Particle ID & 3D reconstruction with the Dual-readout calorimeter simulation

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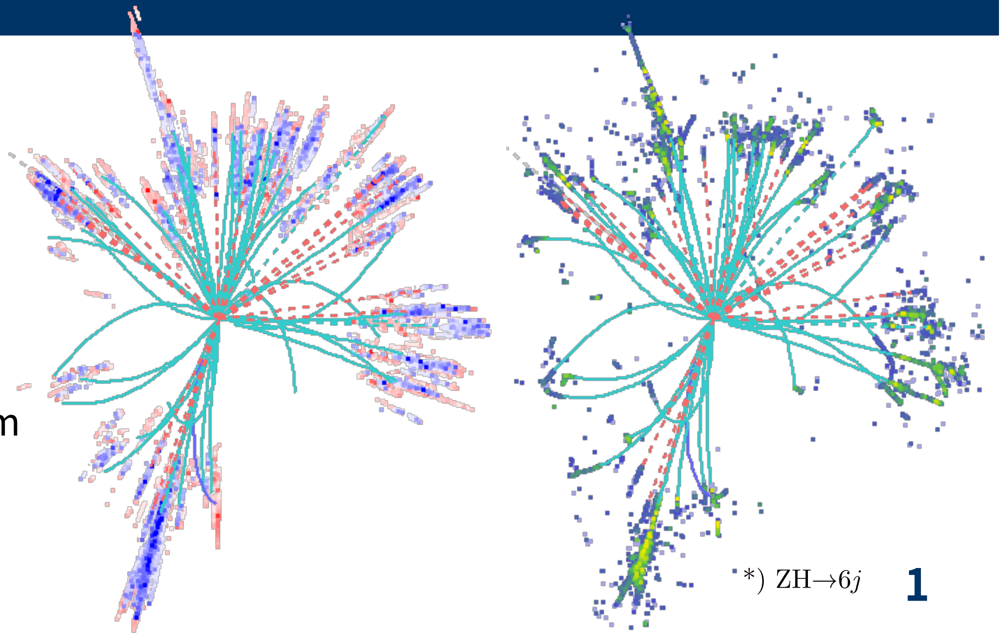
On behalf of the dual-readout calorimeter team



*) ZH→6j

Dual-readout calorimeter

Dual-readout calorimetry

- The major difficulty of measuring energy of hadronic showers comes from the fluctuation of EM fraction of a shower, f_em
- f_em can be measured by implementing two different channels with different h/e response in a calorimeter

$$S = E[f_{em} + \left(\frac{h}{e}\right)_S (1 - f_{em})],$$

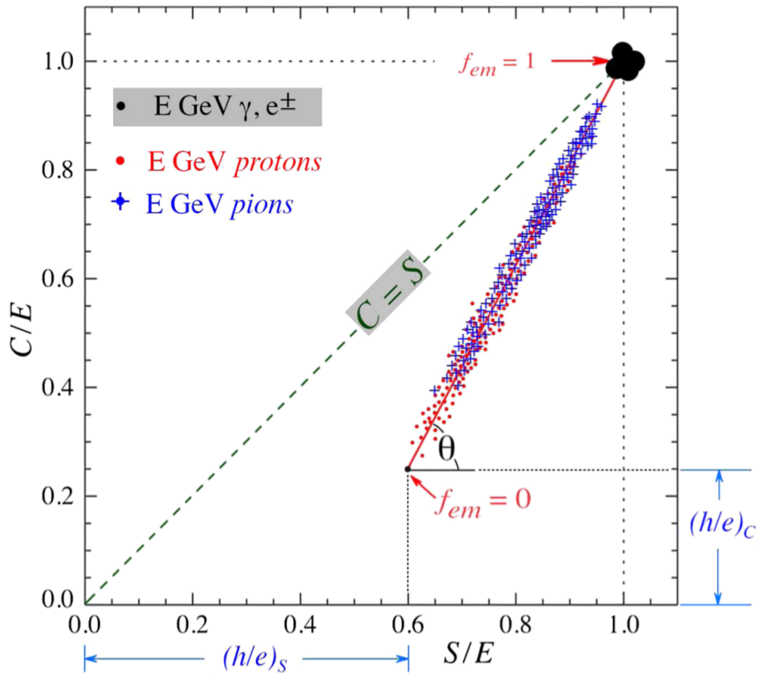
$$C = E[f_{em} + \left(\frac{h}{e}\right)_C (1 - f_{em})]$$

$$f_{em} = \frac{(h/e)_C - (C/S)(h/e)_S}{(C/S)[1-(h/e)_S] - [1-(h/e)_C]}$$

$$\cot\theta = \frac{1-(h/e)_S}{1-(h/e)_C} \equiv \chi,$$

$$E = \frac{S - \chi C}{1 - \chi}$$

- Excellent energy resolution for hadrons can be achieved by measuring f_em and correcting the measurement event-by-event
- Dual-readout fiber-sampling calorimeter is a key element of the IDEA detector concepts



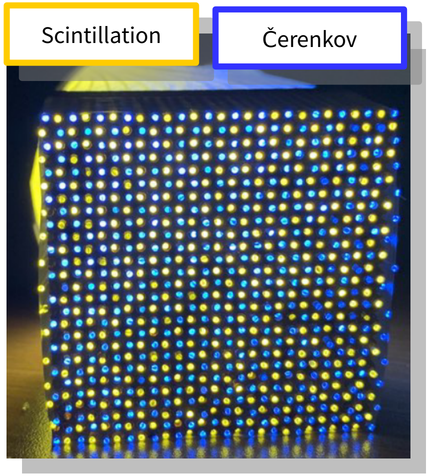
Energy measured from scintillation channel vs Čerenkov channel for EM particle, π & p

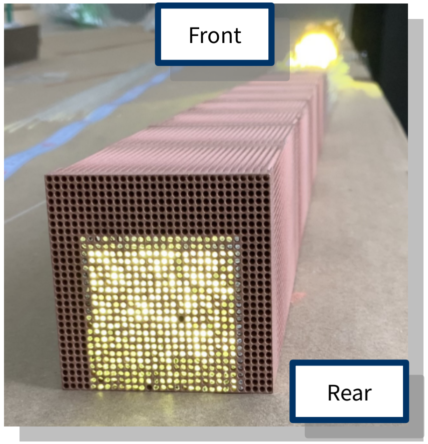
Dual-readout calorimeter

Dual-readout fiber-sampling calorimeter

- Longitudinally unsegmented fiber-sampling calorimeter
  → measure both EM & hadronic components simultaneously
  → fine unit structure with a high granularity

- Projective geometry with a uniform sampling fraction
  → more fibers in the rear than the front

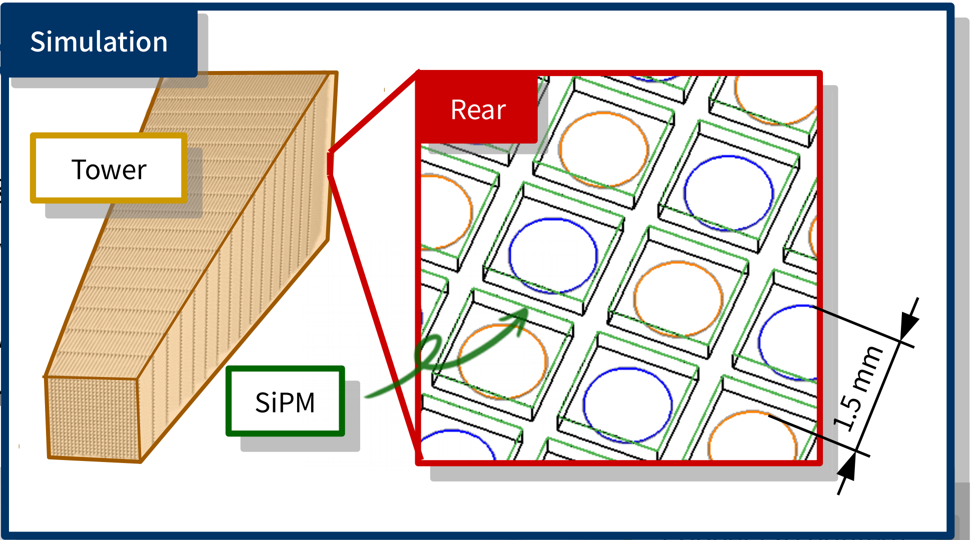


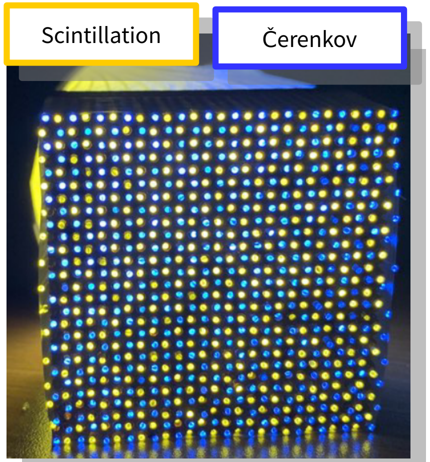


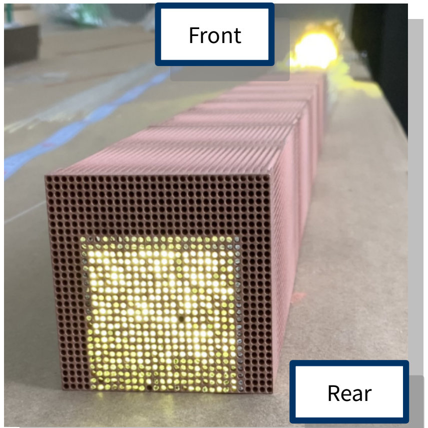
Dual-readout calorimeter

Dual-readout fib

- Longitudinally unseg
  → measure both EM &
  → fine unit structure
- Projective geometry w
  → more fibers in the r



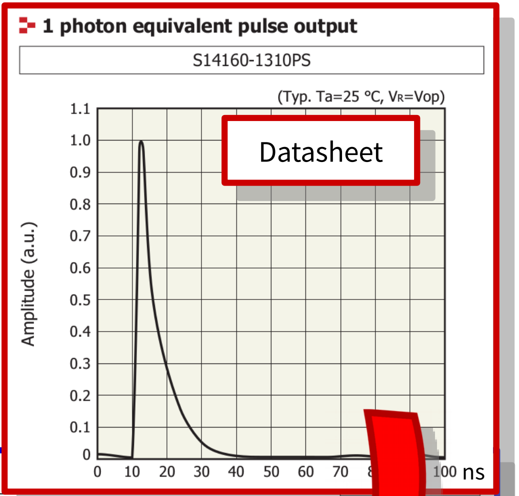


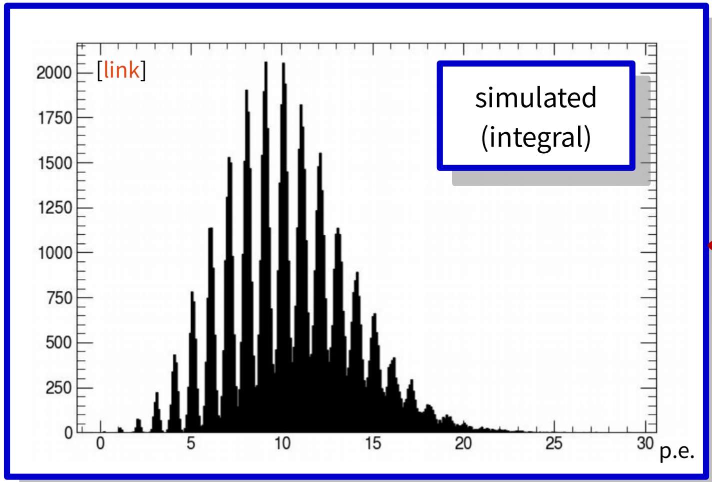


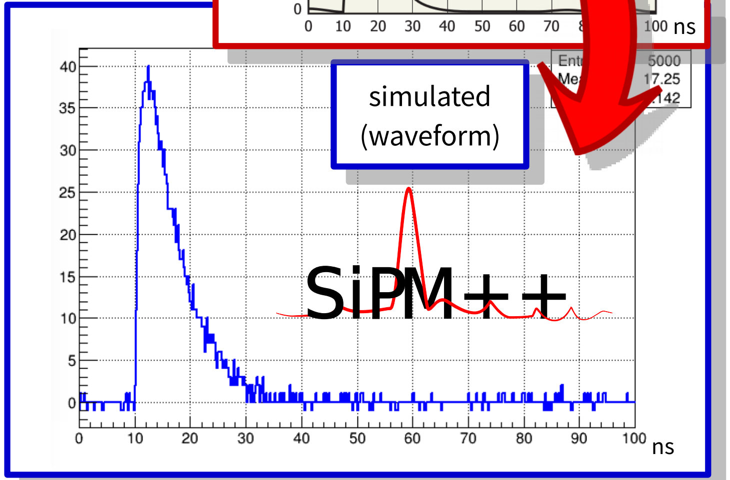
SiPM emulation

Simulating SiPM response with SimSiPM

- SiPM is a major candidate for the photodetector
  → SiPM simulation library [link] is developed
- Parameterized inputs from the datasheet
  → Dark counts, crosstalk, afterpulses, saturation, noise, …
- Minimal dependency – based on the standalone c++/python



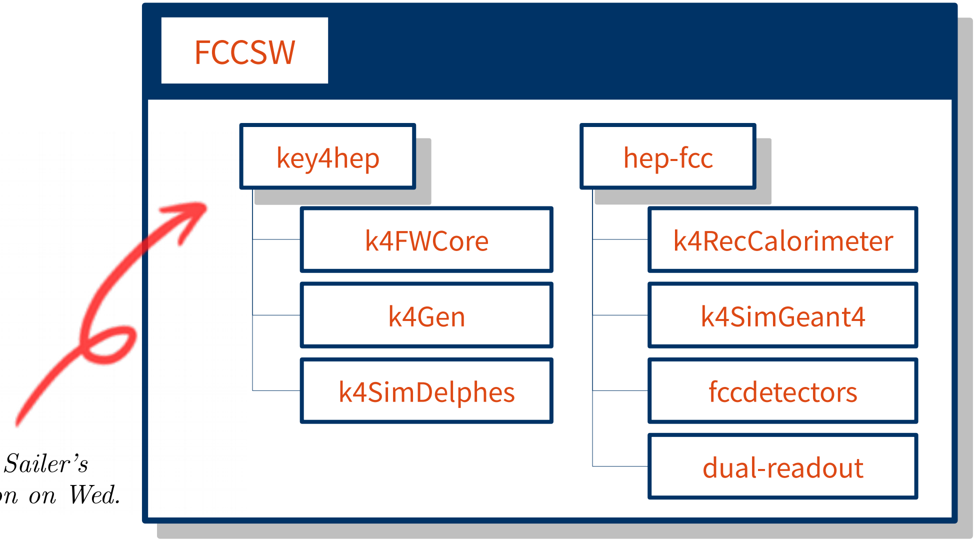




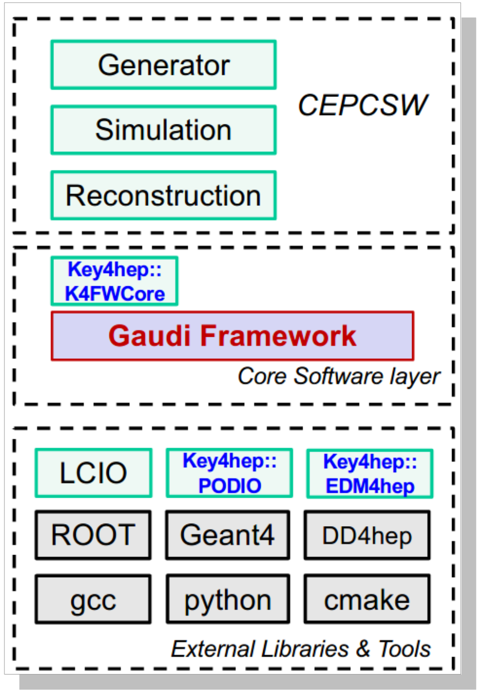
Migration to Key4hep

- Common SW framework for all future HEP experiments (ILC, CLIC, FCC and CEPC) proposed at 2019 workshop [link]
- Encompass typical needs of HEP experiments, provide common turnkey stack covering different domains

- Dual-readout calorimeter successfully migrated to Key4hep
  → shares framework core, EDM, detector description with CEPCSW



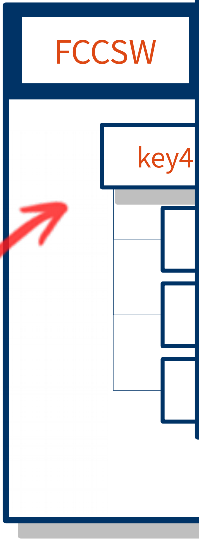
See Andre Sailer's presentation on Wed.

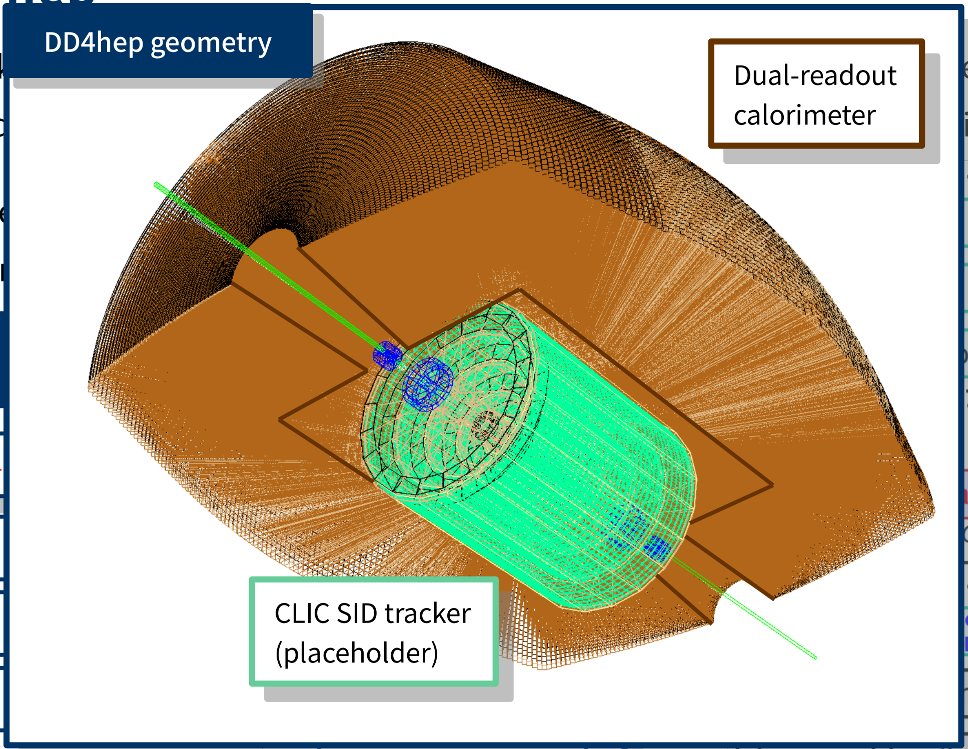


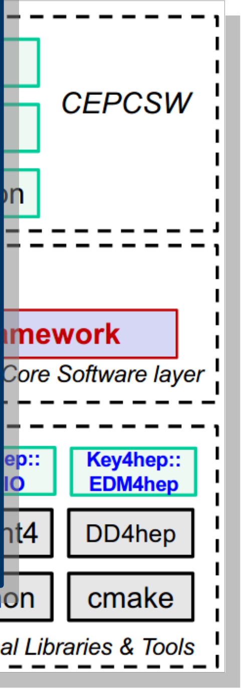
Key4hep

Migration to Key4hep

- Common SW framework ... ed at 2019 workshop [link]
- Encompass typical need ... ifferent domains
- Dual-readout calorimete...
  → shares framework co...





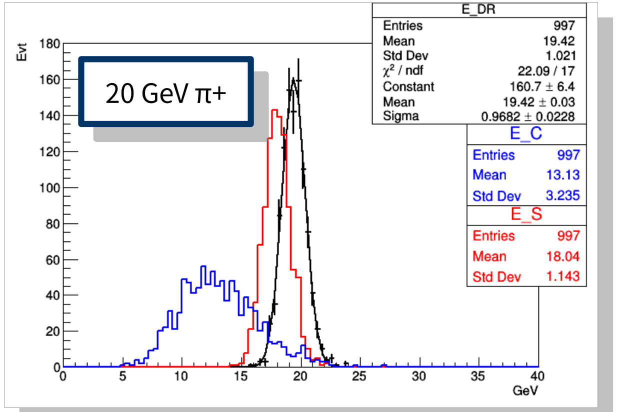


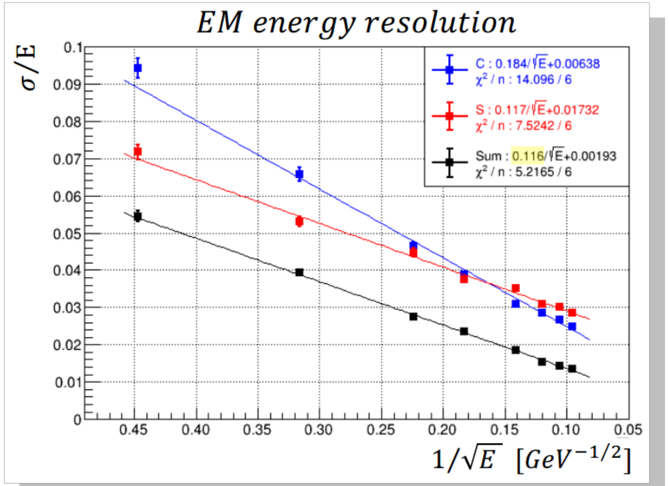
See Andre Sailer's presentation on Wed.

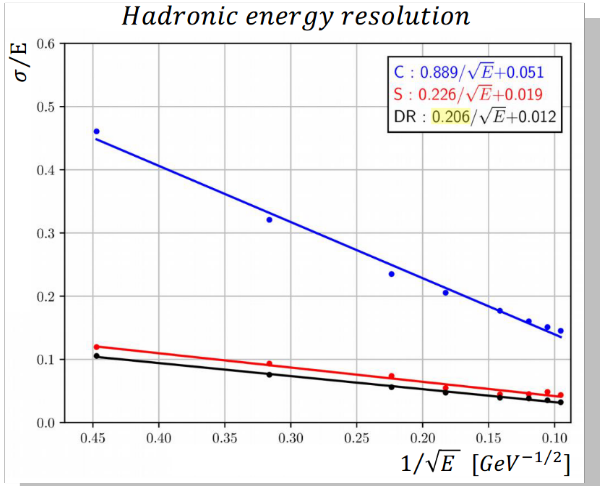
Energy resolution

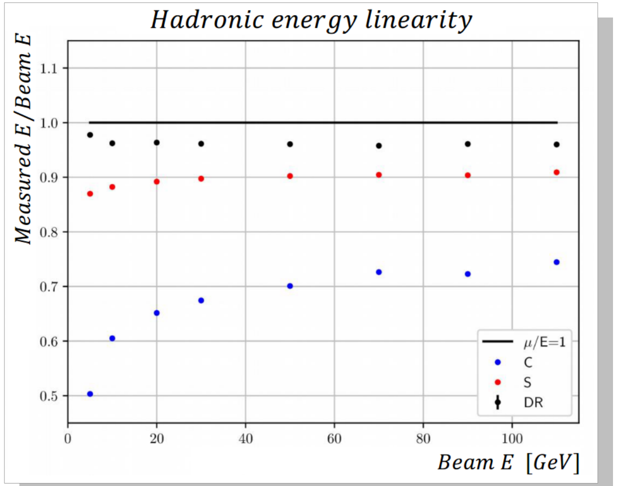
Estimation of energy resolution with GEANT4

- GEANT4 shows excellent energy resolution for both EM & hadronic showers
  → details presented several times in the past workshops [2019][2020-1][2020-2]
- Moving forward to demonstrate energy resolution with the beam test data
  → details presented at the Monday session [link]









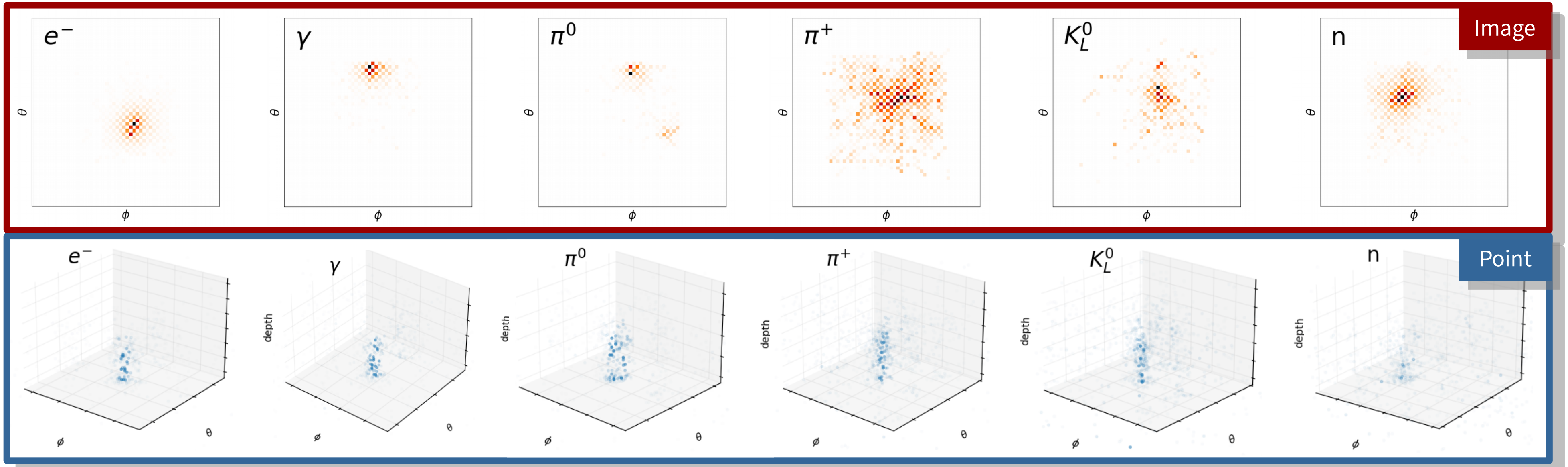
Particle identification

Image-based (CNN) vs Point-cloud (PointNet) method

- Imaged-based data consists of pixelated energy deposits of 3×3 towers (1 tower = 56×56 fibers)
- Point-cloud data represents energy deposits as (points) = (η, ϕ, depths) ⊗ (fiber type) ⊗ (Energy)

**depths = preprocessed timing (ToP)*

- Particle gun simulations are used as the training set with the uniform energy distribution (10 GeV < E < 100 GeV)



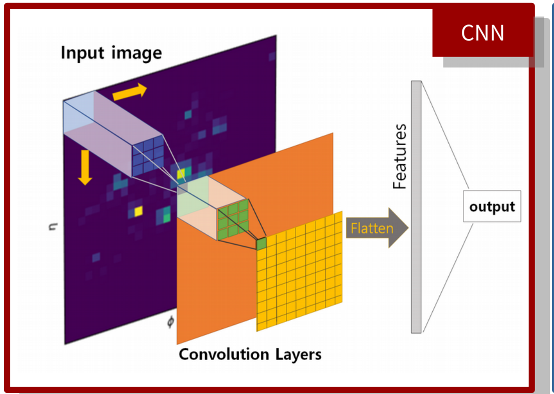
Particle identification

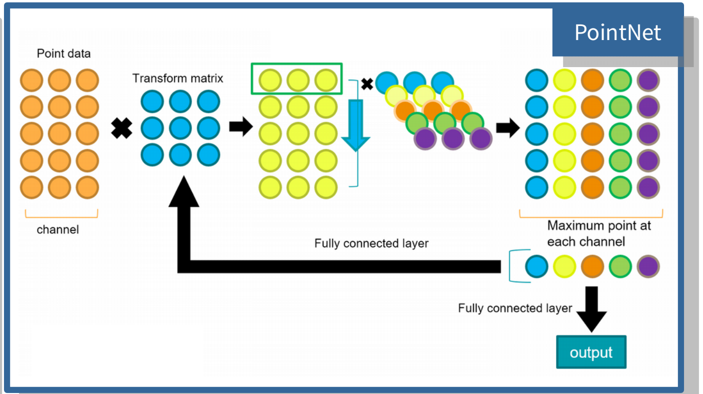
Classification performance

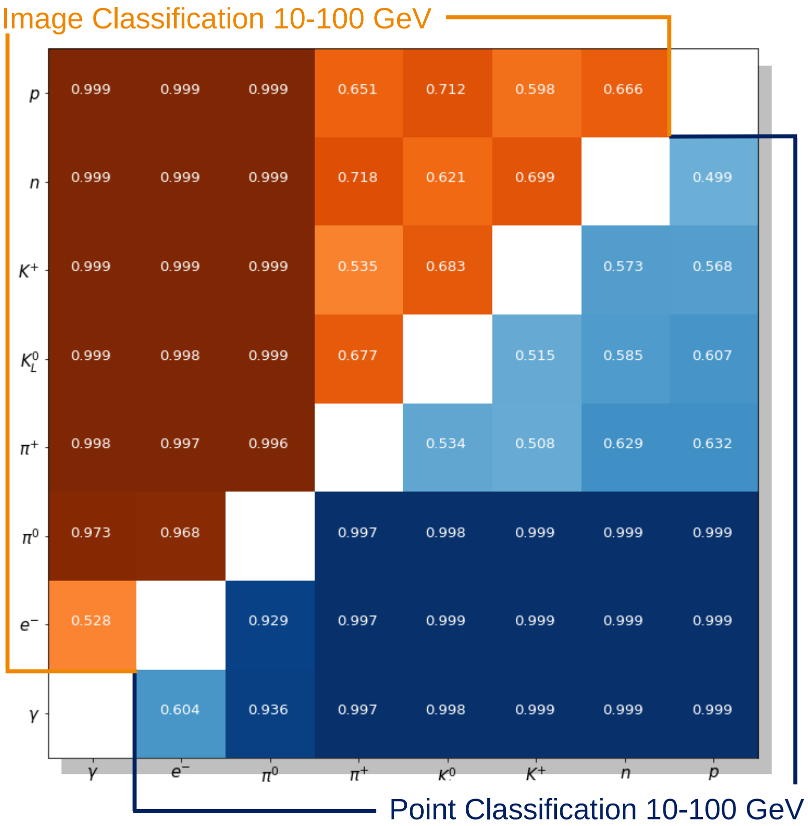
- Calorimeter standalone identification performance
  - No tracker information
  - No magnetic field is applied
- Numbers show AUC of the classification between row vs column

  → Excellent π0 identification against both EM & hadronic particles

  → Potential contribution to meson vs baryon (if combined with the tracker's dE/dx)





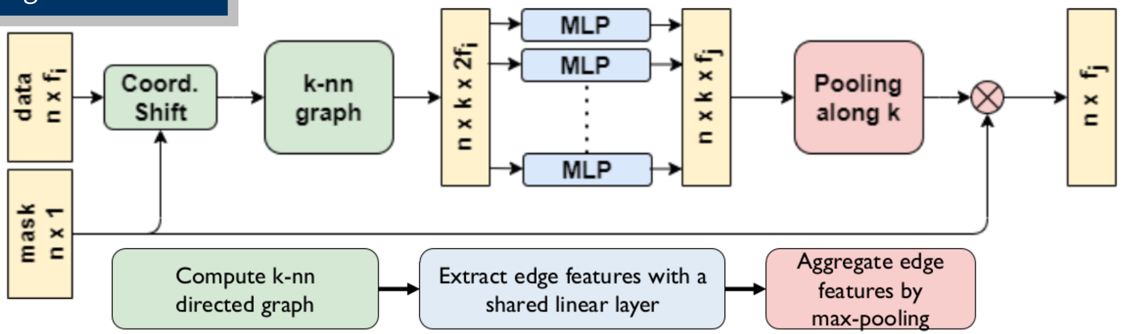


τ identification

with Dynamic Graph CNN (DGCNN)

- Conventional image-based data can be very sparse in e+e- collision
  → Point-cloud approach with timing information incorporated
- Representing a point-cloud as a graph
  - Inputs = (Δθ, Δϕ) ⊗ (SiPM's integral, ToA, ToP, ToT) ⊗ (fiber type) — *(timing)* over ToA, ToP, ToT
  - Vertices → points, Edges → connections between k-NN

Edge convolution



Truth BR \ Predicted BR	τ →eνν	τ →πν	τ →ππ^{0}ν	τ →ππ^{0}π^{0}ν	τ →πππν	τ →ππππ^{0}ν	τ → μνν	Z →qq jets
τ →eνν	98.81	0.26	0.79	0.00	0.00	0.00	0.13	0.00
τ →πν	2.07	90.69	3.75	0.91	1.94	0.13	0.26	0.26
τ →ππ^{0}ν	1.03	1.41	89.46	6.04	0.26	1.16	0.00	0.64
τ →ππ^{0}π^{0}ν	0.26	0.26	9.85	88.24	0.13	0.90	0.13	0.26
τ →πππν	0.13	3.70	1.79	0.38	86.61	5.99	0.13	1.28
τ →ππππ^{0}ν	0.13	0.38	1.78	3.18	5.46	87.67	0.00	1.40
τ → μνν	0.79	0.53	0.00	0.00	0.00	0.00	98.55	0.13
Z →qq jets	0.00	0.28	0.41	1.24	1.24	1.93	0.00	94.90

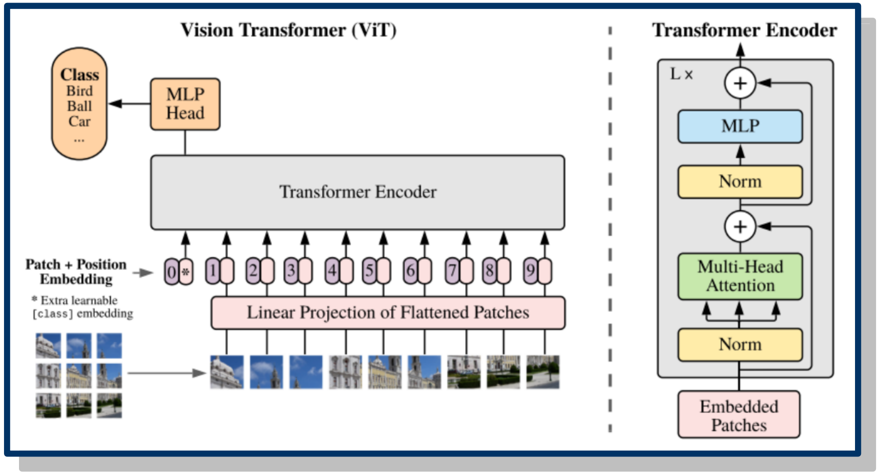
*) *see Stefano Giagu's talk on Thu.*

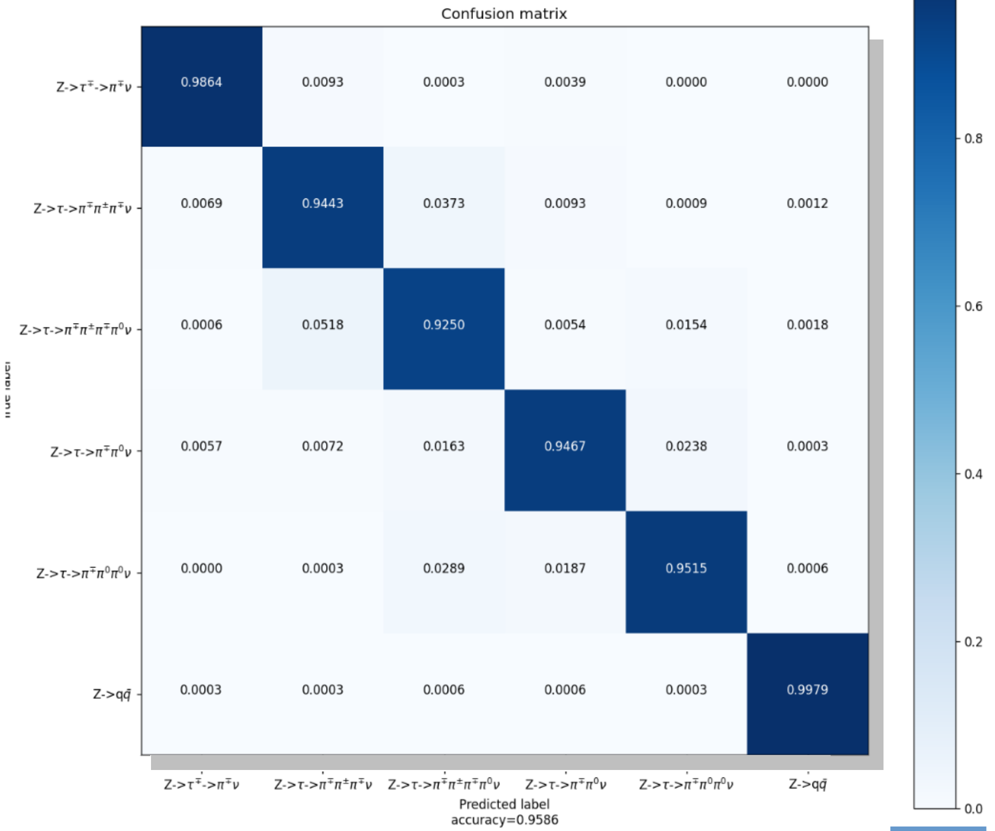
τ identification

with Vision Transformer (ViT)

- Alternative approach – use state-of-the-art ML technique
- ViT is rapidly replacing CNN
  - Uses flattened image patches (no more convolution)
  - Pre-training & fine-tuning (variable resolution)

  → scalable image recognition & classification





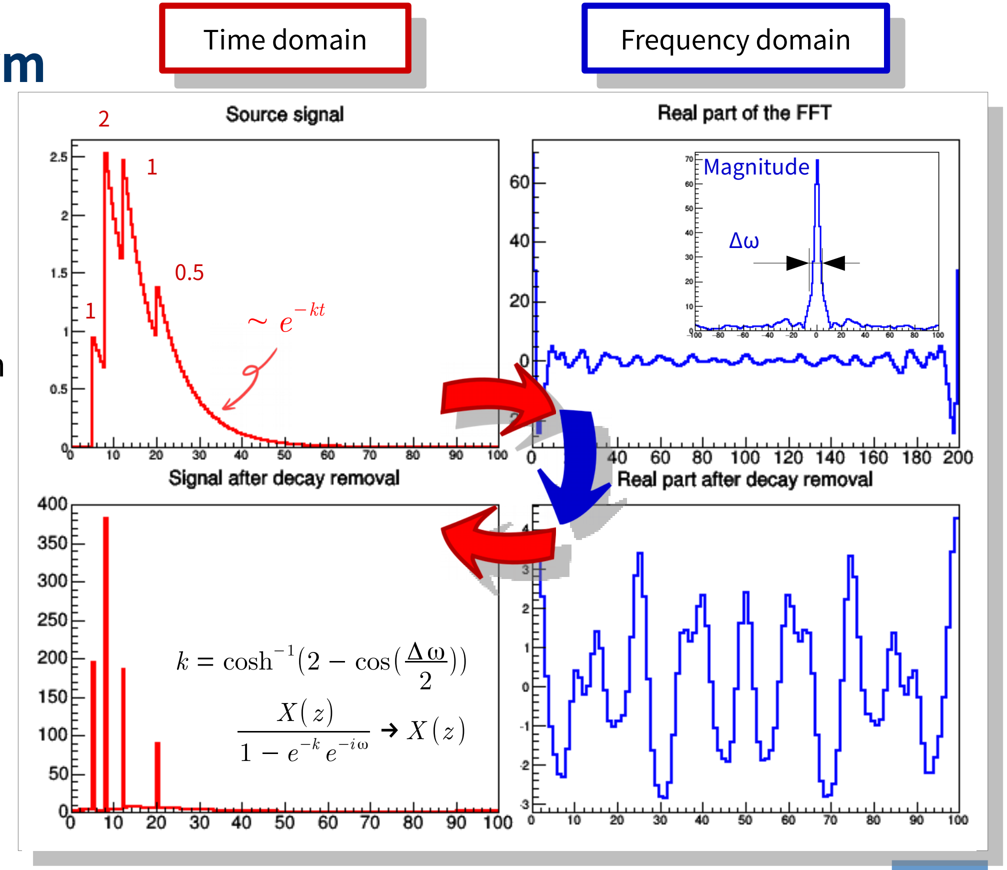
True label \ Predicted label	$Z\to\tau^{\mp}\to\pi^{\mp}\nu$	$Z\to\tau\to\pi^{\mp}\pi^{\pm}\pi^{\mp}\nu$	$Z\to\tau\to\pi^{\mp}\pi^{\pm}\pi^{\mp}\pi^{0}\nu$	$Z\to\tau\to\pi^{\mp}\pi^{0}\nu$	$Z\to\tau\to\pi^{\mp}\pi^{0}\pi^{0}\nu$	$Z\to q\bar{q}$
$Z\to\tau^{\mp}\to\pi^{\mp}\nu$	0.9864	0.0093	0.0003	0.0039	0.0000	0.0000
$Z\to\tau\to\pi^{\mp}\pi^{\pm}\pi^{\mp}\nu$	0.0069	0.9443	0.0373	0.0093	0.0009	0.0012
$Z\to\tau\to\pi^{\mp}\pi^{\pm}\pi^{\mp}\pi^{0}\nu$	0.0006	0.0518	0.9250	0.0054	0.0154	0.0018
$Z\to\tau\to\pi^{\mp}\pi^{0}\nu$	0.0057	0.0072	0.0163	0.9467	0.0238	0.0003
$Z\to\tau\to\pi^{\mp}\pi^{0}\pi^{0}\nu$	0.0000	0.0003	0.0289	0.0187	0.9515	0.0006
$Z\to q\bar{q}$	0.0003	0.0003	0.0006	0.0006	0.0003	0.9979

** ViT performance does NOT include SiPM emulation*

Longitudinal shower shape

Shower shape & timing – SiPM waveform

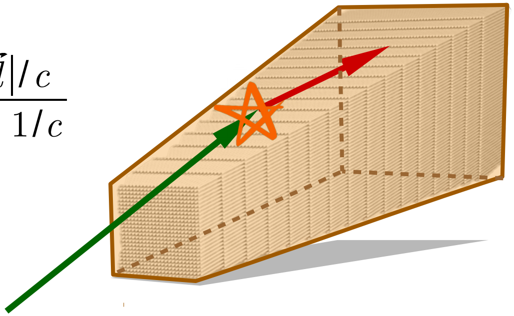
- Unsegmented calorimeter fully depends on the timing to reconstruct longitudinal shower shape
- Is dN/dt → dE/dx possible?
  → very challenging due to many hidden layers
- A SiPM yields exponentially decaying waveform to 1 photon
- FFT can be used to mitigate exponential tail, while preserving time translation & amplitude information



Deposit position $(\vec{x})$ Photon propagation $(\vec{k})$

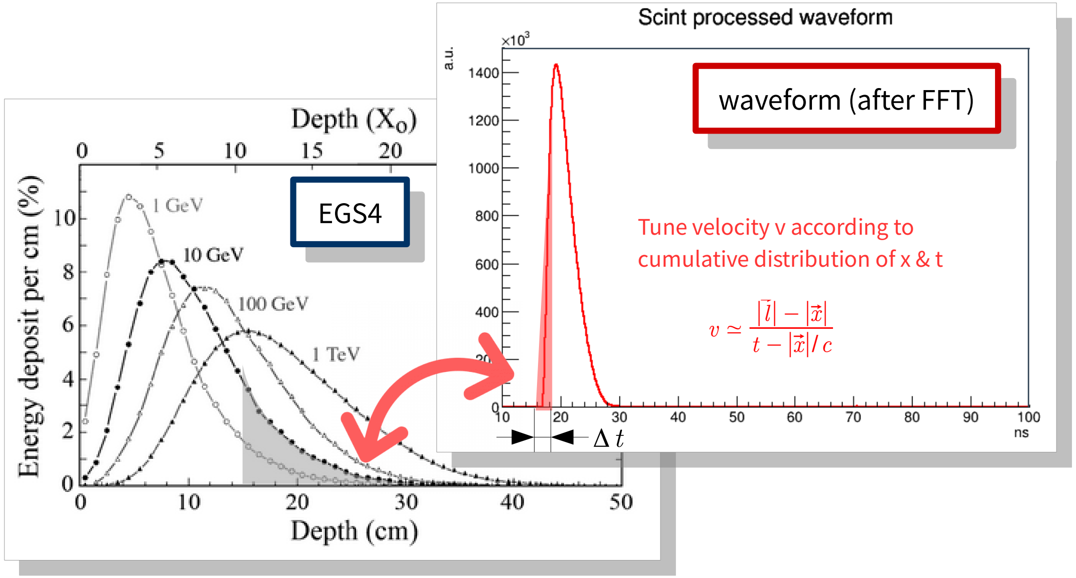
$$t = \frac{|\vec{x}|}{c} + \frac{|\vec{k}|}{v} \qquad |\vec{k}| \simeq \frac{t - |\vec{l}|/c}{1/v - 1/c}$$

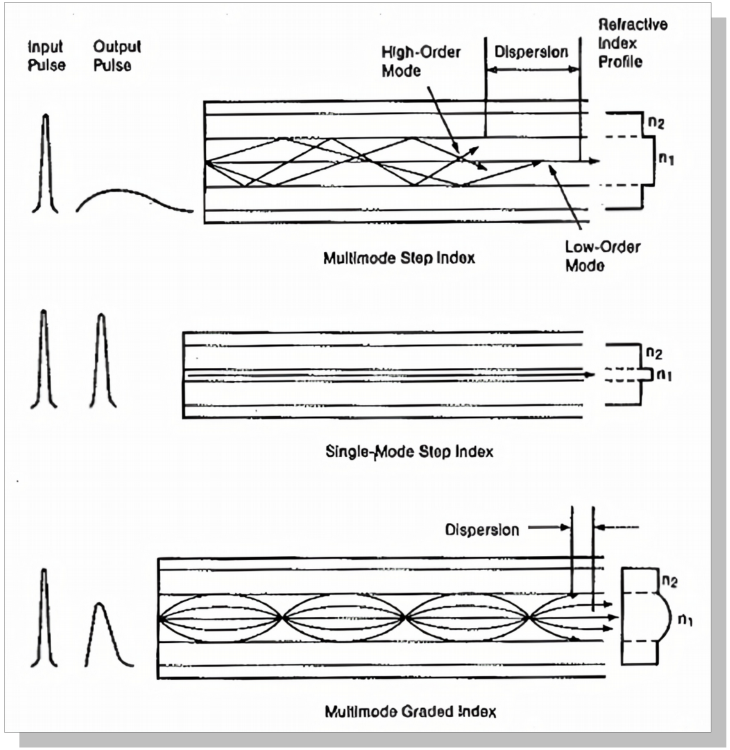
$$\vec{x} \simeq \vec{l} - \frac{t - |\vec{l}|/c}{1/v - 1/c}\hat{k}$$



Shower shape & timing – Dispersion

- Waveform is unlikely a shower shape even after FFT processing
- Late-component of the timing is dominated by the modal dispersion
- Mitigate dispersions by using slower phase velocity for late-components
  → Tune group velocity as a function of Δt using EM shower





Longitudinal shower shape

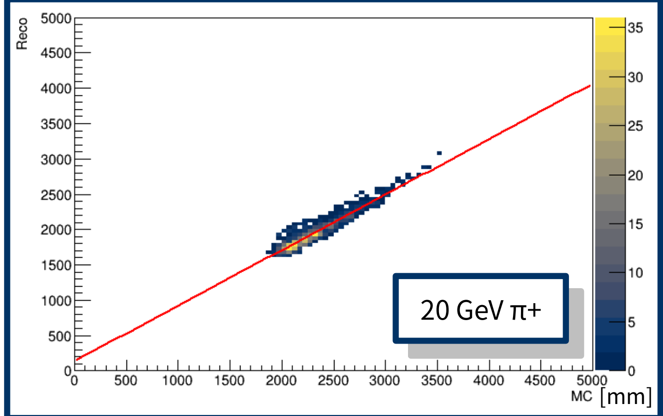
Longitudinal shower depth & length

- Able to obtain linear correlation of both shower depth & length simultaneously
  - Depth shows good correlation between MC vs Reco
  - Length shows moderate correlation

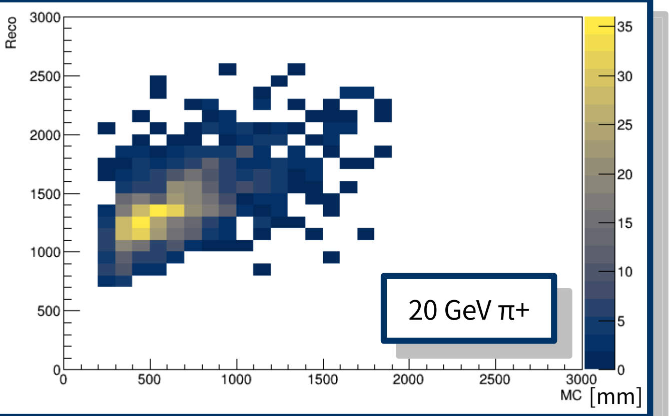
  → remains of unmitigated shower head (mainly dispersion)
- Longitudinal shape with excellent lateral granularity → 3D reconstruction

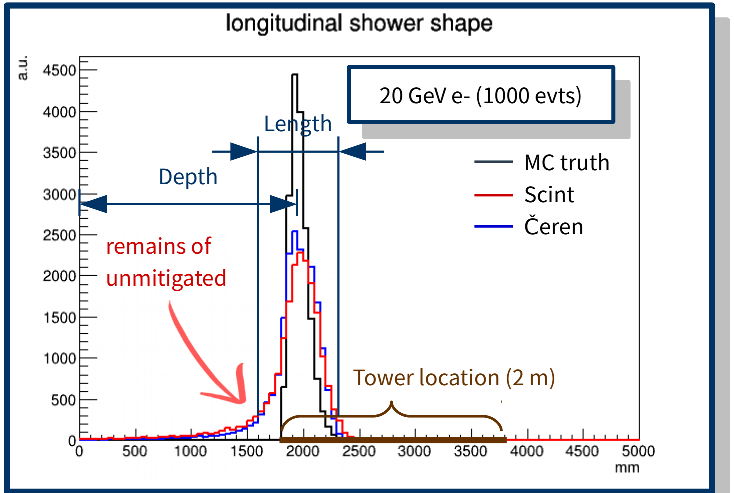
	Simulation setup
Timing resolution	Ideal (assume ~ O(10 ps))
Sampling rate	100 ps

Depth

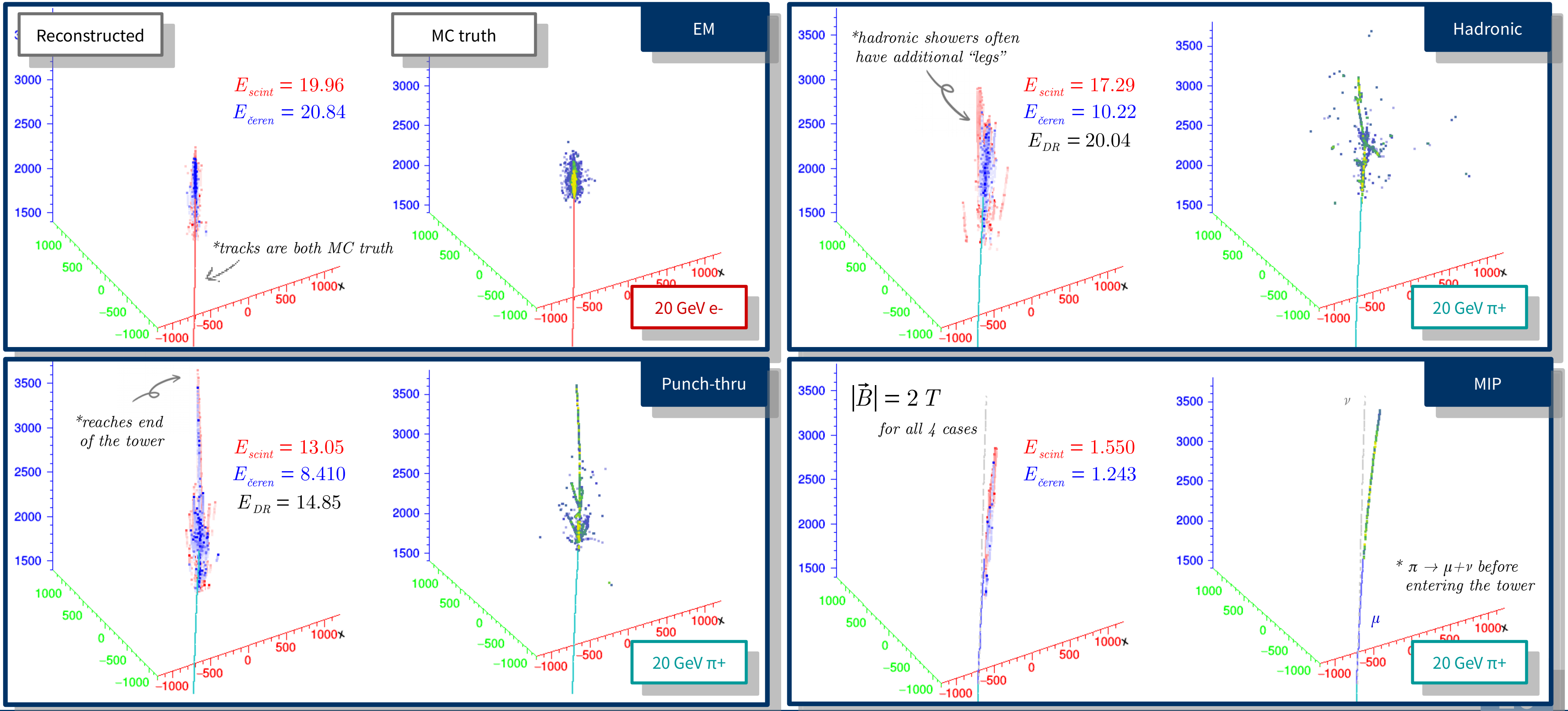


Length





3D reconstruction



Summary

Simulation & SW framework

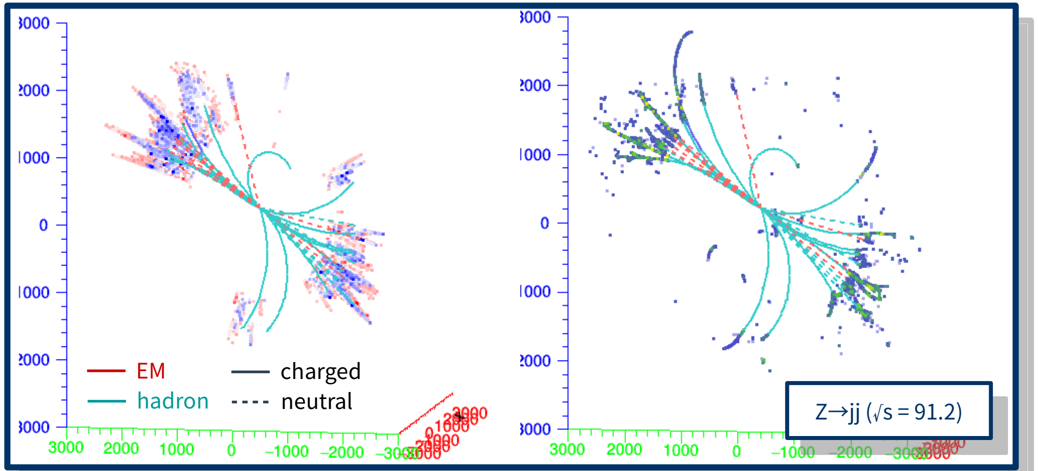
- Dual-readout calorimeter has shown excellent performance with simulations through past years
- Migrated to Key4hep, allows easier integrated usages with the central SW framework

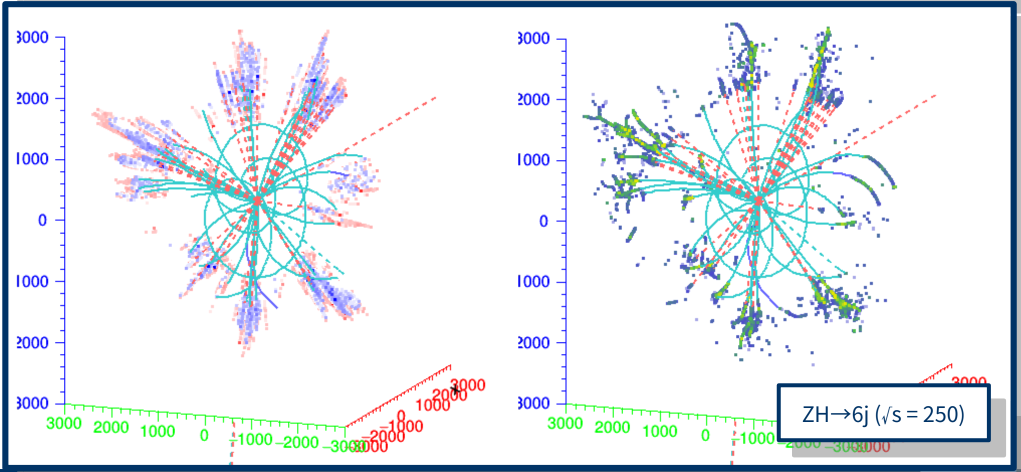
Particle identification

- Image classification with timing shows good discrimination between e-/γ, π0 and other hadrons
- Various methods are being tested to identify τ decays with great accuracy

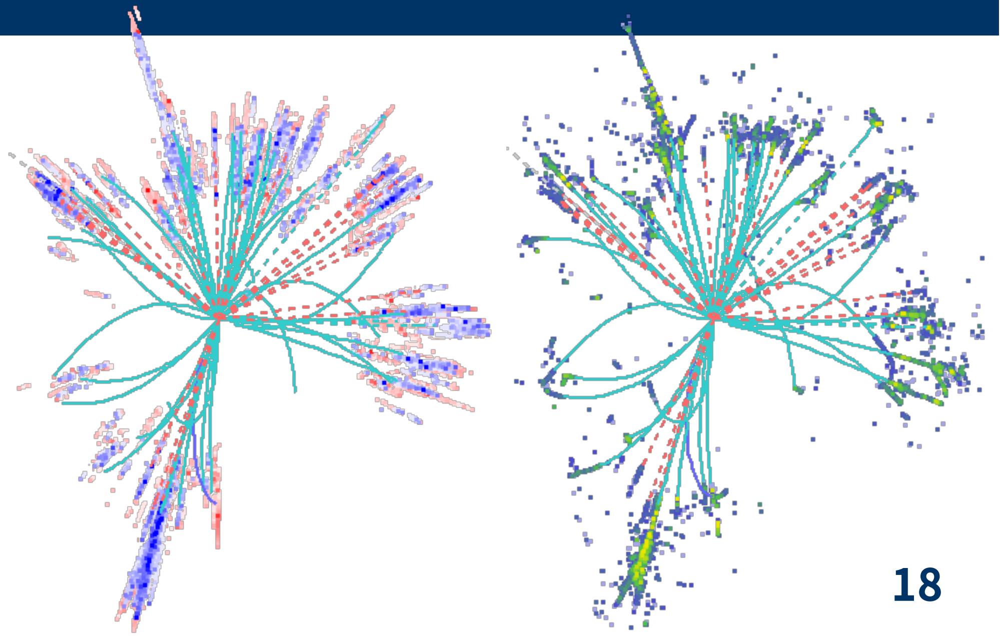
Longitudinal & 3D reconstruction

- Developing novel ideas to exploit timing for longitudinal & 3D reconstruction
- Many exciting challenges are ahead of us…



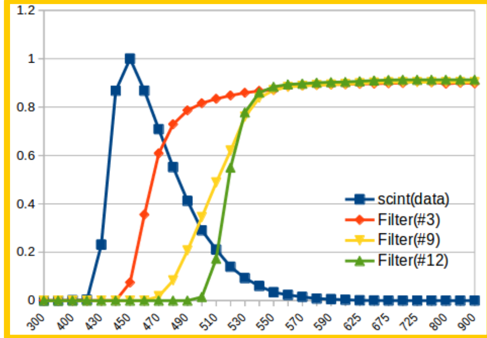


Backups



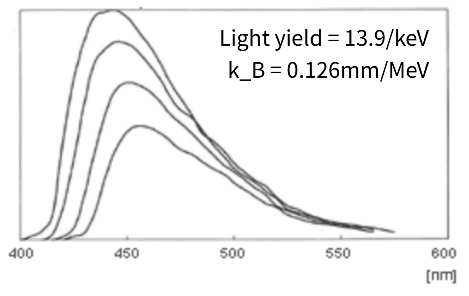
Optical properties in simulation

Transmission eff of filters

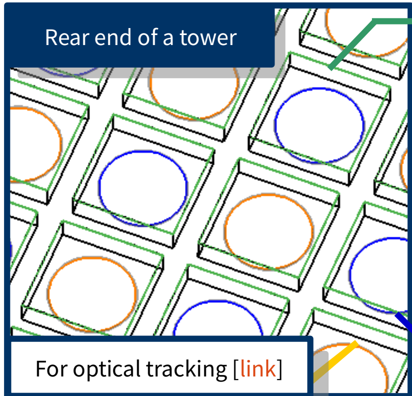


Attenuation loss diverges at 400nm → applied filter to S channel to mitigate it

Scintillation spectra of PS

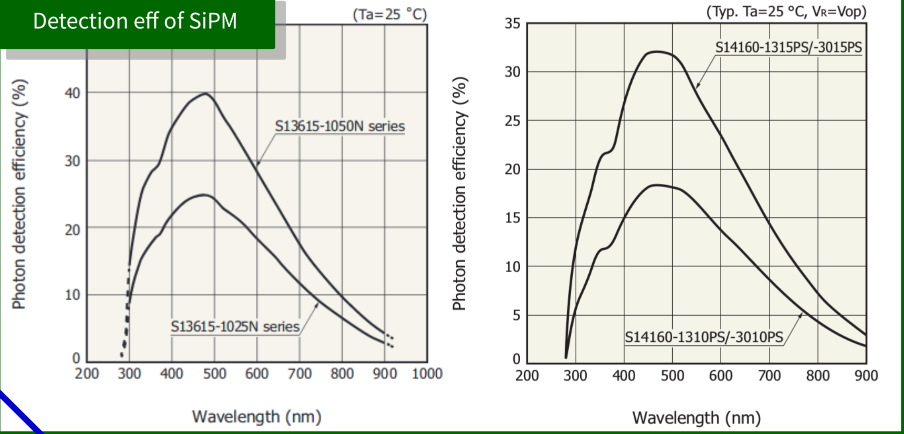


Rear end of a tower



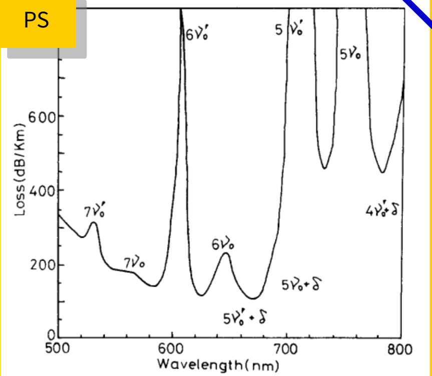
For optical tracking [link]

Detection eff of SiPM

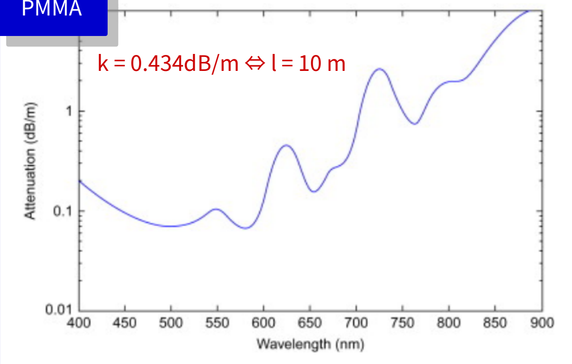


Attenuation loss of Polystyrene (PS) & PMMA

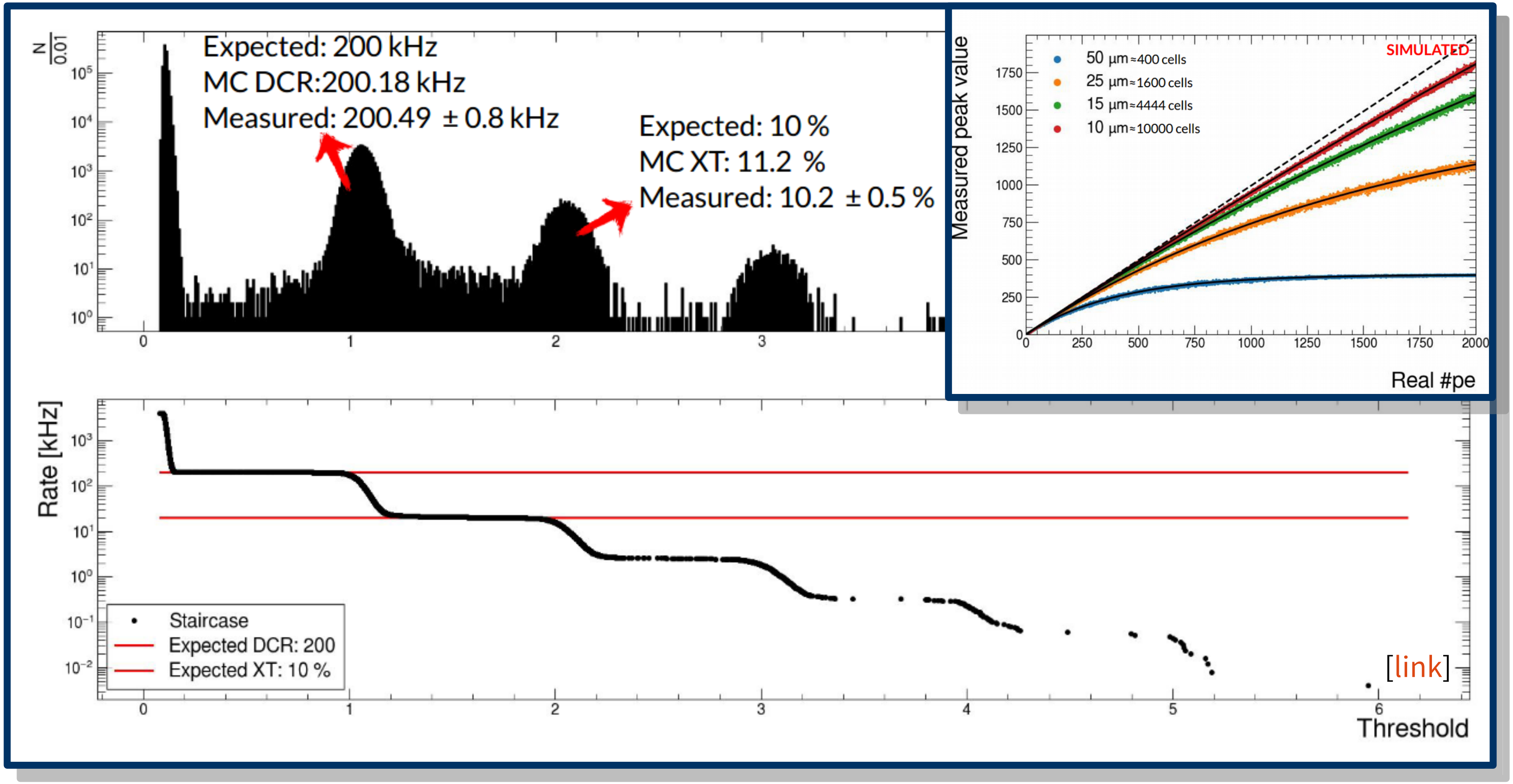
PS



PMMA



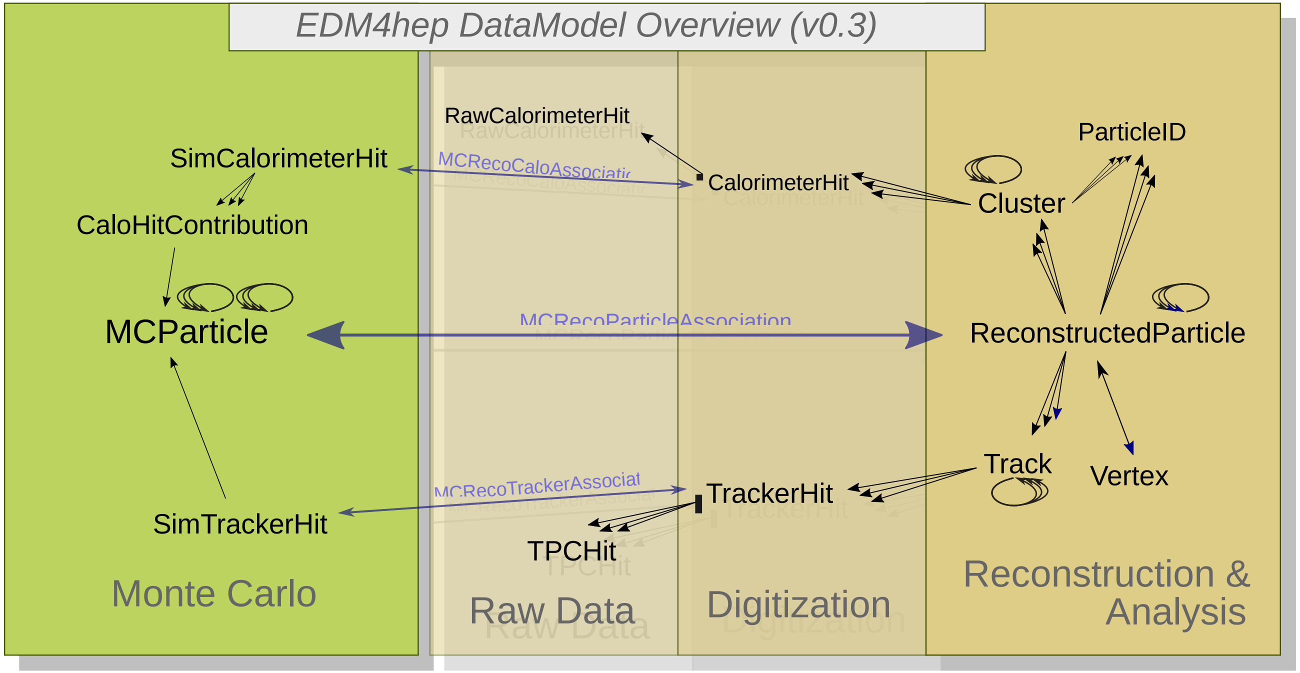
SiPM emulation



EDM4hep

Sharing common EDM

- EDM4hep [link] is the common EDM shared by multiple future collider communities
- Support various use-cases motivated from different experiments



Calibration

Calibration using 20 GeV e-

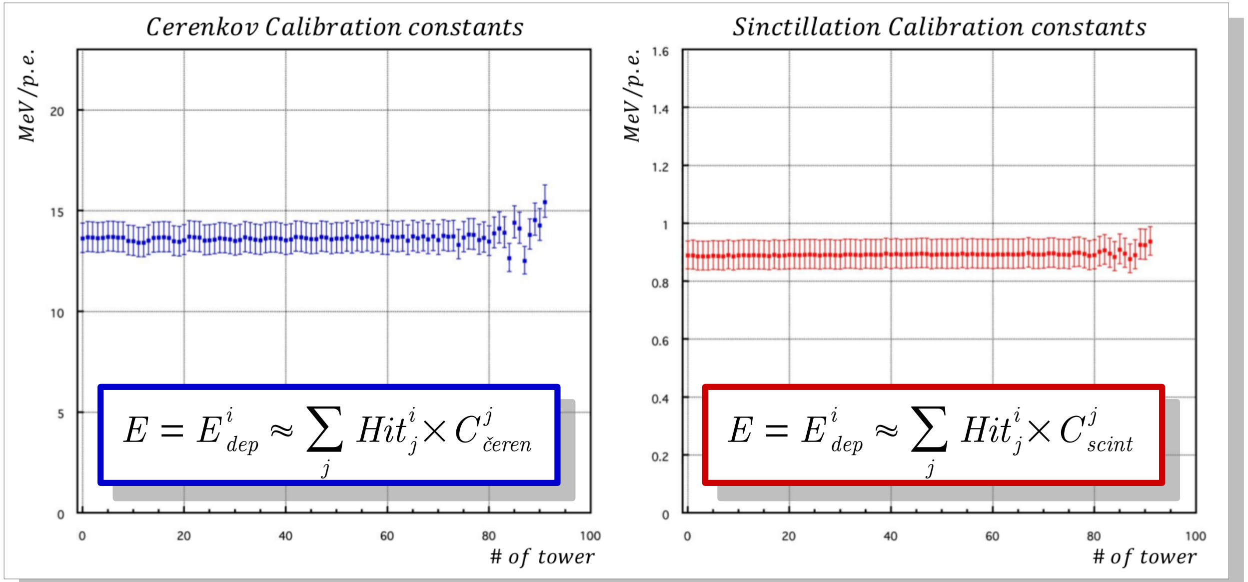
- Measure Energy deposit, scintillation p.e. & Čerenkov p.e. at i-th tower (0th - 91st)
- Energy can be expressed as a linear combination with simulations of 92 towers

  → Estimate calibration constants

- Uniform calibration constants as a function of the tower number

$$Energy = \sum_{i=0}^{92} Hit_{i^{th}\ tower} \times Calibration\ constant^{i^{th}\ tower}$$

$$\Rightarrow \begin{bmatrix} E^0_{dep} \\ E^1_{dep} \\ \vdots \\ E^{90}_{dep} \\ E^{91}_{dep} \end{bmatrix} = \begin{bmatrix} Hit^0_0 & Hit^0_1 & \cdots & Hit^0_{90} & Hit^0_{91} \\ Hit^1_0 & Hit^1_1 & & Hit^1_{90} & Hit^1_{91} \\ \vdots & & \ddots & \vdots & \\ Hit^{90}_0 & Hit^{90}_1 & & Hit^{90}_{90} & Hit^{90}_{91} \\ Hit^{91}_0 & Hit^{91}_1 & \cdots & Hit^{91}_{90} & Hit^{91}_{91} \end{bmatrix} \begin{bmatrix} C^0 \\ C^1 \\ \vdots \\ C^{90} \\ C^{91} \end{bmatrix}$$



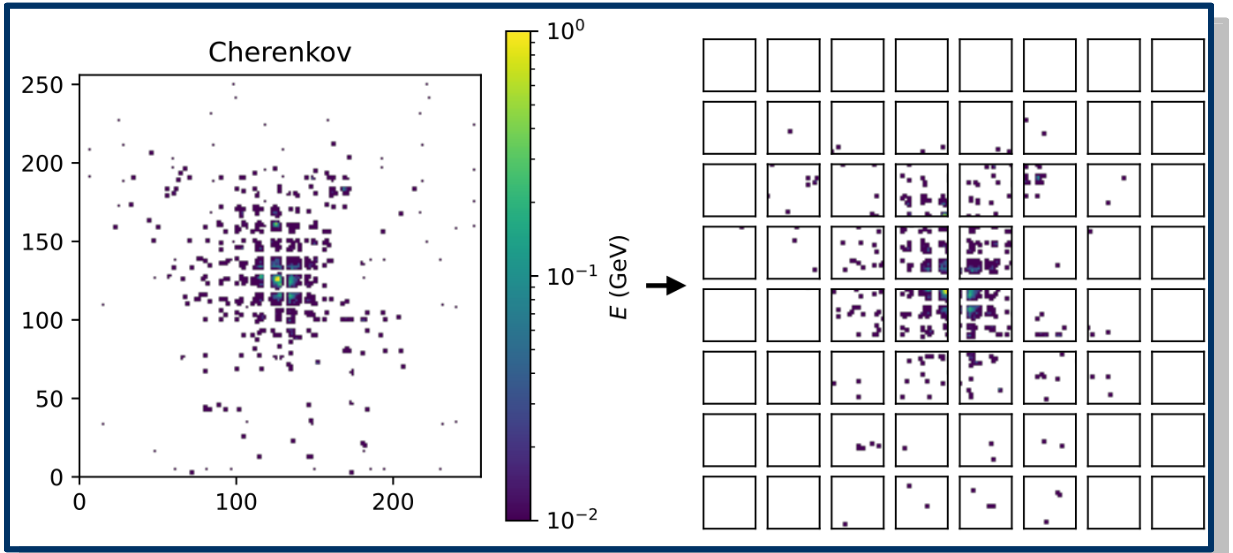
$$E = E^i_{dep} \approx \sum_j Hit^i_j \times C^j_{\check{c}eren}$$

$$E = E^i_{dep} \approx \sum_j Hit^i_j \times C^j_{scint}$$

Vision Transformer

Transformer network

- Z→ττ events are clustered and 256x256 images are generated for each type of fibers
- ViT takes sequential patches of images as input
  → calculates attention values (similarity between hidden states of encoders & decoders) for each patch to other patches



Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 256, 256, 2)	0	
patches (Patches)	(None, None, 2048)	0	input_1[0][0]
patch_encoder (PatchEncoder)	(None, 64, 64)	135232	patches[0][0]
multi_head_attention (MultiHead	(None, 64, 64)	66368	patch_encoder[0][0] patch_encoder[0][0]
flatten (Flatten)	(None, 4096)	0	multi_head_attention[0][0]
dropout (Dropout)	(None, 4096)	0	flatten[0][0]
dense_1 (Dense)	(None, 1024)	4195328	dropout[0][0]
dropout_1 (Dropout)	(None, 1024)	0	dense_1[0][0]
dense_2 (Dense)	(None, 512)	524800	dropout_1[0][0]
dropout_2 (Dropout)	(None, 512)	0	dense_2[0][0]
dense_3 (Dense)	(None, 6)	3078	dropout_2[0][0]

Total params: 4,924,806
Trainable params: 4,924,806
Non-trainable params: 0

Modal dispersion

Group velocity modeling

- Assign slower group velocity for the late-components at $t = t_0^{(\text{ToA})} + \Delta t$
- Apply tuning according to cumulative distribution of dE/dx & dN/dt with 20 GeV e-
  → profile group velocity for every fiber by assuming the longitudinal shape (EM shower template)