

AID2E: AI-assisted Detector Design + optimization Environment for the EIC & beyond

<https://aid2e.github.io/aid2e>



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BNL, W. Guan
CUA, T. Horn
Duke, A. Vossen
JLab, M. Diefenthaler
W&M, CF (PI)

Cristiano Fanelli

AI4muC virtual workshop - Cristiano Fanelli - June 29-30, 2026

Detector Design & Challenges



- **Context:** I have been involved in AI-assisted detector design for the EIC for several years — from early RICH optimization studies to tracking, community AI4EIC efforts, and now AID2E.
- **Key challenge:** The hardest part was not only methodological — it was “**building trust.**”
 - AI-suggested detector configurations can be difficult to adopt unless they are produced within the same validated simulation and reconstruction workflows used by detector working groups.
 - Post-hoc validation is often not enough: residual discrepancies can weaken confidence, and if the final validated design differs from the AI prediction, the method may get less credit — even when it successfully guided the search.
- **AID2E response:** Couple distributed AI optimization directly to ePIC simulation pipelines, enabling efficient exploration of design space and tradeoffs with principled methods, reducing number of expensive sim/reco evaluations needed.
- **Next step:** LLM agents + human-in-the-loop control to assist workflow setup, campaign monitoring, and support expert-guided design steering

E. Cisbani, A. Del Dotto, CF, et al. "AI-optimized detector design for the future Electron-Ion Collider: the dual-radiator RICH case." JINST 15.05 (2020): P05009-P05009.

CF, et al. "AI-assisted optimization of the ECCE tracking system at the Electron Ion Collider." NIM A: 1047 (2023): 167748.

Allaire, C., et al. "Artificial intelligence for the electron ion collider." Computing and Software for Big Science 8.1 (2024): 5.

M. Diefenthaler, CF et al. (AID2E Collaboration) "AI-assisted detector design for the EIC (AID (2) E)." JINST 19.07 (2024): C07001.

AID2E Collaboration. "Scalable AI-assisted Workflow Management for Detector Design Optimization Using Distributed Computing." arXiv:2603.30014 (2026).



Team



Wen Guan, PhD

Expertise: distributed computing, workflow management, ML workflows



coPI



Meifeng Lin, PhD

Expertise: Physics, High performance computing, numerical simulations, Computational physics, exascale



Tianle Wang, PhD

Postdoc - Expertise: Physics, High Performance Computing, Workflow Management, Machine Learning



Torre Wenaus, PhD

Expertise: Nuclear and particle physics software, Distributed Computing, Simulations



Amit Bashyal, PhD

Expertise: AI/ML, optimization algorithms, scientific infrastructures



Fang-Ying Tsai, PhD

Expertise: AI/ML, HPC, and large-scale data processing



Kolja Kauder, PhD

Expertise: Physics, Simulation



consulting



Alex Jentsch, PhD

Expertise: Far Forward physics, EIC



consulting



Tanja Horn, PhD

Expertise: medium energy nuclear physics, EIC, 3D hadron Imaging, calorimetry



coPI



Baptiste Fraisse, PhD

Expertise: medium energy nuclear physics, simulations, calorimetry



Anselm Vossen, PhD

Expertise: Physics, PID and calorimetry for the EIC



coPI



Cynthia Nunez, PhD

Expertise: physics, simulations



Connor Pecar, MS

Expertise: physics, PID and detector simulations for the EIC



Markus Diefenthaler, PhD

Expertise: ePIC Software & Computing Coordinator, EIC Science, Simulations



coPI



Derek Anderson PhD

Expertise: EIC Science, Reconstruction, Simulations, calorimetry, jets

Jefferson Lab



Makoto Asai, PhD

Expertise: Detector Simulations, Geant4

Jefferson Lab

consulting



Cristiano Fanelli, PhD

Expertise: Data Science, Physics, MOO, Bayesian, UQ, Detectors, AI, Deep Learning, HPC



PI



James Giroux PhD

Research Scientist - Expertise: Foundation Models, Agentic Workflows, UQ, Distributed Computing, Detectors



Hemalata Nayak, MS

Expertise: Physics, Data Science, Optimization, Reconstruction



Eric Walter

Expertise: Distributed Computing

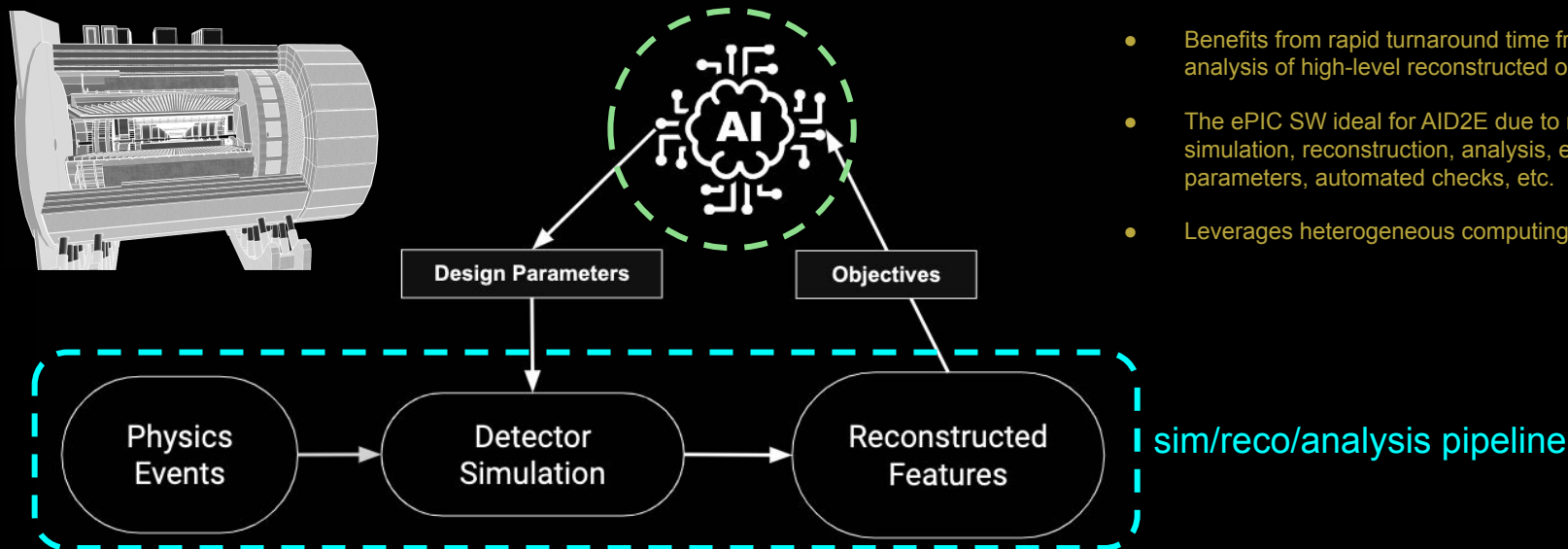


consulting

AI-Assisted Detector Design Workflow



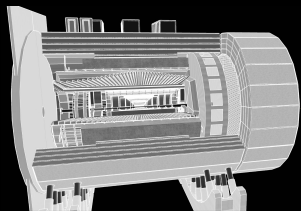
- The AI-assisted detector design embraces all the main steps of the sim/reco/analysis pipeline.



- Benefits from rapid turnaround time from simulations to analysis of high-level reconstructed observables
- The ePIC SW ideal for AID2E due to modularity of simulation, reconstruction, analysis, easy access to design parameters, automated checks, etc.
- Leverages heterogeneous computing

AID2E provides a framework for the holistic optimization of sub-detector systems
A complex problem with (i) **multiple design parameters**, driven by (ii) **multiple objectives** subject to (iii) **constraints**

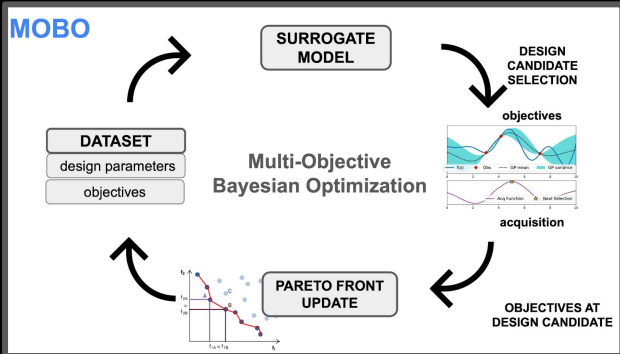
Physics
+ Detector



Multi-Objective Optimization Engines

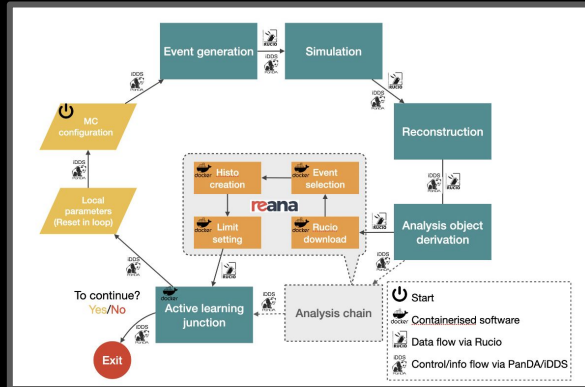
Distribution and Workload Management

Data Science & Analytics



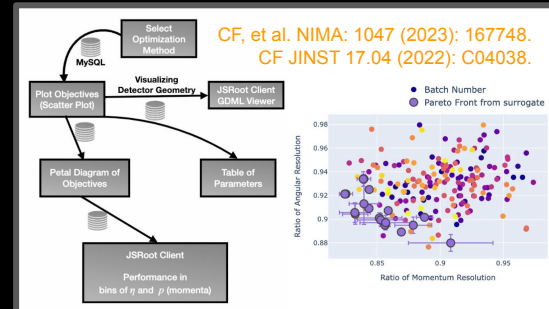
(i) Supporting SOTA Multi-Objective Optimization (MOBO and MOGA); exploring usage of physics-inspired approaches

(Known scaling limitations of MOBO/MOGA with problem complexity)

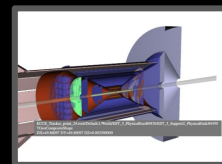


(ii) We leverage cutting-edge workload management systems capable of operating at massive data and handle complex workflows

3 schedulers currently supported:
joblib (local), *slurm* (HPC), *PanDA* (distributed)



(iii) Development of suite of data science tools for interactive navigation of Pareto front (multi-dim design with multiple objectives). Point are determined with uncertainties.



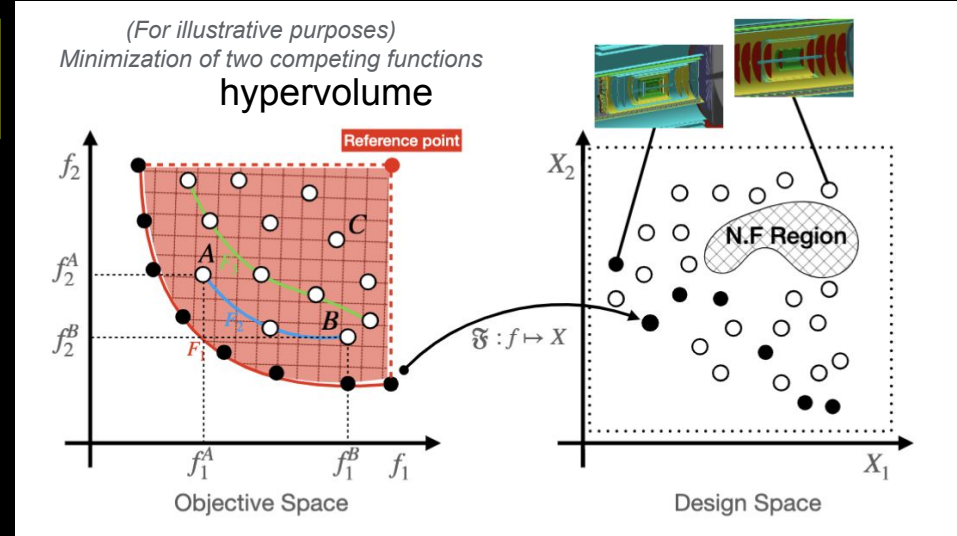
Multi-Objective Optimization



Multi-Objective Optimization

MOO needed to optimize a system of sub-detectors

- 3 Types of Objectives
 - Intrinsic detector performance** (resolutions, efficiencies) for each sub-detector — Tracking, calorimetry, PID — noisy
 - Physics-performance** — Multiple physics channels, equally important in the EIC physics program
 - Costs** (e.g., material costs, provided a reliable parametrization)
- Objectives can be competing with each other
 - E.g. Better detector response come with higher costs; better resolutions may imply lower efficiencies; etc.



A generic MOO problem can be formulated as

$$\begin{aligned}
 \min \quad & f_m(\mathbf{x}) \quad m = 1, \dots, M, \\
 \text{s.t.} \quad & g_j(\mathbf{x}) \leq 0, \quad j = 1, \dots, J, \\
 & h_k(\mathbf{x}) = 0, \quad k = 1, \dots, K, \\
 & x_i^L \leq x_i \leq x_i^U, \quad i = 1, \dots, N.
 \end{aligned}$$

objectives

constraints

PanDA/iDDS: Workflow Backbone



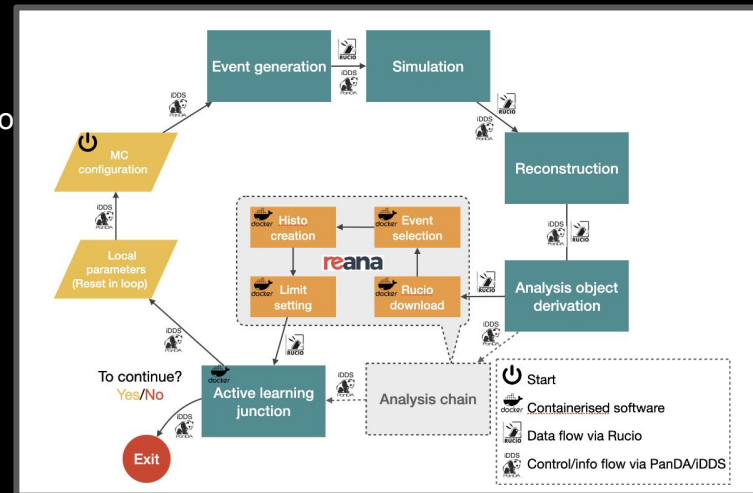
- **PanDA/iDDS turns AI optimization into scalable distributed workflow**
 - PanDA: distributed workload management across Grid, Cloud, HPC, and Kubernetes resources
 - iDDS: workflow orchestration and intelligent data delivery
 - Together: a production-scale layer for running large, reproducible optimization pipelines

- **What it provides**

- Distributed workflow orchestration across heterogeneous computing resources
- Function-as-a-task execution for simulation/reconstruction/analysis loops
- Monitoring, fault tolerance, provenance, and reproducibility
- Integration with active learning, Bayesian optimization, evolutionary algorithms, and MOO loops

- **Why it matters for Detector Design**

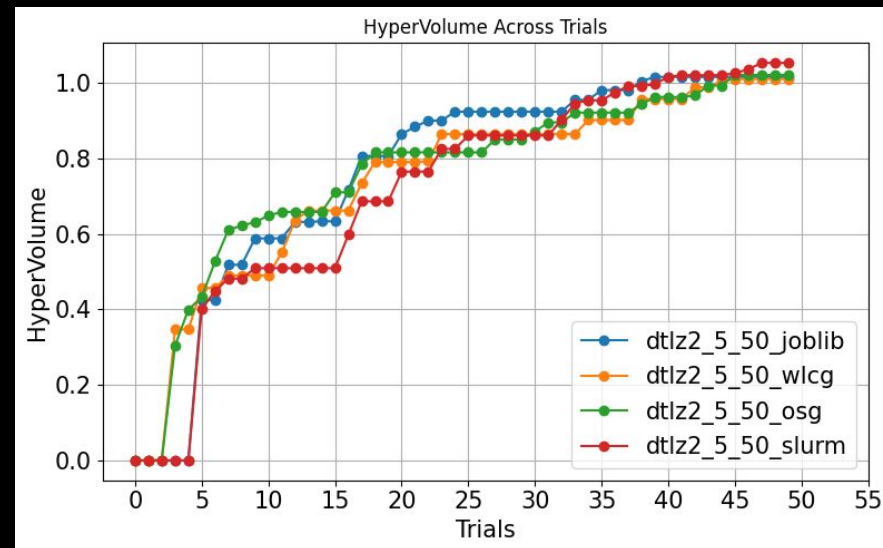
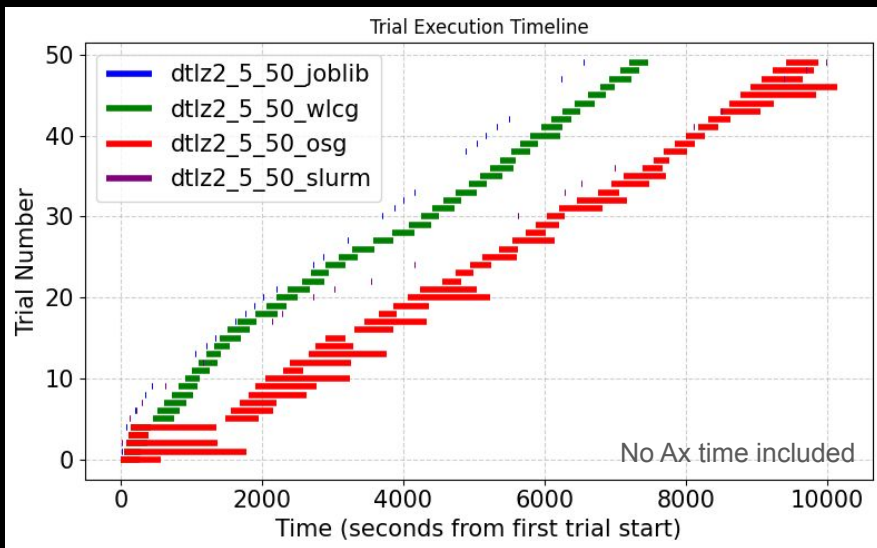
- Enables active-learning / Bayesian-optimization / Evolutionary etc loops.
- Supports multi-objective optimization with high-dimensional design scans for compute intensive simulation campaigns



Stress Tests Across Job Schedulers



- Joblib, Slurm, PanDA (OSG and WLC)
Studies with DTLZ benchmarks (known Pareto front)



- The width of the line represents the total execution time for the trial. Joblib has the least time, followed by Slurm and then WLCG and OSG (across US grids).
- All the runners perform similar optimization (plot on right)

ePIC stands out as a highly **Integrated Detector** encompassing Central, Far-Forward, and Far-Backward regions, all crucial to access the EIC physics.

ePIC extends across -35m to +35m.



A. Deshpande's talk

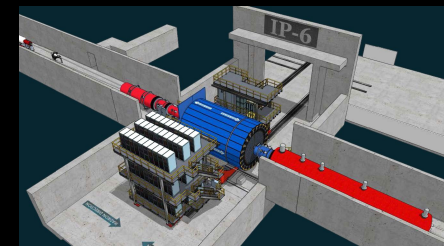
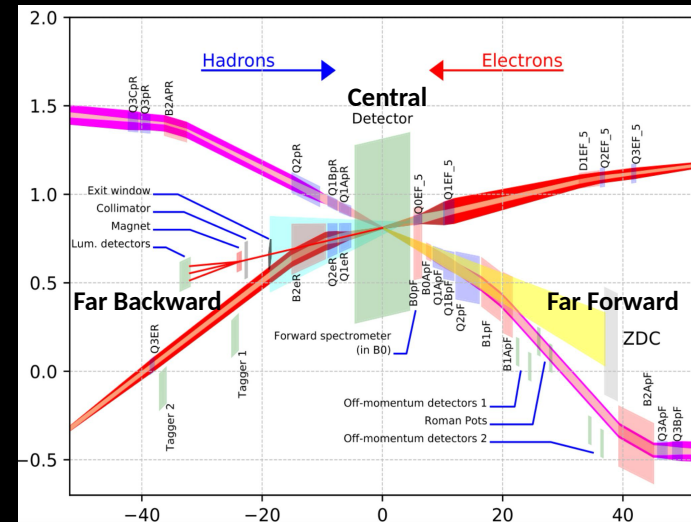
EIC at IWSHO2024-Yerevan



- New 1.7T solenoid
- Si MAPS Tracker
- MPGDs (μ RWELL/ μ Megas)

- hpDIRC
- pFRICH
- dRICH
- AC-LGAD (~30ps TOF)

- Imaging Barrel EMCal
- PbWO₄ EMCal in backward direction
- Finely segmented EMCal + HCal in forward direction
- Outer HCal (sPHENIX re-use)
- Backwards HCal (tail-catcher)



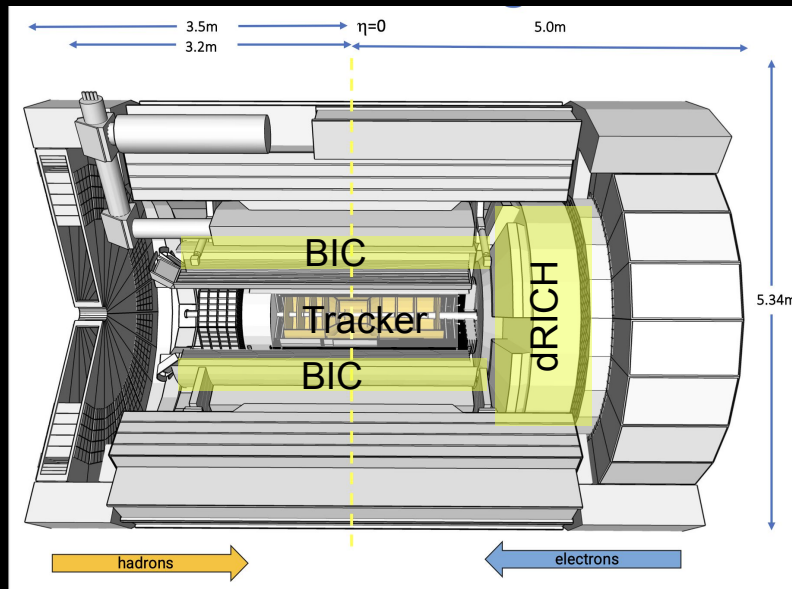
The tightly integrated design of the ePIC detector leads to unique and complex optimization challenges...

Towards Holistic Design

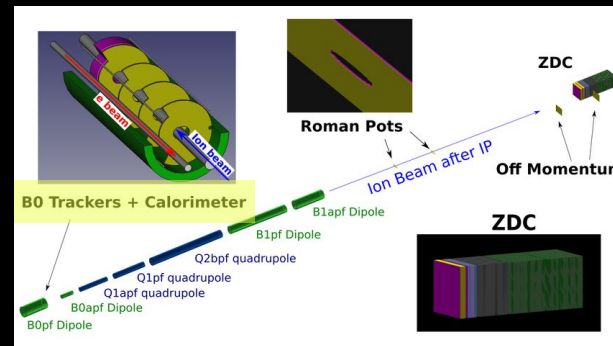


- (Ongoing) Stress-test performance combining Tracker + dRICH + BIC (from central detector) + Far-Forward B0 ~ 50 (to 100) pars + 4-5 objectives → paper in preparation
- Integrating different simulations (particle guns or physics simulators) through ePIC SW stack

Central



+ Far-Forward

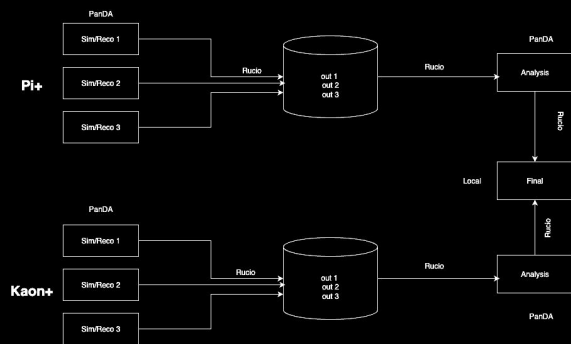


AID2E-enabled Design in ePIC: Examples



dRICH MOBO workflow working as a multistep job:

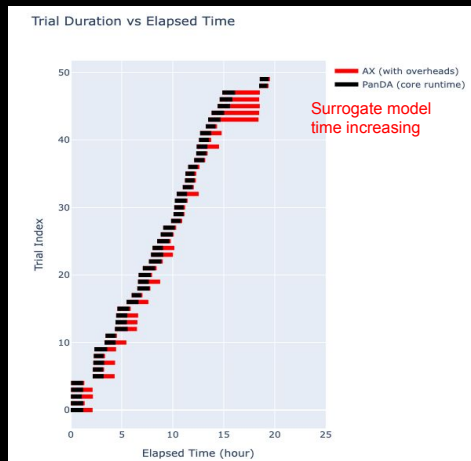
The optimization of parameters depend on pion and kaon ID performance across different momentum ranges in each trial.



Red color shows the overhead for each ax-trial (model's fit time + gen time)

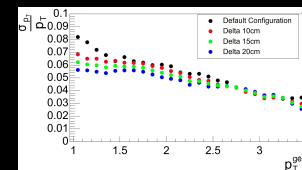
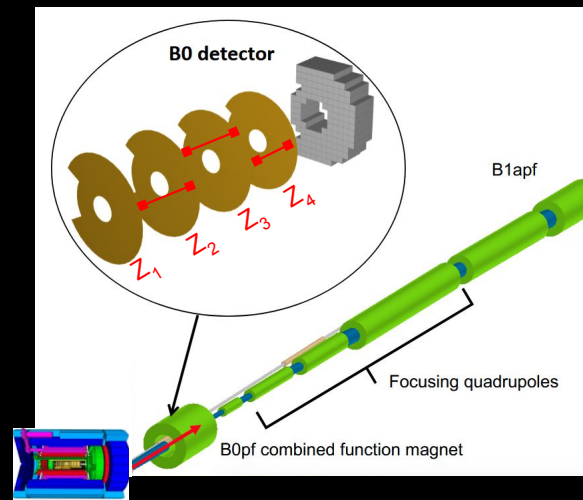
Black color information on cost of overheads when job is idle or in queue. PanDA core time is the time spent on queue and design evaluation time (Sim+Reco+Ana) for each design point

A. Bashyal, W. Guan (BNL);
C. Nunez, C. Pecar (Duke)



Far-Forward workflow

Geometry / active-zone parameters optimized with BO.



- Physics objective: improve proton p_T resolution for Sullivan-process Λ reconstruction.
- Ongoing discussion within ePIC:
 - Λ -reconstruction using ZDC, B0, EndCap, LFHcal
 - Validation: energy correction, vertex resolution, and integration with holistic e^- reconstruction.

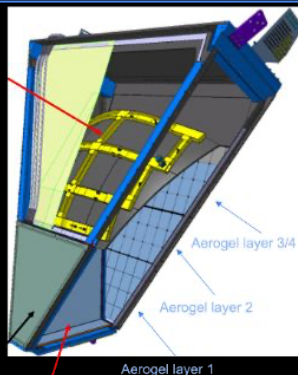
AID2E: Detector Design & Optimization



First successful alignment of CLAS12 RICH

Spherical mirrors

- Multiple mirror geometry
- 480 parameters using TurBO
- Significant improvement in performance



Aerogel layer 3/4

Aerogel layer 2

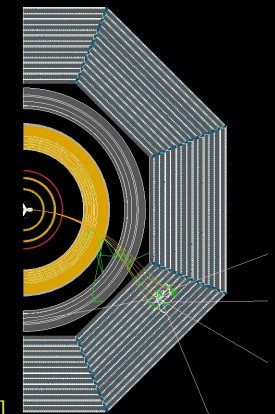
Aerogel layer 1

Planar mirrors

(Duke)

Design of an kKLM at EIC/Detector-2

- μ Id/HCAL/ToF
- Very good MuID and HCAL performance in simulation ($<40\%/\sqrt{E}$)
- Exploration of parameter space provides insights into tradeoffs (e.g., material vs longitudinal segmentation)

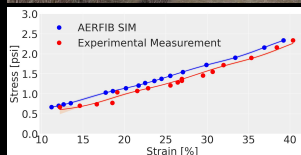
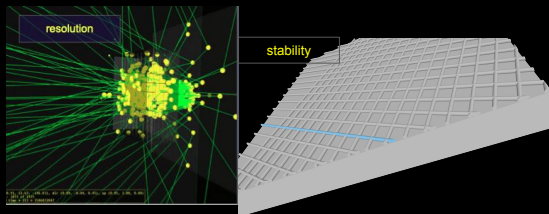


(Duke)

[ArXiv: 2511.08432 \[physics.ins-det\]](https://arxiv.org/abs/2511.08432)

Fiber-reinforced Aerogel material

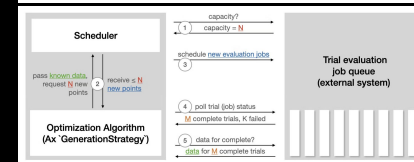
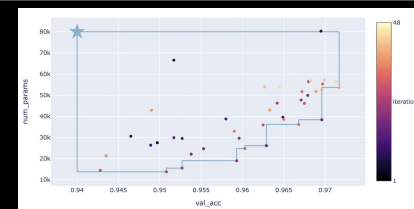
- SW stack with Geant4 (optics) + Gmsh/Elmer (mechanical stability)



(W&M, CUA)

And beyond... Neural Architecture Search

- Optimizing complex neural networks embedded in simulation and reconstruction workflows



<https://pytorch.org/blog/effective-multi-objective-neural-architecture/>

(12)

Extension of AID2E



Augment AID2E's PanDA-orchestrated MOO workflows with LLM agents for workflow assistance, run monitoring, and human-in-the-loop control.

LM Agent



prompt

monitor/control

- Optimization Strategy
- Distribution/Orchestration
- Code Generation

```
for total_epochs in range(epochs):  
    epoch_loss = 0  
    total_graphs = 0  
    not_train = []  
    for batch in train_loader:  
        batch.to(device)  
        optimizer.zero_grad()  
        output = net(batch)  
        loss = F.mse_loss(output, batch.y[:, target_idx].unsqueeze(1))  
        loss.backward()  
        epoch_loss += loss.item()  
        total_graphs += batch.num_graphs  
        optimizer.step()  
    train_avg_loss = epoch_loss / total_graphs
```

Human in the loop



LM automates the workflow:
optimization pipelines, tasks
distribution, code generation

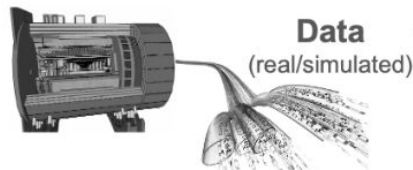
Human-in-the-loop control:
experts monitor, validate,
and guide the process

Multi-objective optimization:
with tools such as BoTorch
and pymoo

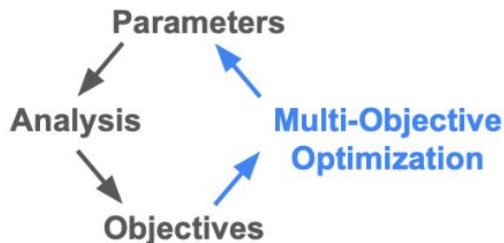
**Distributed workflow
management:** enabled
through PanDA



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Data
(real/simulated)



BoTorch
pymoo
⋮

Conclusions

<https://aid2e.github.io/aid2e>



The EIC could feature the first large-scale experiments designed and optimized with the aid of AI.

By applying AI to detector design and optimization, AID2E is a prime example of AI's role in automating scientific workflows.

- **AID2E** integrates multi-objective optimization, distributed workflow management, and the full ePIC software stack.
- **Holistic detector optimization** is becoming practical: subsystem studies are being extended toward coupled detector/physics objectives.
- The main **practical lesson** is trust: AI optimization must be embedded in validated collaboration workflows.
- ~~(Next)~~ Now: work on “**LLM agents**” for workflow assistance, monitoring, anomaly flagging, and human-in-the-loop steering.



Backup