dRICH optics optimization

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ePIC Collaboration meeting

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Duke contributions to the dRICH

- Simulation
- Mirror quality assurance and evaluation
- **Optics optimization → topic of this talk**

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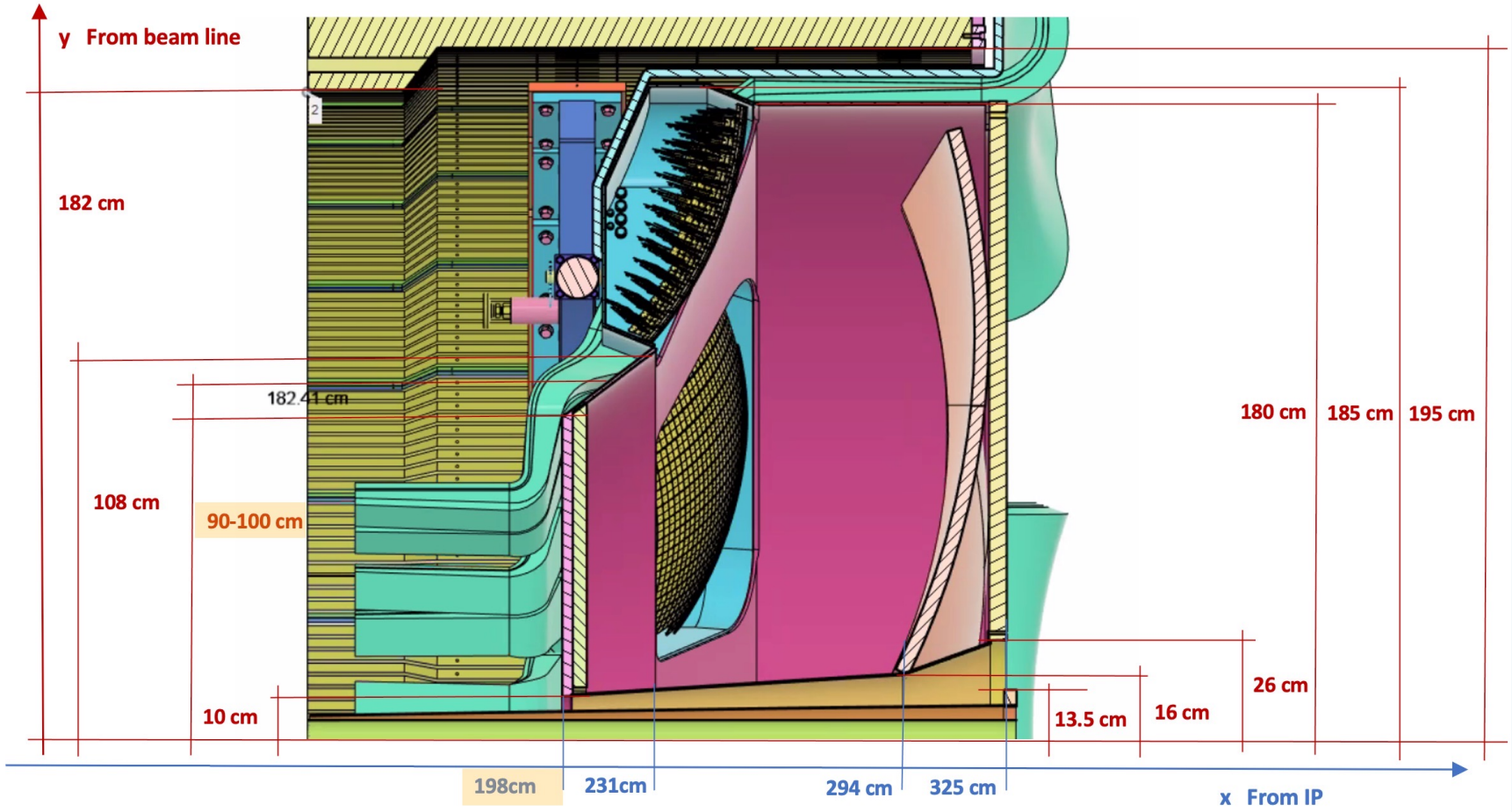
dRICH optical design

- dRICH optics required to focus Cherenkov ring across wide η range, $\mathbf{1.5 < \eta < 3.5}$
- Design highly constrained (length ~120 cm, sensor box size and position)



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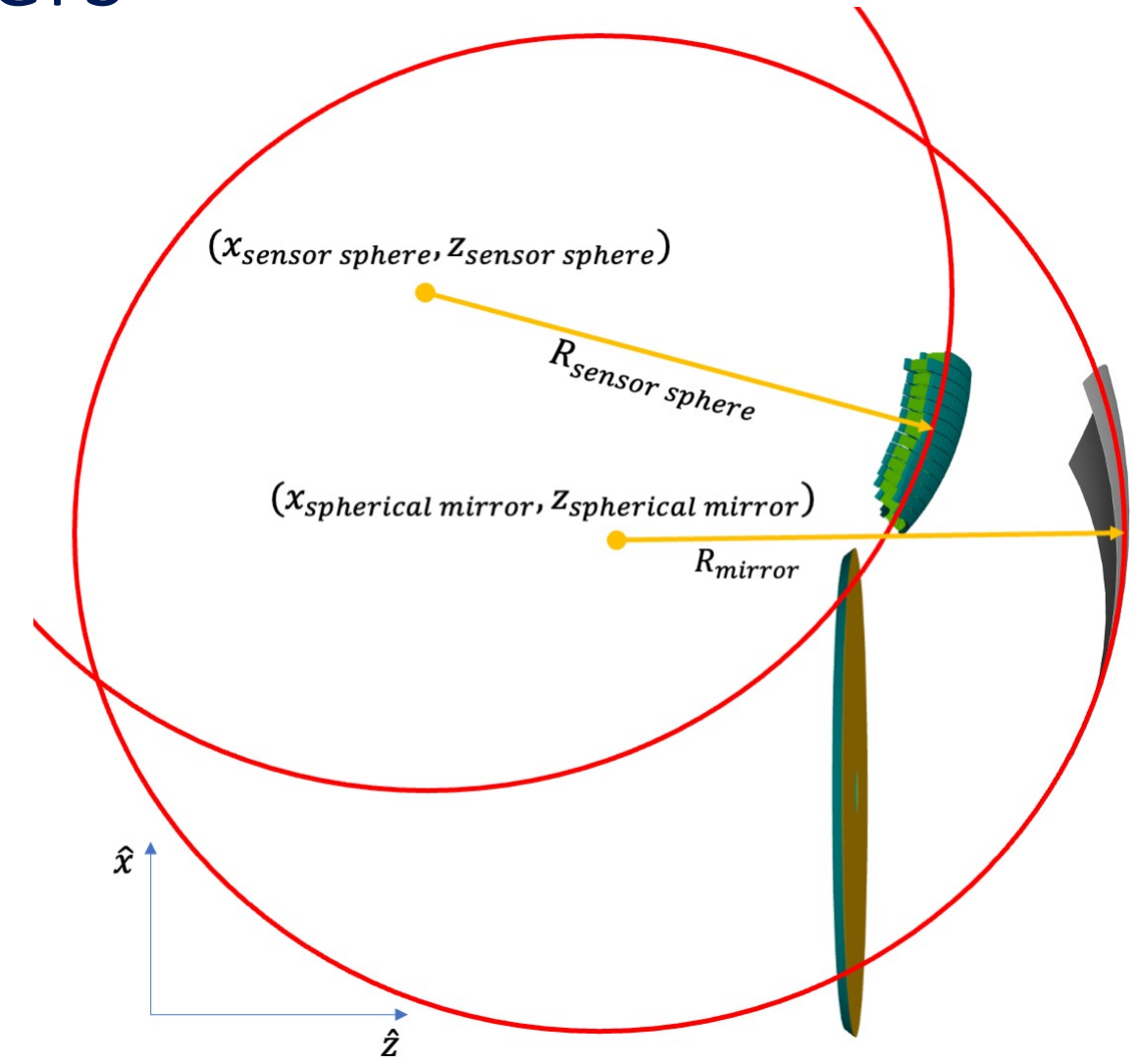
Optical design parameters

Tunable parameters:

- Mirrors:
  - Segmentation of mirrors
  - Mirror radii
- Sensors:
  - Position within sensor box (slight freedom)
  - Sensor sphere radius



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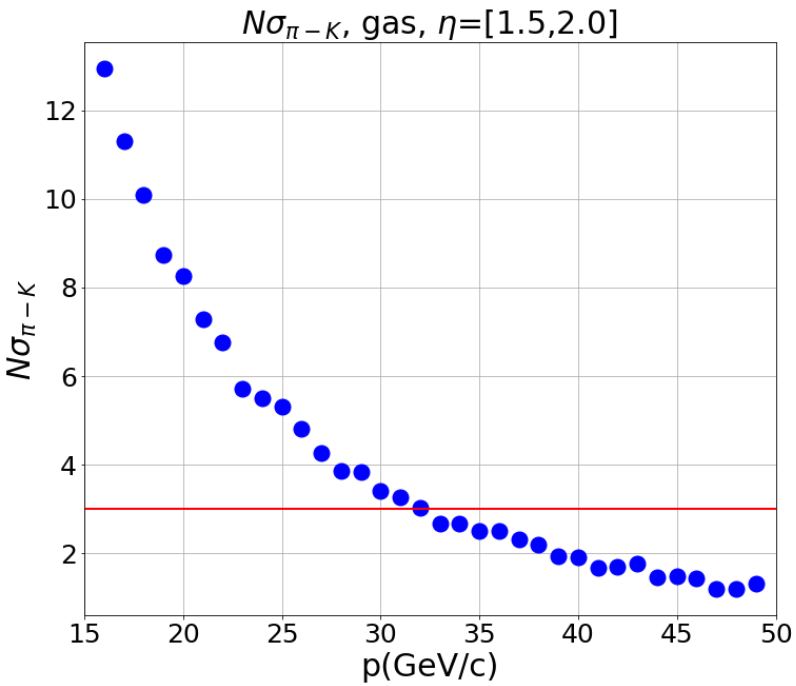
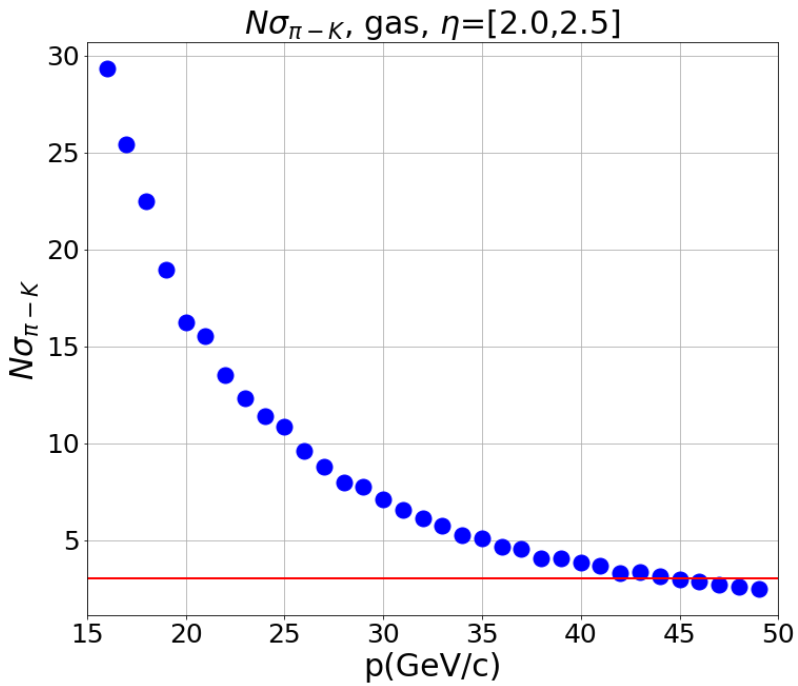
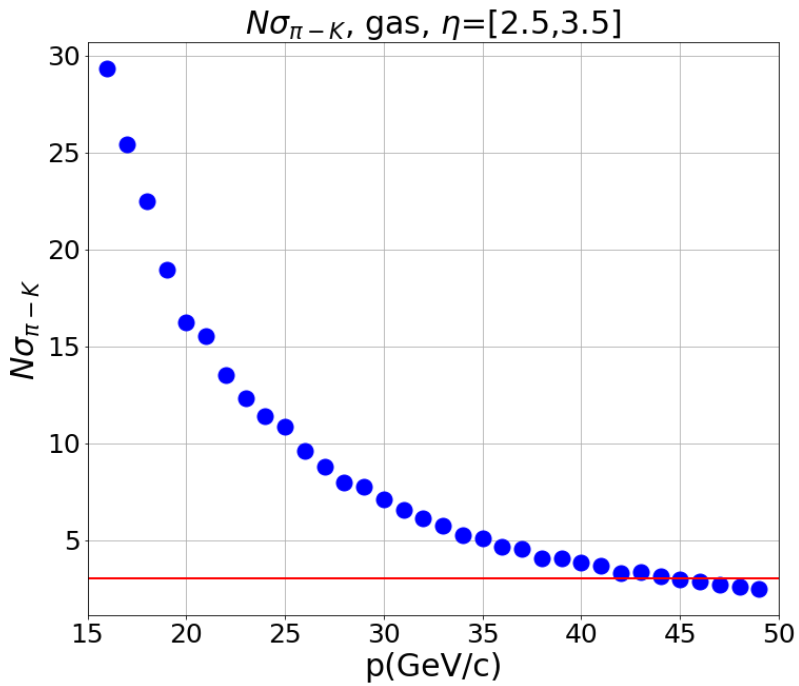
dRICH optical performance







- Current dRICH design optimized for larger η
- Further tuning/optimization required to reach desired performance across full η range

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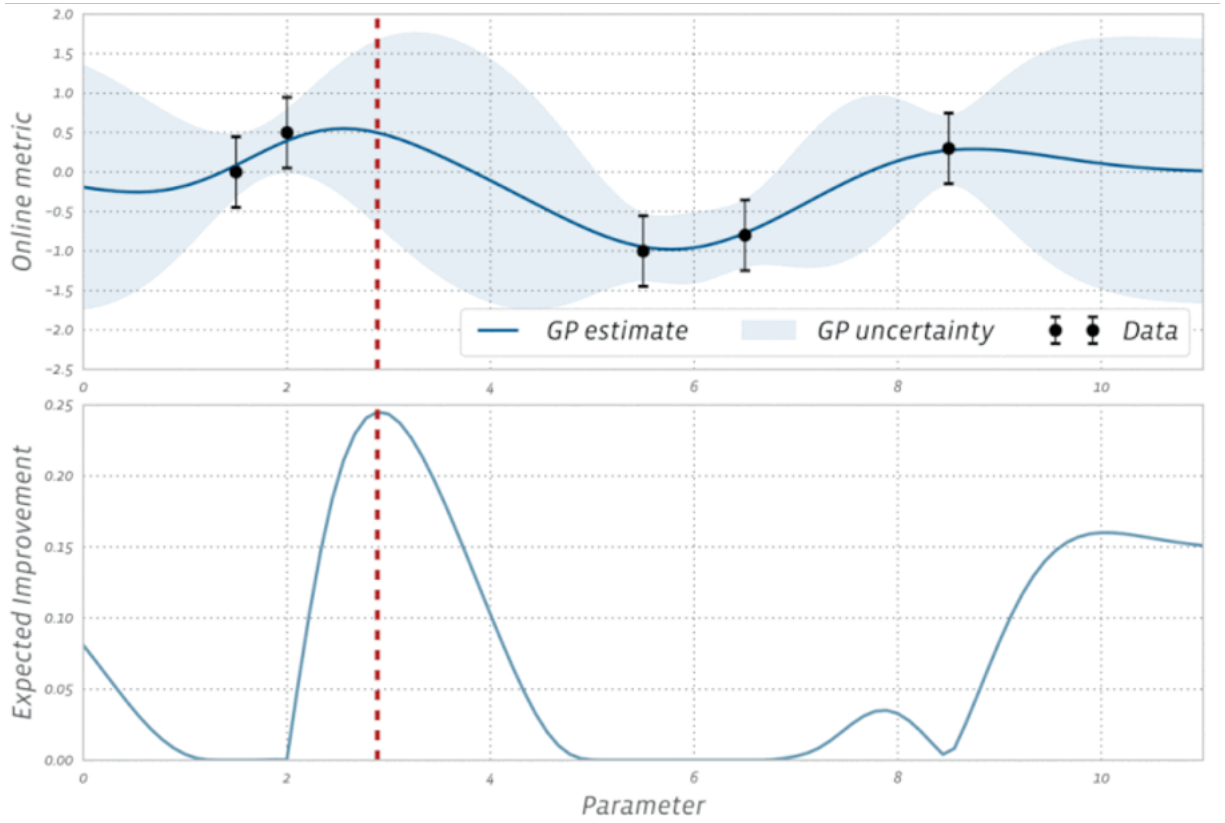
Chosen tool: Bayesian optimization

- Optimization approach employed for hard-to-evaluate problems
- Constructs **surrogate model** (gaussian process) that fits the objectives as a function of design parameters
- **Acquisition function** suggests new points by maximizing expected improvement
  - Balance 1. exploring new design parameter regions and 2. exploiting known well-performing regions



From: https://ax.dev/docs/bayesopt

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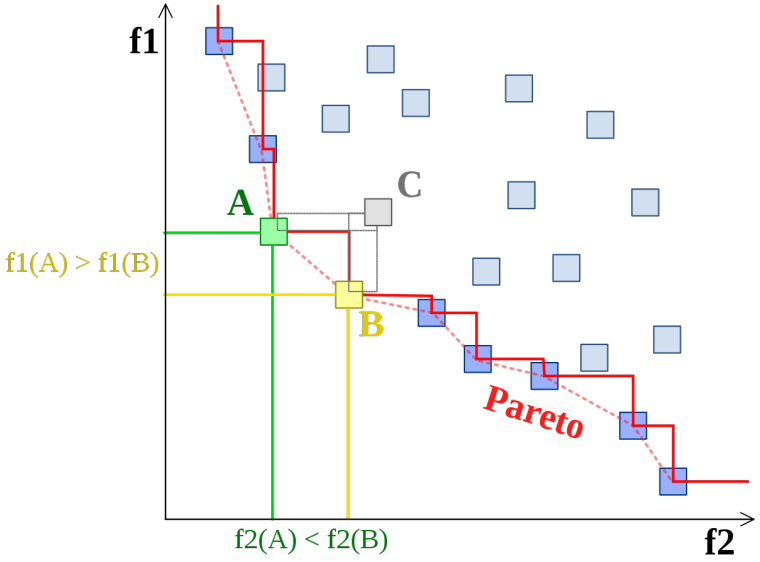
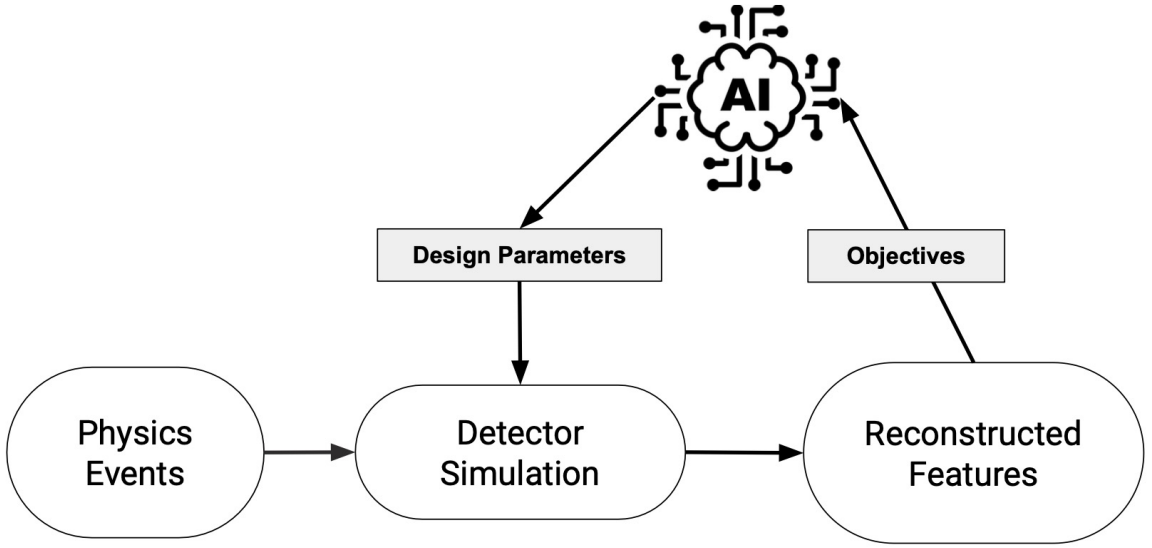
Multi-objective Bayesian optimization (MOBO)

- For a multi-objective problem, aiming to construct best estimate of the Pareto front (optimal designs and tradeoffs)
- For dRICH: acceptance and resolution at different (p, η) as separate objectives



https://en.wikipedia.org/wiki/Pareto_front



- dRICH optimization part of **AID(2)E project: AI-Assisted Detector Design at EIC (BNL, CUA, Duke, JLab, W&M)**
  - Develop infrastructure for MOBO applied to detector design and use of distributed computing in detector optimization
  - Apply MOBO to ePIC subsystems

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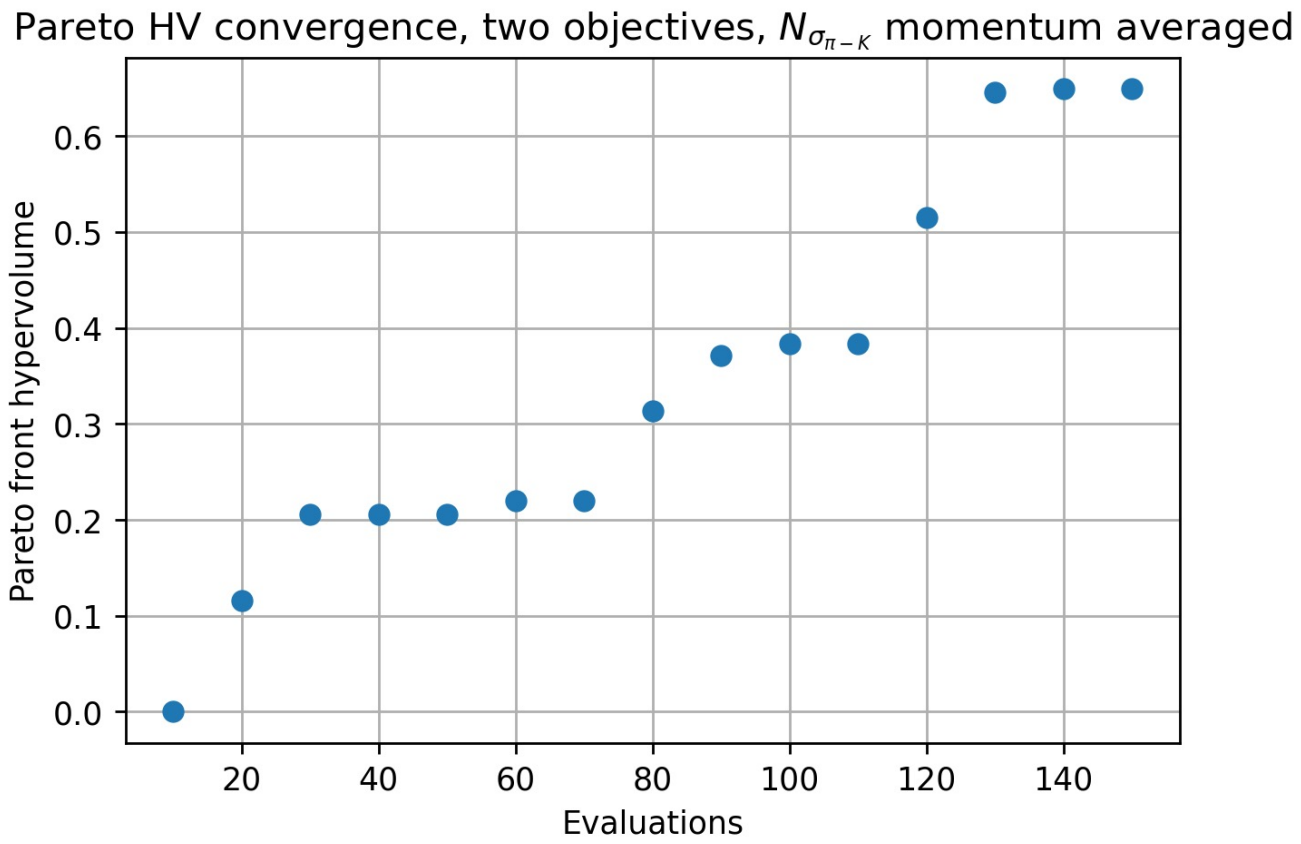
Optimization with single mirror

- Single mirror -> low and high η performances are competing
- Framework test: optimization of $N\sigma_{\pi-K}$ **at 1.3 < η < 2.0** and **2.5 < η < 3.5**
  - Average of p=15GeV/c and 40GeV/c
  - 1000 π^+ and 1000 K^+ per p/η point
  - Design parameters as sensor and mirror sphere radii, positions

Hypervolume dominated by optimal points:



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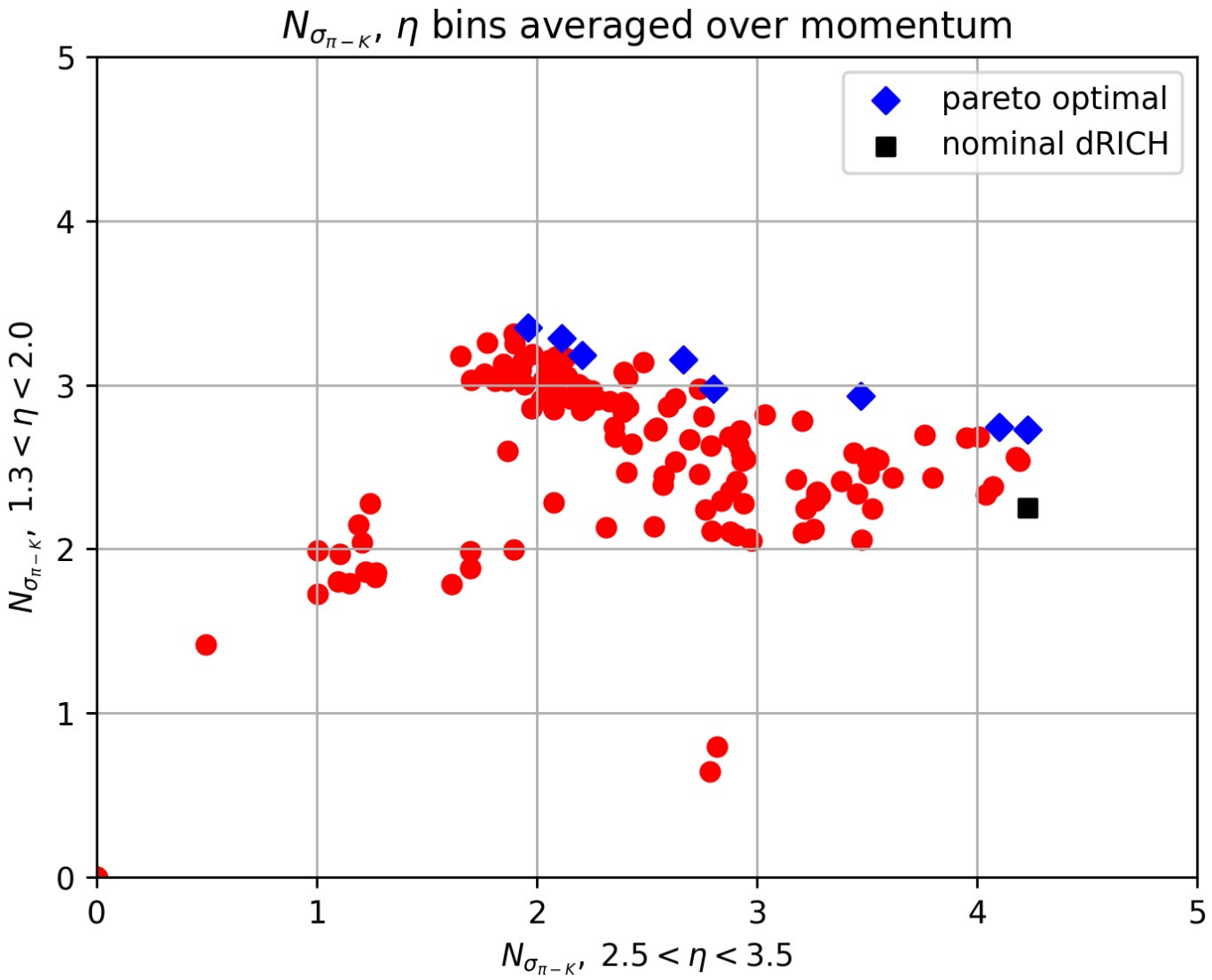
Optimization with single mirror

- Right: $N\sigma_{\pi-K}$ results from sampled points
- Tradeoff visible between low and high η ranges
  - No design found with $N\sigma_{\pi-K}$ >= 3 for both low and high η
  - Need for multiple mirrors



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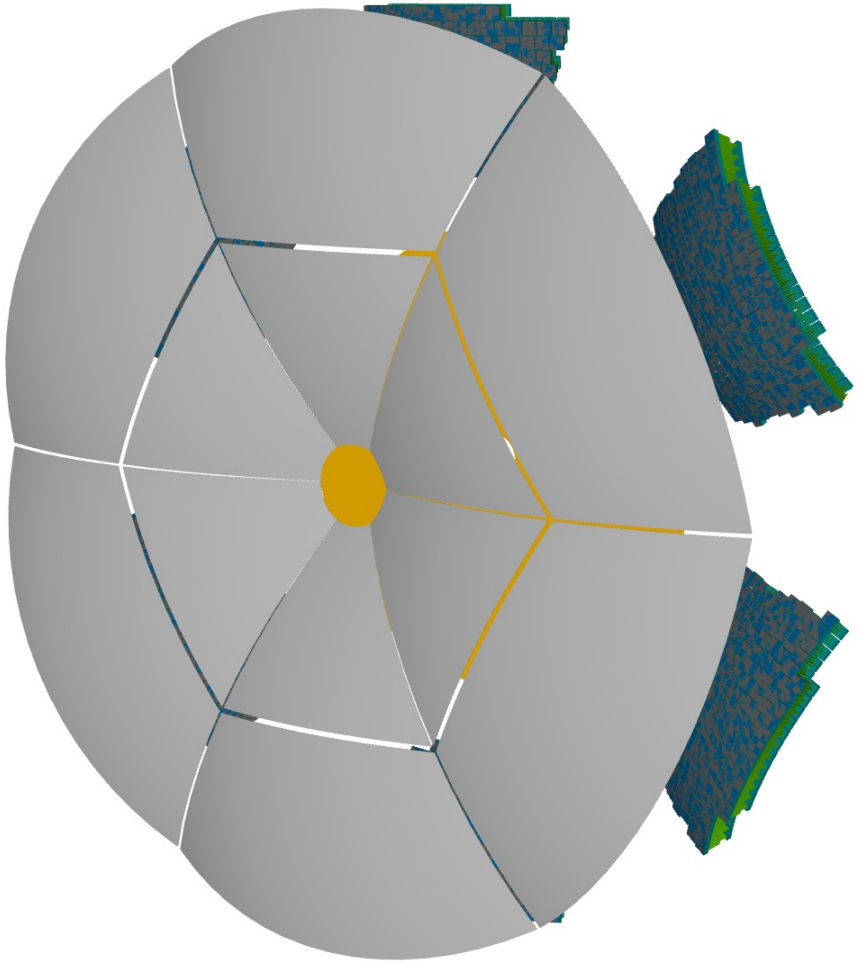
Multi-mirror optimization

- Working on updates to IRT library and EICrecon to utilize multiple mirrors in dRICH (IRT PR)
- Next step: optimizing case of two mirror patches per sector
  - + acceptance as optimization objective
- End goal: use MOBO framework to determine optimal tiling of sub-mirrors



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Conclusion

- MOBO framework for dRICH design is in place and has been tested on single mirror design
- Updates to the IRT algorithm will allow for evaluation of a multi-mirror dRICH
- Work ongoing to optimize a two-mirror dRICH
  - First step towards fully optimizing tiling of dRICH mirrors

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Extra slides

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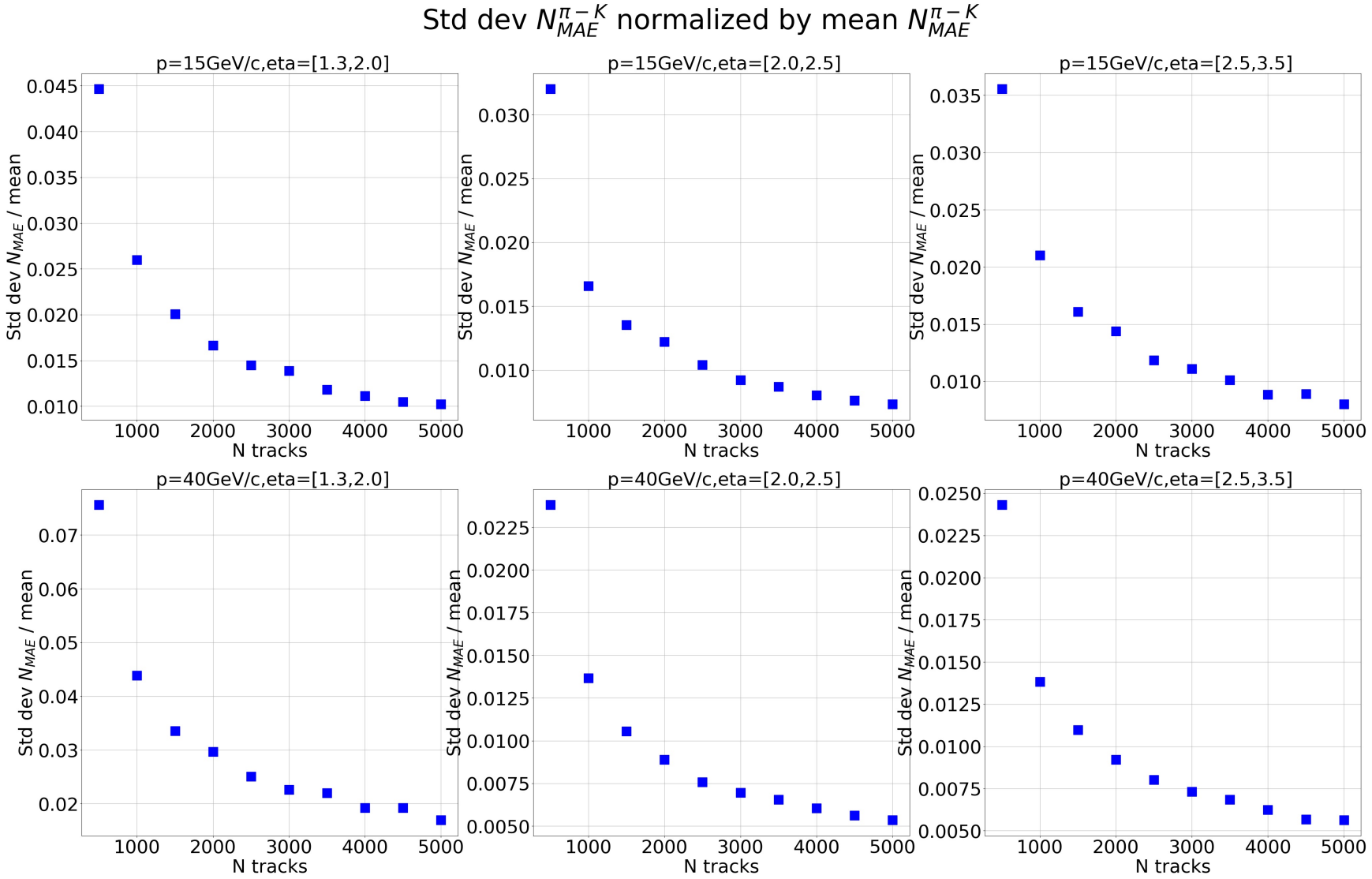
Uncertainty studies, pi-K separation

- Nominal geometry
- Simulated 5k pi+ and 5k K+ tracks
- Re-sample N tracks out of this set 1000 times per N
- Plotted: std. dev.of objectives normalized by mean



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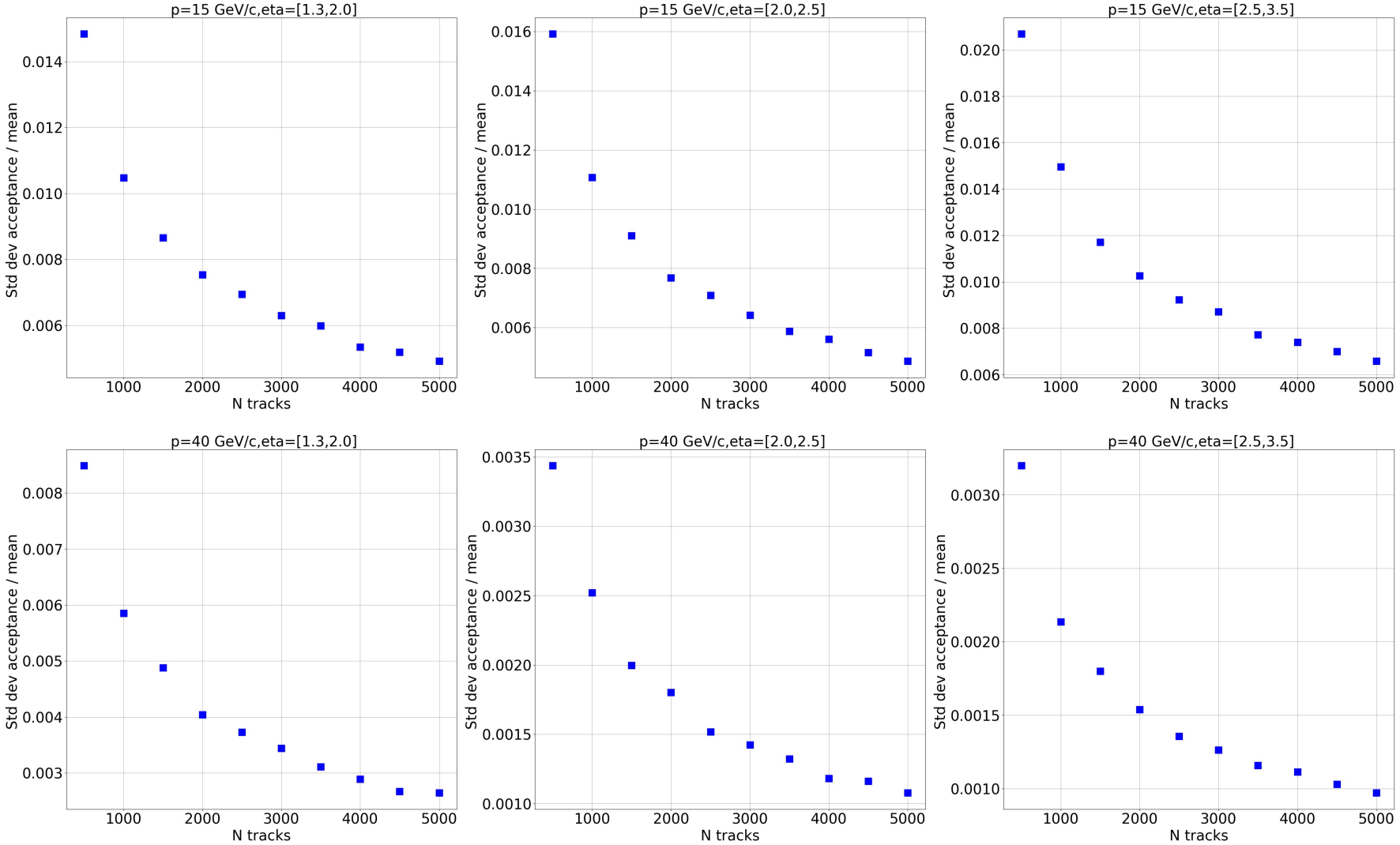
Uncertainty studies, acceptance

Std dev of acceptance normalized by mean acceptance



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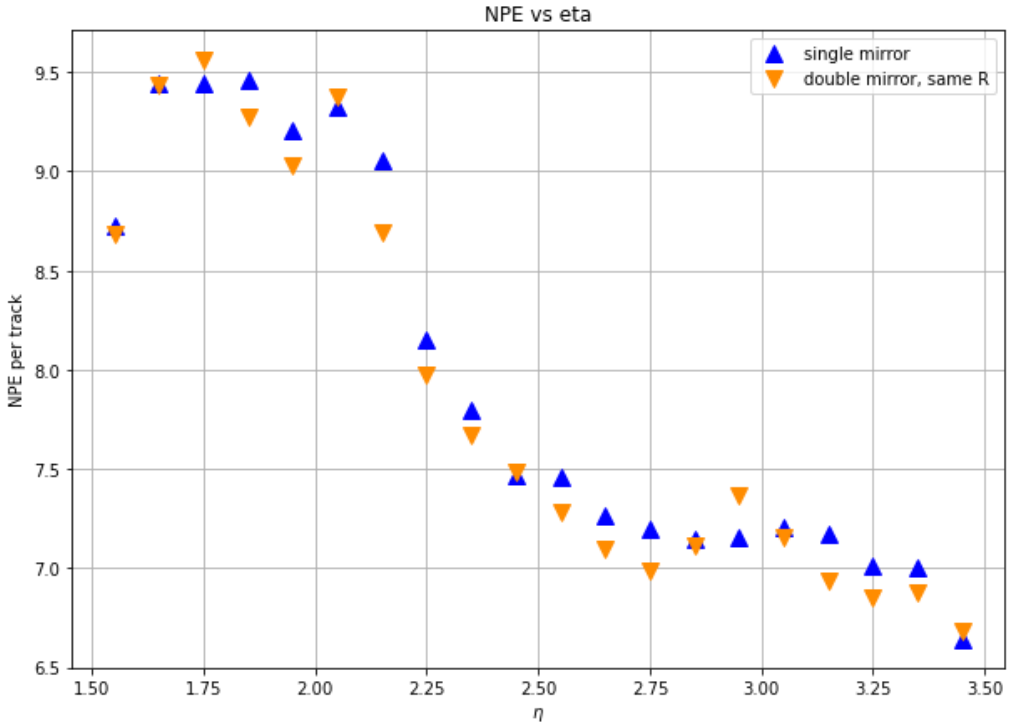
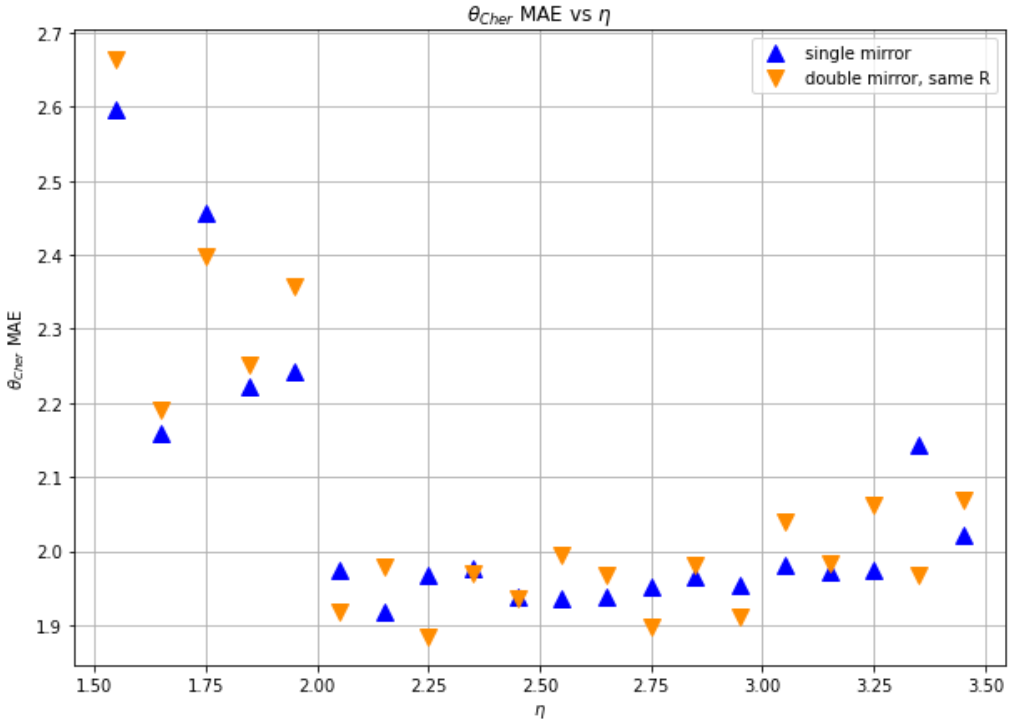
IRT update comparison plot





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