AI-based reconstruction for highly granular calorimeters

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2023 RHIC/AGS Annual Users' Meeting

05/03/2023

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U.S. DEPARTMENT OF ENERGY | Office of Science

DOE grant award number DE-SC0022355

UCR

BERKELEY LAB

Detector optimization

Generators that mimics detector conditions

Reconstruction algorithm to produce physics object

- Traditionally only small number of detector configurations are considered
- Reconstructions algorithm not optimized for a given detector condition
- Allows to have high-fidelity fast simulation and optimized reconstruction algorithms

Our group is working on deploying Artificial Intelligence (AI) methods for EIC hadronic calorimeter design

- Generative models (fast simulation) arXiv: 23307.04780
- **Reconstruction algorithm (Regression)**

AI-Driven Detector Design for EIC

Some of the key questions that our AI-driven optimization approach could answer are:

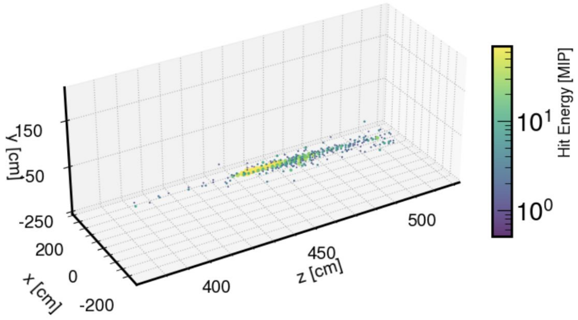
- Given a certain budget, what is the best performance one can expect in longitudinal readout?
- For which angles would a high segmentation have the largest impact?
- Where should the longitudinal layers be placed?

To answer these, we want to train a network conditional on granularity (i.e. number of z sections and their locations).

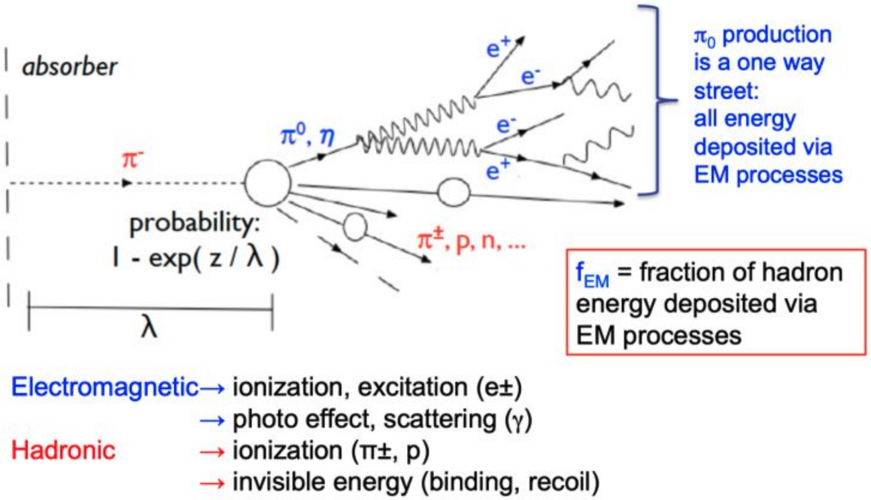
We want to use this to explore a high dimensional space and compute tradeoffs

Outline

- Challenges of non-compensating calorimeters
- “software compensation” for non-compensating calorimeters
  - Traditional Methods
  - AI/ML-based approach
- Impact of longitudinal segmentation and transverse cell information (cell Z, and XY) on model performance



Non-Compensation in Hadronic Calorimeters



Non-compensating calorimeter (e/h ≠1)

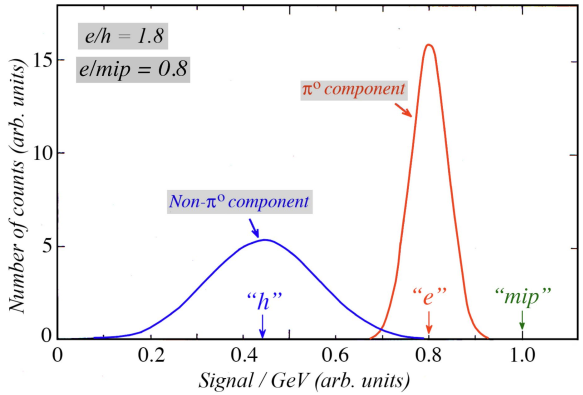


Fig. **arXiv:1710.10535v1**

- Smaller response to hadrons compared to EM particles of the same energy
- Difference in visible signal for EM and purely hadronic energy deposits deteriorates energy resolution

Ways to deal with non-compensation

Hardware compensation

- Imposes very strict requirements on the materials used and the overall geometry. E.g ZEUS Uranium/Sc calorimeter
- Not a viable option due to cost and low beam at EIC

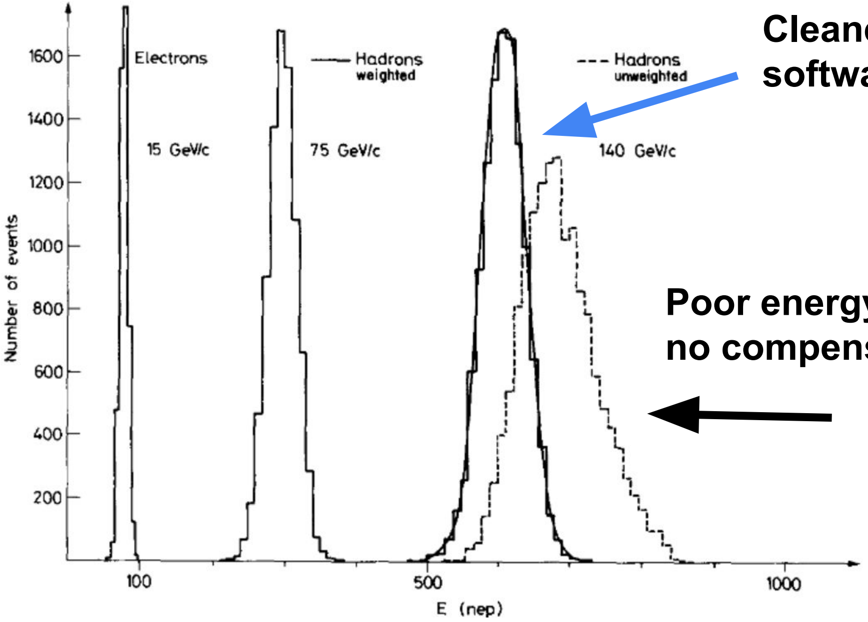
Software compensation ("offline")

- Assigning weights to EM and HAD energy deposits event by event
- As argued in the YR report, the potential of software compensation motivates longitudinal segmentation in calorimeters

> *"a fine granularity of a non-compensating calorimeter allows to improve the resolution by assigning weights to the detector signals ("off-line compensation)...at EIC such methods can be considered where a longitudinal segmentation of the ECAL and HCAL readout appears practical".*

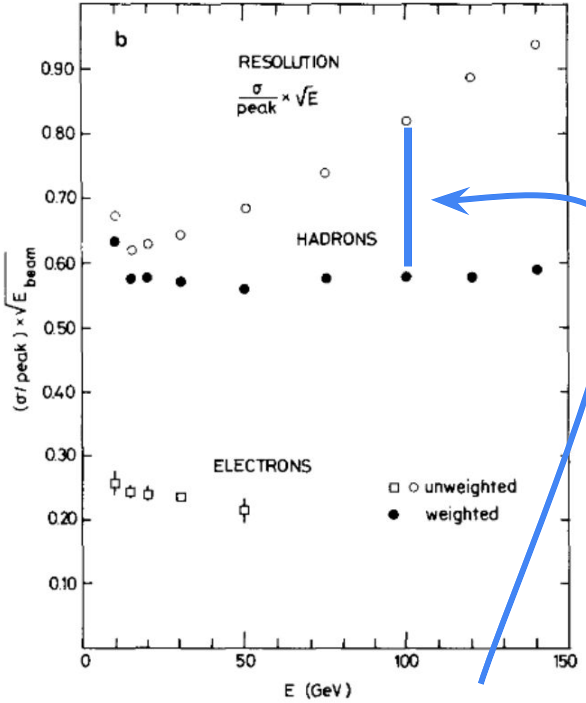
Software compensation has been around since at least 1980!

- CERN study of a longitudinally segmented Fe/Sc scintillator [H. Abramowicz et al., NIM 180 (1981) 429]
- Simple adjustment of cell event energy:
  - $E_{\text{cell, weighted}} = E_{\text{cell, unweighted}}(1 - C \cdot E_{\text{cell, unweighted}})$, $C = 0.03/\sqrt{E_{\text{total}}}$



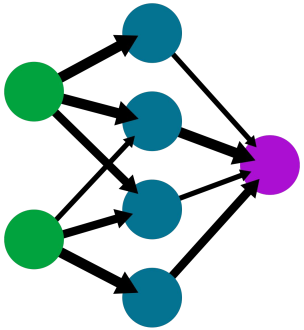
Cleaner Gaussian with software compensation

Poor energy resolution with no compensation



~20% improvement at high energies

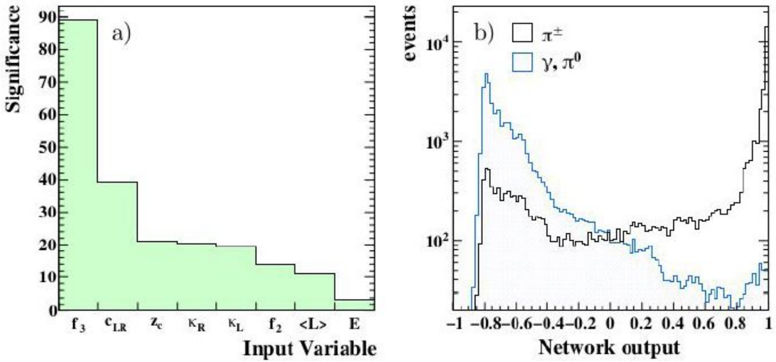
Software Compensation Experience



“Software compensation” was used from the beginning. Spatial structure of EM and hadronic component of showe used to classify energy deposits

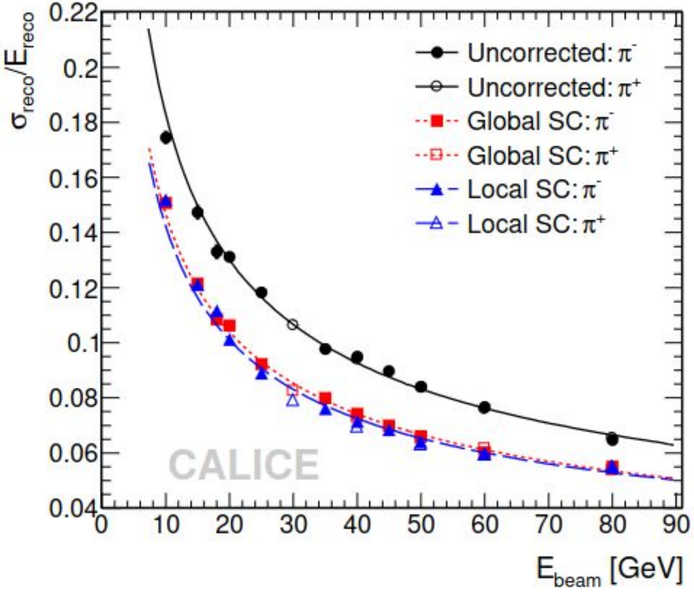
Around 20 years later, in 2013, simple Neural Networks were introduced to improve the procedure and calibration.

Fact: H1 (non-compensating calorimeter) achieved the same energy scale uncertainty than ZEUS (compensating calorimeter). Both cases ultimately achieved 1% uncertain down to 10 GeV.

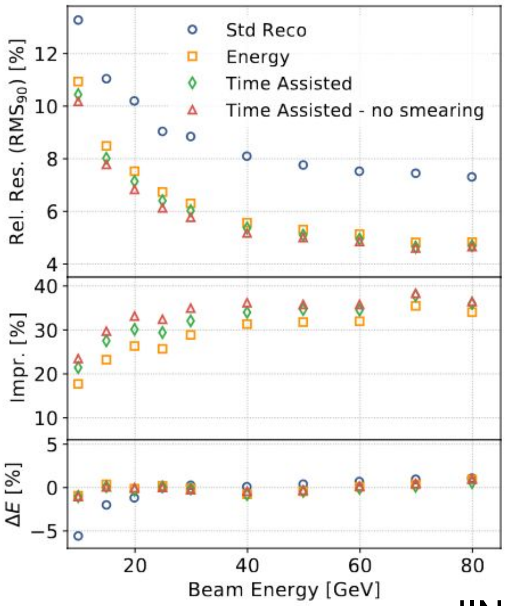


R. Kloger thesis
(Hamburg University)

Modern software compensation with imaging calorimetry (CALICE Collaboration)



CALICE arXiv:1207.4210v2,2012



(b) Local software compensation

JINST 17 (2022) P08027

- **Traditional methods, culmination of many decades of study**
- **Improves resolution by up to 30-40%**

Deep Sets

JHEP 01 (2019) 121

- Deep sets are designed to operate on sets for permutation-invariant and variable length data
- Set collection of object without any order
- Each particle is mapped by Φ to an internal particle representation (latent space)

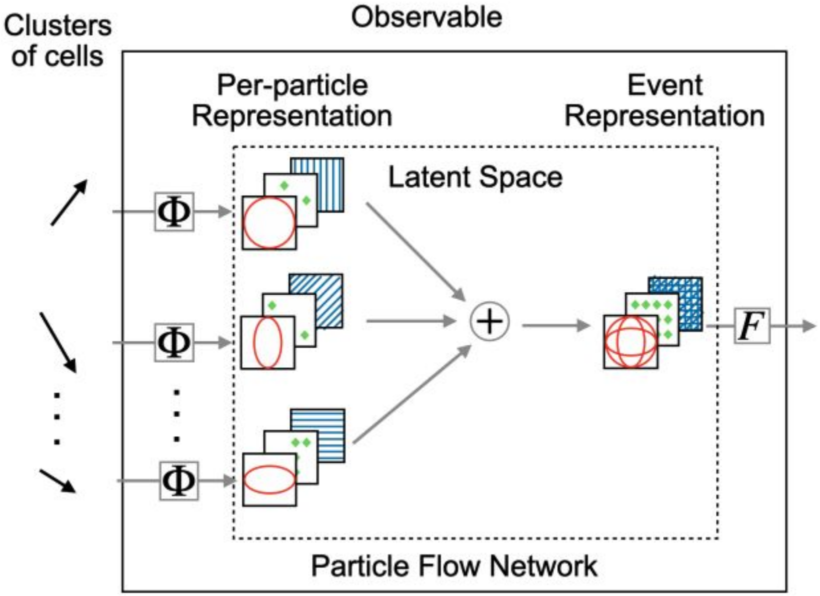
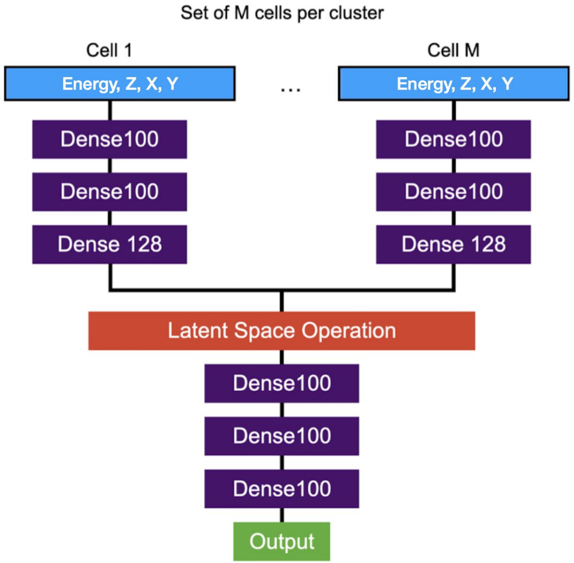
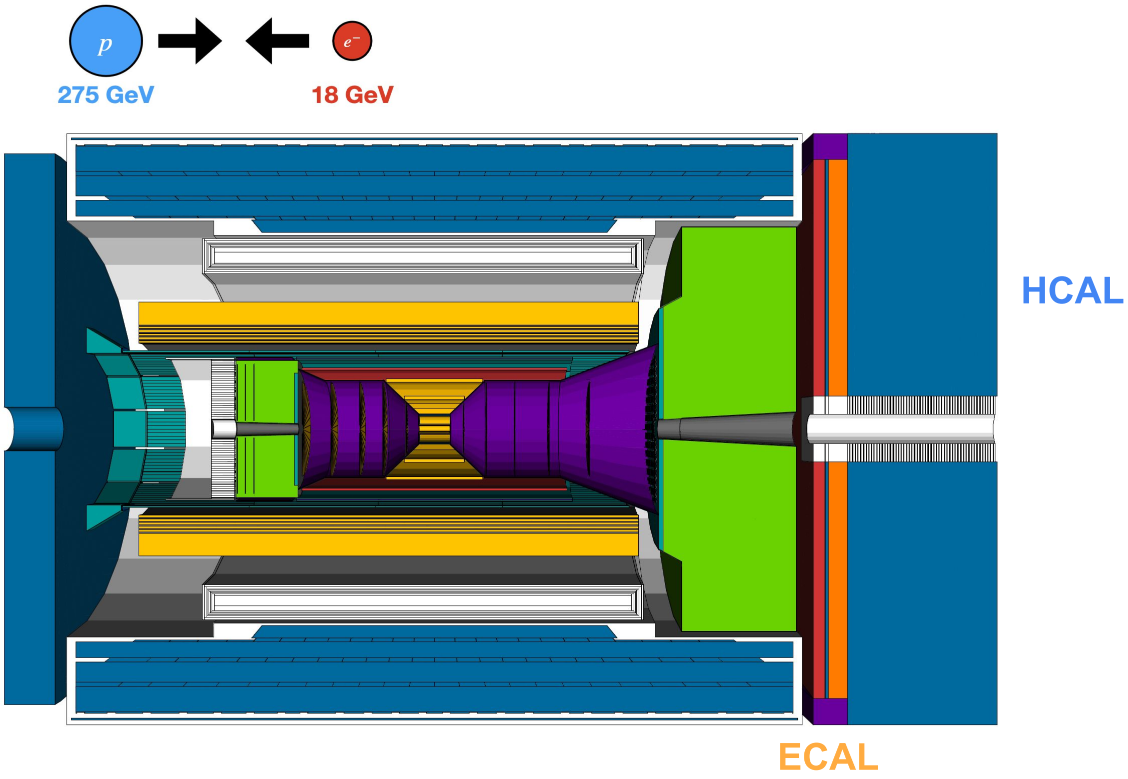


Fig. ATLAS PUB Note



arXiv: 1703.06114

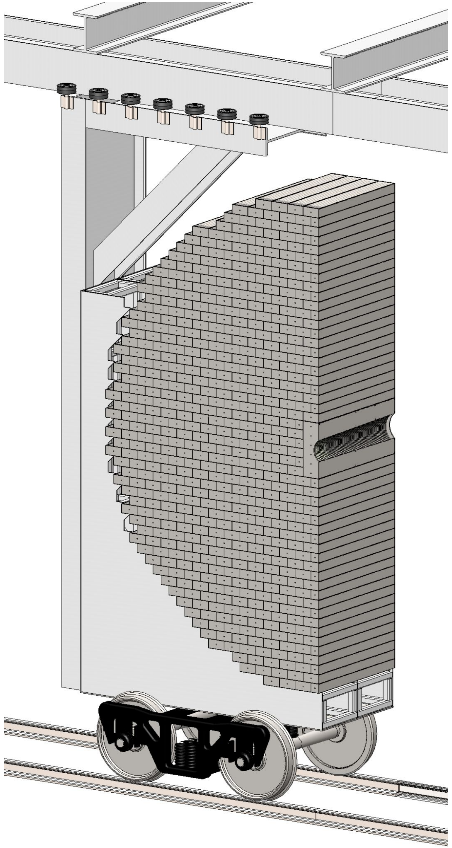
Case Study: Optimization of forward HCAL in ePIC detector



- Proton/ion beam has significantly larger kinetic energy compared to e⁻ beam
- Most of the hadrons are emitted in the same direction as the hadron beam ("forward direction")
- Granularity is key component to measure jets

Figure Courtesy ePIC

HCAL and Insert:



Optimization Possibility in ePIC

- Technology in ePIC HCAL and Insert uses SiPM-on-tile approach.
- Number of longitudinal sections and their position can be easily changed in practice (summing SiPM pulses) before readout.
- Default is 7 equidistant z-sections regardless of radius.
- Energy density varies with radius, so this is likely non-optimal

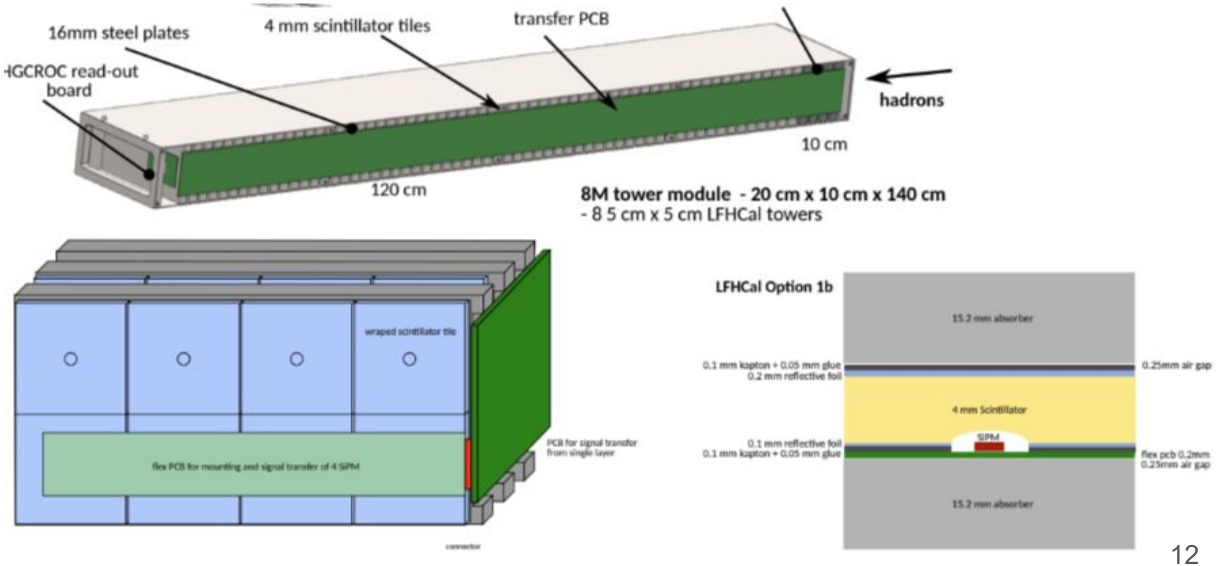


Figure Courtesy ePIC

Detector Simulation and reconstruction

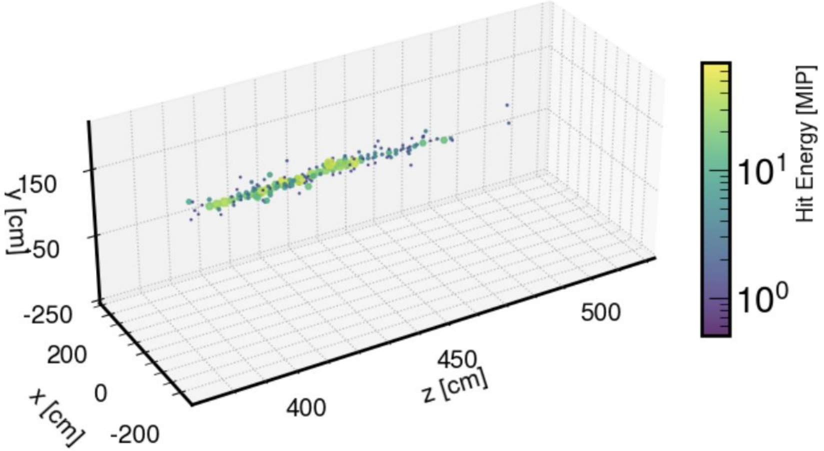
- Using standalone DD4HEP with simplified geometry similar to ePIC HCAL / insert

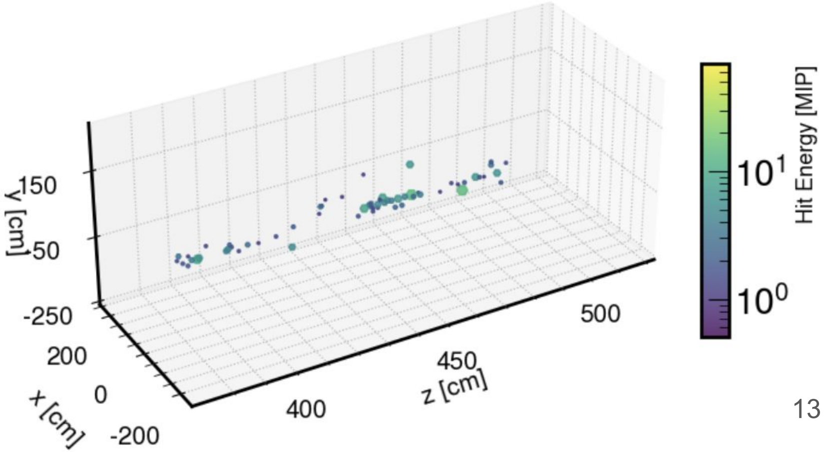
- Single particle Geant4 Simulation
  - Particle: π^+, Polar angle: $10 < \theta < 30$ deg, Azimuthal angle: $0 < \phi < 360$
  - Calorimeter Configuration: ECAL in front of HCAL

- Segmentation:
  Longitudinal segmentation: 55 z-sections
  Transverse segmentation: 10 x 10 cm^2 (55 cells)

- Point cloud representations of calorimeter showers

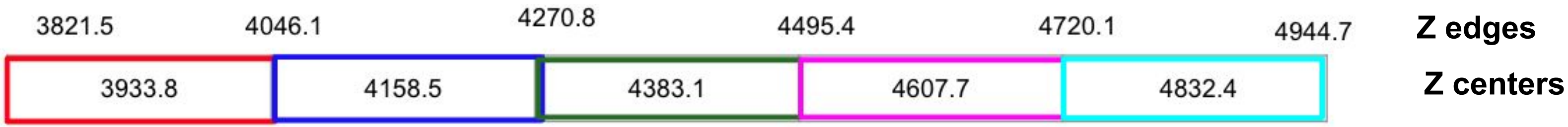
- Established models to predict the generated energy from given cell information
  - With different number of Z- sections
  - With different input features (E, X, Y, Z)

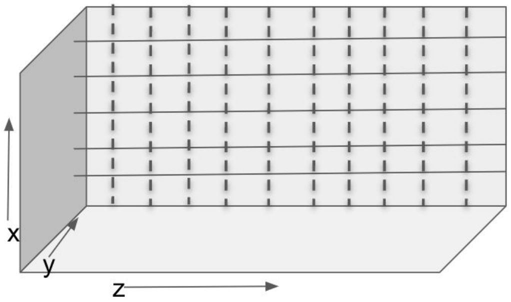


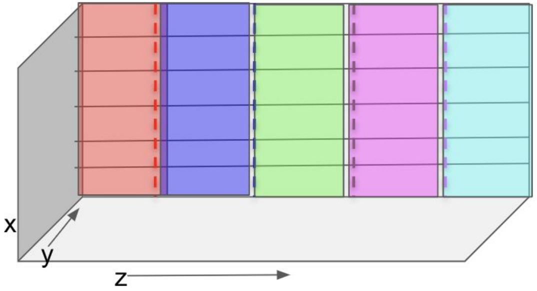


Varying longitudinal segmentation

Regrouping illustration with 5 z sections





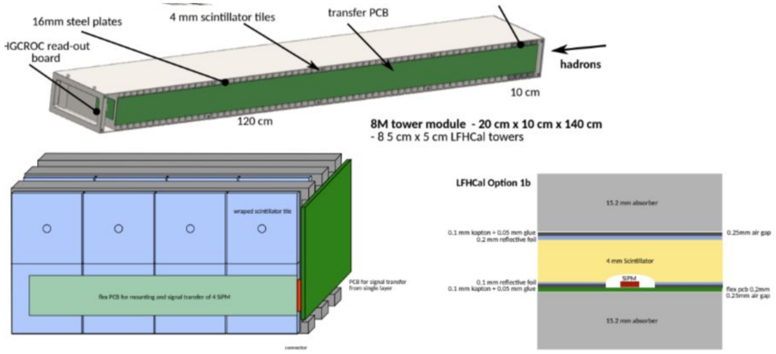


E	Z	Y	X
[[0.028	3821.500	300.000	-1100.000]
[0.058	3844.900	300.000	-1100.000]
[0.092	3938.500	300.000	-1100.000]
[0.070	3961.900	300.000	-1100.000]
[0.109	3868.300	300.000	-1100.000]
[0.132	3891.700	300.000	-1100.000]
[0.116	3915.100	300.000	-1100.000]
[0.001	4429.900	300.000	-1100.000]
[0.001	4359.700	300.000	-1100.000]
[0.003	4055.500	300.000	-1100.000]
[0.016	4008.700	300.000	-1100.000]
[0.032	3985.300	300.000	-1100.000]
[0.003	4032.100	300.000	-1100.000]
[0.003	4125.700	300.000	-1100.000]
[0.001	4172.500	300.000	-1100.000]
[0.003	4078.900	300.000	-1100.000]
[0.001	4149.100	300.000	-1100.000]
[0.001	4640.500	300.000	-1100.000]
[0.001	4242.700	300.000	-1100.000]
[0.002	4102.300	300.000	-1100.000]
[0.001	4195.900	300.000	-1100.000]
[0.001	4336.300	300.000	-1100.000]
[0.001	4289.500	300.000	-1100.000]]

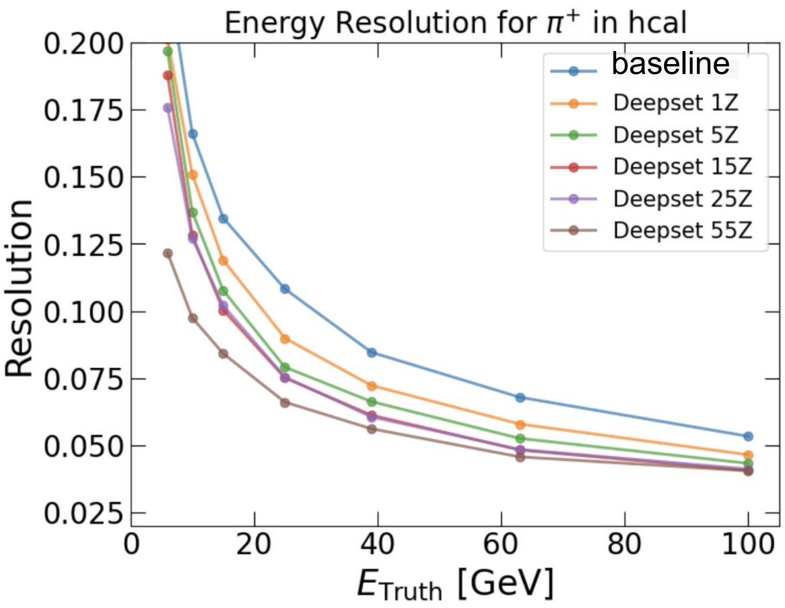
Re-grouping →

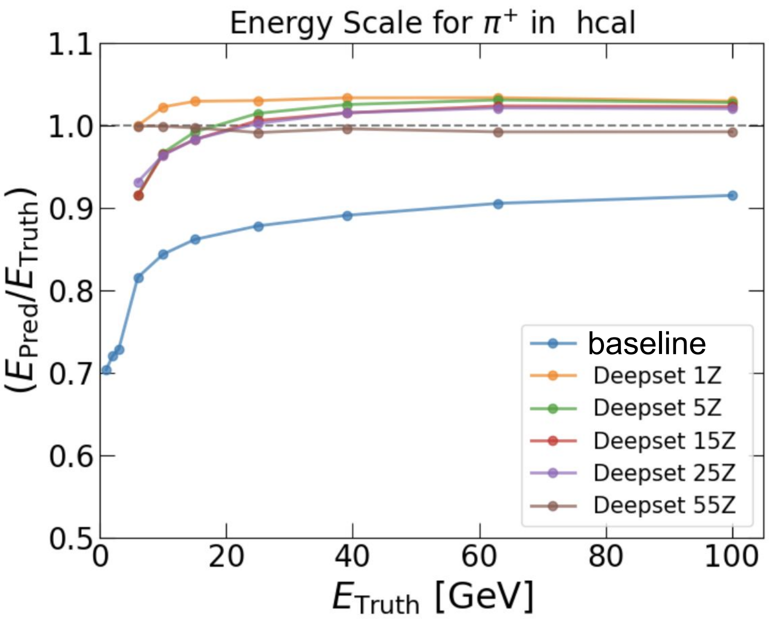
Esum	Z centers	Y	X
[[0.656	3933.820	300.000	-1100.000]
[0.016	4158.460	300.000	-1100.000]
[0.003	4383.100	300.000	-1100.000]
[0.001	4607.740	300.000	-1100.000]]

Regrouping in real world is just summing SiPMs outputs



Performance with Z- sections



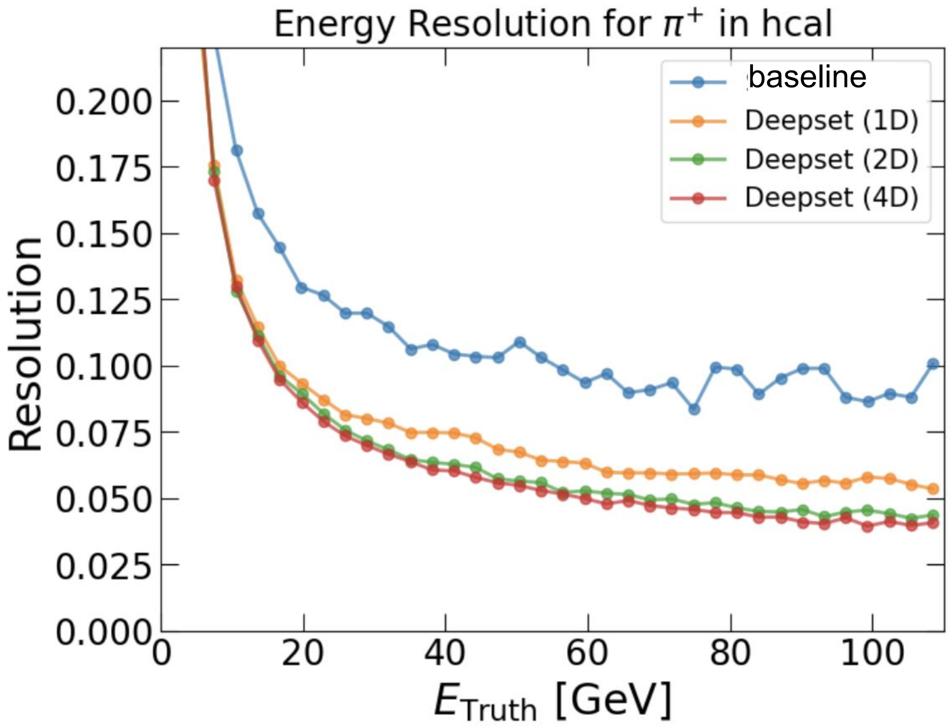


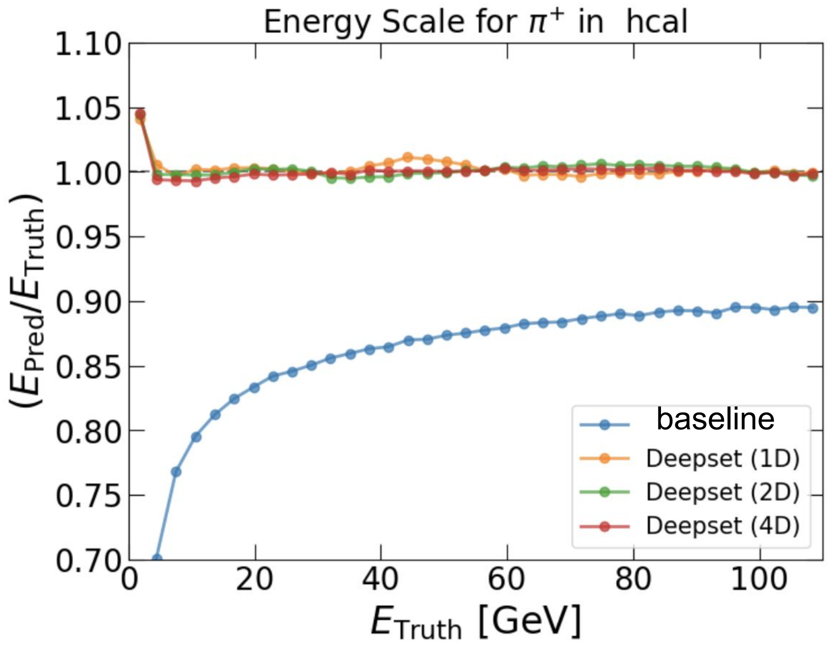
$$Resolution = \sigma\left(\frac{E_{Pred}}{E_{Truth}}\right)_{distribution}$$

- Baseline is sum of cell hit energy corrected by sampling fraction
- Resolution improves with larger number of Z-section (default configuration 7 section)

Performance longitudinal, transverse cell information

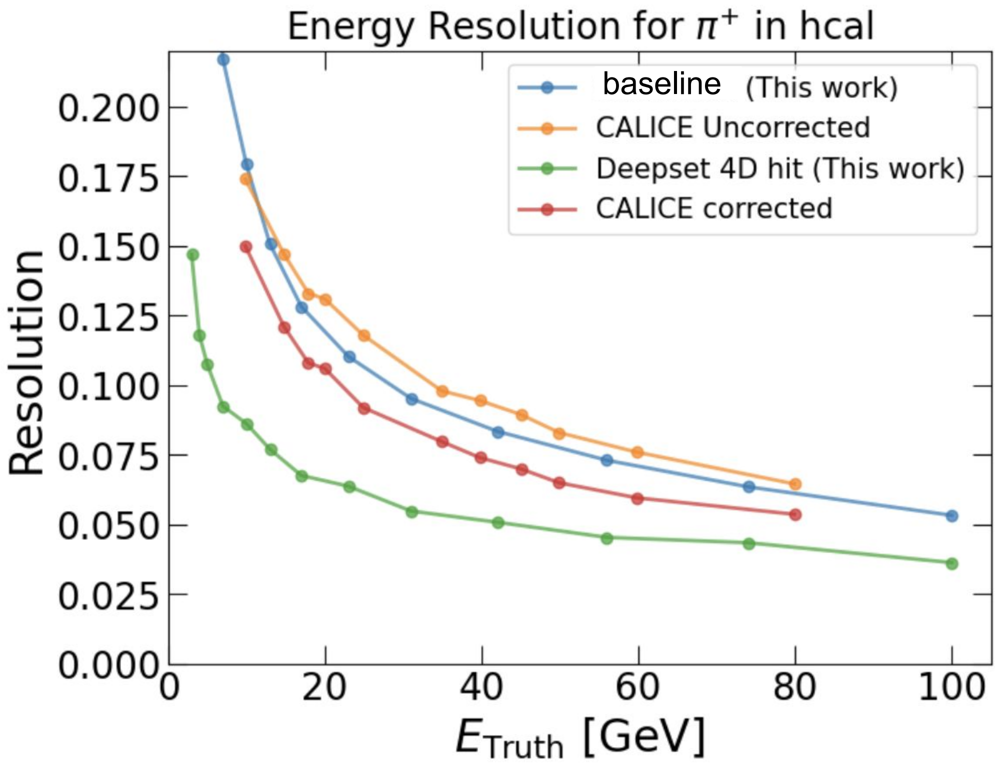
- **1D: cell hits E**
- **2D: cell hits E, Z**
- **4D: cell hits E, Z, X, Y**





Resolution improves most given longitudinal cell information. Transverse cell information improves model performance at high energy

Comparison of performance with existing result



CALICE arXiv:1207.4210v2,2012

- CALICE Fe-Sc calorimeter similar in design
- Our baseline, CALICE uncorrected are sum of cell energy corrected by sampling fraction
- AI based methods yields better performance compared to traditional reconstruction methods

Conclusion:

- Established a point cloud based neural network models to predict the generated energy
  - Given different number of longitudinal segments
  - Given Transverse and longitudinal cell information (Z, XY)
- Resolution improves most given longitudinal cell information
- Transverse cell information improves model performance
- AI based reconstruction performs better than traditional reconstruction methods

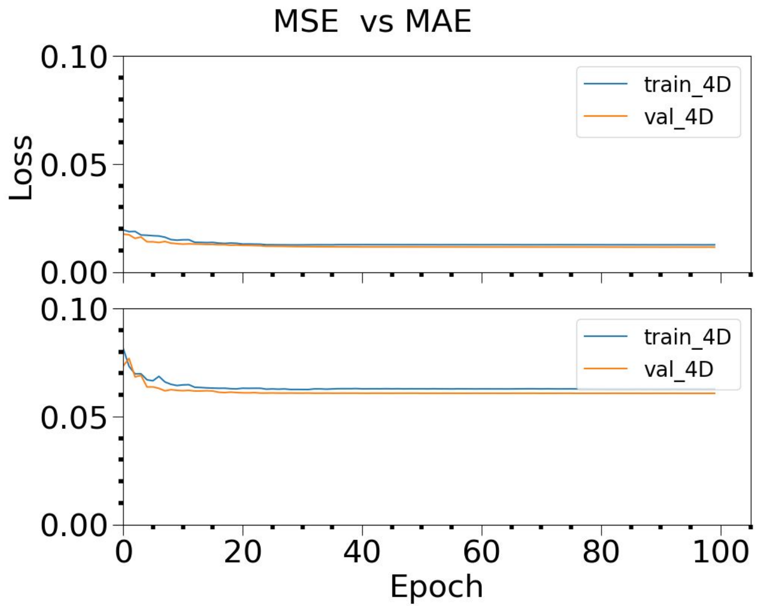
Outlook

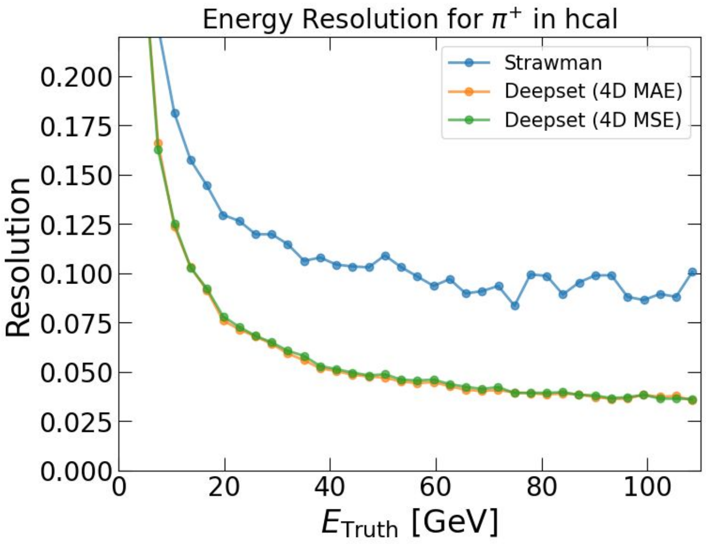
- Manuscript in preparation
- Develop a model condition on Z-sections

Backup

Training input and tuned hyperparameters and architecture

- Used simulated data, 2 M π^+ events,   Data splitted: Training, Validation, and Test
- Batch size =2048, number of layers=4, latent size = 64
- Each dense layer uses Rectified Linear Unit (ReLu) activation functions
- Adam optimizer , Mean Squared Error (MSE) for loss
- Trained until converges (approximately 100 Epochs)





Typical Gaussian Fit