ML/AI for GSI-FAIR accelerators

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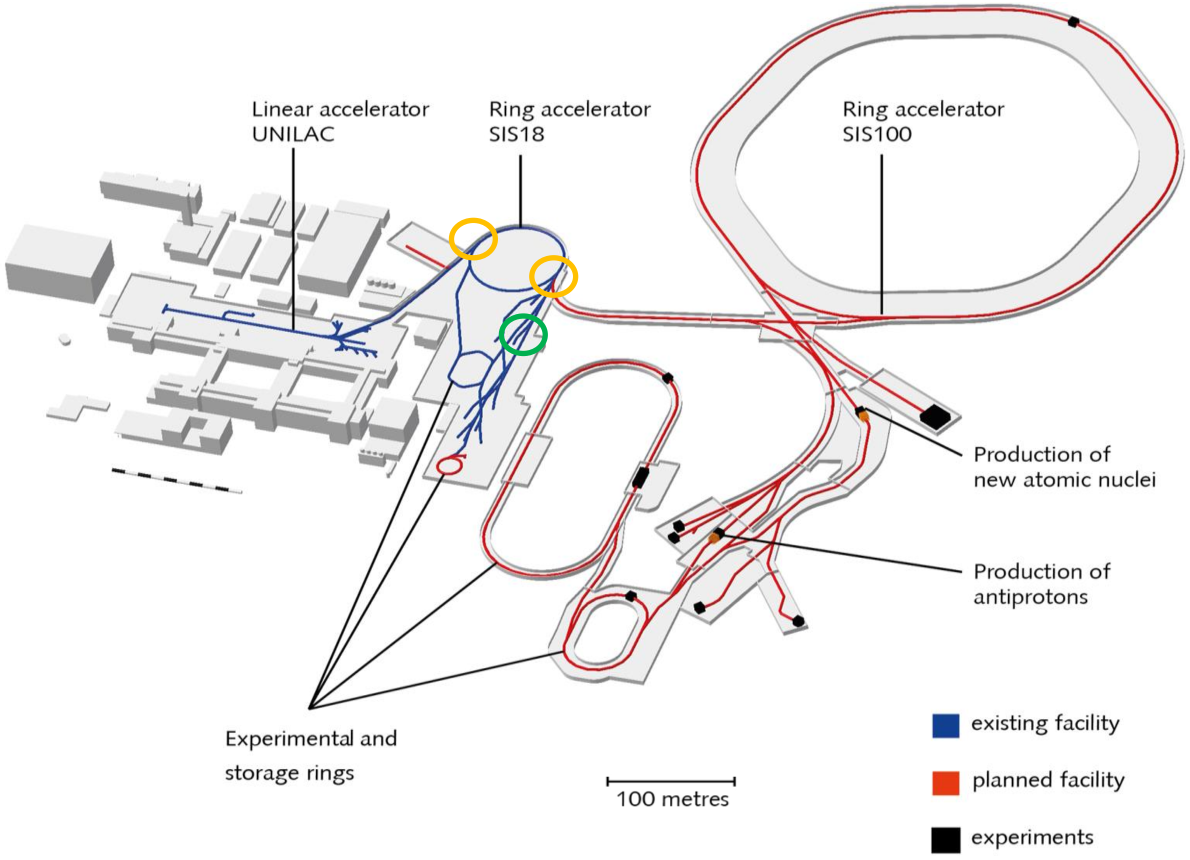
FAIR/GSI

Automation and optimization with Python:

- Multi-turn injection loss minimization (SIS18)
- Beam steering (TK)
- Closed-orbit correction for non-standard optics (SIS18)
- Slow extraction loss minimization (SIS18)
- Beam steering and focusing (FRS)



Methods of interests of automation:

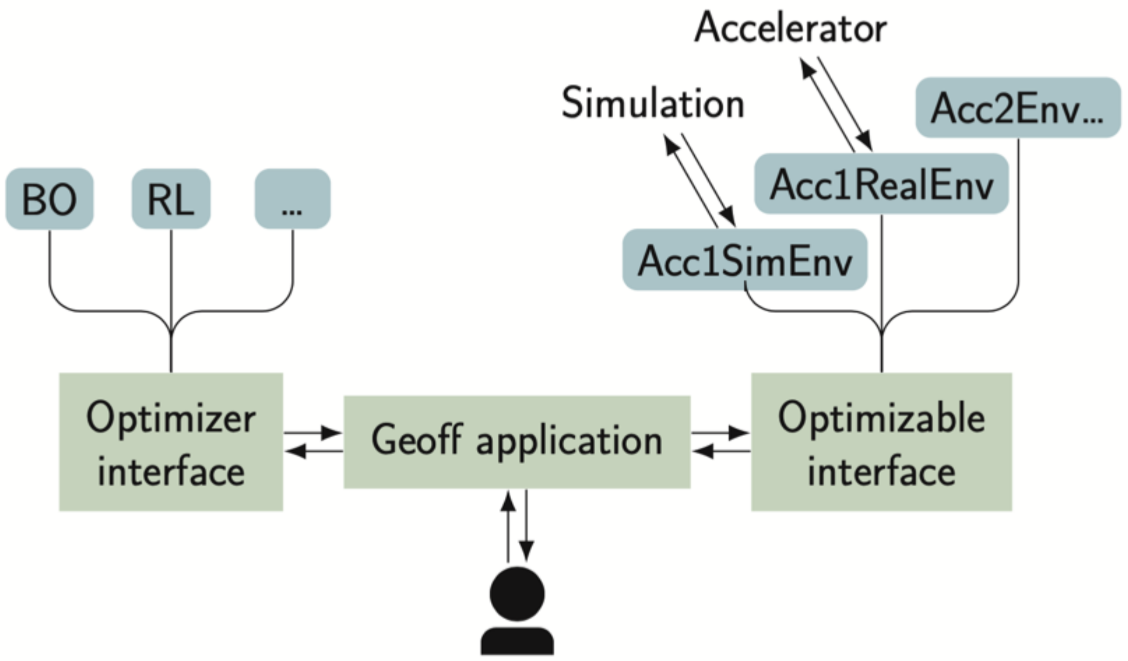
- BOBYQA + Bayesian optimization (BO)
- Physics-information Bayesian optimization
- Multi-objective optimization with BO
- Data-driven model predictive control
- Reinforcement learning

- EURO-LABS finances a scientific staff member for three years (in APH)
- Several TUDa master and PhD students (with TUDa funding)
- One master student from Paris Lodron Universität Salzburg

GeOFF at GSI

GeOFF (Generic Optimization Frontend & Framework) is a widely used framework for deploying automation at CERN

- Python-based framework
- lists, configures and runs optimization problems
- standardized interfaces and adapters for various packages via Common Optimization Interfaces
- Optimization problems formulated as classes
- Class contains logic for live plotting, data logging, and communication with LSA, FESA and the Device Access system
- Quick adaptation of code and on-the-fly during shifts: This is made easy due to flexibility of the framework.



GeOFF Development/Distribution/Maintenance (N. Madysa, APH, EU funded)

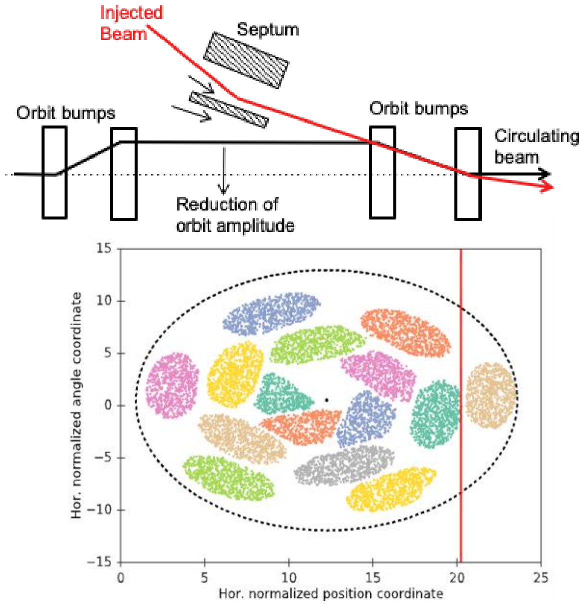
Automation of Multi-Turn Injection

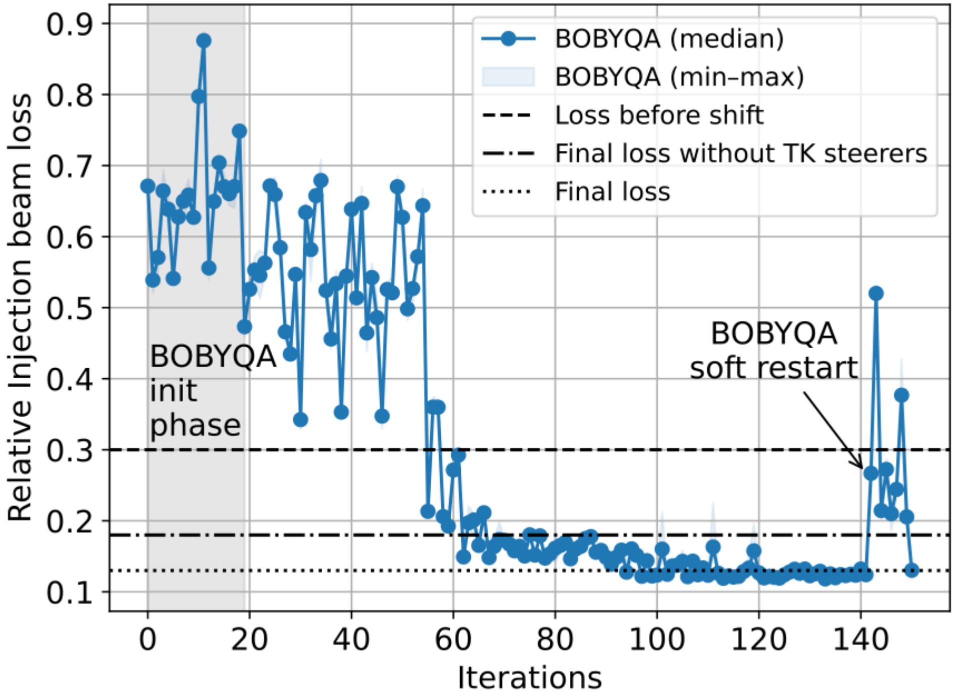
- Usually, MTI is optimized **manually,** with varying success
- Using nine optimization parameters.

Multiturn Injection

Bumper ramp down time	1	110	µs
Bumper amplitude	2	)610443115234	mm
Unilac Offset		100	µs
Chopper delay	3	50	µs
Chopper window		60.0	µs
Chopper correction angle		0.0	mrad
GTK7MU5 correction angle		0.0	mrad
GS12MU3I correction angle	4	-0.07552774331	mrad
I-Septum correction angle	5	-0.44575636275	mrad

+ 4 TK Steers





- 150 iterations required, which took about 30 minutes.
- 1 iteration = median of 3 evaluations (to reduce variance)
- gray area = initialization phase of algorithm.
- Loss could be reduced from 30 % to 12 %.

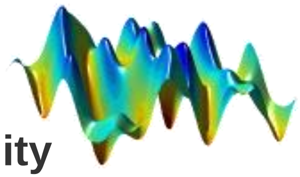
(correction of loss calculation to earlier publications)

✓ successful use of BOBYQA

– algorithm's internal model not reusable

Automatization of FRS & Super-FRS: sub-goals

Why?
- Manual setup is too time consuming
- Increased complexity: different experiments will demand many different optical modes
- Scaling for same optics but different Brho not accurate enough



Preparation:
- FRS simulation model in **COSY Infinity**
- optimization and data analysis in Python

Observables:
- Histograms from current grid detectors / phase space spectra from tracking detectors

Device—Interface:
- LSA (trim steerers + magnets),
- FESA (SIS18 monitoring),
- Experiment instrumentation (TPC via Go4 server, current grids)

Goals of optimization loops:
- 0th order: **center the beam** – vertical steerers, main dipoles (Brho scaling for particular case matter calibration)
- 1st order: **set focus**, dispersion - quadrupoles
- 2nd order: **minimize aberrations** - sextupoles
- 3rd order: **minimize aberrations** – octupoles (S-FRS only)

<u>Classification</u>
(simulation with disabled sextupoles)

Daniel Kallendorf, Master's thesis

-> Team work of Martin + Nico and more

Optimization of separator optics with primary beam

Individual particle tracking detectors + charge states:
-> Lots of information from x-x' spectra at dispersive focal plane

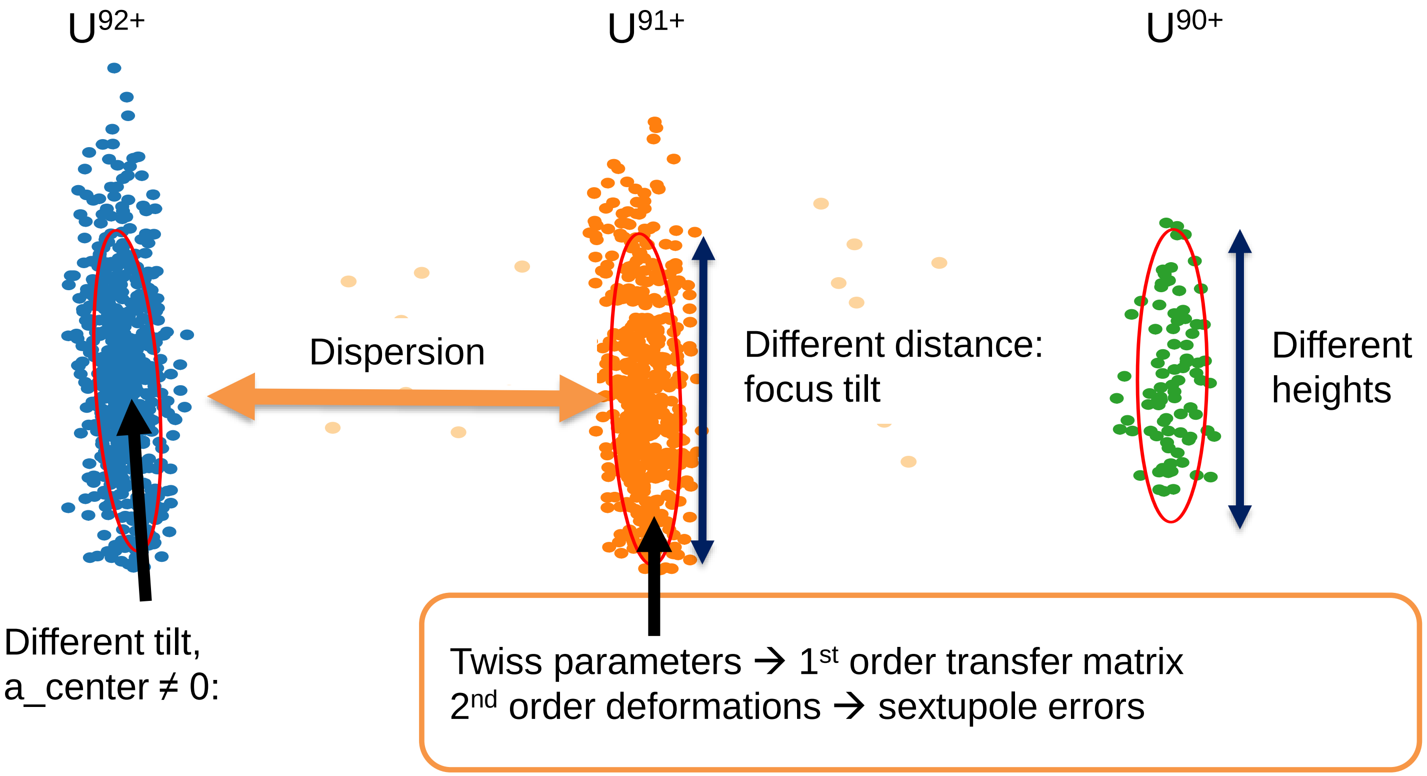
- **Central spot:**
  - x-Twiss parameters
  - Non-dispersive 1st order x-transfer matrix
- **Charge states after target (outer spots):**
  - Dispersive transfer matrix elements of 1st and 2nd order

Goal: Bring the spectra as close as possible to desired 1st order parameters

- Using charge states = more deduced optical properties

! Optimize direct observables instead of individual matrix elements

TPC Data analysis



FRS 1st order: tune quadrupoles

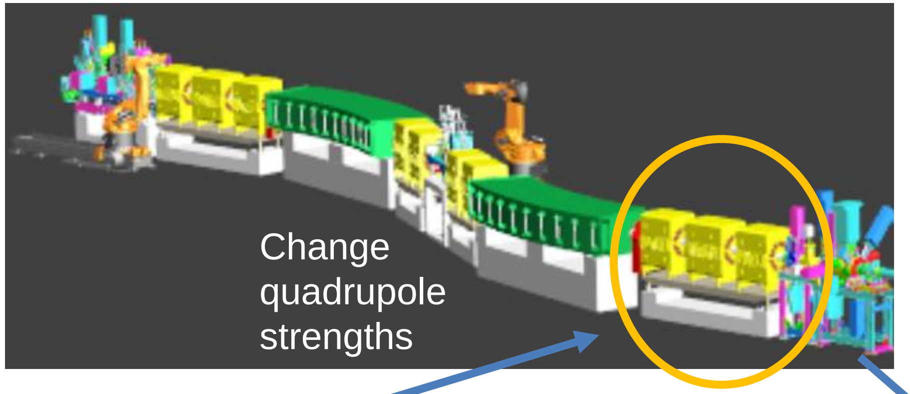
Proof of principle:

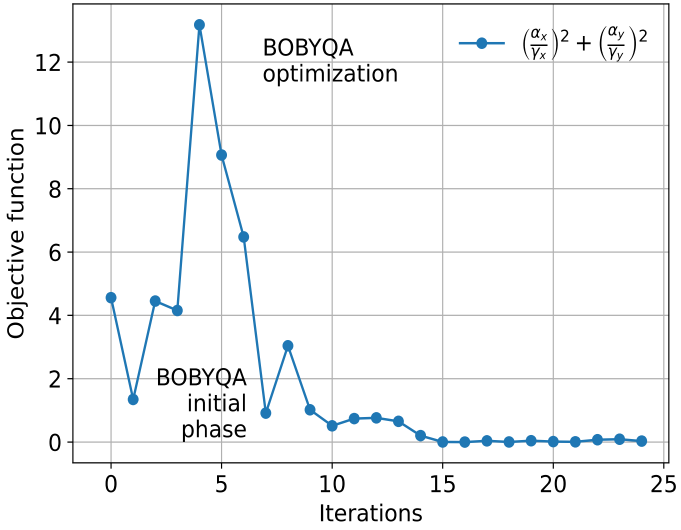
1. **Steer beams** at the target
2. **Tune quadrupoles** to focus the beam (central spot upright)
3. **Tune sextupoles** to remove focal plane tilt and “banana”-deformation

Next step:

- Use other observables to tune the entire 1st order optics (including dispersion)

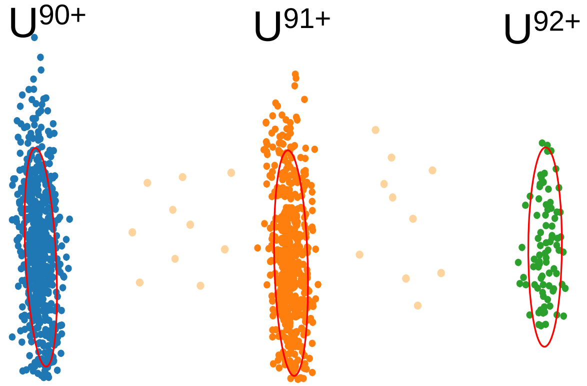
Schematic illustration of FRS Dispersive Focus area





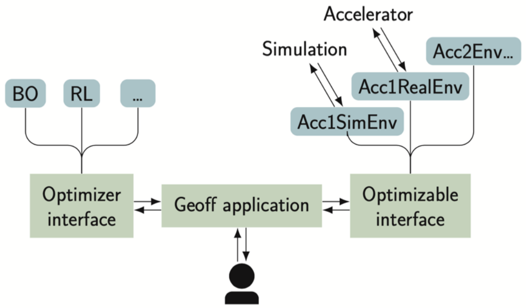
TPC Data analysis

Evaluation of beam spot slope



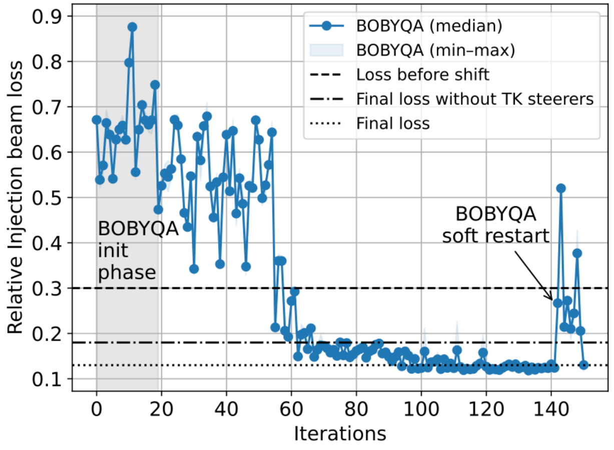
Outlook

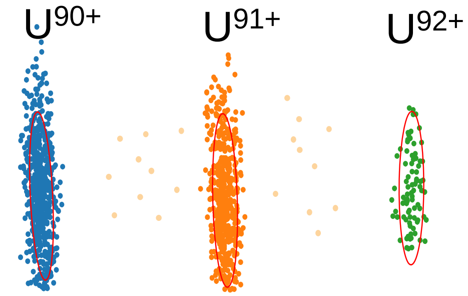
- Towards more comprehensive accelerator models (with the most relevant parameters)
- Optimization of total SIS production cycles (performance on target)
- Control room integration of GeOFF GUI at GSI
- Working group for automated optimization of GSI machines is being formed right now (ask Sabrina for details)



- More advanced ML algorithms, adaptation to GSI
  - student-driven, examples:
    - physics-informed BO
    - data-driven Model Predictive Control

Presented results

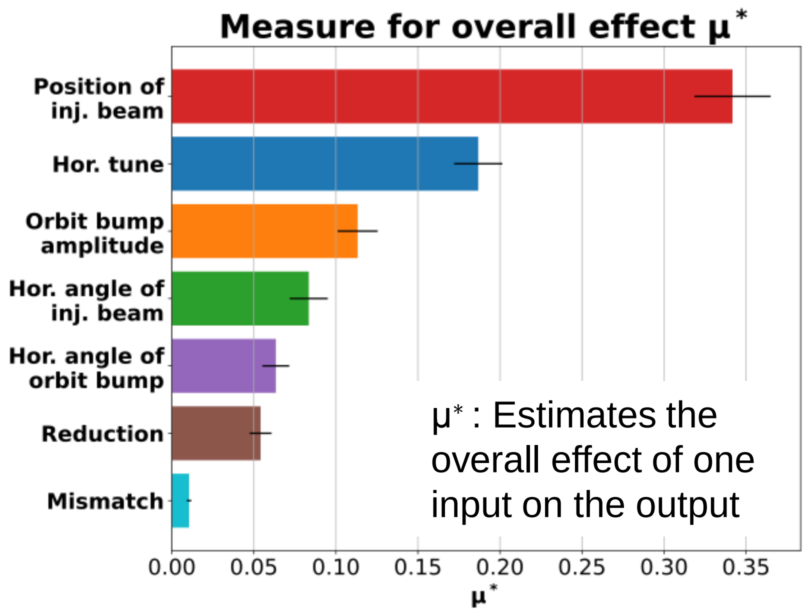


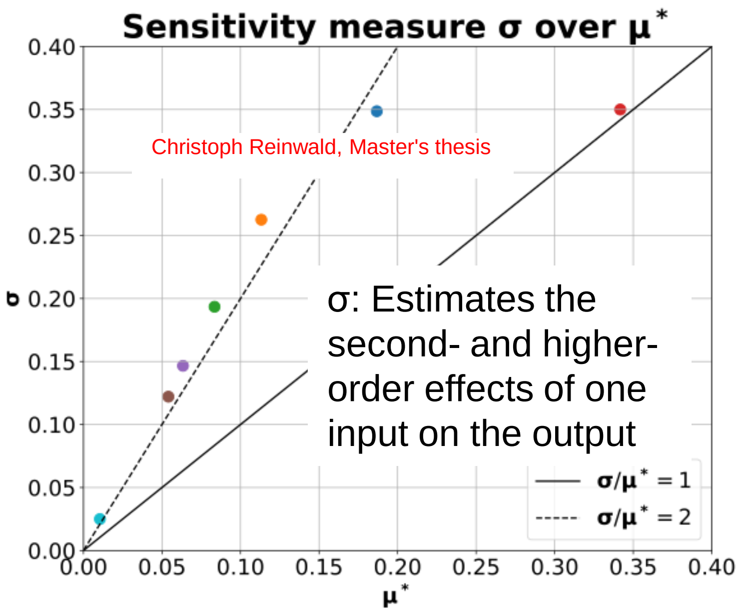


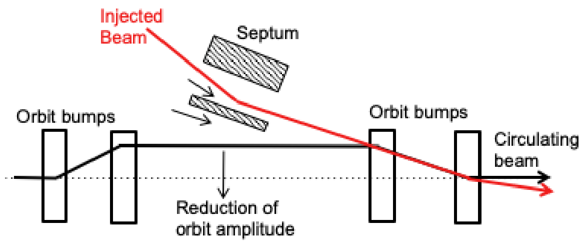
- **EURO-LABS**: generalization + maintenance
  - Prove portability of GeOFF through use at GANIL
  - continued collaboration with CERN on upgrades

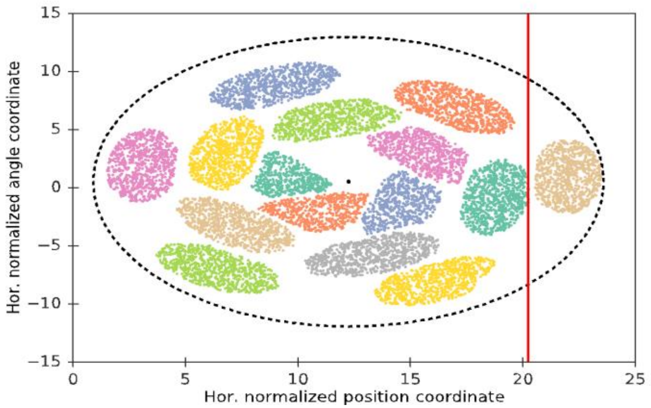
Multi-Turn-Injection into SIS18

- MTI has to respect Liouville's theorem: Injected beams only in free space
- Gain factor should be as high as possible to reach the space charge limit
- Injection loss should be as low as possible to avoid loss-induced vacuum degradation
- Competing goals: Maximize number of injection and minimize loss
- MTI model has been implemented in Xsuite[1] for fast tracking







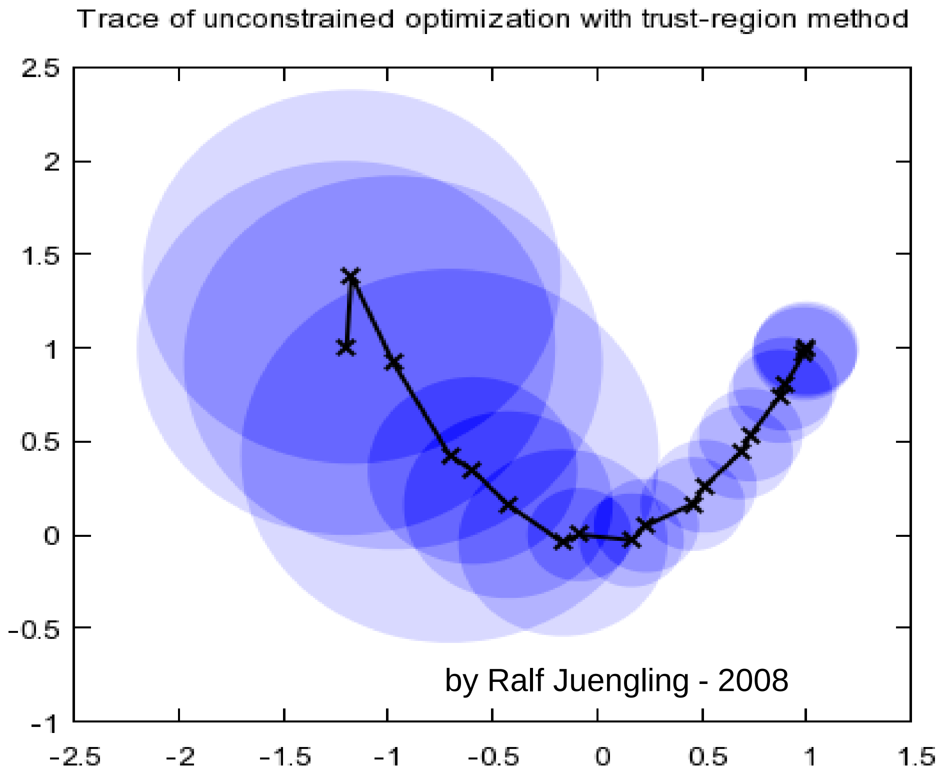


- Especially important: Injected beam position and tune!
- Higher order dynamics for all parameters according to the ratio σ/μ^*

[1]https://xsuite.readthedocs.io/en/latest/

Bound Optimization BY Quadratic Approximation

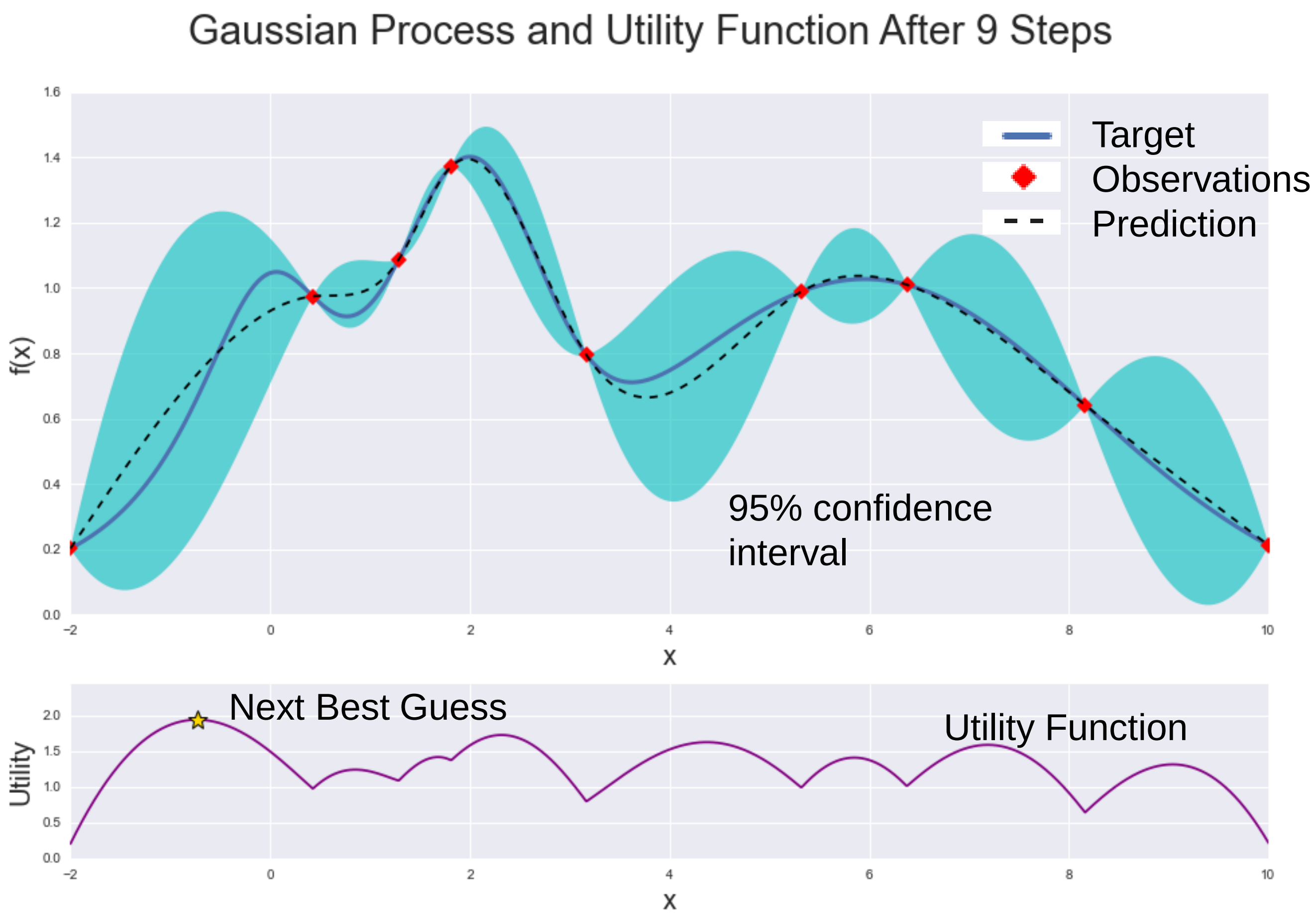
- Developed by Michael J. D. Powell in 2009.
- sequential trust–region algorithm
- quadratic approximations of objective function [1]
- Updates to the model and trust radius on each iteration.
- Py-BOBYQA[2]: adds global optimization and robustness against noise



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

Bayesian optimization

- Constructs probabilistic model of objective
- **Gaussian process** prior express assumption about objective function (mean function)
- **Kernel function** k(x, x′) describes correlation in phase space
- **Acquisition function** use model to decide where to evaluate function next
- Choice of kernel and acquisition function **essential**
- Extension: Multi-objective Bayesian optimization
  (https://ax.dev/tutorials/multiobjective_optimization.html)



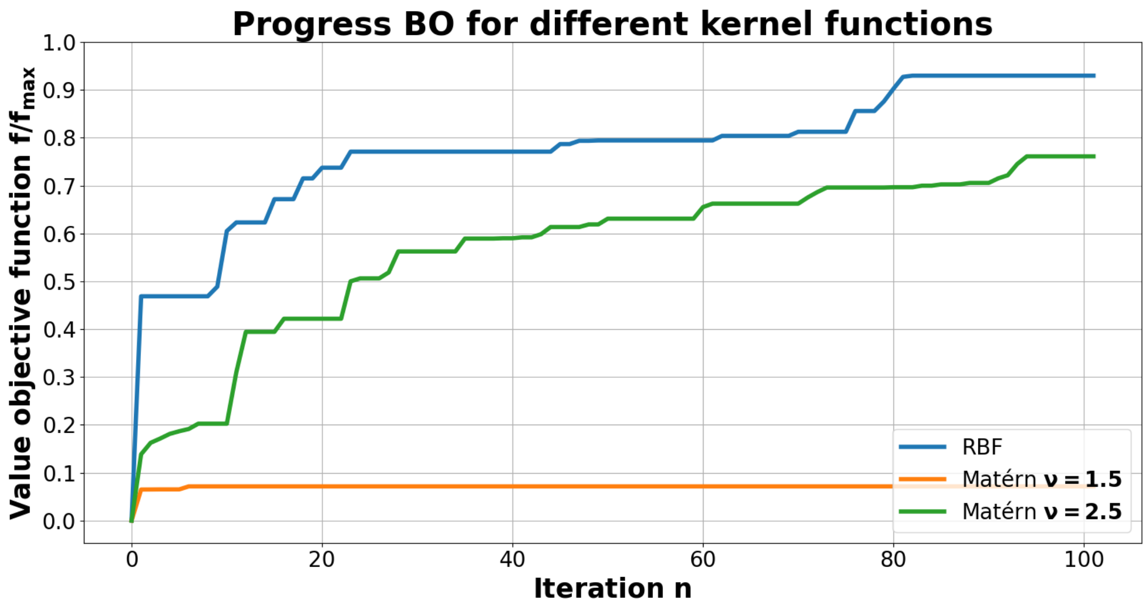
BO - Different kernel functions

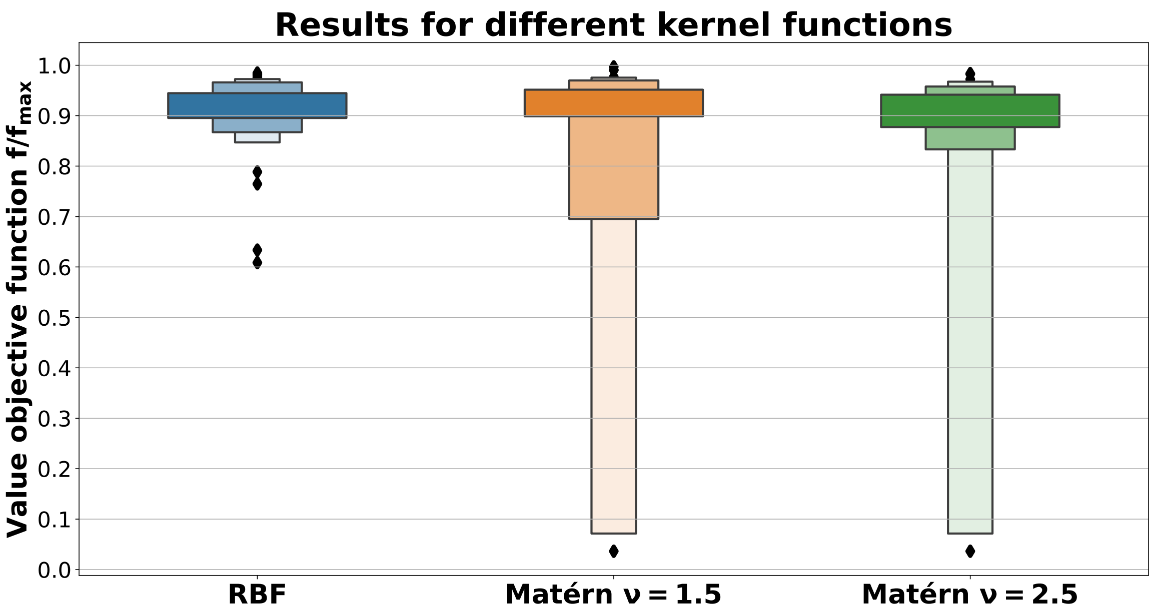
Christoph Reinwald, Master's thesis

- Radial basis function kernel (RBF), with standard parameter $K(\mathbf{x},\mathbf{x}') = \exp\left(-\frac{\|\mathbf{x}-\mathbf{x}'\|^2}{2\sigma^2}\right)$
- and Matern kernel $C_\nu(d) = \sigma^2 \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\sqrt{2\nu}\frac{d}{\rho}\right)^\nu K_\nu\left(\sqrt{2\nu}\frac{d}{\rho}\right),$

f_{max} = Loss-free injection (ideal current)

➢ RBF: Smaller mean as Matern kernel, overall it is better



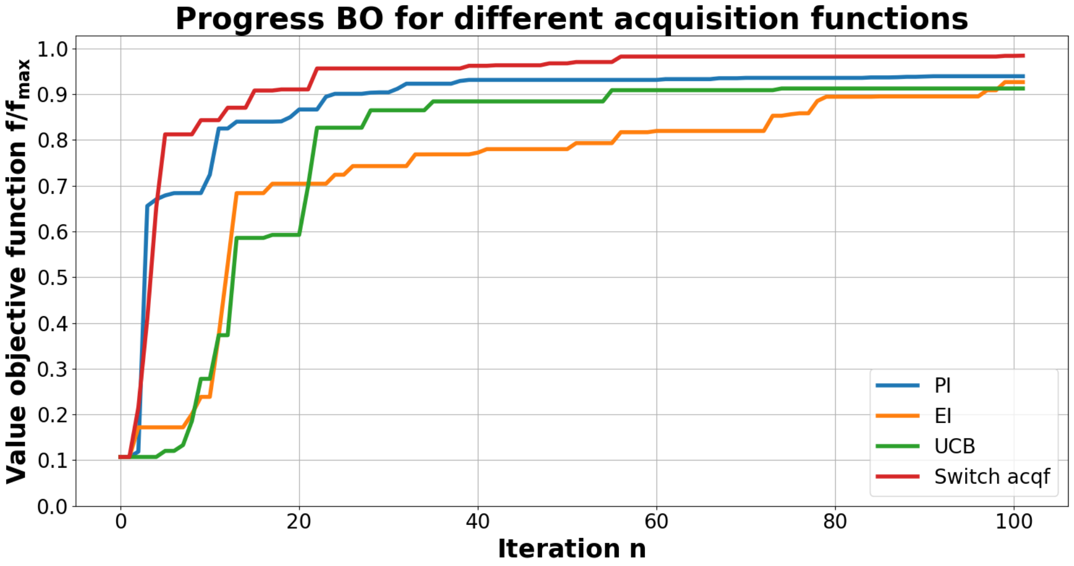


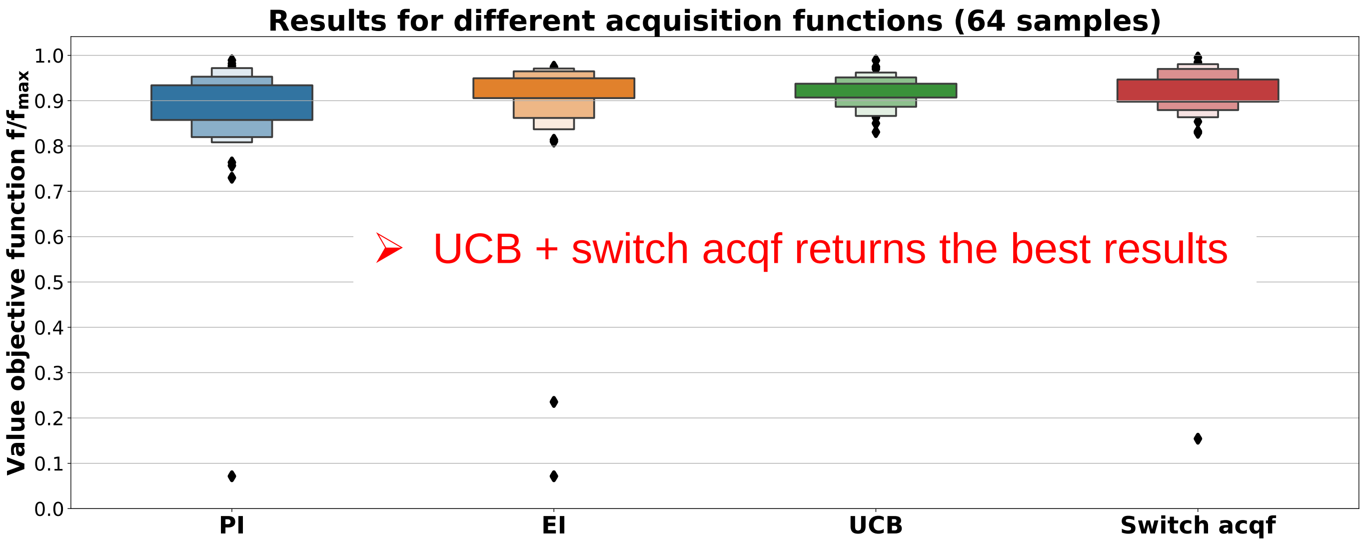
BO - Different acquisition functions

Christoph Reinwald, Master's thesis

- Probability of improvement (**PI**): Sample points which are likely to be greater than best point so far (greedy)
- Expected improvement (**EI**): Sample points which are likely to have a high improvement
- Upper confidence bound* (**UCB**): $\mathrm{UCB} = \mathrm{m}(\mathrm{x}) + \sqrt{\beta}\sigma(\mathrm{x})$ *N. Srinivas, arXiv:0912.3995v4, 2010

  $\beta_t = 4$ has a weaker performance compared to dynamic beta $\beta_t = 0.4 * \ln\left(t^{\frac{d}{2}+2} * \frac{\pi^2}{3 * \delta}\right)$
- Hedging (portfolio of acqf) -> **Switch acqf**: Rotation of UCB -> EI -> PI in this order

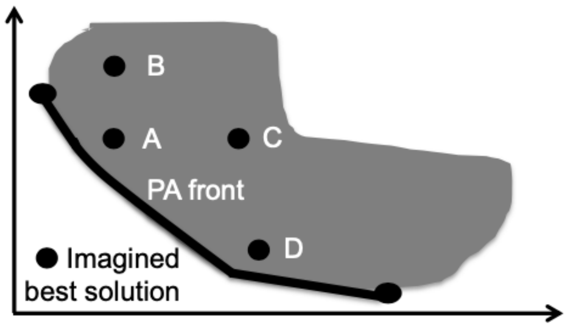




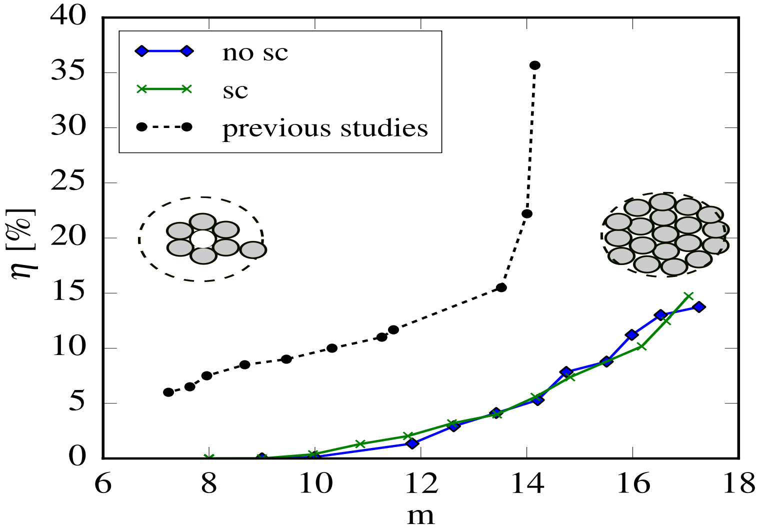
➢ UCB + switch acqf returns the best results

Multi-objective optimization with BO

- Competing: Maximize number of injection and minimize loss
- Pareto front: Find *set* of optimal solutions instead of single one
- Simulation with Genetic algorithms has been performed a while ago

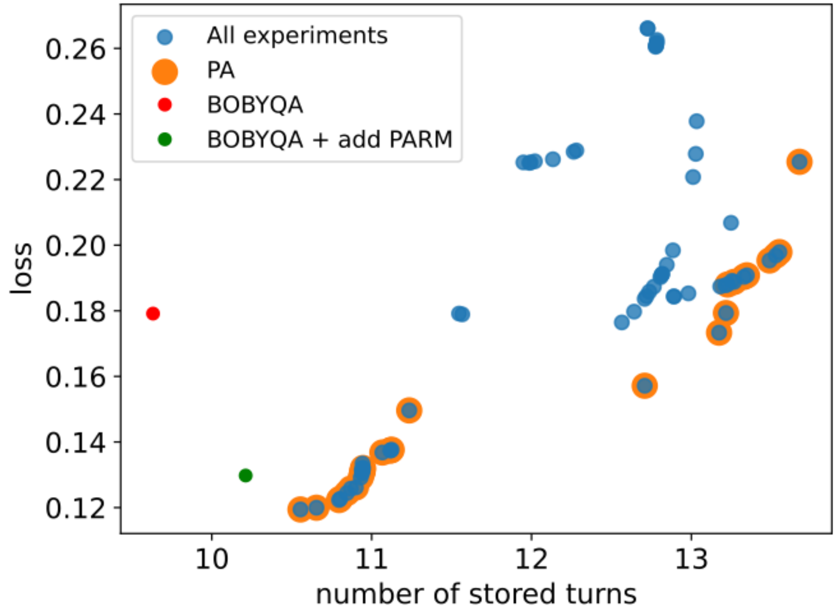


Simulation with Genetic algorithms



Optimization of injector beam line is missing

Measurements

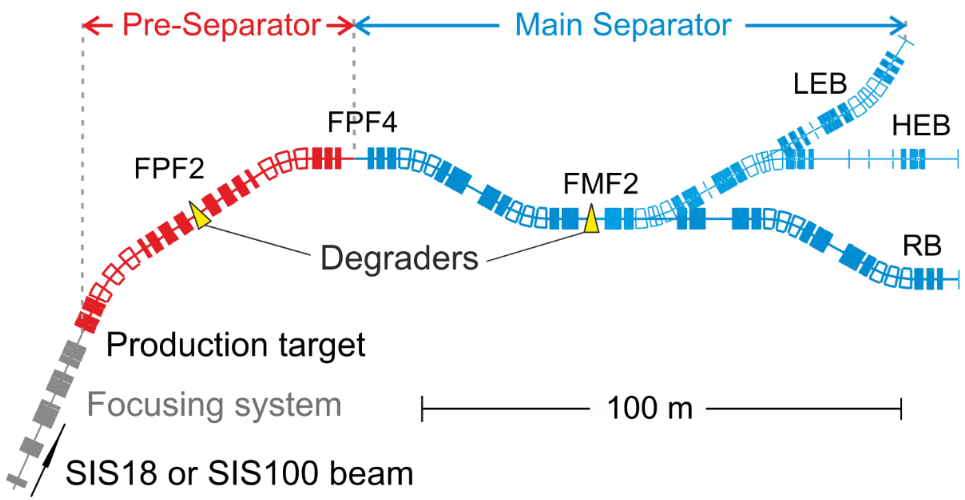


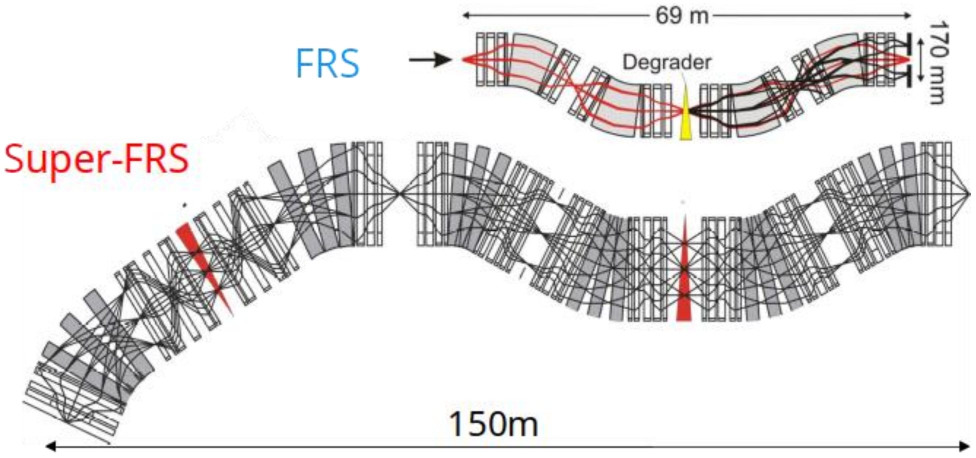
FRS (FRagment Separator) and Super-FRS

- Production and investigation of nuclear structure of exotic nuclei
- Exotic nuclei can be produced, separated, identified and eventually stored in a storage ring
- "Super-FRS: higher acceptance, more complex (4×more magnets), gain factors between 1000 (^{12}C) and 7500 (^{132}Sn)[1].
- Automation of operational tasks **essential**

	$B\rho_{max}$	$\Delta p/p$	$\Delta\Phi_x$, $\Delta\Phi_y$	resolving power	gain factor ^{19}C	gain factor ^{132}Sn
FRS	18 Tm	1.0 %	±13, ±13 mrad	1500	1	1
Super-FRS	20 Tm	2.5 %	±40, ±20 mrad	1500	5	10
				including primary rate	250	20 000

Super-FRS layout:

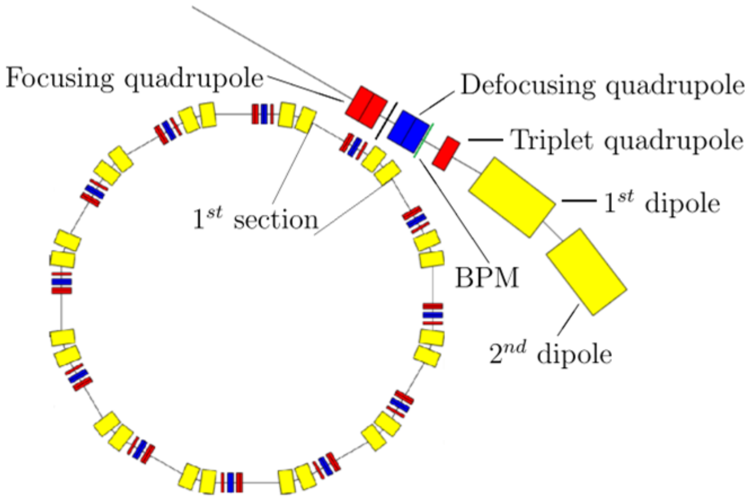


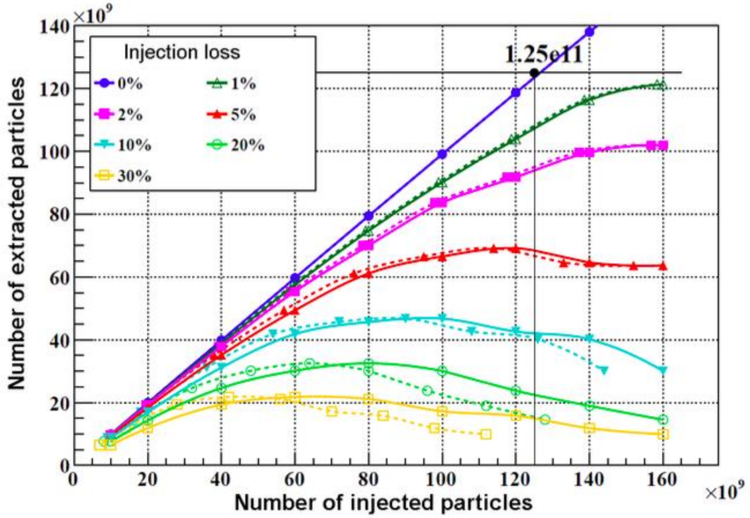


[1]H. Simon et al., EMIS XVIII workshop, 2018.

SIS18 (SchwerIonenSynchrotron)

- Booster for FAIR SIS100 synchrotron
- Offers fast and slow extraction to experiments and subsequent accelerators.
- Main bottleneck for intense FAIR beams: **multi-turn injection into SIS18**
- Main limiting effect: **(incoherent) transverse space charge force**
- Also important limiting effect: **loss-induced vacuum degradation for intermediate charge state ions**





Beam Energy	U : 50-1000 *MeV/u* Ne: 50-2000 *MeV/u* p : 4,5 *GeV*
Particle Number Per Cycle	10^{10} (U^{73}) – 10^{12}(p)
Typical Cycle	3 *s (FAIR 2.7 Hz)*
Extraction	fast: 1 μs with compression: 200 *ns* slow: 10-8000 *ms*