Machine learning for tuning, prediction, and control at the KIT electron accelerators

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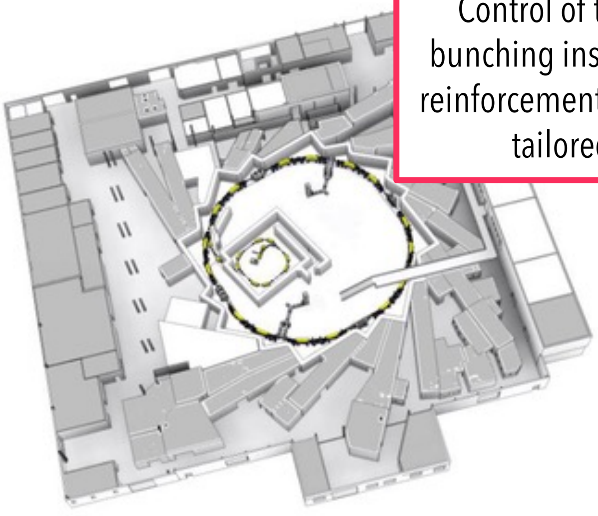
3rd ICFA Beam Dynamics Mini-Workshop on Machine Learning Applications for Particle Accelerators
Nov. 2022, Chicago

ACCELERATOR FACILITIES AT KIT

Karlsruhe Institute of Technology



Control of the micro-bunching instability with reinforcement learning for tailored CSR

THz light

KARA

Karlsruhe Research Accelerator

Synchrotron light source & storage ring

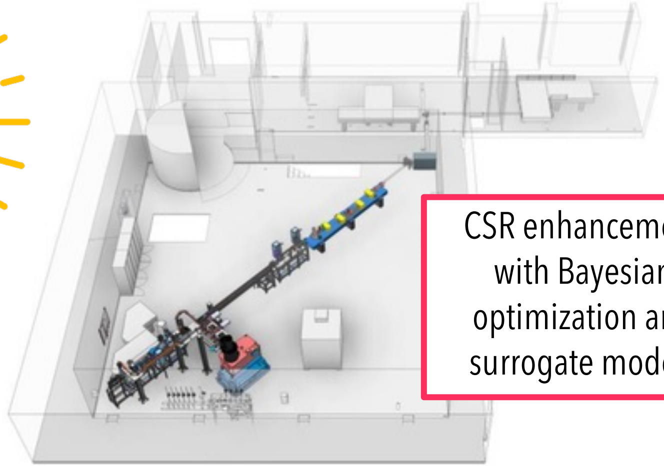
2.5 GeV top energy

FLUTE

Ferninfrarot Linac- und Test-Experiment

Linac-based THz source

41 MeV top energy



CSR enhancement with Bayesian optimization and surrogate models

*CSR = Coherent Synchrotron Radiation


ScandiNova

THE THZ FREQUENCY

Great scientific potential!

$1\ \text{THz} \leftrightarrow 1\ \text{ps} \leftrightarrow 300\ \mu m$

microwaves visible x-rays γ-rays

10^0	10^3	10^6	10^9	10^{12}	10^{15}	10^{18}	10^{21}
	kilo	mega	giga	tera	peta	exa	zetta

Frequency (Hz)

Same scale as…

- Frequency of rotation of small molecules
- Duration of collisions between gas molecules at room temp.
- Peak frequency of blackbody-like emission of galaxies
- Oscillation of gaseous and solid-state plasmas
- Frequency of resonance of electrons in semiconductors
- Frequency of superconducting energy gaps
- Frequency of vibration of biologically-relevant collective modes of proteins
- …

"THz techniques" E. Bründermann et al.

THE THZ FREQUENCY

Great scientific potential!

Common desiderata:

- High peak fields
- Coverage to higher frequencies with coherent broadband sources
- Full pulse-shaping
- Excellent source stability

↳ Accelerator-based sources provide THz radiation with high **brightness**, **power**, and **repetition rate**

More generally:

Non-destructive ↑

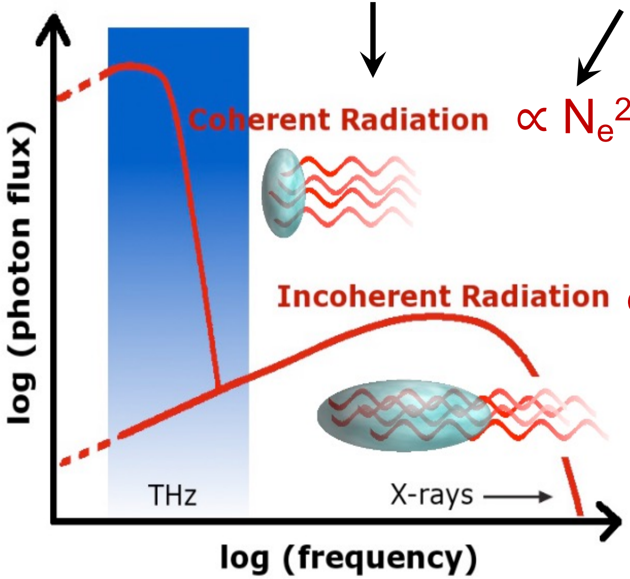
Single-shot
Bunch-by-bunch ↑

Constant delivery of high quality, intense and stable photon beams to a variety of beamlines

↓ Feedback

"Accelerator-Based THz Radiation Sources", A.-S. Müller & M. Schwarz

COHERENT SYNCHROTRON RADIATION (CSR)



*N = number of electrons

Courtesy of Prof. A.-S. Müller

Synchrotron radiation spectral intensity

$$\frac{dI}{d\omega} = [N_e + N_e(N_e - 1)F(\omega)]\frac{dI_0}{d\omega}$$

Incoherent radiation

Coherent radiation

Form factor

Single particle spectrum

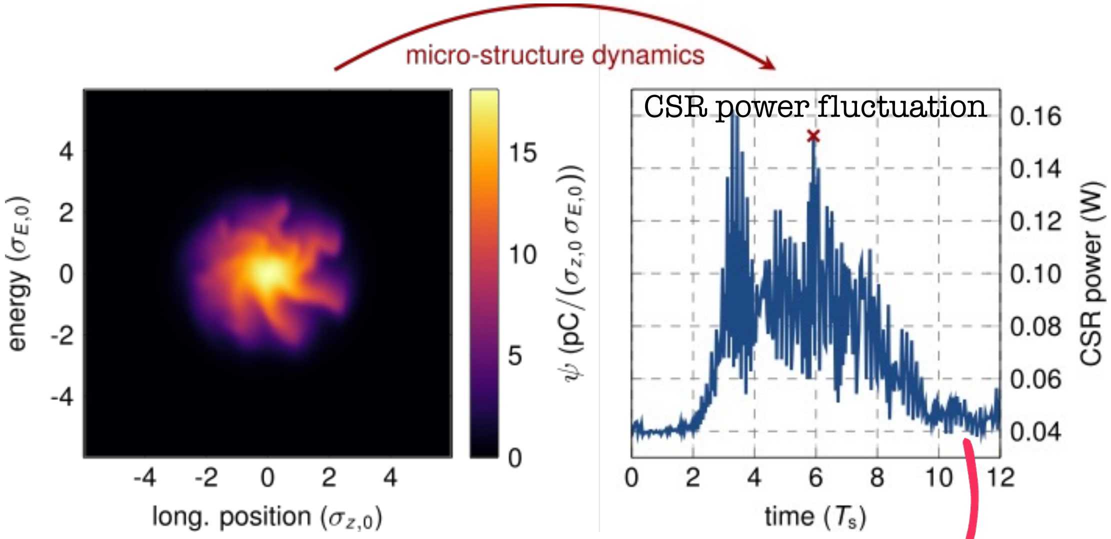
$$F(\omega,\vec{n}) = \left| \int \rho(\vec{r}) e^{i\omega\,\vec{n}.\vec{r}/c}\, \mathrm{d}^3\vec{r} \right|^2$$

Highly dependent on the **shape** of the generating **charge distributions**

["Accelerator-Based THz Radiation Sources", A.-S. Müller & M. Schwarz]

CONTROL OF INSTABILITIES WITH RL

for stable, enhanced, or damped CSR



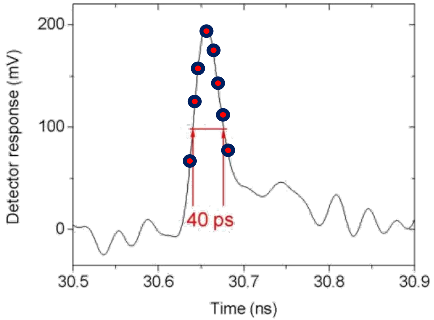
We would like a high average, low variance emission

- How to influence the instability? (actions)
- How fast does the action need to be to influence a physical phenomenon?
- How fast can we detect THz radiation? (observable)
- Can we achieve the required latency?

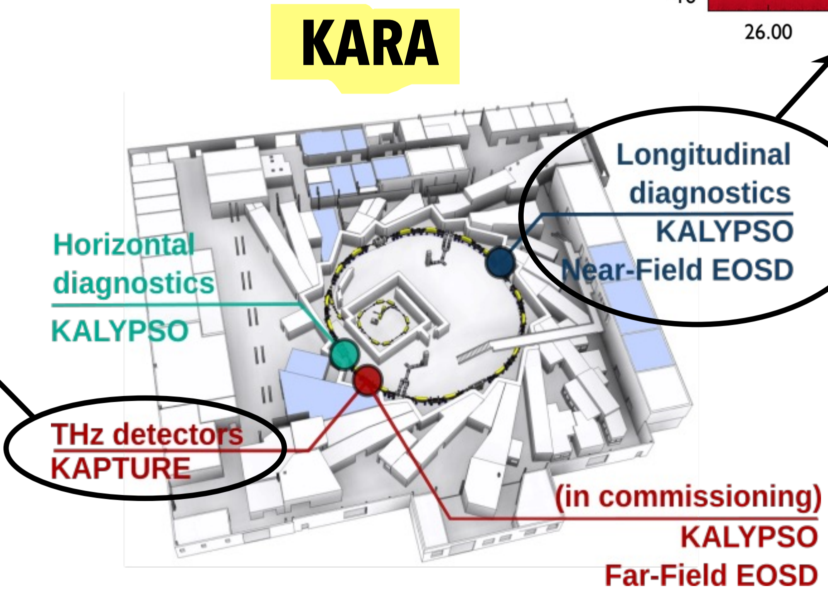
["Micro-Bunching Control at Electron Storage Rings with Reinforcement Learning", T.Boltz]

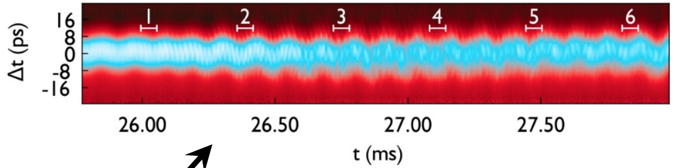
REAL-TIME, HIGH-REPETITION DATA ACQUISITION

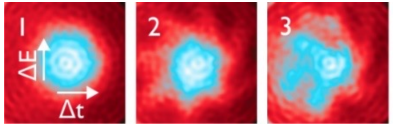
State-of-the-art detectors



Turn by turn sampling (2.7 MHz)
1024 samples







Phase space density reconstruction

"High throughput data streaming of individual longitudinal electron bunch profiles", S. Funkner

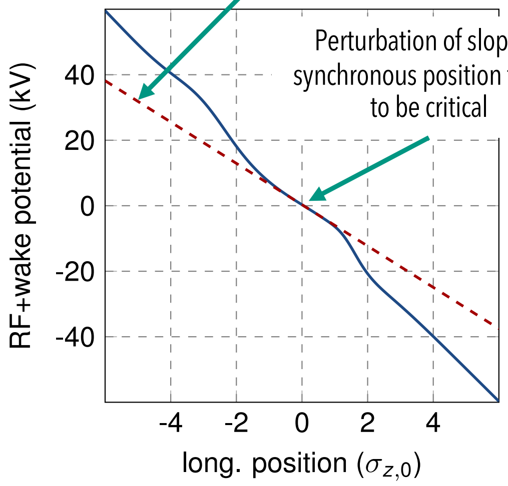
"KAPTURE-2. A picosecond sampling system for individual THz pulses with high repetition rate", M. Caselle

Revealing the dynamics of ultrarelativistic non-equilibrium many-electron systems with phase space tomography

INFLUENCING THE INSTABILITY

CSR self interaction

$$V_{eff}(q) = V_{RF}(q) + V_{CSR}(q)$$

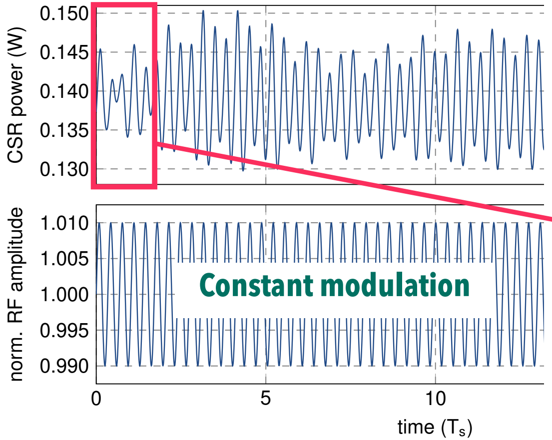


Courtesy of T. Boltz

Compensate the effect of the CSR perturbation by **modulating the RF voltage (amplitude)**

$$V_{RF} = \hat{V}(t)\sin(2\pi f_{RF} t)$$

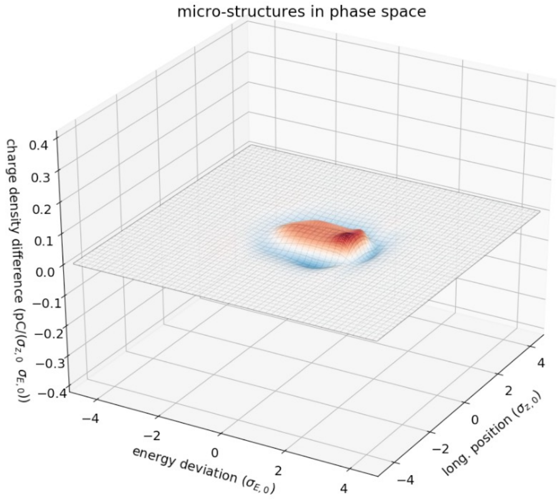
$$\hat{V}(t) = \hat{V}_0 + A_{mod}\,\sin(2\pi f_{mod} + \varphi_{mod})$$

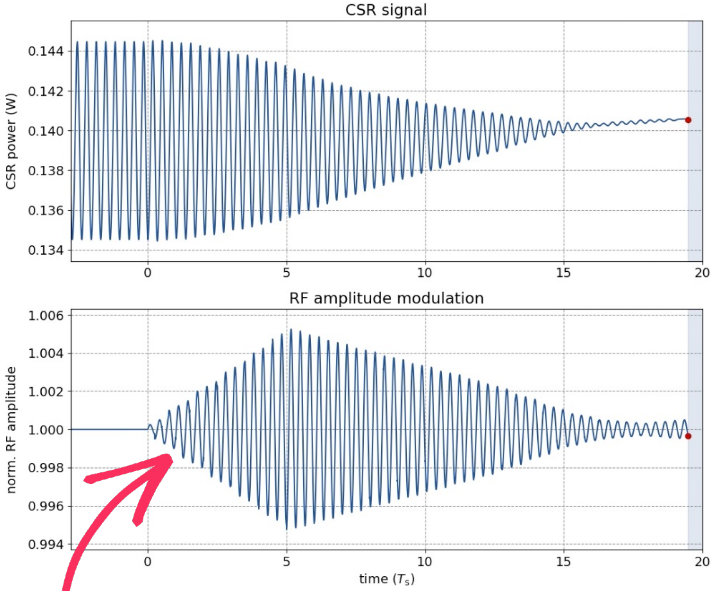


Initial damping, but quickly out of sync…we need **dynamic control**!

INFLUENCING THE INSTABILITY

Mitigation via Dynamic RF Amplitude Modulation





High average, low variance CSR!

$$V_{RF} = \hat{V}(t)\sin(2\pi f_{RF} t) \qquad \hat{V}(t) = \hat{V}_0 + A_{mod}\ \sin(2\pi f_{mod} + \varphi_{mod})$$

Courtesy of T. Boltz

Simulation done with Inovesa, Vlasov-Fokker-Plack solver developed at KIT

APPLYING REINFORCEMENT LEARNING

Action

$$\hat{V}(t) = \hat{V}_0 + A_{mod}\ sin(2\pi f_{mod} + \varphi_{mod})$$

Reward

R = $\mu_{CSR} - w\ \sigma_{CSR}$ where w is a weight

Observable

Charge distribution (simulation, KALYPSO)

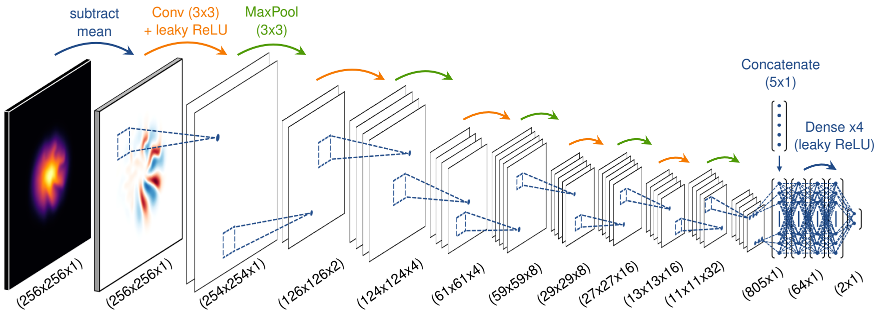
Input: (256x256) matrix + (5x1) feature vector

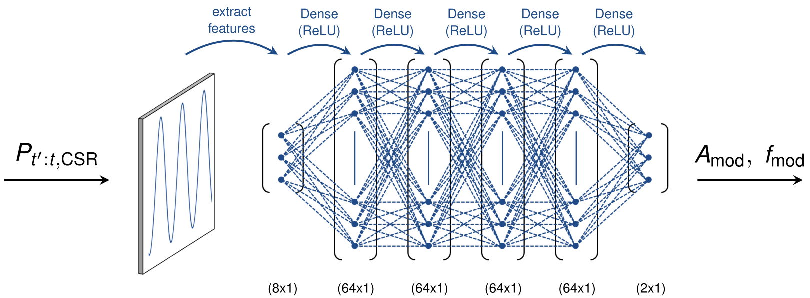
Observable

CSR signal (simulation, KAPTURE)

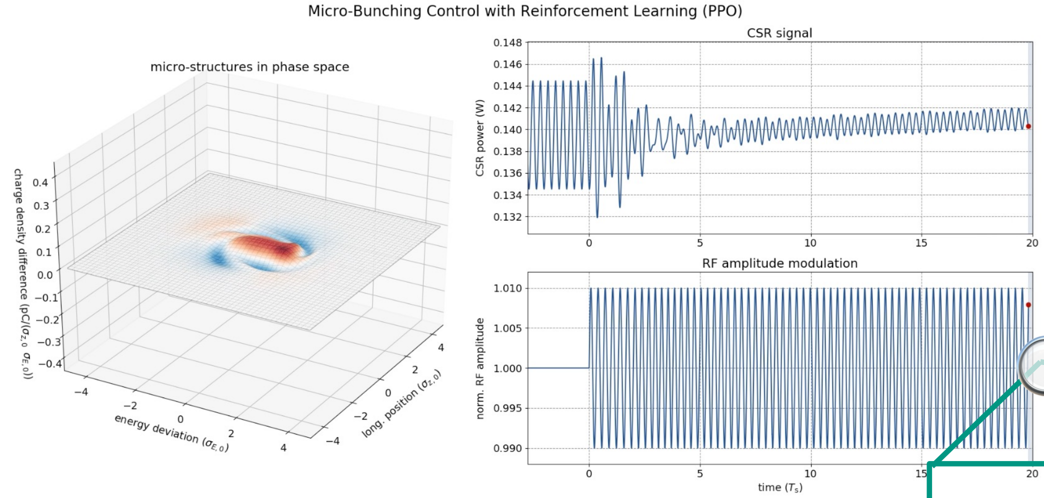
Input: (8x1) feature vector

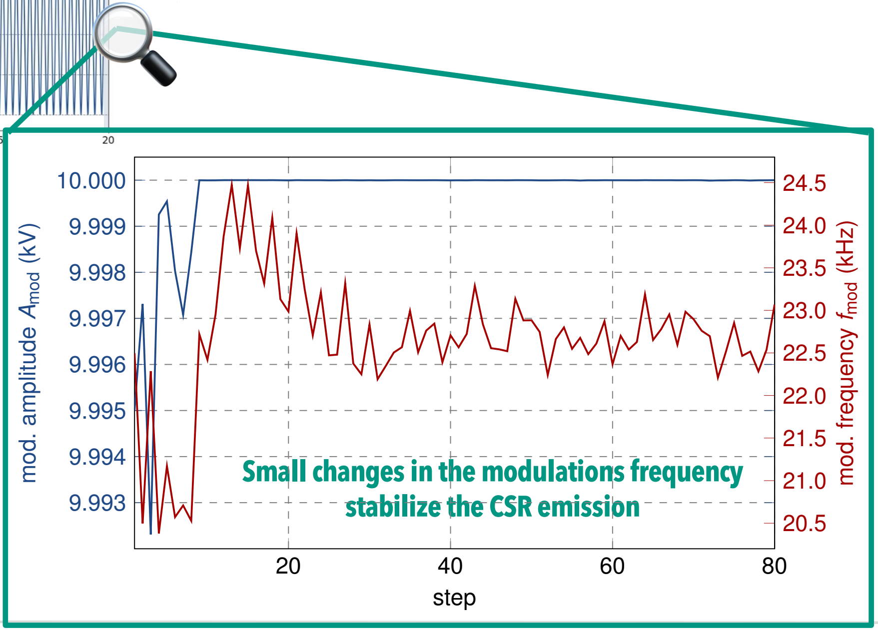
Easier to measure & process





Courtesy of T. Boltz



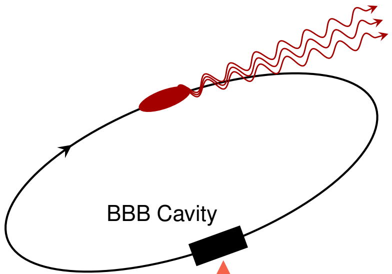


Courtesy of T. Boltz

IN PRACTICE: WE NEED HARDWARE!

Fast feedback for real-time optimization

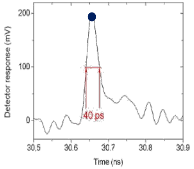
Karlsruhe Institute of Technology



Detector

Schottky diode
50 GHz – 2 THz

KAPTURE
Fast digitizer



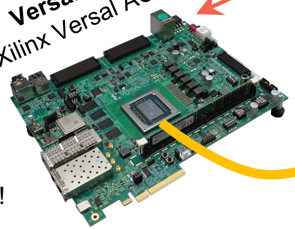
HighFlex 2 DAQ card
Xilinx ZYNQ

Custom modular readout DAQ optimized for AI applications

Ethernet 1GbE

$\Delta t < 1$ ms

Versal board
Xilinx Versal ACAP



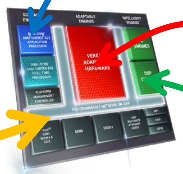
RF modulation computed by Versal

Feedback

Bunch-by-bunch / LLRF

400 tiles x 8 FP multiplications x 0.5 GHz
→ up to 1.6 Tera FP operations per second !!!

Latency measured with Versal: 4.5 μs



Scalar processor (ARM-PS) for the implementation of the "critic" neural network

Large **FPGA**/DSP for data management

Dedicated programmable **AI-engines** for the deployment of fast inference "actor" neural network + feature extraction

All linked by high bandwidth Network on a Chip (NoC)
full customization of dataflow

"KINGFISHER: a framework for fast machine learning inference for autonomous accelerator systems", L. Scomparin

"Accelerated deep reinforcement learning for fast feedback of beam dynamics at KARA," W. Wang

THZ PULSE OPTIMIZATION AT FLUTE

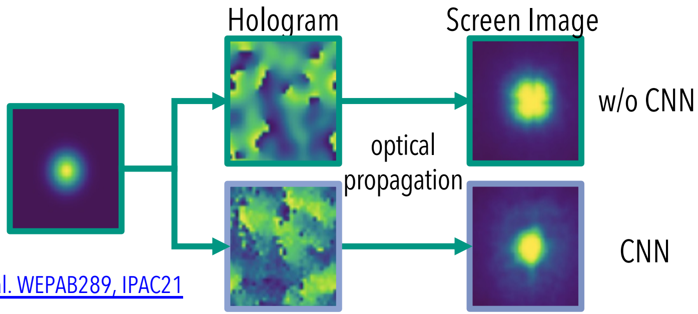
Karlsruhe Institute of Technology

Will be varied in other studies

Photoinjector

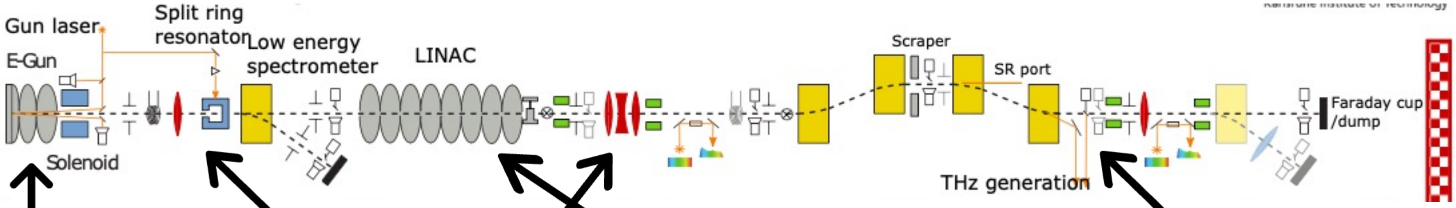
- Laser pulse length = 700 fs (1 pC) or 2 ps (100 pC)
- Laser pulse shape = Circular
- Laser spot size = 250 μm radius
- Laser spot position = Centered in cathode

Laser pulse shaping with Spatial Light Modulators and convolutional neural networks



C. Xu et al. WEPAB289, IPAC21

...



RF gun

- RF amplitude
- RF phase

Magnets

- Quadrupoles
- Solenoid

Traveling wave structure

- Amplitude
- Phase

Chicane

- Bending radius

THZ PULSE OPTIMIZATION AT FLUTE

Surrogate model

input

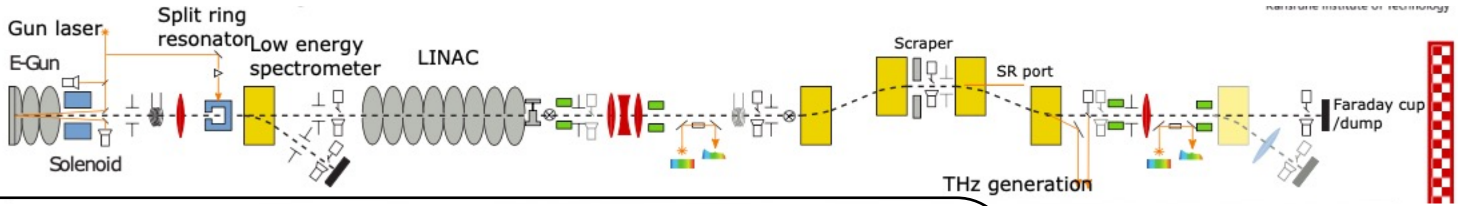
1. RF gun phase
2. RF gun amplitude
3. Solenoid current
4. Bunch charge

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

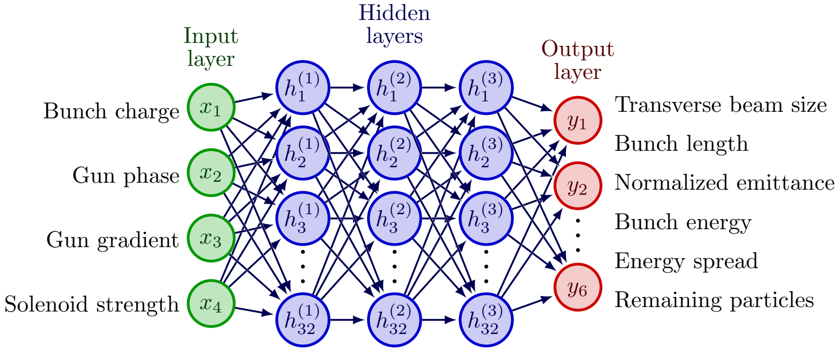
objective

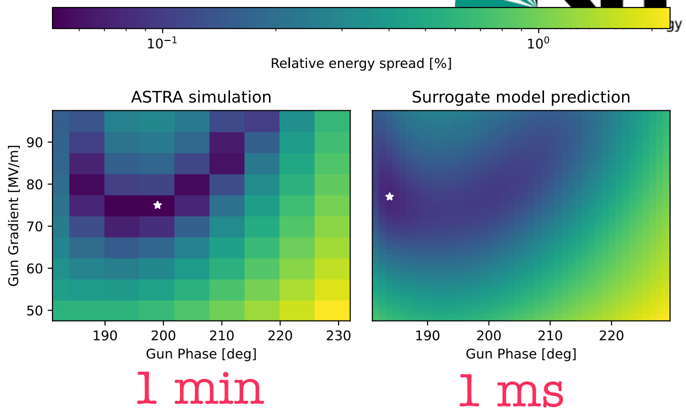
- Min. RMS bunch length after chicane
- Max. peak E-field of CSR pulse

observation

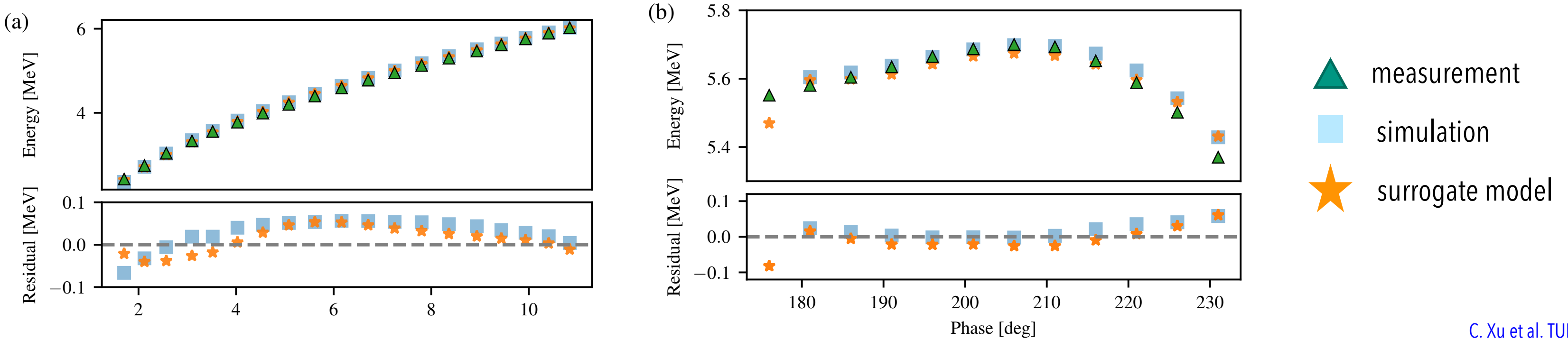
- Long. phase space
- Spectral intensity
- Form factor
- Bunch current profile
- THz pulse E-field

SURROGATE MODEL AS VIRTUAL DIAGNOSTIC



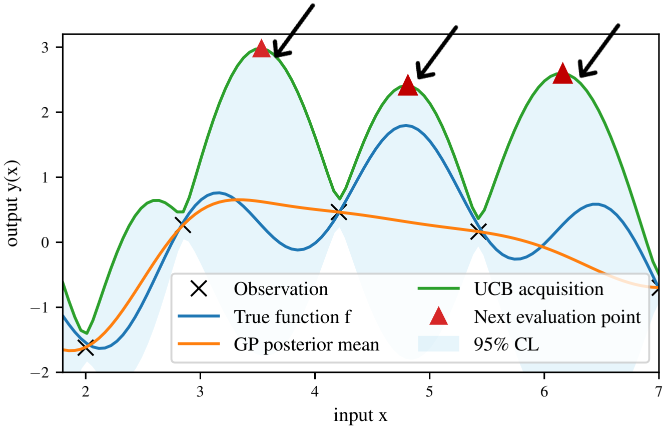


Great agreement with measurements:

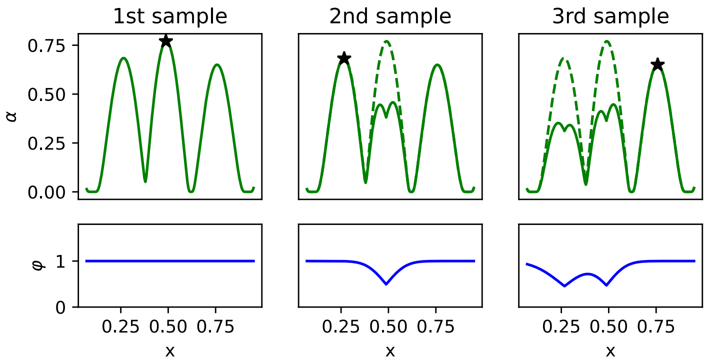


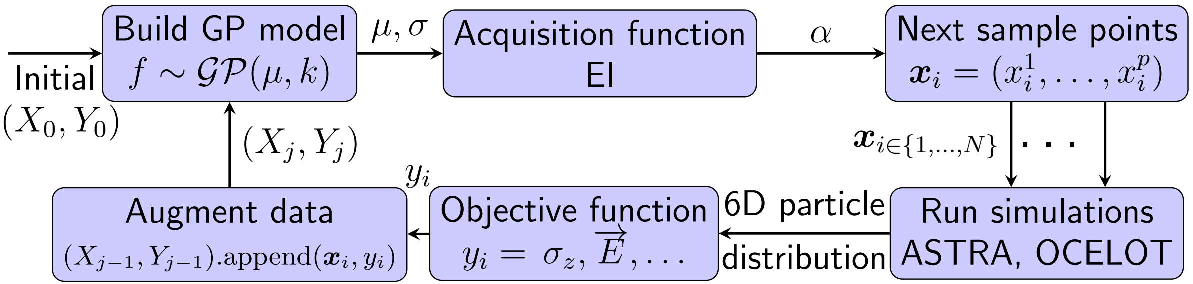
C. Xu et al. TUPOPT070, IPAC22

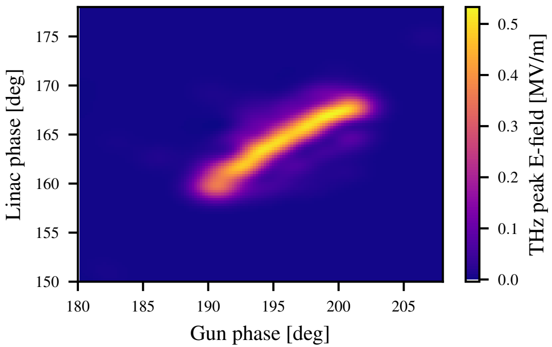
PARALLEL BAYESIAN OPTIMIZATION

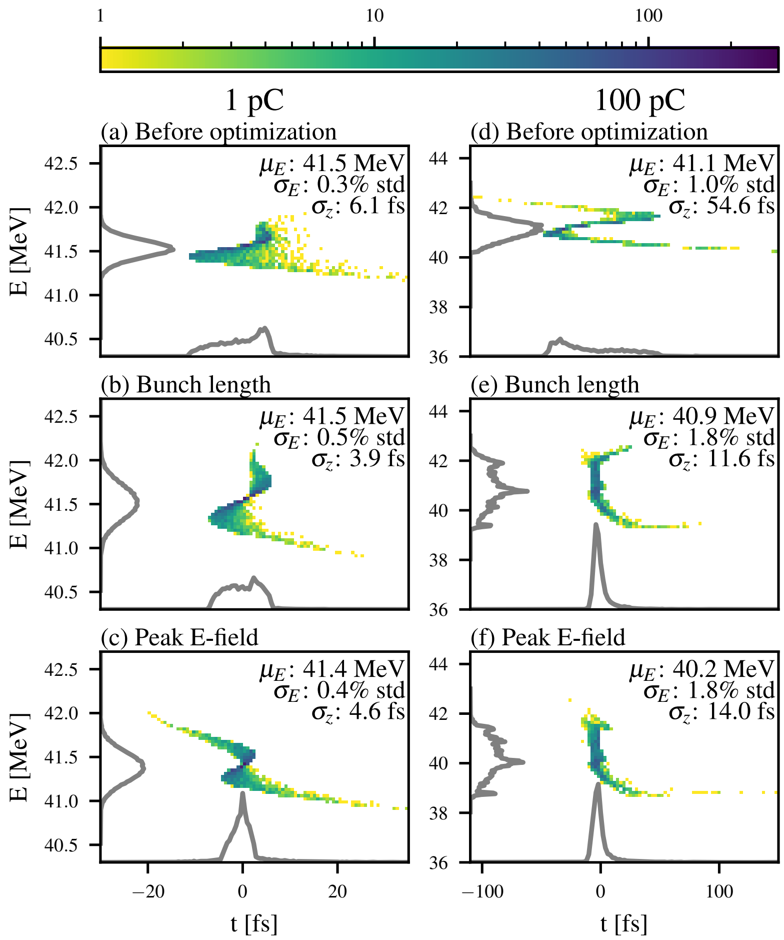


A batch of points is selected to be processed in parallel

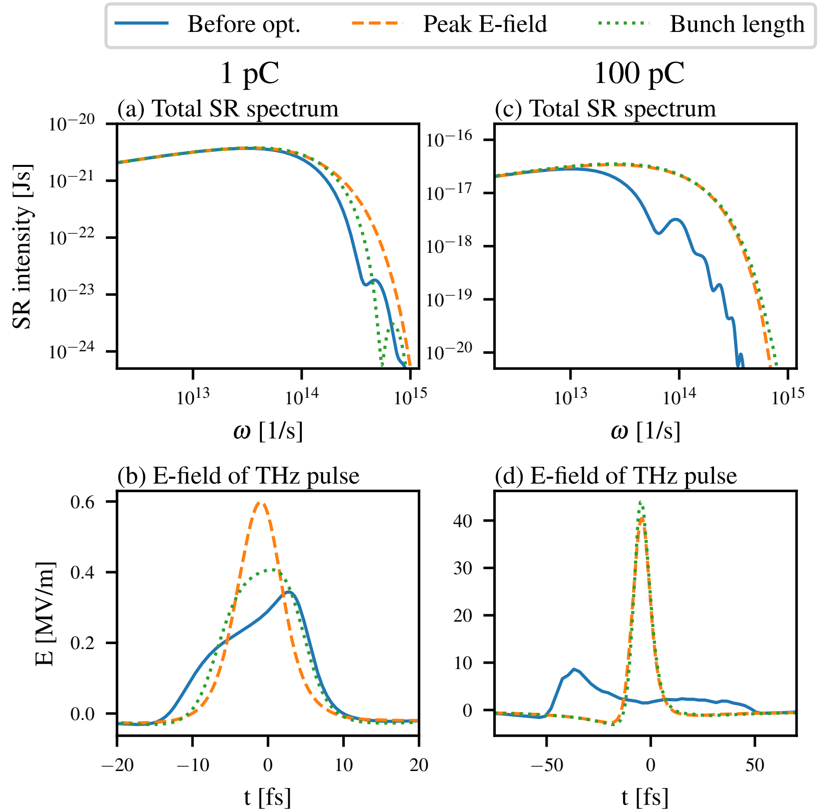








1 pC
100 pC
(a) Before optimization
μ_E: 41.5 MeV
σ_E: 0.3% std
σ_z: 6.1 fs
(b) Bunch length
μ_E: 41.5 MeV
σ_E: 0.5% std
σ_z: 3.9 fs
(c) Peak E-field
μ_E: 41.4 MeV
σ_E: 0.4% std
σ_z: 4.6 fs
(d) Before optimization
μ_E: 41.1 MeV
σ_E: 1.0% std
σ_z: 54.6 fs
(e) Bunch length
μ_E: 40.9 MeV
σ_E: 1.8% std
σ_z: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

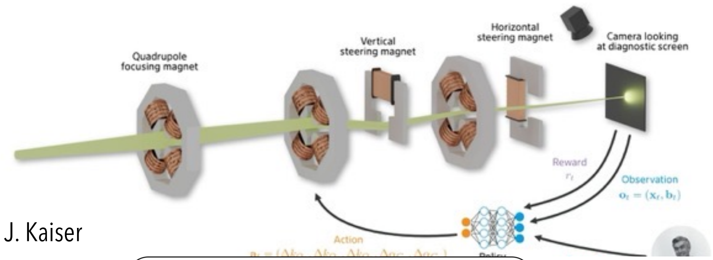


Before opt.
Peak E-field
Bunch length
1 pC
100 pC
(a) Total SR spectrum
(c) Total SR spectrum
SR intensity [Js]
ω [1/s]
(b) E-field of THz pulse
(d) E-field of THz pulse
E [MV/m]
t [fs]

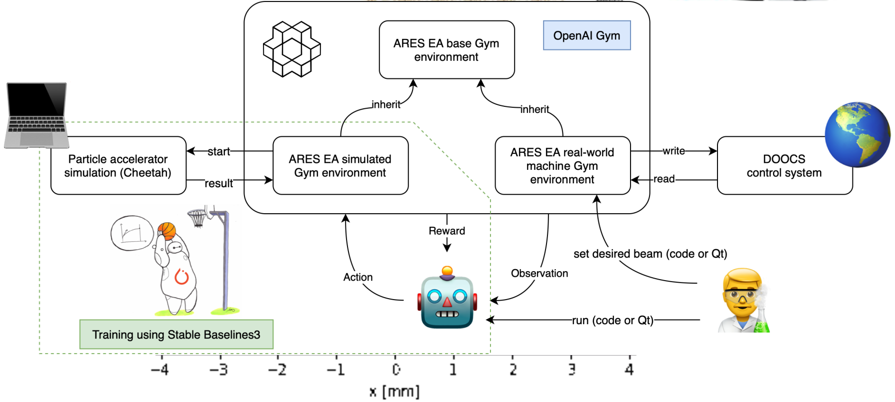
AND MANY OTHER PROJECTS…

"Machine Learning Toward Autonomous Accelerators"

Helmholtz AI funded project (2020-2022)



Courtesy of J. Kaiser



ARES beamtime 12-10-2021 during the Autonomous Accelerator workshop

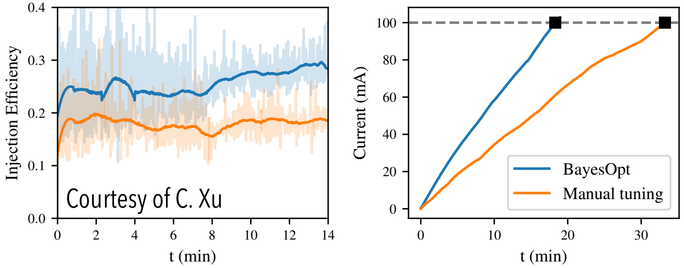
["First steps toward an autonomous accelerator, a common project between DESY and KIT", A. Eichler]()

https://scitechdaily.com/autonomous-particle-accelerators-accelerate-smarter-with-artificial-intelligence/

AND MANY OTHER PROJECTS...

Bayesian optimization of injection at KARA

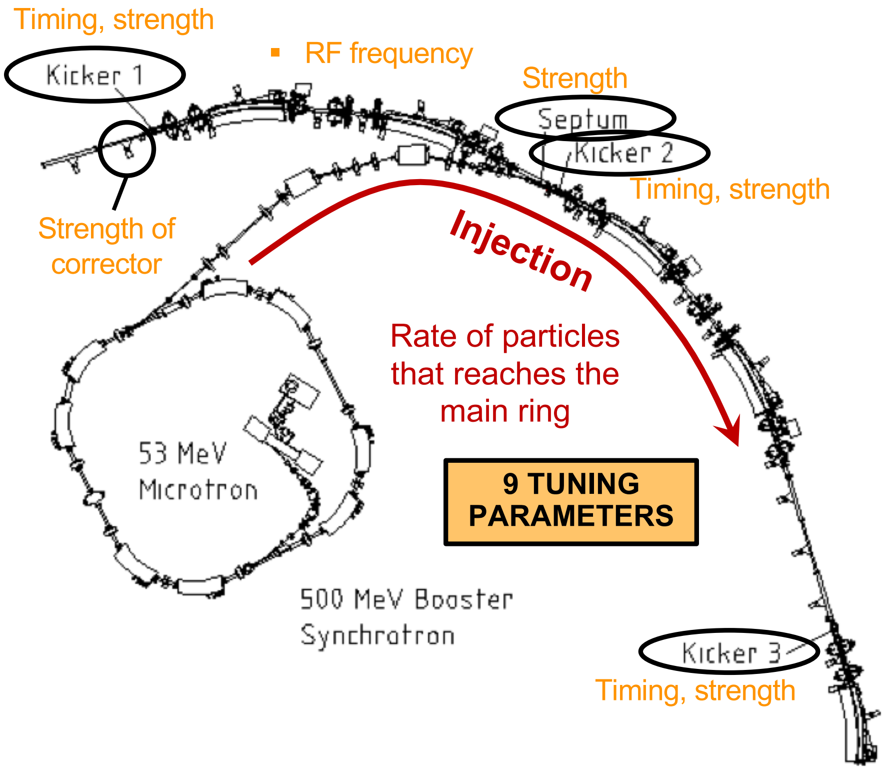
Two times faster than manual operation!



Code succesfully optimizes the injection efficiency two times faster than manual tuning

Code used in commissioning phase of new injection magnets

Stored current used as contextual parameter correctly predicts Touschek scattering effects



Conclusions

Surrogate models

- Helpful in the design and commissioning phases (probing possible working points)
- Can give a smart starting point to optimizers to reduce optimization time
- Can be used as a virtual diagnostic with experimental input
- Can be partially re-trained with experimental data
- Curse of dimensionality: training only worth it for a limited number of parameters

Parallel Bayesian optimization

- Speeds up optimization considerably
- Gives you a stochastic model of your machine
- Helpful in the design and commissioning phases (probing possible working points)
- Can be extended to multiple objectives

Reinforcement learning

- Extremely promising for online control of instabilities
- Requires hardware development for experimental implementation

Karlsruhe Institute of Technology

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Thank you for your attention!

What questions do you have for me?