AI-based reconstruction for highly granular calorimeters

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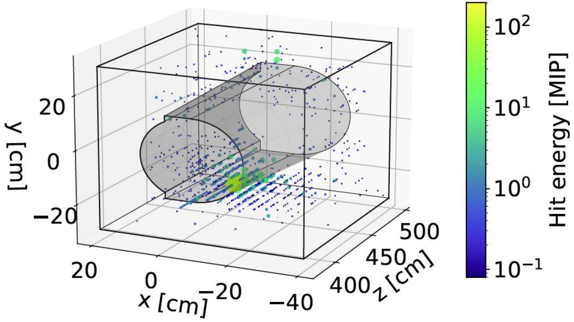

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In Collaboration with:
LBNL - B. Nachman, F. Torales-Acosta et al.
LLNL- A. Angerami, R. Soltz, P. Karande et al.

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Introduction

We have been working on AI methods for EIC calorimetry into two fronts: generative models (fast simulation) and regression with the goal of combining the two fronts to use them in co-optimization.

In this talk, I will present some results on regression models.

The outline of the talk is as follows:

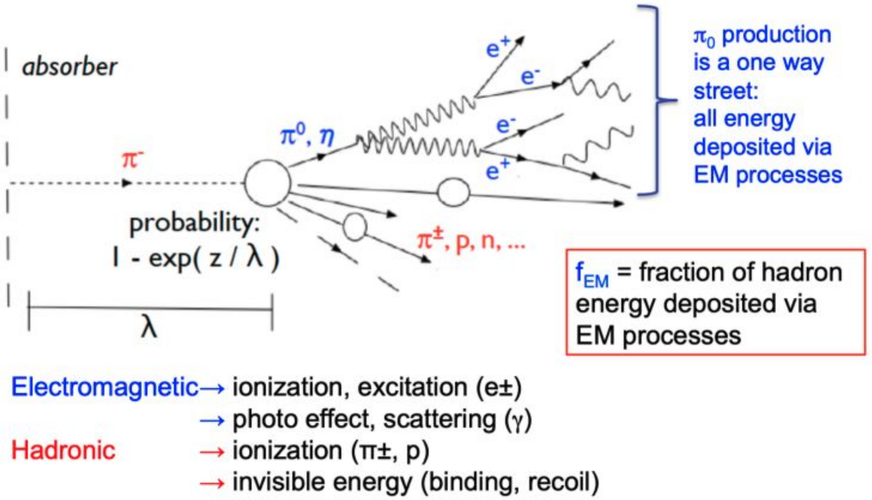
- Challenges with non-compensating calorimeters

- Traditional ways to achieve “software compensation”

- AI/ML-based approach

- Results

Non-Compensation in Hadronic Calorimeters



Non-compensating calorimeter (e/h ≠1)

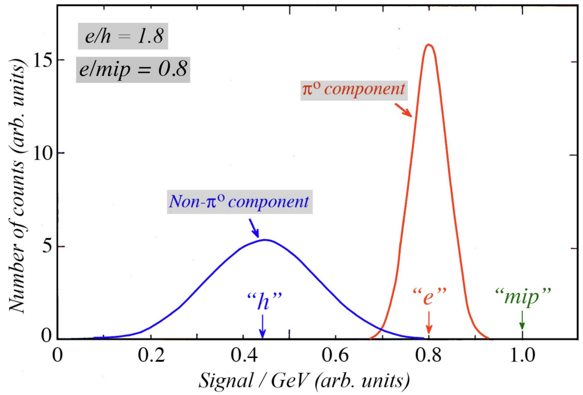


Fig. **arXiv:1710.10535v1**

- 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

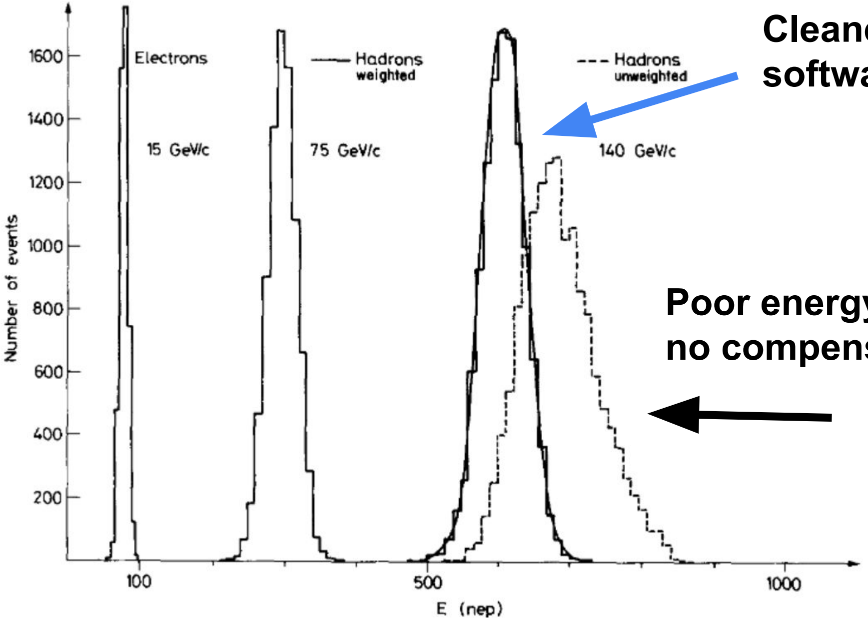
Software compensation

- Assigning weights to EM and HAD energy deposits event by event
- Used in CDHS, H1, ATLAS and CALICE calorimeters
- As argued in the YR report, the potential of software compensation motivates longitudinal segmentation in calorimeters

See O.Tsai's slides for a detailed discussion of the role of compensation in an EIC context
See M. Arratia's slides for more info motivating software compensation & calo segmentation at EIC

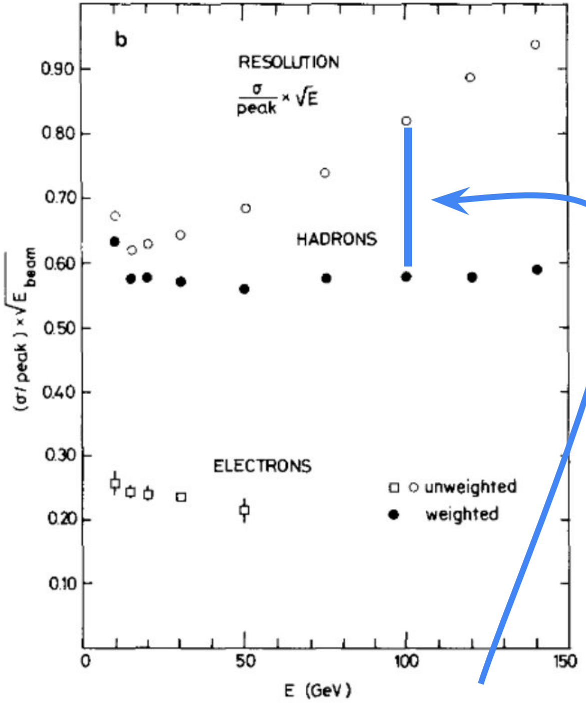
Software compensation has been around since at least 1980!

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



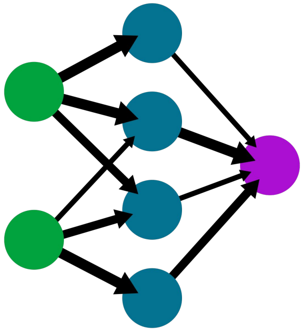
Cleaner Gaussian with software compensation

Poor energy resolution with no compensation



~20% improvement at high energies

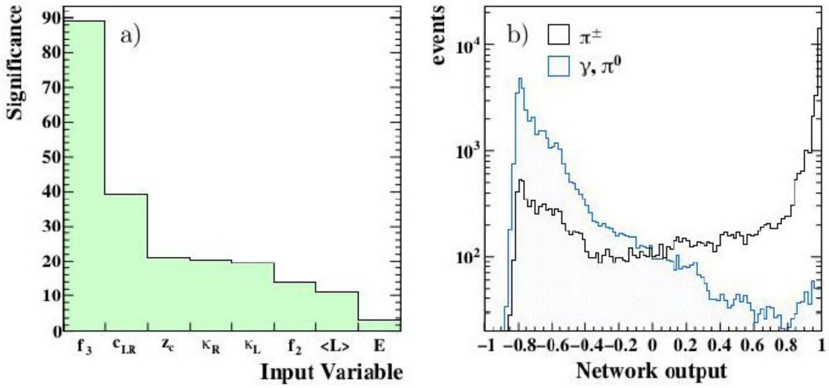
Software Compensation Experience



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

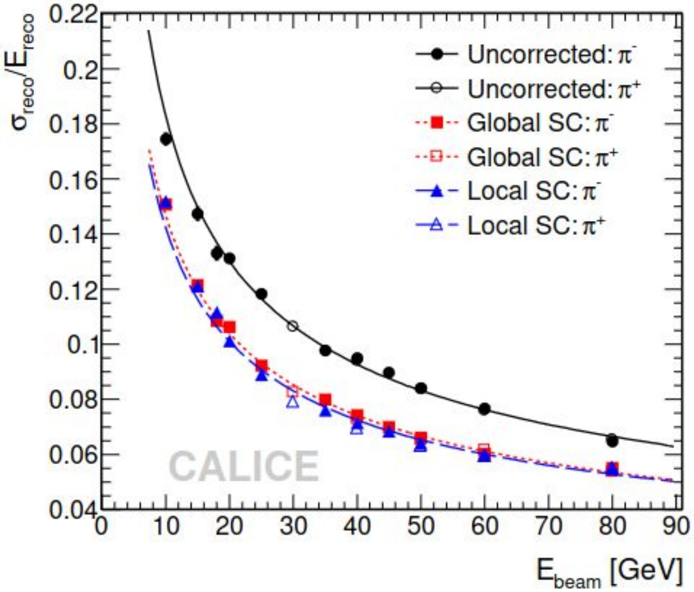
Around 20 years later, in 2013, simple Neural Networks were introduced to improve the procedure and calibration.

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.

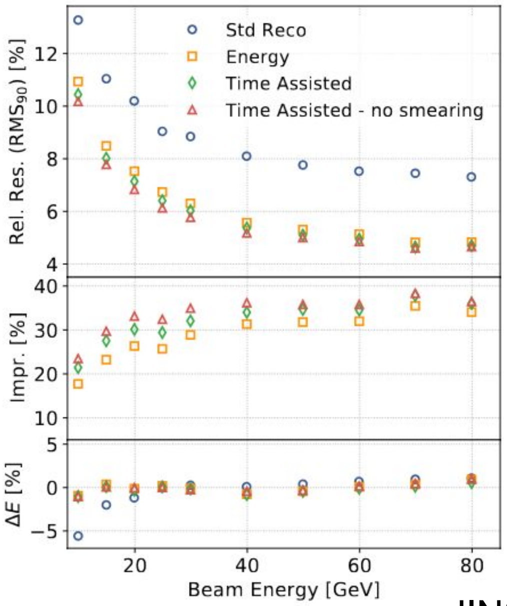


R. Kloger thesis
(Hamburg University)

Modern software compensation with imaging calorimetry (CALICE Collaboration)



CALICE arXiv:1207.4210v2,2012



(b) Local software compensation

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- **Human-made algorithm, culmination of many decades of study**
- **Improves resolution by up to 30-40%**

An example of state-of-the art AI/ML based reconstruction

Approach: Point Cloud Representation (pion reconstruction in the ATLAS Detector)

- Pion deposits in detector can be thought as of a point cloud or collection of points in space (“3D object”)
- More natural representation of nonuniform 3D structure of calorimeter than series of images
- Tracks can included as an additional point or points in a cloud by extrapolating them to a calorimeter

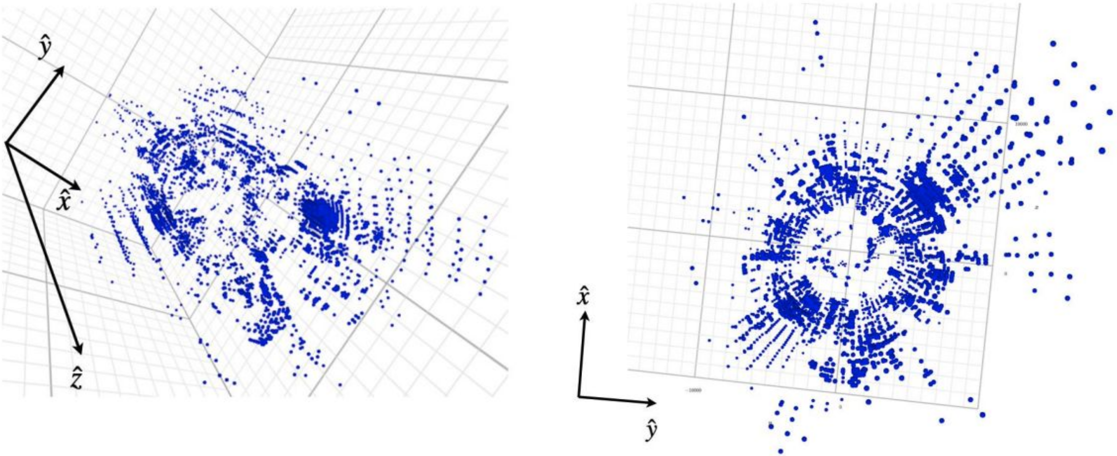

Fig. ATLAS PUB Note

Deep Sets (Particle-flow network)

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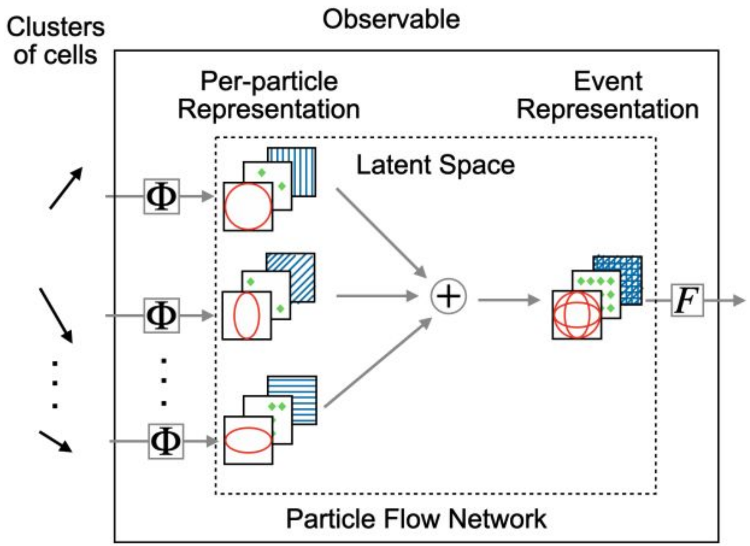
- Deep sets are designed to operate on sets for permutation-invariant and variable length data
- Set collection of object without any order
- Each particle is mapped by $\mathbf{\Phi}$ to an internal particle representation (latent space)



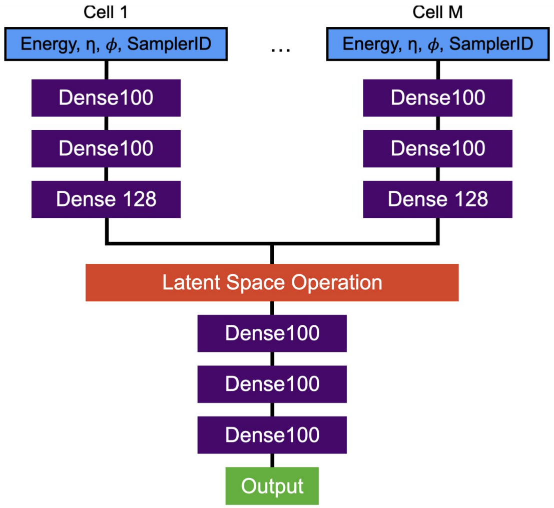
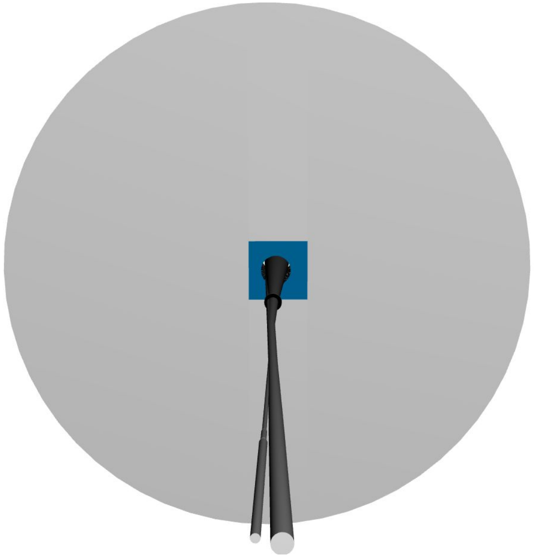


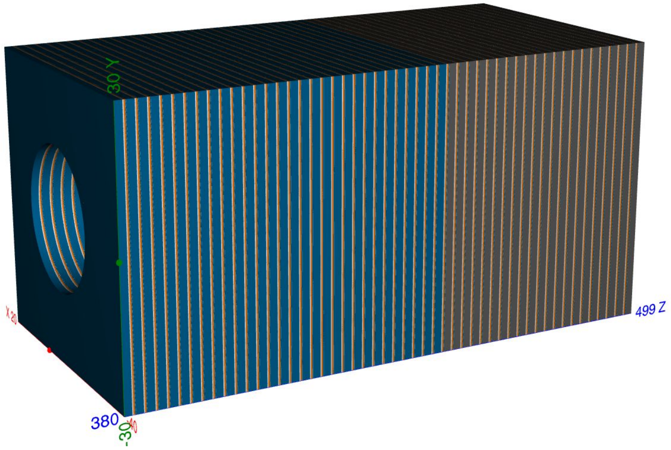
Fig. ATLAS PUB Note

Simulation Details

- SiPM on tile Fe/Sc sampling Calorimeter similar to CALICE and Calorimeter Insert
- DD4hep framework for geometry with G4.10.7.p3
- FPFP_BERT_HP list of G4 for particle shower

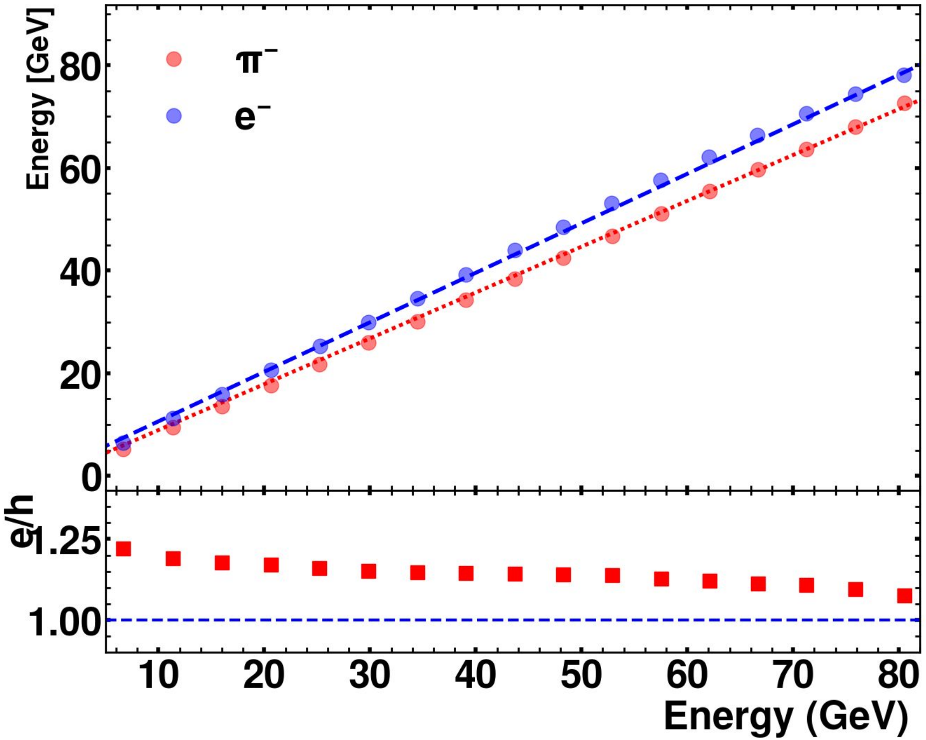
Component	Thickness (per layer mm)
Absorber (Fe)	20
Scintillator	3
Air thickness	0.4





DD4hep images of simulation model

Linearity of Fe/Sc HCal (Non-compensating)



- As expected, see higher energies for electrons than pions

Simple Reconstruction ("strawman")

$$Strawman = \frac{\sum \text{Cell Energy}}{\text{Sampling Fraction}}$$

$$\text{Sampling Fraction} = \left(\frac{\sum \text{Cell Energy}}{E_{Truth}}\right)_{\text{at 40 GeV electron}}$$

Training input and tuned hyperparameters and architecture

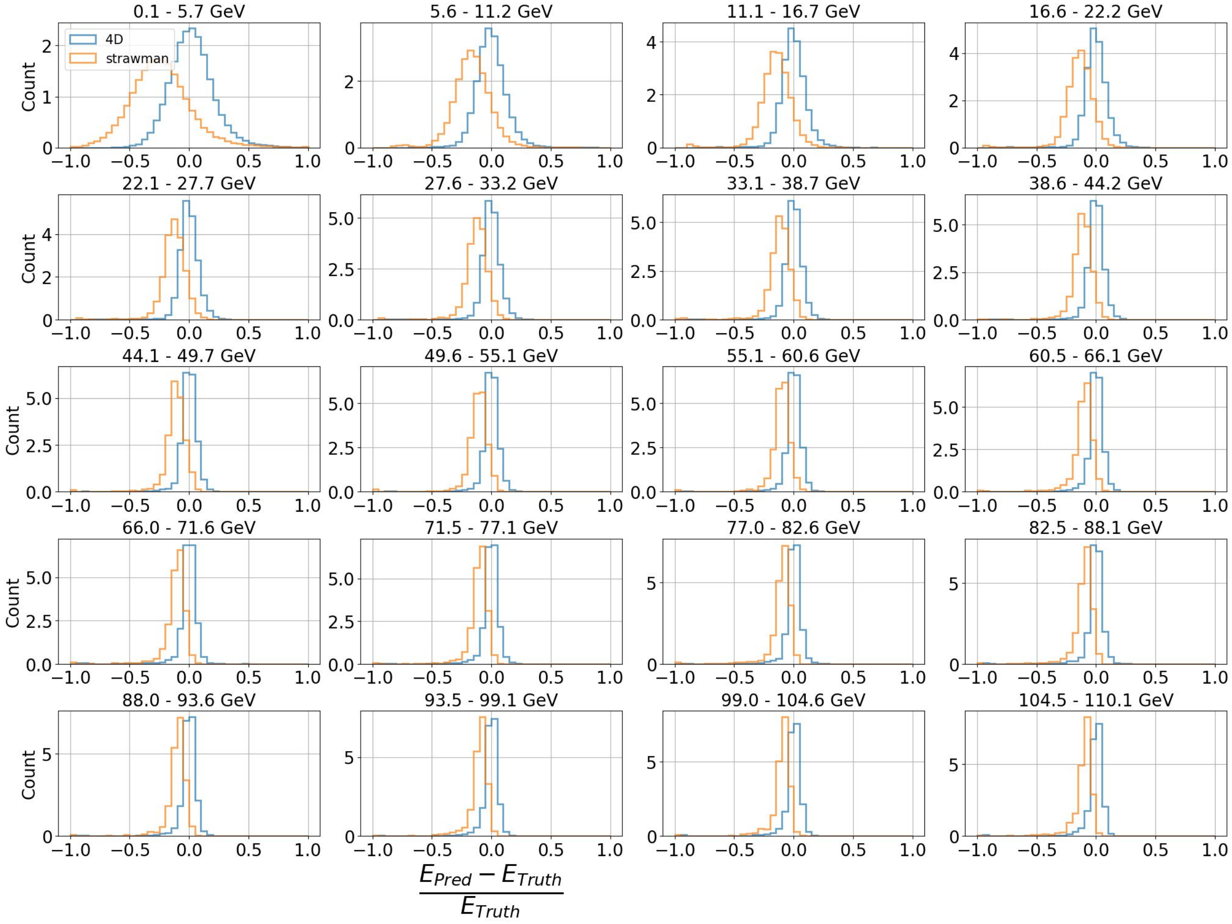
- Used simulated data, 2 M π^+ events, in continuous log10 space, constant angle = 17 deg (center of HCAL)
- Input ("4D"): cell hits E, X ,Y, Z and 1 output (energy regression)
- Batch size =1024, number of layers=4, latent size = 64
- Rectified Linear Unit (ReLu) activation functions
- Adam optimizer
- Mean absolute error for loss
- Trained until converges (approximately 100 Epochs)

Predicted energy distribution HCAL (π^+)

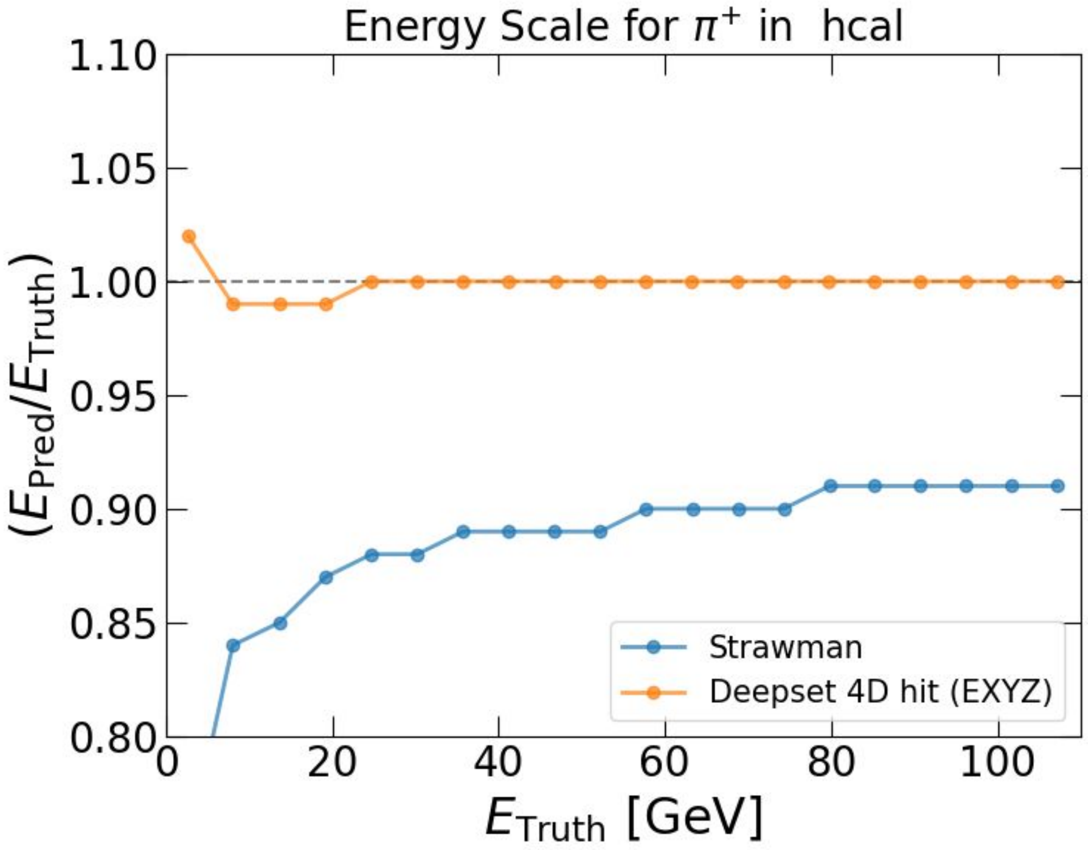
Deep sets “4D” input (EXYZ) vs strawman

- Machine learning does fix the energy scale for pions in non-compensating calorimeter based on shower-shape information.

- It also improves resolution

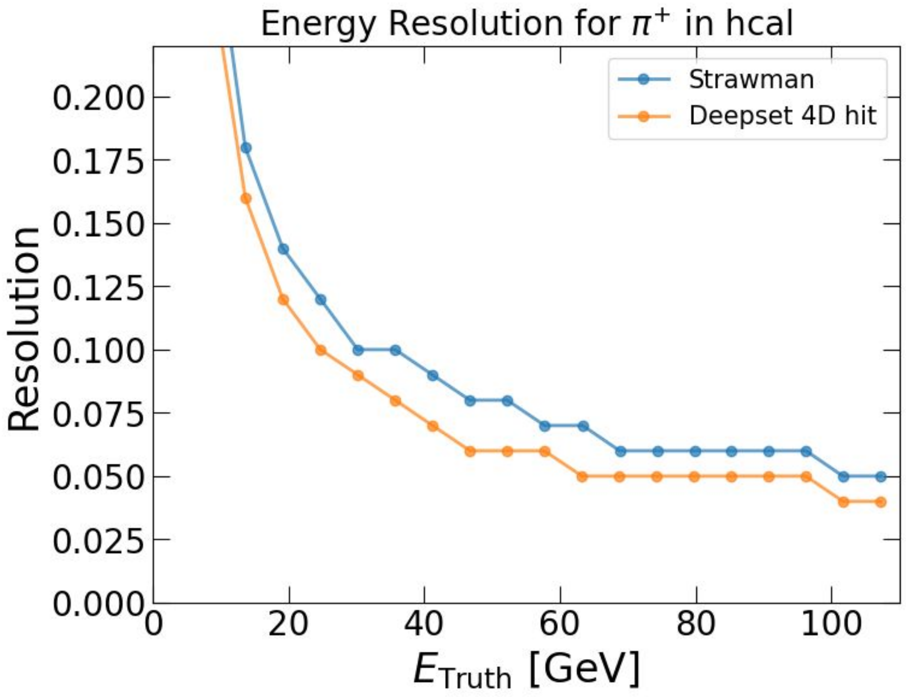


Regression for π^+ with "4D" hit inputs (HCAL)



Deep-set based regression corrects for scale and non-linearity seen in non-compensated Fe/Sc calorimeter

Energy resolution for **π**$^+$ with "4D" inputs (HCAL)



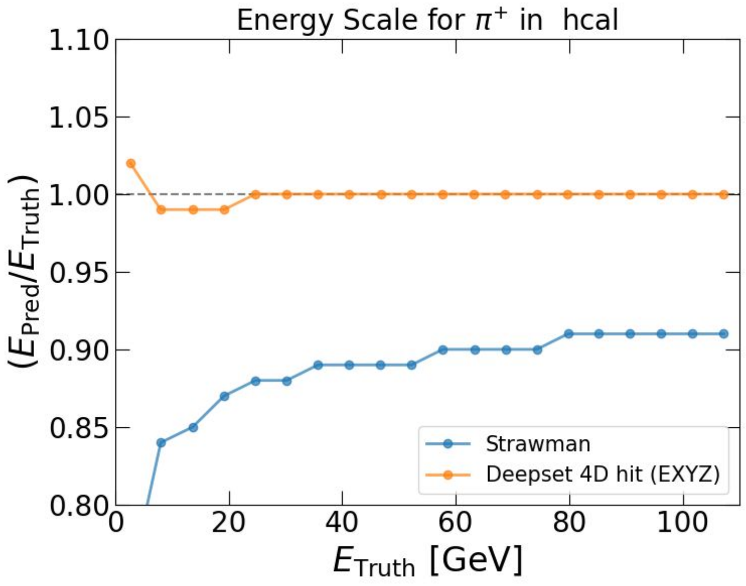
$$Resolution = \left(\frac{\sigma_E^{Pred}}{E_{Truth}}\right) \times \left(\frac{1}{\text{Correction\_Factor}}\right)$$

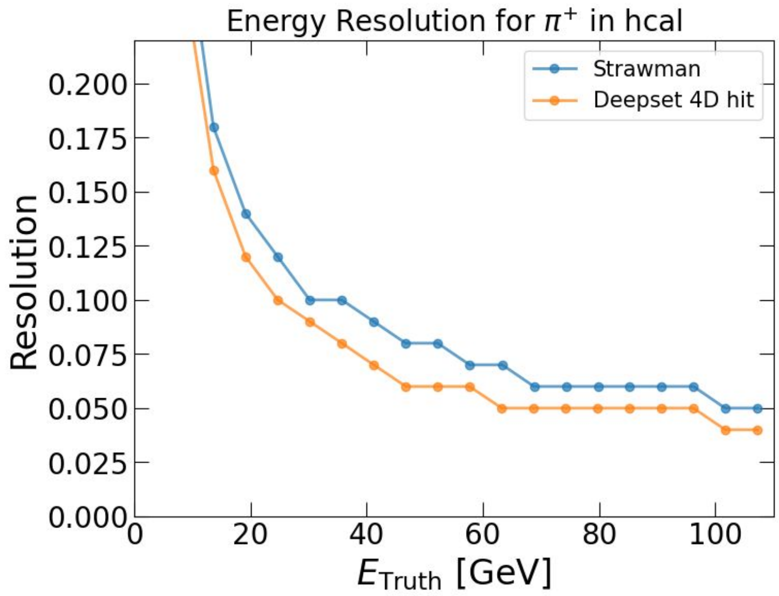
$$\text{Correction\_Factor} = \frac{\mu_E^{Pred}}{\mu_E^{Truth}}$$

AI approach able to improve resolution by up to ~30%

Note that improving resolution is very hard because it adds in quadrature. This improvement means that we have removed about half the source of resolution (subtracted in quadrature)

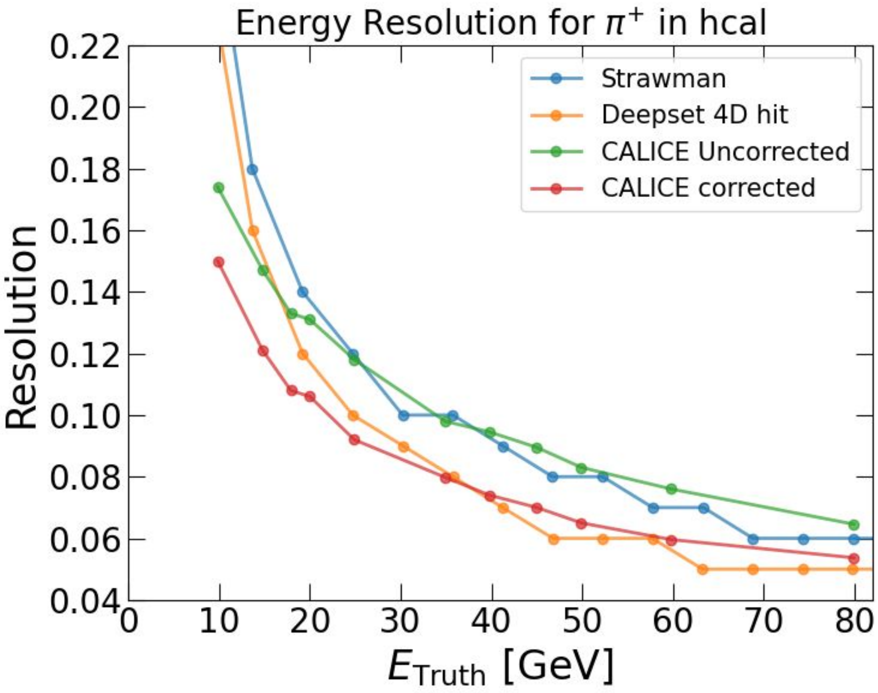
Summary of regression for π^+ with "4D" hit inputs (HCAL)





These results are linked because the response of the calorimeter it is "compensated" at the software level, **the impact of event-by-event fluctuations of the EM-fraction is eliminated.** The remainder resolution comes from fluctuations of non-visible energy, etc.

Our results vs CALICE results (π^+)



Our result:

- **Strawman (blue)**
- **Deep sets (orange)**

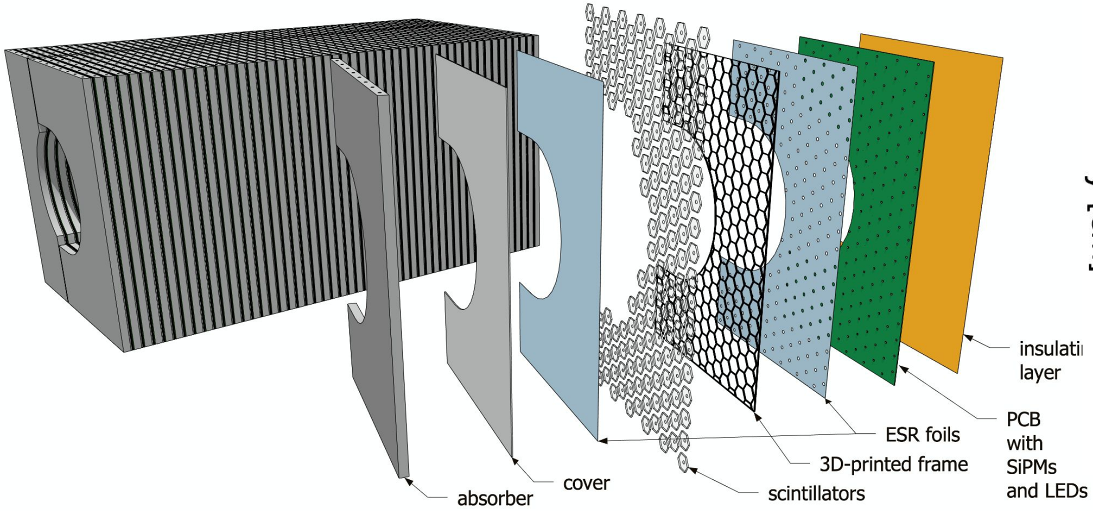
CALICE Fe/Sc Calo result from Ref.

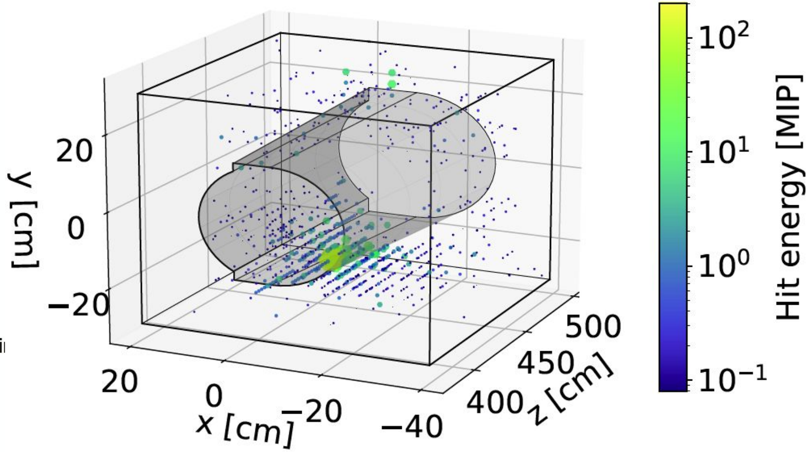
- **Green (before software compensation)**
  Is about ~58%/sqrt(E)
- **Red (after software compensation)**
  Is about ~45%/sqrt(E)

- Strawman (simple hit sum) is similar to CALICE uncorrected data.
- Deepset result similar performance to human-made software-compensation algorithm

→ Our simulation details is good enough to resemble reality, and CALICE algorithm was already closed to optimal.
AI method offers a faster, more versatile to achieve this optimal result
It can also be generalized to include other calorimeters and tracks (i.e. particle-flow)

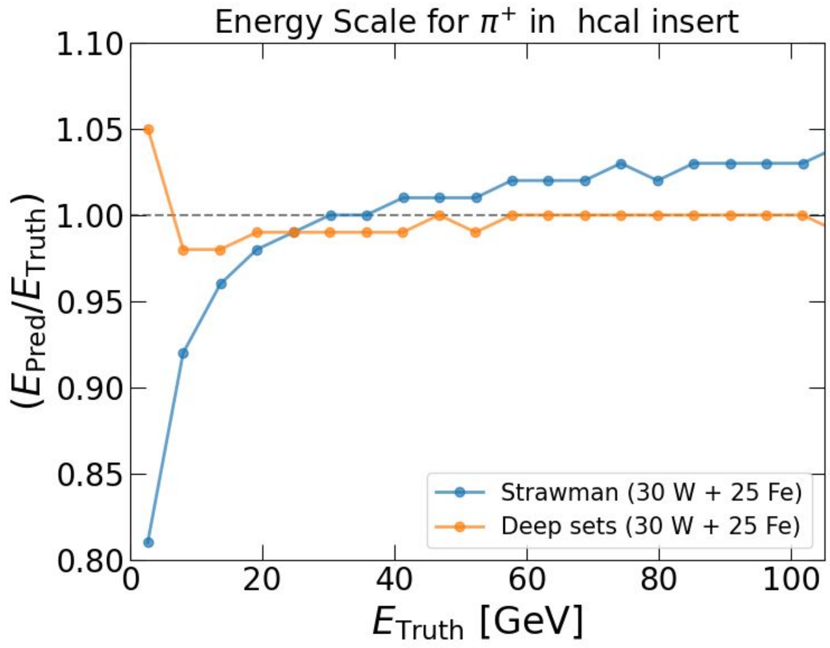
We also deployed this tool for Calorimeter Insert studies

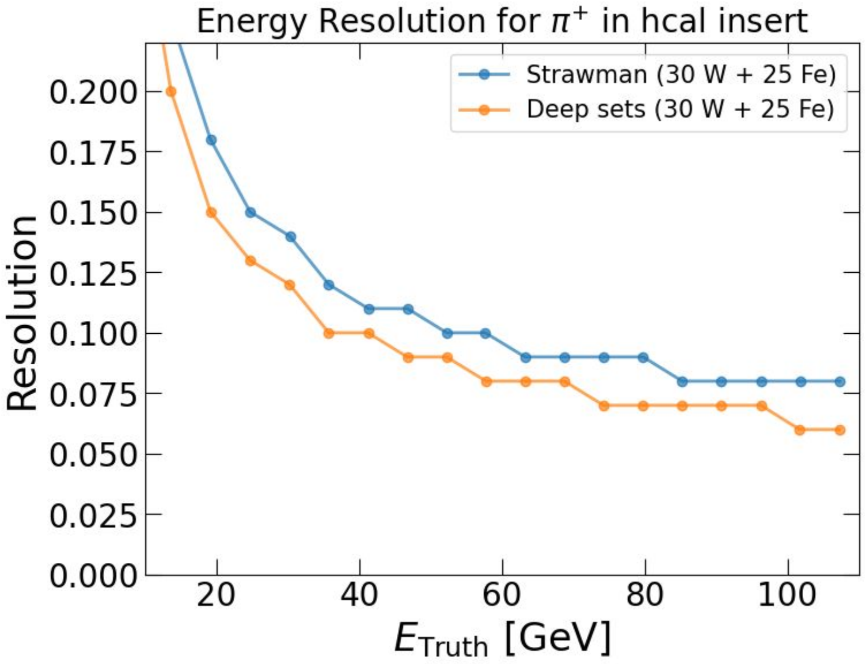




- Mixture of W-Fe/Sc
- Generated particle $\boldsymbol{\pi}^+$ (η^*=3.7)
- “4D” inputs (E, X, Y, and Z)

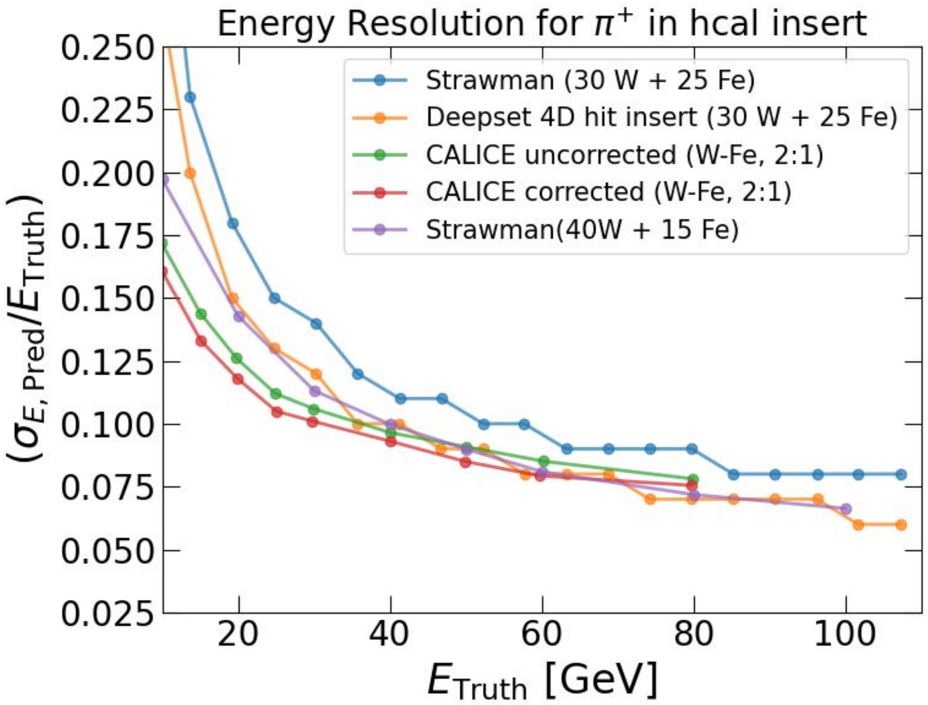
Deepsets/PFN results for Calorimeter Insert





- By design, insert is closer to unity in energy scale but AI still improves it, especially at low energies
- Deepsets/PFN improves the resolution about 20%

Insert vs CALICE W/Sc HCAL



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W-AHCAL Layer

Component	d [mm]
Steel Support	0.5
Tungsten	10
Air	1.25
Steel Cassette	2.0
Cable Mix	1.5
PCB	1.0
Scintillator	5.0
Steel Cassette	2.0
Air	1.25
Total	24.5

- Our simulation setup 30 W layer are followed by 25 Fe (same data for deep sets)
- In CALICE set up about 2:1 (W/Fe) thickness in each layer (total 38 layers)

Summary

- We explored energy regression in non-compensated calorimeters

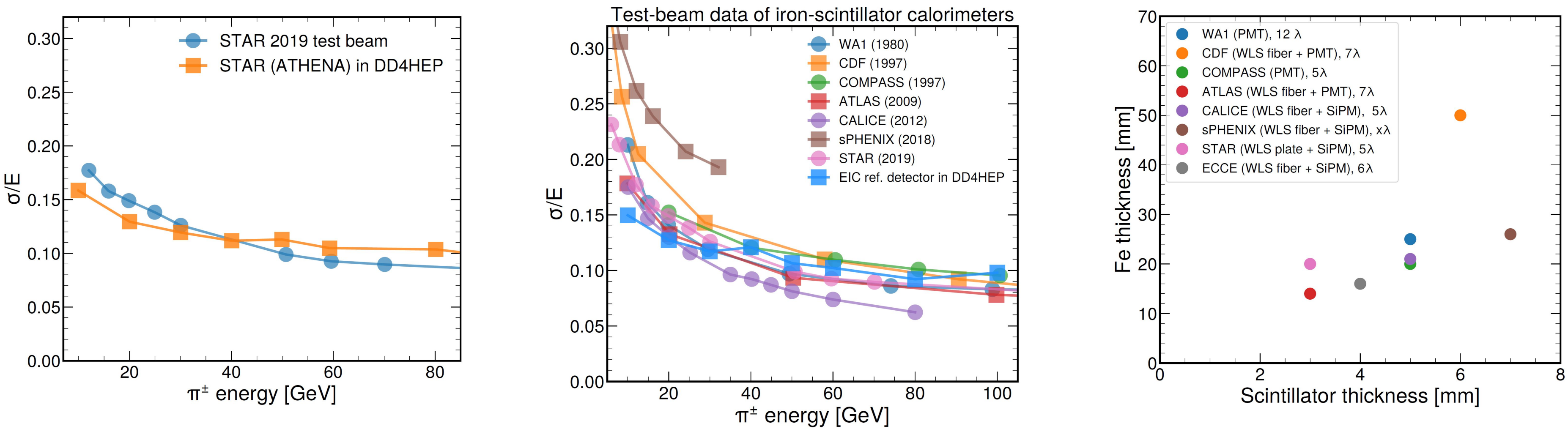
  - Simple approach reproduced CALICE Fe/Sc test beam data (before software compensation)
  - AI approach (deep sets /particle-flow network) yields similar results to CALICE with human-made “software compensation” algorithm, which is a many person-year development

- Take-home message: **We demonstrate that state-of-the-art AI methods can be employed to achieve optimal software compensation in a straightforward manner. It can also be extended to encompass multiple calorimeters and tracking to yield particle-flow reconstruction.**

- In the near future, we will adapt these studies to EPIC and will include ECAL & track information in the point-cloud architecture, and eventually share our results and methods with you all.

Back up

Simulation Validation (Fe/Sc calorimeters)



- Various possible combinations of readout have been tried over time. It seems that resulting changes in resolution are modest at best. Expected as resolution is not driven by photo-statistics but sampling fluctuations and total thickness.
- We think that refining simulation to include the readout details are unlikely to change results much, so it does not seem a good investment of time

Software compensation since 1980!

7. Conclusion

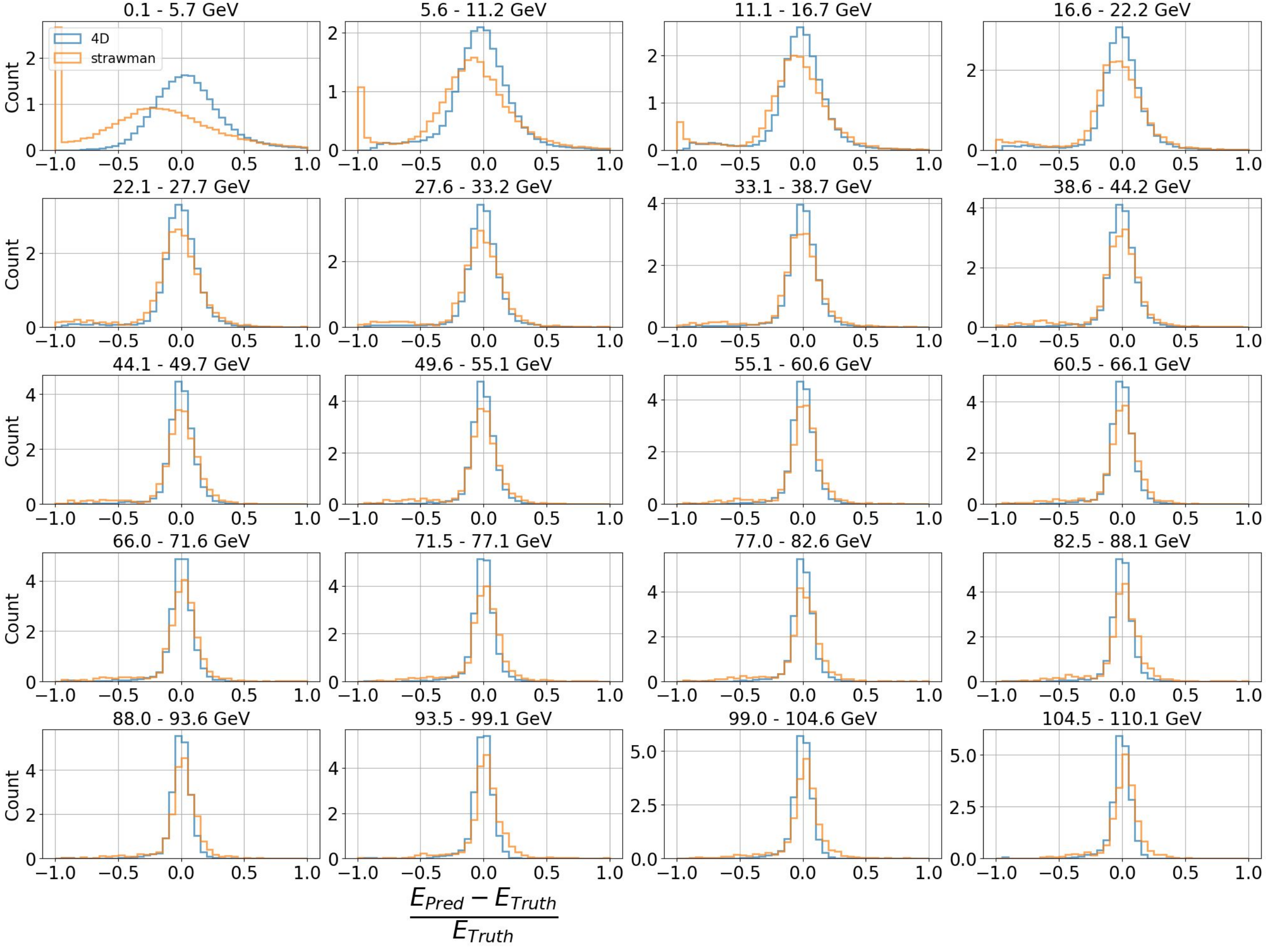
We have measured the response and the resolution of an iron–scintillator test calorimeter with 2.5 cm iron and in the 5 cm sampling WA1 modules. Compared to the 5 cm modules a ≈20% gain in resolution could be achieved for 2.5 cm sampling thickness. At 10 GeV the calorimeter response to electrons is about 30% higher than to hadrons. We have observed a tail on the high side of the pulse height distribution for high energy hadrons which we believe to be due to an unusually large electromagnetic component in some of the showers.

A weighting procedure was found to compensate for this effect, which results in Gaussian response curves, nearly linear dependence of response on hadron energy above 30 GeV, and improved energy resolution following a $0.58/\sqrt{E}$ law. The energy resolution for electrons is approximated by a $0.23/\sqrt{E}$ behaviour.

- Software compensation has been improving resolution for a long while
- Inspired more robust and advanced techniques in the future

Predicted energy distribution HCAL Insert (π^+)

Deep sets "4D" input (EXYZ) vs strawman



- Compensating HCAL (Insert)
- Mixture of W-Fe/Sc
- Generated particle π^+ (η^*=3.7)
- "4D" inputs (E, X, Y, and Z)