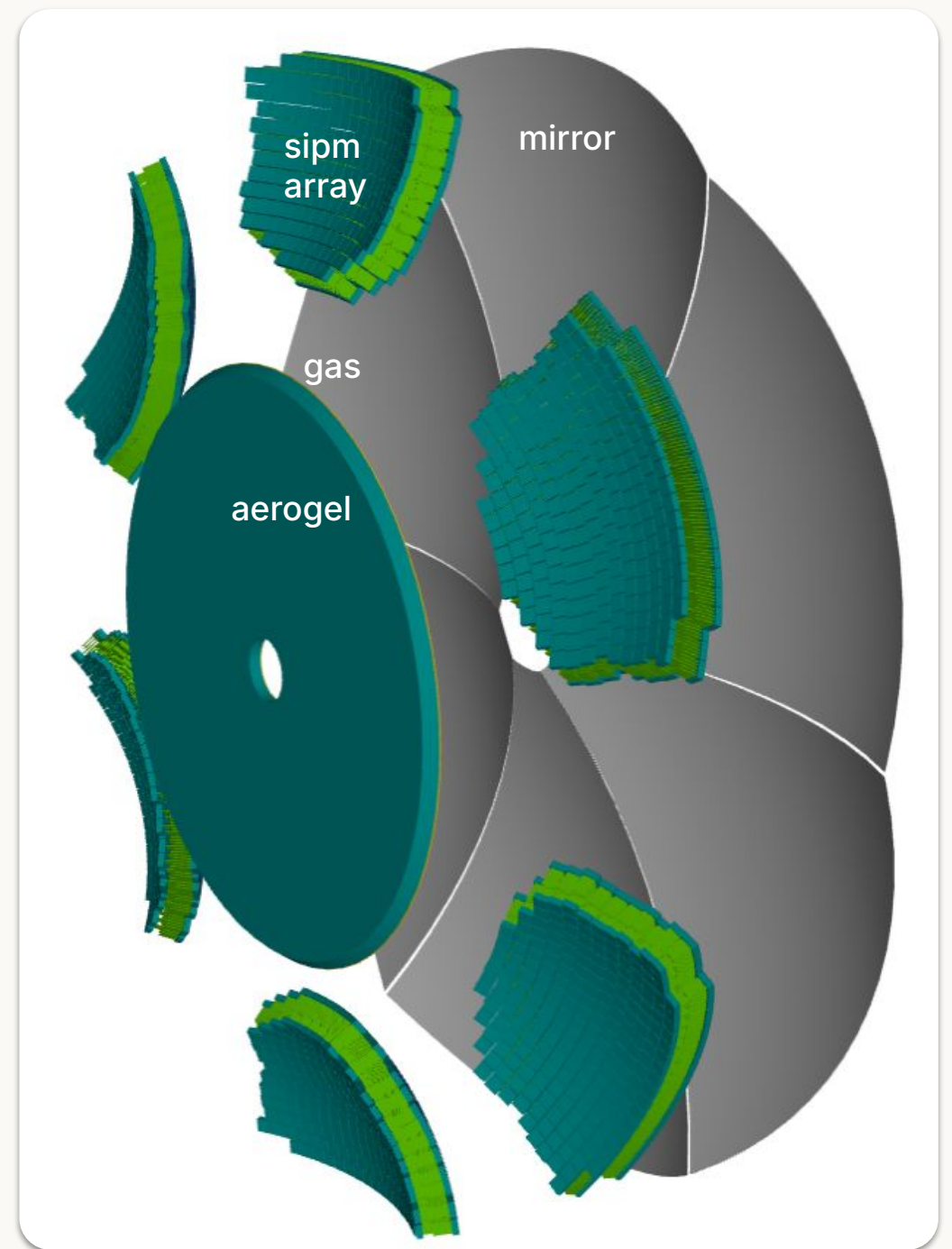


CNN and Vision Transformers for DRICH- PID

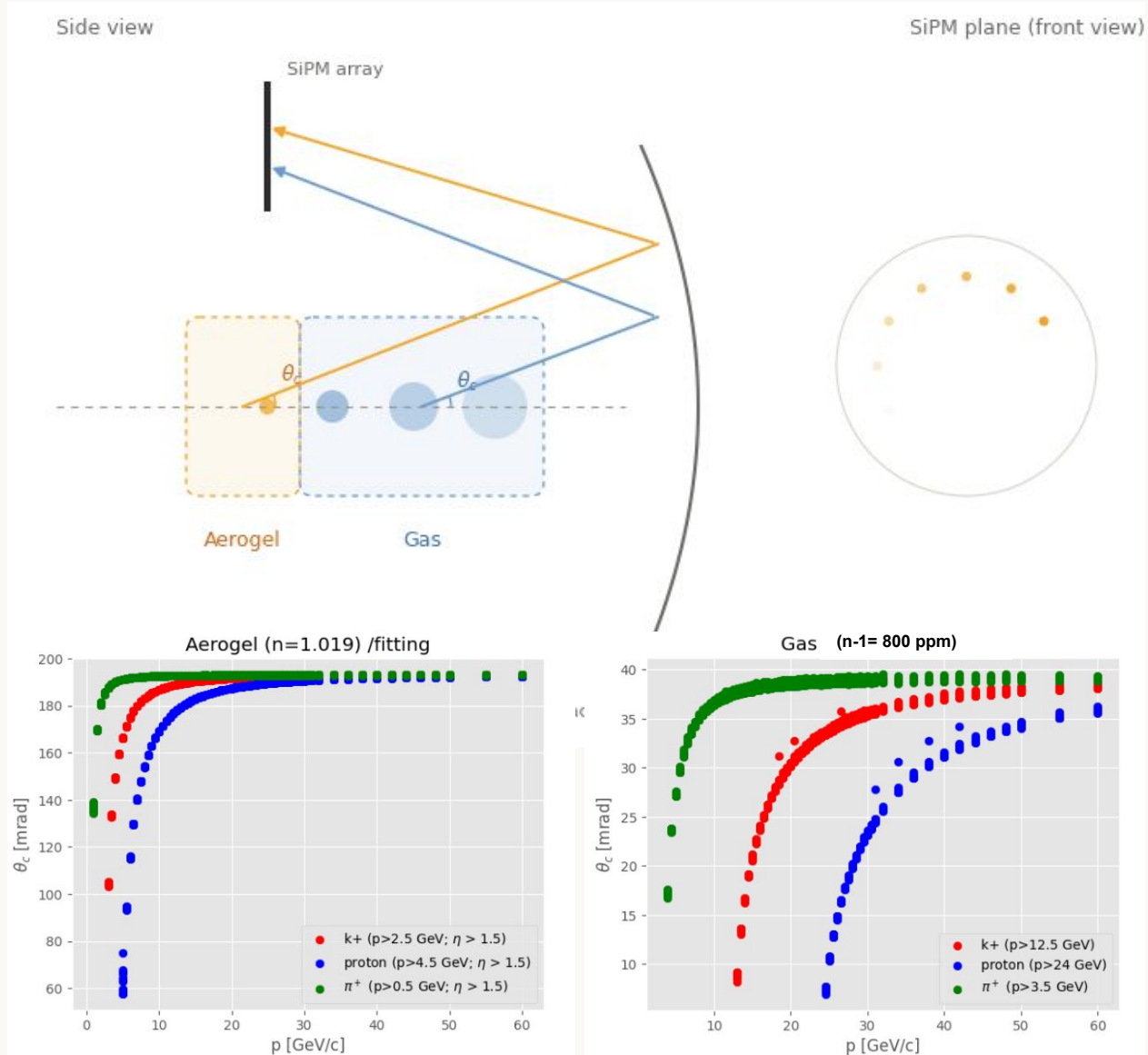
Current status and future prospects

The DRICH detector

- Particle identification in the hadronic end-cap
- $3\text{-}\sigma$ separation of particles in a broad momentum range from a few GeV/c up to 50 GeV/c
- Cherenkov light produced by two different mediums to cover the full momentum range

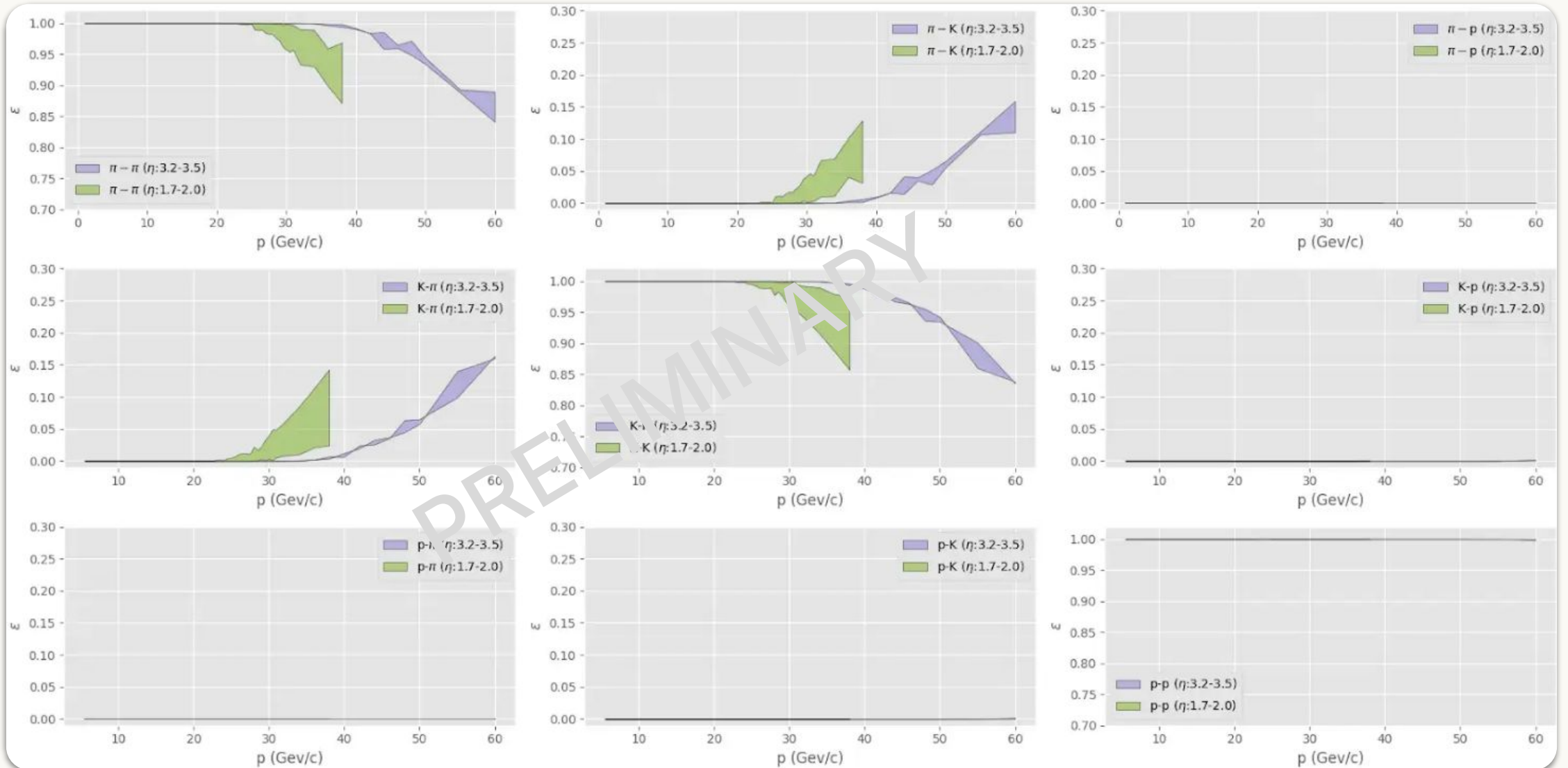


Existing algorithm: Inverse Ray Tracing (IRT) for DRICH PID



- **Constructs using ray tracing,**
 - θ_c for aerogel rings and gas rings (if present) for every hit.
- **Use θ_c and σ_θ to estimate the PID**
 - on a track by track basis
 - Event level chi-square (IRT-2)
- **Well tested and benchmarked**
 - for single particle analysis
 - with and without dark current effect
 - Efficient handle to calibrate the detector optics, geometry and other components.

IRT PID performance (preliminary)



AI-based PID for the DRICH



Objectives

Quantify performance of ML-models with respect to efficiency, speed and robustness



Motivations

Performance of DRICH under noisy conditions and possibility multi-particle identification

Can **timing information** improve the performance of PID. If yes, to what extent?



Models considered

CNN and the more recent Vision Transformers

Vision Transformer (ViT) attains excellent results compared to state-of-the-art convolutional networks while requiring substantially fewer computational resources to train

[Dosovitskiy, Alexey. et al. "An image is worth 16x16 words: Transformers for image recognition at scale." arXiv preprint arXiv:2010.11929 \(2020\).](#)

Status

Team

Chandra, Raman (INFN, Trieste), Tanya Tanvi (CU Haryana), and myself

Datasets

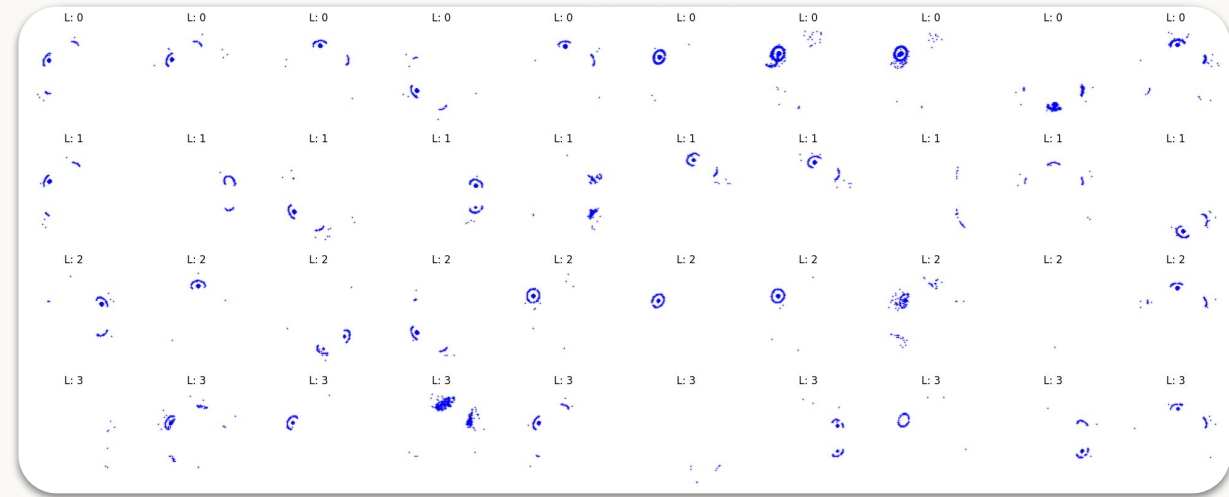
10K events each for e , π , p and K for training, 2K for testing

<https://github.com/deepaksamuel/drich-ml-analysis/>

Simulation hits, scaled to 100×100 pixels

Phase 2

Increase sample size for training ViT



Status



Progress made so far

Tanya has started training with a basic CNN but more fine-tuning is required to achieve IRT-level efficiency



Future work

Increase data samples and start training with ViT

Make comparison of IRT / CNN / ViT

Prepare performance benchmark with various noise rates and QEs

Study performance of CNN/ViT for multi-ring scenarios



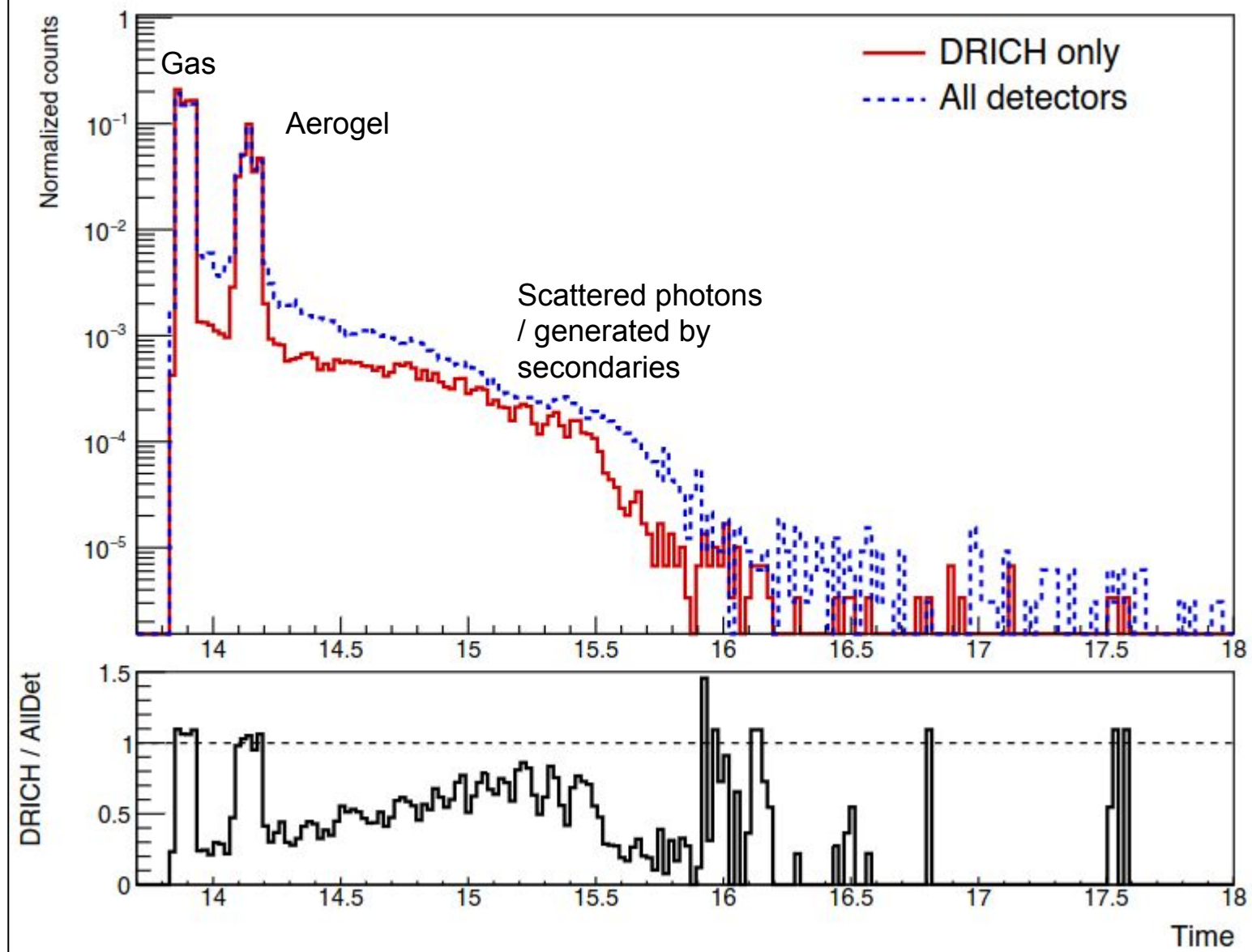
First results expected

December 2026

Backup

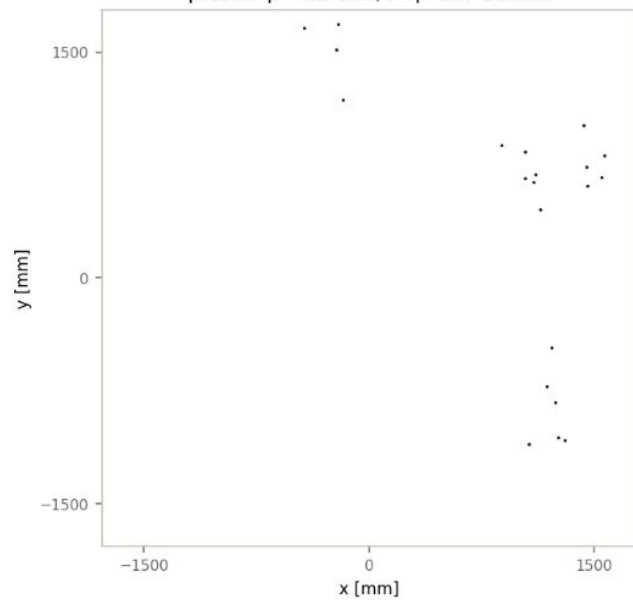
particle	mass [GeV/c ²]	aerogel threshold (n = 1.026)	gas threshold (n = 1.0008)
electron	0.000511	0.0022 GeV/c (2.2 MeV/c)	0.013 GeV/c (13 MeV/c)
pion	0.13957	0.61 GeV/c	3.49 GeV/c
kaon	0.49368	2.15 GeV/c	12.34 GeV/c
proton	0.93827	4.09 GeV/c	23.45 GeV/c

Normalized time distribution, $\eta = 3.0$

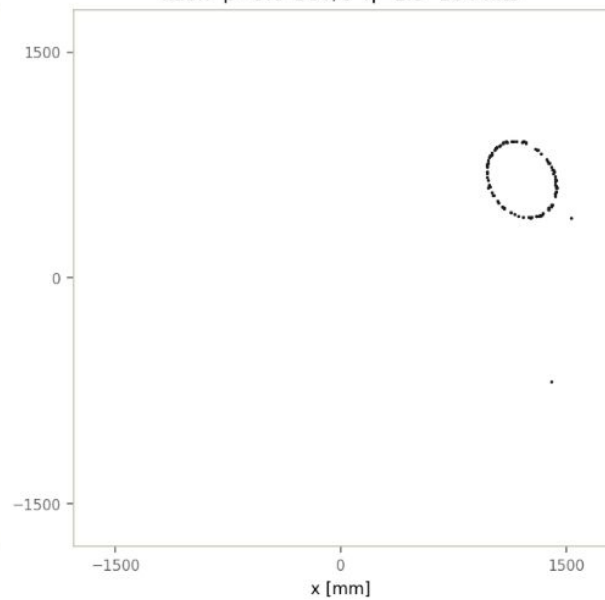


dRICH event topologies — full detector extent (simulation)

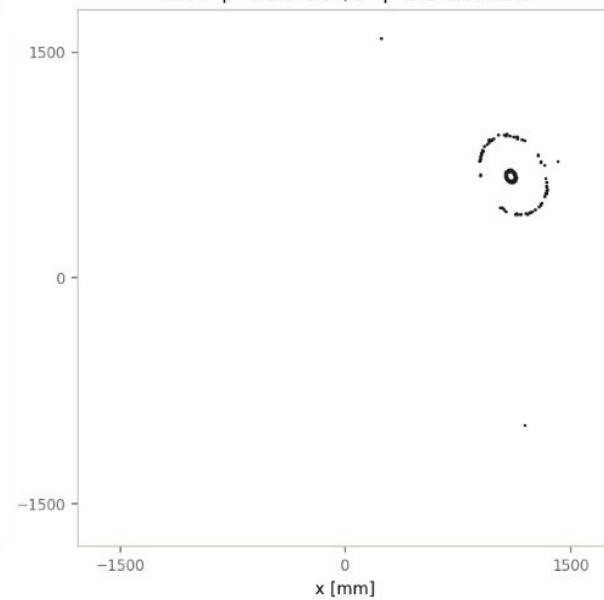
(a) sparse event — below/near threshold
(< 30 hits)
proton $p=4.2$ GeV/c $\eta=1.9$ 21 hits



(b) aerogel ring only
(gas below threshold)
kaon $p=9.6$ GeV/c $\eta=1.9$ 104 hits



(c) aerogel + gas rings
(both radiators active)
kaon $p=31.0$ GeV/c $\eta=2.1$ 293 hits



(d) showering event
(> 400 hits)
pion $p=56.9$ GeV/c $\eta=2.0$ 1479 hits

