DRAFT: Correcting for Leakage Energy in the SiD Silicon-Tungsten ECal

Lucas Braun, D. Austin, J. Barkeloo, J. Brau, C.P.

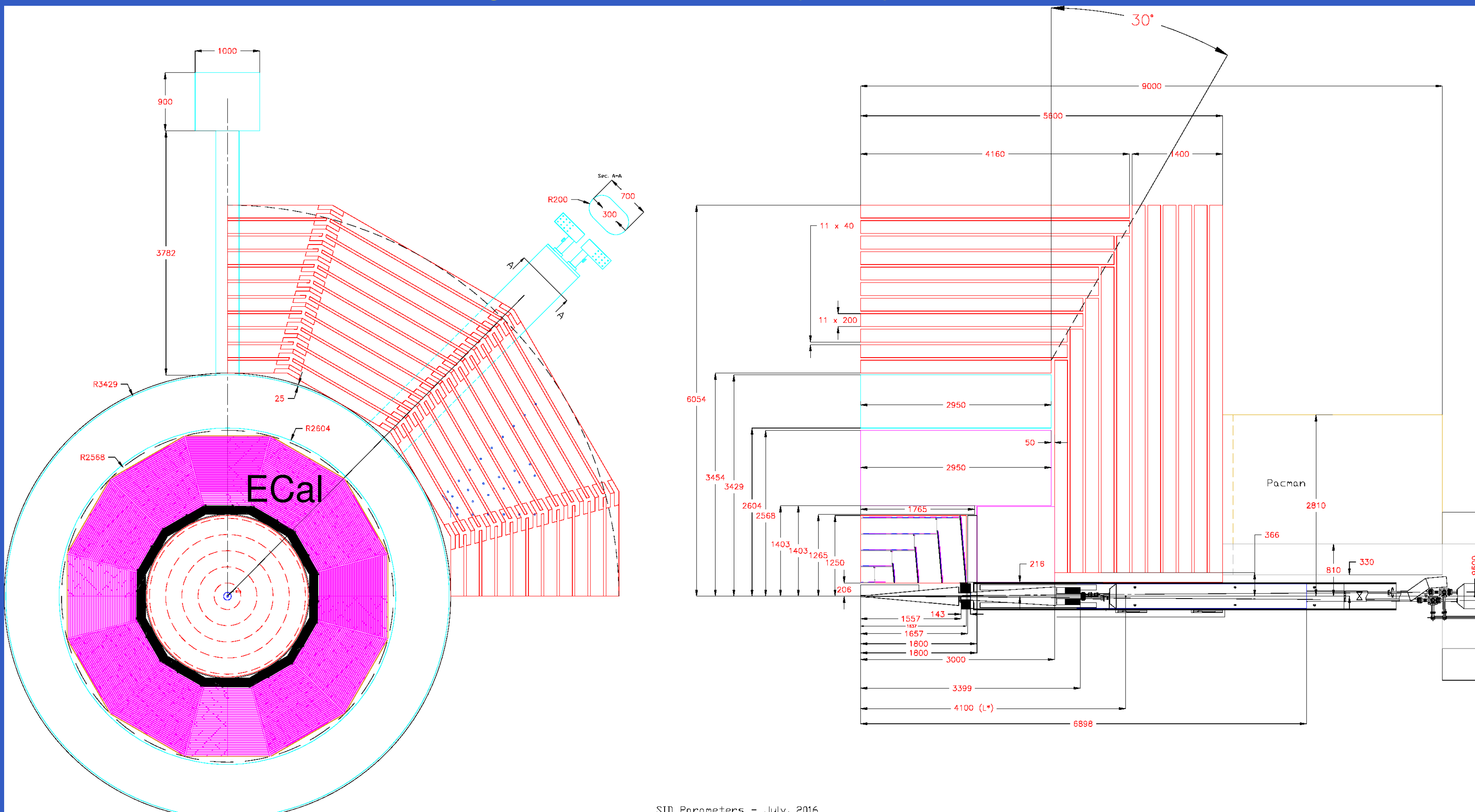
University of Oregon

Introduction

- Nominal SiD ECal Design (20+10):
  - Absorbing Tungsten layers alternate with sensitive Silicon layers ($26X_0$).
  - 20 thin (2.5mm) Tungsten layers followed by 10 thick (5.0mm) layers.
  - Energy resolution $\frac{\Delta E}{E} = 0.01 \oplus \frac{0.17}{\sqrt{E}}$.
  - Some showers develop late: ECal resolution is limited by energy leakage.
- Alternative SiD ECal Designs:
  - Reduced SiD ECal (16+8): 16 thin Tungsten layers followed by 8 thick layers.
  - Ideal SiD ECal: 60 thin Tungsten layers with no thick, for comparative purposes.
- Simulation models for Ideal SiD: simple G4 stack and full geometry simulation
  - Simple 16+8 standalone Geant4 stack of Silicon/Tungsten slabs, with SiD material.
  - ILCsoft v02-00-02 DD4hep/Geant4 simulation with compact 20+10 SiD description
- TensorFlow Neural Network: recovering leakage, thereby improving resolution
  - Inputs: energies layers 1-40, total energy, hit multiplicity, incidence angle θ, azimuthal ϕ.
  - Multilayer perceptron with one hidden layer, simple topology.
  - One ouput: sum of energy deposited in layers 41-60 (leakage)

Nominal SiD Design

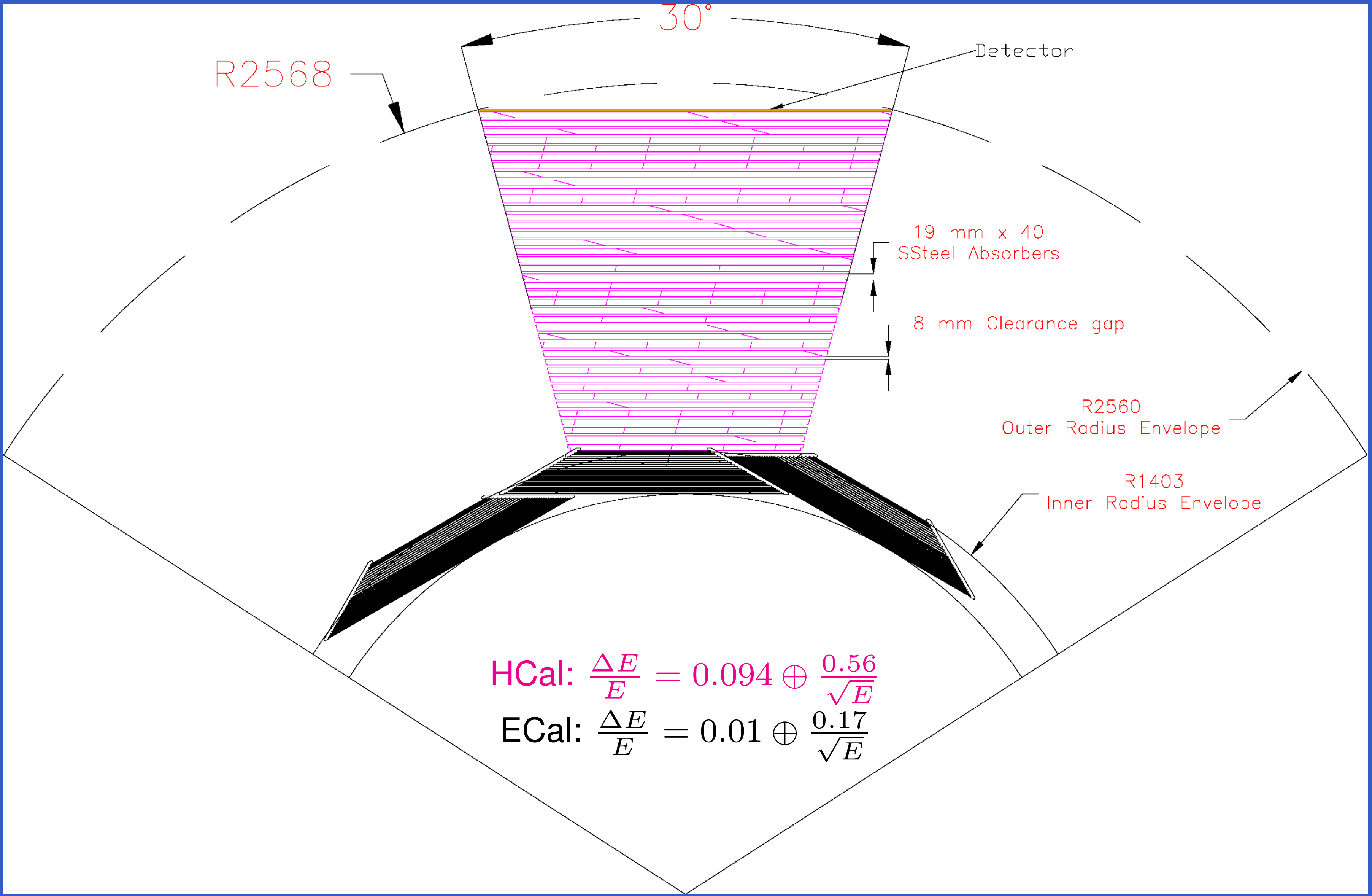
Electromagnetic Calorimeter (ECal) is in black at left.



In the ECal, absorbing Tungsten layers alternate with sensitive Silicon layers for a total of $26 X_0$

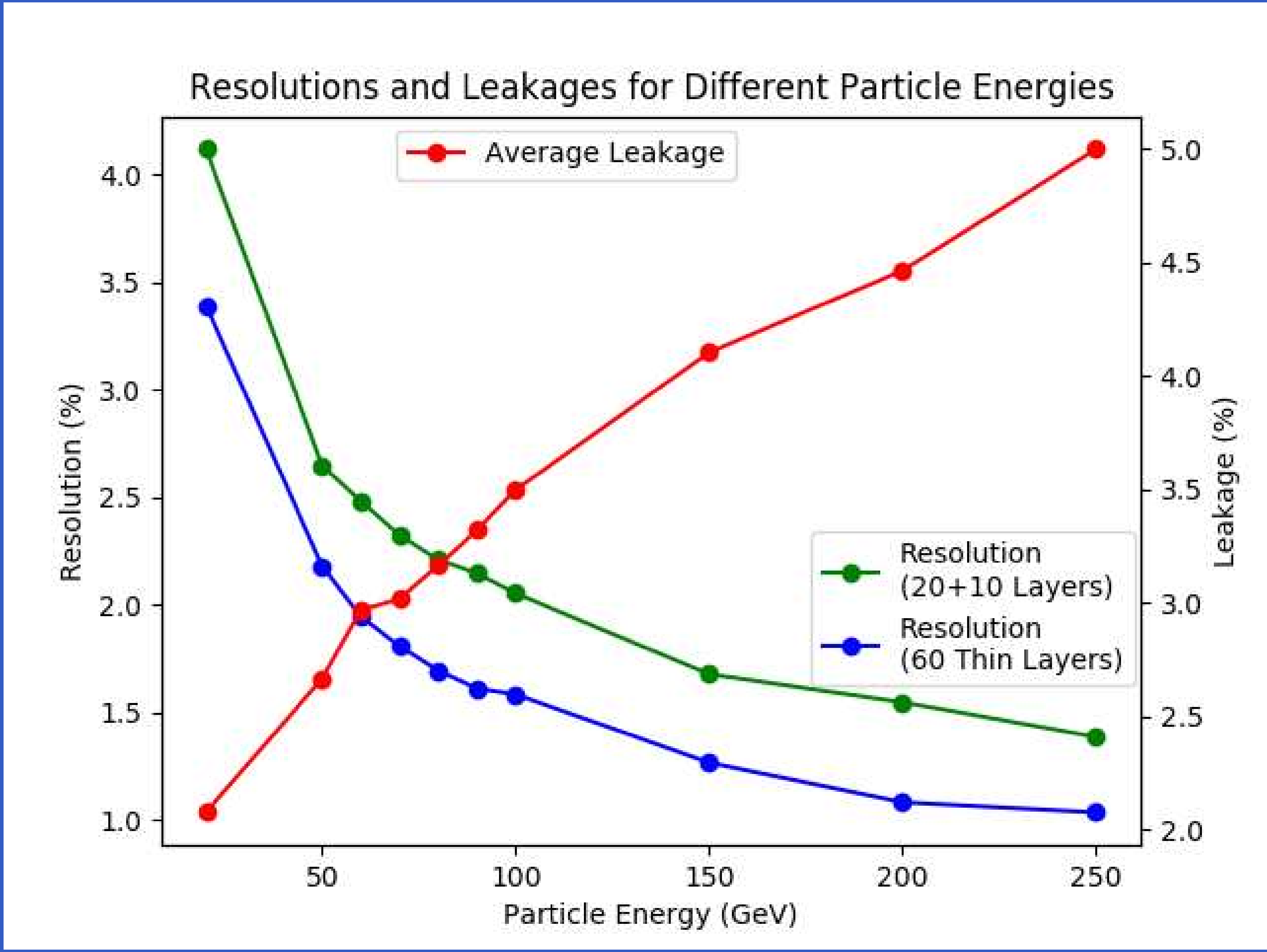
Nominal SiD ECal/HCal Design

Overlapping staves regions every 30 degrees for mechanical stability.



Can the reduced ECal (16+8) performance approach the nominal (20+10) with leakage recovery?

Motivation: Reduce Layers but Maintain Performance



Can the reduced 16+8 SiD performance approach the nominal 20+10 performance using a neural network trained on the ideal 60 layer SiD?

Neural Network: Simple Stack and Full SiD ECal Models

Low-Bias Correction Energy

L. Braun
J. Barkeloo
J. Brau

University of Oregon

October 7, 2019

Simple Stack Setup

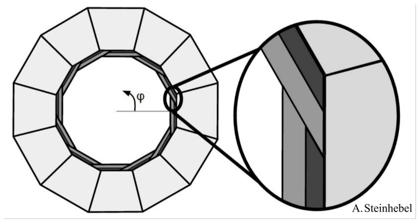
- Electrons fired perpendicular to calorimeter
- Data generated with 60 thin layers
- Model undersampling of deep layers by ignoring data from alternate silicon layers
  - Thin layer $\approx 0.64X_0$
  - Thick layer $\approx 1.28X_0$
- Correction methods here use only **16 thin layers and 8 thick layers** to measure energy and make correction
  - SiD uses 20 thin and 10 thick layers

Neural Network using Only Discrete Particle Energies

- One hidden layer
- Batch size = 32
- Epochs = 1000
- Train on each data set separately
- Weight each fit based on how close a given particle's energy deposition is to the average deposited by each training set: $\frac{1}{(E_{avg}-E_{32})^{10}}$
  - E_{avg} is average energy deposited by each training set
  - E_{32} is the energy deposited for the event being corrected

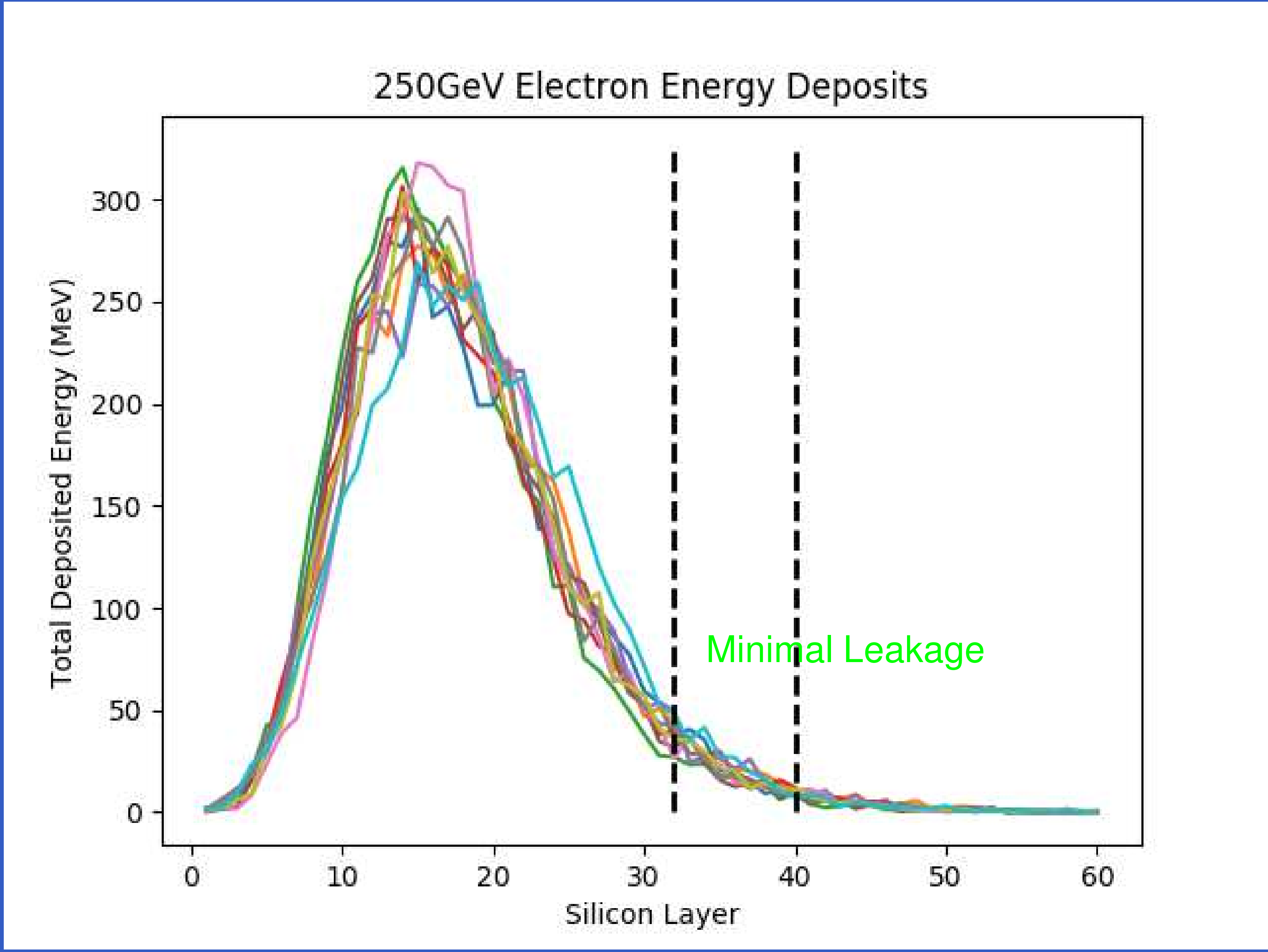
Full SiD Model

- More thorough geometry model
- Modified SiD specifications:
  - No solenoid, $B = 0$
  - No vertex detector, tracker, HCal, or muon system
  - Extended ECal to 60 layers
- Tested NN on distribution of energies (20-300GeV) and angles ($\theta \in (0°, 45°)$, $\phi \in (0°, 360°)$)



Typical Showers in Ideal/Nominal/Reduced SiD ECal

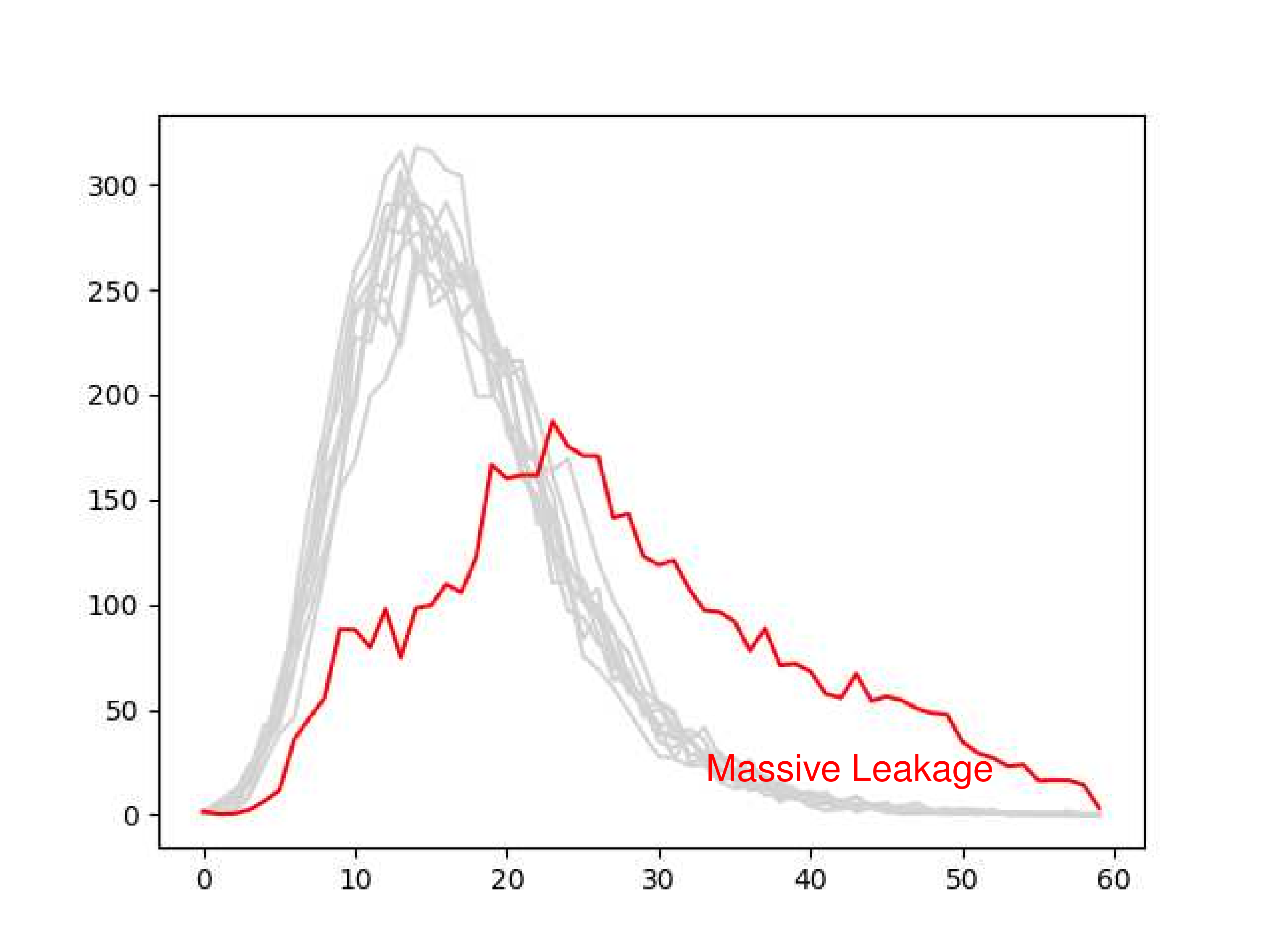
Energy deposition vs layer number in 60 layer simple stack.



Energy above layer 32 for the reduced ECal, or above 40 for the nominal ECal, is leakage.

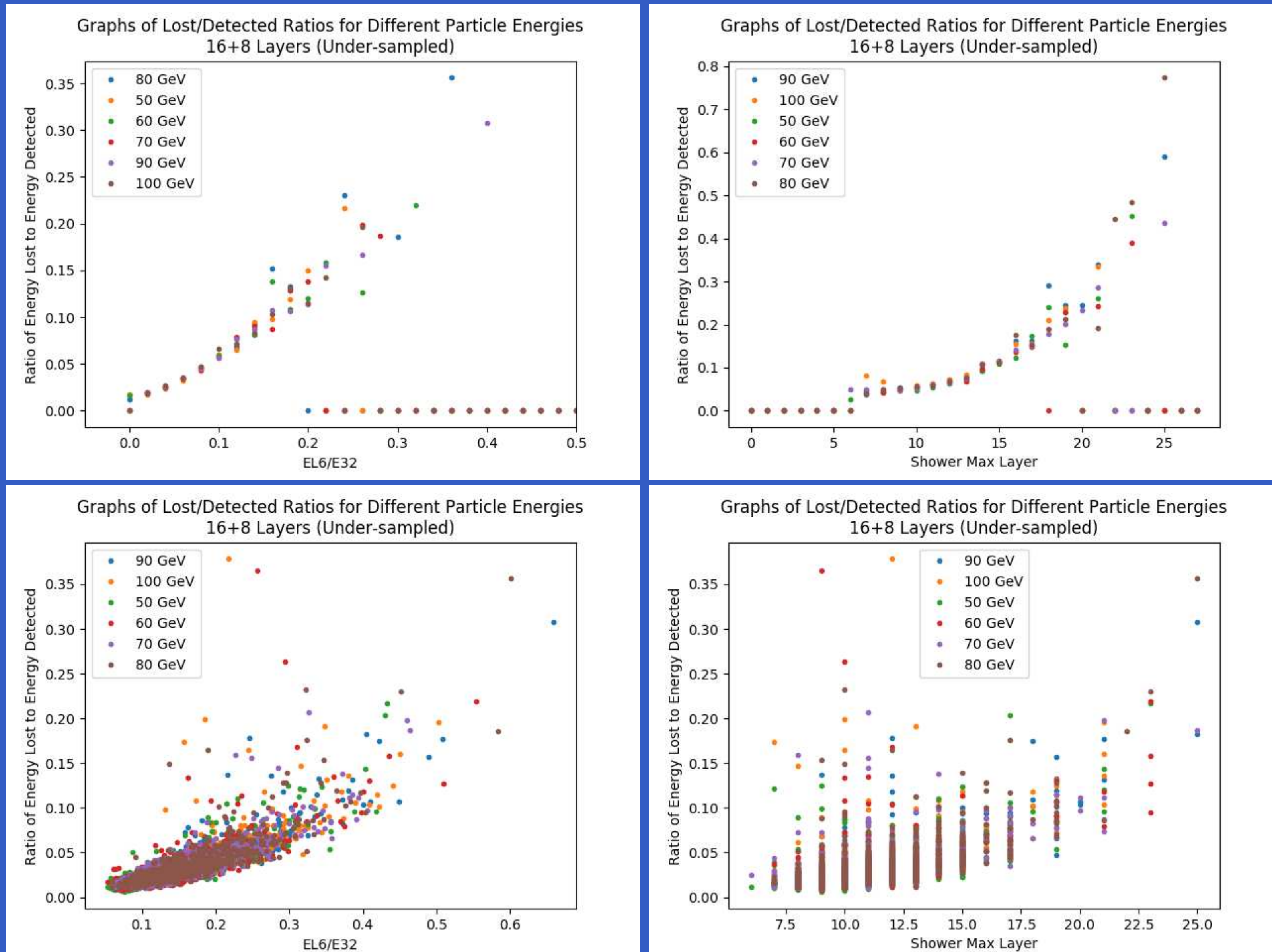
Electrons: Pathological Profile in Simple Stack ECal

Energy deposition vs layer number for shower with large leakage (red).



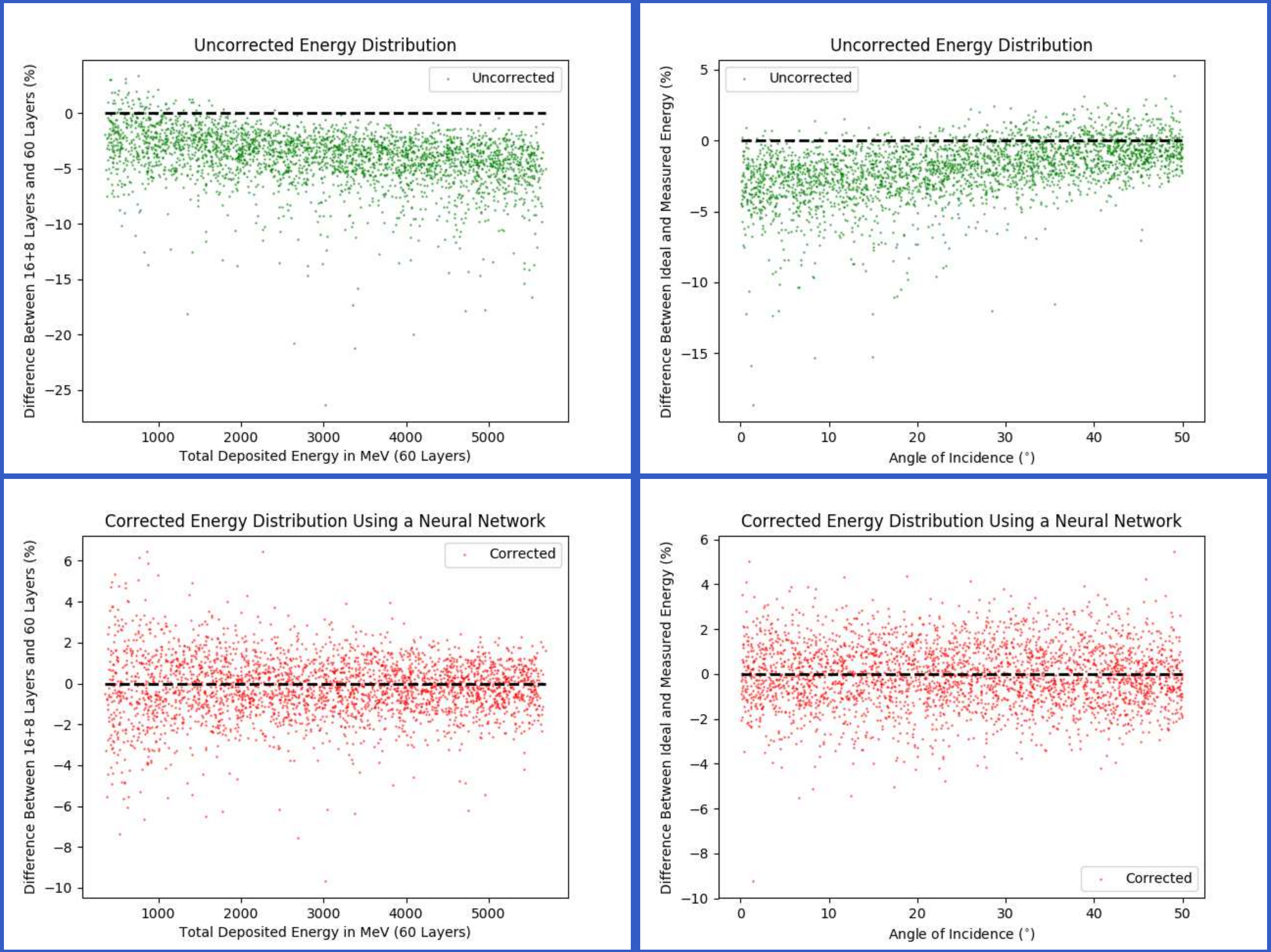
Energy deposited above layer 32 is leakage for the 16+8 layer simple stack.

Energy Layer Correlation: Simple Stack ECal Model



Uniformity of shower profiles yield correlations between energy deposits in layers.

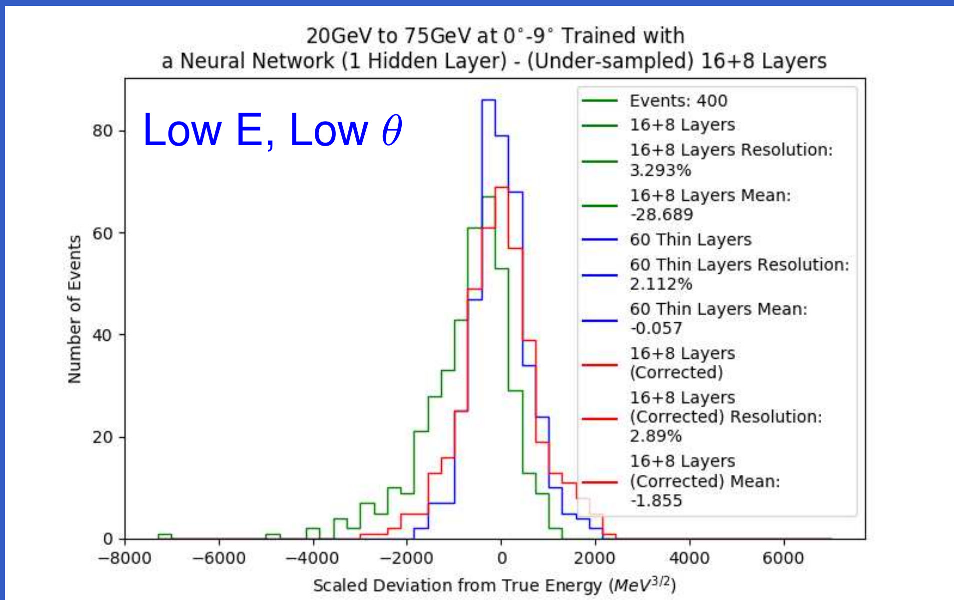
Electron E and θ: Simple Stack ECal Model

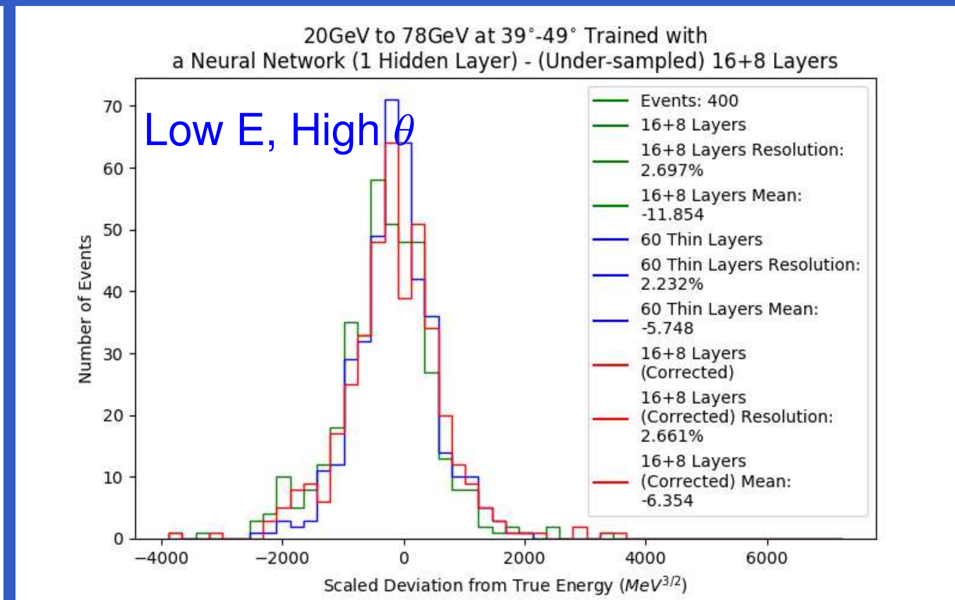


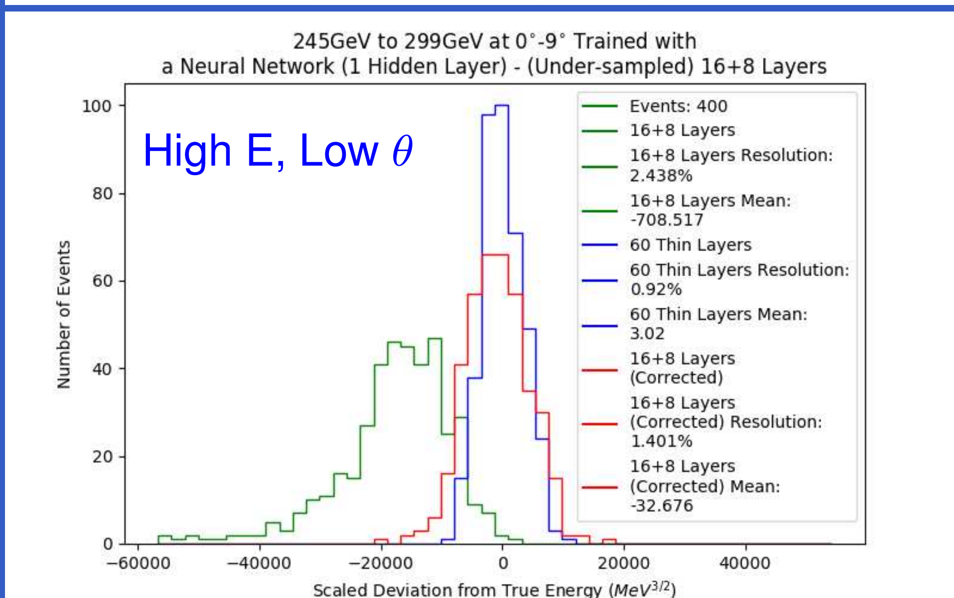
Large leakage at high energy and low angle of incidence can be corrected with a Neural Network.

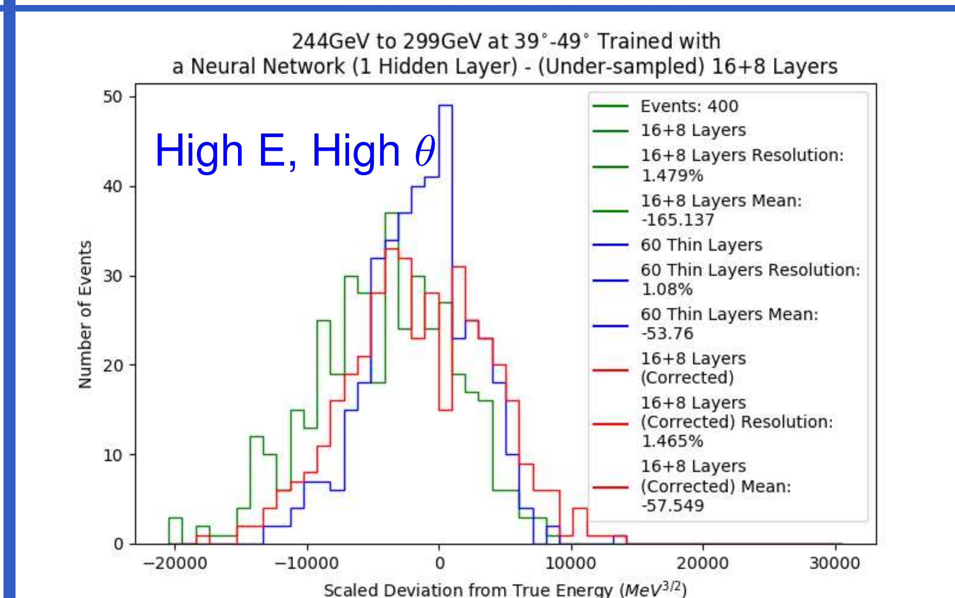
Results: Simple Geant4 Stack ECal Model

Measured (16 thin + 8 thick layers)/Neural Network Corrected/Ideal (60 thin layers)



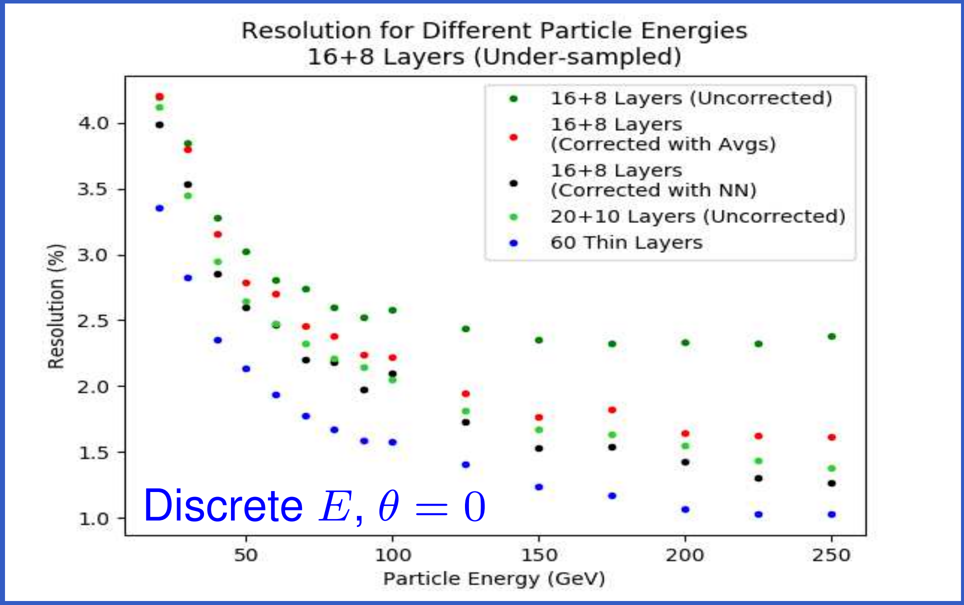


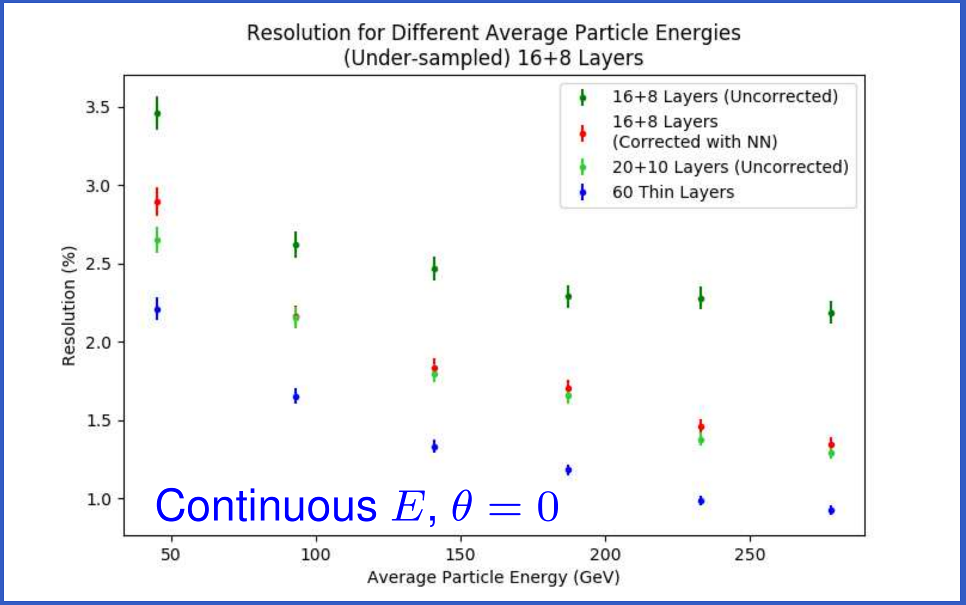


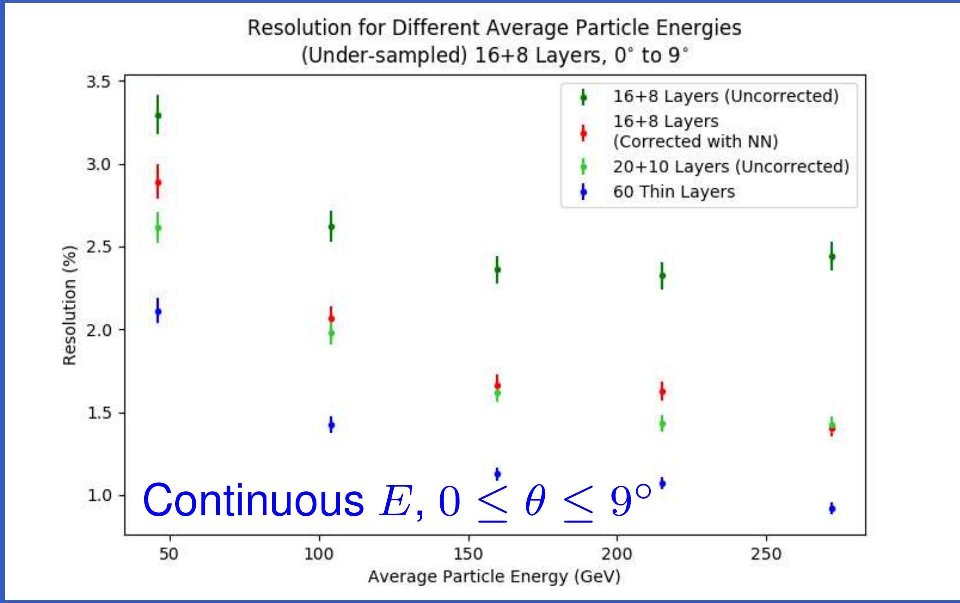


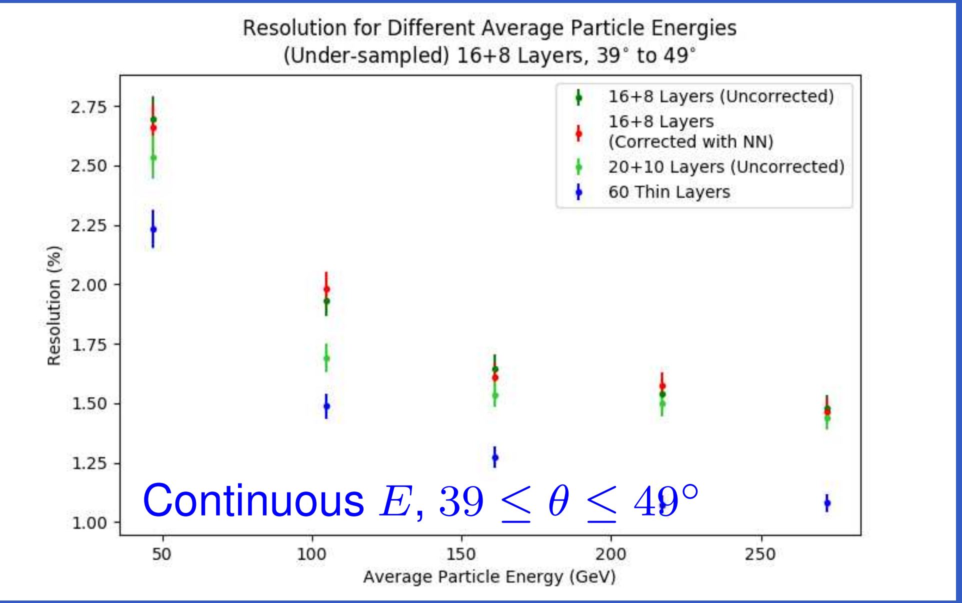
Results: Simple Geant4 Stack ECal Model

Measured (16 thin + 8 thick layers)/Neural Network Corrected/Ideal (60 thin layers)









ECal Overlap Regions: $\phi = 15^\circ + n \times 30^\circ, n = 0, \ldots, 11$

Correction Energy with Modified SiD Model

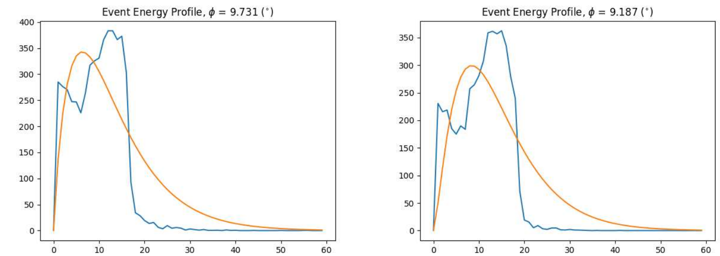
L. Braun
J. Barkeloo
J. Brau
C. Potter

University of Oregon

October 7, 2019

Energy-per-Layer Problem

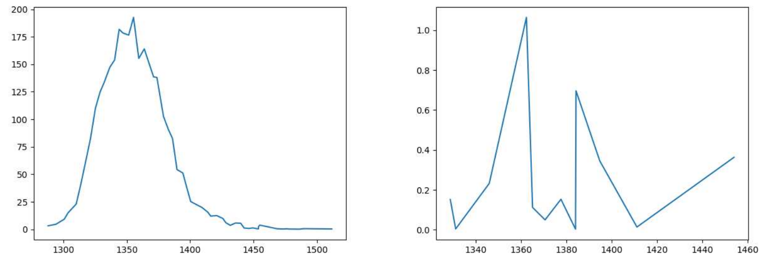
- In overlapping region, treating layer numbers the same as in non-overlapping regions distorts shower profiles
- Prevents standard best-fit method from working



Plotting Profiles for Each Module Separately

- Allows for profile analysis without ignoring low-deposit layers
- Low-deposit layers inconsistent in deposition trend
- Deposits in low-deposit layers are low enough that best-fit correction is not as important

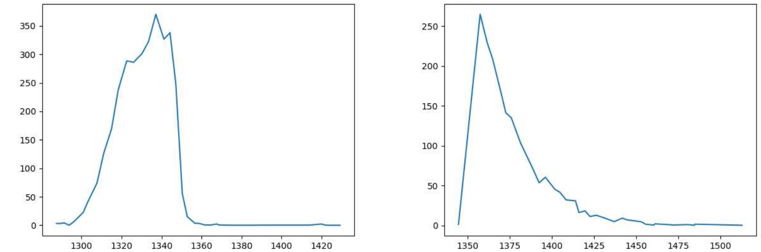
Phi = 17.38°



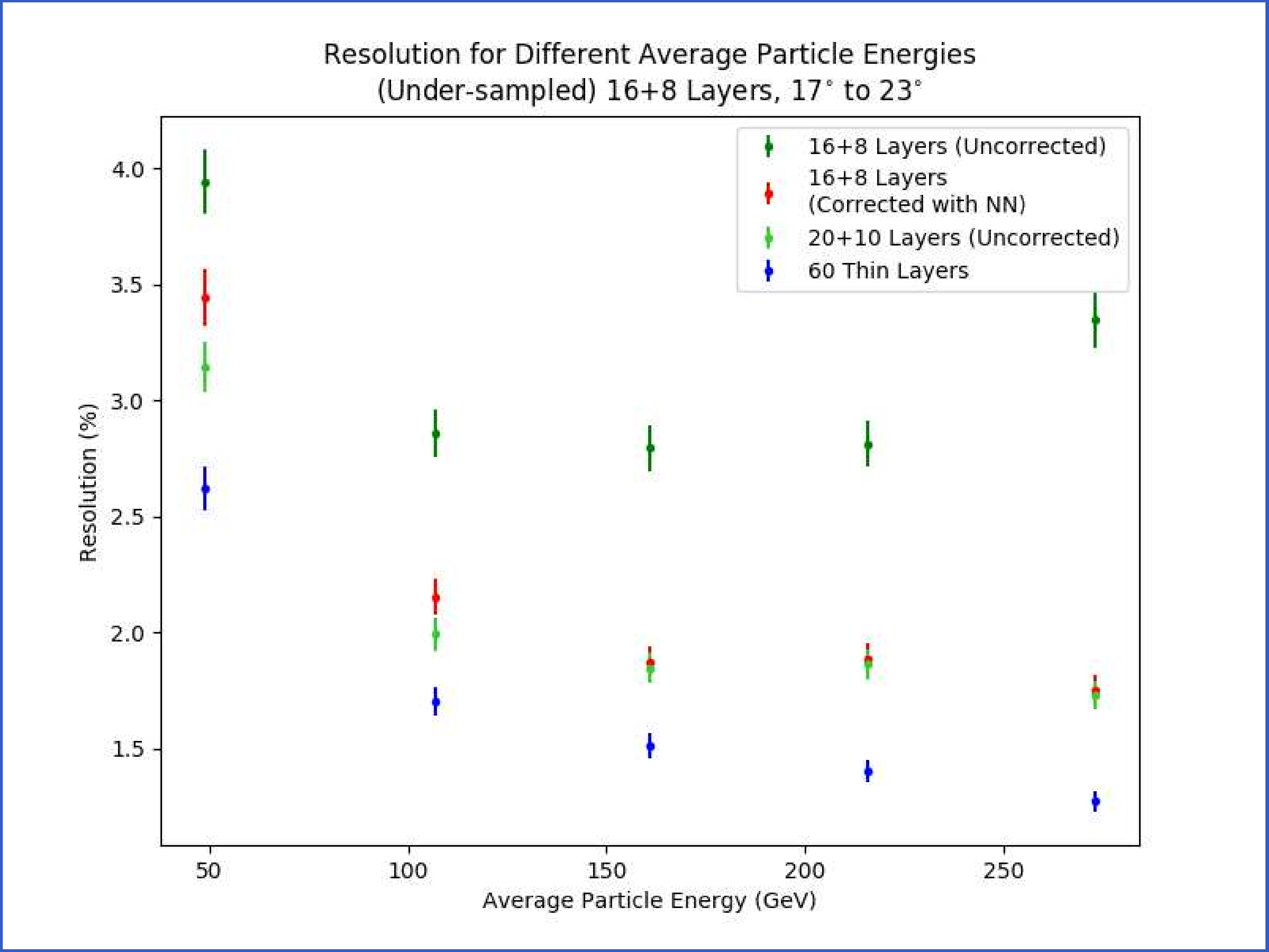
Plotting Profiles for Each Module Separately

- Some events have large deposits in both modules
- In this case, energy deposit trends are consistent enough to apply a best fit

Phi = 9.27°

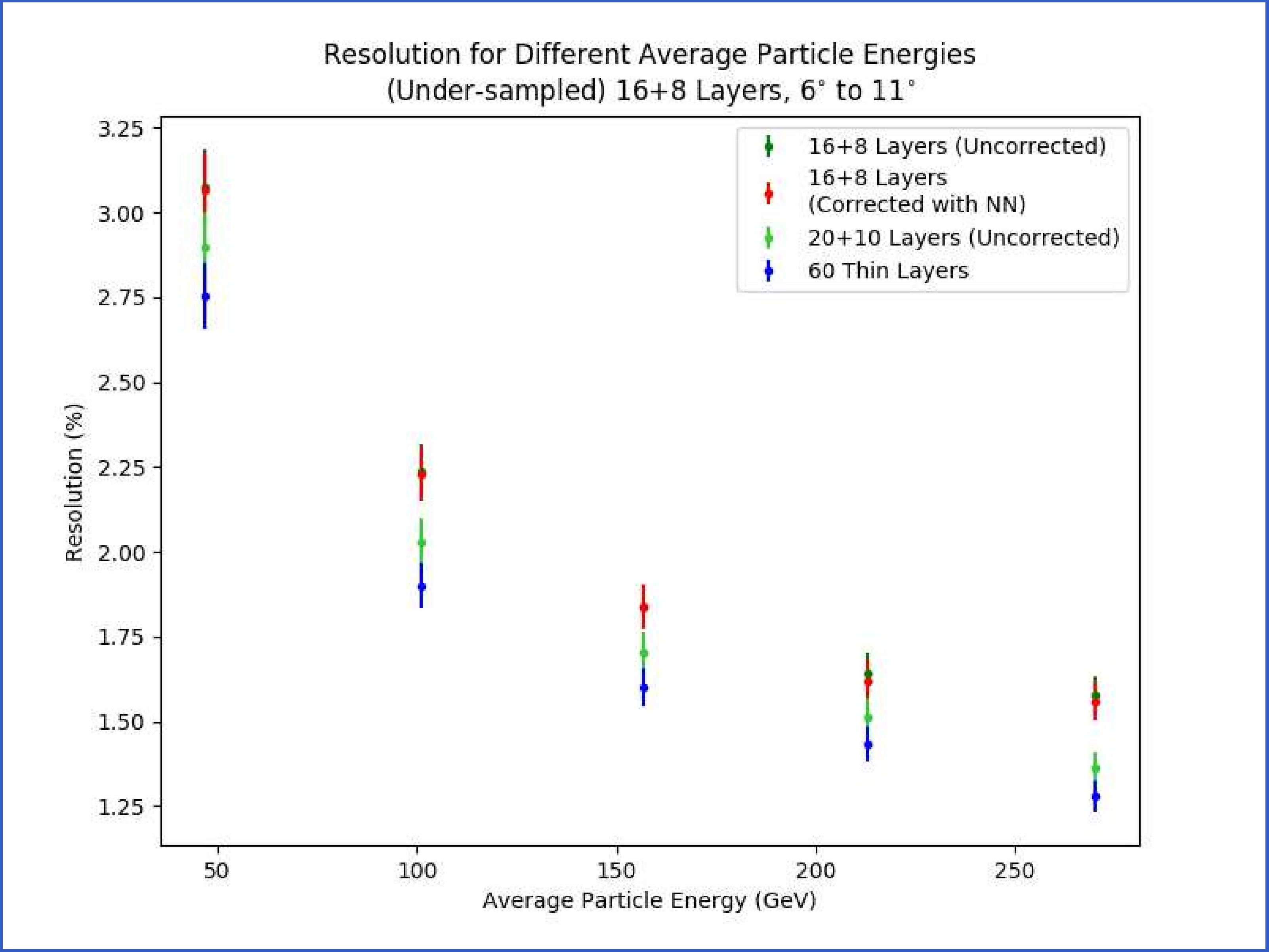


Results: Full SiD ECal Model, Non-Overlap Regions



Improvement in resolution similar to simple stack. The reduced SiD ECal performance is comparable to the nominal performance with leakage corrections.

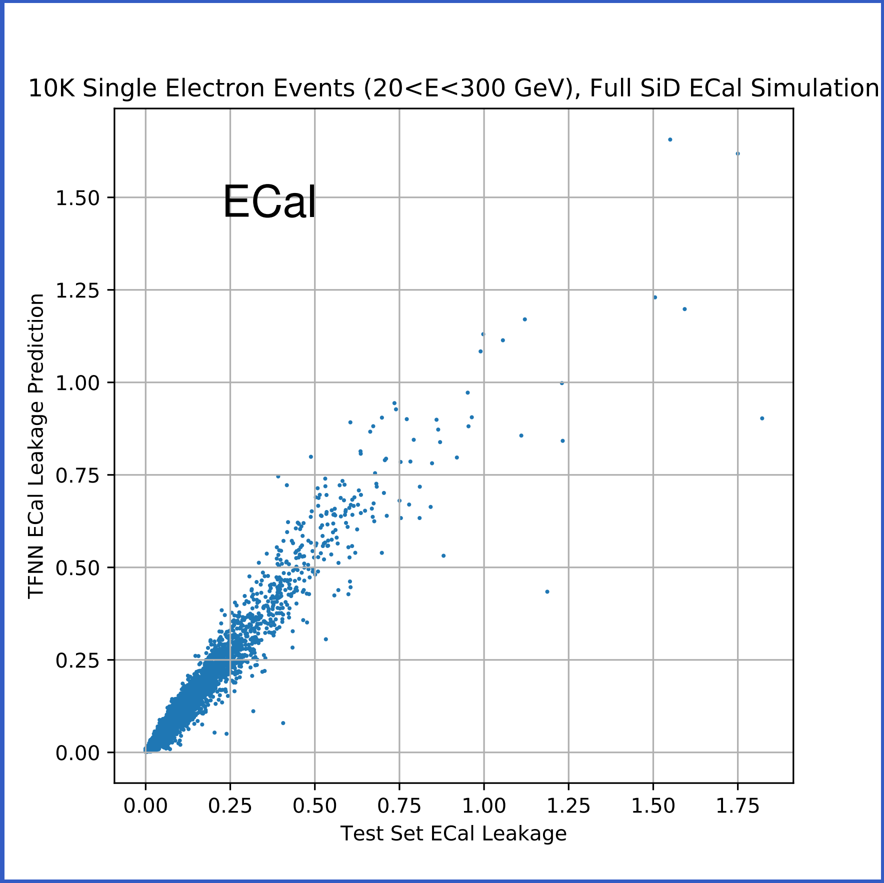
Results: Full SiD ECal Model, Overlap Regions

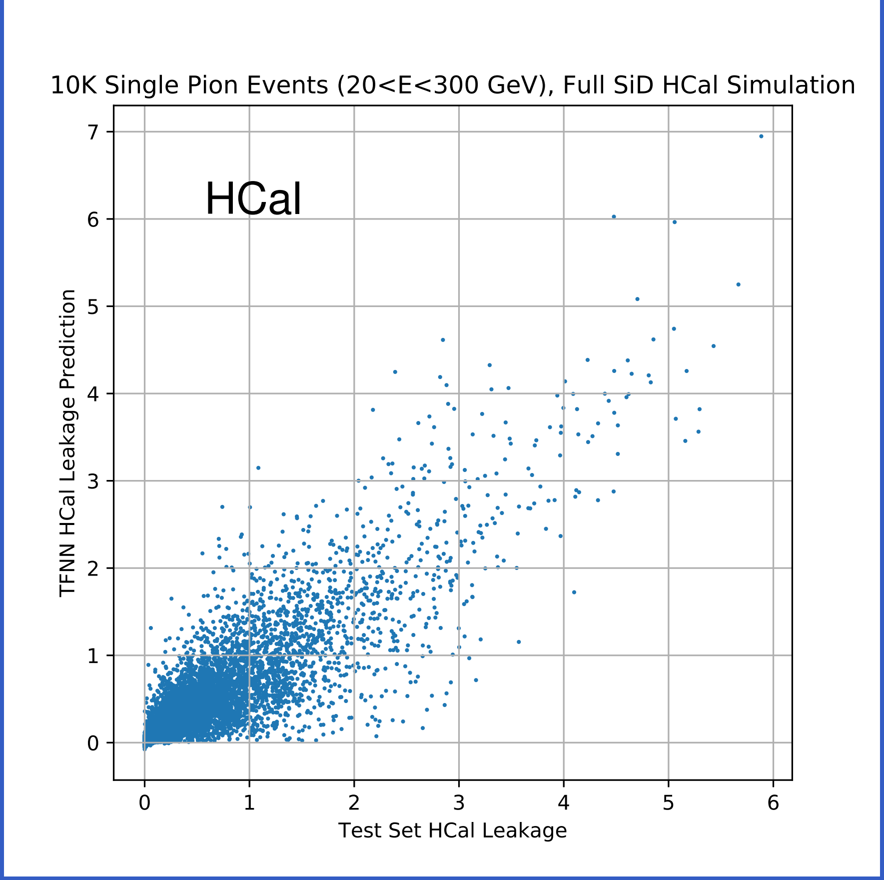


No improvement in resolution due to layer geometry in overlap regions, as expected, since the leakage is minimal there.

Preliminary Application to SiD HCal Leakage

In the HCal, 40 absorbing Steel layers alternate with sensitive RPC layers for a total of 5λ





TensorFlow NN uses Full SiD 80 layer HCal simulation. Above, predicted vs actual leakage.

DRAFT Conclusions

- SiD ECal exhibits correlations between energy deposition by Silicon/Tungsten layer.
- Such correlations can be exploited using a Neural Network to predict energy leakage.
- Correcting ECal measurements with predicted leakage yields improved energy resolution.
- Specifically, the Reduced SiD ECal (16+8) performance can match the Nominal SiD ECal (20+10) by correcting measurements with Neural Network predicted leakage.
- Nominal performance can be maintained with fewer layers, and therefore lower cost.
- While ECal leakage can be measured in the HCal, we expect that the Silicon based prediction will be more precise than the RPC based measurement.
- We reach no conclusions about the application to HCal leakage, studies are ongoing.