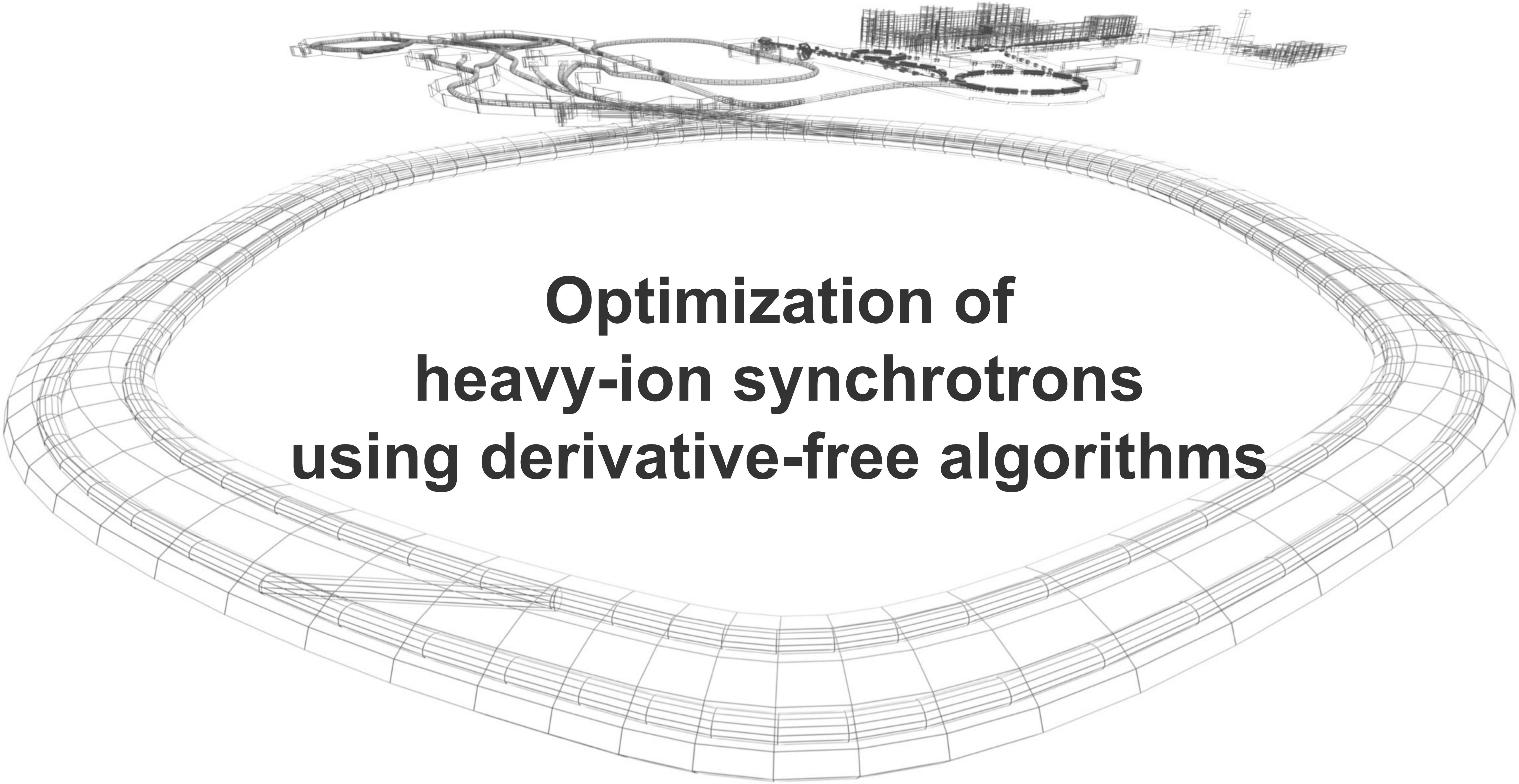
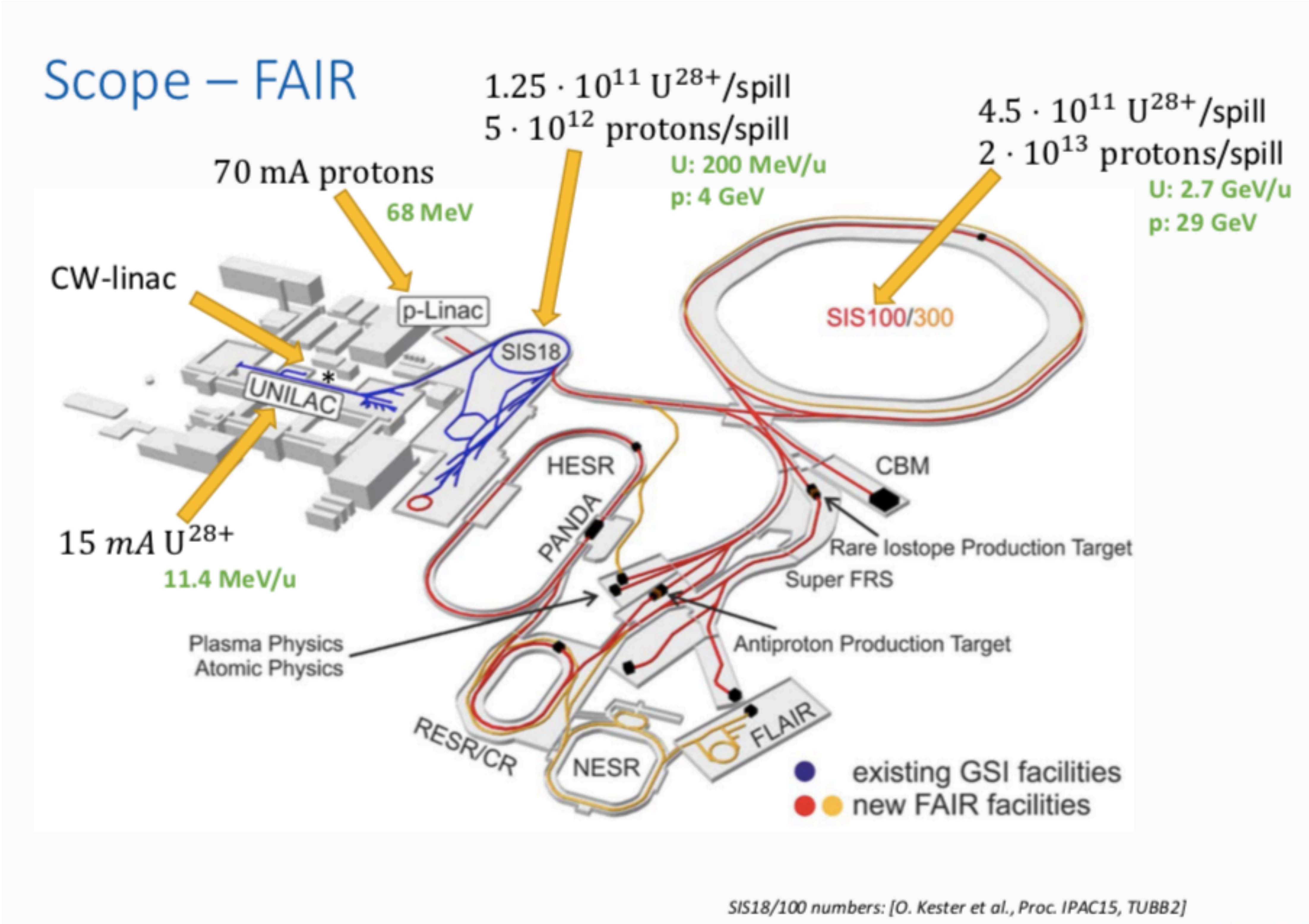


Optimization of heavy-ion synchrotrons using derivative-free algorithms

Dr. Sabrina Appel, Accelerator Physics Department, GSI, Darmstadt

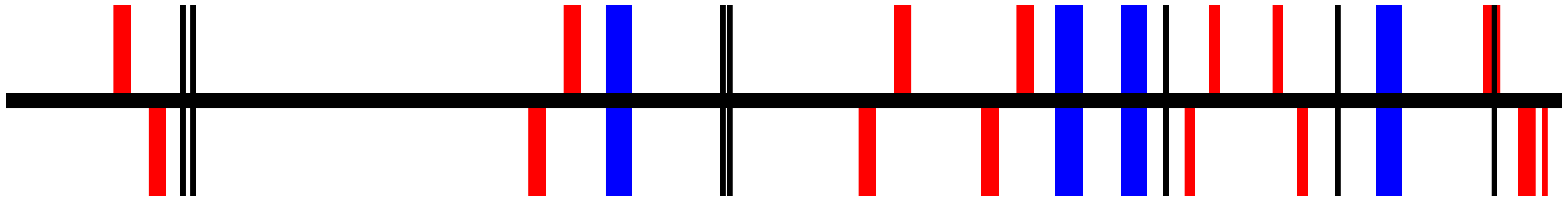
FAIR

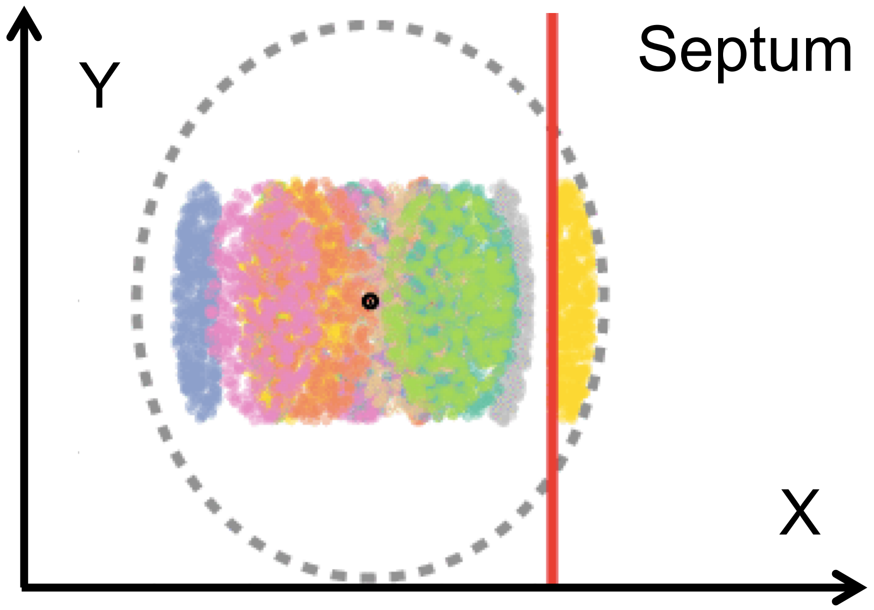

Scope – FAIR
1.25 · 10^11 U^28+/spill
5 · 10^12 protons/spill
U: 200 MeV/u
p: 4 GeV
4.5 · 10^11 U^28+/spill
2 · 10^13 protons/spill
U: 2.7 GeV/u
p: 29 GeV
70 mA protons
68 MeV
CW-linac
p-Linac
SIS18
UNILAC
SIS100/300
HESR
PANDA
CBM
Rare Isotope Production Target
Super FRS
15 mA U^28+
11.4 MeV/u
Plasma Physics
Atomic Physics
Antiproton Production Target
RESR/CR
NESR
FLAIR
existing GSI facilities
new FAIR facilities
SIS18/100 numbers: [O. Kester et al., Proc. IPAC15, TUBB2]

Outline

- **Derivative-free optimization**
  - BOBYQA
  - Evolutionary algorithms
  - Bayesian optimization

- **Example optimization problem:**
  - Multi-Turn Injection
  - Optimization of beam lines





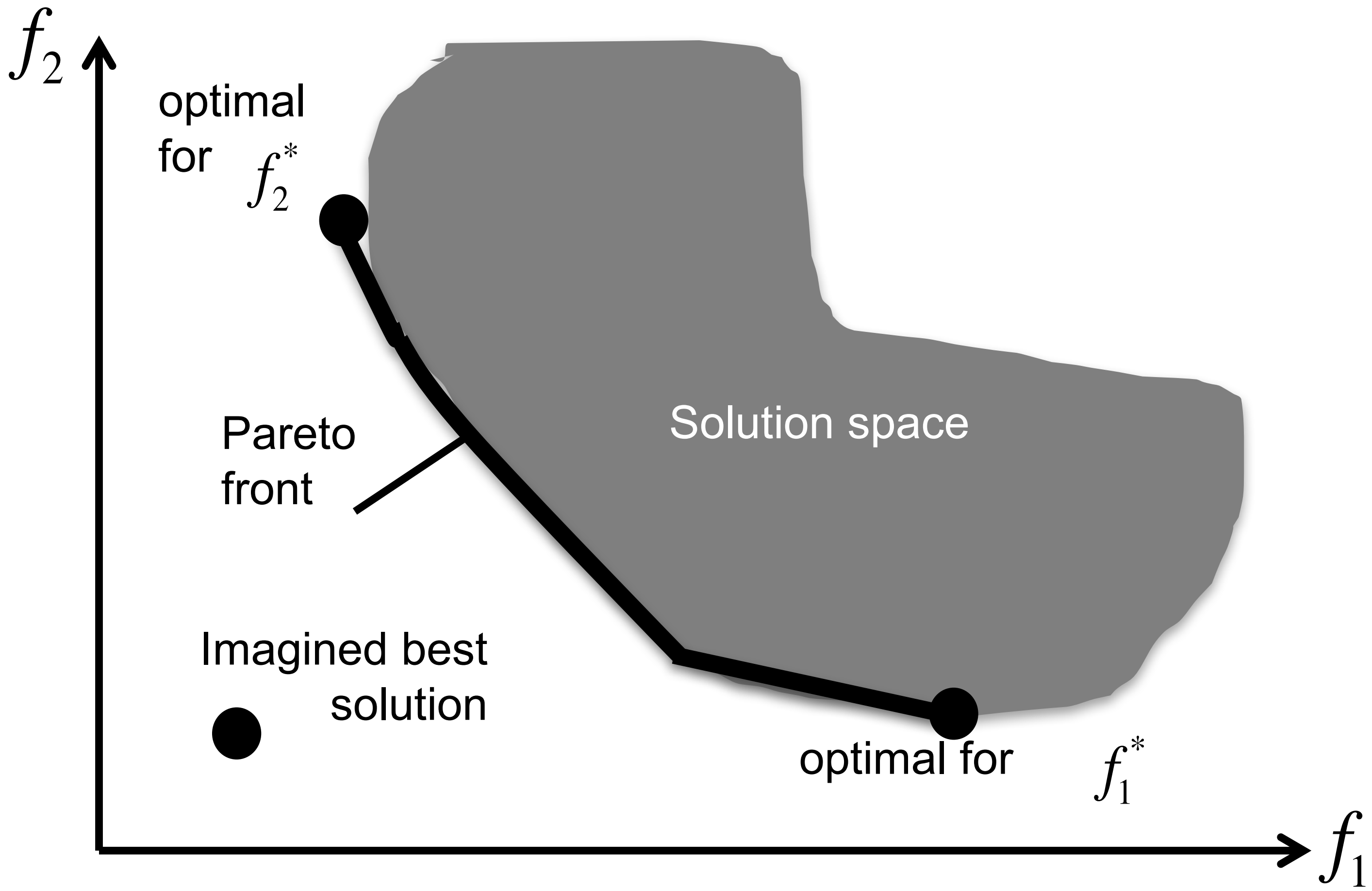
Optimization of particle accelerators

General:

The optimization problem is multi-objective

$$\min(f_1(x), f_2(x), \ldots)$$

(several criterions to optimize)

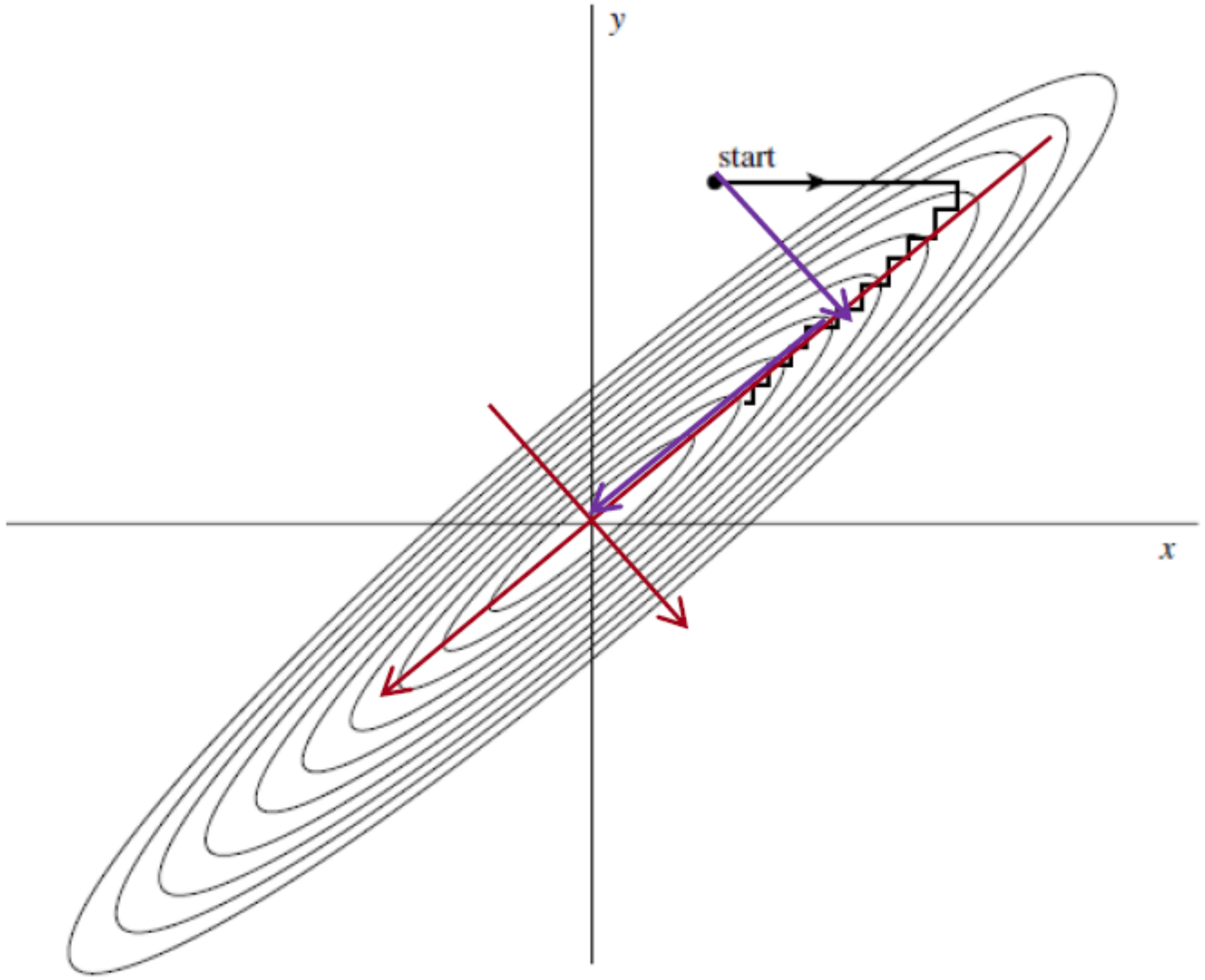


- The criterions can be contradicting:
Improving one criterion means worsening others

➢ Find set of optimal solutions instead of single solution (Pareto front)

Powell Method

- Proposed by Michael J. D. Powell in 1964 [2]
- The function need not be differentiable, and no derivatives are taken.
- Pattern or Direction Search Methods
- Powell's method can update the directions using past search results to develop a conjugate set.
- Only conjugate direction sets are be used to avoid infinite rotation in a circle.

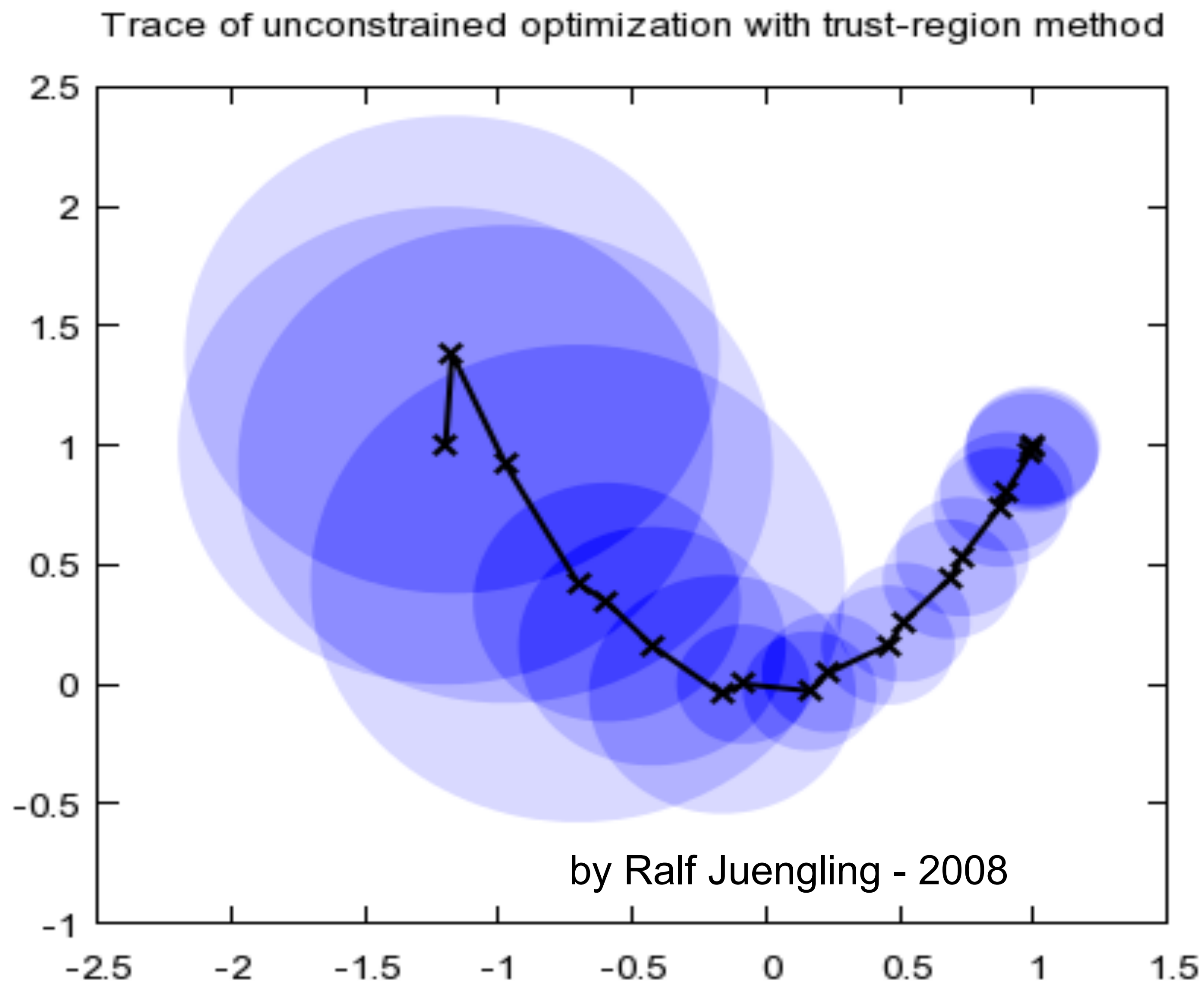


- 1D optimizer with multi variables

[2] M.J.D. Powell. Comput. J., 7, 155–162, 1964. doi: 10.1093/comjnl/7.2.155

Bound Optimization BY Quadratic Approximation (BOBYQA)

- BOBYQA is a deterministic method and no derivatives are taken during the optimization.
- Proposed by Michael J. D. Powell in 2009.
- BOBYQA is sequential trust–region algorithm that employs quadratic approximations to the objective function [2].
- The quadratic models are updated regularly to include new information about the objective function, such as the difference between two gradient vectors.

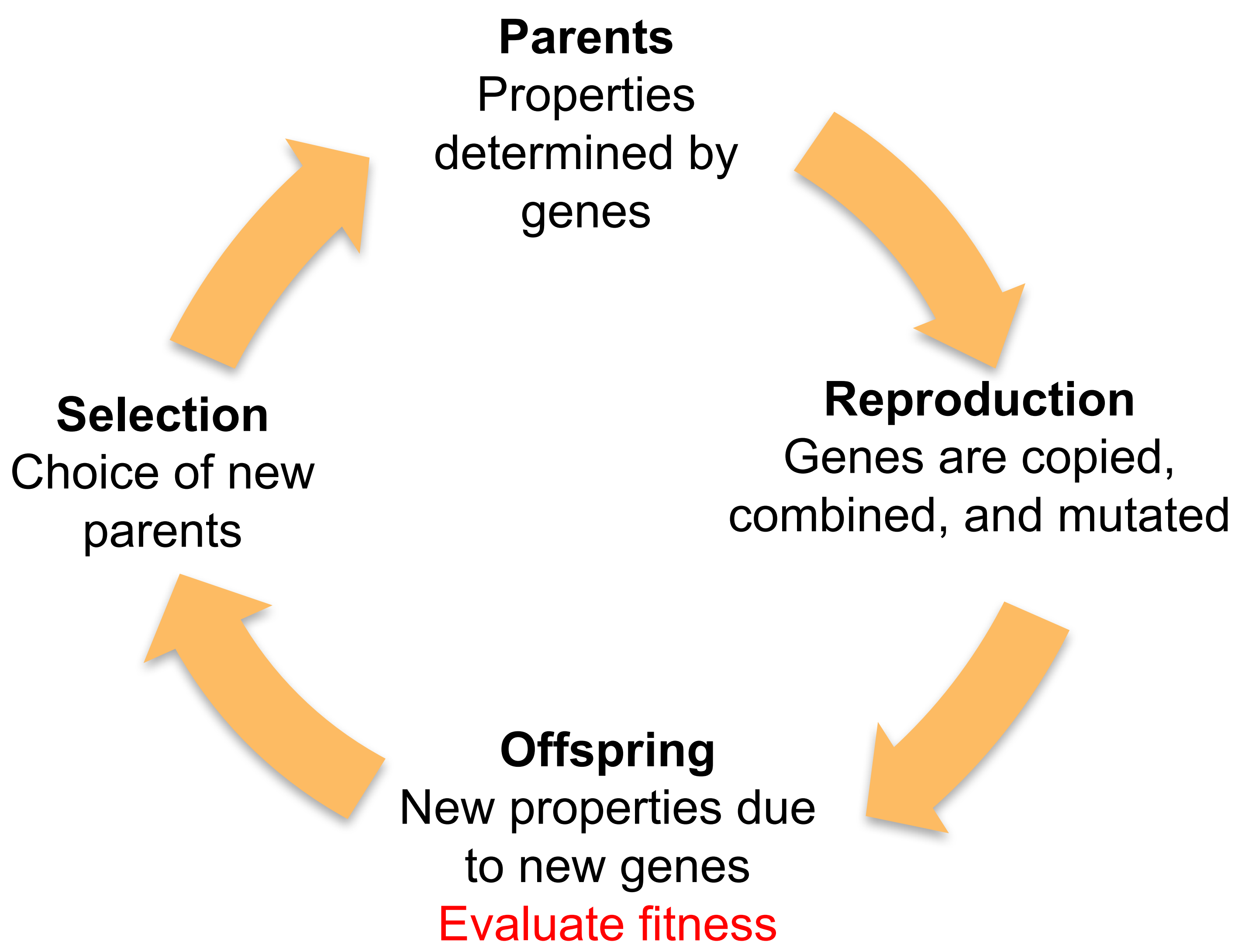


- In Py-BOBYQA robustness against noise is implemented. [3]

[2] M. J. D Powell, technical report DAMTP 2009/NA06, Cambridge (2009),
[3] C. Cartis, arXiv:1804.00154, (2018), https://pypi.org/project/Py-BOBYQA

Nature-inspired optimization

Genetic algorithms

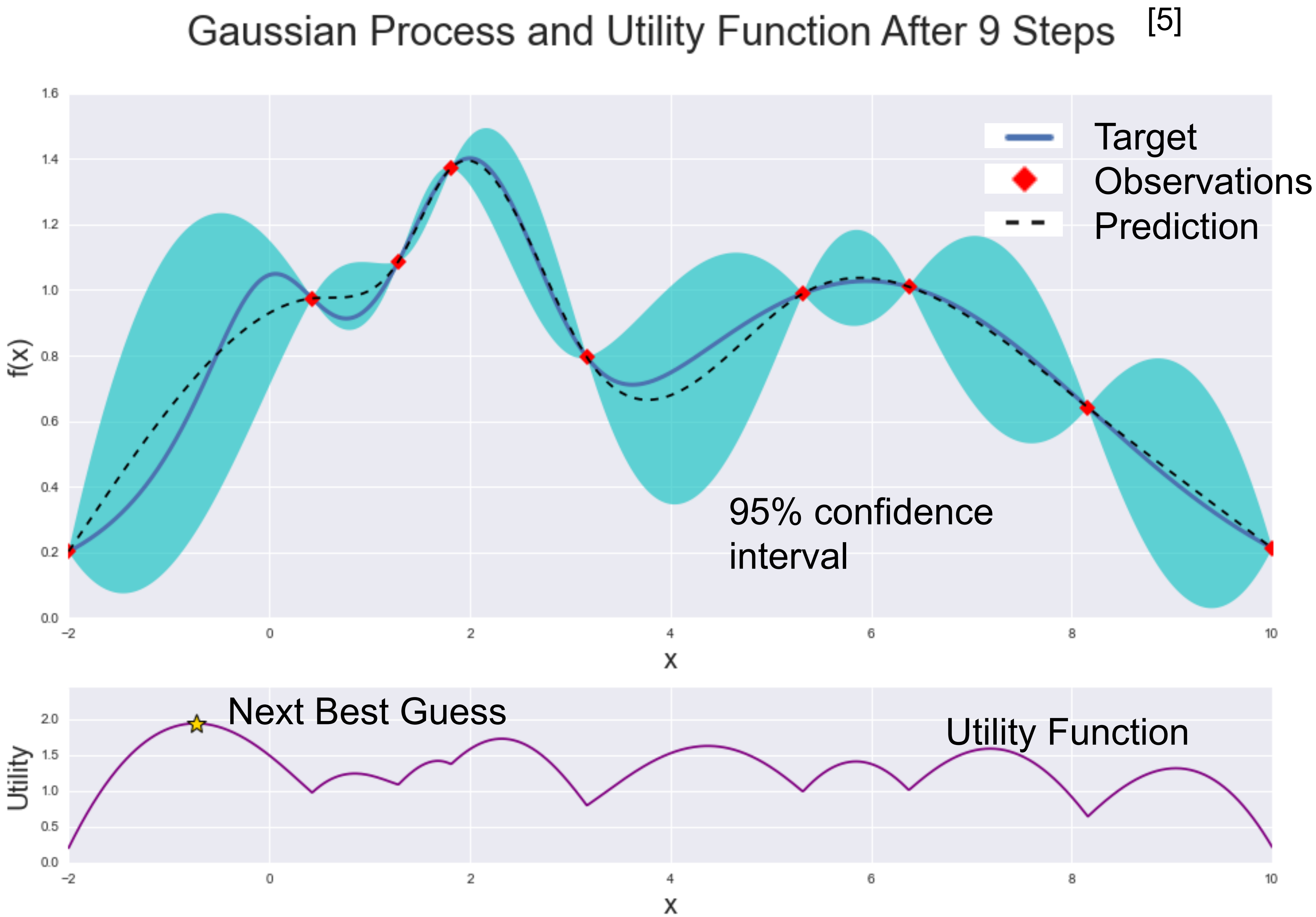


- Nature-inspired algorithms are smart parameter scans:
  - Genetic algorithms
  - Particle swarm algorithms
- Genetic algorithms allow multi-objective optimization
- Equally valid solution form a so-called Pareto front (PA front) [4]
- Search for solutions using techniques such as mutation, selection and crossover
- The fitness measures how good an individual is adapted

[4] A. Konak, Reliab. Eng. Syst. Saf.}, 91 (9), pp. 992--1007, 2006.

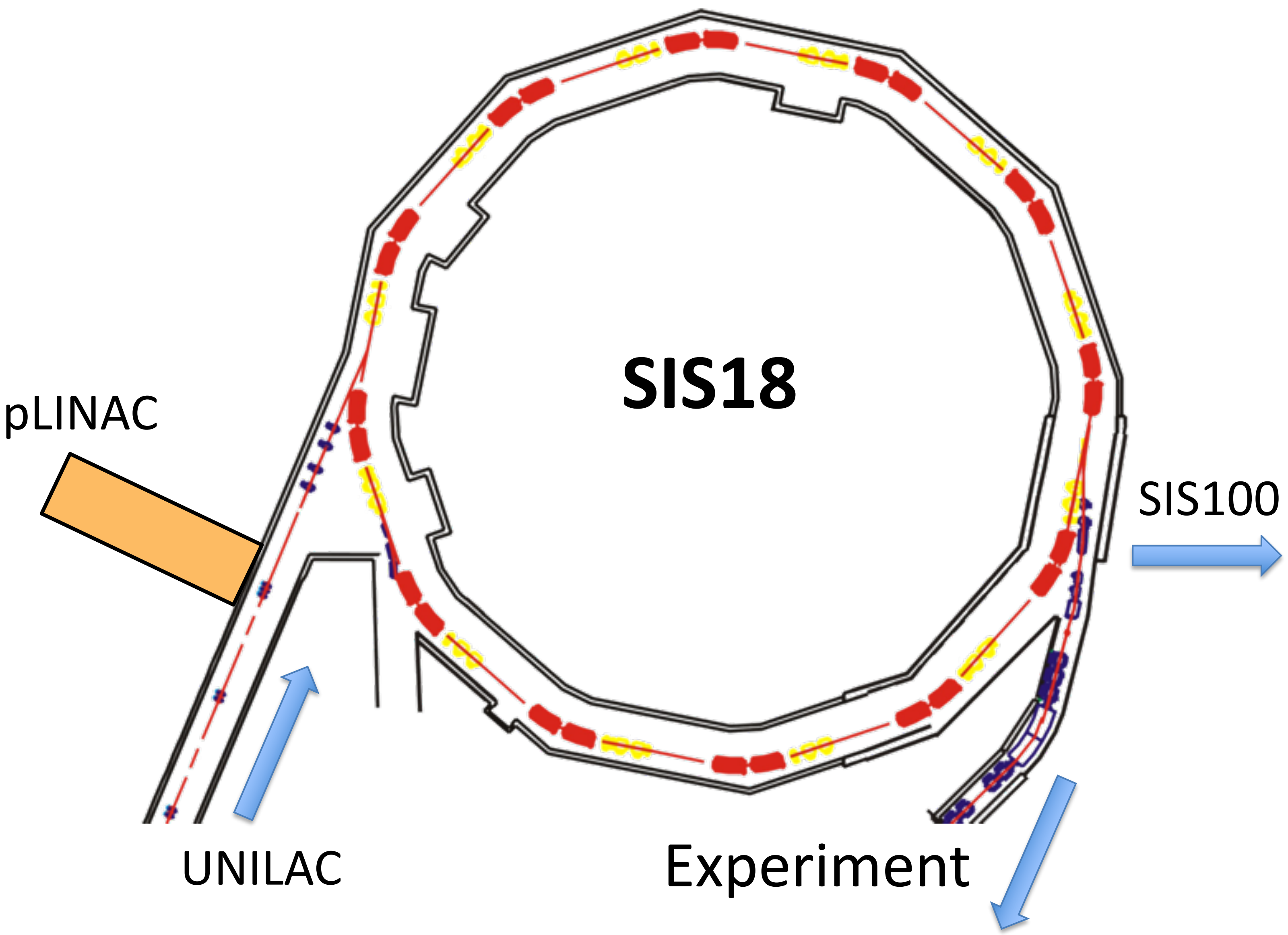
Bayesian optimization

- Probabilistic model of optimization function is construed and then exploits this model to make decisions where to evaluate the function next.
- Gaussian process prior will express assumption about the optimization function.
- Chosen utility function defined from this surrogate model where to evaluate the function next.
- Multi-objective Bayesian optimization algorithm (recently available) [6]



[5] F. Noqueira, https://github.com/fmfn/BayesianOptimization
[6] https://github.com/ppgaluzio/MOBOpt/wiki

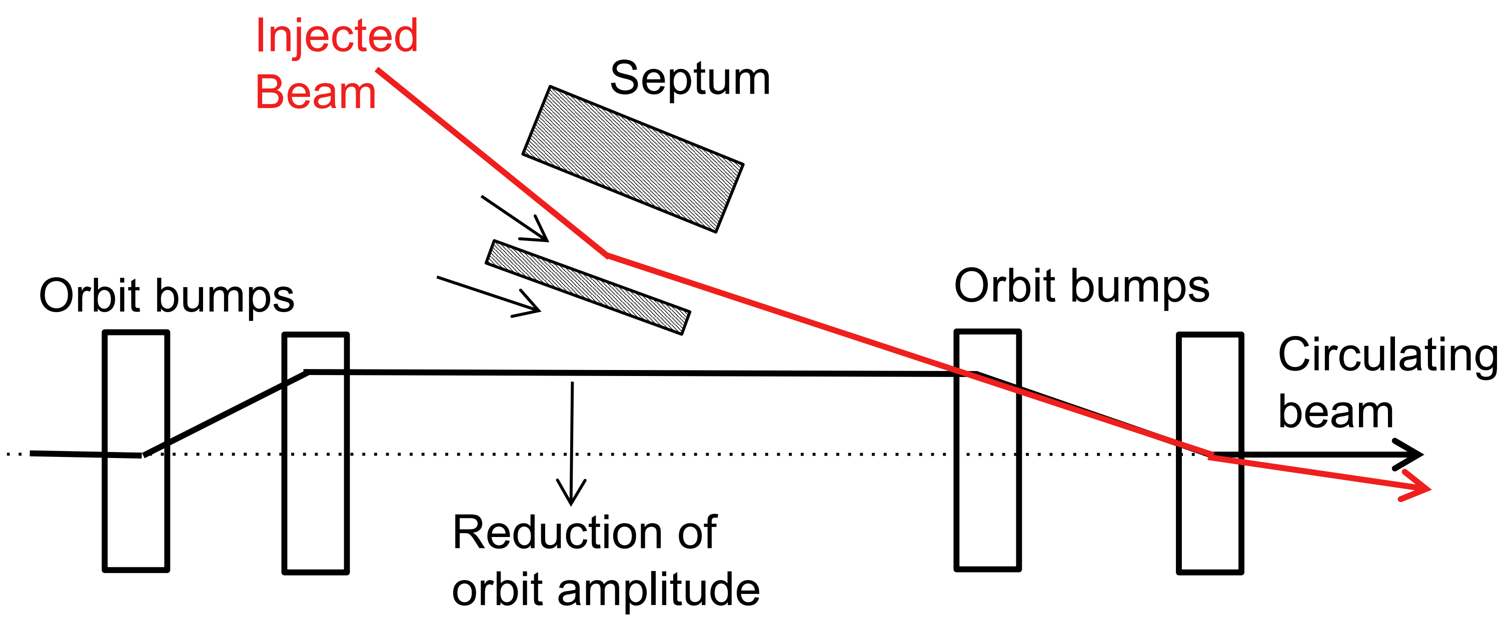
Heavy-ion synchrotron SIS18

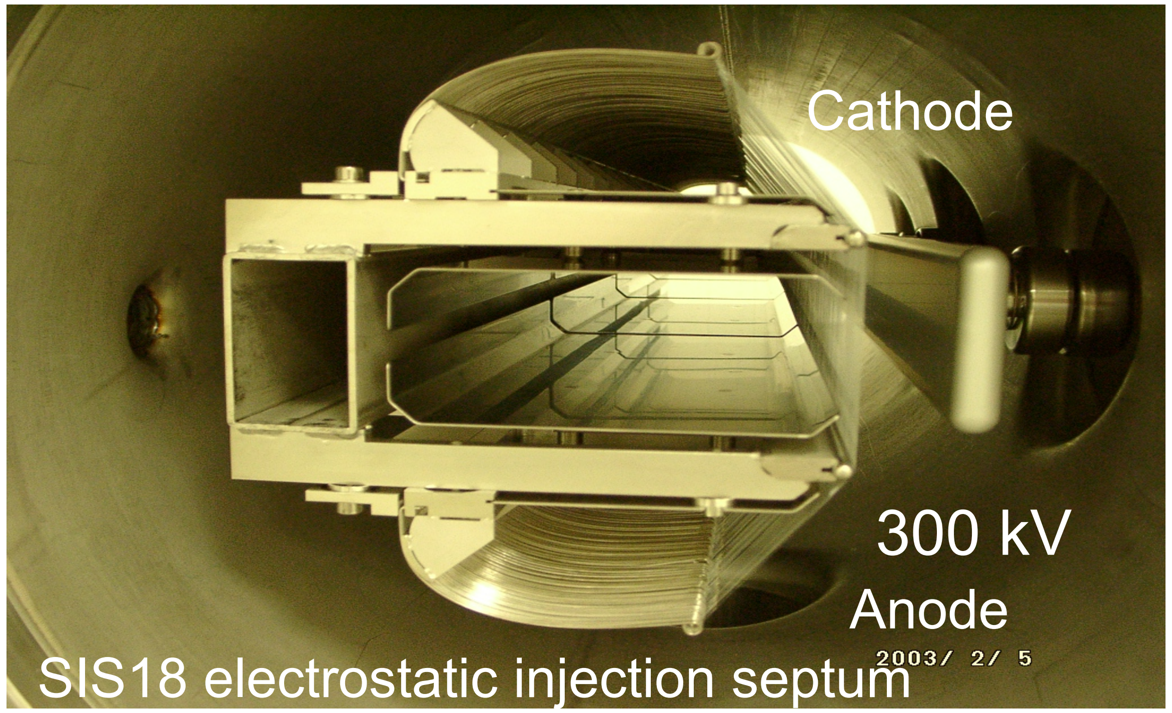


- SIS18 will serve as a booster for SIS100.
- MTI bottleneck to reach intense beams for FAIR.
- Loss-induced vacuum degradation is key intensity-limiting factor.
- Injector upgrade
  - pLINAC: New injector for protons.
  - UNILAC: Replacing of post-stripper section.
- GA optimization has been performed to define interface parameters.

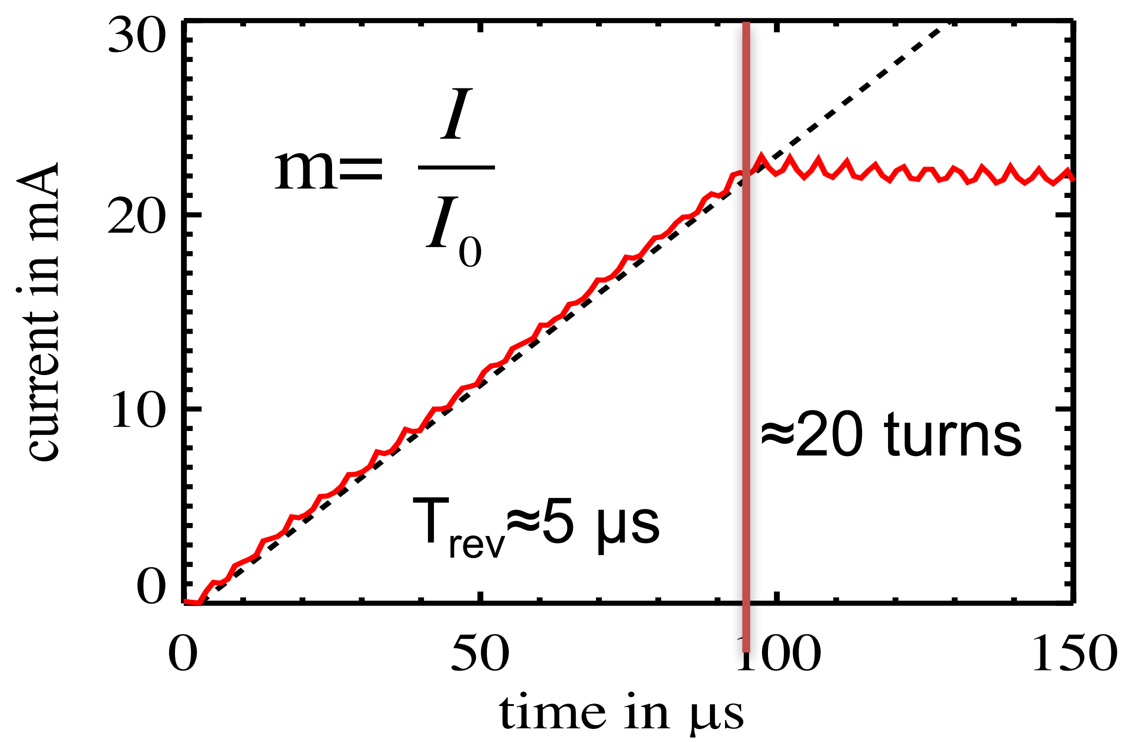
Model: Multi-turn injection

MTI has to respect Liouville's theorem:
Injected beams only in free space





Measured MTI performance in SIS18

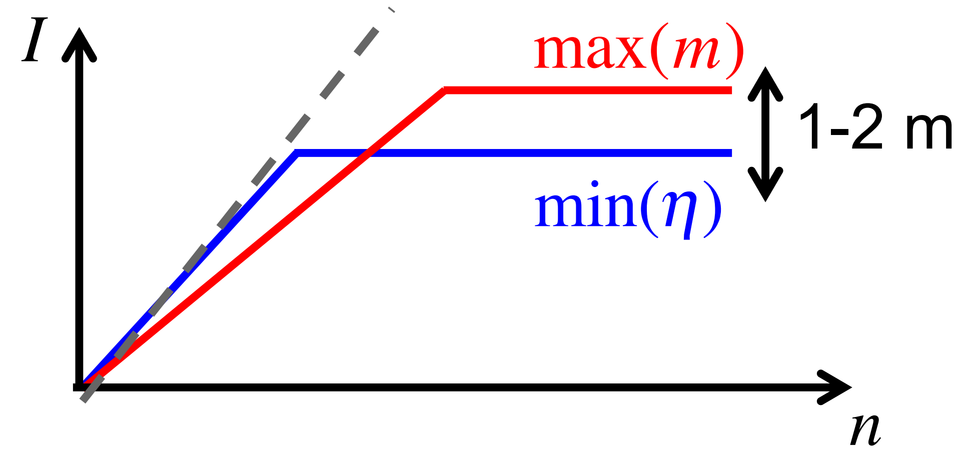


Gain factor should be high as possible $$m = \frac{I}{I_0}$$

Injection loss should be low as possible $$\eta = \frac{I_{loss}}{nI_0}$$

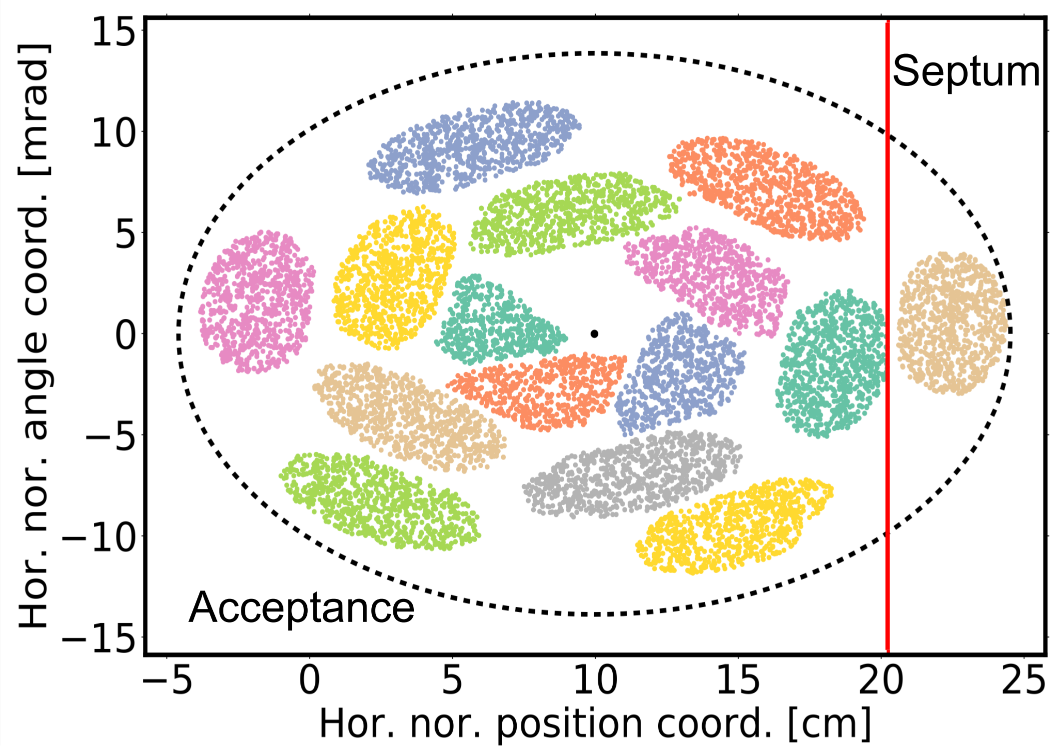
MTI into SIS18: Model

- **Multi-objectives:**
  - Gain factor (maximize) $I = mI_0$
  - Beam loss (minimize) $\eta = \frac{I_{loss}}{nI_0}$
  - Emittance ε_x



- **Constraints:**
  - Position of septum, machine acceptance

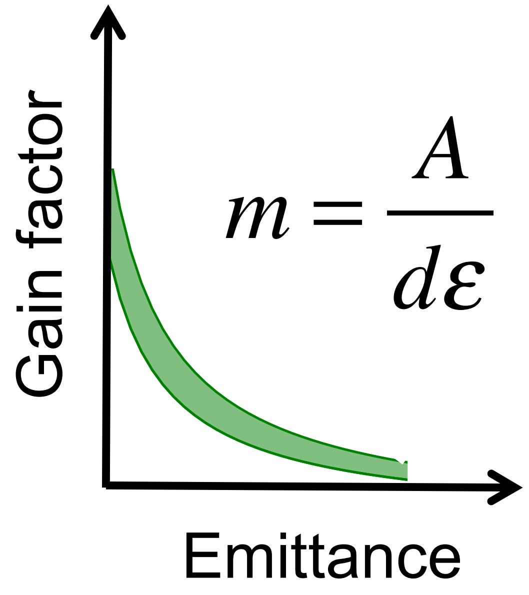
Model in simulation code



- **Parameters:**
  - Position of incoming beam at septum
  - Initial bump amplitude and its decreasing
  - Injected turns
  - Horizontal tune and emittance

Injector brilliance depending

EMittance Transfer EXperiment (EMTEX)[7]



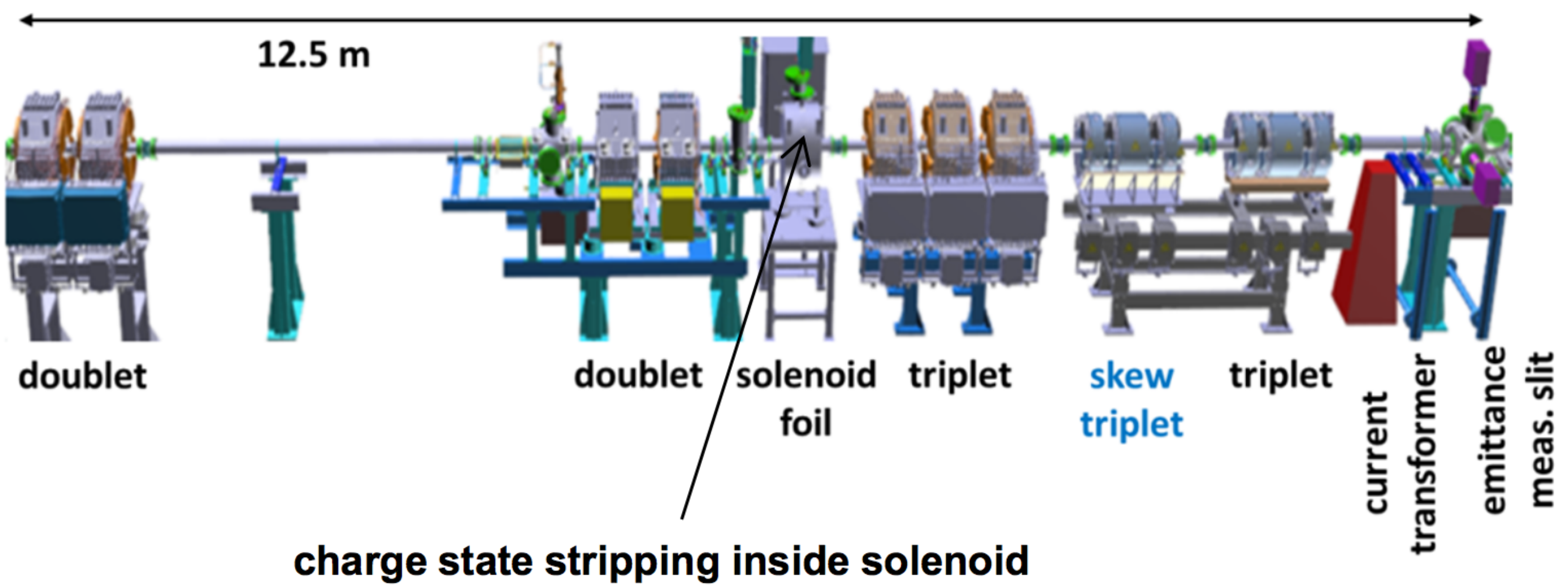
$$m = \frac{A}{d\varepsilon}$$

Re-partitioning of beam emittances increase efficiency

Beam flatness amount is controlled by solenoid field

Twiss-parameters are preserved

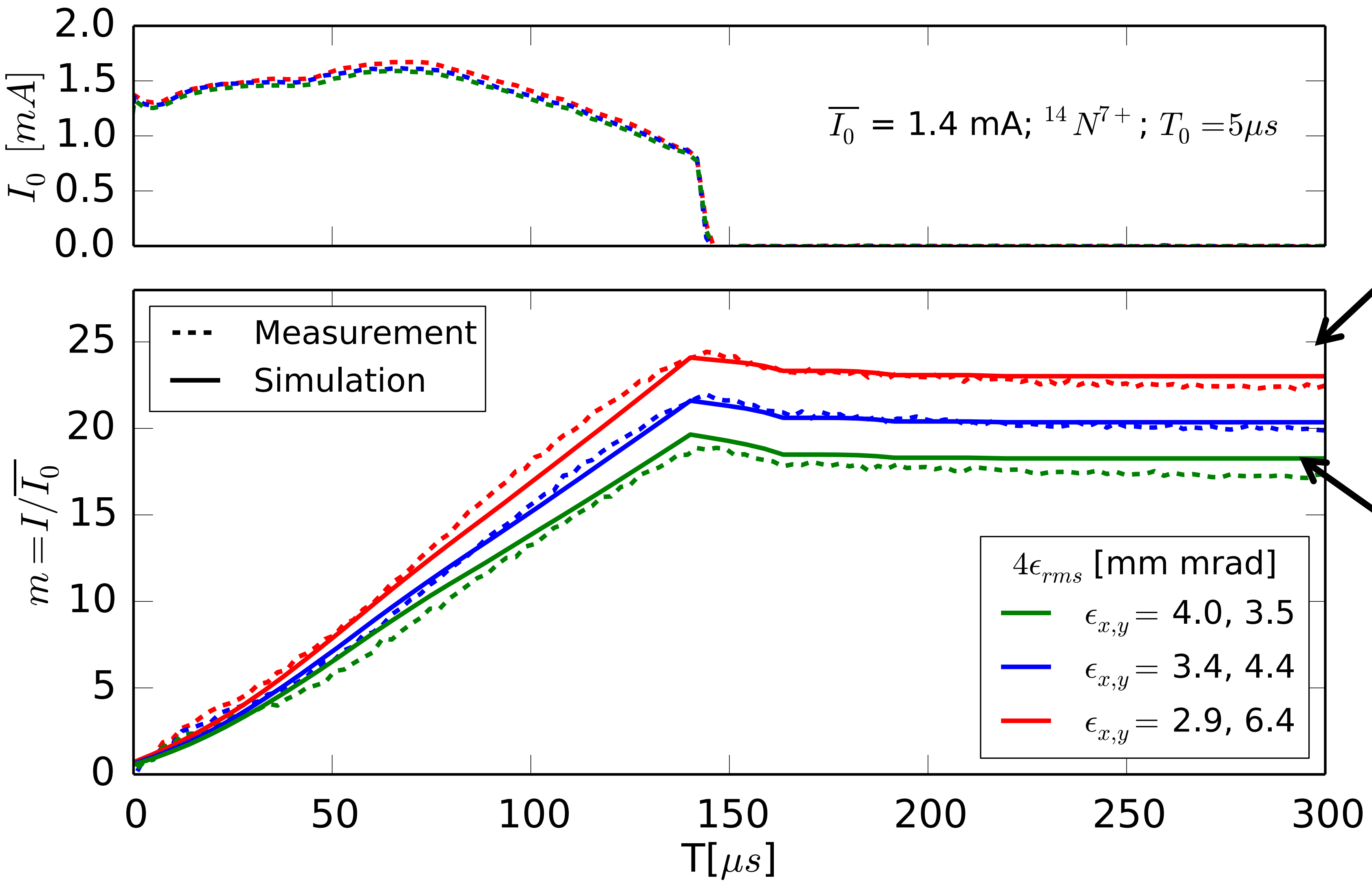
EMTEX Beam line

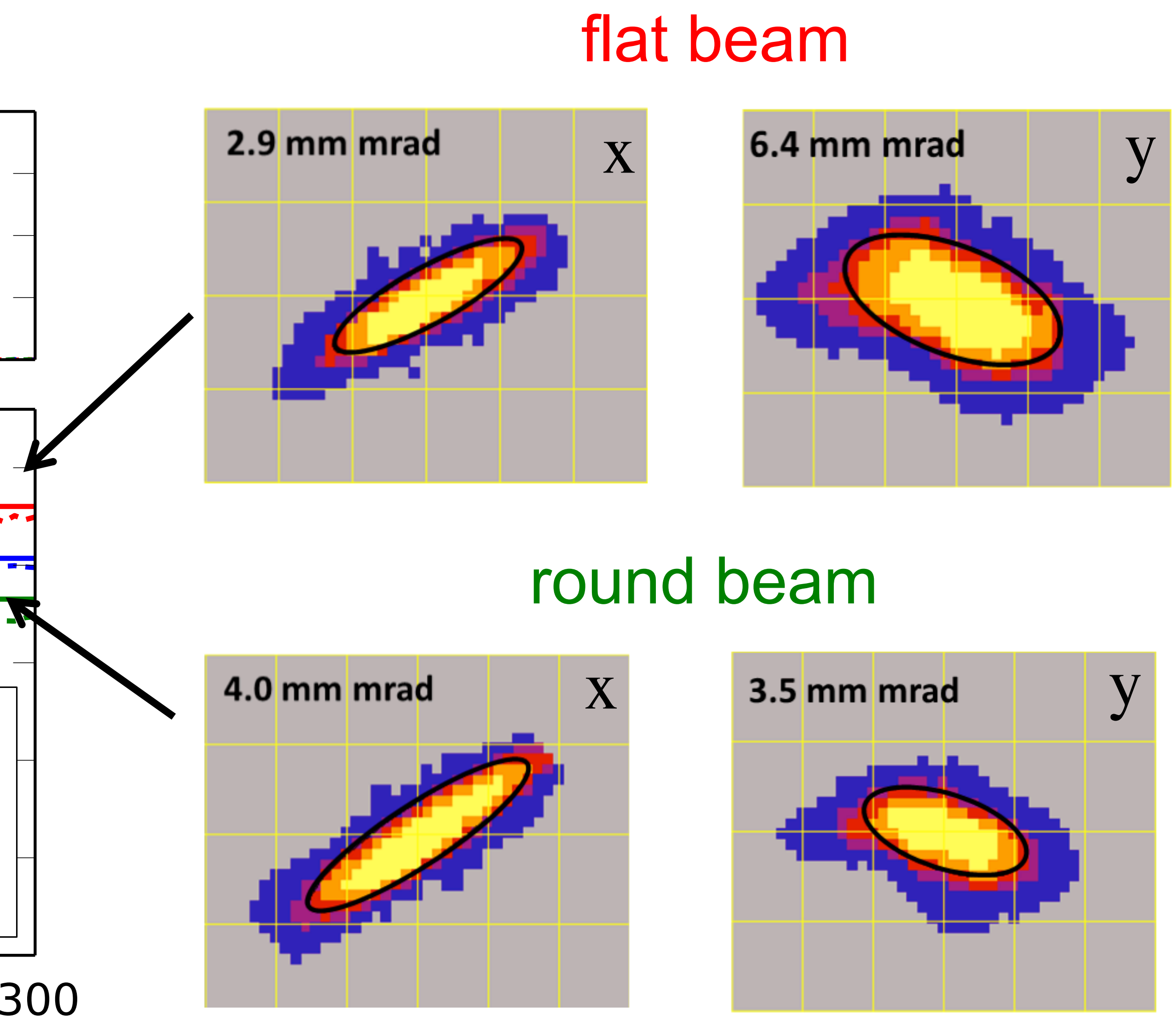


[7] L. Groening et al: Phys. Rev. Lett. 113 264802 (2014)

Implementation and validation

MTI has been implemented in pyorbit code [8]
MTI performance has been measured as a function of injector emittance [9].





Excellent agreement between simulation and measurement!

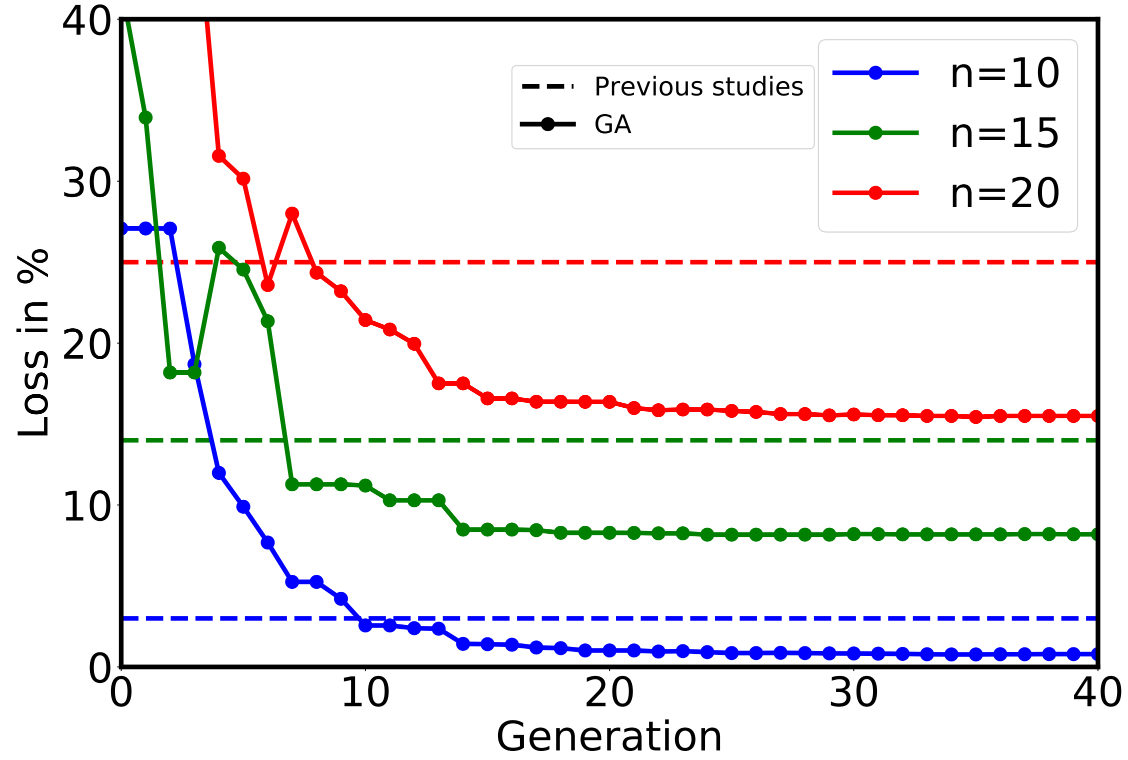
[8] https://github.com/PyORBIT-Collaboration, [9] S. Appel et al: Nucl. Instrum. Methods A 866 (2017), pp. 36-39,

Optimization results

Optimization of loss

Genetic algorithms can improve MTI.

Especially for longer injection GA discovers a much better solution.

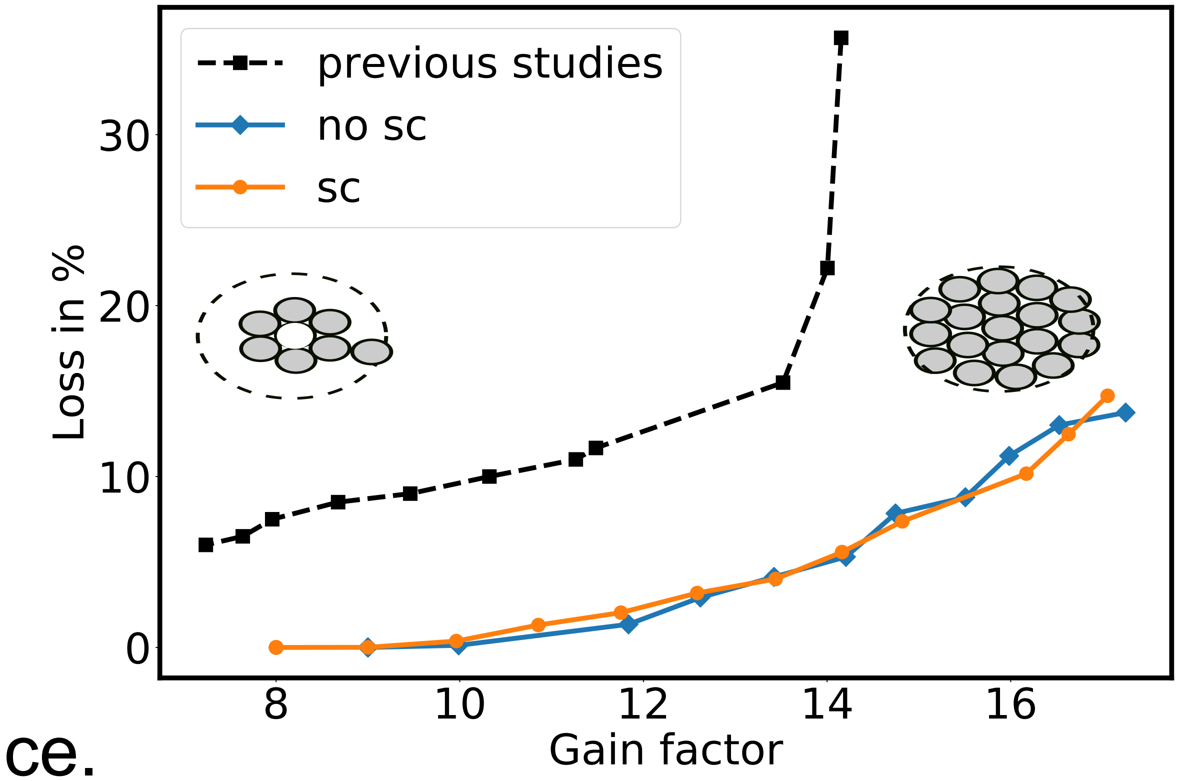


Optimization of loss and gain factor

Dependence of gain factor on loss.

Loss-free injection could be found.

Space charge results in a similar PA front, but with different injection settings.



MOPSA shown similar result with faster convergence.

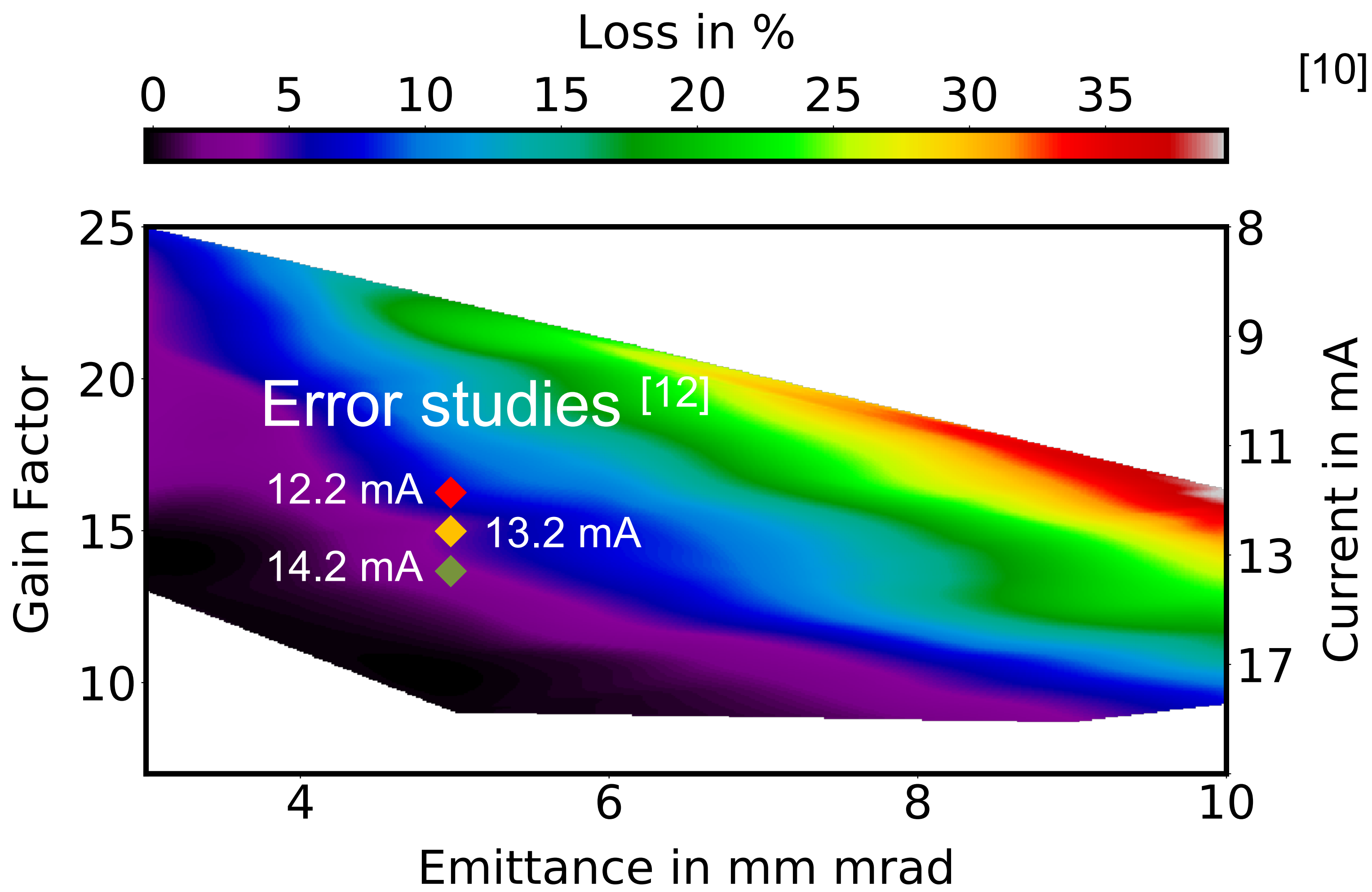
Optimization results

Optimization of loss, gain factor and beam emittance (injector)

Dependence of interface parameter

$$B = \frac{I}{\varepsilon} \qquad m(\eta) = \frac{N}{I} q f_0$$

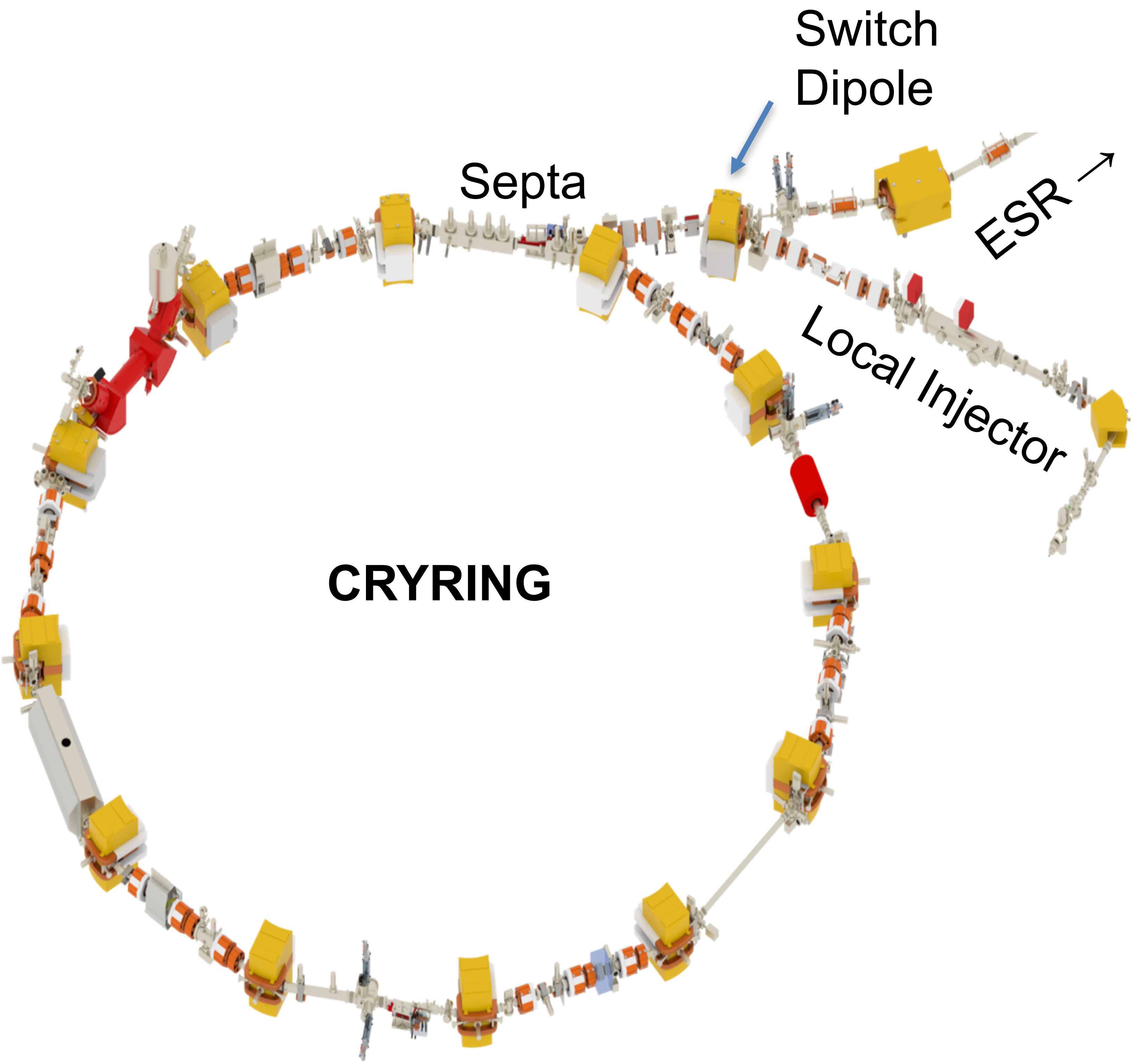
allows to define a frame, in which the required beam parameter can be matched at best.



→ 3D Pareto front for proton injector has generated also.
pLINAC: Relaxed situation, generous beam parameter margin [11]

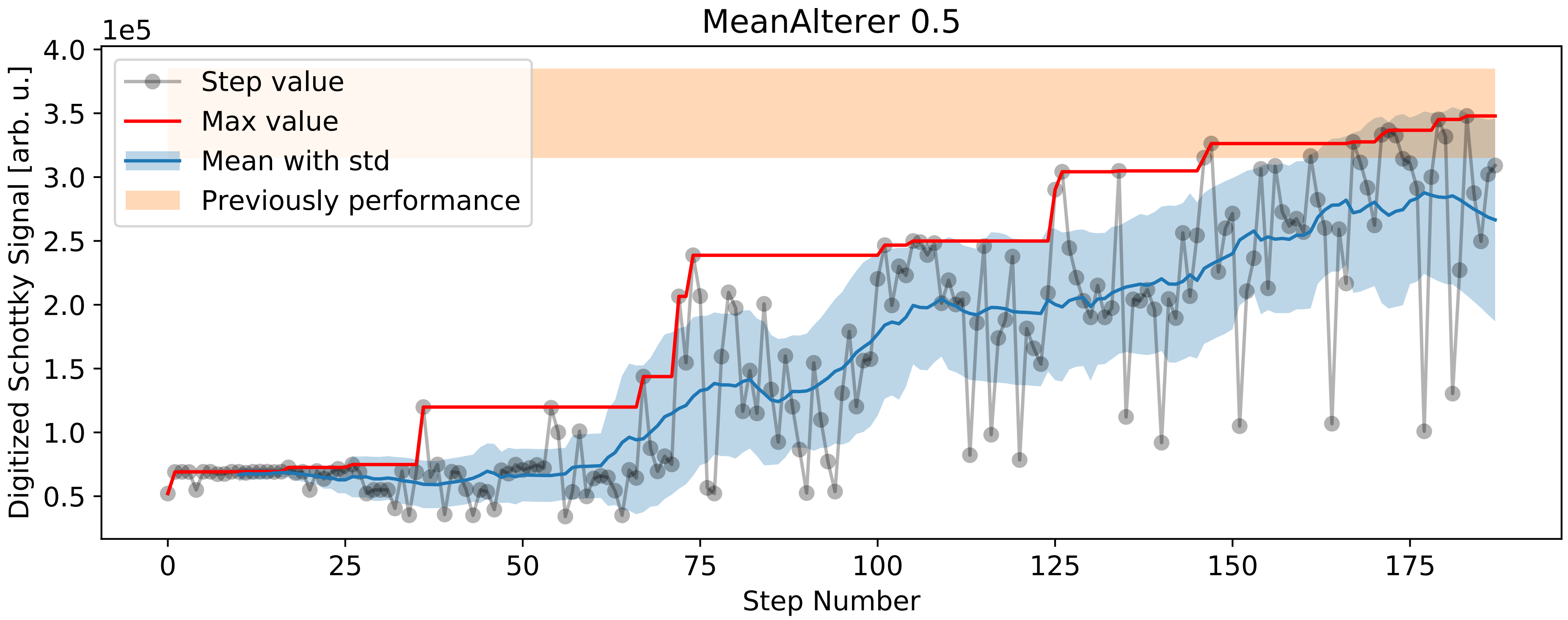
[10] S. Appel et al: Nucl. Instrum. Methods A 852 (2017), pp. 73-79
[11] C. Kleffner, LINAC2018, THPO046 (2018)
[12] A. Rubin, Beam dynamics design of the new FAIR post-stripper linac, GSI Accelerator Seminar, 14.05.17

CRYRING@ESR

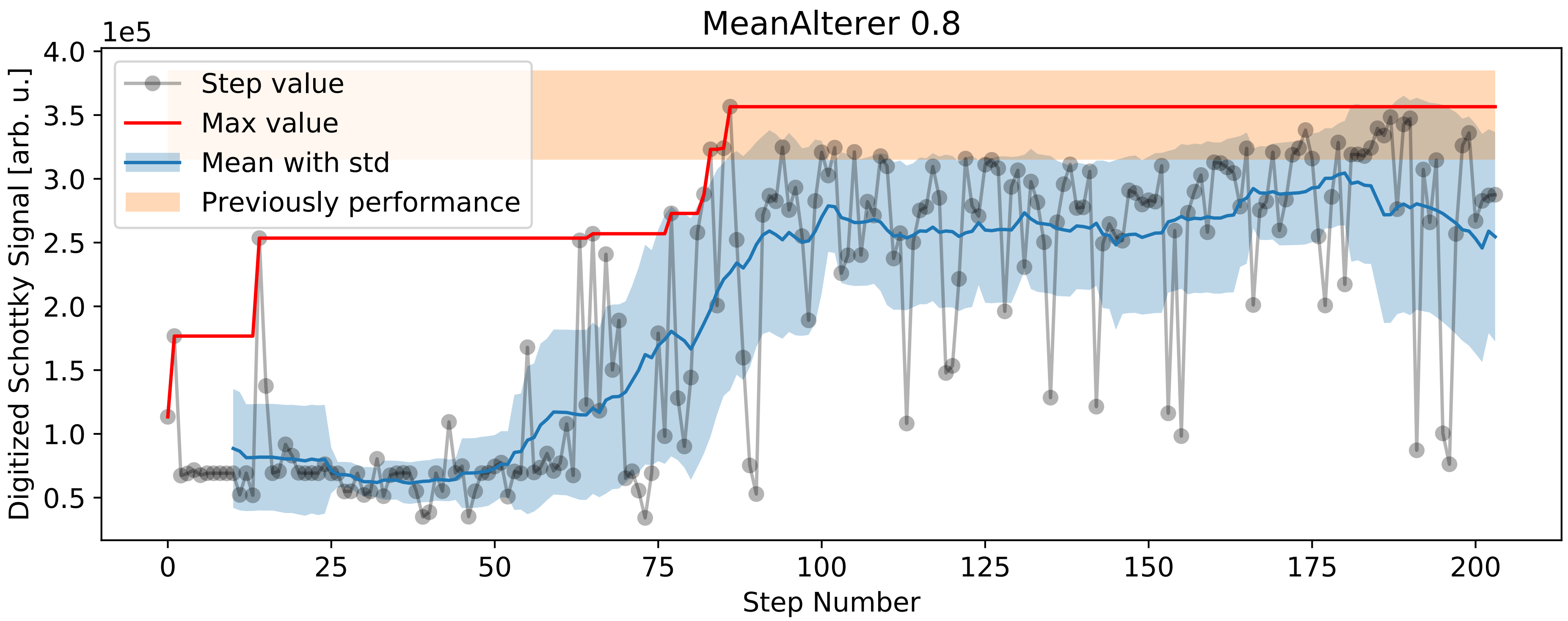


- Swedish in-kind contribution to FAIR
- CRYRING@ESR can be used stand-alone for testing novel technical developments.
- Control system is Java based.
- Jenetics end-user ready software library implementing an genetic algorithm in Java.
- Choice to use Jenetics was obvious although faster algorithm are known.

CRYRING@ESR: Online optimization



[13]



Large tournament size has been chosen to reach fast convergence.

~ 90 minutes

[13] S. Appel et al: Int. J. Mod. Phys. A. 34, 1942019, (2019)

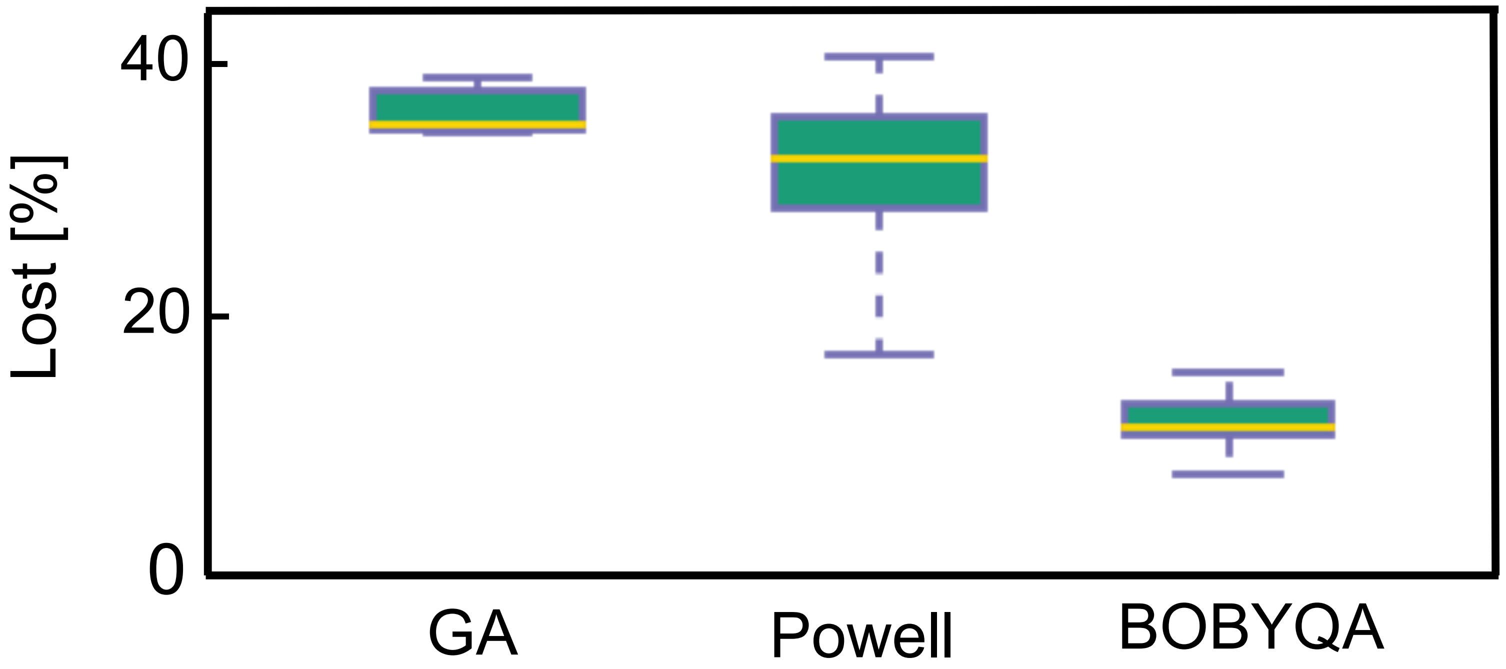
Optimization of beam lines

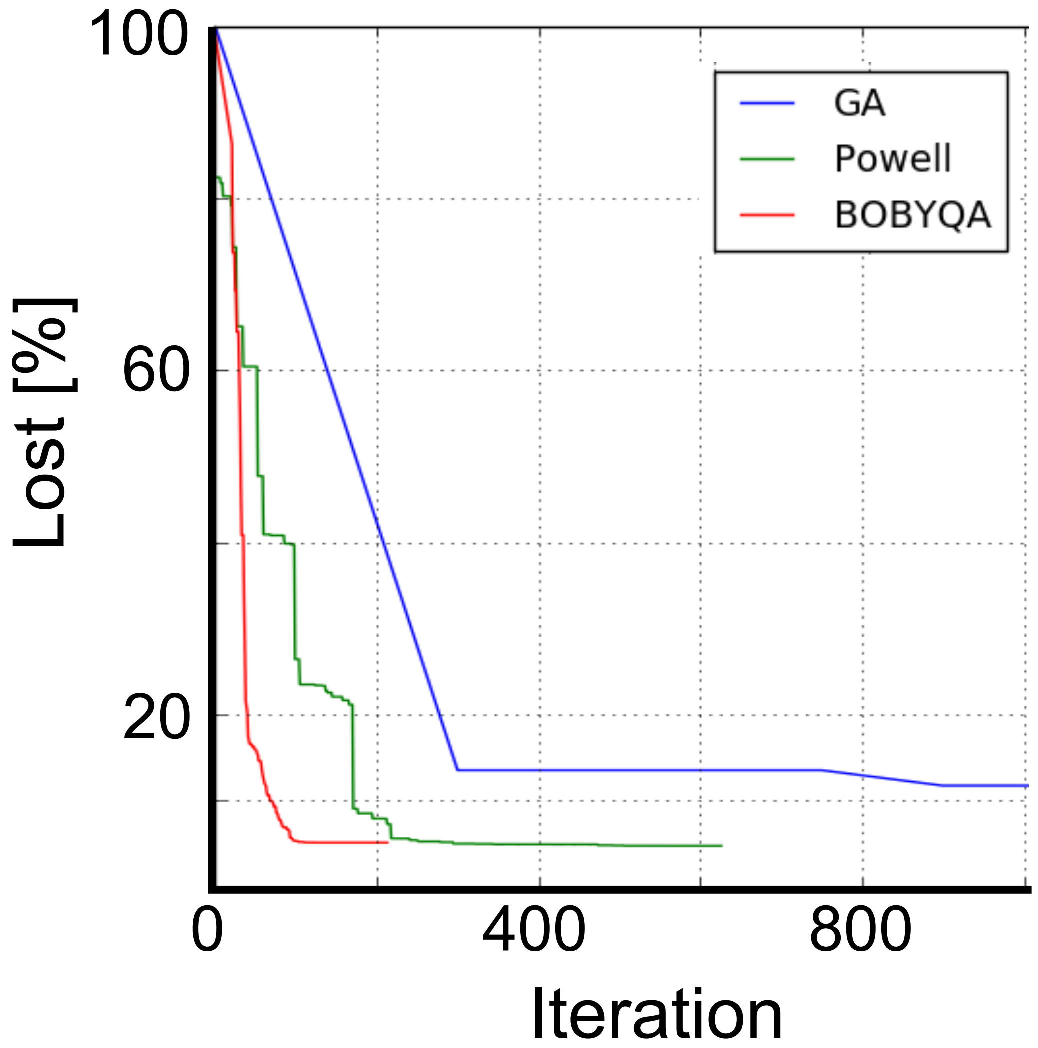
- Comparison between GA, Powell, BOBYQA for beam line optimization
- Optimization aim is to minimize beam loss

➤ BOBYQA is the fastest of the examined algorithms

Part of CRYRING@ESR Local Injector

Fix iteration (30 minutes)





[14] Bachelor-Thesis von Maike Wolf (2019)

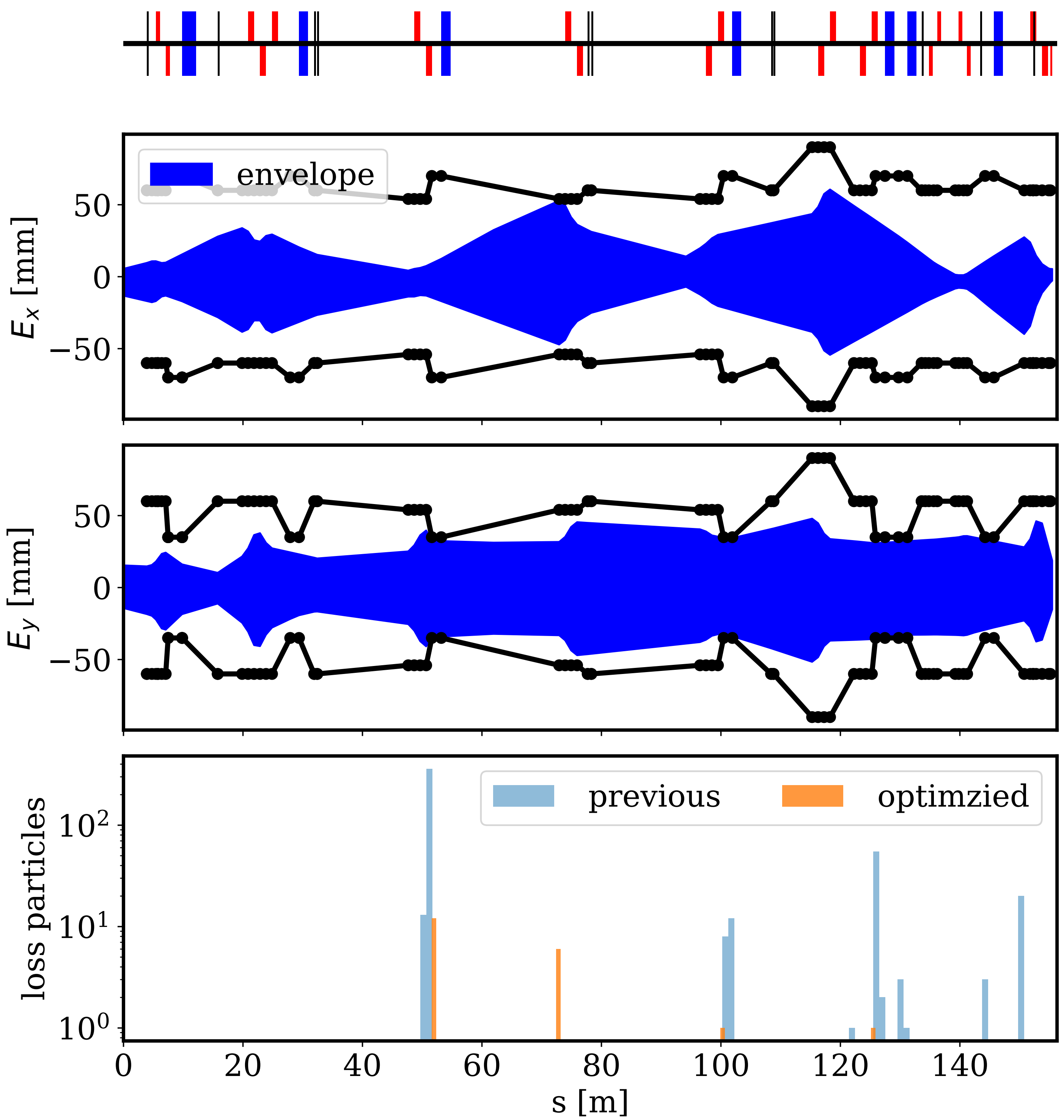
Optimization of beam lines

- Optimization aim is to minimize beam loss and reach simultaneous a small focused beam at the experiment target.
- Weighting factor approach is used for multi-objective reduction and the composite objective function is than optimized.

  loss, betaX, betaY = sis18 hades(..)
  comp_func = w1*loss + w2*betaX + w3*betaY

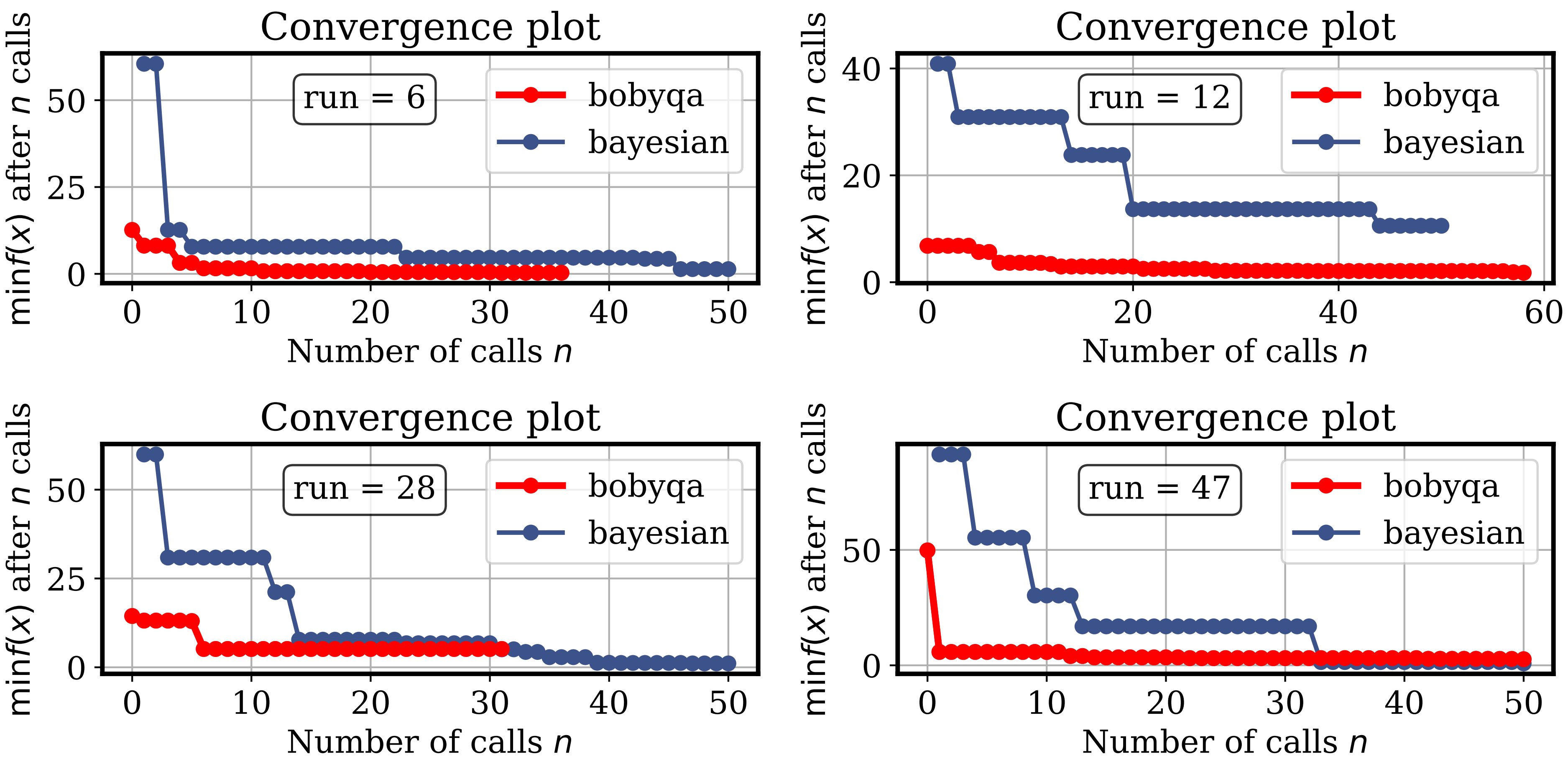
- Online algorithm needs to be aware of the noise like Py-BOBYQA[3] or RCDS[15].

HADES beam line

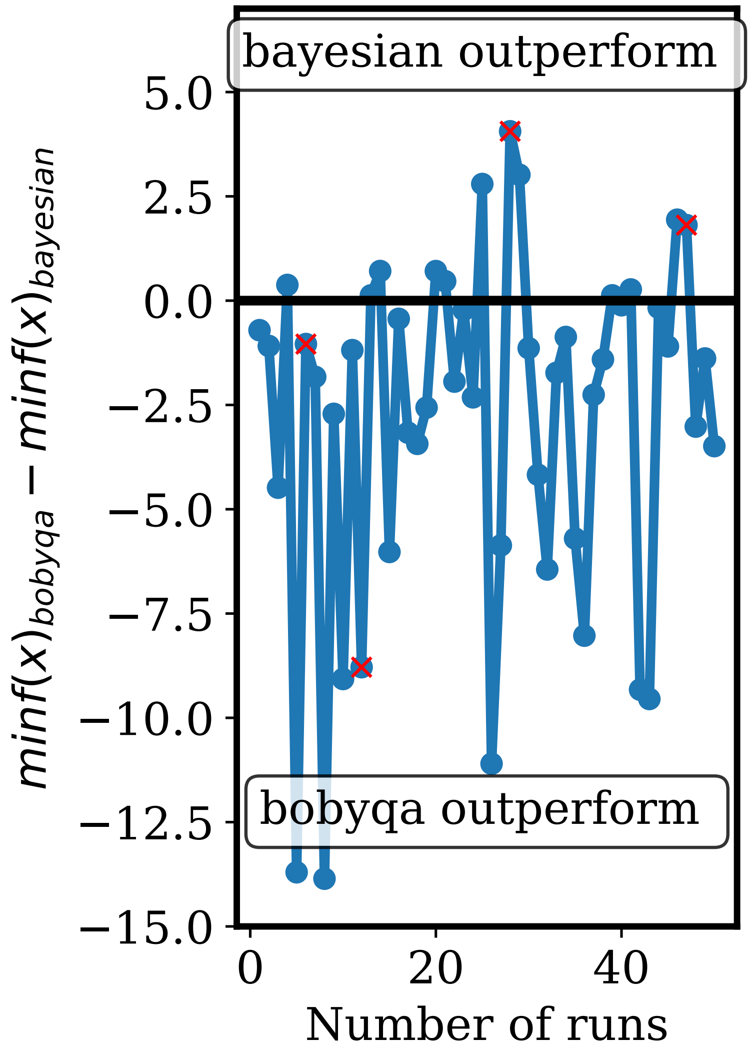


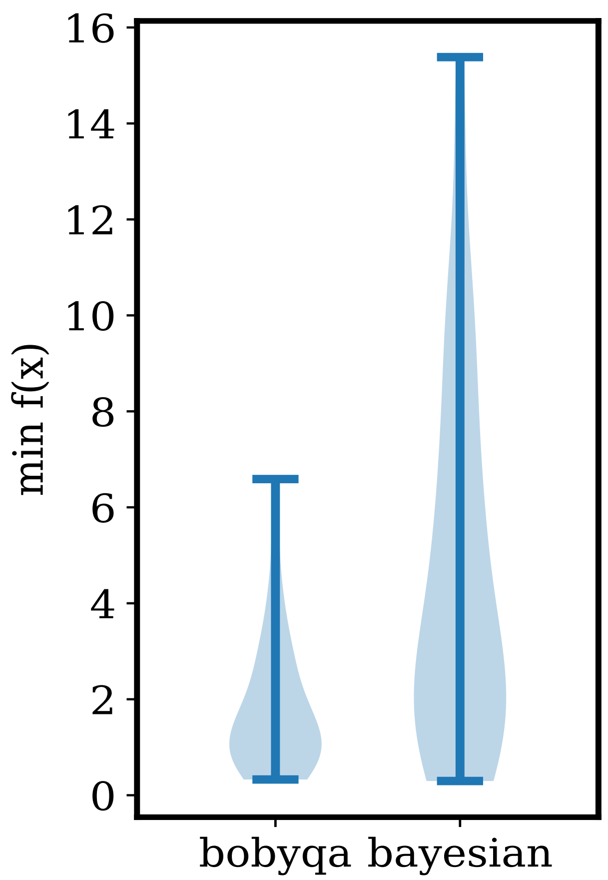
[15] X. Huang, Nucl. Instrum Methods A, 726, 77-83 (2013)

Optimization of beam lines



[17]





- The Bayesian Optimization[4] is often outperform by Py-BOBYQA [3], as good initial values are available.
- As next step, external boundary conditions has to be taken into account. Such an optimization problem prefer must likely the adaptive and safe Bayesian optimization[16].

[16] J. Kirschner et al., arXiv 1902.03229 (2019)
[17] S. Appel et al., J. Phys. Conf. Ser 1350 (2019) 012104

Summary

- **Derivative-free optimization**
  - Multi-object optimization: Identification of injector brilliance range.
  - Reach after ~1.5 hours of online optimization time previous transmission.
  - Deterministic methods (BOBYQA) typically require fewer executions than non-deterministic procedures, if good initial values are available.

- **Outlook: Machine Learning**
  - Reinforcement learning including transfer learning should be applied for the optimization of beam injection as well as beam line
  - In cooperation with COSY

Thank you for your attention