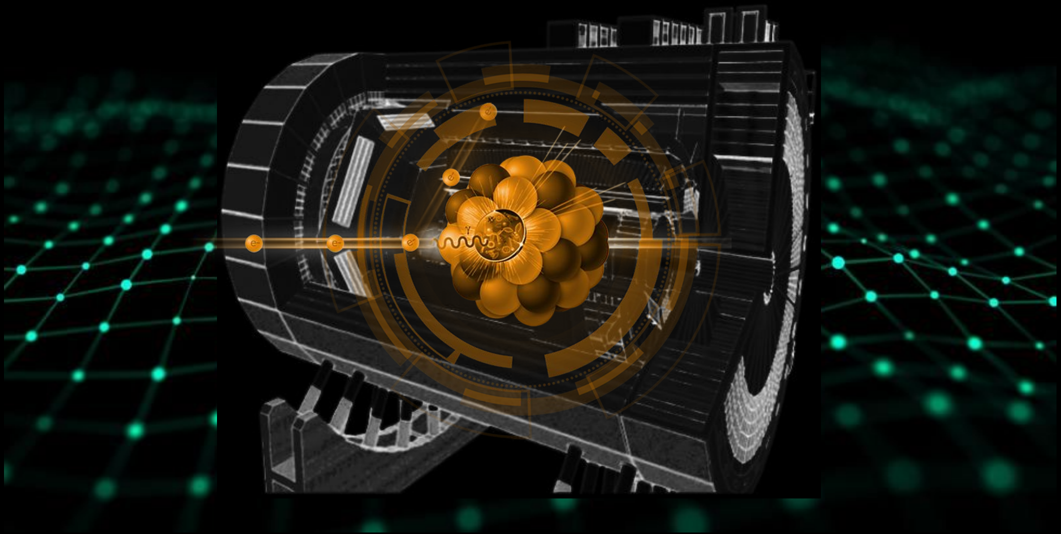
AI/ML + Data Science tools for detector design at the EIC



5/26/2023

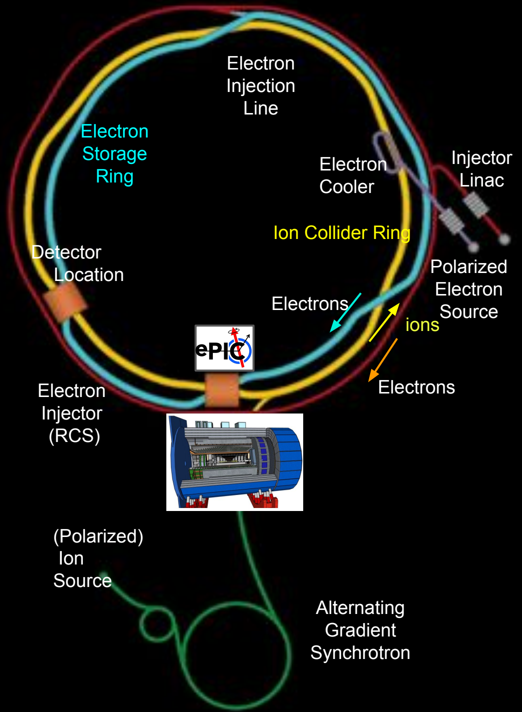
Cristiano Fanelli (and Authors in the slides)

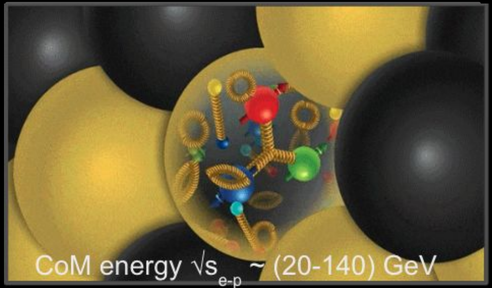
ISNET-9 INFORMATION AND STATISTICS IN NUCLEAR EXPERIMENT AND THEORY

Electron Ion Collider (EIC)

EIC @BNL:
a precision machine to study the “glue” that binds us all

polarized electron - polarized protons/ions



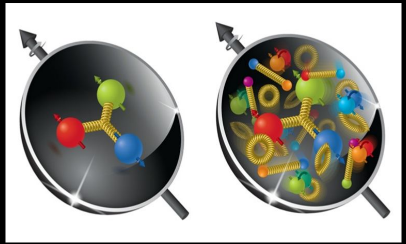


World-wide interest in EIC, thousands of users and hundreds of institutions involved

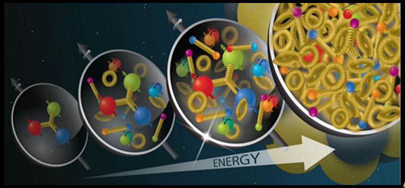
Total estimated cost ~ $1.6-2.6B

How does the mass of the nucleon arise?

How does the spin of the nucleon arise?



What are the emergent properties of dense systems of gluons?



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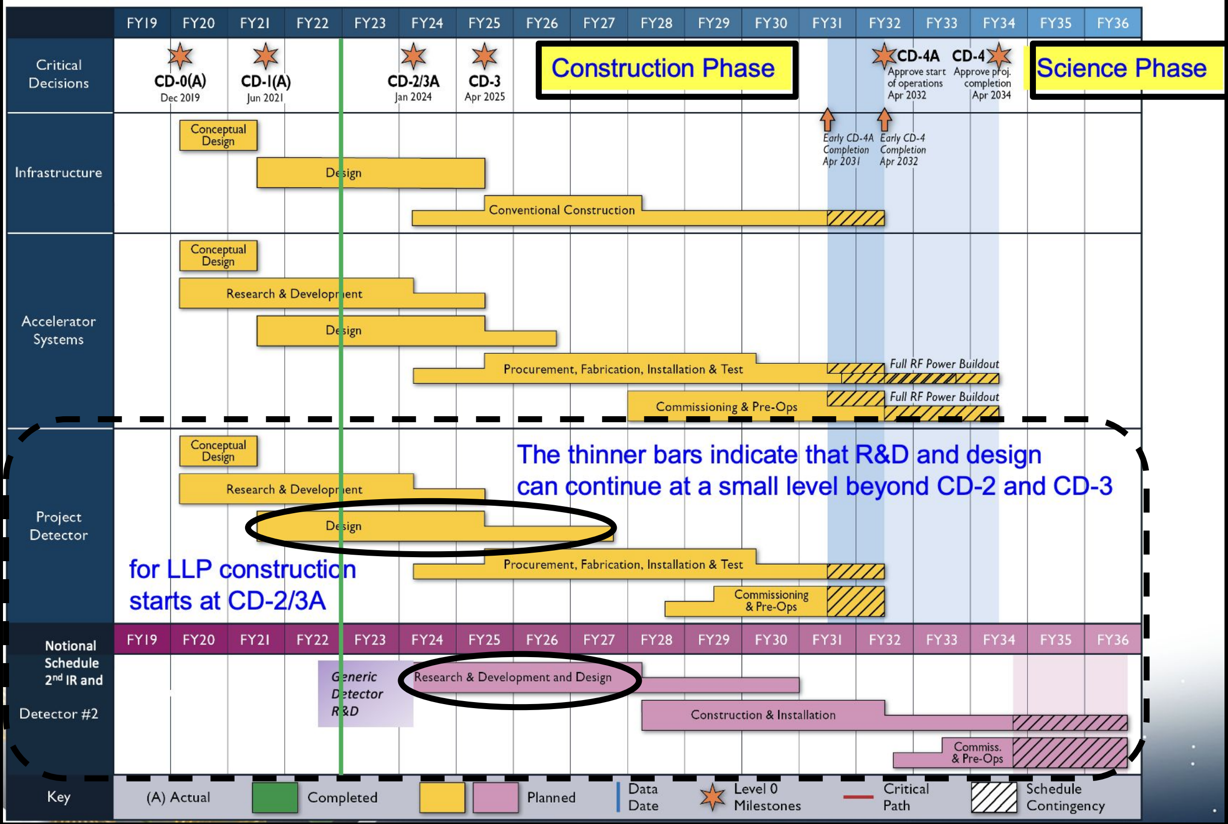
EIC Schedule

R. Ent, AI4EIC workshop, October 2022

Magnet landed in the partially assembled flux return and outer HCAL (in 2021)

ePIC Collaboration recently formed (previously ECCE proto-collaboration selected as reference detector)

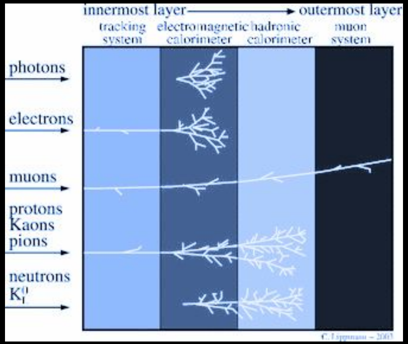
Detector-2 ePIC accelerator

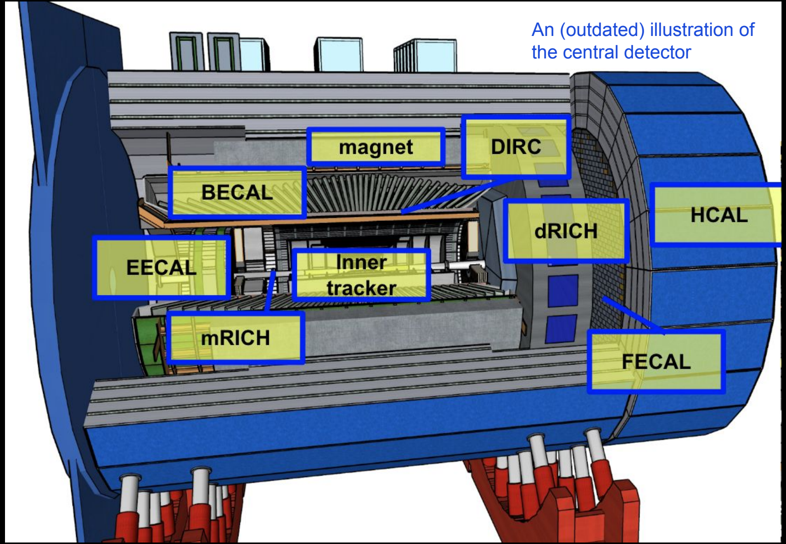


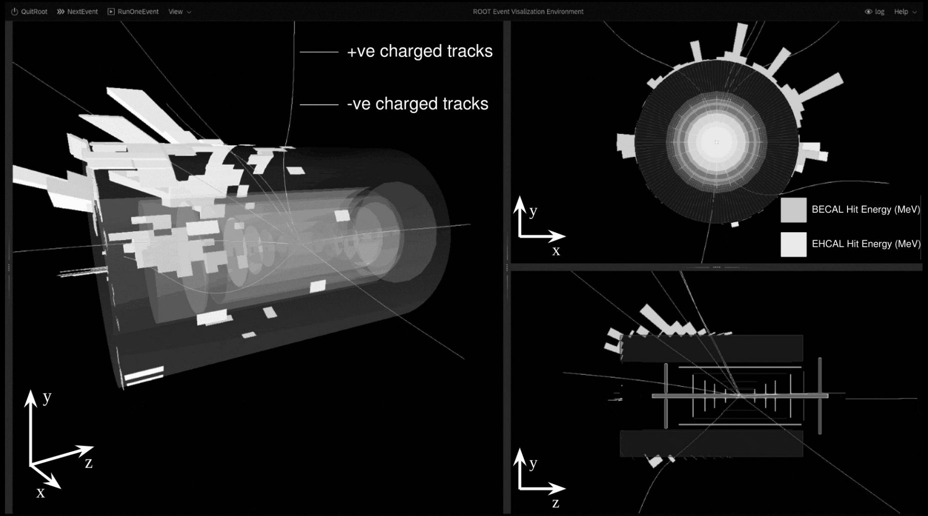
Opportunities for (Detector Design) Optimization!

The ePIC Detector

- A large-scale experiment with an integrated detector that extends for ~ ± 35 m to include the central, far-forward, and far-backward regions.
- To enable the EIC physics we need a central detector that is: hermetic and asymmetric
- From fundamental physics, we know that different types of particles interact differently with matter and we need to develop specific devices to identify them

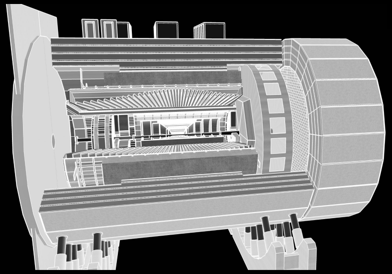


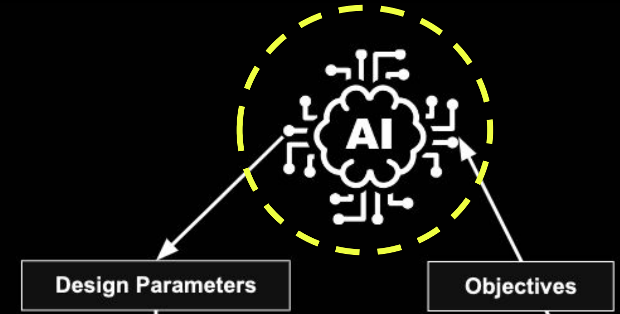


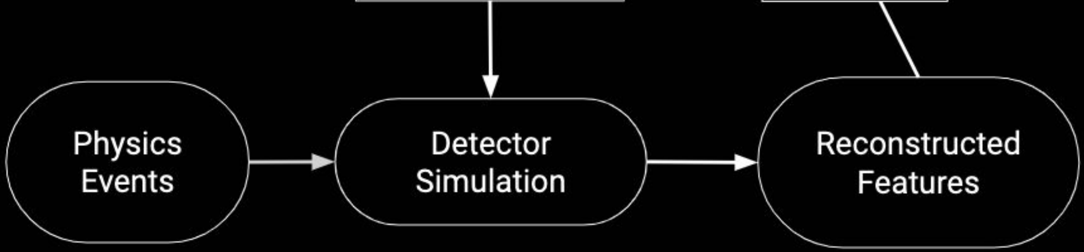


AI-assisted design

The AI-assisted design is a good example of how AI can be folded into the SW planning as it embraces all the main steps of the simulation/reconstruction/analysis pipeline







- Leverages heterogeneous computing
- Benefits from rapid turnaround time from simulations to analysis of high-level reconstructed observables
- The ePIC SW stack offers multiple features that facilitate AI-assisted design (e.g., modularity of simulation, reconstruction, analysis, easy access to design parameters, automated checks)

helps steering the design (and eventually fine-tune it)

can capture hidden correlations among design parameters

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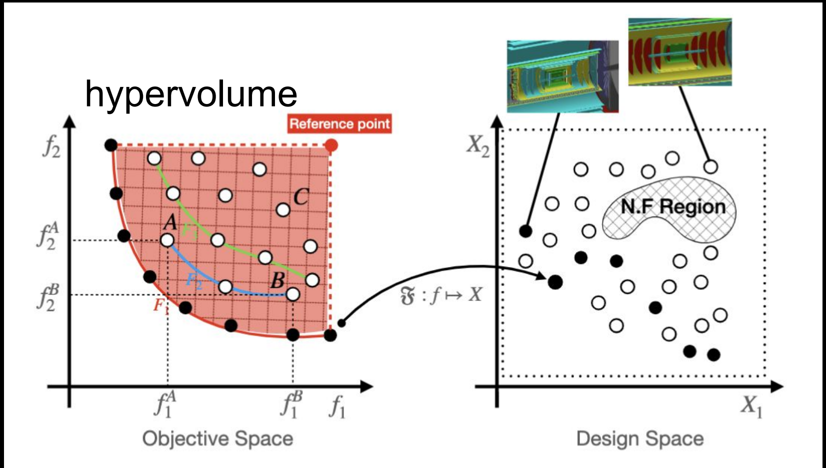
Why Multi-Objective Problem?

Hot take: every optimization problem is fundamentally a multi-objective optimization problem.

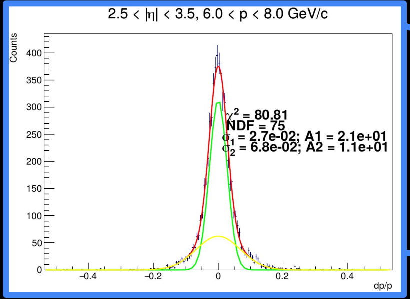
- 3 Types of Objectives
  - **Intrinsic detector performance** (resolutions, efficiencies) for each sub-detector — Tracking, calorimetry, PID — noisy
  - **Physics-performance** — Multiple physics channels, equally important in the EIC physics program
  - **Costs** (e.g., material costs, provided a reliable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

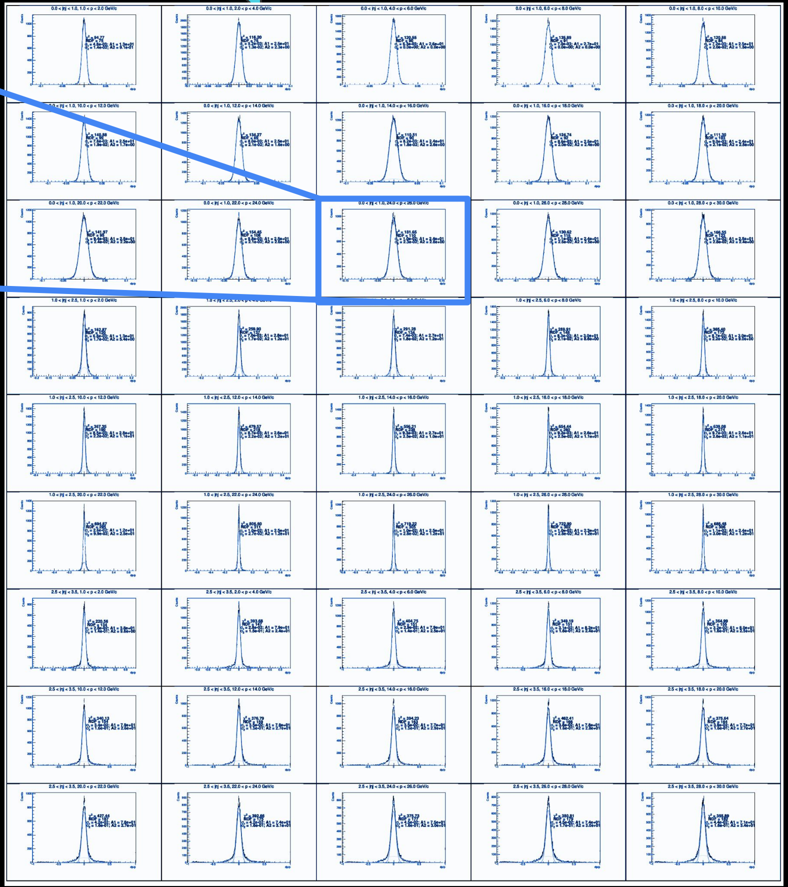


For illustrative purposes

Fine-grained analysis

Weighted sum with errors





Weighted sum with errors

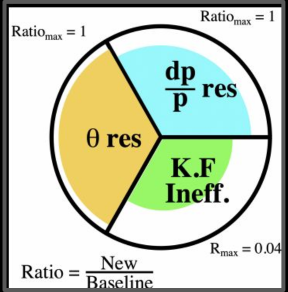
1. Robust fitting procedure in fine-grained phase-space
2. Propagate uncertainties

$$\bar{x_\eta} = \frac{\sum_p x_p w_p}{\sum_p w_p} \qquad \bar{x} = \frac{\sum_\eta^{N_\eta} \bar{x_\eta}}{N_\eta}$$

(sum in bins of P) (Average objective in a η bin)

$$\Rightarrow R(f) = \frac{1}{N_\eta} \sum_\eta \left(\frac{\sum_p w_{p,\eta} \cdot R(f)_{p,\eta}}{\sum_p w_{p,\eta}} \right)$$

3. Do this for several objectives



Example for tracking system

(more details in C. Fanelli et al (ECCE Coll.), NIMA Vol 1047, Feb 2023, 167748)

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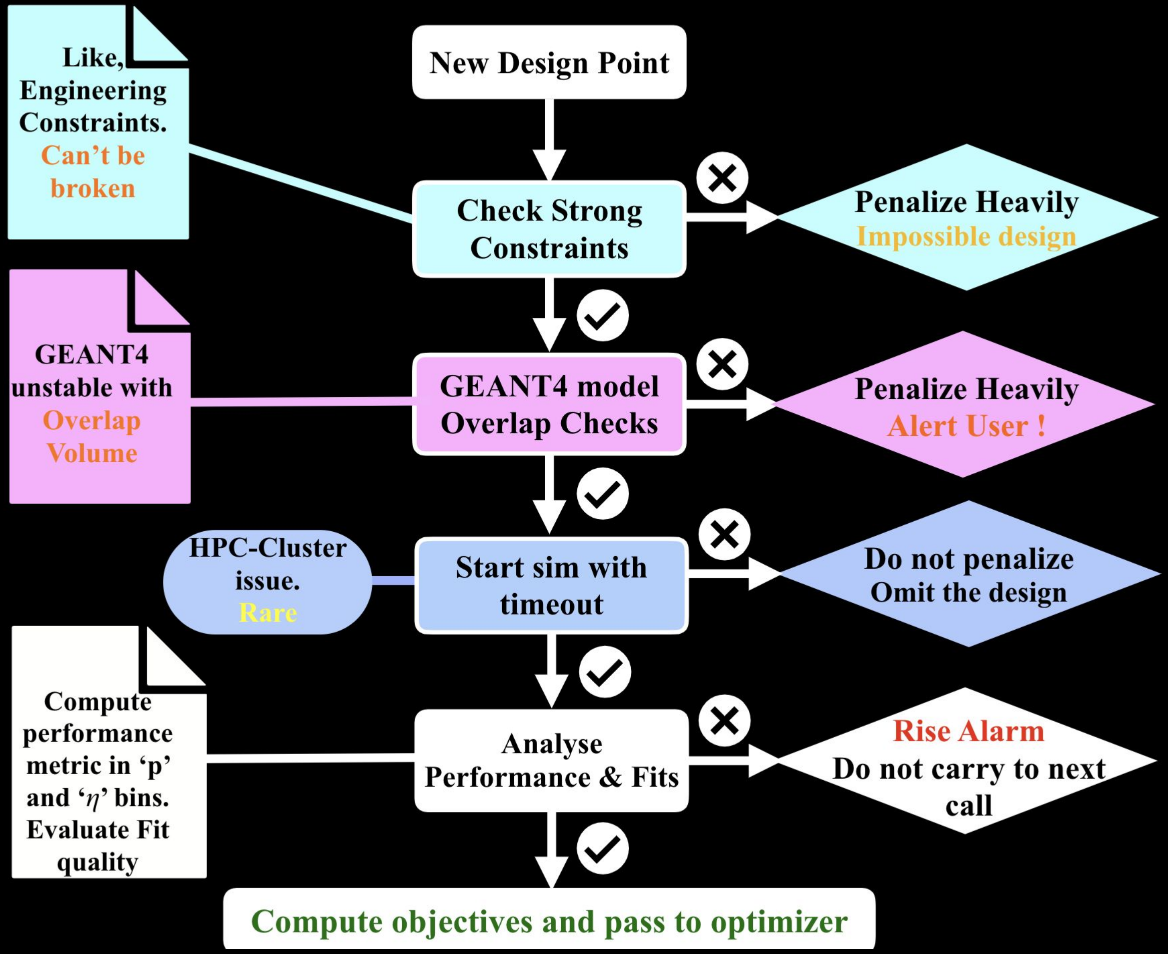
Checks performed



(more details in C. Fanelli et al (ECCE Coll.), NIMA Vol 1047, Feb 2023, 167748)

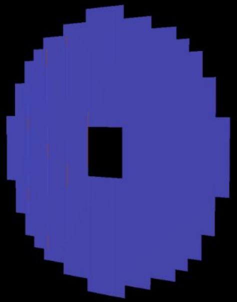
Constraints

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

sub-detector	constraint	description
EST/FST disks	$min\left\{\sum_{i}^{disks}\left\|\frac{R^i_{out}-R^i_{in}}{d}-\left\lceil\frac{R^i_{out}-R^i_{in}}{d}\right\rceil\right\|\right\}$	**soft constraint**: sum of residuals in sensor coverage for disks; sensor dimensions: $d = 17.8$ (30.0) mm
EST/FST disks	$z_{n+1} - z_n >= 10.0$ cm	**strong constraint**: minimum distance between 2 consecutive disks
sagitta layers	$min\left\{\left\|\frac{2\pi r_{sagitta}}{w}-\left\lceil\frac{2\pi r_{sagitta}}{w}\right\rceil\right\|\right\}$	**soft constraint**: residual in sensor coverage for every layer; sensor strip width: $w = 17.8$ mm
μRWELL	$r_{n+1} - r_n >= 5.0$ cm	**strong constraint**: minimum distance between μRwell barrel layers

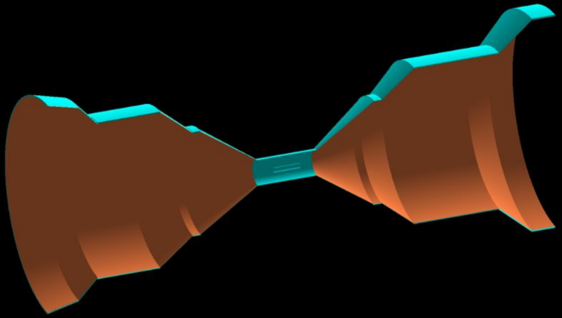
Example of constraints implemented for the tracking system

(more details in C. Fanelli et al (ECCE Coll.), NIMA Volume 1047, Feb 2023, 167748)



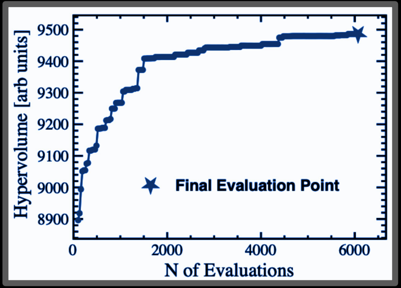
FST/EST Disks

Barrel Si Layer

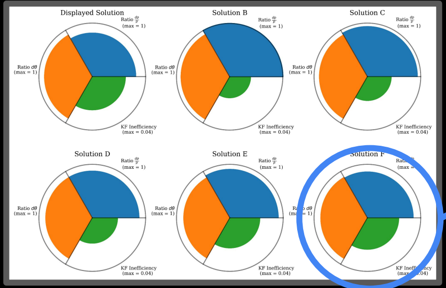


Analyzing the results

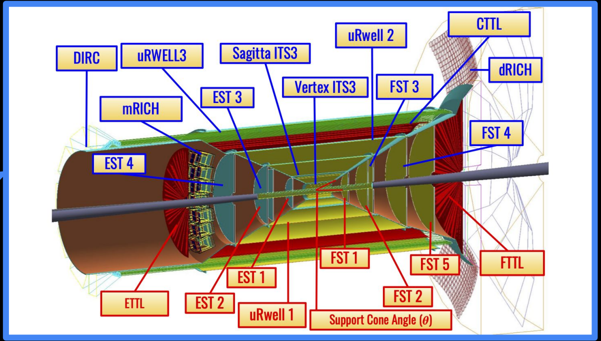
1 Can take a snapshot any time during evaluation



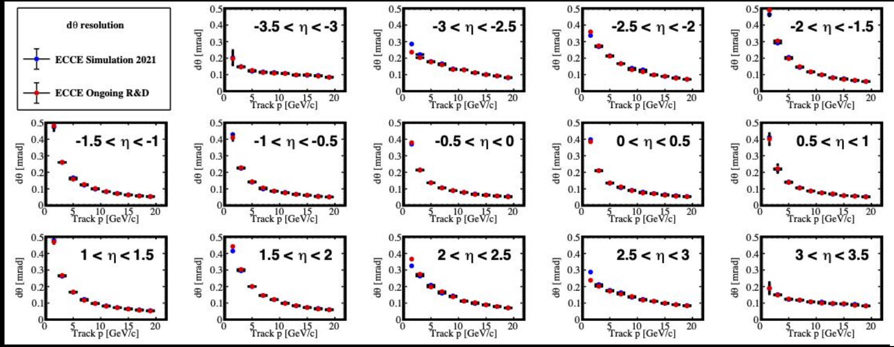
2 Updated Pareto Front at time t

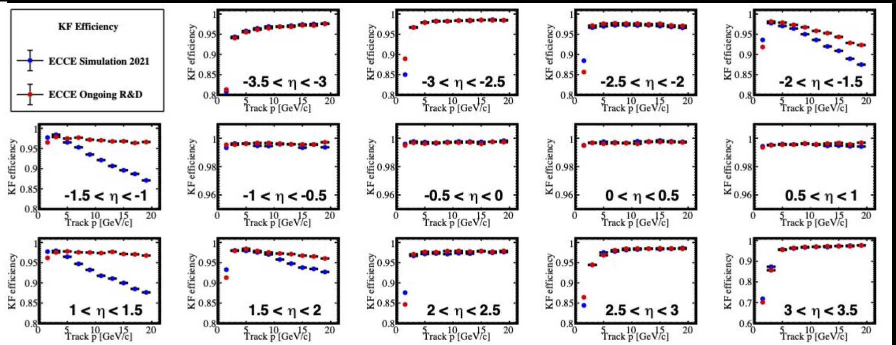


3 At each point in the Pareto front corresponds a design



4 Analysis of Objectives (momentum resolution, angular resolution, KF efficiency)





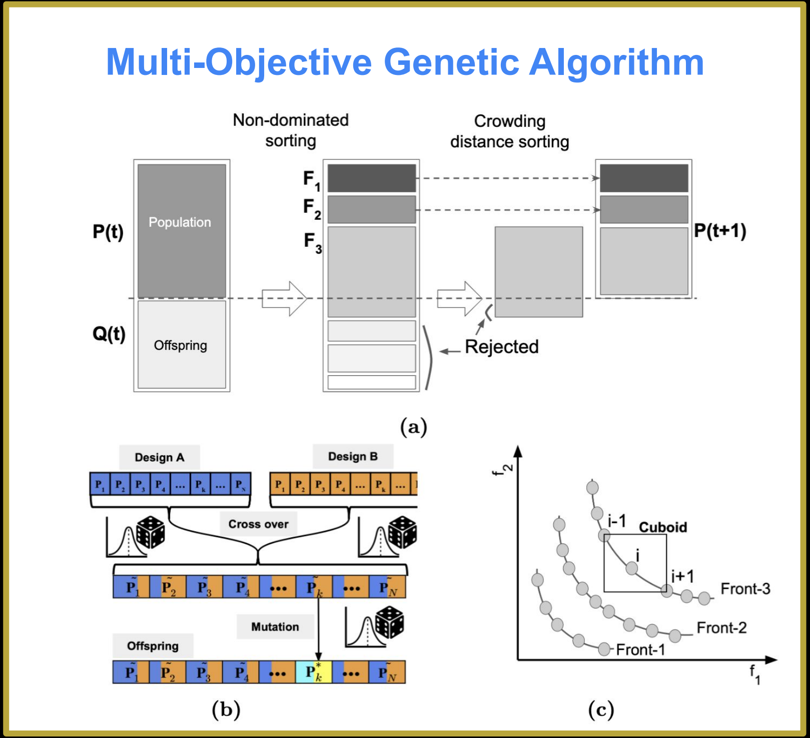
MOO Pipelines: MOGA

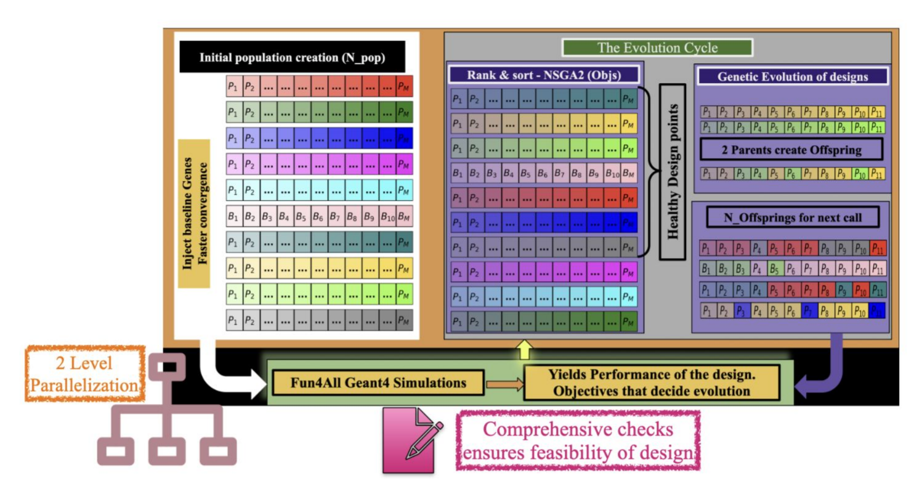
CF et al., NIM-A Vol 1047, Feb 2023, 167748

arXiv:2205.09185

- Engage with Open Source projects
- In a first exploratory phase*, we used MOGA (NSGA-II)

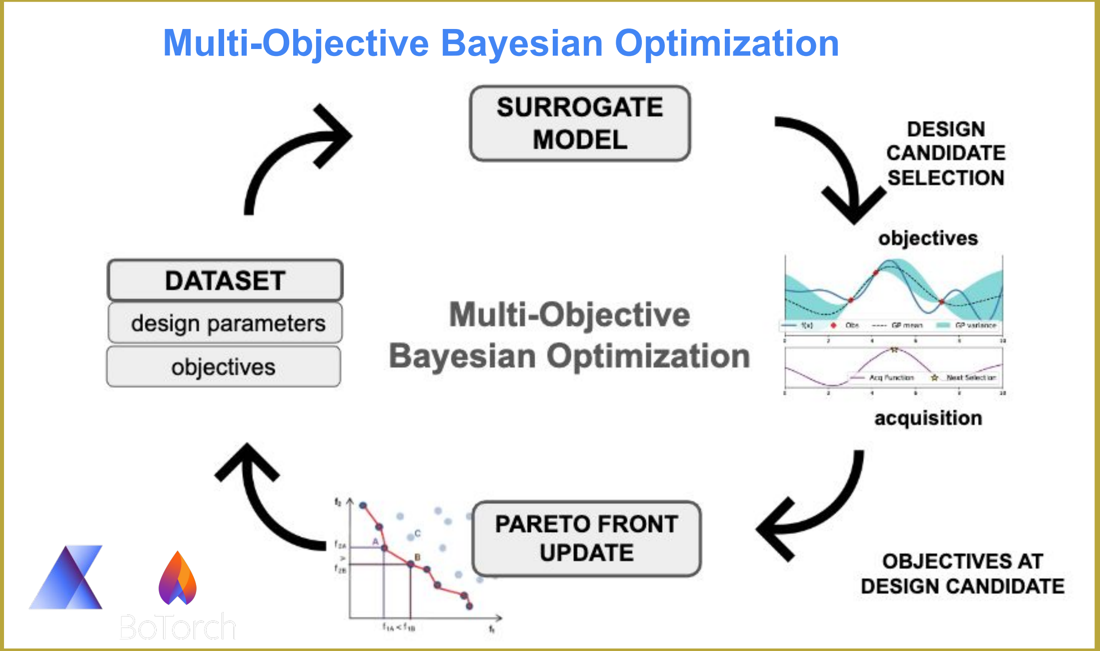
Description	Symbol	Value
Algorithm used	MOEA	NSGA-II
# Objectives	M	3
# Offspring	O	30(50)
# design Parameters	D	11
# calls (tot. budget)	-	200
# Cores	-	same as offspring
# Charged π^- tracks	N_{trk}	80k
Population Size	N	100





MOO Pipelines: MOBO

- As the project evolved, so did our understanding of the design space and the possible ranges for each design parameter.
- With MOBO, we aim to determine a more accurate approximation of the Pareto front



- Using Ax/BoTorch and novel qNEHVI acq. function with improved computational performance arXiv:2105.08195
- Currently in the process of generalizing the design problem and increase its complexity

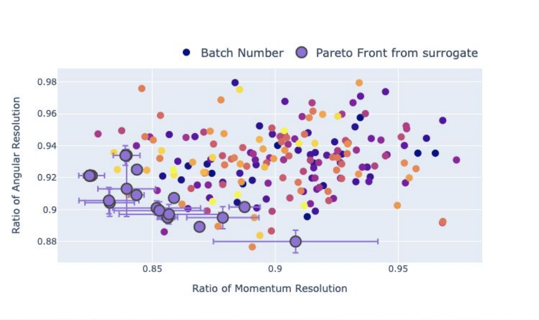
(e.g., Ax: adaptive experimentation platform supported by Meta AI)

See 2nd AI4EIC workshop, https://indico.bnl.gov/e/AI4EIC

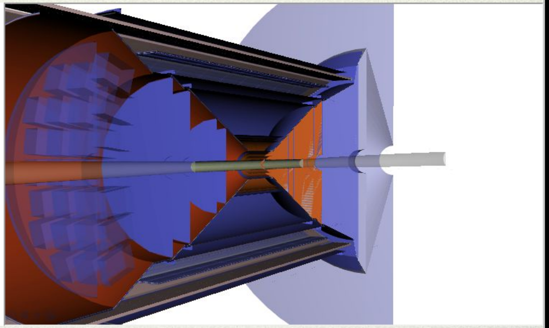
Navigate the Pareto front

C.Fanelli et al, NIM A, 2023, 167748, arXiv:2205.09185

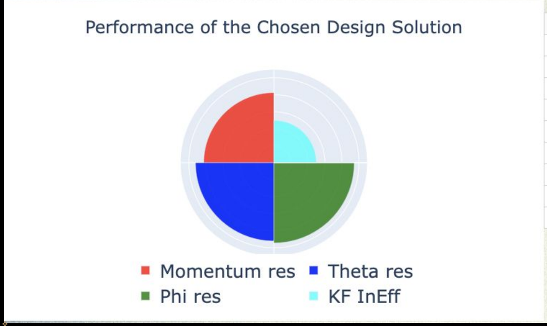
Multi Objective Bayesian Optimization



GEANT4 Visualization of the design



Click on petals for finer evaluations

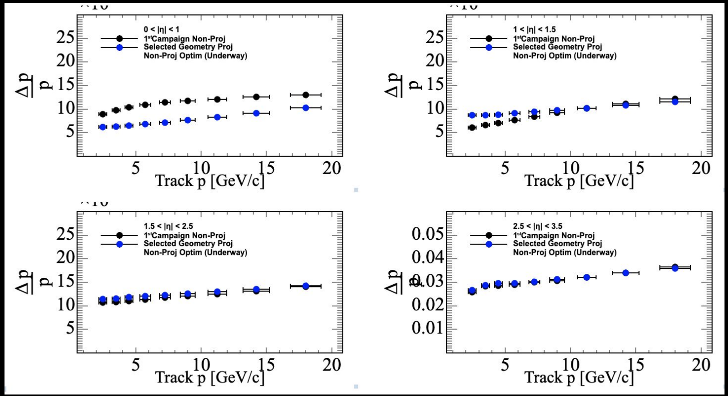


Design Parameters Table

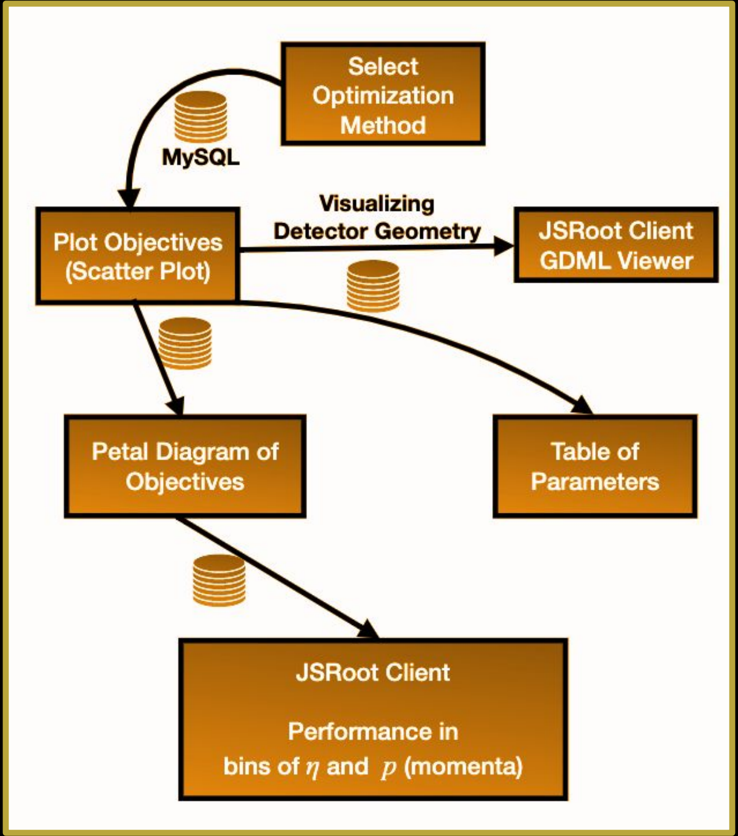
Parameter Name	Parameter Value
Angle of cone [deg]	25.00
Radius of uRwell-1 [cms]	32.47
z E-TTL [cms]	171.00
z F-TTL [cms]	157.60
z EST-1 [cms]	40.39
z EST-3 [cms]	85.09
z FST-1 [cms]	35.03
z FST-3 [cms]	83.78
z FST-5 [cms]	131.27

The whole idea of the AI-assisted design is that of determining trade-off optimal solutions in a multidimensional design space driven by multiple objectives

For an interactive visualization:
https://ai4eicdetopt.pythonanywhere.com

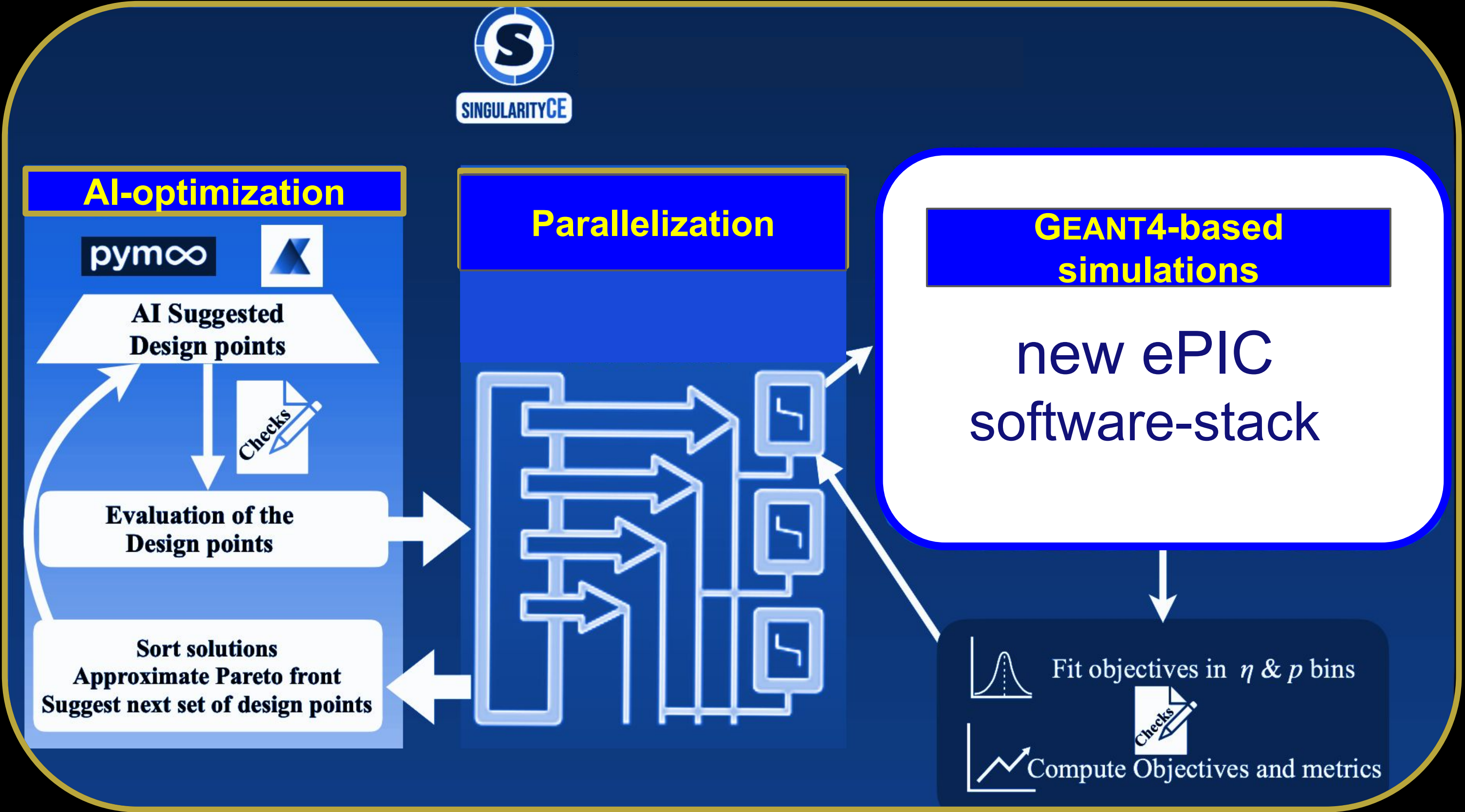


Visualization



- The interactive visualization employs several Python and JavaScript libraries/packages to visualize the results from the optimization
  - Plotly-dash - click&play interface; interactive navigation; expanded dashboard
  - JSRoot — JSRoot project allows reading binary and JSON ROOT files in JavaScript; drawing of different ROOT classes in web browsers; reading TTree data; using node.js used to visualize the detector geometry which is stored in GDML format
  - Pandas: read source data (Pareto front solution)
  - MySQL DB: most convenient DB that is used alongside Flask based applications. Meta-data like location of Geometry files, Location of parameters file are stored in the form of a database

Workflow utilized in the ECCE proposal (2022)

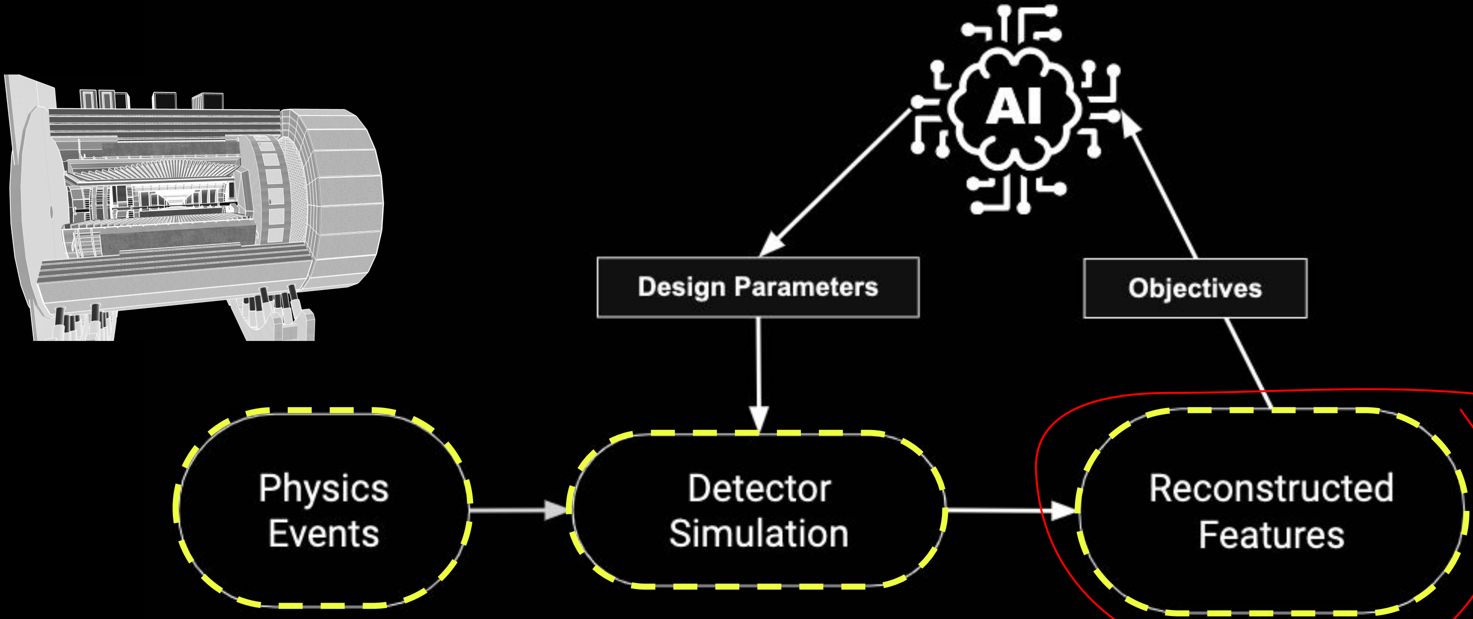


*Future implementations will explore a scalable and distributed AI-assisted design framework

ePIC SW Features Streamlining AI-Assisted Design

- Design:
  - Geometry implementation via data source makes transparent the coupling of AI to the software stack design parameters
  - Modularity of geometry description
  - Automated features (checking overlaps)
- General Properties:
  - Code repository, continuous integration, containerization
  - Open, simple, self-descriptive data formats (flat data model in general allows flexibility for AI/ML applications)
  - Support for truth information
  - Use of ML-supported packages (e.g., ACTS, includes ONNX plugin)
  - JANA2 with integrated Python interface
  - etc.

AI-assisted design



See example (3)

Event level

⇑

Particle level

See examples (1) and (2)

*AI/ML can potentially enter in all the steps of the design pipeline

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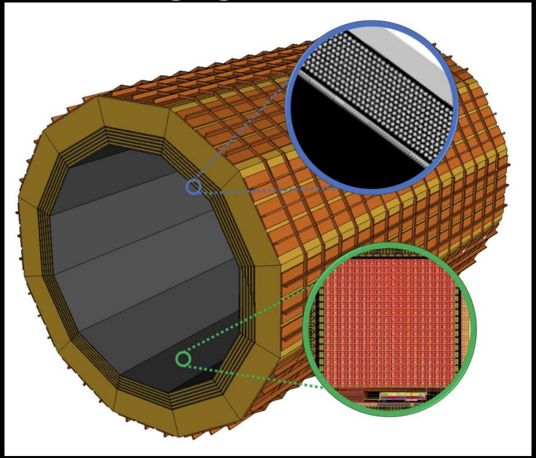
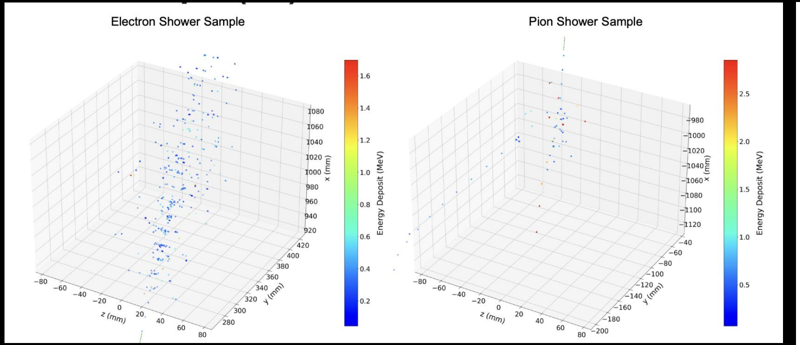
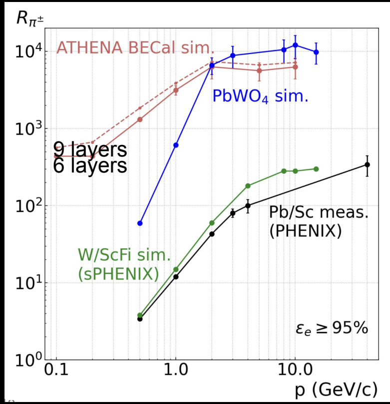
(1) ML-based PID for Shower Imaging

Imaging Calorimeter



shower examples





ML model: Sequential CNN + MLP

red: imaging detector and ML
blue, green and the black: other technology and traditional cut-based strategy

Hybrid Concept

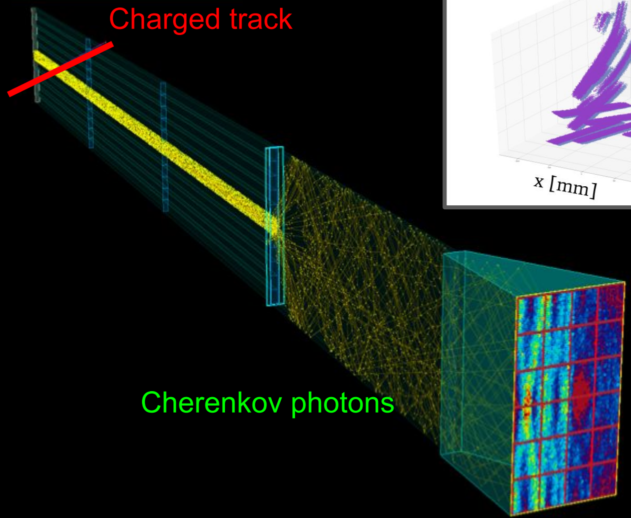
- Monolithic Silicon Sensors AstroPix
- Scintillating fibers embedded in Pb (Pb/ScFi similar to GlueX Barrel Ecal)
- “Sandwiched” 6 layers of AstroPix and 5 layers of Pb/ScFi (~1X0) followed by a large chunk of Pb/ScFi
- Total thickness ~43 cm (~21 X0)
- Large amount of data (3D shower imaging)

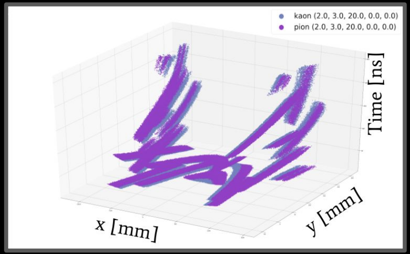
- ML with shower imaging significantly improves e/π rejection compared to traditional E/p cut — impact on DIS
- Separation of γ’s from π^0 at high momenta (40 GeV/c) and precise position reconstruction of γ’s (<1 mm at 5 GeV) — DVCS and γ physics
- Tagging final state radiative γ’s from nuclear/nucleon elastic scattering at low x to benchmark QED internal corrections
- Improving PID, providing a space coordinate for DIRC reconstruction

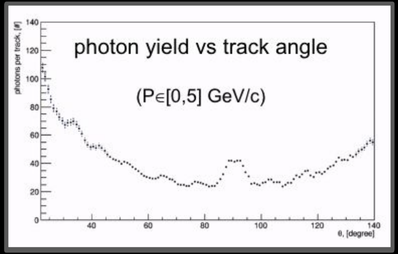
[1] N. Apadula, et al. "Monolithic active pixel sensors on cmos technologies." arXiv preprint arXiv:2203.07626 (2022).
[2] C. Peng, ML Particle Identification with Measured Shower Profiles from Calorimetry, AI4EIC 2nd workshop (2022)

(2) ML-based PID for Cherenkov

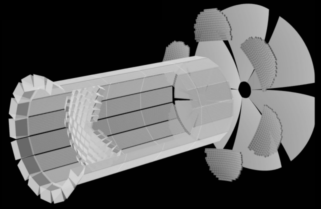
DIRC at GlueX is instrumental for PID



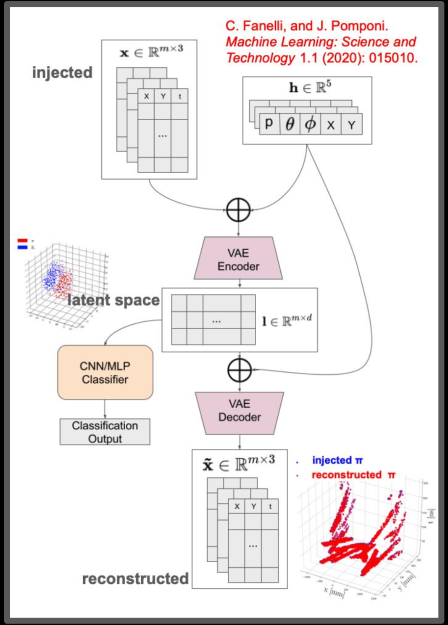




Cherenkov detectors will be the backbone of PID at EIC



DeepRICH



- Need for faster and accurate simulations and reconstruction
- Complex hit patterns (DIRC is the most complex), sparse data, response vs kinematics
- DeepRICH: same reconstruction performance of best reconstruction algorithm with ~4 orders of magnitude speed-up in inference time on GPU
- Possibility to learn at the event-level rather than at the track/particle level. Can generate hit pattern.

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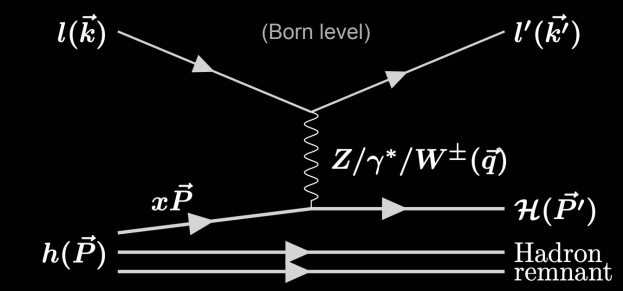
[1] C. Fanelli, J. Pomponi, “DeepRICH: learning deeply Cherenkov detectors”, Mach. Learn.: Sci. Technol., 1.1 (2020): 015010
[2] C. Fanelli, "Machine learning for imaging Cherenkov detectors." JINST 15.02 (2020): C02012.

(3) Deeply Learning DIS

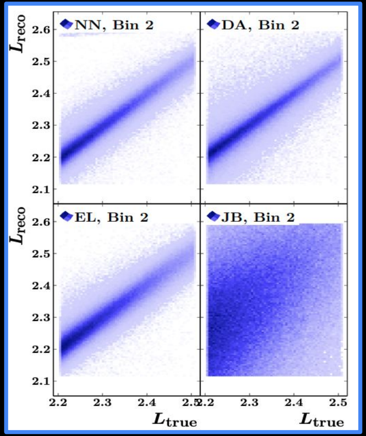
DIS fundamental process @EIC



DIS beyond the Born approximation has a complicated structure which involve QCD and QED corrections

- Use of DNN to reconstruct the kinematic observable Q^2 and x in the study of neutral current DIS events at ZEUS and H1 experiments at HERA.
- The performance compared to electron, Jacquet-Blondel and the double-angle methods using data-sets independent of training
- Compared to the classical reconstruction methods, the DNN-based approach enables significant improvements in the resolution of Q^2 and x

Example in one specific bin



Bin	Events	Resolution of $\log x$, $\times 10^3$		Resolution of $\log Q^2/1\,\text{GeV}^2$, $\times 10^3$	
1	301780	**NN: 70**	EL: 83	**NN: 35**	EL: 35
		JB: 180	DA: 103	JB: 203	DA: 62
2	350530	**NN: 69**	EL: 82	**NN: 40**	EL: 43
		JB: 167	DA: 96	JB: 192	DA: 64
3	138456	**NN: 98**	EL: 130	NN: 55	**EL: 53**
		JB: 138	DA: 100	JB: 150	DA: 77
4	74844	**NN: 67**	EL: 84	**NN: 44**	EL: 46
		JB: 117	DA: 77	JB: 138	DA: 63
5	31043	**NN: 64**	EL: 91	**NN: 36**	EL: 41
		JB: 102	DA: 73	JB: 117	DA: 53
6	11475	**NN: 53**	EL: 79	**NN: 33**	EL: 36
		JB: 83	DA: 61	JB: 100	DA: 45
7	3454	**NN: 50**	EL: 69	**NN: 36**	EL: 38
		JB: 74	DA: 55	JB: 93	DA: 42
8	624	**NN: 36**	EL: 55	**NN: 33**	EL: 37
		JB: 67	DA: 45	JB: 95	DA: 41

Table 4: Resolution of the reconstructed kinematic variables in bins of x and Q^2. The resolution for x and Q^2 is defined as the RMS of the distributions $\log(x) - \log(x_{\text{true}})$ and $\log(Q^2) - \log(Q^2_{\text{true}})$ respectively.

[1] M. Diefenthaler, et al. "Deeply Learning DIS Kinematics" arXiv:2108.11638, EPJC 82, 1064 (2022)
[2] M. Arratia, et al., "Reconstructing the kinematics of DIS with DL", NIM-A 1025 (2022): 166164

AI4EIC community

https://eic.ai

- AI will be an integral part of the EIC science and to work in this direction, a dedicated AI Working Group (AI4EIC) has been established 2 years ago within the EICUG (https://www.eicug.org)
- AI4EIC serves as an entry point to AI applications and organizes workshops, tutorials, hackathons, challenges, etc.
- AI4EIC fosters connections between ePIC and the Data Science / Computer Science community

- Workshops —2 workshops, 200+ participants each (https://eic.ai/workshops)— serve as a body of essential knowledge for AI4EIC, and produce proceedings, annual report, journal special issues.
- Educational activities and outreach are aimed at disseminating AI in the EIC community
  - Several tutorials (https://eic.ai/community)
  - Hackathon events are built around specific challenges for EIC and help identify strategies, architectures and algorithms that will benefit the EIC physics program (https://eic.ai/hackathons)
  - Additionally, AI4EIC is committed to establishing educational events (e.g., schools) designed to enhance AI and ML proficiency within the EIC community (https://eic.ai/community), (https://eic.ai/ai-ml-references)

AI4EIC

https://eic.ai

https://eic.ai/workshops

- Workshop: (2022)

  Total of 220 registered participants (also last year, >200!)
  - Very good attendance in person!

  6 sessions (15 conveners, 40+ speakers)
  - Design
  - Theory/Exp connections (morning + afternoon sessions)
  - Recon & PID
  - Infrastructure (+ Panel Discussion)
  - Streaming

- **Discussion from this workshop contributed to NSAC LRP**
- **Paper in preparation**

- Tutorials:
  - MOBO
  - OmniFold
  - MLFlow
  - GNN

https://eic.ai/community

- Hackathon:

  (10 teams from North, South America, Asia, Europe)

https://doi.org/10.5281/zenodo.7197023

Jefferson Lab
Exploring the Nature of Matter

Forthcoming AI4EIC workshop from Nov 28 to Dec 1, 2023 — CUA, Washington, D.C.

Conclusions

- **Next generation QCD experiments like ePIC are being designed during the AI revolution:**
  - AI can assist the design and R&D (two phases, slightly different needs) of complex experimental systems
    - providing more efficient design (considering multiple objectives)
    - utilizing effectively the computing resources needed to achieve that.
- **EIC will be one of the first large-scale experiments (involved hundreds of institutions world-wide) to be designed with the support of AI**
  - The reference detector has been already designed taking advantage of a multi-objective optimization approach and a complex parametrization of its design which takes into account constraints.
  - The optimization framework utilizes accurate full simulations based on Geant4, identify the tradeoffs in the Pareto front (and reduce the total computational budget to converge to Pareto).
- **This workflow can be further extended for ePIC (and Detector-2)**
  - More realistic effects in the simulation and reconstruction techniques
  - A larger system of sub-detectors, e.g, detectors like the dRICH — increased complexity, e.g.
    - $\mathcal{O}(100)$ pars, 4-8 objectives, $\mathcal{O}(10)$ constraints
    - Room for ideas, e.g., explore physics-inspired acquisition functions — exciting work ahead!!