Charged pion energy reconstruction in HGCAL TB prototype using graph neural networks

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On behalf of the CMS Collaboration

Abstract

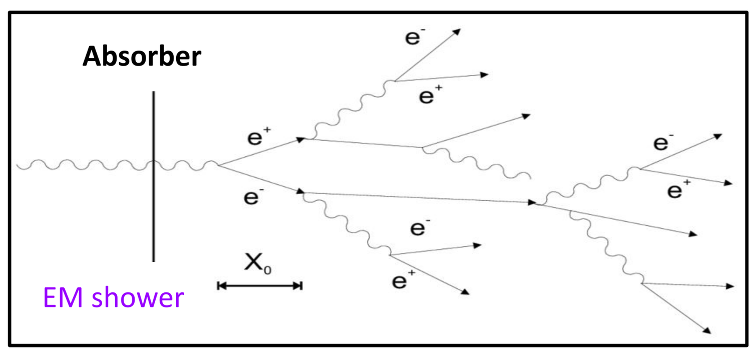
The CMS Collaboration is preparing to replace its endcap calorimeters for the HL-LHC era with a high-granularity calorimeter (HGCAL)[1]. The HGCAL will have fine segmentation in both the transverse and longitudinal directions, and will be the first such calorimeter specifically optimized for particle-flow reconstruction to operate at a colliding-beam experiment.

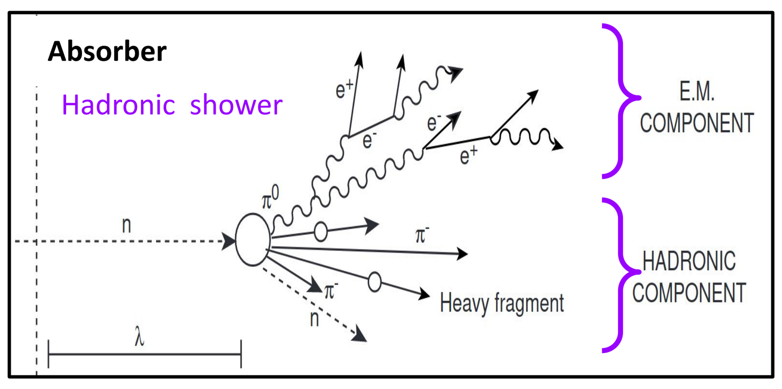
The proposed design uses silicon sensors as active material in the regions of highest radiation and plastic scintillator tiles equipped with on-tile silicon photomultipliers (SiPMs), in the less-challenging regions. The unprecedented transverse and longitudinal segmentation facilitates particle identification, particle-flow reconstruction and pileup rejection. A prototype of the silicon-based electromagnetic and hadronic sections along a section of the CALICE AHCAL prototype was exposed to muons, electrons and charged pions[4] in beam test experiments at the H2 beamline at the CERN SPS in October 2018 to study the performance of the detector and its readout electronic components.

Given the complex nature of hadronic showers, energy reconstruction is expected to benefit from detailed information of energy deposits and its spatial distribution of the individual showers in the detector, which can be well utilized by advanced machine learning algorithms. Here we present reconstruction of hadronic showers created by charged pions of momenta 20-300 GeV using a dynamic reduction network (DRN) based on graph neural networks (GNNs)[6].

Nature of Electromagnetic (EM) & Hadronic showers

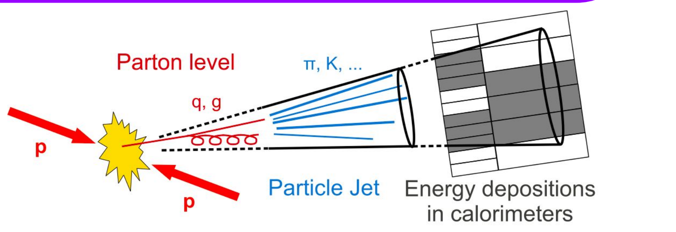
- Electrons loses energy via ionization & bremsstrahlung.
- Photons loses energy via photoelectric effect, compton scattering & pair production.
- **In EM showers, complete deposition of energy to detectable signal inside the calorimetry.**



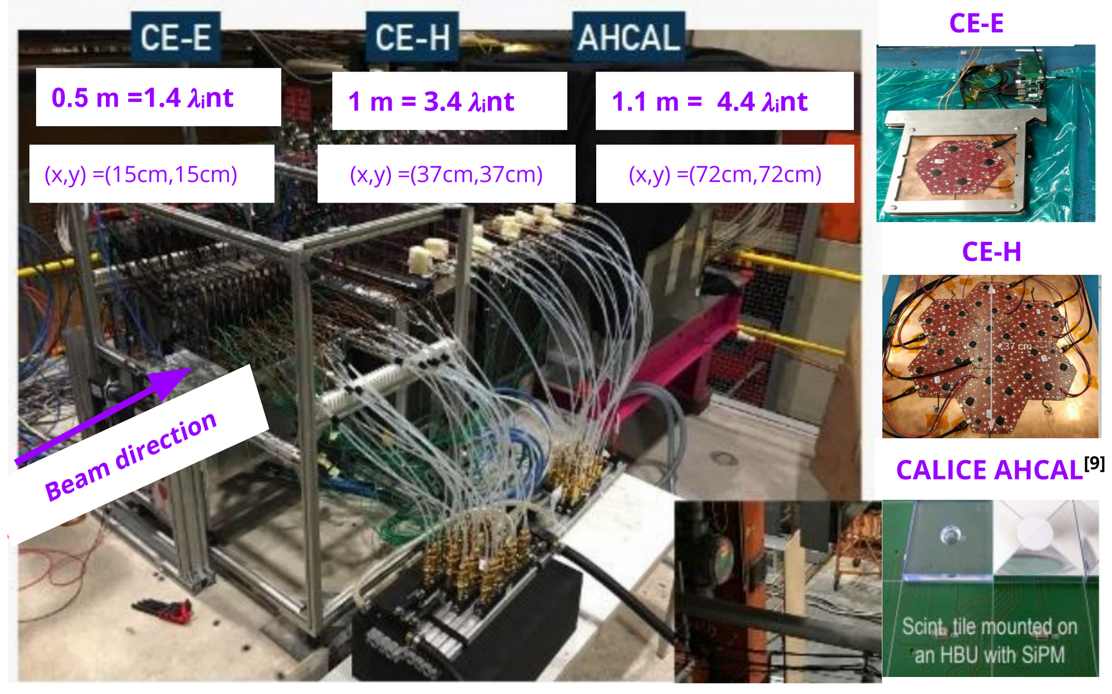


- Energy fraction carried by EM component is energy dependent,
  - Resulting in **a nonlinear response of calorimeters for hadrons.**
- The hadronic component- definite contribution from invisible energy goes into breaking up of nuclei etc.
  - **Non-compensating nature of calorimetry.**

- Quarks and gluons manifest themselves as jets of charged and neutral hadrons.
- **Jets are important discovery tools at the LHC.**



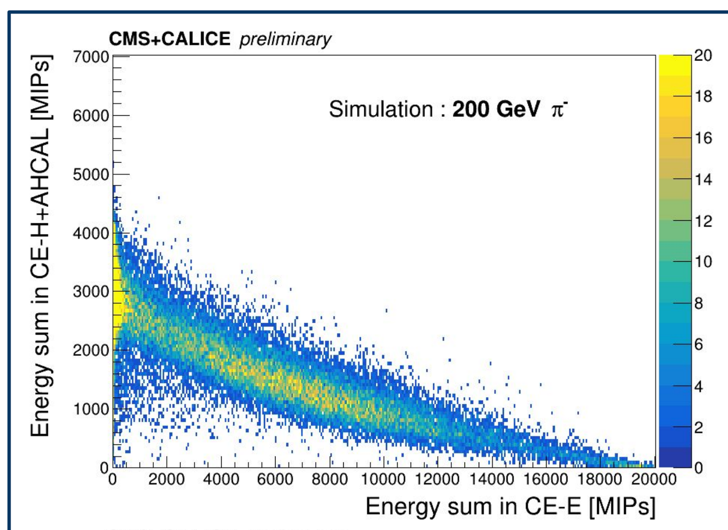
HGCAL Prototype Beam Test at CERN in 2018

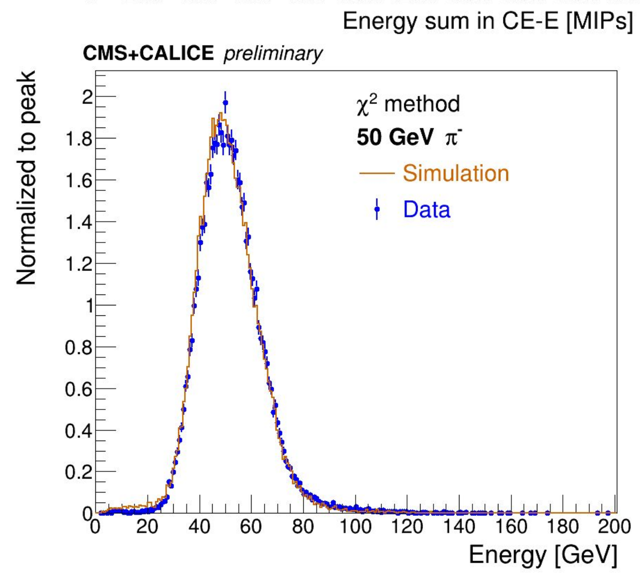


- -Si sensors + Cu/CuW/Pb as absorbers
  -28 sampling layers, $27X_0$
- -Si sensors+steel/Cu/CuW as absorbers
  -12 sampling layers with last three layers with 1 module
- -Scintillators on SiPMs+Steel as absorbers
  -39 sampling layers (Only 10 layers are used for this study)

- This prototype HGCAL detector was exposed to **e^+ and π^- beams of energies ranging from 20–300 GeV.**
- Achievements: **Large scale testing of ~100 Si modules[4], measurement of energies and characteristics of hadronic[2] and electromagnetic[5] showers, validation of simulation & readout electronics[3].**

Energy reconstruction of pions using χ^2-method





- Generated signal in each cell by the traversing particles is converted into energy in units of number of MIPs.
  - **Energy deposited in number of MIPs is not uniform across the CE-E and CE-H/AHCAL because of different absorbers & sampling fraction.**
  - **Detector level calibration[2] (E_{fix}):** Calibrate CE-E (CE-H+AHCAL) using a 50 GeV e+ (a 50 GeV π⁻) beam.

- **χ^2-method[2] :** Energies deposited in CE-E, CE-H and AHCAL are combined using energy dependent weight factors extracted after minimizing χ^2,

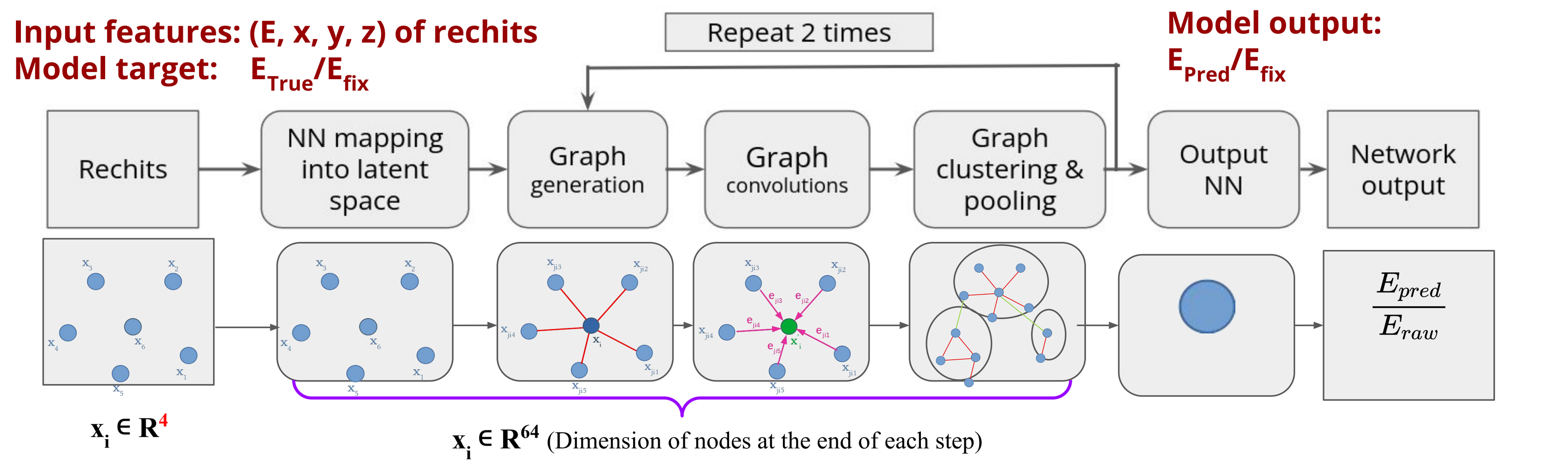
$$\chi^2 = \sum_{pions} \frac{(E_{beam} - E_{corr})^2}{\sigma^2(E_{fix})}$$

- **This χ^2-method does not take into account the event-by-event fluctuations of showers,**
  - **Does not make use of the high granularity of the detector.**
- **One will look for advanced ML algorithms!!**

Dynamic Reduction Network (DRN)

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

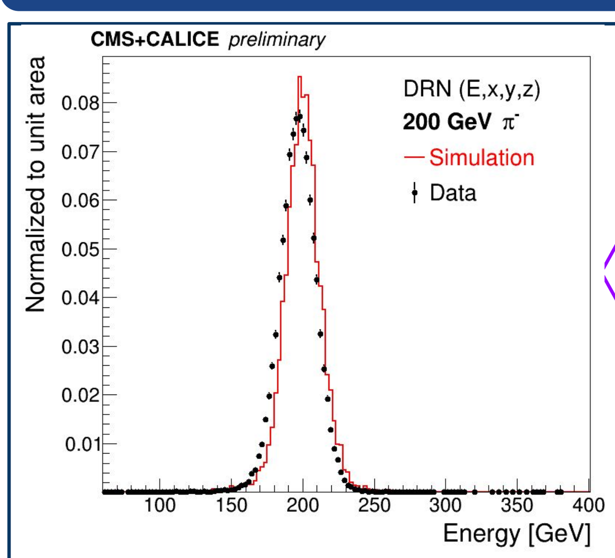
- **Advantages of graph approach:**
  - Preserves **permutation-invariance** of input data.
  - **No padding or truncation necessary** unlike in case of convolutional NNs.



- A model[7] is defined based on Dynamic Reduction Graph Neural Network[8]:
  - **Input features are mapped to a higher dimensional latent space**
  - **Add clustering & pooling step to learn high level information iteratively.**

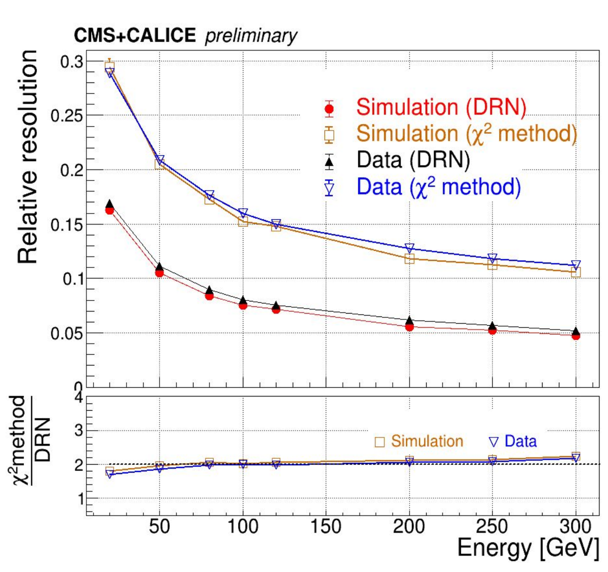
- **Sample details:** 4.1M events with pion energy in 10-350 GeV simulated using GEANT4.10.4.p03 and FTFP BERT EMT hadronic physics list.
- **The most expensive step in training is** the graph convolutions, followed by construction of the nearest neighbors graph.

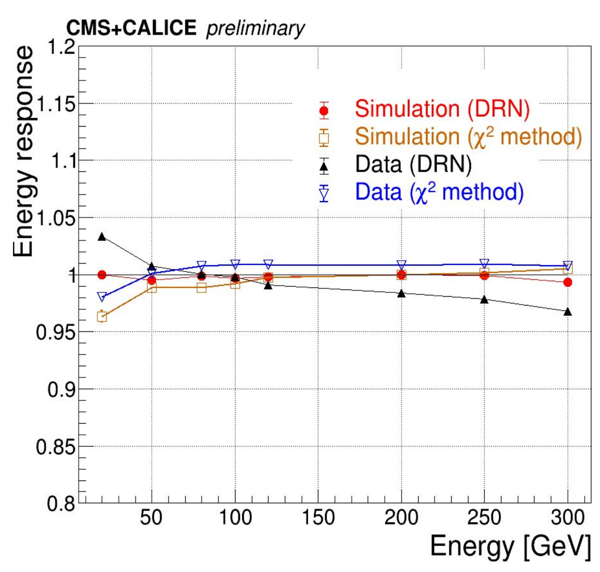
Comparison of χ^2-method & DRN method



- **Reconstructed energy distributions in data and simulation using DRN,**
  - With target as E_{True}/E_{fix} .
  - Input features as rechit energy [GeV] and rechit position(x,y,z) coordinates.
- 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[5].

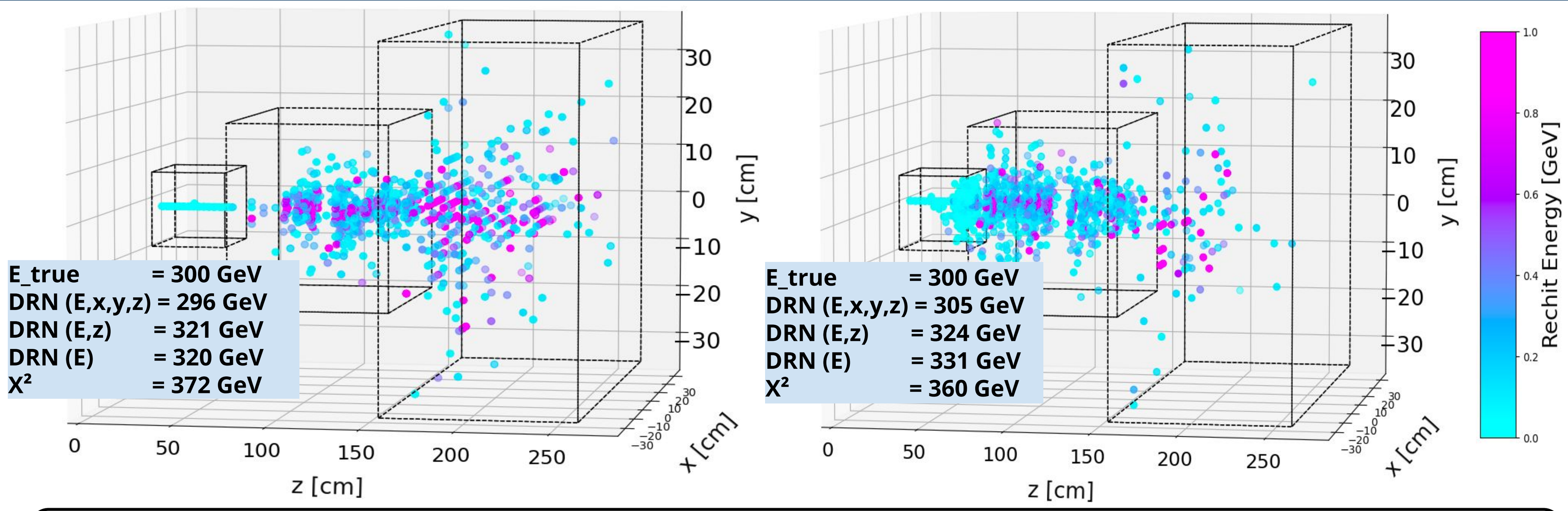
- Energy resolution & response using **χ^2-method** and **DRN method** in data and simulation.





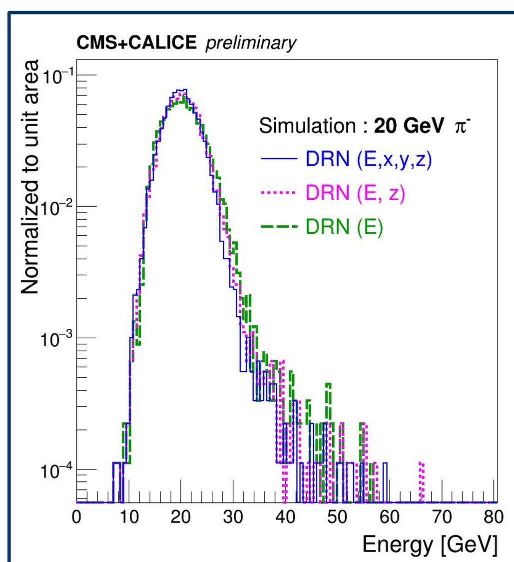
- **Good level of** agreement between data and simulation.
- **Improvement in resolution** by a factor of two.

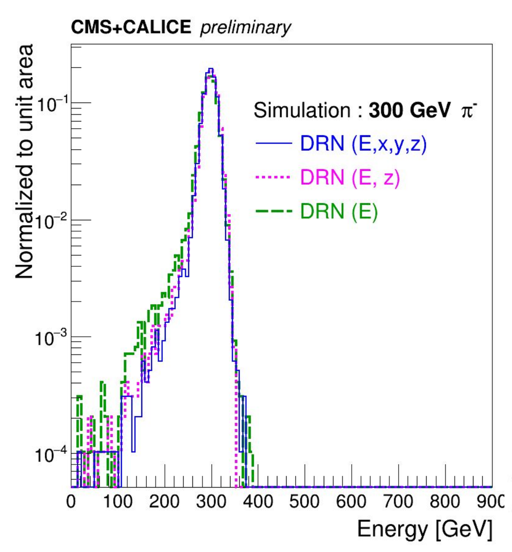
Event displays showing the E_{pre} using different methods



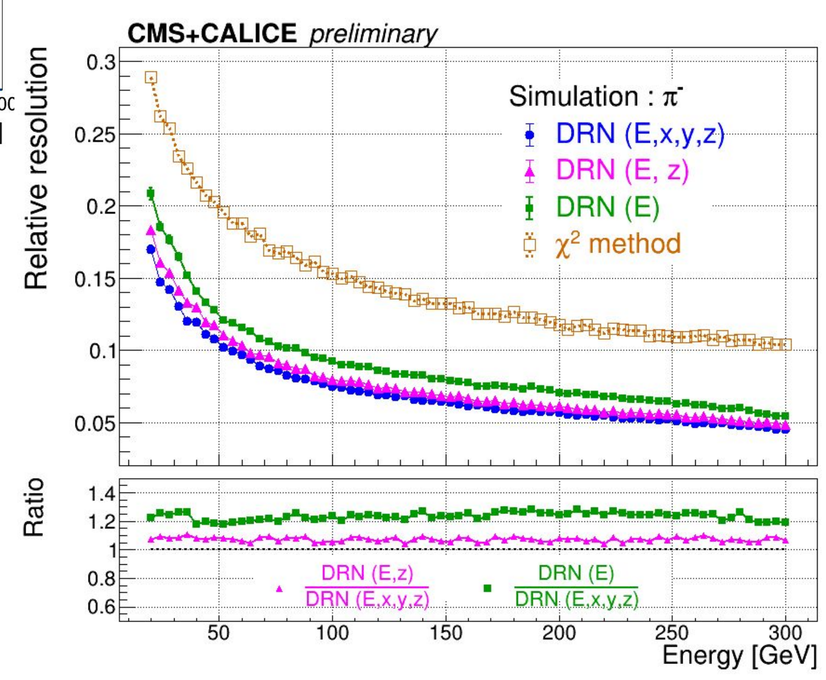
Given the two very differently developed showers for the same true energy, **DRN (E,x,y,z)** predicts the energy very close to true value **using the information of the transverse & longitudinal development of the showers.**

Training DRN with different input features





- DRN (E) - energy of the rechits as input feature
- DRN (E, z) - uses in addition the z coordinate (longitudinal development) of the rechits,
- DRN (E, x, y, z) - using full information about the longitudinal and transverse development of the showers.



- **DRN(E) -** improvements majorly coming from **compensating the shower-to-shower fluctuations.**
- **DRN(E,z) & DRN(E,x,y,z) -** Adding the spatial coordinates gives the DRN information about the spatial development of the shower.
  - **Helps DRN to better compensate the fluctuations and leakage on top of shower-to-shower fluctuations.**

Summary & references

- Novel algorithms based on graph neural networks (GNNs) are used to reconstruct pion energy[6].
- 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.
  - **Even without any spatial information provided, the DRN improves the resolution substantially compared to χ^2.**

References :

HGCAL-TDR [1] | TB-Pion paper [2] | TB-DAQ paper [3] | TB-Construction [4] | TB-posi-tron [5] | DRN-DPS-2022/22 [6] | DRN-Paper [7] | DGNN [8] | CALICE AHCAL [9]