π^- energy reconstruction in HGCAL Beam Test prototype detector using Graph Neural Networks

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(On behalf of the CMS collaboration with an acknowledgement to the CALICE collaboration)

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Overview

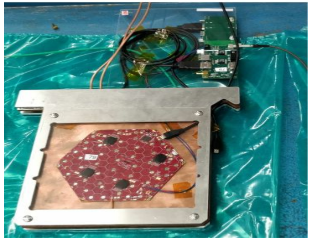
Aim: π^- energy reconstruction in the high granularity calorimeter (HGCAL) beam test prototype detector using Graph Neural Networks (GNNs)

- ➢ Experimental setup of HGCAL detector prototype
- ➢ Classical method of π^- energy reconstruction : χ^2-method
- ➢ The Dynamic Reduction Network (DRN)
- ➢ π^- energy reconstruction using DRN
- ➢ Understanding the improvements in energy resolution using DRN based on different input features provided to the model for learning the details of the event.

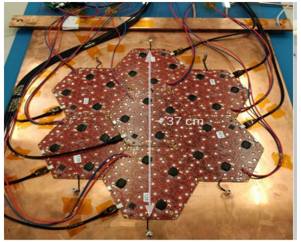
Experimental setup of HGCAL detector prototype
(Beam test experiments of Oct 2018 at H2 Beamline, CERN)

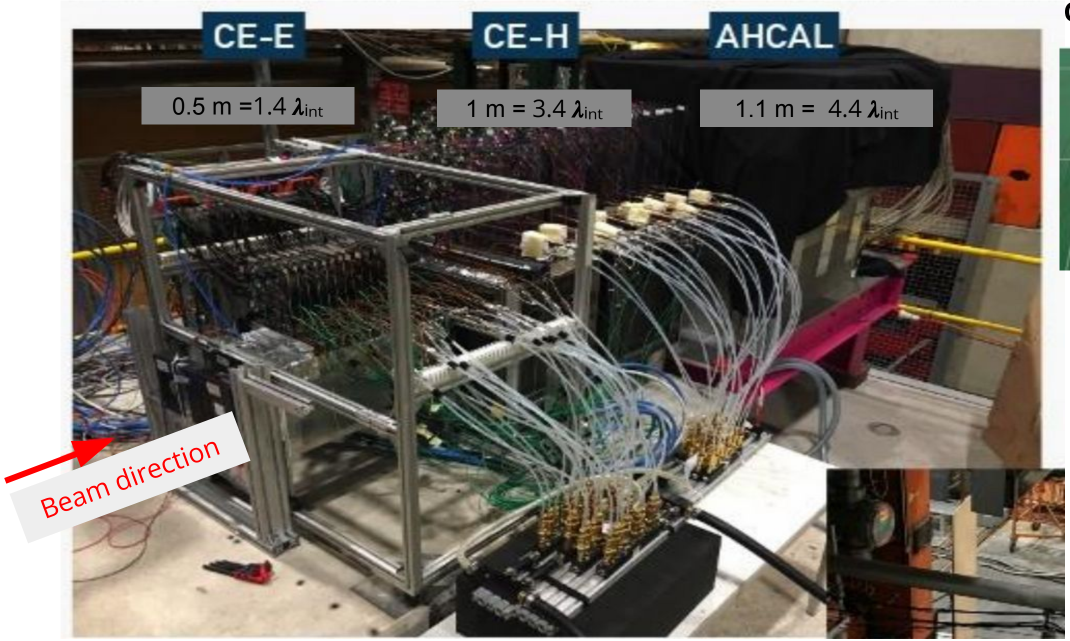
- Prototype HGCAL detector setup comprised of Si-based electromagnetic (CE-E) and hadronic (CE-H) sections followed by scintillator tile-based CALICE AHCAL
  - Exposed to $\mathbf{e^+}$ and $\boldsymbol{\pi^-}$ beams of energies ranging from 20 – 300 GeV.

A sampling layer of CE-E

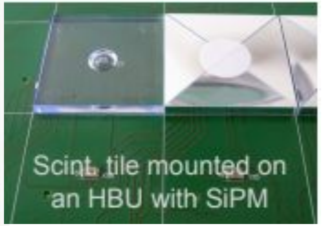


A sampling layer of CE-H





CALICE AHCAL



For more details on SiPMs: Mr. Malinda's talk at 11 AM today

For more details on CALICE AHCAL: Antoine Laudrain's talk at 12PM today

For more details about instrumentation, DAQ, calibration, and simulation, please refer to 2021 JINST 16 T04001, 2021 JINST 16 T04002 and 2022 JINST 17 P05022.

Detector setup and simulation

CE-E

- Si sensors (1.1 cm^2) + Cu/CuW & Pb absorbers
- 28 sampling layers
  - one module per layer
- Lateral dimensions (x,y) = (15 cm x 15 cm)

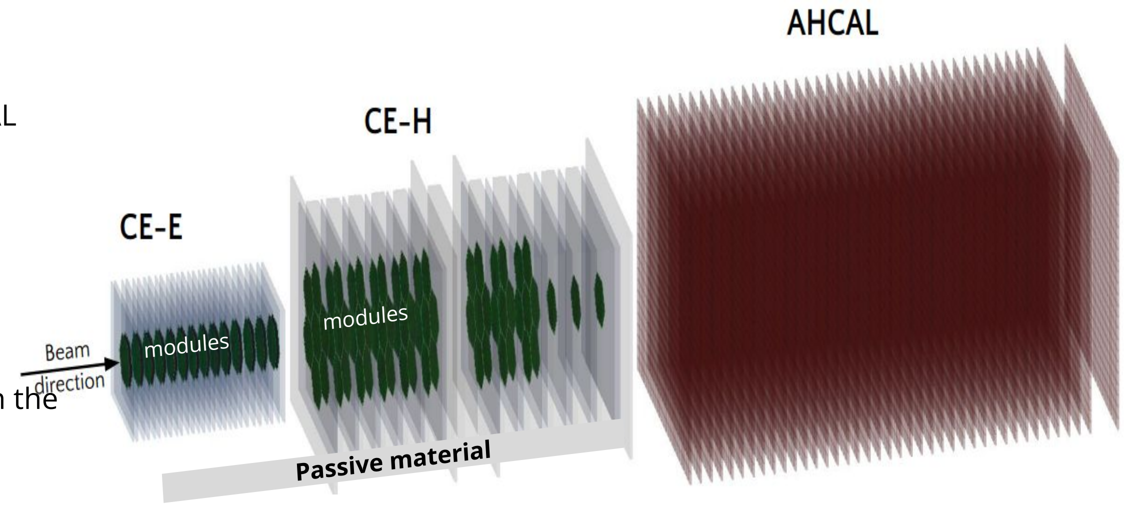
CE-H

- Si sensors (1.1 cm^2) + Cu/CuW & Steel absorbers
- 12 sampling layers
  - 7 modules per layer, arranged in a daisy structure
  - last three layers have only one module
- Lateral dimensions (x,y) = (37 cm x 37 cm)

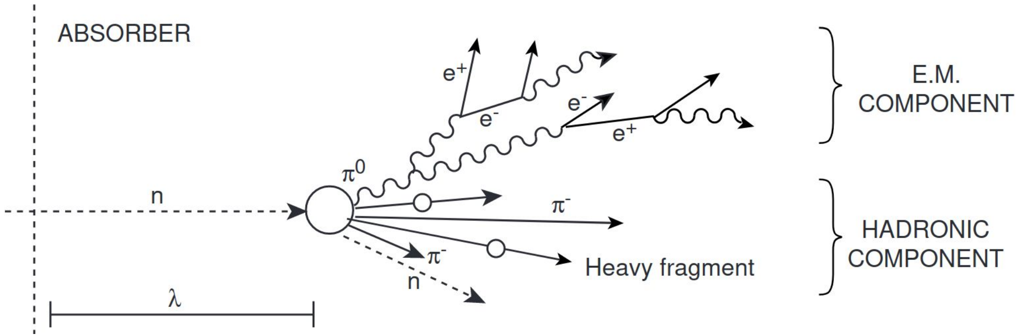
CALICE AHCAL

- Scintillators on SiPMs ($3 \times 3 \times 0.3$ cm^3) + Steel absorbers
- 39 sampling layers
- Lateral dimensions (x,y) = (72 cm x 72 cm)

- A total of 12k & 22k readout channels in Si HGCAL prototype & Scint. AHCAL prototype.
- The detector setup, along with absorbers and electronics board material, is simulated using GEANT4.10.4.p03.
- The absorber plates with slightly larger area than the sensors in CE-E & CE-H are used.

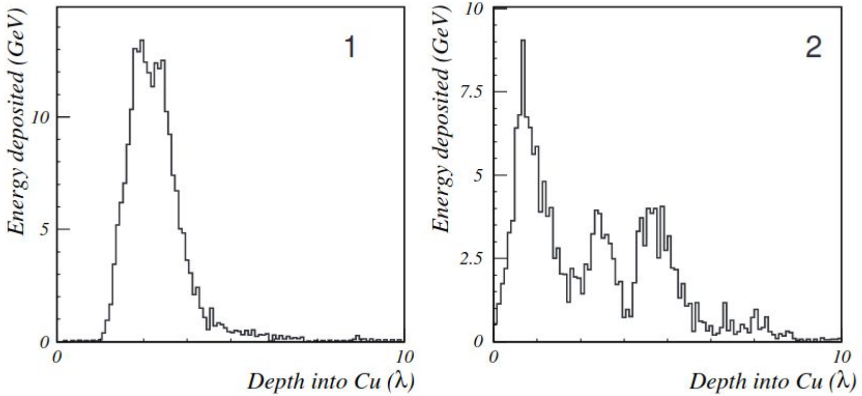


Complex nature of hadronic showers



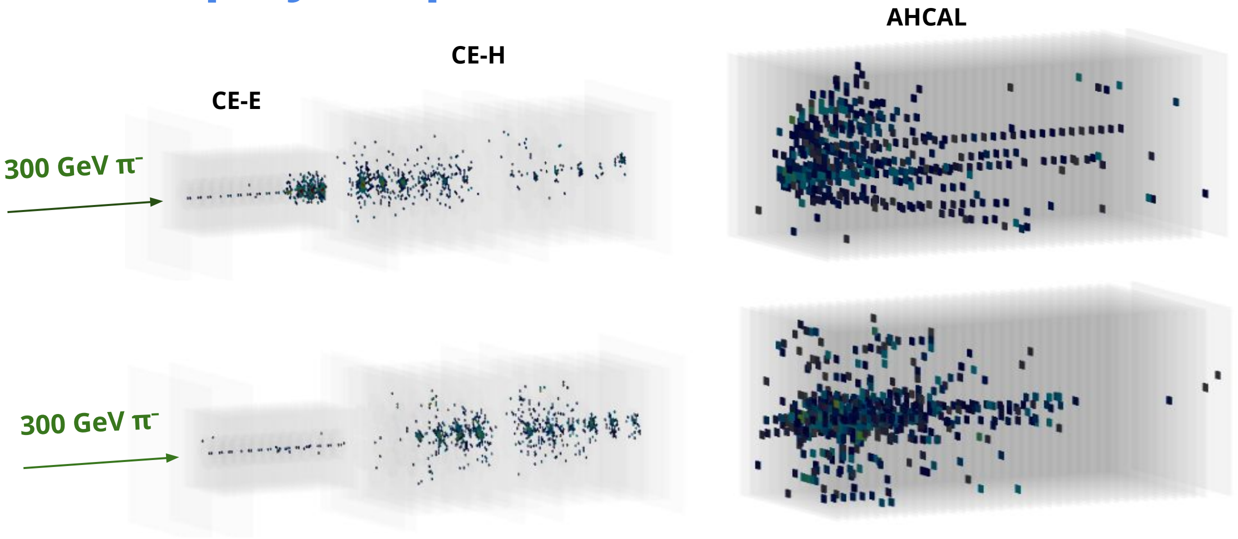
- ➢ Hadronic showers have electromagnetic (EM) (π^0/η -> $\gamma\gamma$) & hadronic component.
- ➢ The fraction of energy carried by EM component depends on energy of incident hadrons,
  - results in a nonlinear response.
- ➢ The hadronic component has some definite contribution from invisible energy (breaking up of nuclei etc.) .

Paper on experimental technique in nuclear physics by T.S. Virdee



- ➢ The right figure shows simulation of the development of 2 showers induced by 270 GeV pions in copper block.
- ➢ Fluctuations in energy deposited across the detector are due to fluctuations in production & energy carried by π^0s.

Event displays of pion showers in HGCAL beam test prototype



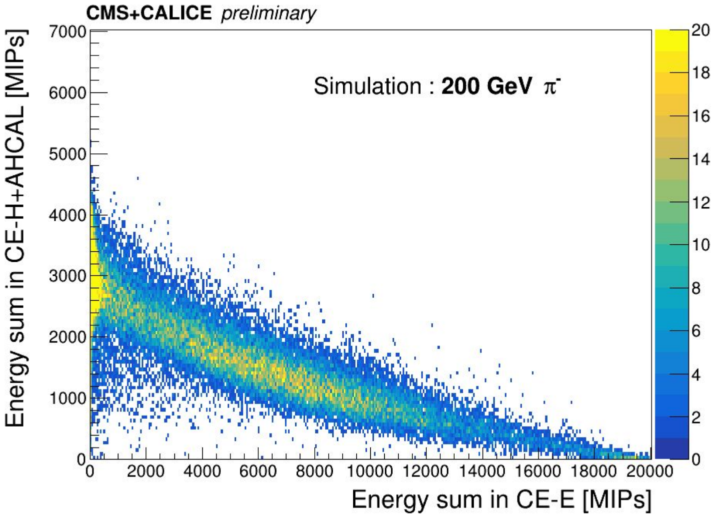
Pion started showering in later part of CE-E.

Pion started showering in one of first few layers of CE-H.

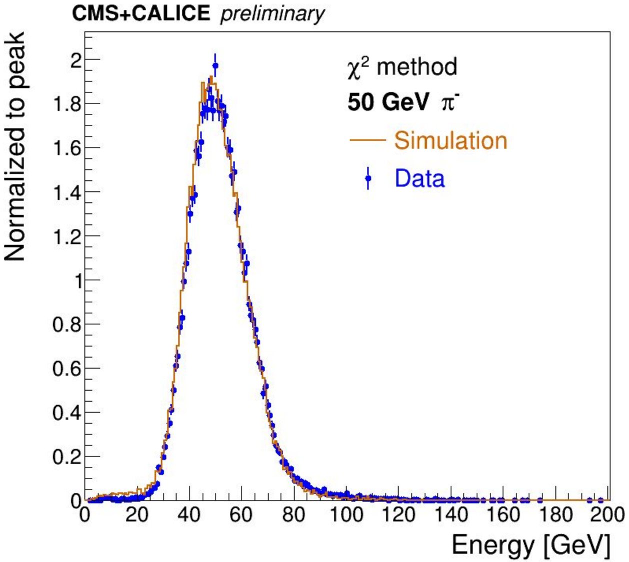
- Event displays are showing AHCAL with 39 sampling layers whereas in our studies we have opted only 10 layers of AHCAL (information from every 4th layer) to make prototype geometry consistent with final HGCAL geometry.

- In addition to intrinsic fluctuations, transverse and longitudinal leakage of energy also contribute to fluctuations of the measured energy of pions.
  - Transverse leakage is mostly due to single modules used in CE-E and last three layers of CE-H.

Energy reconstruction of pions - classical method



- The signal generated in each cell by the traversing particles is converted into energy in units of MIPs.
  - MIP scale is not uniform across the CE-E and CE-H/AHCAL because of different absorbers & sampling fraction.
  - Detector level calibration: calibrate CE-E (CE-H+AHCAL) using a 50 GeV e+ (a 50 GeV π⁻) beam.



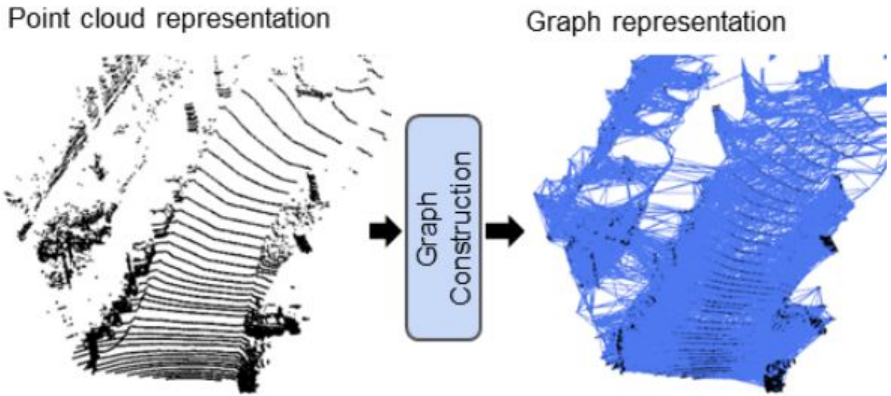
- χ^2-method : energies deposited in CE-E, CE-H and AHCAL are combined using energy dependent weight factors extracted after minimizing an estimator defined as,

$$\chi^2 = \sum_{pions} \frac{(E_{beam} - E_{corr})^2}{\sigma^2(E_{fix})}$$

- The χ^2-method in this form does not take into account the event-by-event fluctuations of showers and also it does not make use of the high granularity of the detector.

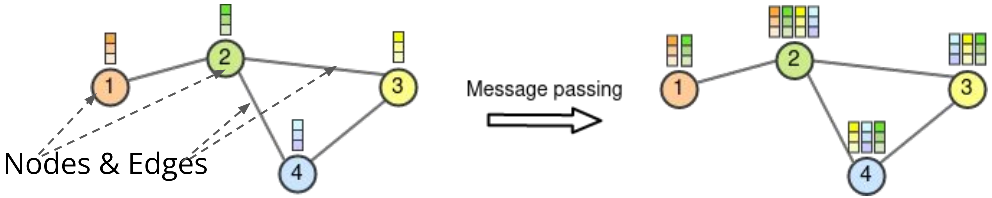
Graph Neural Networks

- ➢ Pion showers are reconstructed as large point clouds of reconstructed hits (rechits),
  - ○ Variable in number of rechits and in how the rechits are distributed.
  - ○ Such highly irregular input data can be represented by graphs.



arXiv:2003.01251

- ➢ Graphs are formed by drawing edges in between k nearest rechits.
- ➢ Each node learns about its neighbor & about itself using the message passing layer called the graph convolutions.



https://uvadlc-notebooks.readthedocs.io/en/latest/tutorial_notebooks/tutorial7/GNN_overview.html

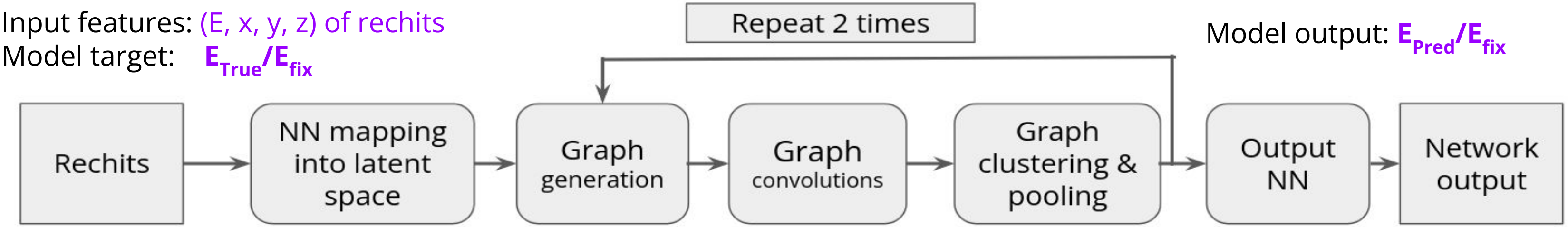
- ➢ Advantages of graph approach:
  - ○ Preserves permutation-invariance of input data (the order in which rechit are fed to the network does not matter).
  - ○ No padding or truncation necessary like it is needed in case of convolutional NNs.

Dynamic Reduction Network (DRN)

- Based on Dynamic Graph Neural Networks (1801.07829), a model is defined with the following differences(2003.08013v1)
  - Input features are mapped onto a higher dimensional latent space
  - Add clustering & pooling step to learn high level information iteratively.

Input features: (E, x, y, z) of rechits
Model target: E_{True}/E_{fix}

Model output: E_{Pred}/E_{fix}



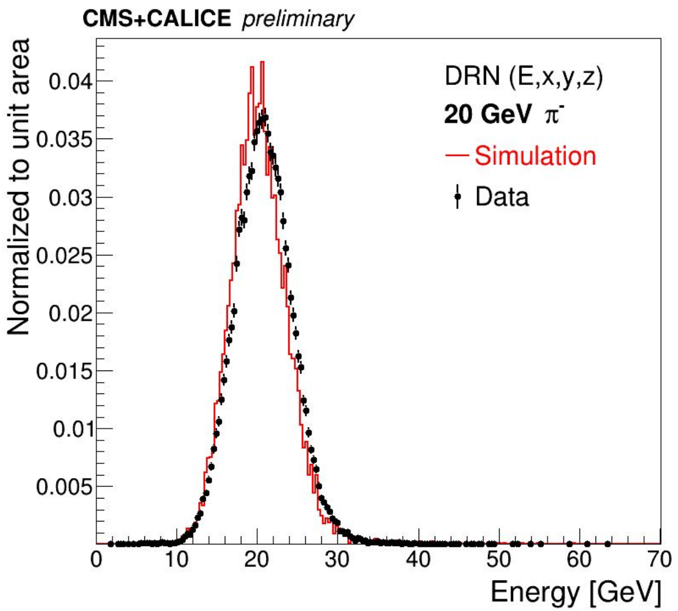
E_{True} is the true energy of particle & E_{fix} is reconstructed energy using detector level calibration
E_{Pred} is the energy reconstruction using DRN weights.

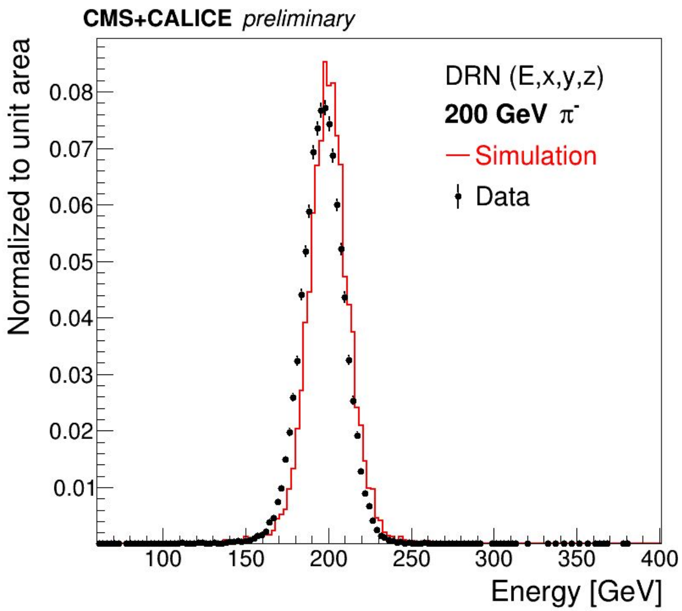
- The model is trained on a flat energy sample of 10-350 GeV with a total of 4.1M events simulated using GEANT4.10.4.p03 and FTFP BERT EMN hadronic physics list.
- AdamW optimizer with a constant learning rate of 10^{-4} is used while training the model & a total of 63k parameters to learn in the model.
- The most expensive step is the graph convolutions, followed by construction of the nearest neighbors graph.

Performance of DRN in energy reconstruction of charged pions

Energy reconstruction of charged pions using DRN

- Energy reconstructions in data and simulation using DRN:
  - In data, rechit energy in CE-E is scaled by 3.5% and in CE-H/AHCAL by 9.5% to account for the difference in energy scales in data and simulation
    - As per measured using independent studies with the positron and the pion datasets. More information at arxiv : 2111.06855 .

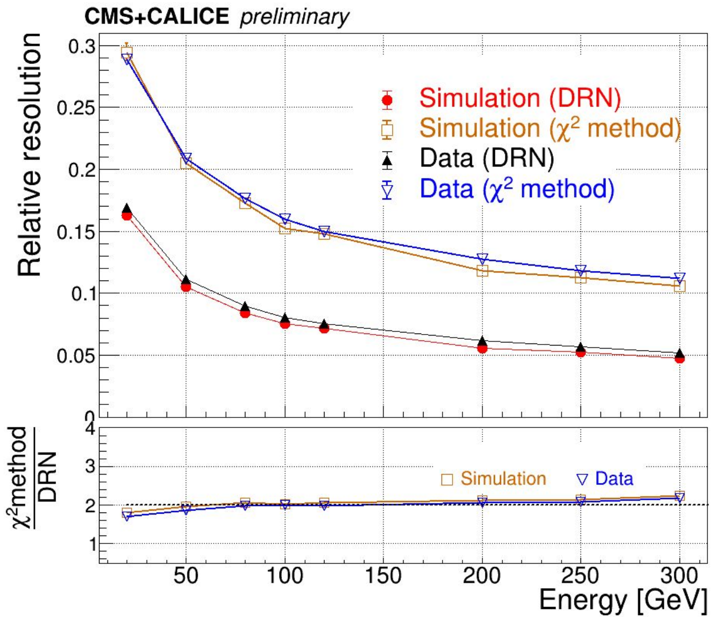


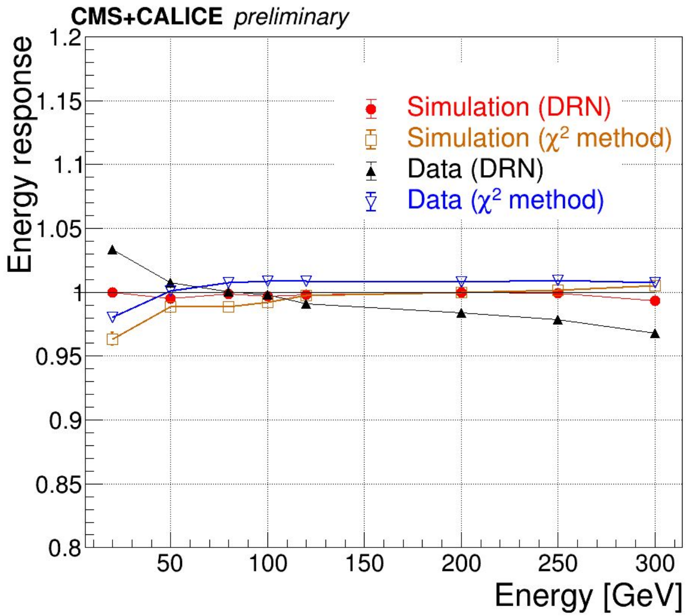


- The bulk of distribution in simulation & data is matching.

Energy resolution & response of charged pions

- The distributions of the reconstructed energy in data & simulation are fitted with a Gaussian function to obtain μ and σ, and define the relative resolution as σ/μ and response as μ/E_{true}.



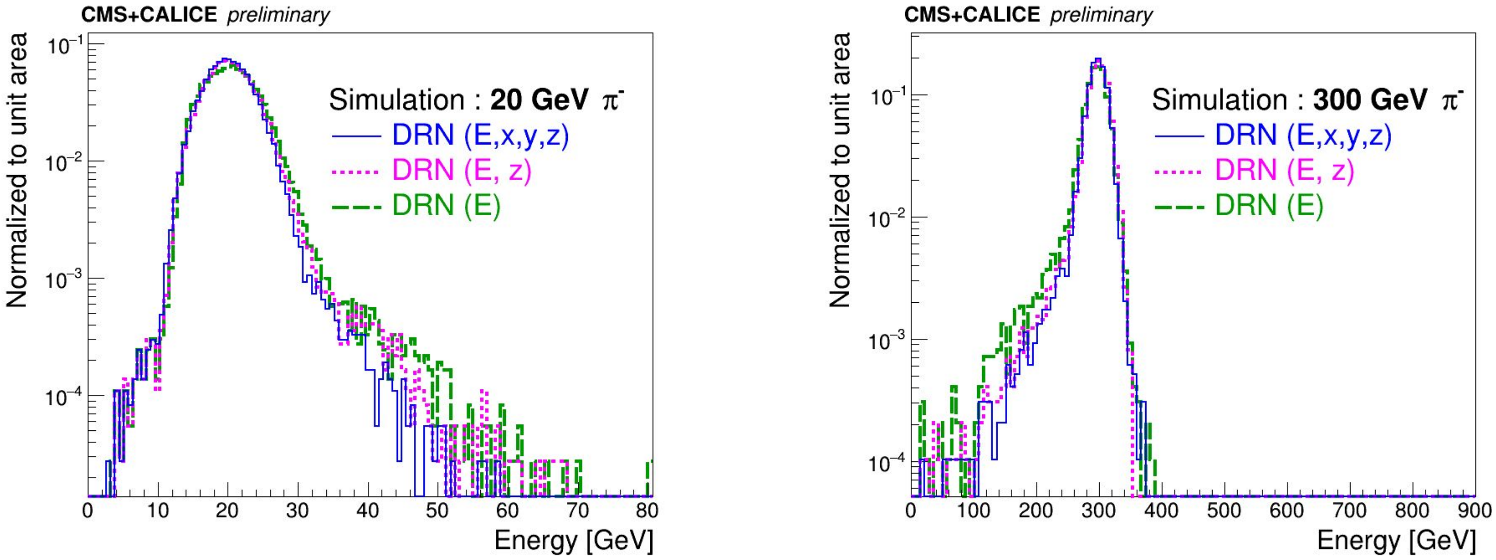


- A very large improvement in energy resolution using DRN as compared to simple χ^2 method at all the energies.
  - The scale factors in χ^2 method are calculated on average for a given pion energy and applied to all events with the same true energy irrespective of the shower fluctuations.

Understanding the improvements in energy resolution using DRN

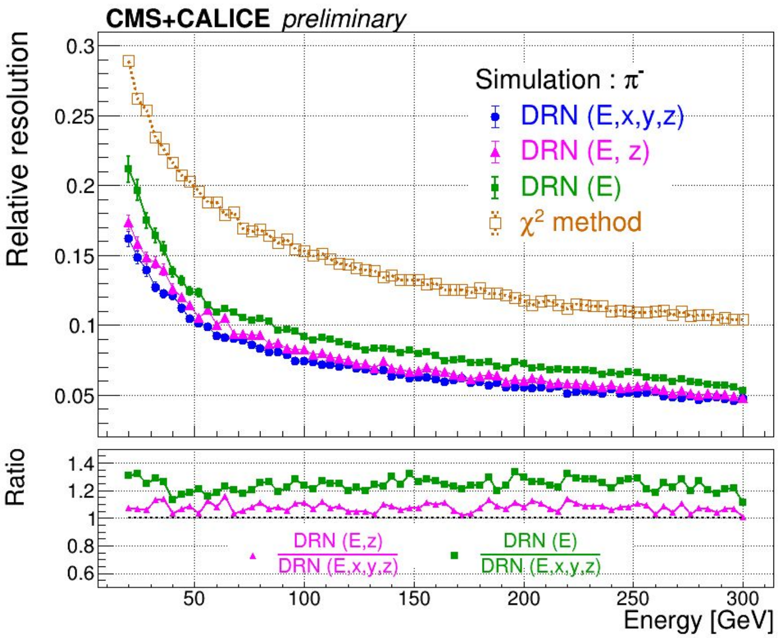
Training DRN with different input features

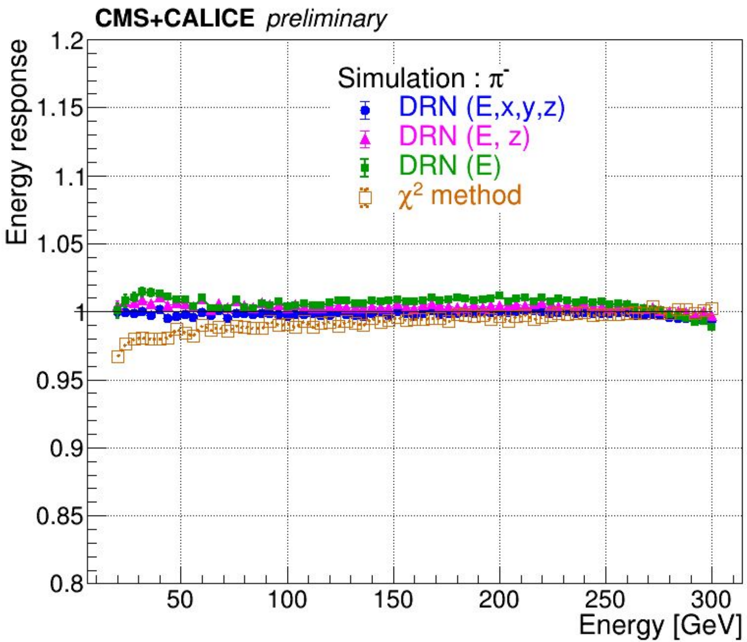
- ➢ To understand the role of input features used to train the DRN, we considered three combinations of these input information:
  - DRN (E) uses the energy values of all rechits as input feature
  - DRN (E, z) uses in addition the z coordinate of the rechits to allow the DRN to track the longitudinal development of each shower
  - DRN (E, x, y, z) using 4 input features (E, x, y, z) has full information about the longitudinal and transverse development of the showers.



- ➢ By increasing the input features the resolution improves overall and the tails are reduced.

Improvement in energy resolution with different DRNs

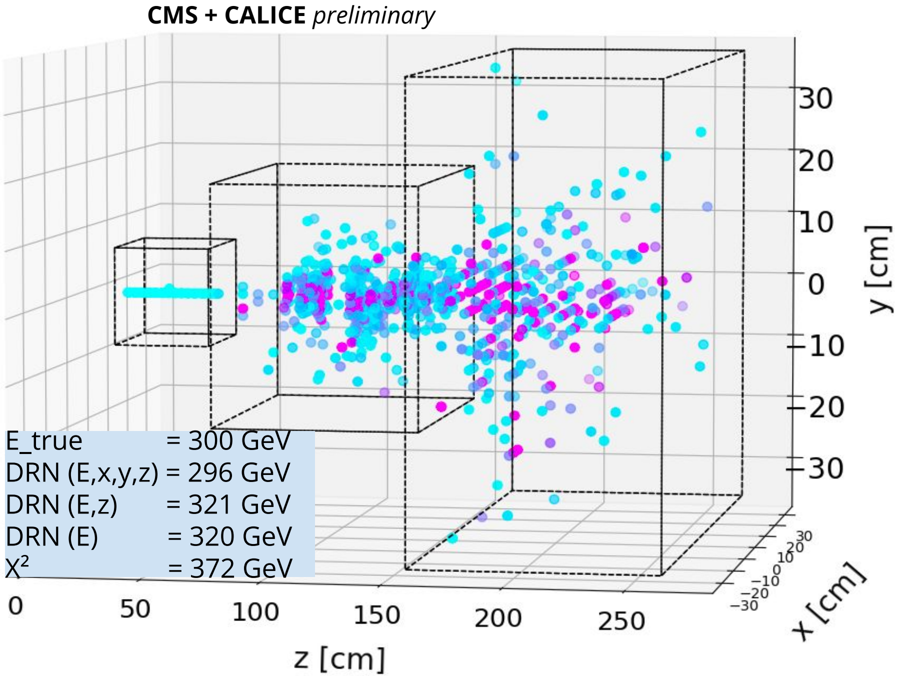


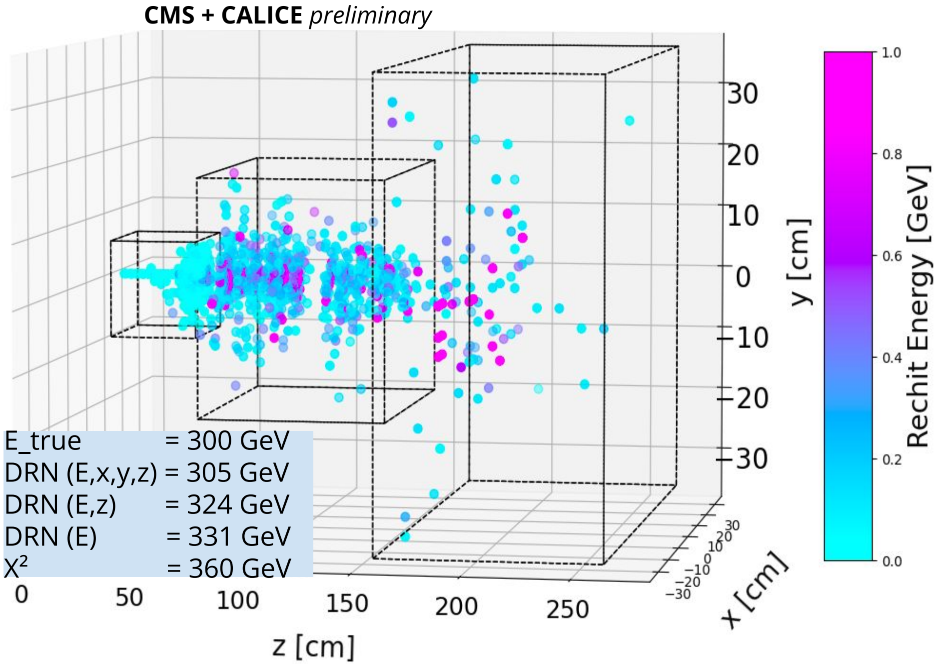


- The improvement from χ^2 method to DRN (E) essentially coming from learning event-by-event fluctuations in EM fraction.
  - There is a margin of improvement in this simple χ^2 method as well.
- Adding the spatial coordinates gives the DRN information about the spatial development of the shower.
  - Helps DRN to better compensate all kind of fluctuations and also learn about transverse leakage along with longitudinal leakage.

Event displays illustrating the impact of input features on DRN's learning

- ➢ Event displays for two representative simulated showers with the hits plotted according to their (x,y,z) position.
  - ○ The color is representative of the rechit energy in units of GeV using the detector-level calibration (E_{fix}).
    - ■ Hits with >1 GeV are represented with the same color as 1 GeV.
- ➢ The energy reconstructed by different methods is shown in the legends.





Summary

- The reconstruction of pions using DRN benefits from the detailed input features provided per event in terms of energies and full 3D coordinates of the reconstructed hits in the CE-E, CE-H and AHCAL sections.
  - This method substantially improves the energy resolution when compared to a simple energy reconstruction based on a χ^2-minimization method.

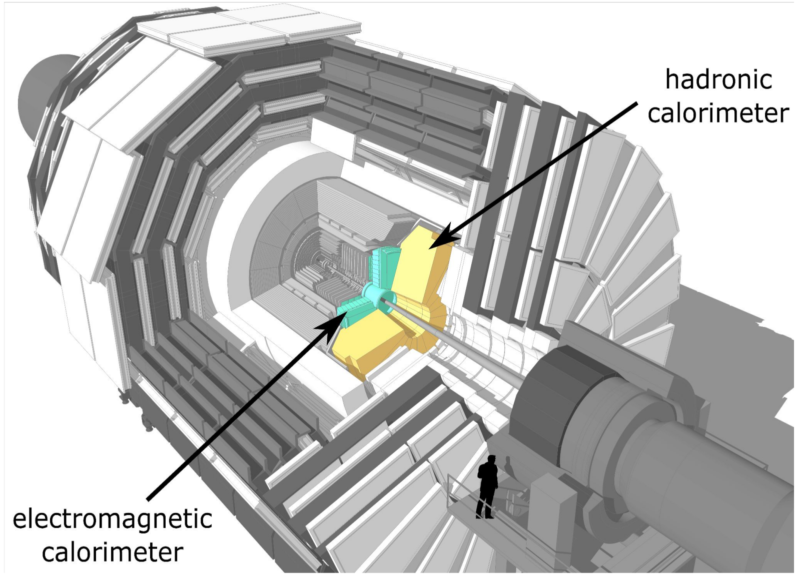
- Future steps:
  - Reconstruction of positrons using DRN in HGCAL beam test prototype.
  - Reconstructions of pions in full HGCAL detector geometry.

Thank you!!

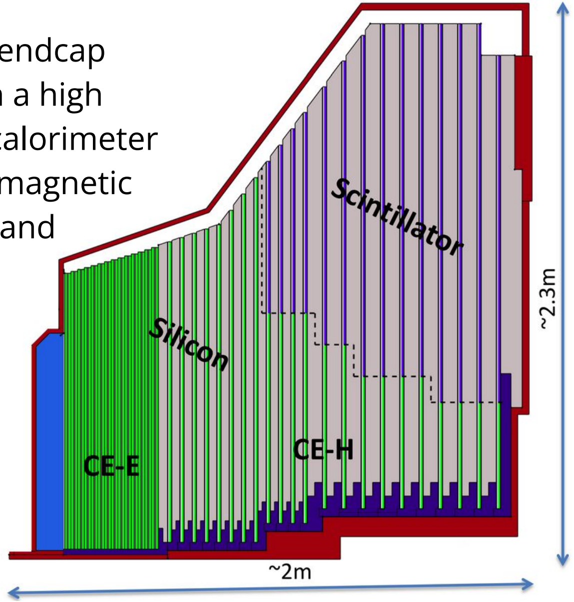
BACKUP

HGCAL - CMS endcap calorimeter for HL-LHC

- At HL-LHC:
  - Average pileup (PU) interactions of 140 or 200 (current value ~40).
  - Significant challenges for radiation tolerance on detectors and individual particle reconstruction in higher pseudorapidity regions.

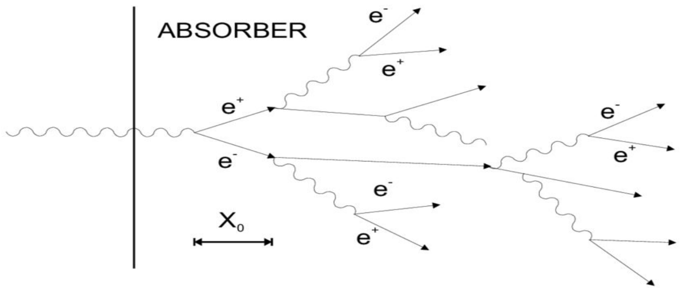


CMS will be replacing endcap calorimeters with with a high granularity sampling calorimeter comprising an electromagnetic section of Si & Pb/Cu, and hadronic section of Si or Sci & steel.



To test the detector performance & readout electronics, beam test was done during Oct 2018 using prototypes of Si sections and CALICE AHCAL prototype for Scintillator section.

Electromagnetic & hadronic showers in calorimetry



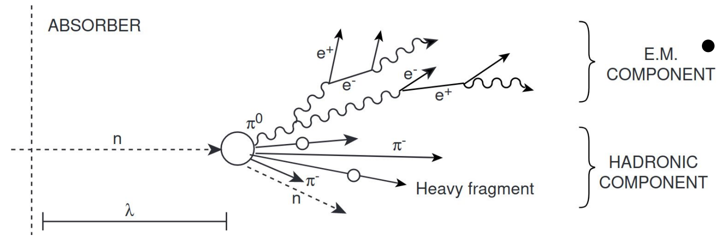
- Electrons:
  - Ionization
  - Bremsstrahlung
- Photons:
  - Photoelectric effect
  - Compton scattering
  - Pair production

Complete deposit to the detectable signal in calorimetry.

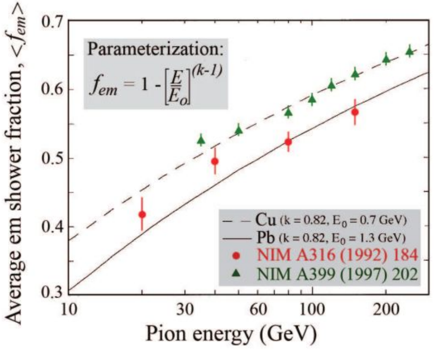
Response ~1 in homogenous calorimetry.

Resolution →For full contained shower, the energy resolution is governed by number of shower particles generated.

For sampling calorimeter → depends on sampling fraction

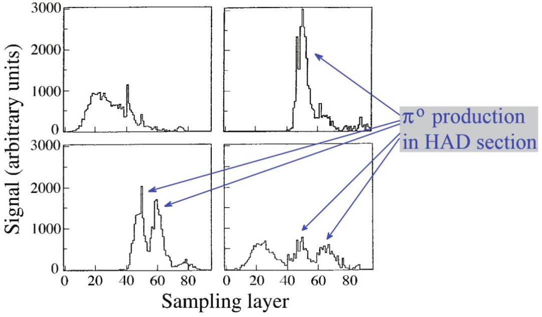


- Hadrons (pions, kaons, protons)
  - Ionization (if charged)
  - Strong interaction



Non linearity due to energy dependent EM component.
→ Response for EM = 1

Response <1 in homogenous calorimetry → energy lost in breaking up the nuclei.

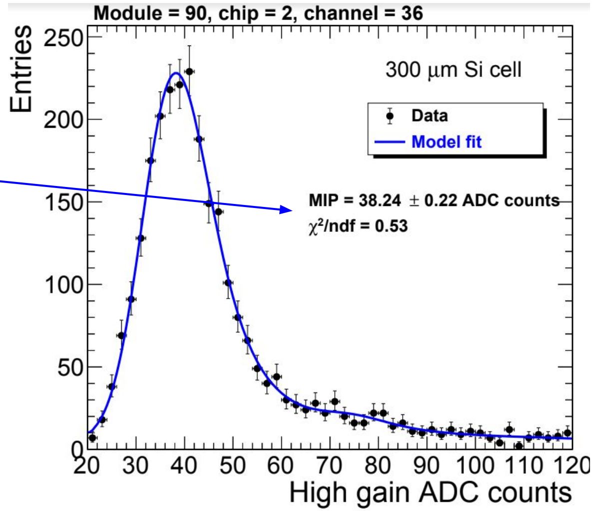


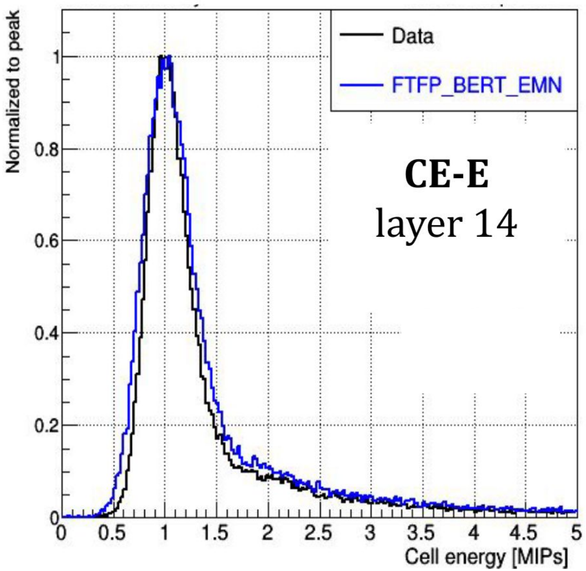
Resolution:
The number of particles < that in EM showers
intrinsic energy resolution will be much worse than EM showers (by a factor of ~10).

ADC to Mip conversion

- The ADC spectrum of muons (200 GeV) is fitted with a Landau convoluted with Gaussian to extract MIP values for each channel.

MIP is defined as the maximum of the fitted function (Gaus+Landau).





- In CE-E & CE-H simulation, detailed electronics noise has not been simulated.
- Therefore, the MIP signal is smeared by a width of 1/6th of a MIP.
- **The MIP signal peaks at 1 in both data and MC muon samples shows good agreement in data & sim.**