Performance optimization for a scintillating glass electromagnetic calorimeter at EIC

Dmitry Kalinkin for the ePIC collaboration

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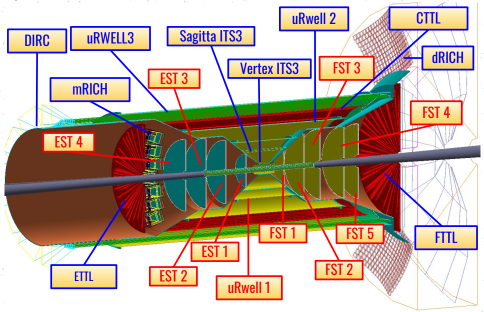
Examples detector optimization at EIC

ECCE Tracker Plane and Disk proportions

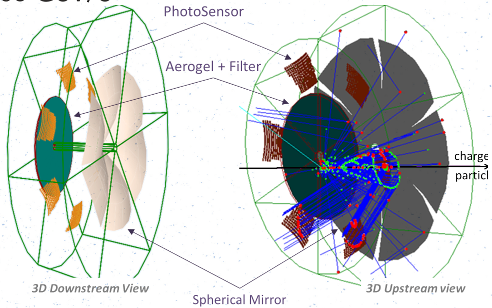
Objectives: KF efficiency, θ and $|\vec{p}|$ resolutions



Multi-Objective Optimization using NSGA-III (see arXiv:2205.09185) and Bayesian MOO (see talk by Karthik Suresh from last year)

dual-radiator RICH

Objective: FOM over $N\sigma_{K\pi}$ at $p = 14$ and 60 GeV/c



Single-Objective Optimization using BO (see 2020 JINST 15 P05009)

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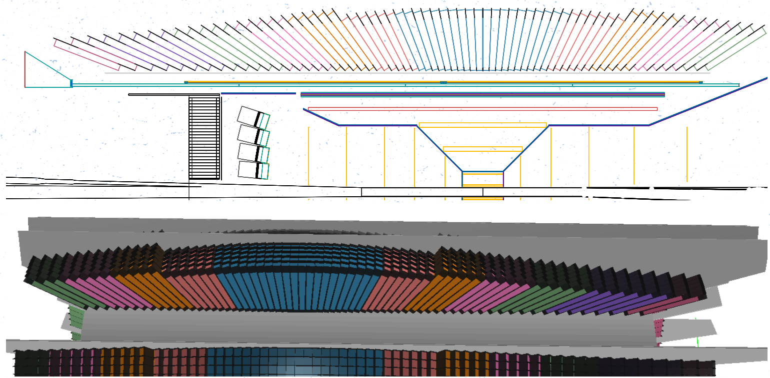
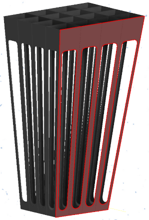
SciGlass projective calorimeter

Tower dimensions and placement implemented based on mechanical design: pyramidal towers, angles tweaked by hand





SciGlass lengths of 45.5 and 40 cm ($\approx$ 16.3 and 14.3 X_0)
– originally chosen for a calorimeter that fits inside the BaBar solenoid (Detector I)
Main purpose: measurement of $e^{\pm}/\gamma$ energy, $e^{\pm}/\pi^{\pm}$ and $(\pi^0 \to \gamma\gamma)/\gamma$ discrimination

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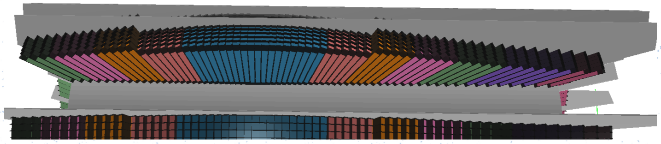
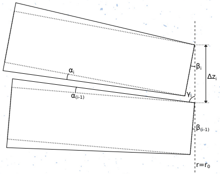
Parametrization





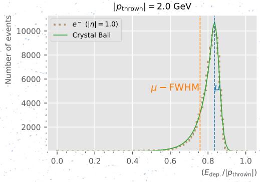
- 7 shapes of cells – “families”
- Families are stacked from $\eta = 0$ in $-\hat{z}$ and $+\hat{z}$ directions
  - 5 integer numbers (0-9) of towers for negative
  - 7 integer numbers (0-9) of towers for positive
- Each shape is a “G4Trap”
  - azimuthal flaring and at-face flaring angles can be calculated to preserve fixed gaps
  - 7 floating point (0.0-2.0 degrees) longitudinal flaring angles determine η projectivity
- Altogether 19 parameters considered
- DD4hep allows detector configuration from “compact” XML files

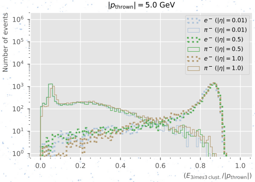
Optimization objectives

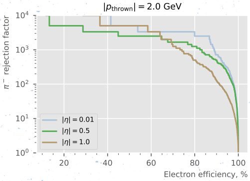
» Single particle simulations: e^-, π^- ($p_T = 2$ GeV)

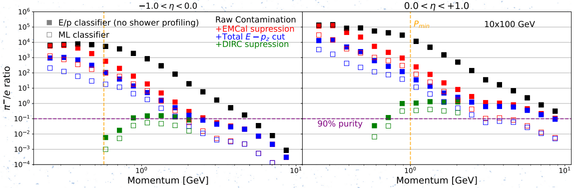
» Key metrics:

- Energy resolution
- Charged pion rejection factor
- Neutral pion to photon discrimination (not considered yet – relies on ML)









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Multi-objective Optimization using Genetic Algorithms

1 Initialize population (100 samples $\times$ 19 parameters $\leftarrow$ RNG)

2 Evaluate objective functions $\{f_i\}$ for each specimen in the population
    Pick them so that the minimized $f_i \leq 0$, then for invalid geometries use dominated $f_i \equiv N_{\text{overlaps}}$

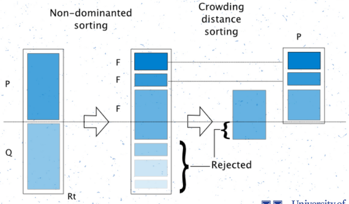
3 Survival, Selection (specified by NSGA-II)

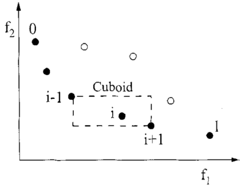
4 Crossover, Mutation (exchange and RNG re-init of individual parameters)

5 Repair (optional)

6 Goto 2

Easy to program with `pymoo`, works out of the box.





Constraints and dimensional reduction

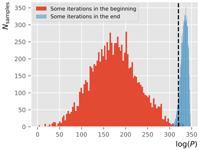
» **Problem:** objective evaluation $\mathcal{O}$(minutes), overlap evaluation $\mathcal{O}$(seconds).
Any way to precompute later for a given geometry?

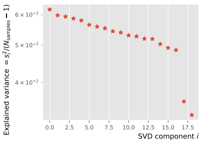
» **Solution:** explore and learn the manifold of valid parameter combinations

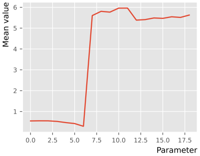
- Could use GA for exploration, but **MCMC** has nice implementations of walkers (we want a "stretch" move)

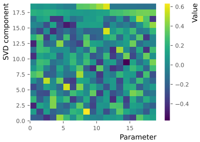
$$\log(P) = \begin{cases} -\infty, \text{ if parameter set doesn't pass overlap check} \\ z_{\text{rightmost tower}} - z_{\text{leftmost tower}} / (1 \text{ cm}), \text{ otherwise} \end{cases}$$

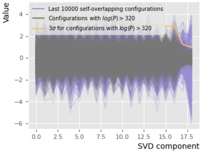
  Run default implementation from `emcee` with $10,000$ walkers for ≈ 1000 iterations
- Almost linear constraints $\Rightarrow$ **PCA** was used to obtain linear transformation and limits (set at 3σ).











2 dimensions effectively removed!

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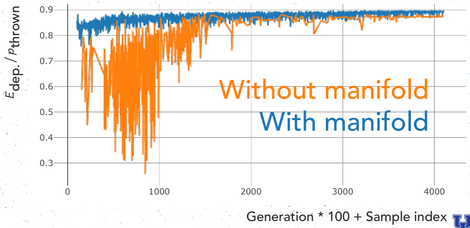


Nice improvement demonstrated for NSGA!

Bayesian Optimization

Gaussian Process allows for probabilistic surogate modeling

Expected Improvement (EI) acquisition function:

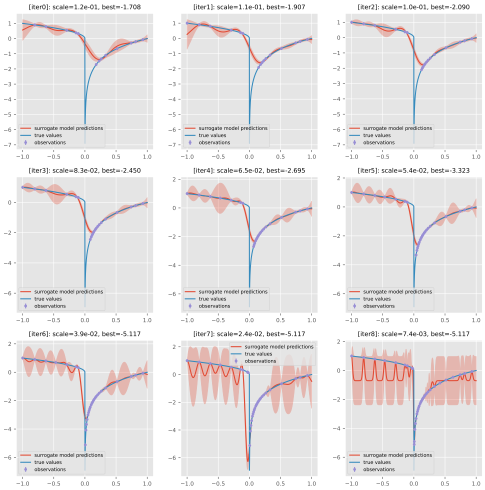
$$\mathbf{EI}(x) = \mathbb{E}[\max(f(x) - f_{\text{best known}}, 0)]$$

Illustration using a toy function:

$$f(x) = \begin{cases} \log(x), \text{ if } x > 0 \\ \sqrt{|x|}, \text{ if } x < 0 \end{cases}$$

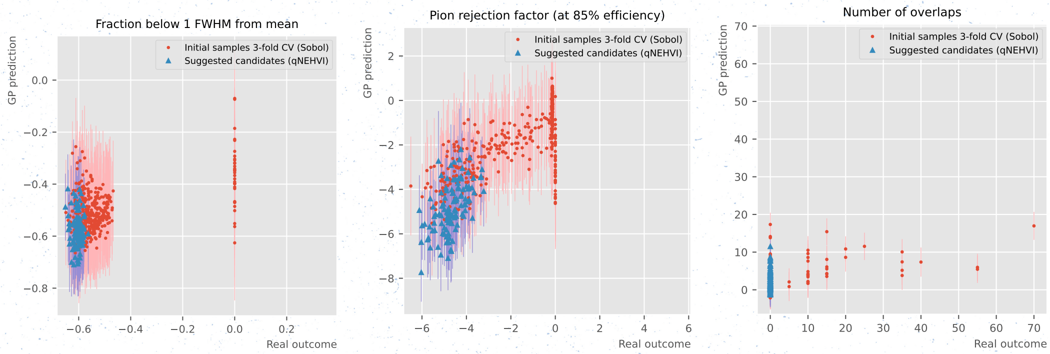
Reporting fake dominated values may not an option – could spoil the fit!

In the MOO case, Expected Improvement is commonly taken for a HyperVolume (qEHVI).



Cross Validation

Important step: cross validation for the surrogate model for a given problem



- Number of overlaps was originally split into a separate "`OutcomeConstraint`" Didn't work well – killed optimization progress.
- Objective value of `0` with an uncertainty is reported for overlapping configurations
- The GP hardcoded for SAASBOO in `Ax` gives a decent CV
- qNEHVI is effective at picking improving points

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Software stack

pymoo

or

GPyTorch

BoTorch

Ax

Dask.Distributed

dask-jobqueue

Awkward Array

uproot

GEANT4
A SIMULATION TOOLKIT

DD4hep

`epic_arches` geometry

mlflow™

joblib.Memory

emcee

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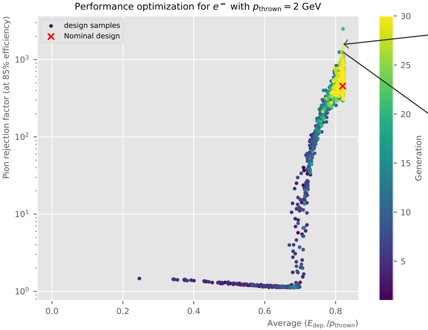
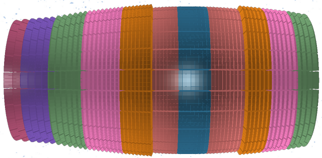
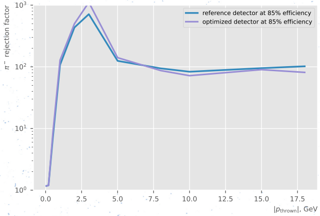
Some results (GA)

2-objective MOO (de-facto single objective)

NSGA-II (100 samples/generation)







Analysis in full benchmark

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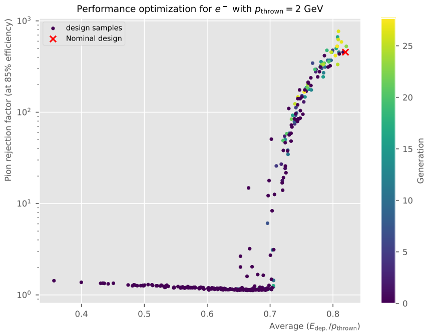
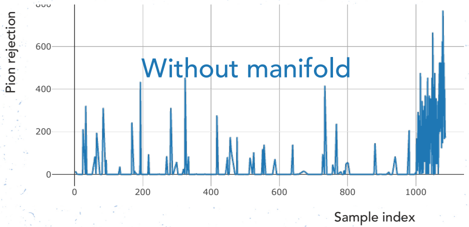
Some results (BO)

2-objective MOO (de-facto single objective)

SAASBO qNEHVI (3 samples/generation)




```
GenerationStrategy(
    steps = [
        GenerationStep(
            model=Models.SOBOL,
            num_trials=1000,
            max_parallelism=1000,
        ),
        GenerationStep(
            model=Models.FULLYBAYESIANMOO,
            num_trials=1000,
            max_parallelism=3,
            model_kwargs=dict(
                num_samples=256,
                warmup_steps=512,
                gp_kernel="rbf",
                torch_device=torch.device("cuda"),
                torch_dtype=torch.double,
                verbose=False,
            ),
        ),
    ],
)
```



Would be interesting to fit solutions from NSGA and see if those can be improved with BO.

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Summary

» Several working approaches specific to optimization of particle detectors have been demonstrated

» Practical application of SciGlass (e.g. at EIC Detector II) can benefit from ML optimization

- Going beyond pure geometrical optimization
- Proper tooling to scale production and analysis of large optimization workflows
- Are there any issues with objectives involving ML? (for PID)

Acknowledgements

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