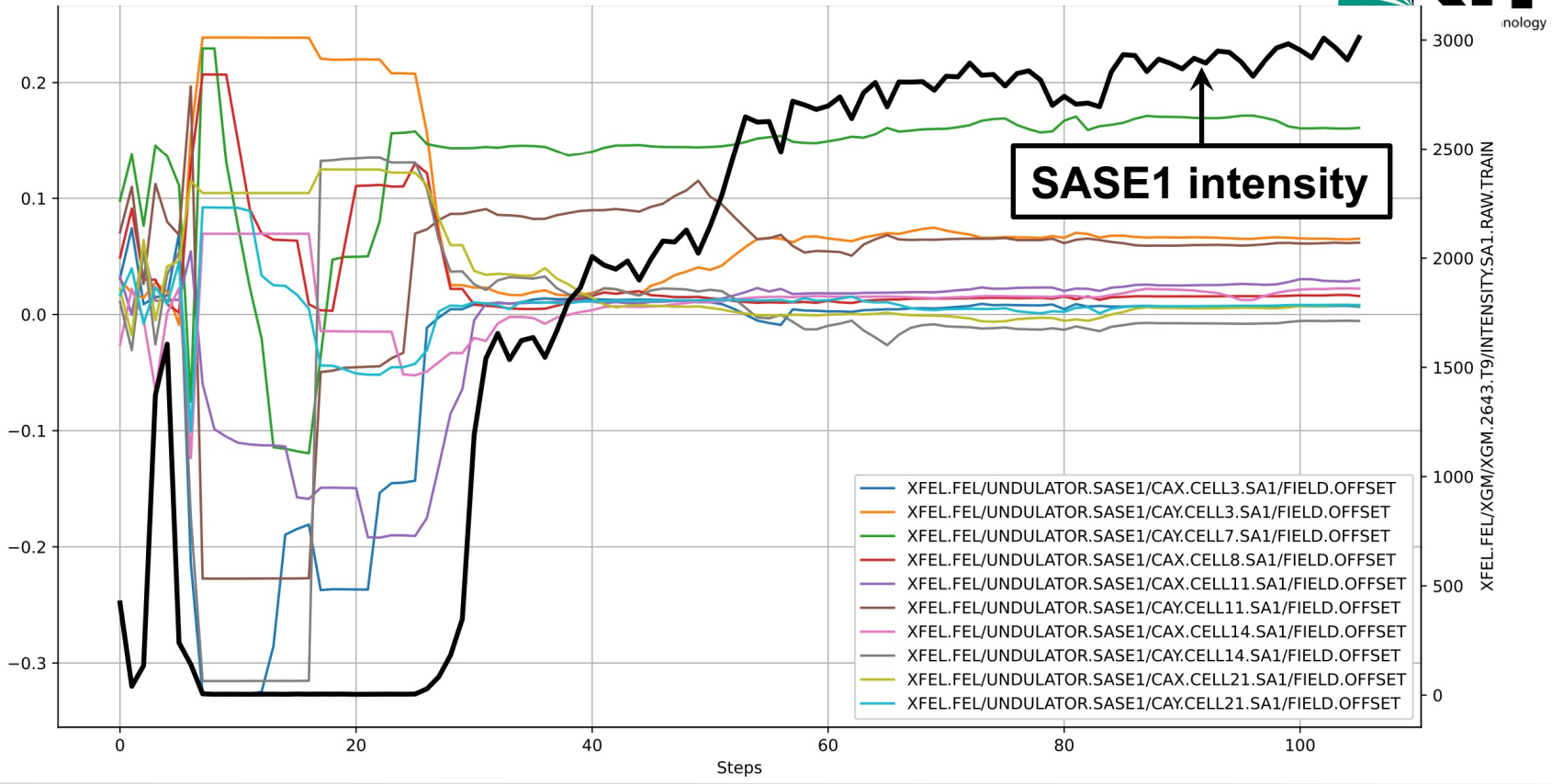


- **Goal**: increase the photon intensity at SASE1 by tuning air coils
- **Air coils**: provide small beam trajectory corrections (max. steering power +/- 0.6 T.mm)
- **SASE1**: 35 undulators of 5m length and 1m separation. Two air coils (H,V) upstream and downstream of each undulator

Bayesian optimization of SASE signal with 10 air coils



1 step = 30 shots at 10 Hz = 3 s

THZ PULSE OPTIMIZATION AT FLUTE

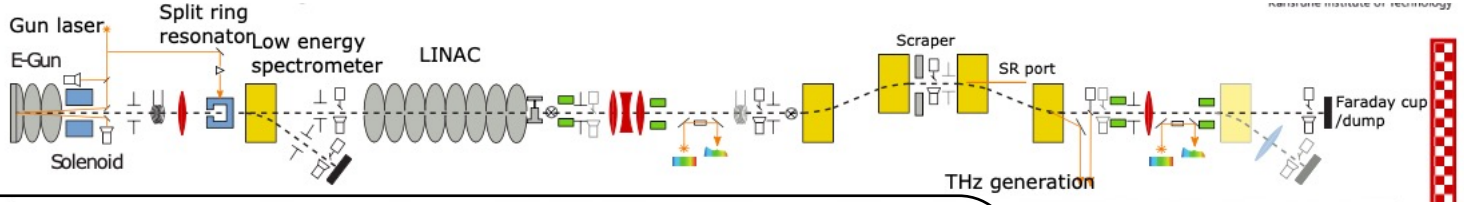
Surrogate model

input
1. RF gun phase
2. RF gun amplitude
3. Solenoid current
4. Bunch charge

output
1. Mean energy
2. Energy spread
3. RMS bunch length
4. Beam size
5. Emittance
6. % remaining part.

C. Xu et al. TUPOPT070, IPAC22

Can inform/guide the optimization with smart initial guesses



Parallel Bayesian optimization

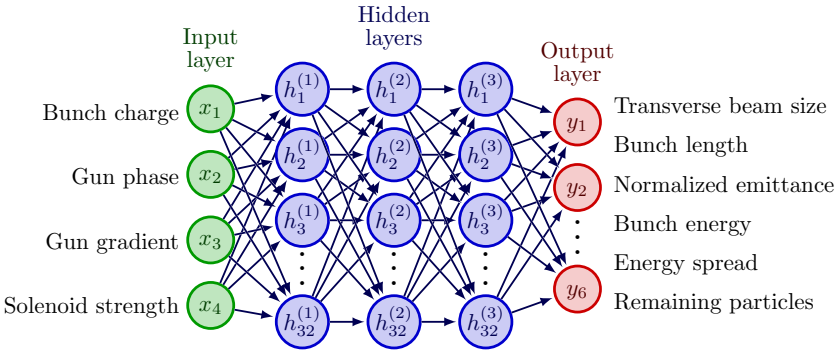
C. Xu et al. WEPOMS023, IPAC22

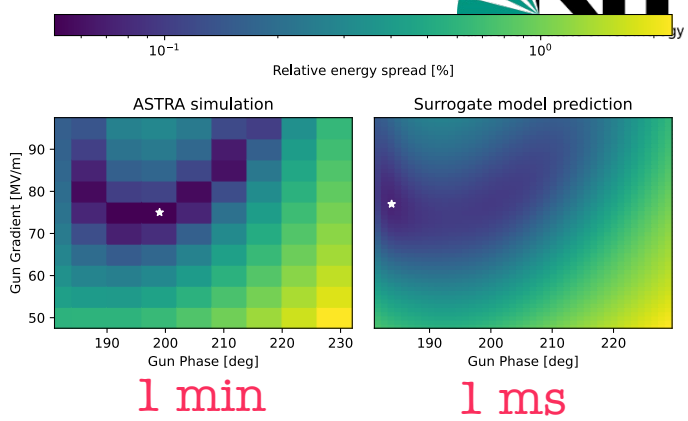
input
1. RF gun phase
2. RF gun amplitude
3. Solenoid current
4. Linac phase
5. Linac amplitude
6. Chicane bending radius

objective
- Min. RMS bunch length after chicane
- Max. peak E-field of CSR pulse

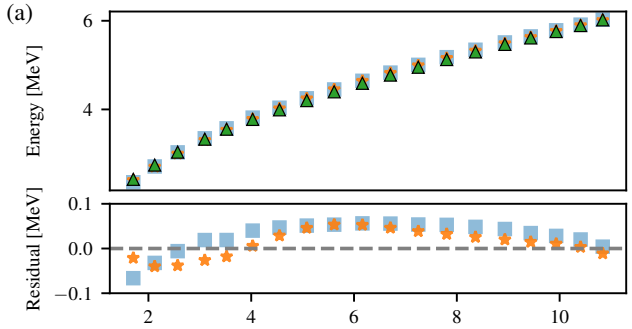
observation
- Long. phase space
- Spectral intensity
- Form factor
- Bunch current profile
- THz pulse E-field

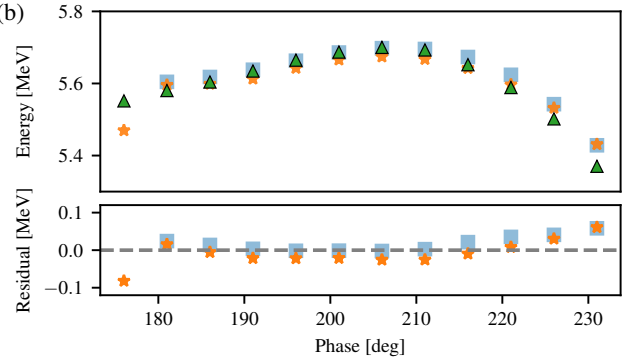
SURROGATE MODEL AS VIRTUAL DIAGNOSTIC





Good agreement with measurements:

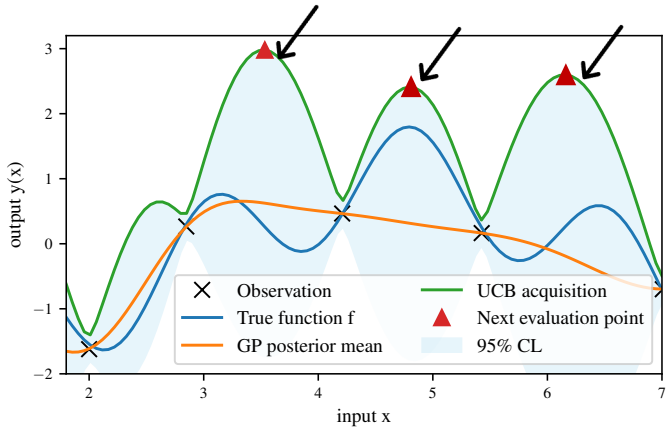




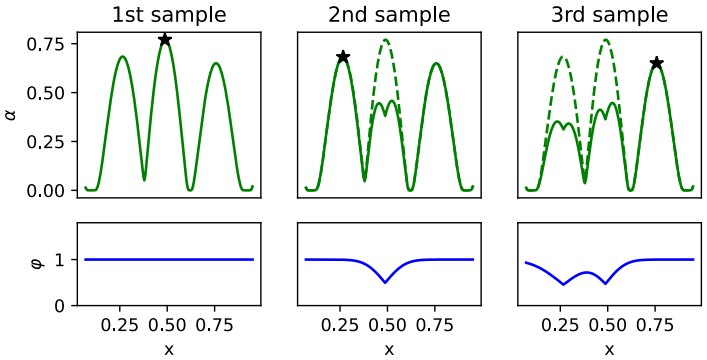
measurement
simulation
surrogate model

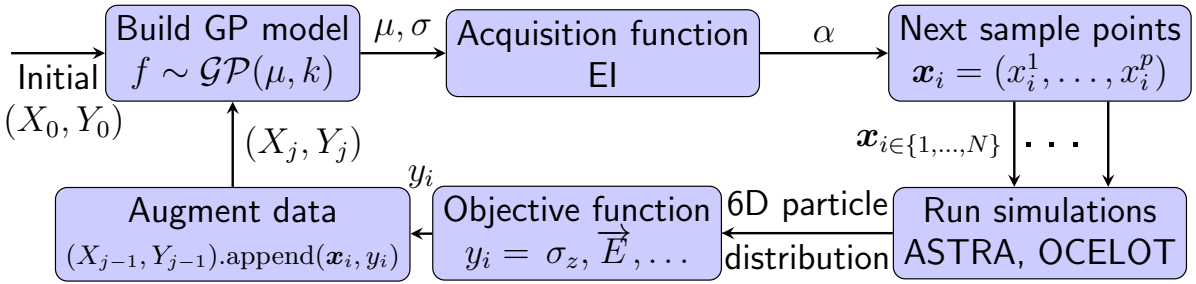
C. Xu et al. TUPOPT070, IPAC22

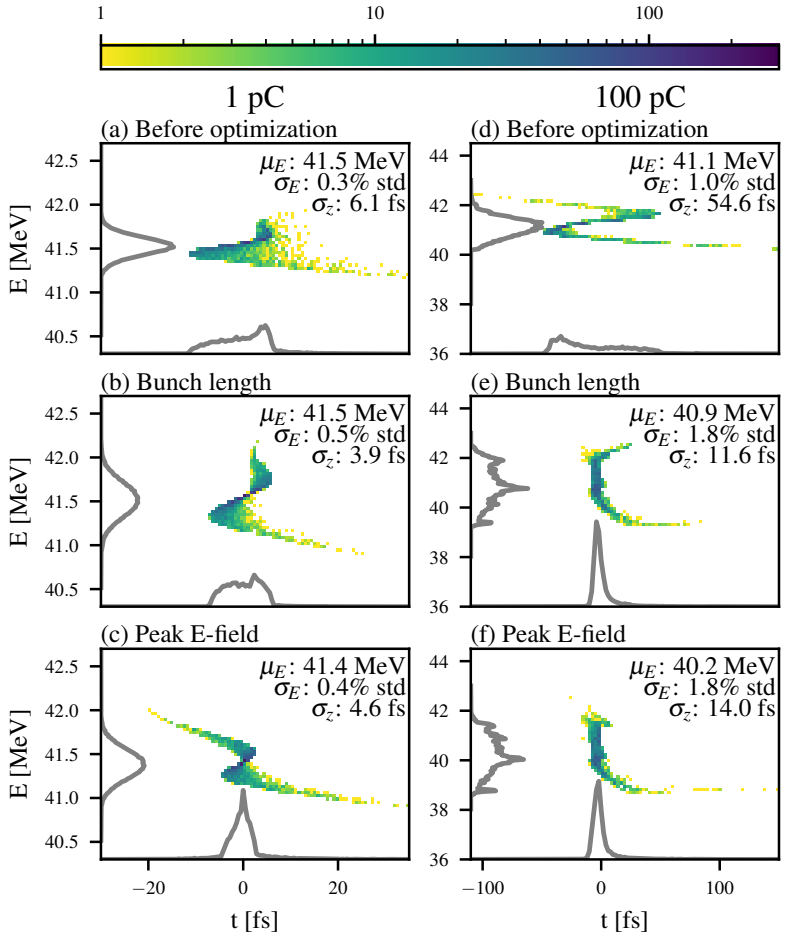
PARALLEL BAYESIAN OPTIMIZATION

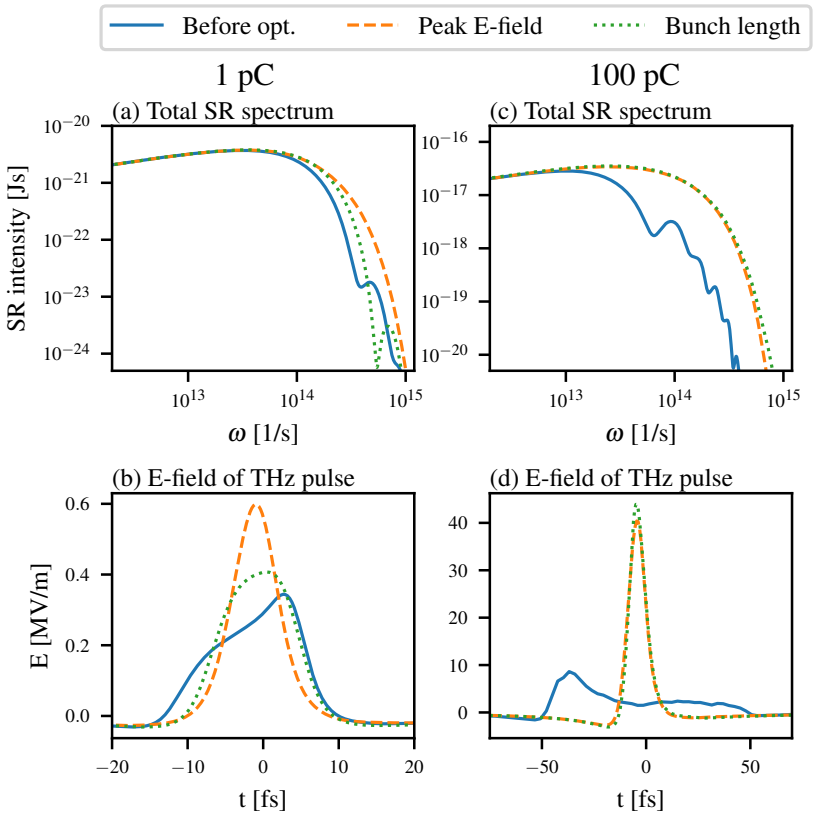


A batch of points is selected to be processed in parallel






1
10
100
1 pC
100 pC
(a) Before optimization
(d) Before optimization
μ_E: 41.5 MeV
σ_E: 0.3% std
σ_z: 6.1 fs
μ_E: 41.1 MeV
σ_E: 1.0% std
σ_z: 54.6 fs
(b) Bunch length
(e) Bunch length
μ_E: 41.5 MeV
σ_E: 0.5% std
σ_z: 3.9 fs
μ_E: 40.9 MeV
σ_E: 1.8% std
σ_z: 11.6 fs
(c) Peak E-field
(f) Peak E-field
μ_E: 41.4 MeV
σ_E: 0.4% std
σ_z: 4.6 fs
μ_E: 40.2 MeV
σ_E: 1.8% std
σ_z: 14.0 fs
E [MeV]
t [fs]


Before opt.
Peak E-field
Bunch length
1 pC
100 pC
(a) Total SR spectrum
(c) Total SR spectrum
SR intensity [Js]
ω [1/s]
(b) E-field of THz pulse
(d) E-field of THz pulse
E [MV/m]
t [fs]

Thank you for your attention!