Particle reconstruction for dual-readout calorimeter

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On behalf of the Korean DRC Collaboration

KSHEP workshop
2025-11-20

DREAM FOR FUTURE

Overview

- Motivation: precision calorimetry for FCC-ee
- Dual-readout calorimeter basics
- DRC prototype and test-beam
- Simulation & reconstruction
- Deep-learning-based PID & energy regression
- Summary & outlook

Future Circular Lepton Collider(FCC-ee)

- FCC-ee targets:
  - W, Z, Higgs precision measurements
  - Search for beyond-SM signals
  - High-statistics program requiring sub-percent systematics
- Needs for advanced calorimeters:
  - Insufficient jet energy resolution
    - limits W/Z separation
    - degrades Higgs recoil and $\nu\nu$ final states
  - Non-linearity of hadronic energy response
    - biases precision measurements
  - Limited particle identification (PID)
    - reduced sensitivity to rare decays and complex final states

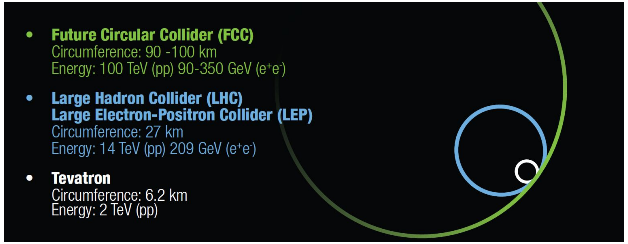
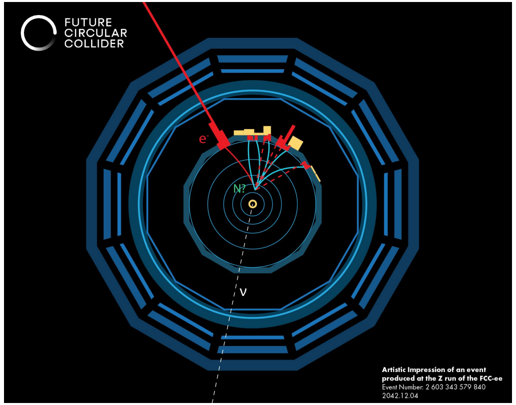


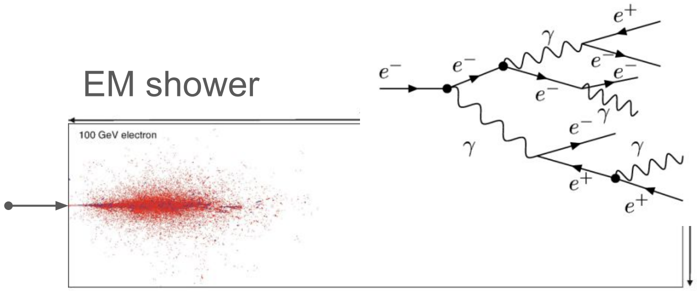
Image of rare process



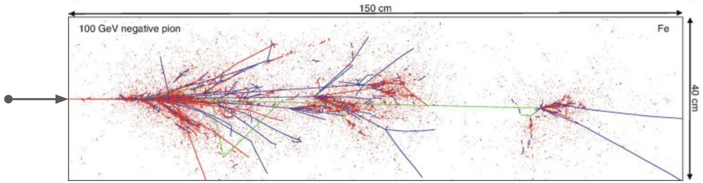
Calorimeter Fundamentals

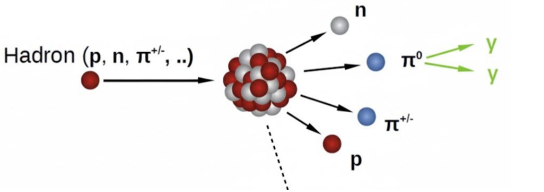
- A high energy particle makes shower of particles interacting with material.
- Electromagnetic(EM) shower
  - Initiated by electron and γ
  - Chain reaction of pair production and bremsstrahlung
- Hadronic shower
  - Initiated by hadrons(π^+, p, n, …)
  - Complex structure due to strong interaction.
  - Nuclear binding energy, neutrons, slow hadrons

EM shower



Hadronic shower



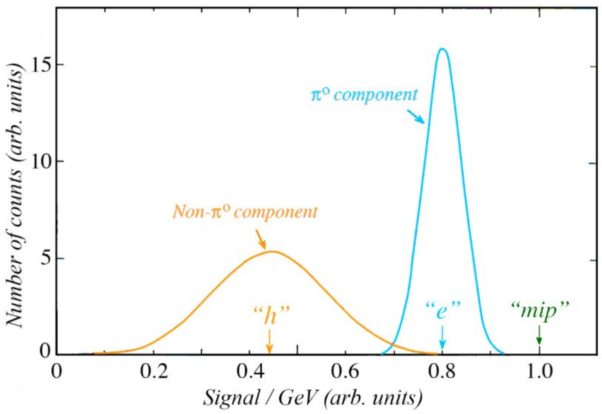


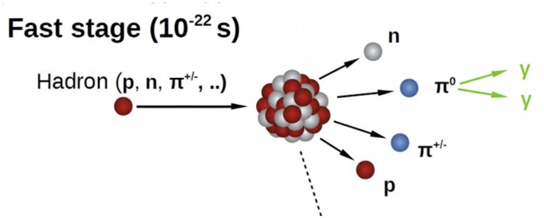
Hadronic shower energy fluctuation

- Hadronic shower measurements suffer from:
  - Non-linearity of energy response
    - Invisible energy losses
    - EM fraction rises with energy
  - Poor hadronic energy resolution
    - Large event-by-event fluctuation

- Fundamental issue:
  - Non-compensation(e/h ≠ 1)
  - EM fraction fluctuation
  - Invisible energy losses
    - nuclear binding energy
    - neutrons & slow hadrons
    - non-ionizing energy

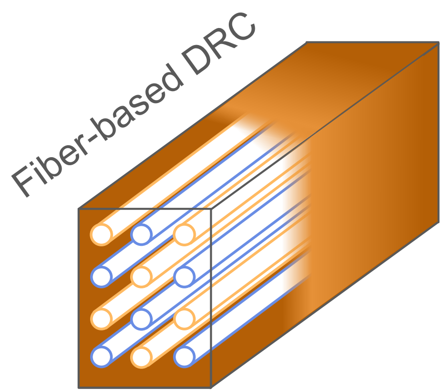
Signal yield for hadronic shower



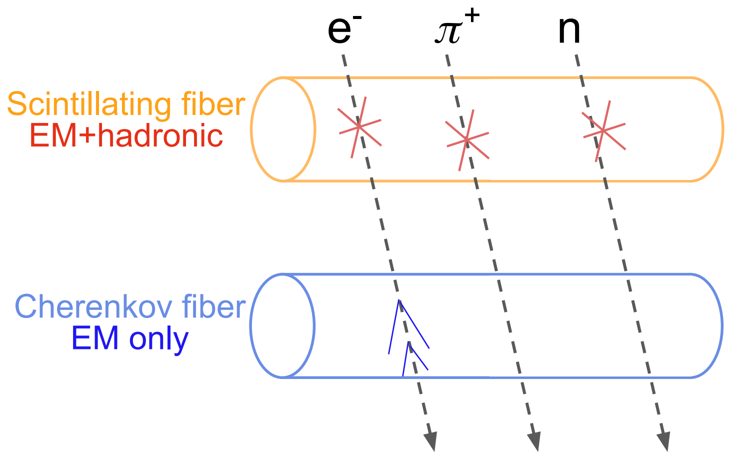


Dual-readout calorimeter

- Dual-readout calorimeter has two type of readout from Cherenkov material and scintillation material.
- Event-by-event compensation of fluctuation between hadronic and EM component.



- Scintillation fiber
  - Light from both EM and hadronic components
- Cherenkov fiber
  - Light only from fast particles (mostly e^- in EM subshowers)
  - Effectively measure the EM component only

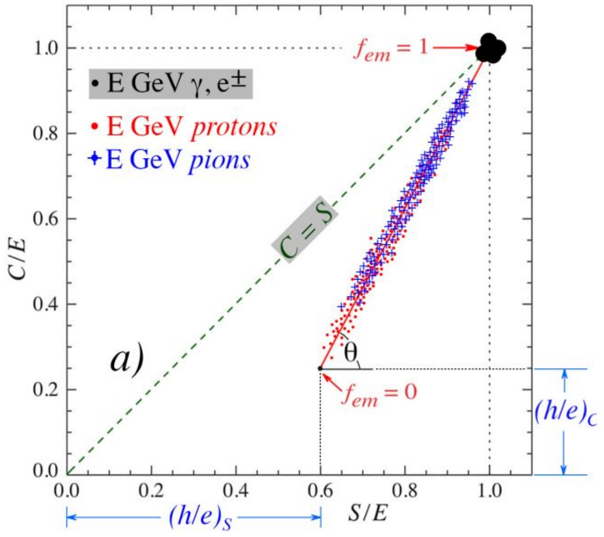


Dual-readout Method

- For EM showers, both C and S are proportional to the total energy.
  - Initial Calibration as $C=S=E=E_{EM}$ at e^- shower
- At Hadronic shower, proportion of hadronic component makes response to S.
  - $C=E_{EM}$, $S=E_{EM}+(1-\chi)E_{had}$
  - total $E=E_{EM}+E_{had}=C+(S-C)/(1-\chi)$

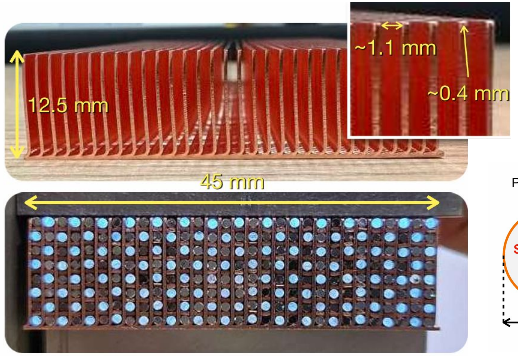
$$E = \frac{S-\chi C}{1-\chi}$$, (χ: dual-readout correction constant)

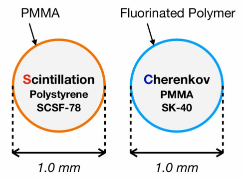
  - Event-by-event compensation



Korea DRC collaboration

- Calorimeter Prototype
  - Fiber-module manufacturing feasibility study
  - Prototype test beam experiments
- Simulation
  - Absorber performance studies
    - Cu, Pb, W, Brass
  - ML-based PID & energy reconstruction
  - 3D hit position reconstruction





Test beam experiment

- EM performance: linearity and resolution
- Hadron performance: linearity and resolution
- Time resolution and position resolution

EM & Hadronic Performance Study

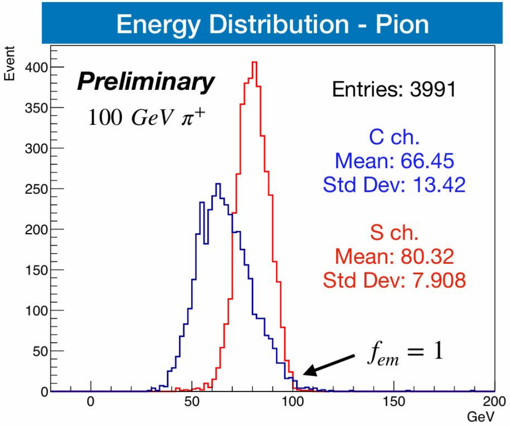
Skived Fin Heat Sink (SFHS) Module

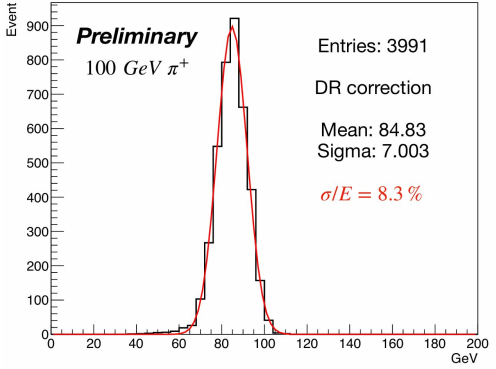
Depth 2.5 m (~10 λ_{int})

Effective radius 17 cm (~0.8 λ_{int})

PMT, MCP-PMT

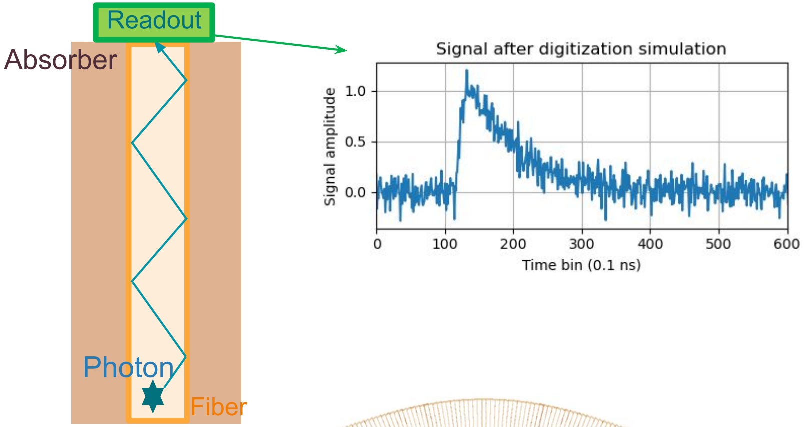
10~120 GeV e^+, 20~120 GeV hadrons

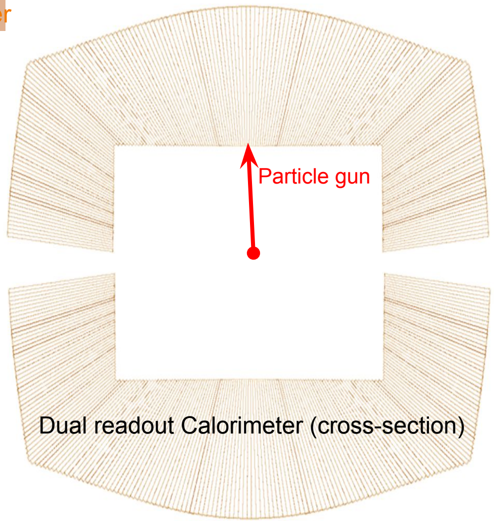




Simulation setup

- Simulation performed by GEANT4.
  - Dual-readout calorimeter only.
  - No magnetic field.
  - Copper as absorber.
  - SiPM readout count photoelectron.
- Particle guns are simulated at the calorimeter center
  - e^-, γ, π^+, $\pi^0\,(\rightarrow\gamma\gamma)$
  - Energy range in 1 - 100 GeV
  - Incident region around a tower 2.5°×2.5° ($\Delta\phi$:0.044 $\Delta\theta$:0.044)

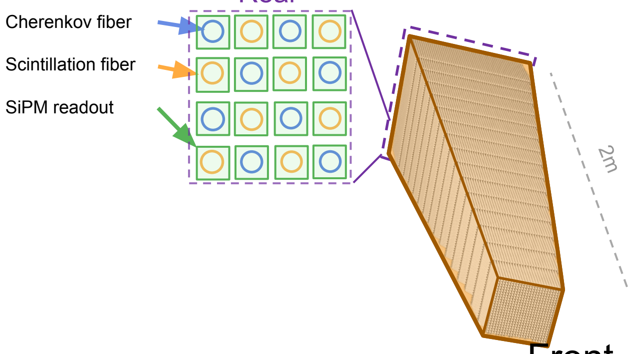




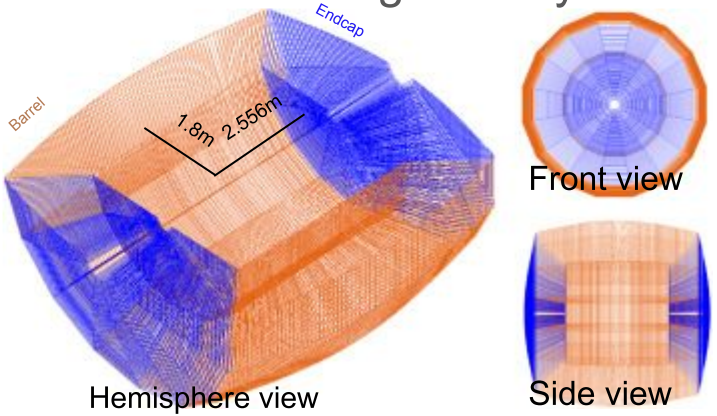
Calorimeter geometry

- Fiber implementation
  - Scintillation fiber and Cherenkov fiber in check pattern(pitch: 1.5mm)
  - fiber diameter: 1mm, SiPM width: 1.2mm
- Tower geometry
  - Length: 2m
  - Angular coverage: ~1.15°($\Delta\theta$:0.022,$\Delta\phi$:0.022)
  - Fiber array perpendicular to tower base plane
- Tower arrangement
  - Position
    - barrel: r = 1.8m cylindrical
    - endcap: z = ±2.556m circular
  - Longitudinally aligned toward the center
  - Total 283(θ)×182(ϕ) towers

Tower geometry

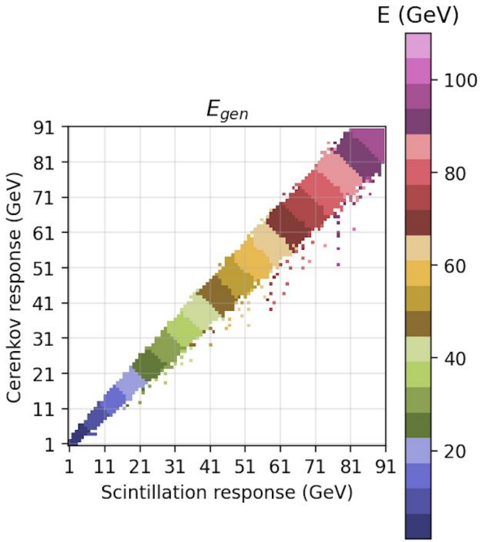


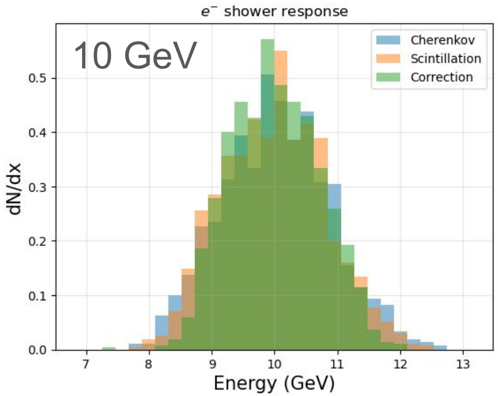
Calorimeter geometry

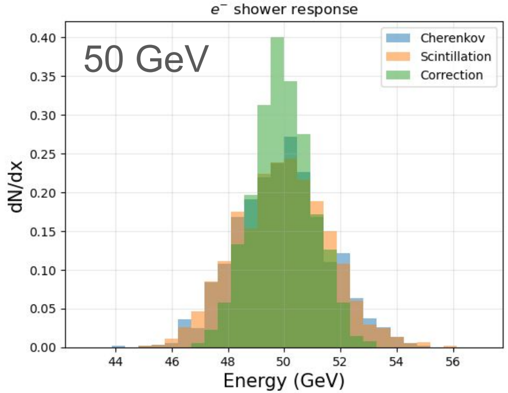


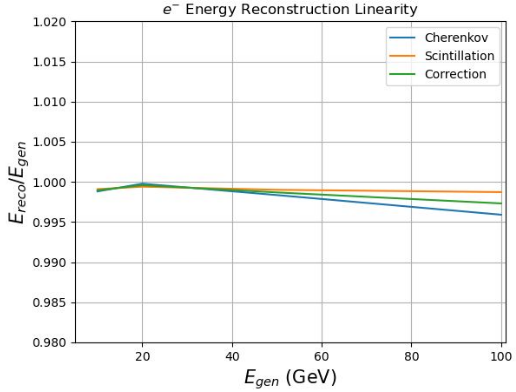
Electron shower

- Calibrate average C,S matched with E_{gen}
- C and S responses are linear at 1-100 GeV
- (C+S)/2 shows the best linearity and resolution.



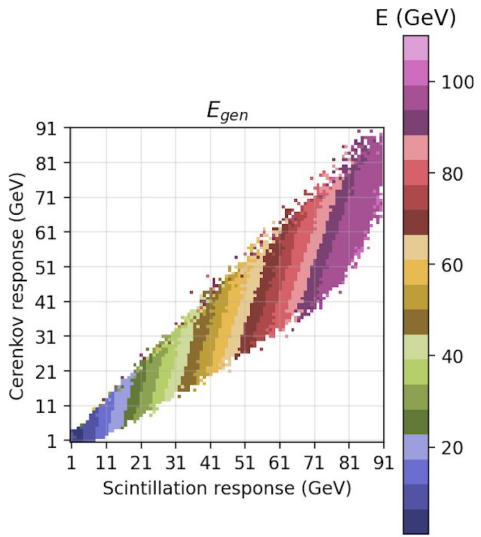


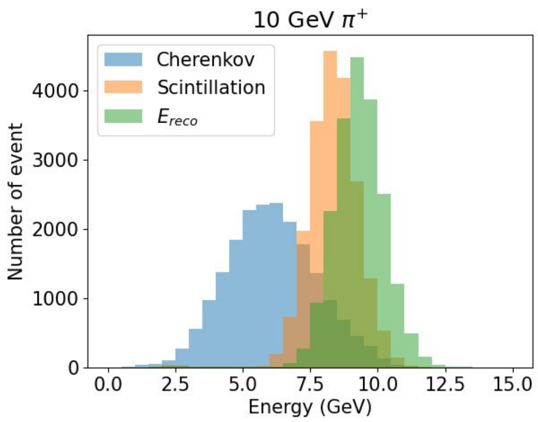


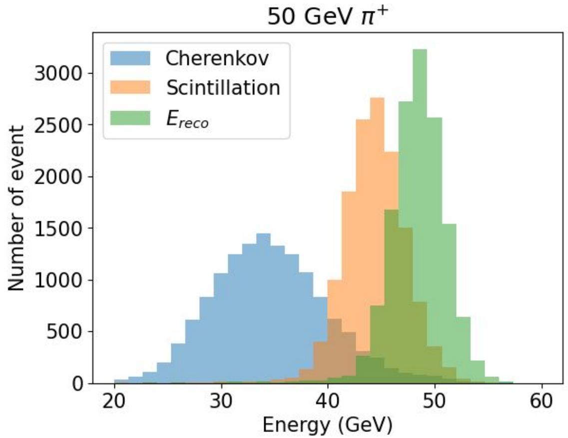


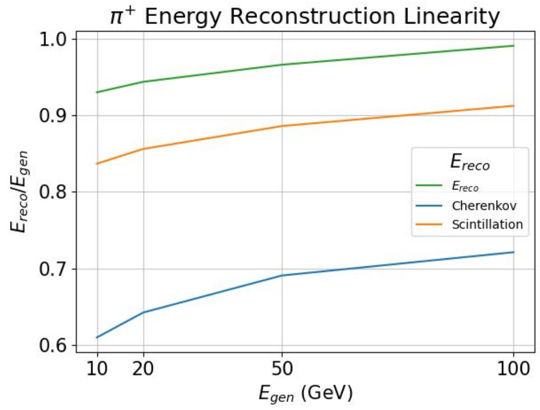
π+ shower

- Responses are calibrated with prior e⁻ shower.
- C and S responses are reduced than E_{gen} due to invisible energy loss.
- Dual-readout correction restores linearity. $E = \frac{S - \chi C}{1 - \chi}$





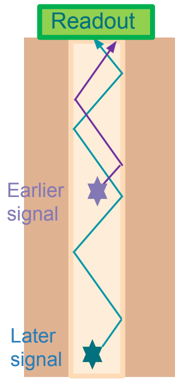


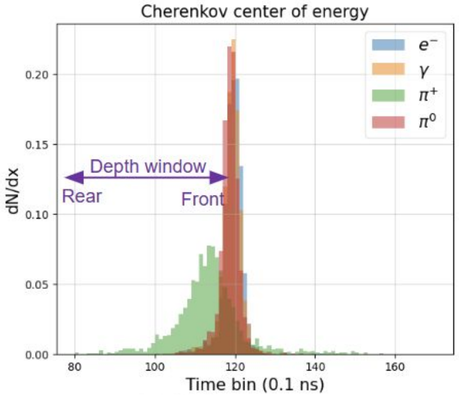


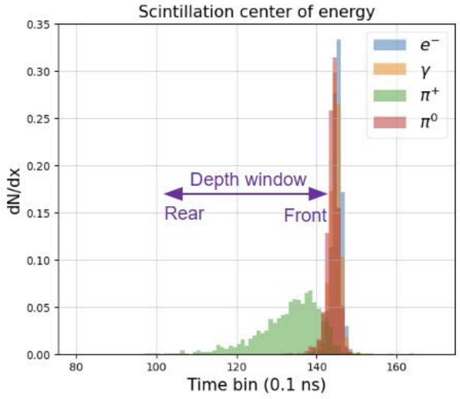
3D Shower reconstruction

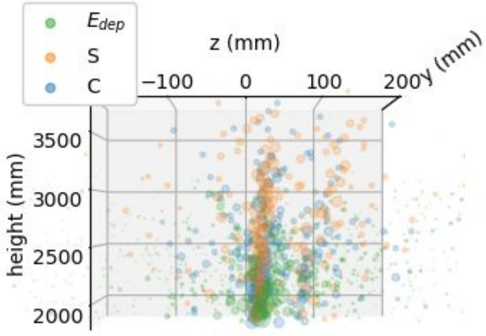
- Photons generated deeper in the fiber arrive earlier at the readout.
- The longitudinal position of photon reconstructed using time differences.

$$xyz_{hit} = xyz_{readout} - v_{eff}(t - t_r), \quad v_{eff} = \frac{2\,m}{t_f - t_r}$$





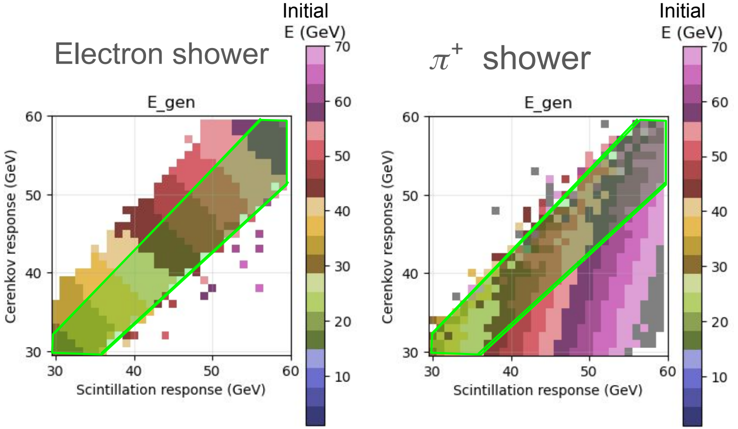




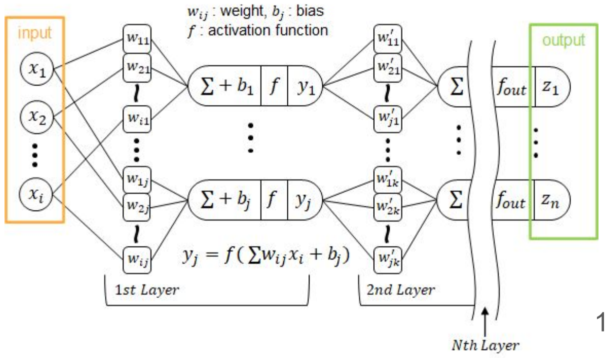
π^+ shower

Deep learning for PID

- Using C,S responses for PID is limited.
  - Overlapped region but different initial energy
  - Need for proper energy correction method.
    - $E_{reco}^{EM} = \frac{S+C}{2}$
    - $E_{reco}^{had}(C,S) = \frac{S-\chi C}{1-\chi}$
- We apply deep learning to exploit:
  - Timing, position, and fiber-type information to utilize correlations in detailed shower shapes
- A multilayer perceptron (MLP) is used as the basic model for PID and regression.

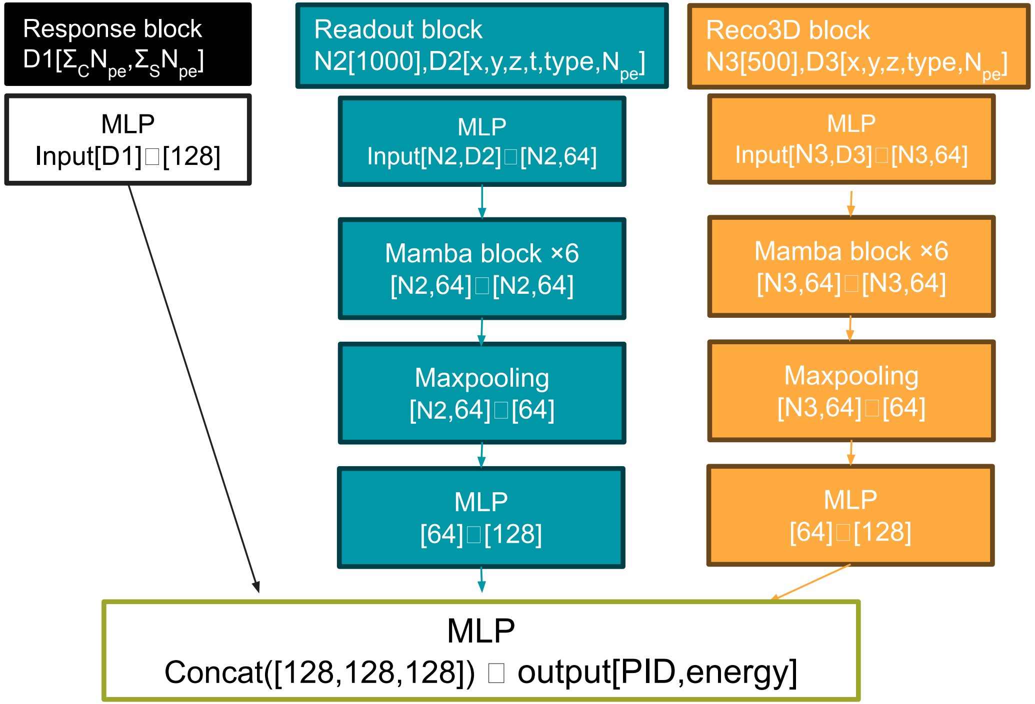


Multilayer Perceptron



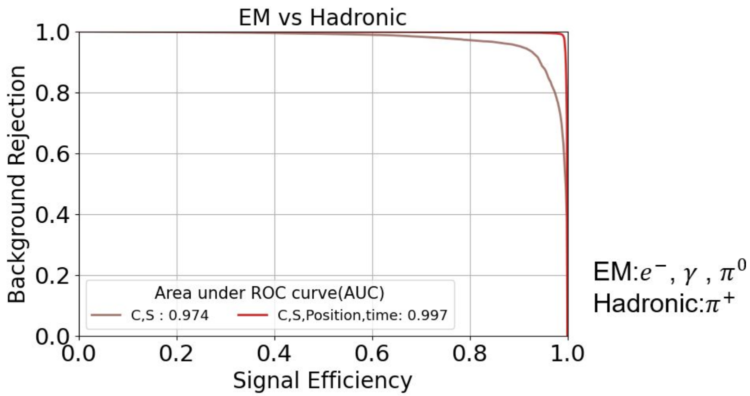
Deep learning model architecture

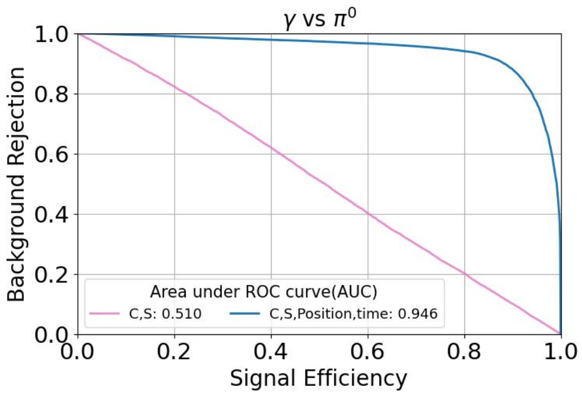
- Three input branches:
  - Response block: total C and S
  - Readout block: per-readout position, time, fiber type
  - Reco3D block: reconstructed 3D hit positions
- Each branch:
  - Feature extraction with Mamba blocks and MLPs
  - Global pooling to obtain 128-dimensional features
- Final stage:
  - Branch features to PID and energy prediction



PID performance

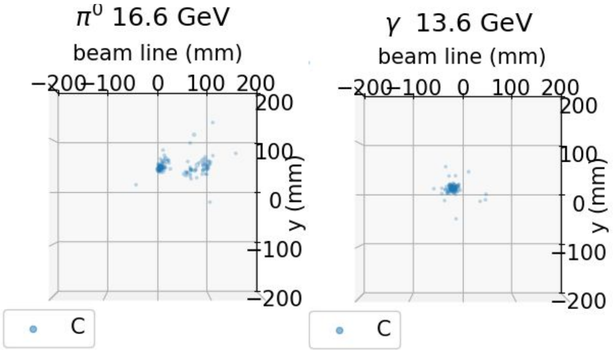
- Model compared with different input block
  - Response block: total C,S responses
  - Combination of response block, Readout block, Reco3D block
- Position and timing information significantly improve PID:
  - EM vs hadron efficiency > 99%
  - π^0 shower discriminated with single γ shower.
- A model without position and timing cannot discriminate π^0 and γ

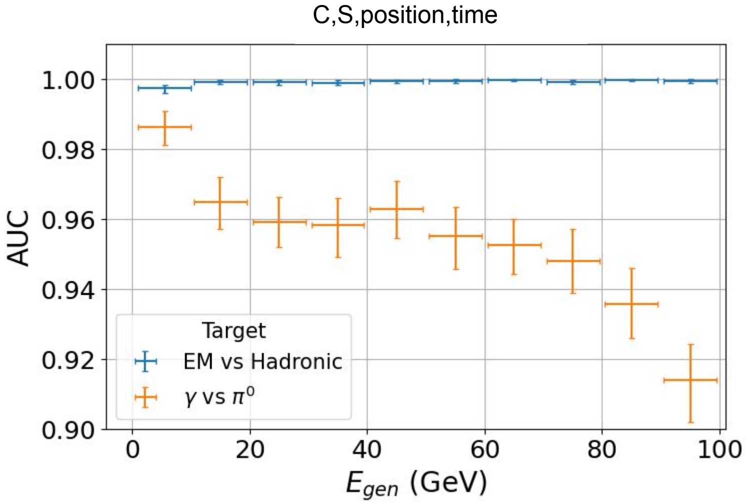


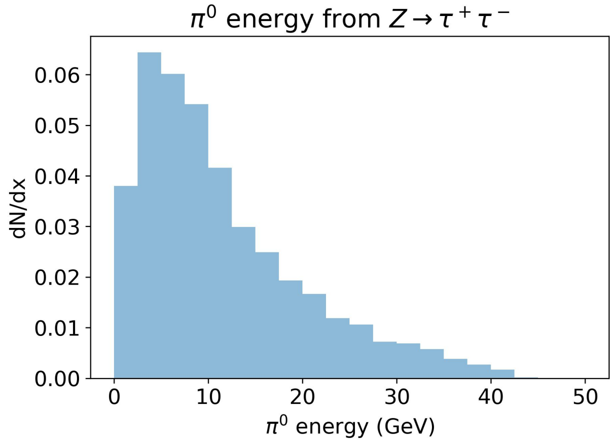


PID performance by energy

- EM vs hadron efficiency > 99% above 10 GeV.
- π^0 vs γ efficiency > 90% below ~50 GeV
  - At FCC-ee, most π^0 are expected below ~40 GeV



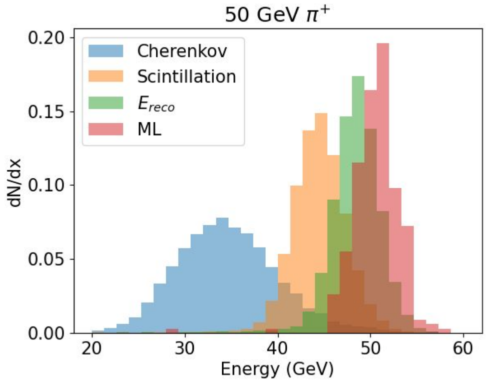


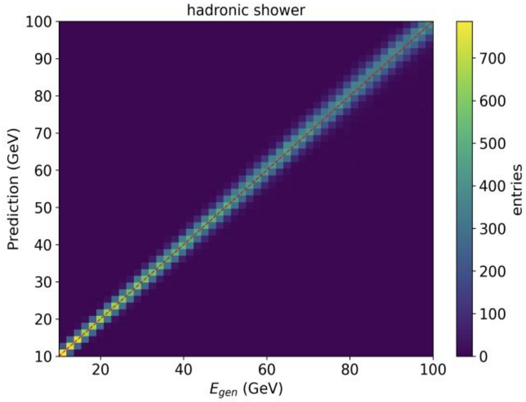


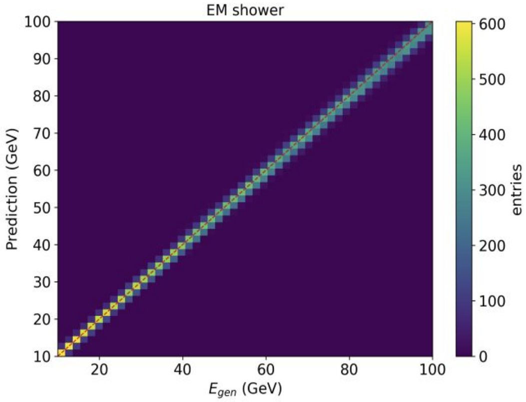
EM: e^-, γ , π^0
Hadronic: π^+

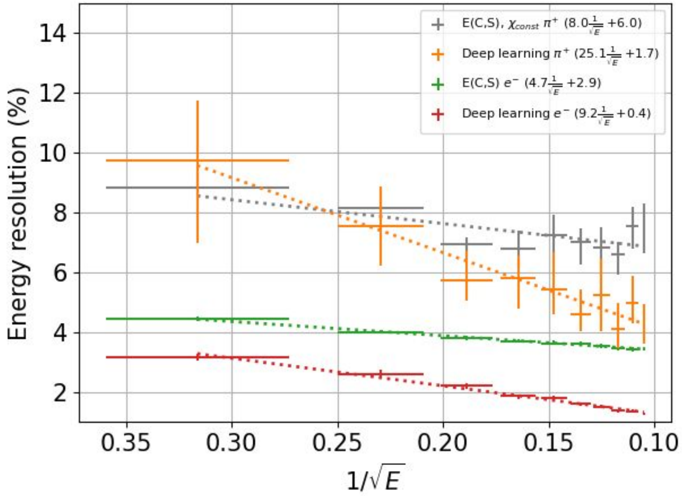
Energy reconstruction

- ML model provides better energy resolution than the analytical dual-readout correction.
- In particular, the constant term is significantly reduced, indicating improved high-energy behavior.









Outlook

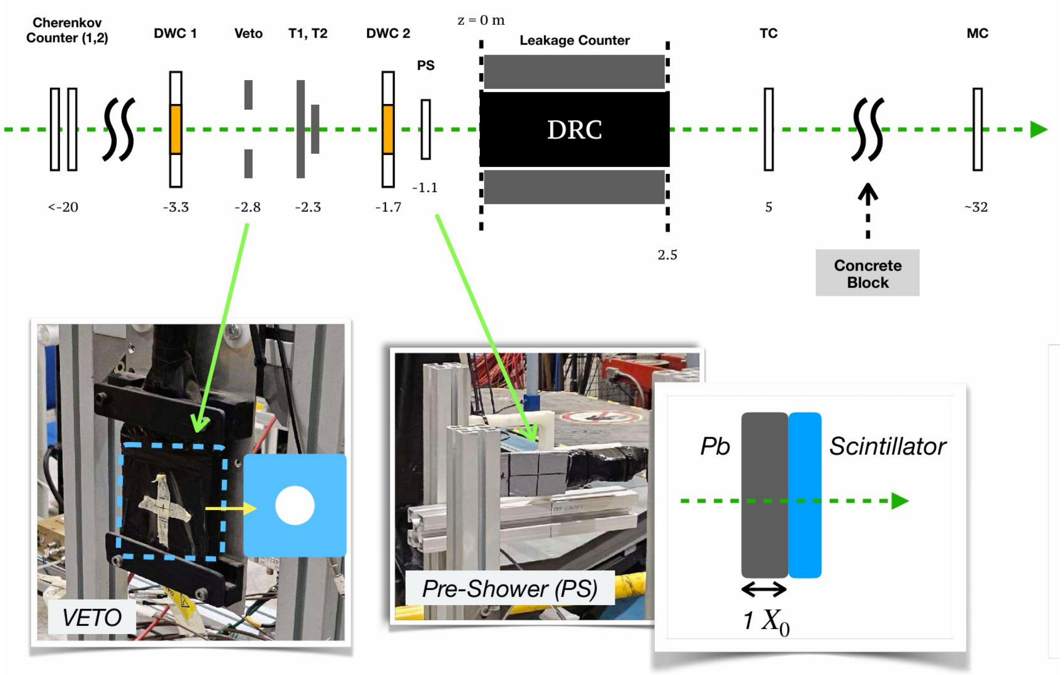
- Validate simulation using TB2025 data: quantify data–MC differences in shower profile
- Incorporate realistic detector effects (saturation, crosstalk, attenuation, jitter) into ML training
- Fine-tune ML models on test-beam data for simulation to data domain adaptation
- Extend ML reconstruction to jet-like topologies
- Evaluate impact of particle reconstruction on physics performance
  - jet energy resolution, π^0/γ separation, and precision measurements at FCC-ee

Summary

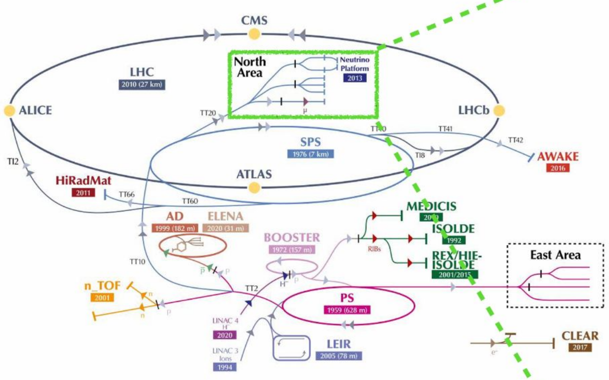
- Dual-readout calorimeter compensates shower fluctuations, improving hadronic energy resolution.
- The Korean DRC collaboration has made major progress in prototype development and test-beam experiment.
- ML-based PID exploits spatial and timing shower features, achieving strong EM–hadronic discrimination and π^0/γ separation, with precise energy reconstruction.
- These particle reconstruction studies indicate strong potential to expand accessible physics channels and improve calorimetric performance in future.

Backups

Test beam setup

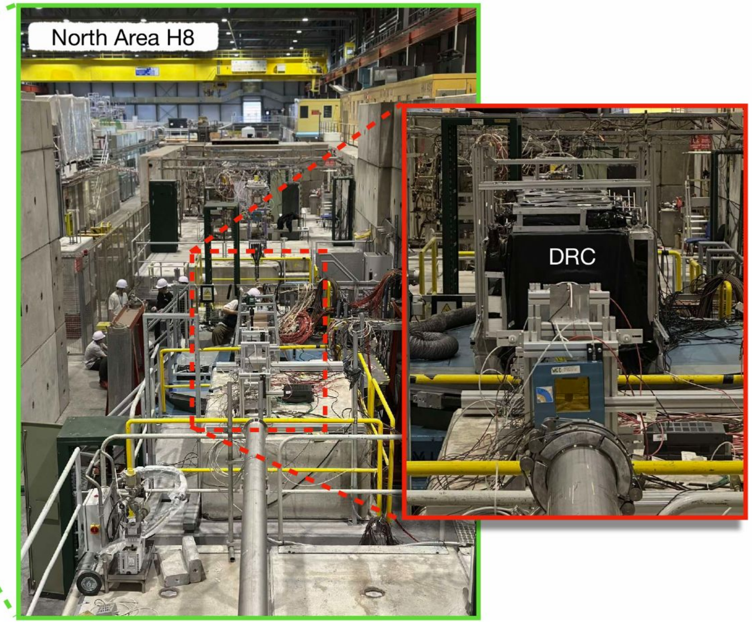


Test beam setup



EM : 10 ~ 120 GeV

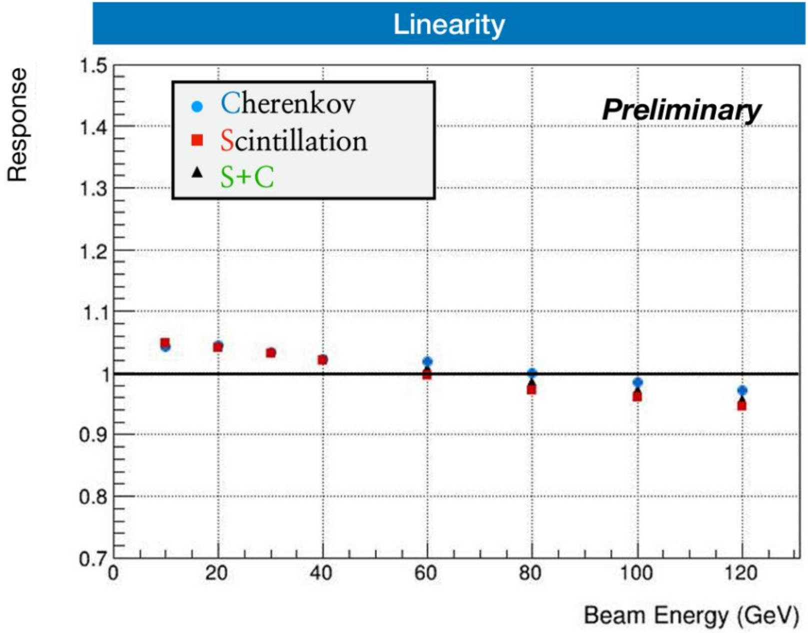
Hadron : 20 ~ 120 GeV

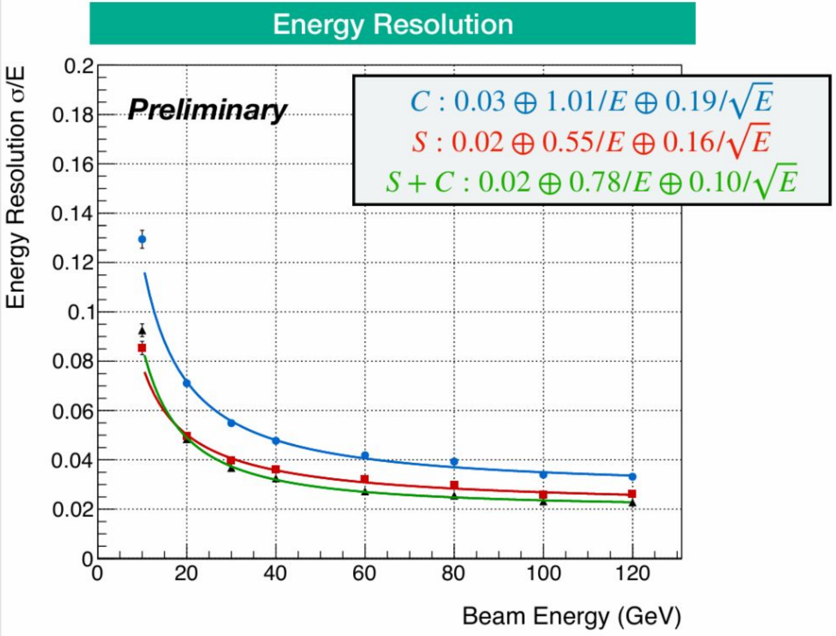


Testbeam: EM performance

~96 % EM deposit

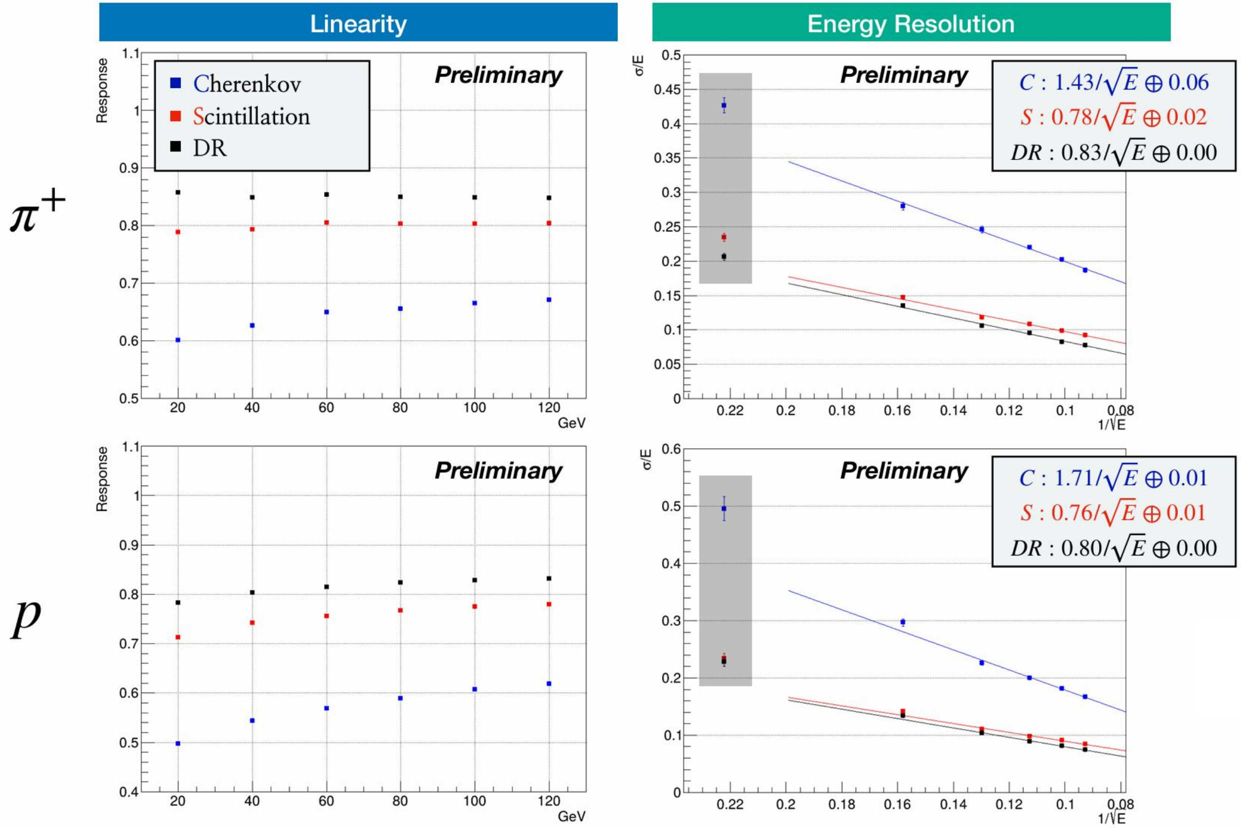
3 x 3 Matrix Response



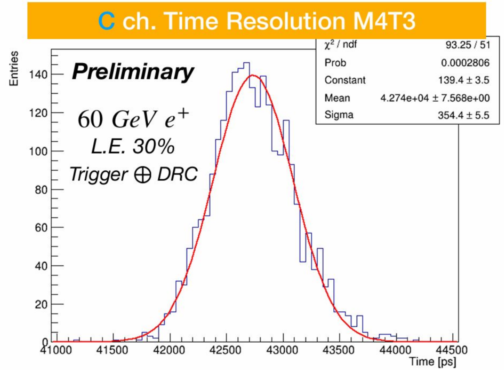


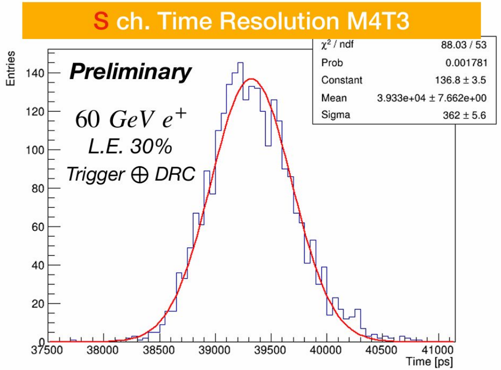
10, 20, 30, 40, 60, 80, 100, 120 GeV e^+

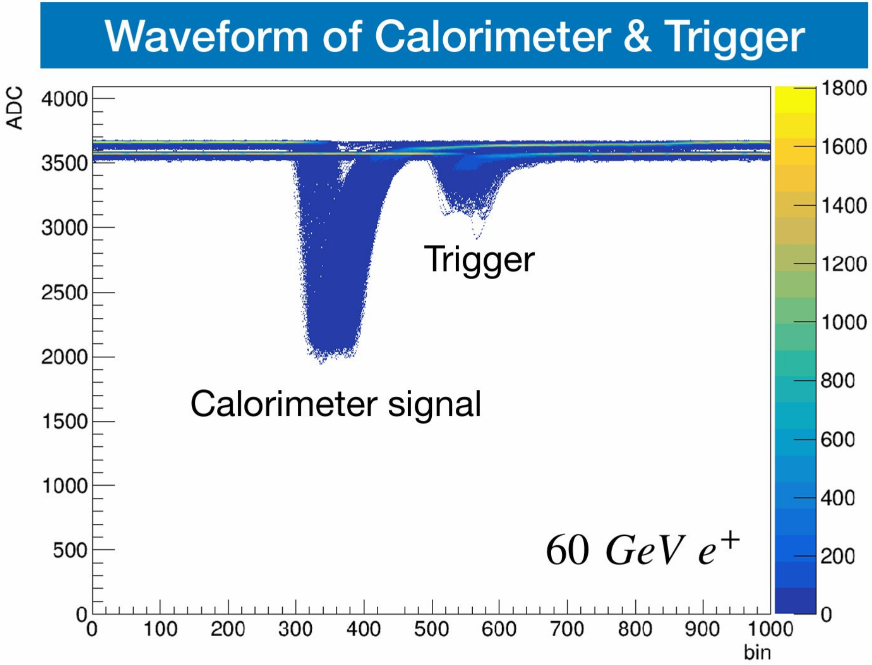
Testbeam: hadron performance



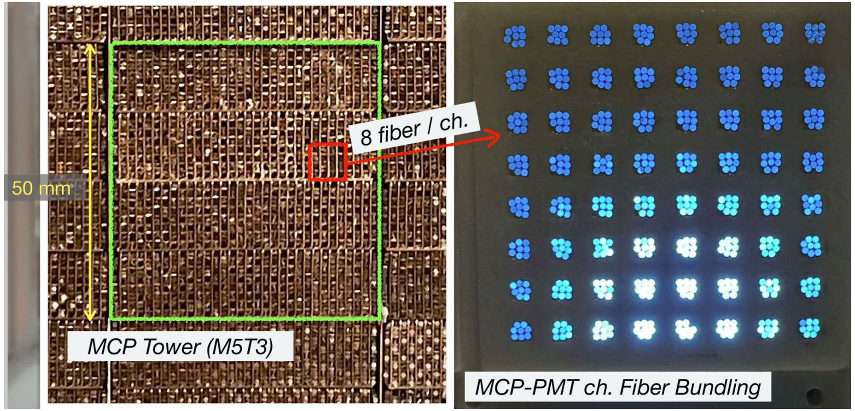
Testbeam: time resolution

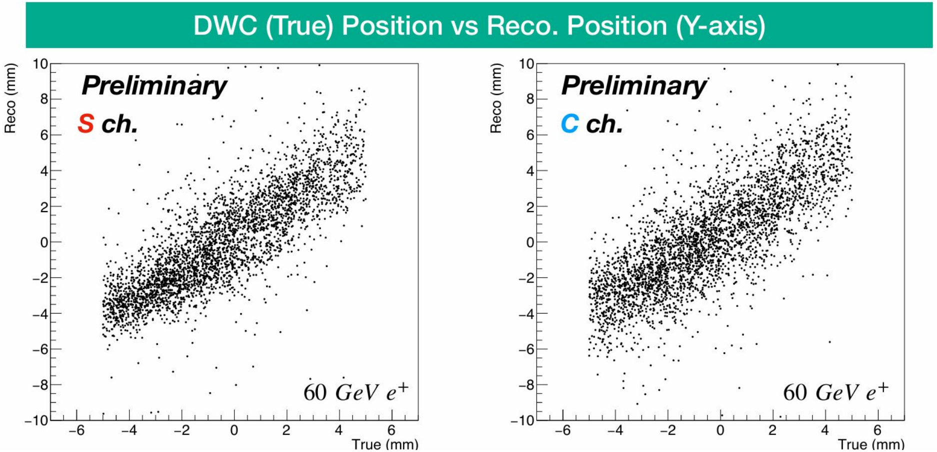






Testbeam: position reconstruction

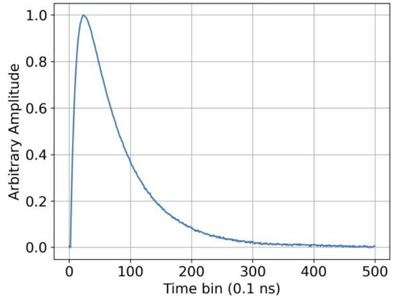




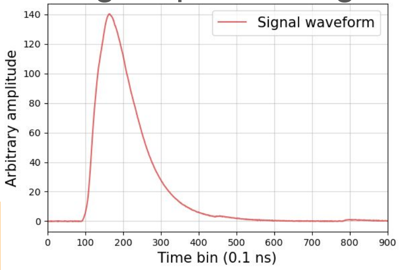
Simulation signal processing

- Light measured by silicon photomultipliers(SiPMs).
- SiPM signal has fast rising exponential decay by photon deposit
- Reconstruct photon deposit from deconvolution of SiPM signal.

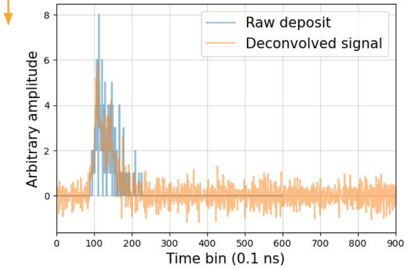
Impulse response



Signal processing

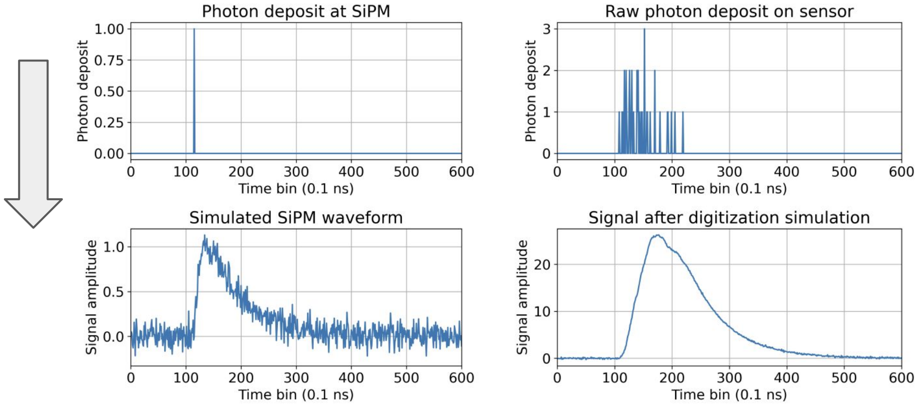


$\mathcal{F}^{-1}[\hat{X}(f)]$



Signal simulation

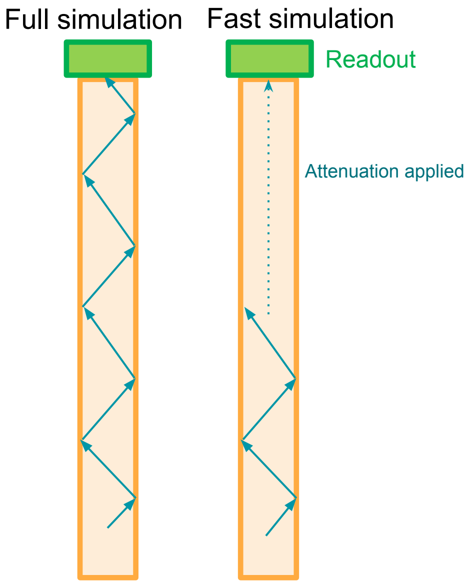
SiPM simulation



Detector simulation

- Geant4 simulation for shower particle inside calorimeter.
- Readouts count photon at end of fiber.
- Photon counts are processed to signal with SiPM simulation.

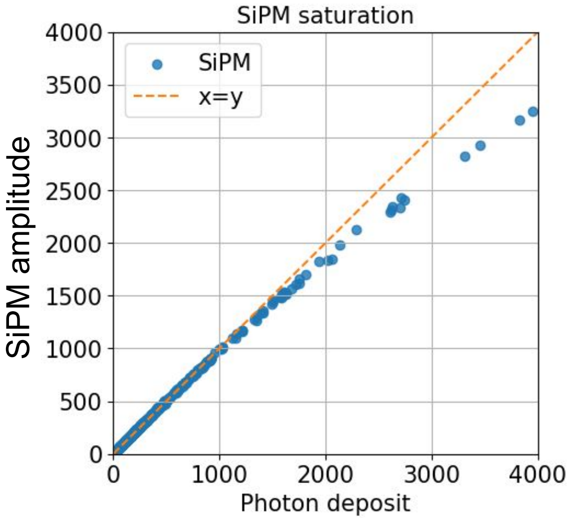
- Fast simulation algorithm applied for photon propagation inside fiber.
- Full simulation
  - compute total reflection and attenuation of every path
  - photons which not reach to readout are also computed
- Fast simulation
  - Photon selected in angular window to reach the readout
  - apply expected time of flight and attenuation
  - place photon to end of fiber

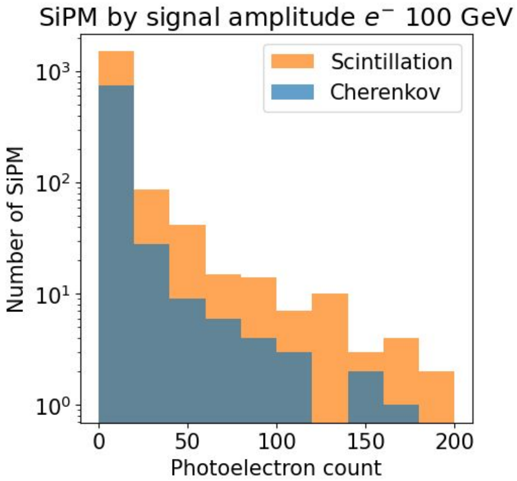


SiPM saturation

SiPM signal saturated at high photon flux

Scintillation fiber yield much more photon than Cherenkov fiber

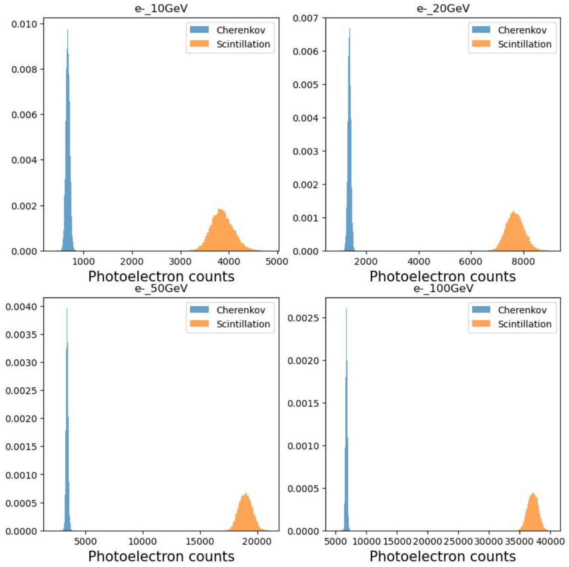




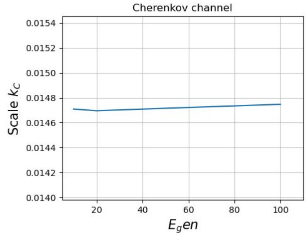
Calibration

- Reconstructed photon deposit → calibration
- Energy dependent scale factor applied at scintillation channel.

Raw response

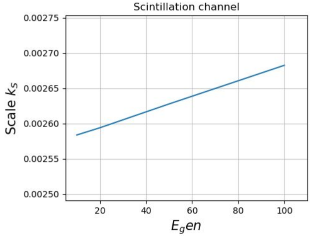


$$C = k_C * \sum C_{raw}$$

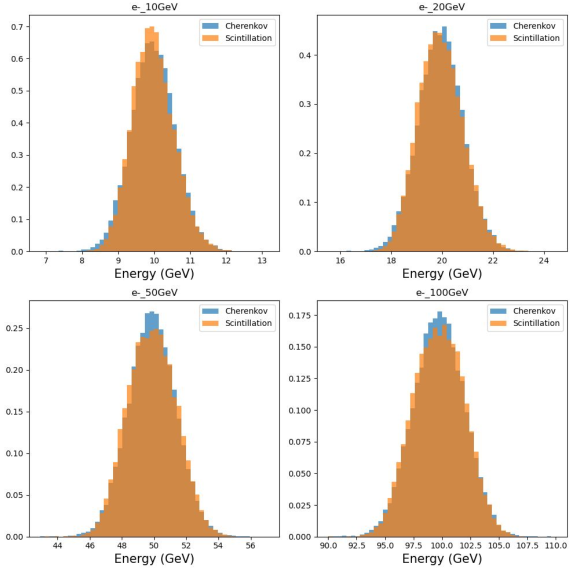


$$S = k_s * \sum S_{raw},\ k_S = a * E + b$$

$$\rightarrow S = \frac{b}{1 - a \sum S_{raw}}$$



Calibrated response



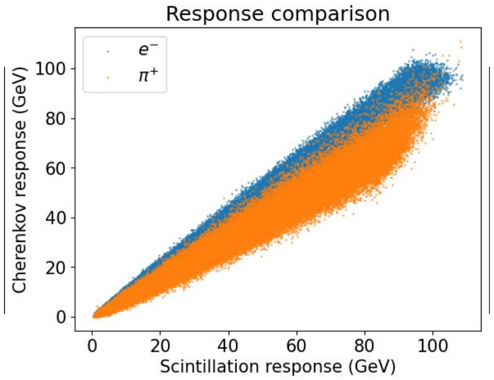
deep learning input

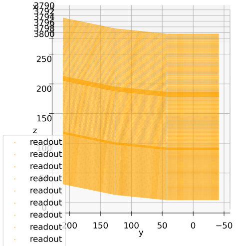
$D1(\Sigma_C N_{pe},\Sigma_S N_{pe})$□ Response block

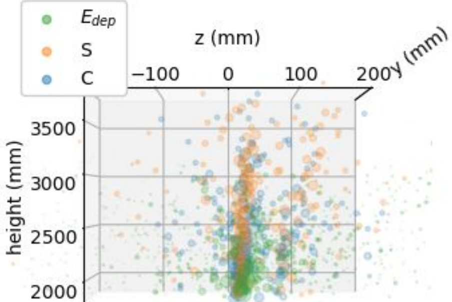
1000 points of $D2(x,y,z,t,type,N_{pe})$ □ Readout block

500 points of $D3(x,y,z,type,N_{pe})$ □ Reco3D block

Each block extract features for PID and energy







Response block([D1])□[128]

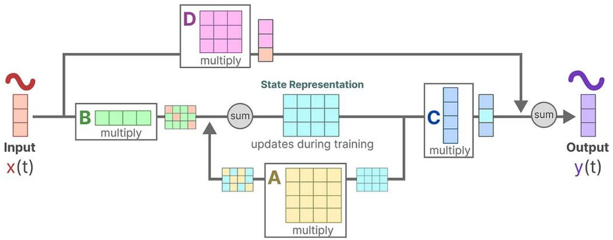
Readout block([1000,D2])□[128]

Reco3D block([500,D3])□[128]

MLP([128,128,128])□[PID, Energy]

Model training setup

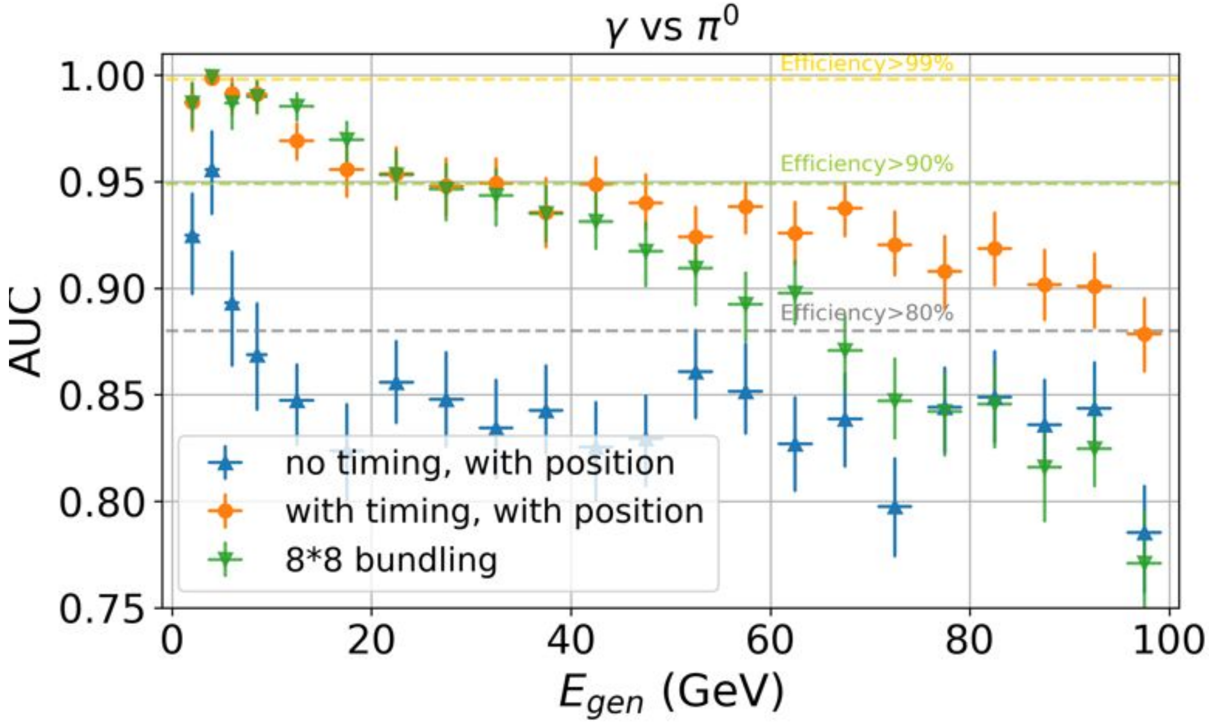
- MLP(S,C), Mamba (readout position, signal timing, amplitude, fiber type), Mamba(hit position, amplitude, fiber type)
  - 3 model combined to MLP
  - 2 Million parameters



State Space Model

- 40k dataset each particle 50% train 20% validation 30% test
- Training time - 1 day(mostly input lag) torch v2.5.1

Fiber bundling performance



Missing energy