R&D of the Energy Calibration for the SiD EM Calorimeter based on Machine Learning

2019/11/28

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Introduction

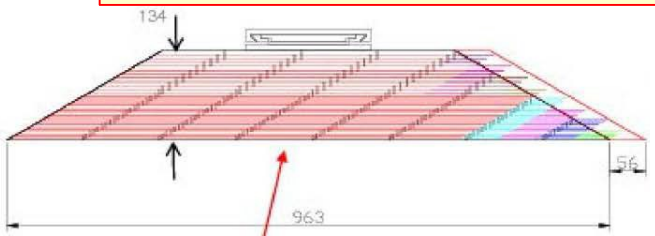
We have developed the energy calibration method using machine learning for the ILC SiD EM Calorimeter (ECAL).

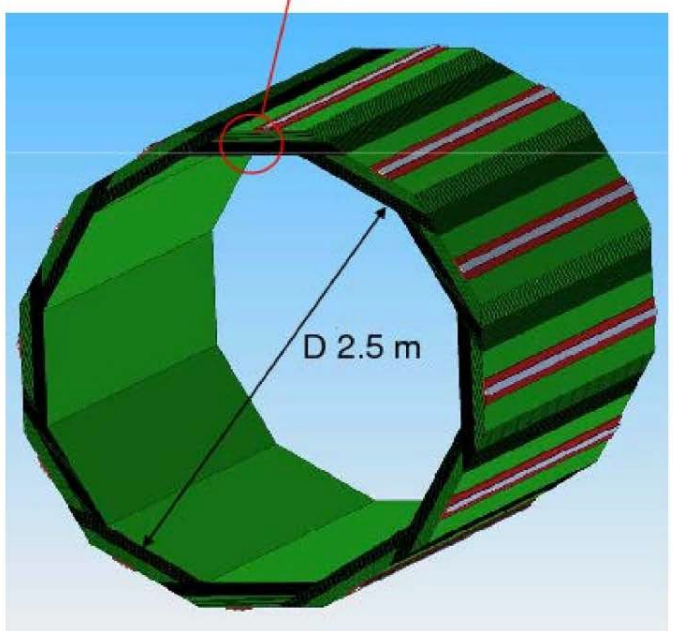
Machine Learning based on the Neural Network (NN) is expected to improve calibration performance over the simple reconstruction method.

In this talk, we report the status of the R&D.

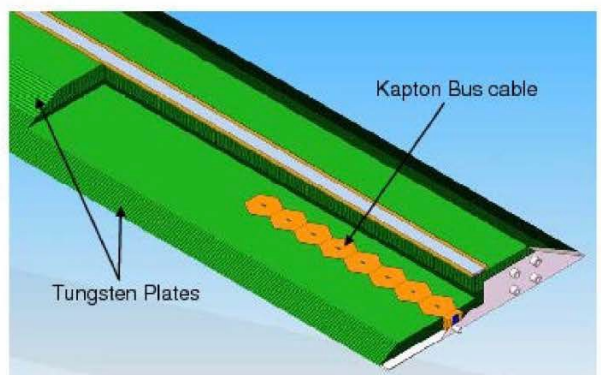
SiD EM Calorimeter (ECAL)

- 30 Layer Si + W sampling calorimeter
- ~26X_0 in total
- Energy resolution(design value) $(17/\sqrt{E}\oplus 1)\%$

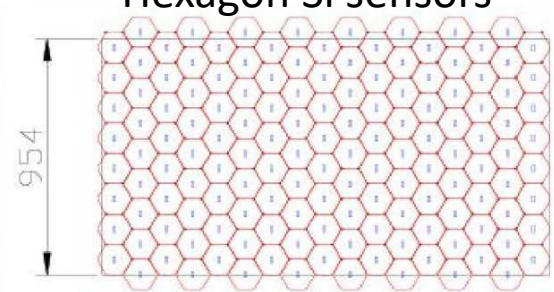




inner radius of ECL barrel	1.27 m
maximum z of barrel	1.76 m
longitudinal profie	20 layers × 0.64 X_0
	10 layers × 1.30 X_0
EM energy resolution	$(17/\sqrt{E}\oplus 1)\%$
readout gap	1.25 mm (or less)
effective Molire radius(R)	14 mm



Hexagon Si sensors



1024 pixels per Si sensor

Pixel size = 13mm^2

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Energy Calibration of the Calorimeter

In this study, we try the SiD EM calorimeter (ECAL) energy calibration using <u>Deep Neural Network</u>

Simple Energy Reconstruction "Simple Recon"

$$E = \alpha * (\Sigma E_{i \leq 20} + 2 \Sigma E_{i > 20})$$

Since last 10 layers have double thick Tungsten

Energy Calibration of the Calorimeter

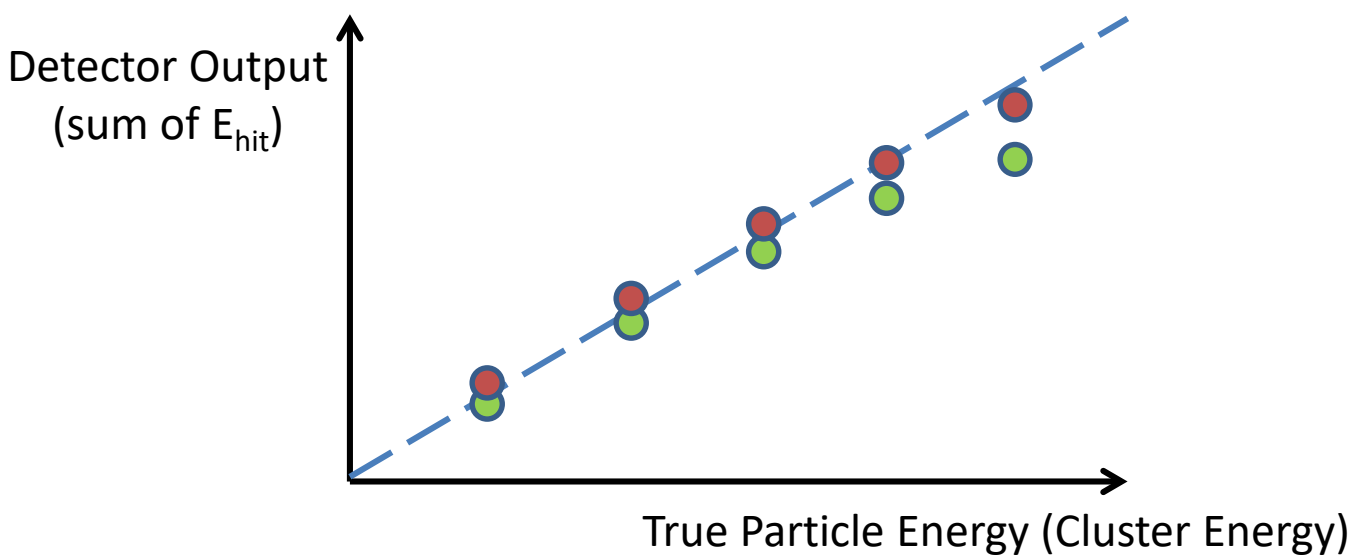
In this study, we try the SiD EM calorimeter (ECAL) energy calibration using <u>Deep Neural Network</u>

Several problems on the "Simple Recon" energy calibration

1. <u>Nonlinear</u> detector response

(due to shower leakage, detector geometry etc..)

2. Different detector response for e and γ (<u>particle-species</u> dependence)



Energy Calibration of the Calorimeter

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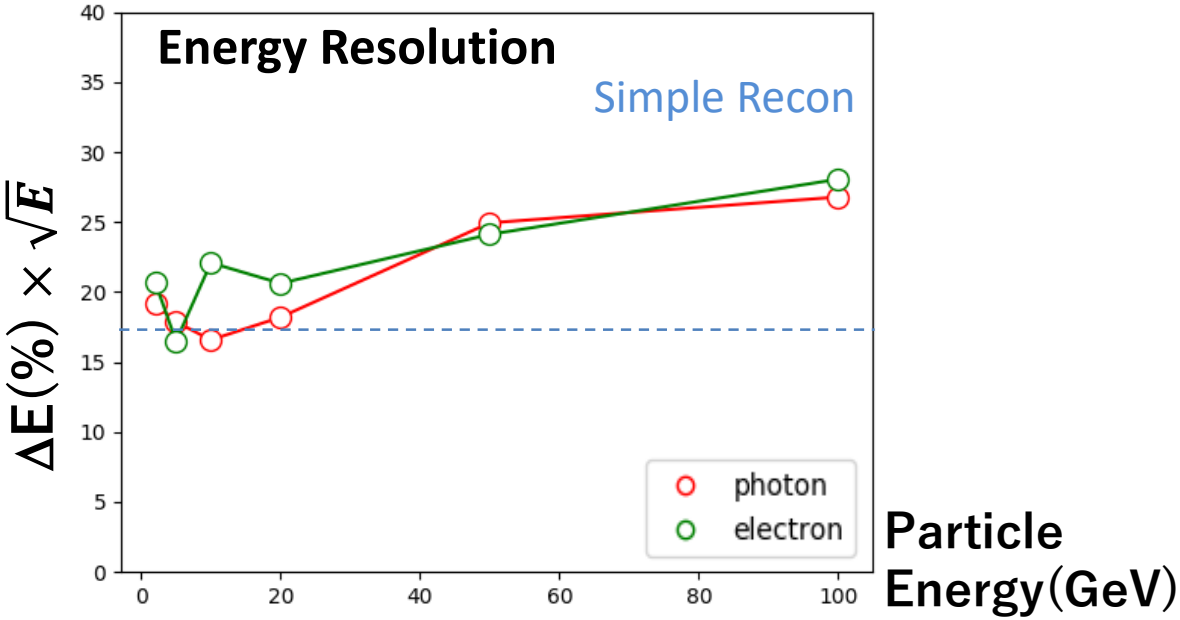
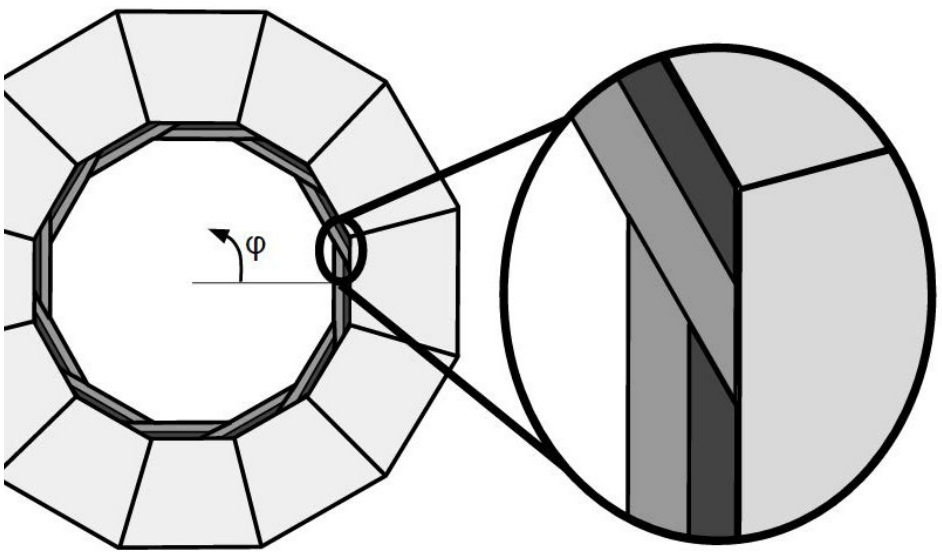


Energy Calibration of the Calorimeter

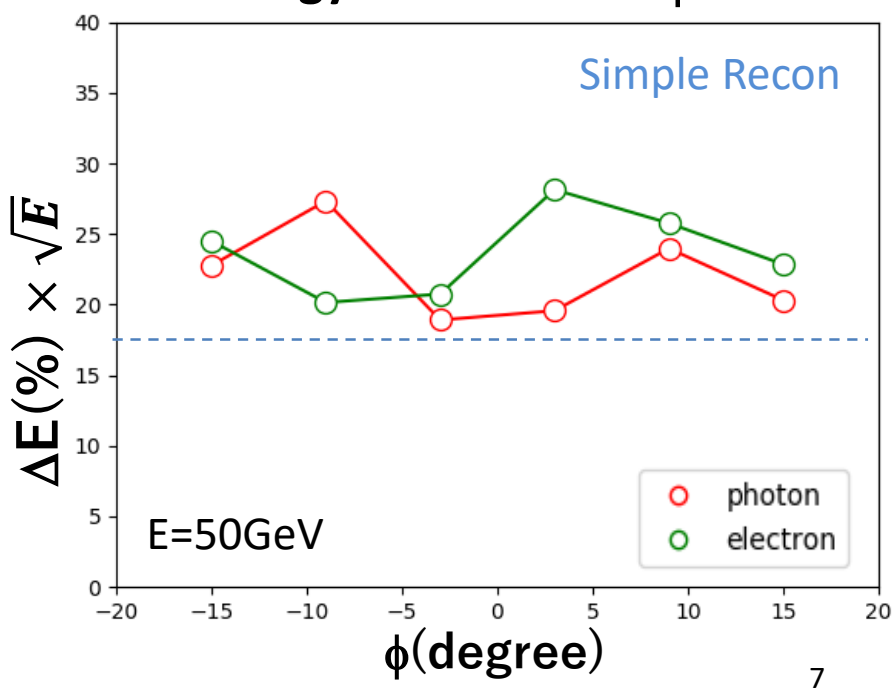
In this study, we try the SiD EM calorimeter (ECAL) energy calibration using <u>Deep Neural Network</u>

Several problems on the "Simple Recon" energy calibration

3. <u>Angular dependence</u> due to the detector geometry



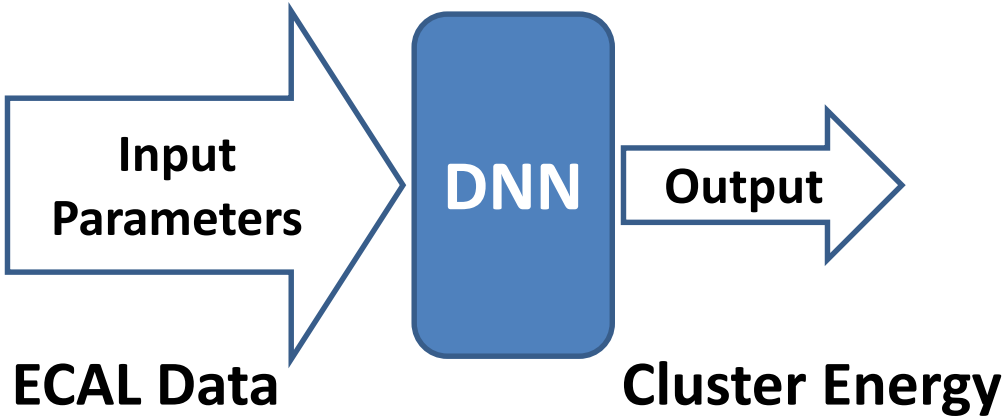
Energy Resolution in ϕ-bin



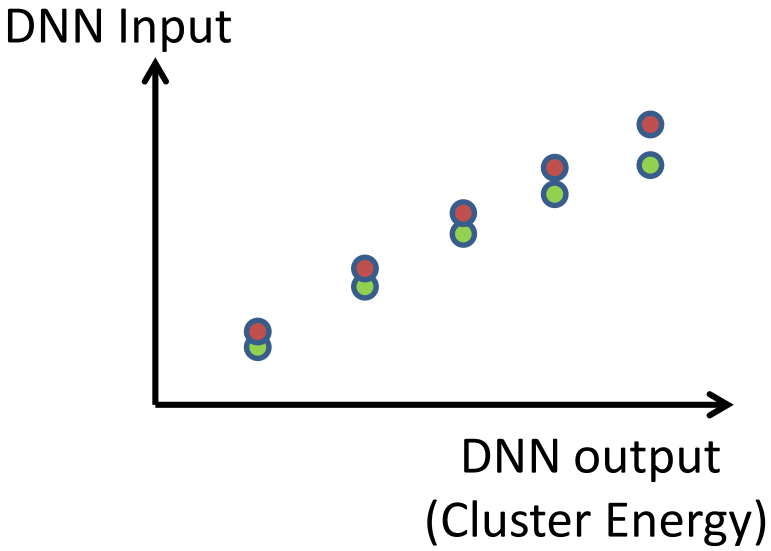
Energy Calibration using DNN

Neural Network can express the non-linear response

We use DNN regression <u>to obtain the cluster energy</u>

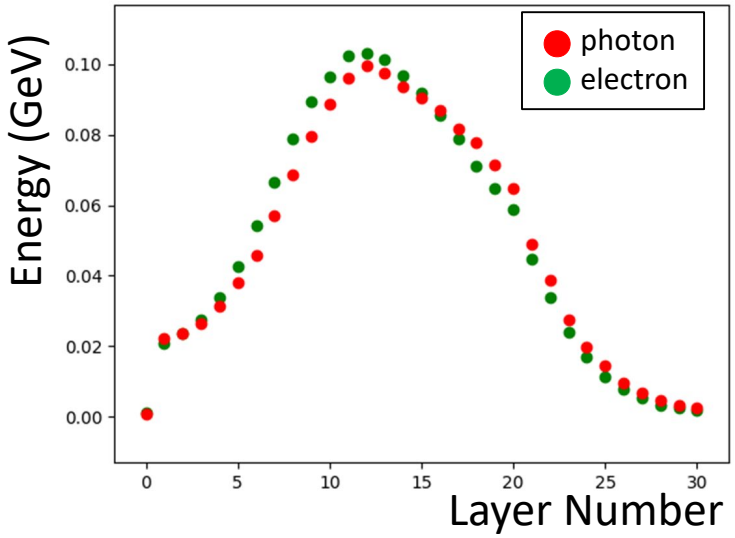


Sum of E hit,
r, ϕ, ...

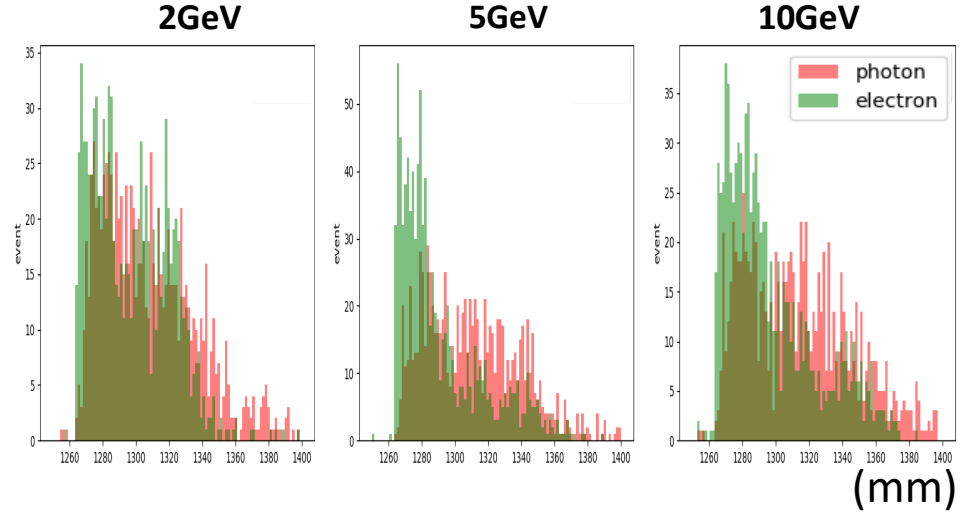


Input parameters for DNN

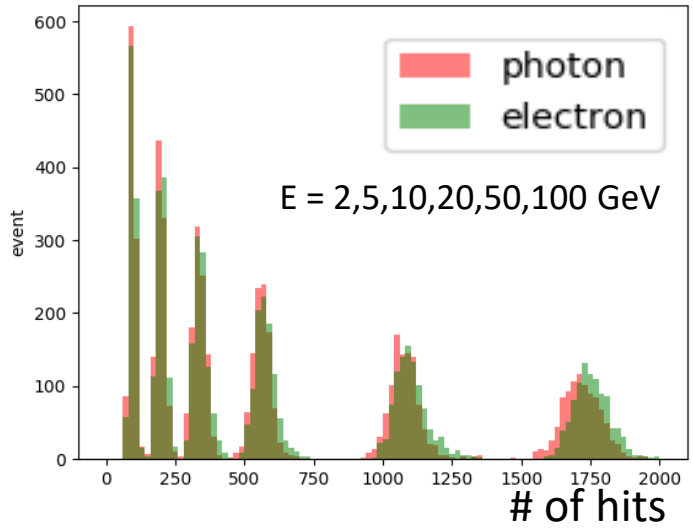
Energy sum in a layer



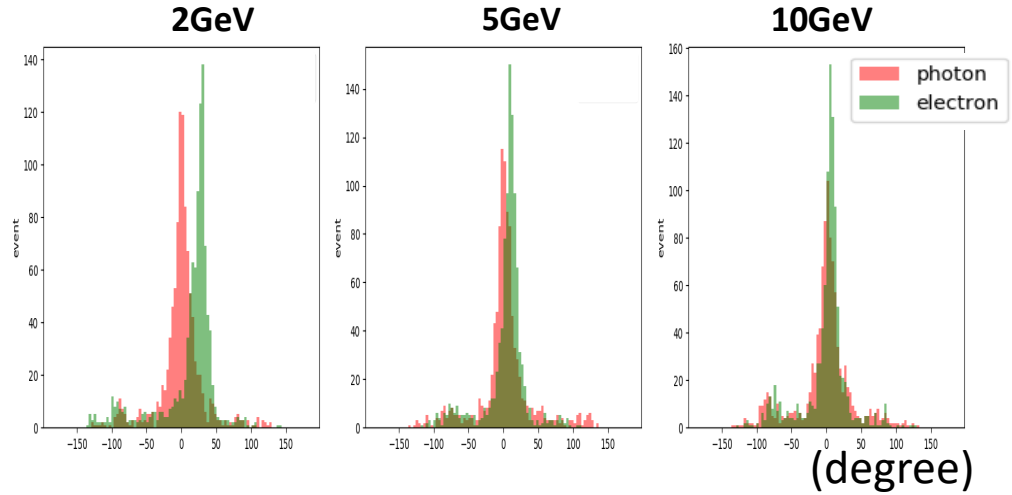
Distance btw IP and 1st hit



of hits in a cluster



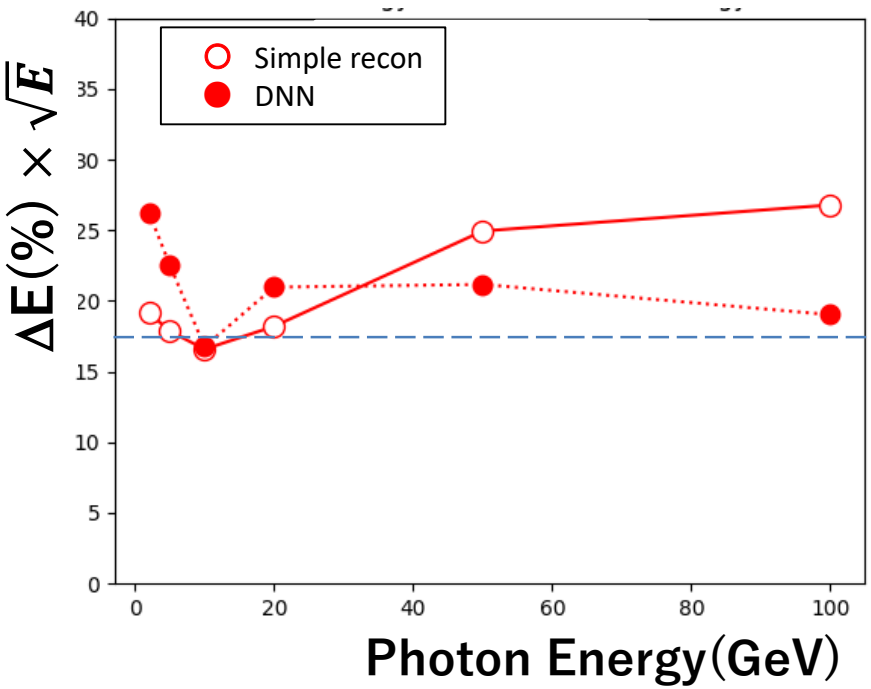
Δϕ btw 1st and last hit



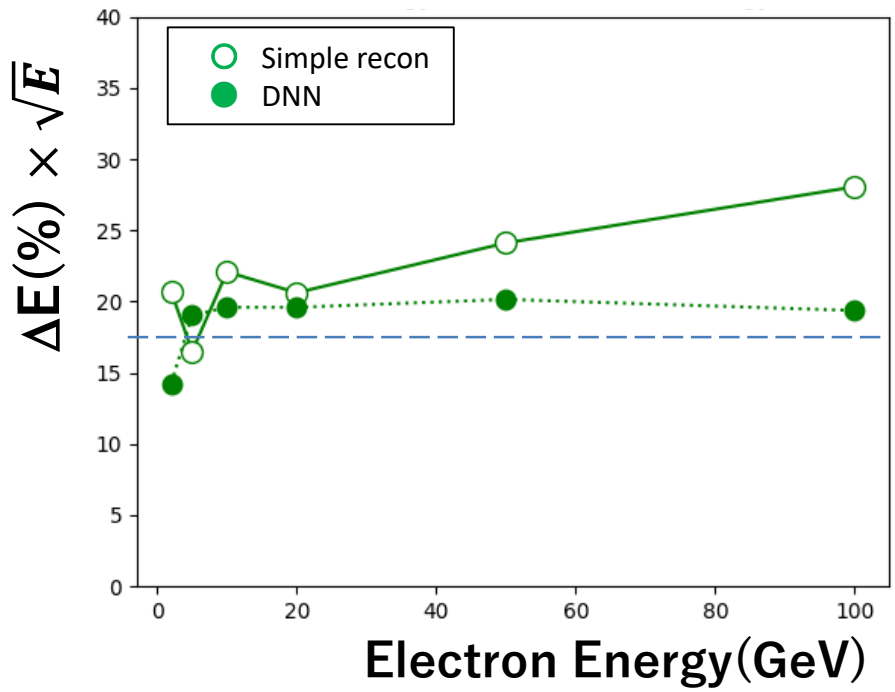
Results : Energy calibration with DNN

Preliminary

Photon Energy Resolution $\Delta E(\%) \times \sqrt{E}$



Electron Energy Resolution $\Delta E(\%) \times \sqrt{E}$

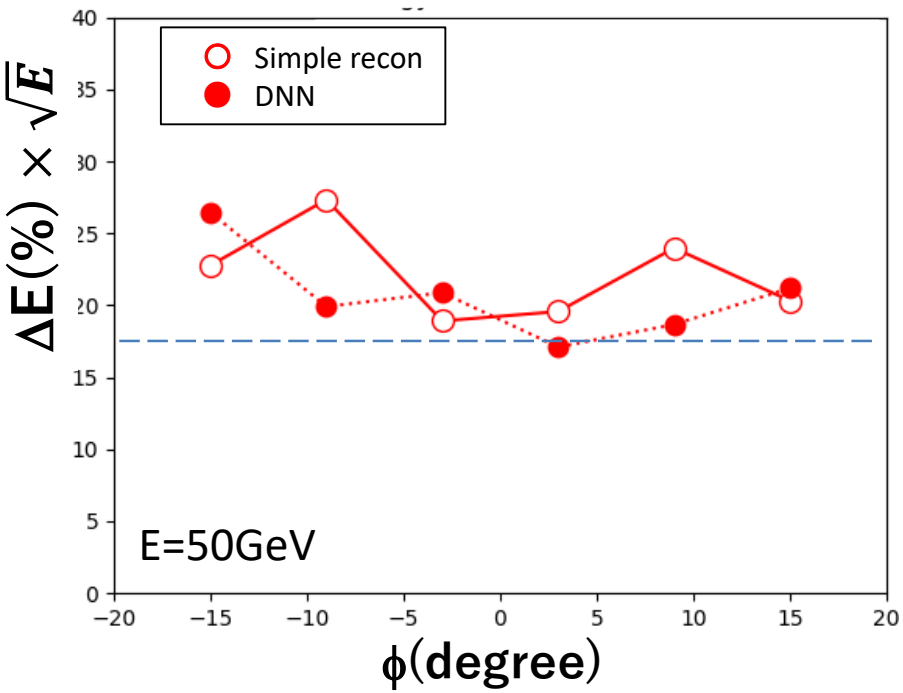


Using DNN, we get better resolution for both photon and electron in wide energy region

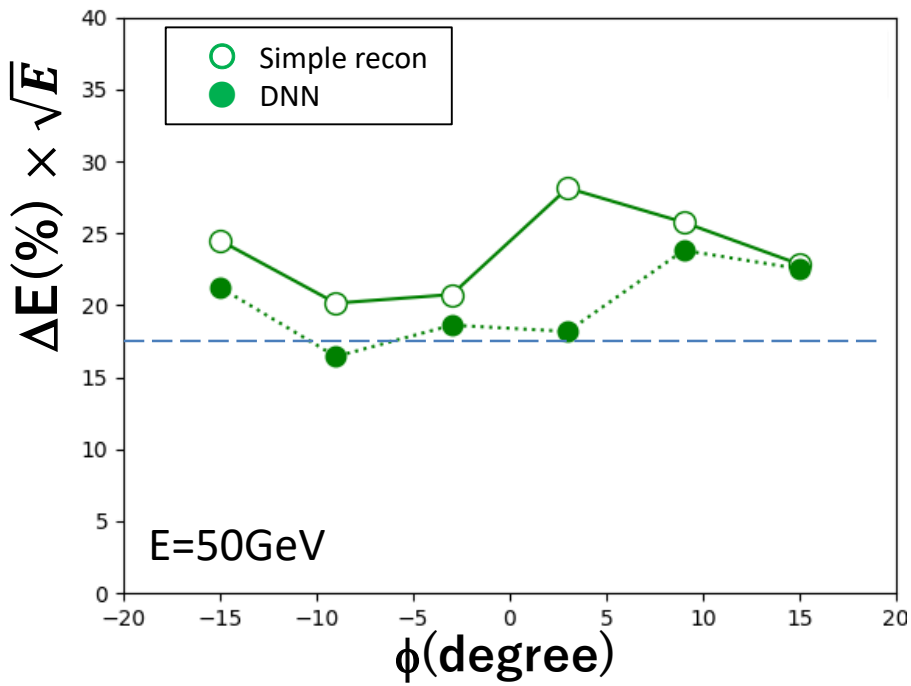
Results : Energy calibration with DNN

Preliminary

Photon Energy Resolution in ϕ-bin



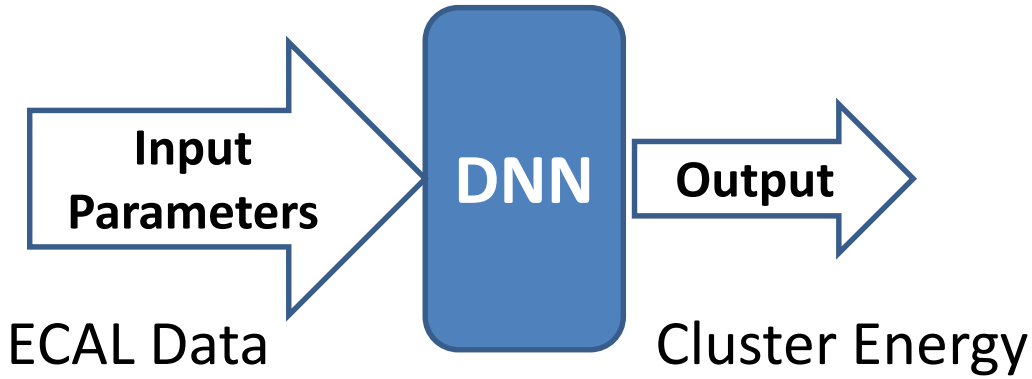
Electron Energy Resolution in ϕ-bin



Using DNN, we get better resolution for both photon and electron

There still exist angular dependence

What kind of data do we input?



There are several reports that **Low-level feature data** (pre-processing data) provides better DNN performance than **High-level feature data** (physics-inspired engineered)

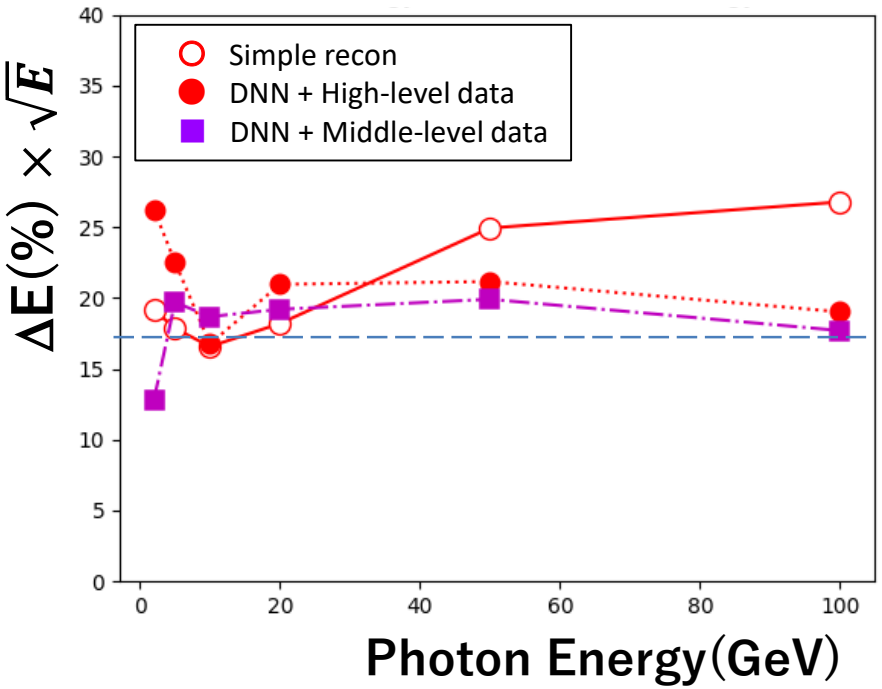
Low-level data	**Hit data** (position, Energy)
Middle-level data	**Layer data** (CM position, Sum of E hit in layer)
High-level data	**Cluster data** (CM position, Sum of E hit, …)

In this study, we also try <u>Middle-level data</u> for the DNN input

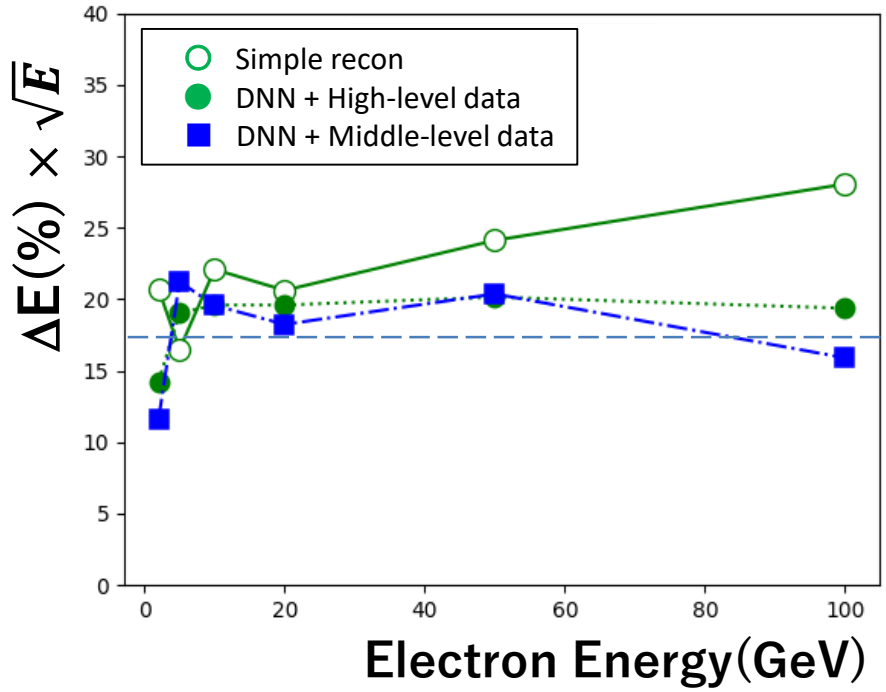
Results : E calib. with Middle-level data

Preliminary

Photon Energy Resolution $\Delta E(\%) \times \sqrt{E}$



Electron Energy Resolution $\Delta E(\%) \times \sqrt{E}$

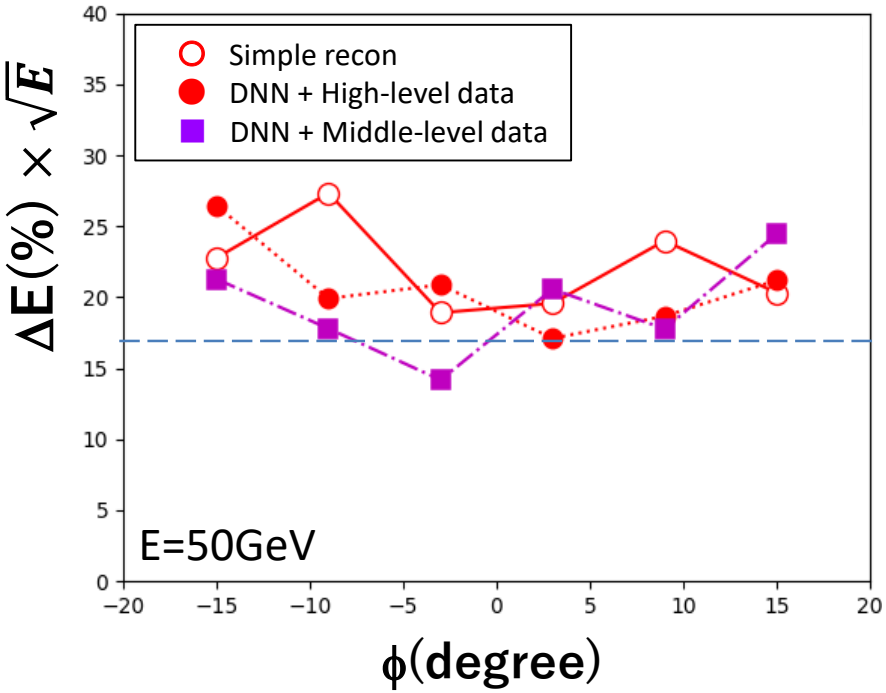


Using DNN + Middle-level data we get better resolution for both photon and electron

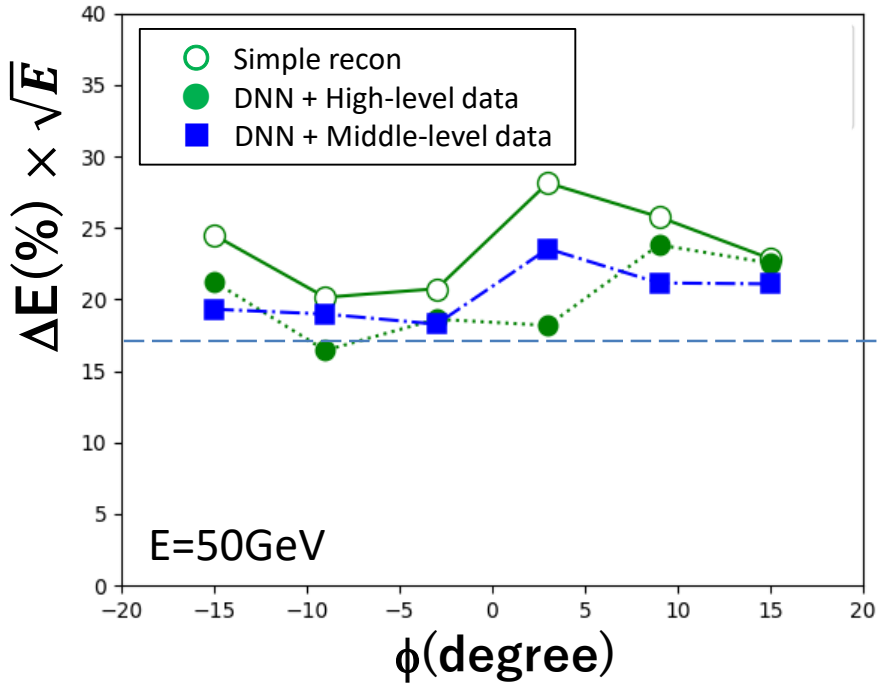
Results : E calib. with Middle-level data

Preliminary

Photon Energy Resolution in ϕ-bin

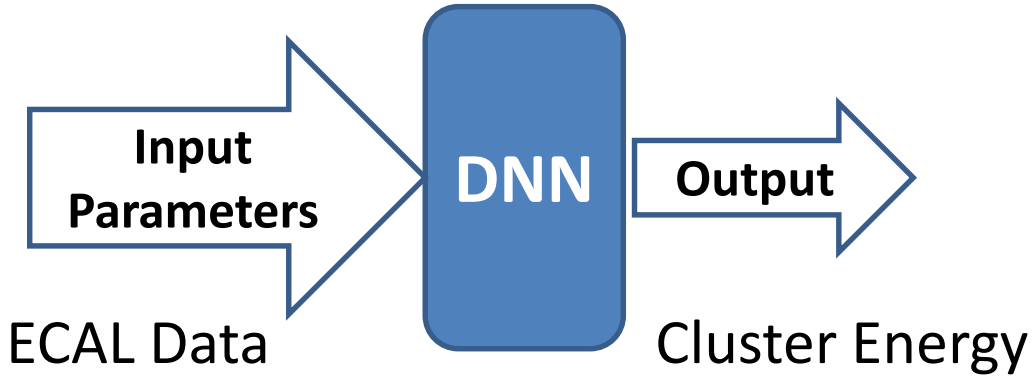


Electron Energy Resolution in ϕ-bin



- **E calibration with DNN + Middle-level data gives better Energy resolution for photon.**
- **Little difference btw Middle-level and High-level data for electron.**
- **There still exists angular dependence.**

Middle + High level data input



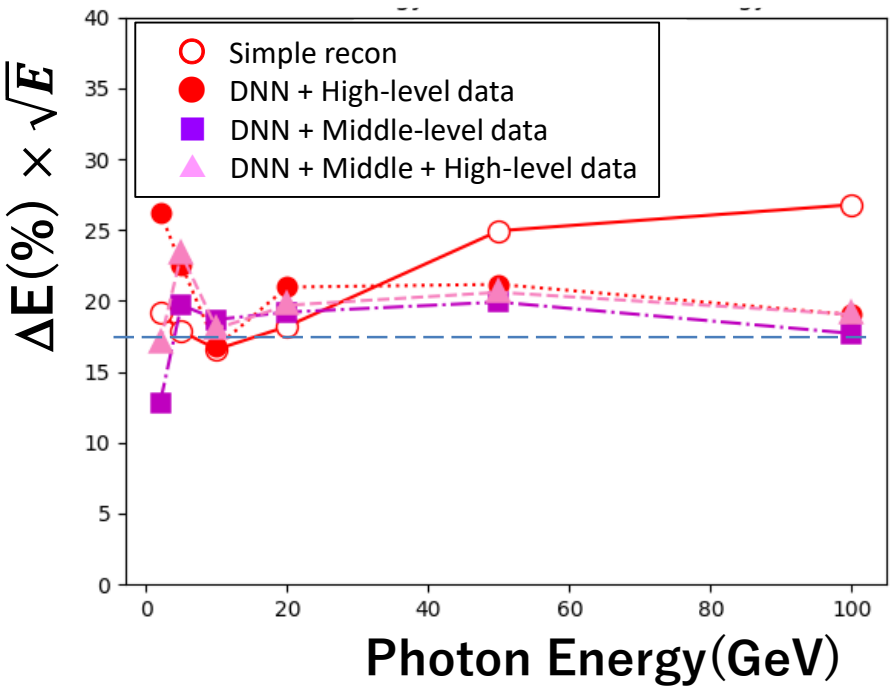
As Input parameters for DNN, we also try Middle-level + High-level data

Low-level data	**Hit data** (position, Energy)
Middle-level data	**Layer data** (CM position, Sum of E hit in layer)
High-level data	**Cluster data** (CM position, Sum of E hit, …)

E calib. with Middle + High level data

Preliminary

Photon Energy Resolution $\Delta E(\%) \times \sqrt{E}$



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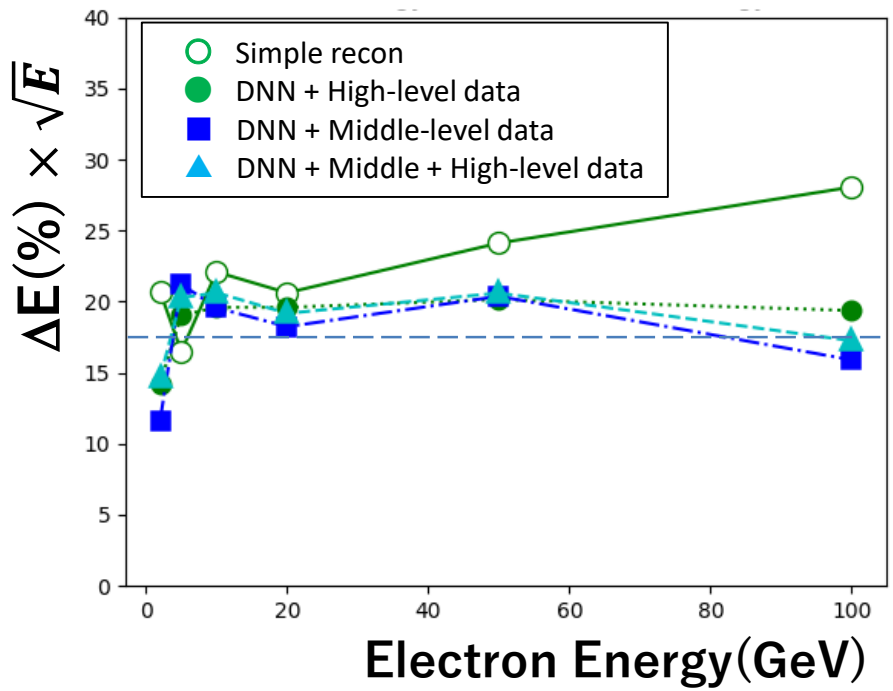
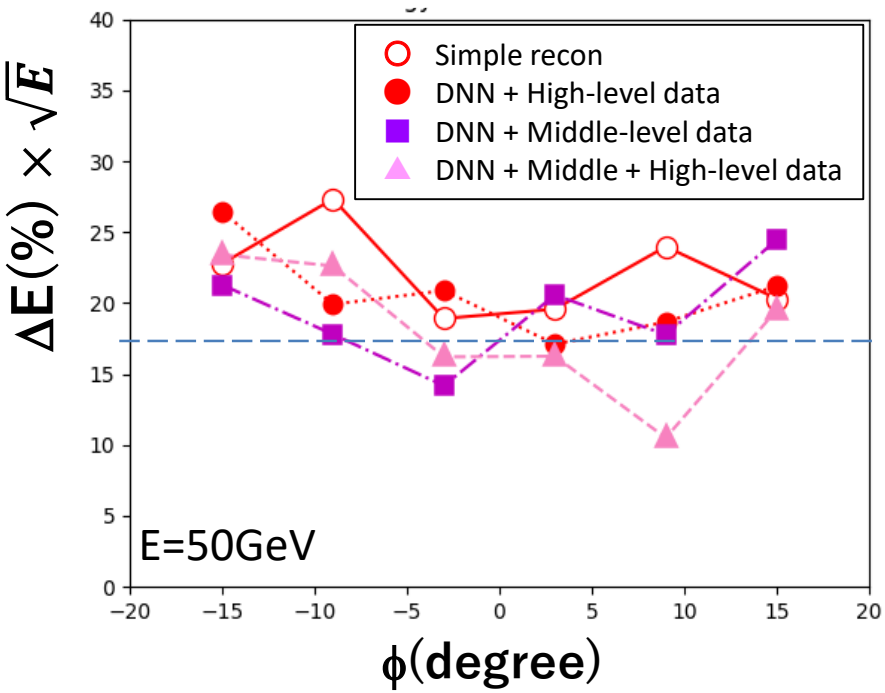


- We construct E calibration with DNN using both Middle and High-level data → Still under optimization

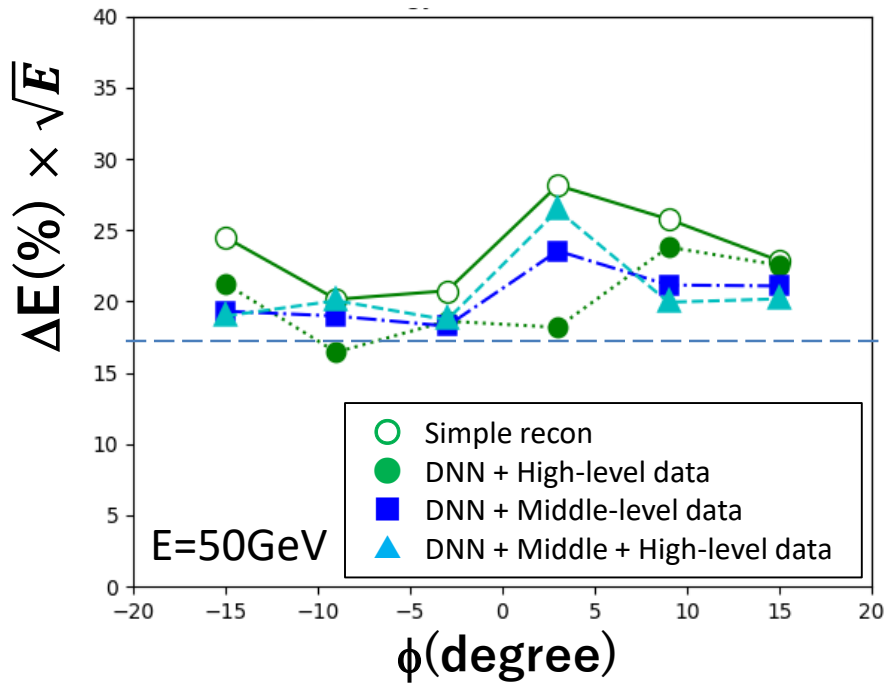
E calib. with Middle + High level data

Preliminary

Photon Energy Resolution in ϕ-bin



Electron Energy Resolution in ϕ-bin



- **We construct E calibration with DNN using both Middle and High-level data → Still under optimization**
- **We still have ϕ-dependence**

Further studies are on going

DNN optimization, DNN with low-level data??

Summary

We have developed the Energy Calibration using DNN for SiD ECAL

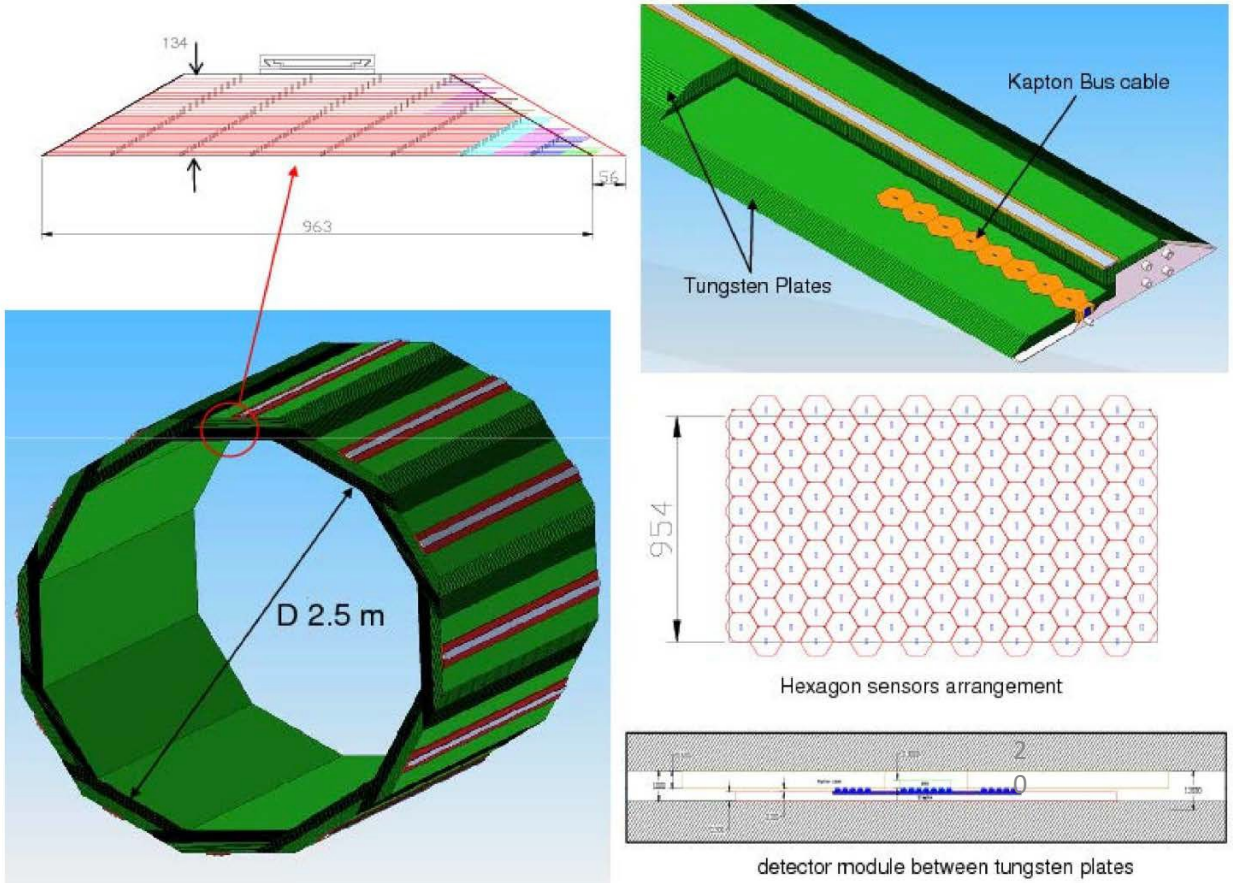
- We get **better Energy resolution using DNN**
- As input parameters for the DNN,
  we try High-level data, Middle-level data,
  and High + Middle-level data
  → **Middle-level data gives better performance**
- We still have angular-dependence

Further studies are on going

DNN optimization, DNN with low-level data

SiD ECAL

Figure II-4.1
Overall mechanical layout of the ECAL.



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[arXiv:1306.6329 [physics.ins-det]]

Figure II-4.2
Drawing of a silicon sensor for the ECAL. The sensors are segmented into 1024 13 mm^2 pixels.

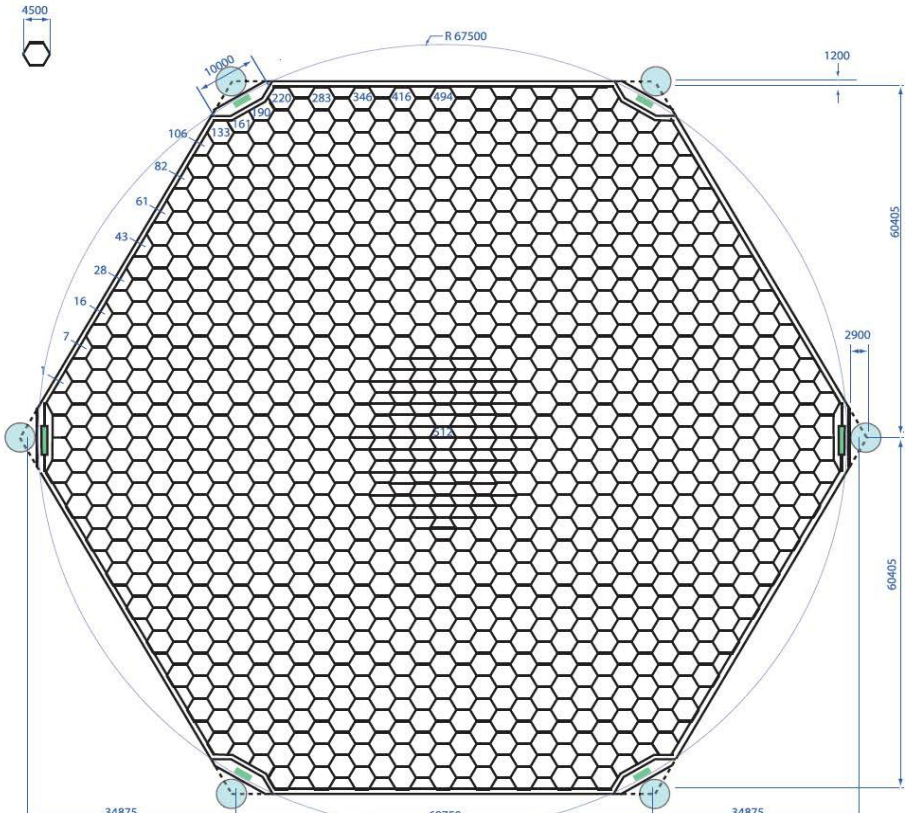

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Table II-4.2
Parameters of baseline silicon-tungsten ECAL and the MAPS option.

	Baseline	MAPS option
pixel size	13 mm^2	50× 50 μm
readout gap	1.25 mm (incl. 0.32 mm thick Si sensors)	similar
effective Molière radius	14 mm	14 mm
pixels per silicon sensor	1024	$1 \cdot 10^6$
channels per KPiX chip	1024	-
dynamic range	∼ 0.1 to 2500 MIPs	1 MIP
heat load	20 mW per sensor	20 mW per sensor

Sampling

Design based on sampling 30 times:
20 layers of 0.64 X_0
followed by 10 layers of 1.30 X_o

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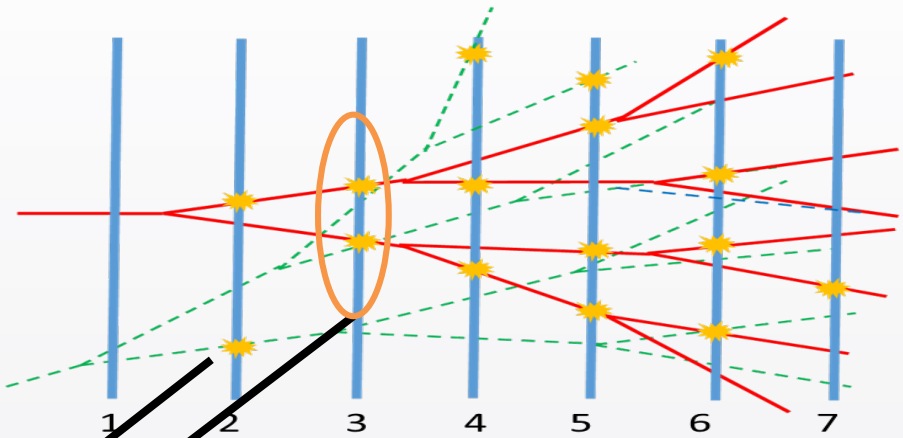
inner radius of ECAL barrel	1.27 m
maximum z of barrel	1.76 m
longitudinal profile	20 layers $\times$ 0.64 X_0
	10 layers $\times$ 1.30 X_0
EM energy resolution	$0.17/\sqrt{E} \oplus 1\%$
readout gap	1.25 mm (or less)
effective Molière radius ($\mathcal{R}$)	14 mm

Table II-4.1
Nominal parameters of the silicon-tungsten ECAL for SiD.

1024 channels read out by single KPiX chip

NN with Middle-level data



Low-level data	Hit data (x, y, z, Energy, layer)
Middle-level data	Layer data (CM x,y,z, Energy sum for a layer)
High-level data	Cluster data（CM r,ϕ, Energy sum, .. for a cluster）

For more precise energy calibration, we try energy calibration using NN with Middle-level data

ECAL calibration with NN :Parameters

Keras + TensorFlow

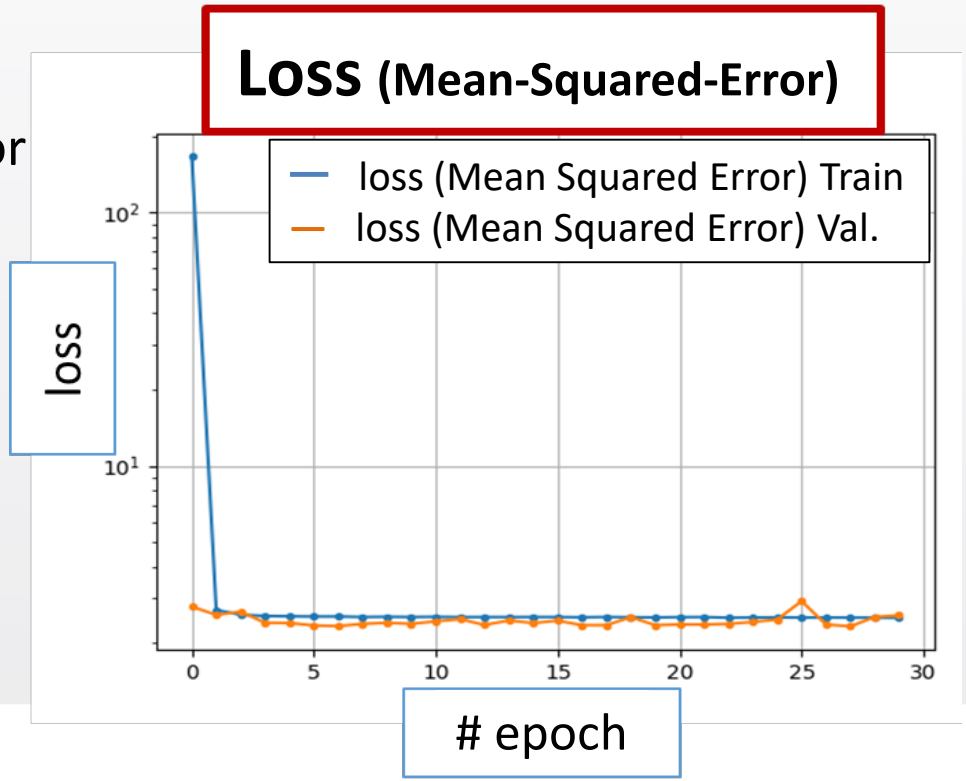
Input	High-level data	Middle-level data	High + Middle
Activation	Relu		
Optimization	Adam		
Loss	Mean Squared Error		
# hidden layers	3	3	4
#epoch	30	30	30
Training	400,000	300,000	300,000
Test	100,000	100,000	100,000
Validation	100,000	100,000	100,000

Training results for NN

High-level data (Cluster data)

Keras+TensorFlow

Input params.	: Sum of E_hit in a cluster, CM r, ϕ for cluster, … 7 params
Activation	: Relu
Optimization	: Adam
Loss	: Mean Squared Error
# of hidden layers	: 3 layers
# of Epoch	: 30
Training data	: 400,000 events
Test data	: 100,000 events
Val. data	: 100,000 events



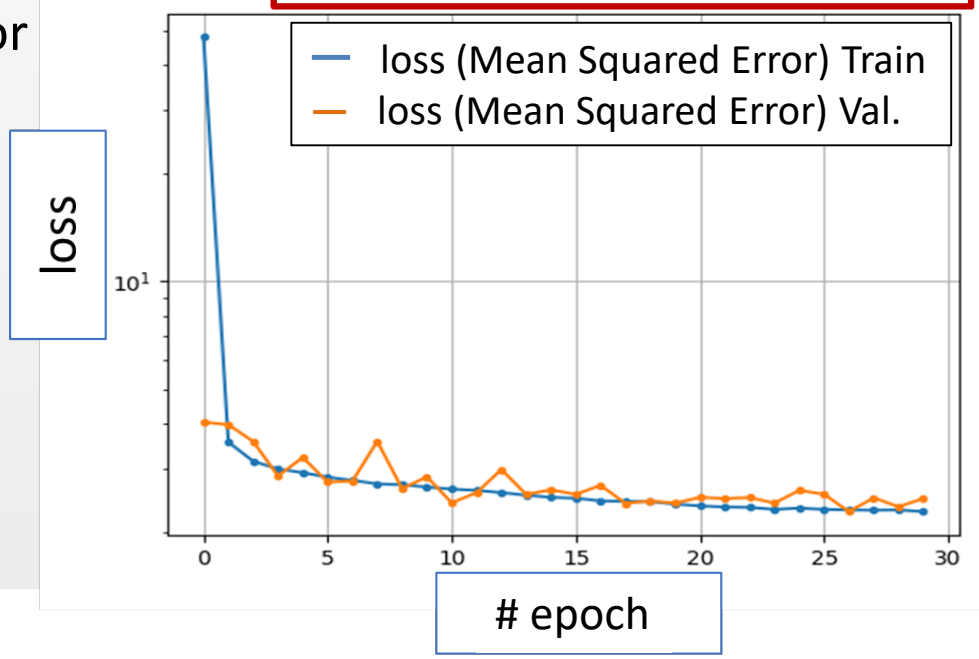
Training results for NN

Middle-level data (Layer data)

Keras+TensorFlow

Input params.	: Sum of E_hit in a layer, CM x,y,z for layer
Activation	: Relu
Optimization	: Adam
Loss	: Mean Squared Error
# of hidden layers	: 3 layers
# of Epoch	: 30
Training data	: 300,000 events
Test data	: 100,000 events
Val. data	: 100,000 events

Loss (Mean-Squared-Error)



Training results for NN

High-level + Middle-level data

Keras+TensorFlow

Input params.	: High-level + Middle-level data
Activation	: Relu
Optimization	: Adam
Loss	: Mean Squared Error
# of hidden layers	: 4 layers
# of Epoch	: 30
Training data	: 300,000 events
Test data	: 100,000 events
Val. data	: 100,000 events

Loss (Mean-Squared-Error)