Beam Test Analysis of 1st Prototype of ZDC ECal ePIC-ZDC@20240613

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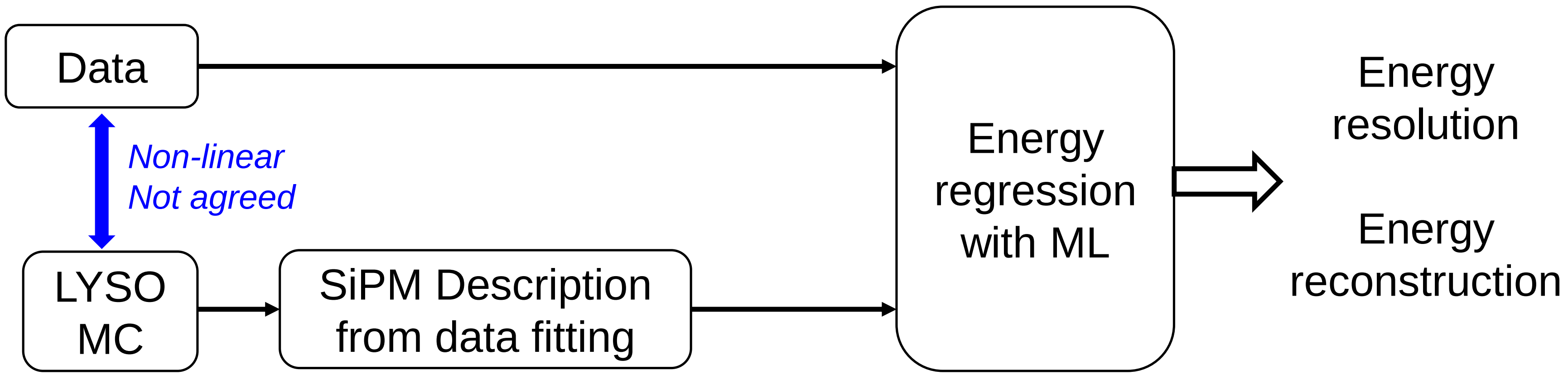
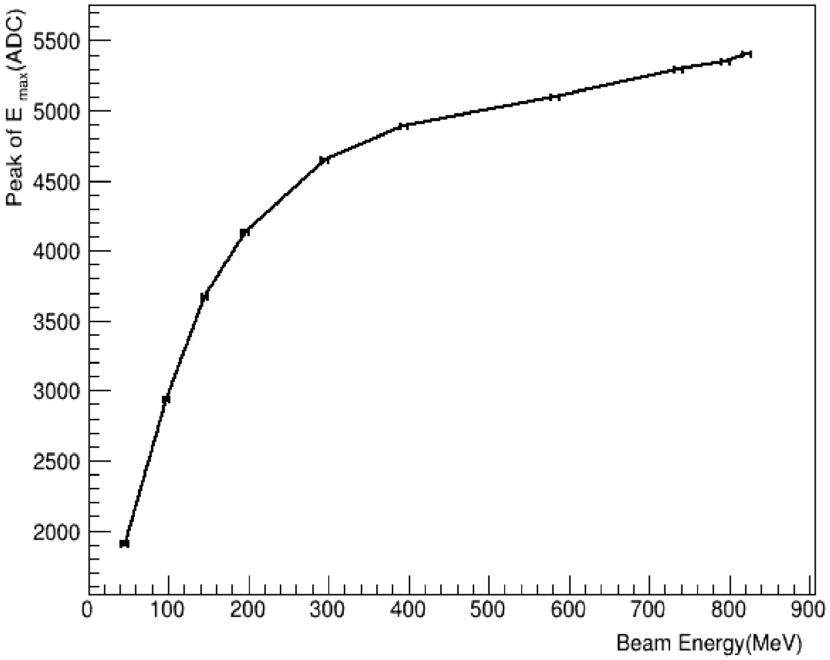
Outline

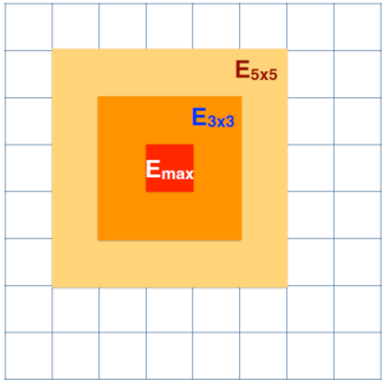
- Non-linear response of ZDC ECal
- Standalone MC of ZDC ECal with only LYSO crystal (Backup)
- Description of SiPM behavior through data fitting
- Preparation of Energy regression



Non-linear response of ZDC ECal

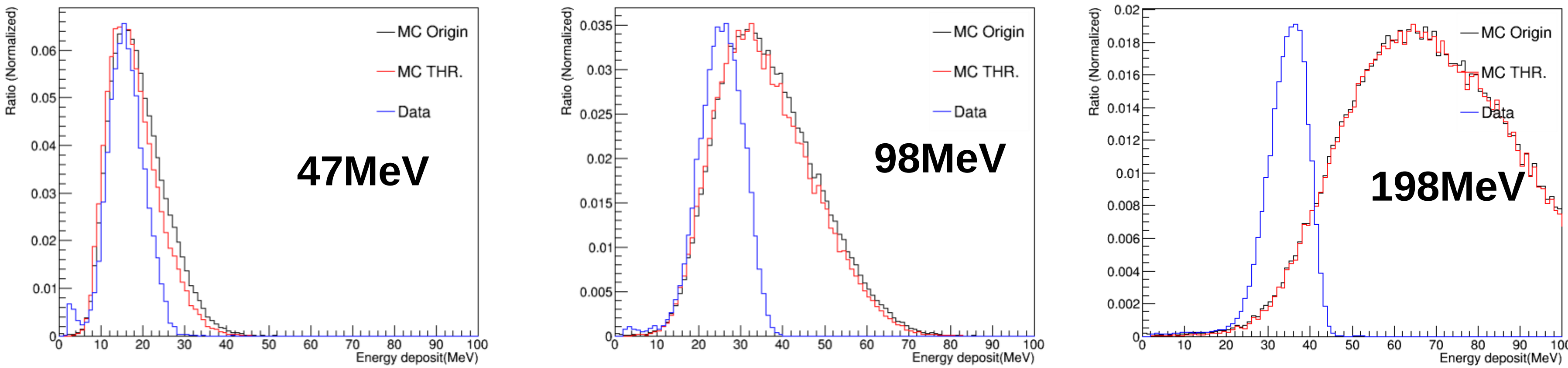
Reminder : Beam Test of 1st Prototype ZDC ECal





- We performed beam test w/ 1st prototype at ELPH on Feb, 2024.
- Nonlinearity between beam and measured energy is observed.

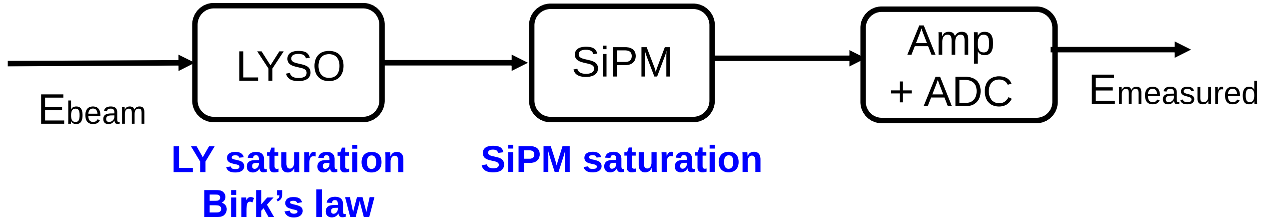
Reminder : Compare Data VS MC with Emax



- There is more energy deposit in MC simulation. Disagreement gets worse towards to higher beam energy.
- Case of energy saturation :

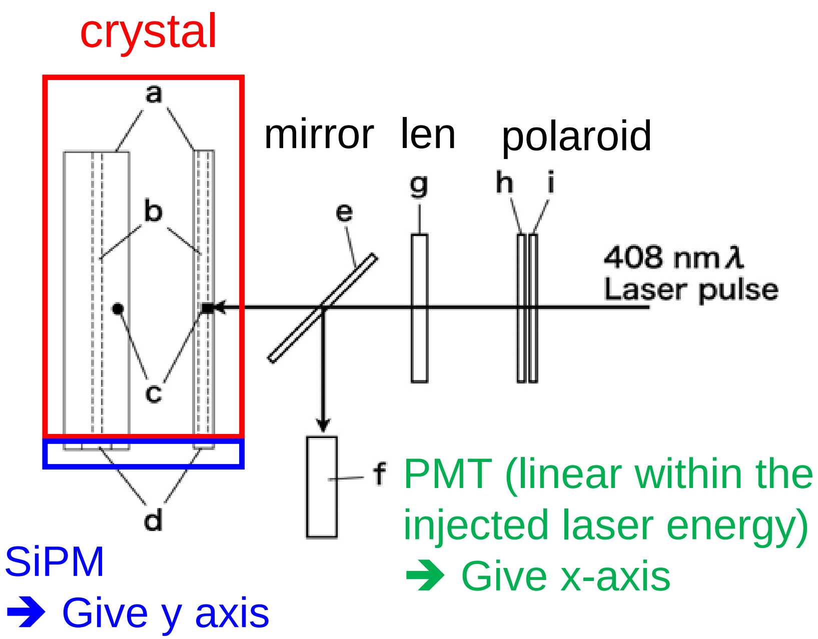
(1) Gain of SiPM is too large and easily get saturated. <= main reason

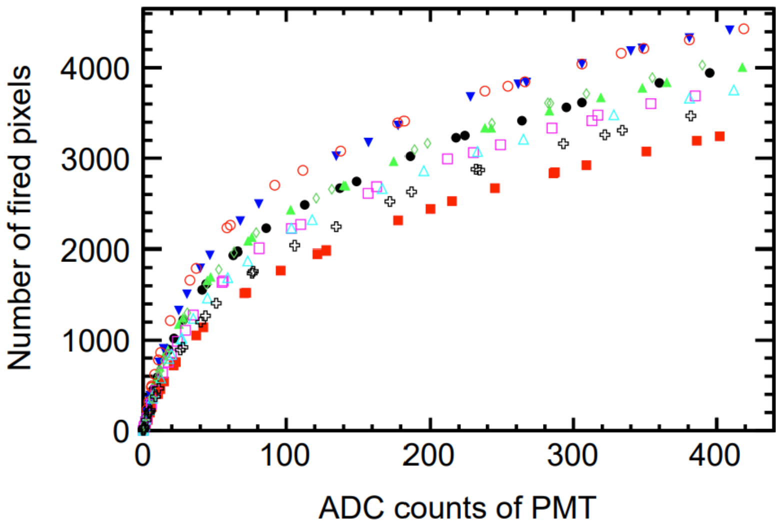
(2) Light yield is saturated in crystal, called Birk’s law.



Description of SiPM Behavior

Description of SiPM Behavior



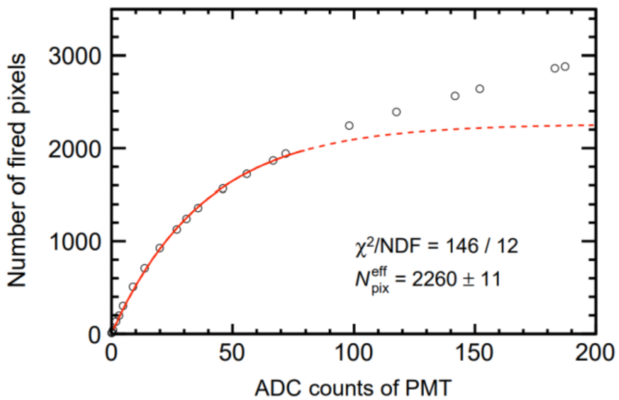


https://arxiv.org/abs/1510.01102

This paper measures and provide an equation to describe the SiPM behavior.

Description of SiPM Behavior

LO ➔ ϵ

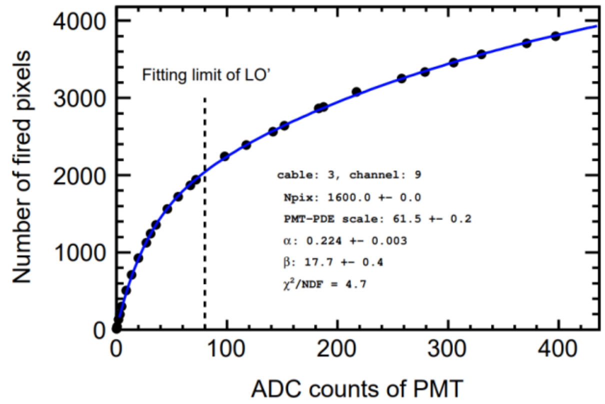


$$N_{fire}^{LO} = N_{pix}\left[1 - \exp\left(-\frac{\epsilon N_{in}}{N_{pix}}\right)\right]$$

- N_{fire}^{LO} = Num of fired pixcel of SiPM
- $\mathrm{N_{pix}}$ = Num of pixcel of SiPM
- $\epsilon = photon\ detection\ efficiency\ of\ SiPM$

There are three different levels one could describe SiPM behavior. All of them can be acess through the fit of measurement.

NLO’ ➔ α, β



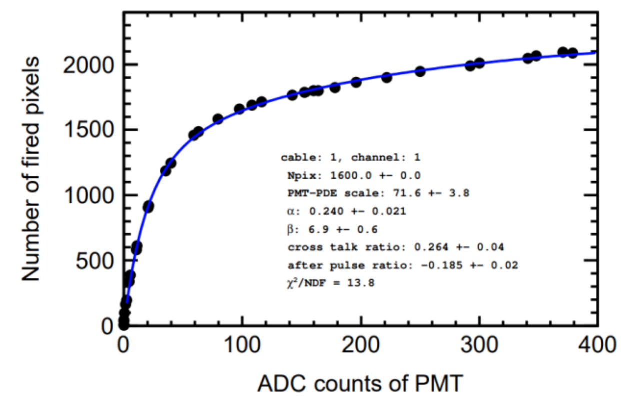
$$N_{\mathrm{R}} = \epsilon N_{\mathrm{in}} - N_{\mathrm{fire}}^{\mathrm{LO}}$$

$$N_{\mathrm{fire}}^{\mathrm{NLO}} = N_{\mathrm{fire}}^{\mathrm{LO}} + \alpha N_{\mathrm{R}}$$

$$N_{\mathrm{fire}}^{\mathrm{NLO}'} = N_{\mathrm{fire}}^{\mathrm{NLO}}\frac{\beta + 1}{\beta + \epsilon N_{\mathrm{in}}/\mathrm{LO}}.$$

- $\boldsymbol{\alpha}$ = the average charge contribution of remaining photon.
- $\boldsymbol{\beta}$ = the charge contribution of remaining photon and it **decreases as the number of photons on a pixel increases.**

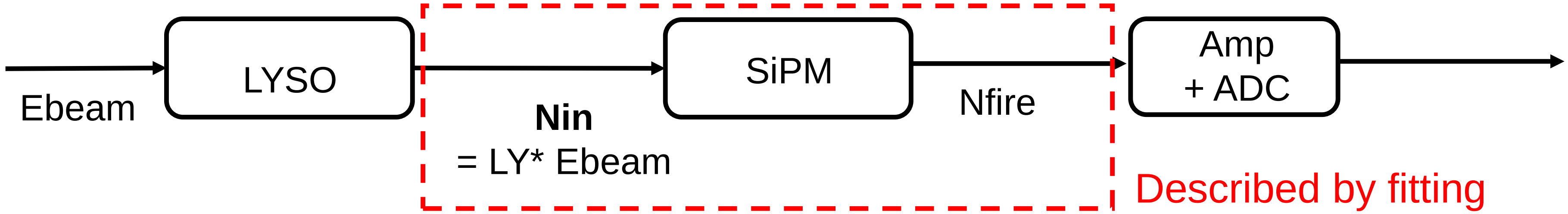
NLO’(C.A) ➔ Pcross, Pafter

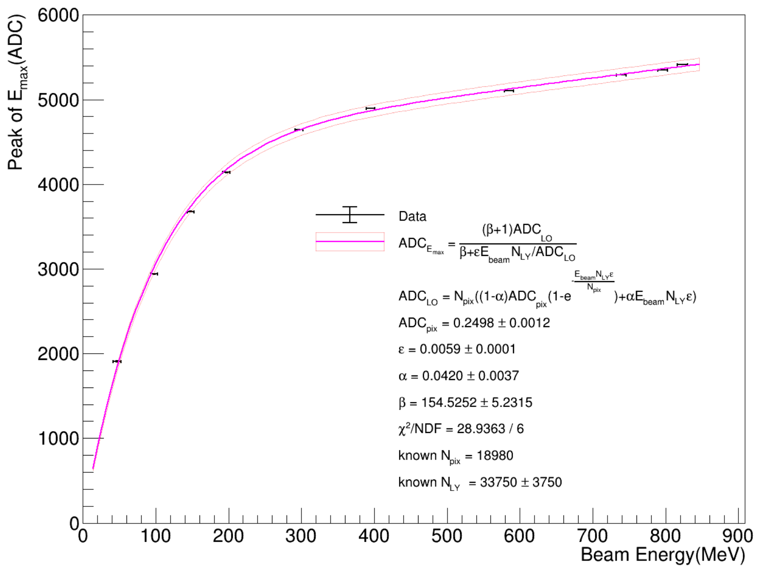


$$N_{\mathrm{fire}}^{\mathrm{NLO}'_{\mathrm{C\cdot A}}} = N_{\mathrm{fire}}^{\mathrm{NLO}'}\left(1 + P_{\mathrm{cross}} \cdot \mathrm{e}^{-\epsilon N_{\mathrm{in}}/N_{\mathrm{pix}}}\right) \cdot (1 + P_{\mathrm{after}})$$

- **Pcross = crosstalk**, induces a second avalanche in a neighboring pixel.
- **Pafter = after pulse** occurs when a second avalanche is seeded by the release of an electron trapped in a lattice defect of the depletion zone, or a hole defuses toward the depleted layer and, consequently, induces a second avalanche. The hole is created by a photon in the same mechanism as the crosstalk, and this diffusion delays the after pulses because the electric field of the bulk is weak.

Fit Data to Extract the Parameters of SiPM Behavior





$$ADC_{Emax} = \frac{(\beta + 1)ADC_{LO}}{\beta + \varepsilon N_{in}/ADC_{LO}}$$

$$ADC_{LO} = N_{pix}[(1-\alpha)ADC_{pix}(1 - exp\left(\frac{\varepsilon N_{in}}{N_{pix}}\right) + \alpha\varepsilon N_{in}]$$

$ADC_{pix} = 0.2498 \pm 0.0012$

$\varepsilon = 0.0059 \pm 0.0001$ Photon detection efficiency of SiPM

$\alpha = 0.0420 \pm 0.0038$ average charge contribution of remaining photons

$\beta = 154.5352 \pm 5.2206$ charge contributiondecrease as the increase of Nphoton

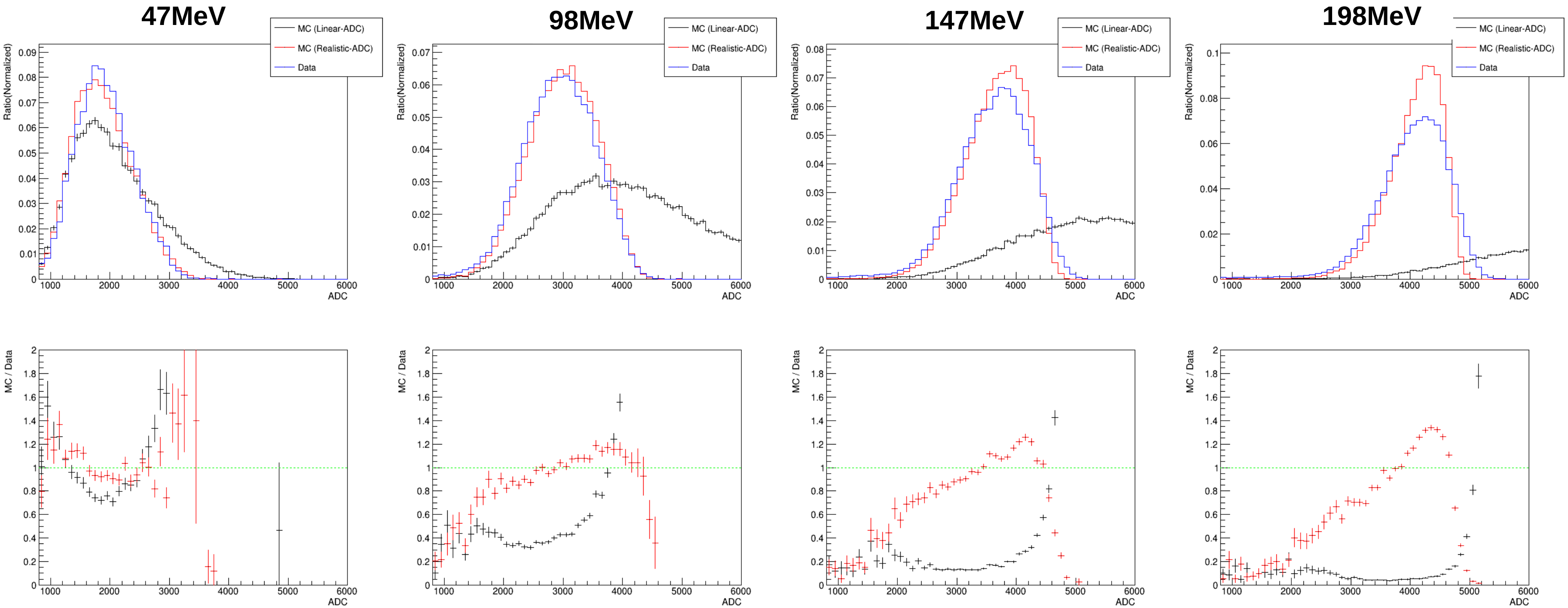
$\chi^2/NDF = 28.9377 / 6$

known $N_{pix} = 18980$ Num. pixel of SiPM (fix)

known $N_{LY} = 33750 \pm 3750$ Light yield of SiPM (fix)

- We apply the fitting function provided by the paper to extract the parameters for SiPM behavior.
- SiPM behavior could be later apply to MC in order to achieve better data and MC comparison.

Data and MC Comparison after applying SiPM Behavior Curve to MC



- Data
- LYSO MC
- LYSO MC * SiPM curve

- After applying SiPM curve, the consistency between data and MC is much improved.
- However, the consistency is worse in higher energy beam.
- Problem could come from LYSO simulation, we will are still tuning LYSO MC.

Energy Regression

Energy Regression Calibration with Machine Learning Method

- **Purpose of energy regression : Energy deposited in the calorimeter may not always be directly proportional to the energy of the incident particle** due **leakage**, noise, etc. By accurately estimating the particle energy, energy regression **improves the energy resolution and energy reconstruction.**

- **Machine learning techniques** can be used as a method to perform the energy regression.

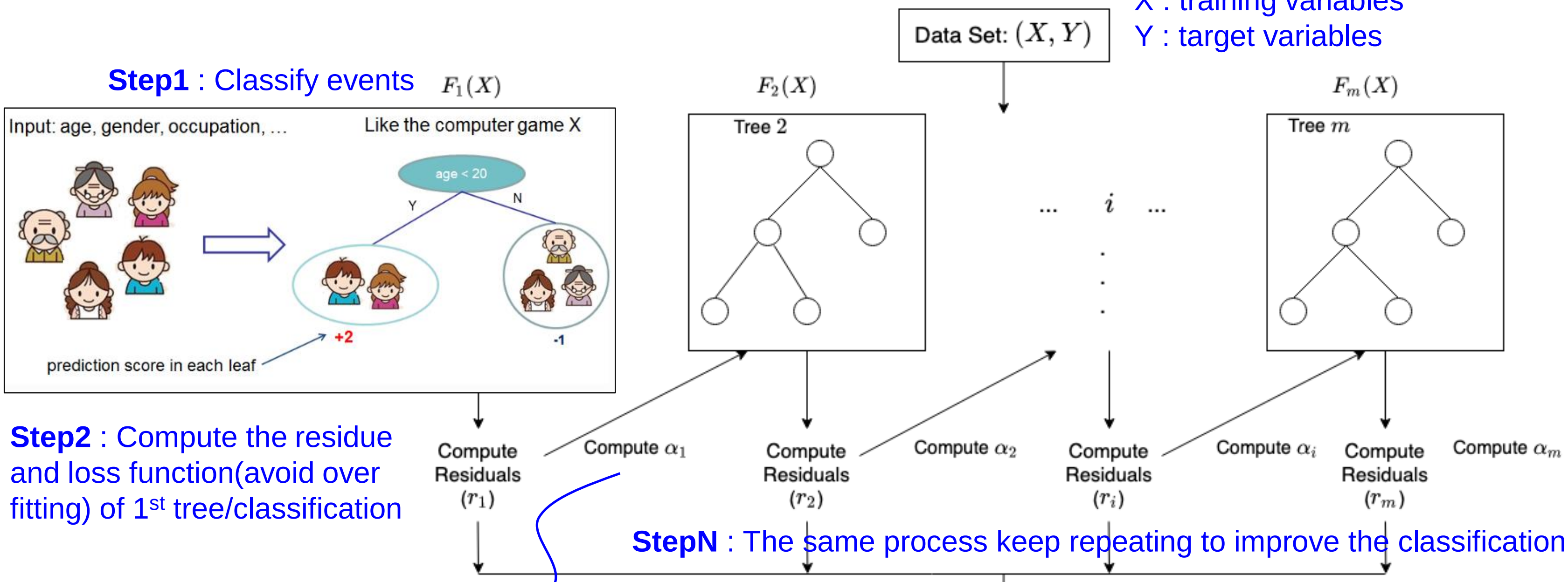
(1) Collect large MC sample and **select training parameters (Emax, E3x3, E5x5)**
target parameters (ratio of Ebeam/E5x5).
(1) Model training with large MC sample.
(2) Validate trained model with separated MC sample.
(3) Apply the trained MC to data.

Attention : One have to make sure **MC and data are agreed at certain level. We are still working on it!**

XGBoost (Extreme Gradient Boosting)

Step0 : Data set
X : training variables
Y : target variables

Step1 : Classify events



Step2 : Compute the residue and loss function(avoid over fitting) of 1st tree/classification

StepN : The same process keep repeating to improve the classification.

Step3 : The 1st tree is usually not the best classification. The 2nd tree/classification add a parameter obtained from the 1st tree, $\alpha 1$, to improve the classification.

$$F_m(X) = F_{m-1}(X) + \alpha_m h_m(X, r_{m-1}),$$

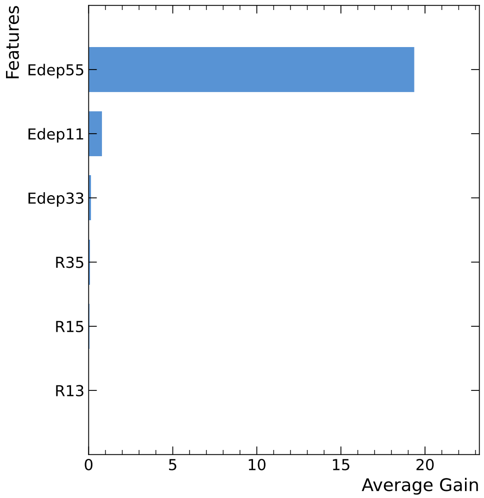
where α_i, and r_i are the regularization parameters and residuals computed with the i^{th} tree respectfully, and h_i is a function that is trained to predict residuals, r_i using X for the i^{th} tree. To compute α_i we use the residuals computed, r_i and compute the following: $arg \min_{\alpha} = \sum_{i=1}^{m} L(Y_i, F_{i-1}(X_i) + \alpha h_i(X_i, r_{i-1}))$ where $L(Y, F(X))$ is a differentiable loss function.

➔ **Final output :**
The predictions of all trees/classifications are combined to produce the final output.

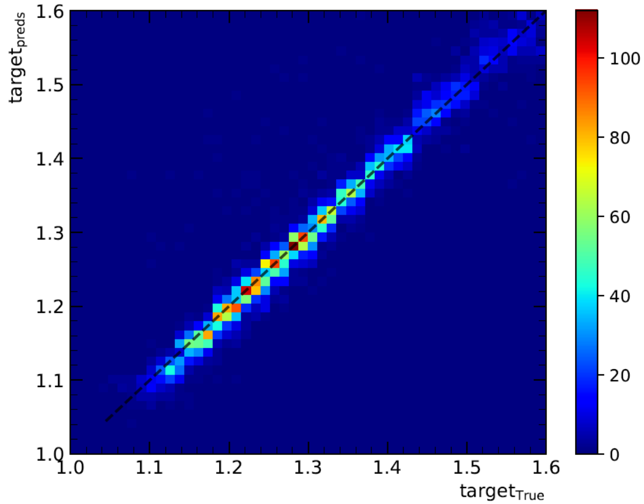
Reference : https://xgboost.readthedocs.io/en/stable/tutorials/model.html
https://docs.aws.amazon.com/zh_tw/sagemaker/latest/dg/xgboost-HowItWorks.html

Validate ML Model

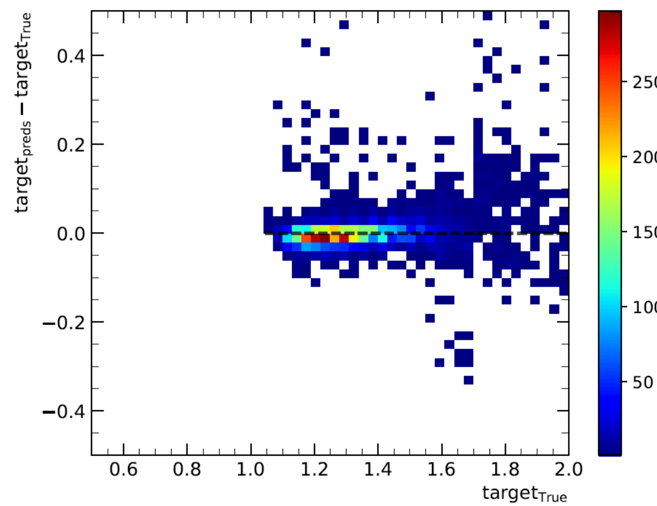
Importance of train variables, X



Target = Ebeam/E5x5
True VS predicted



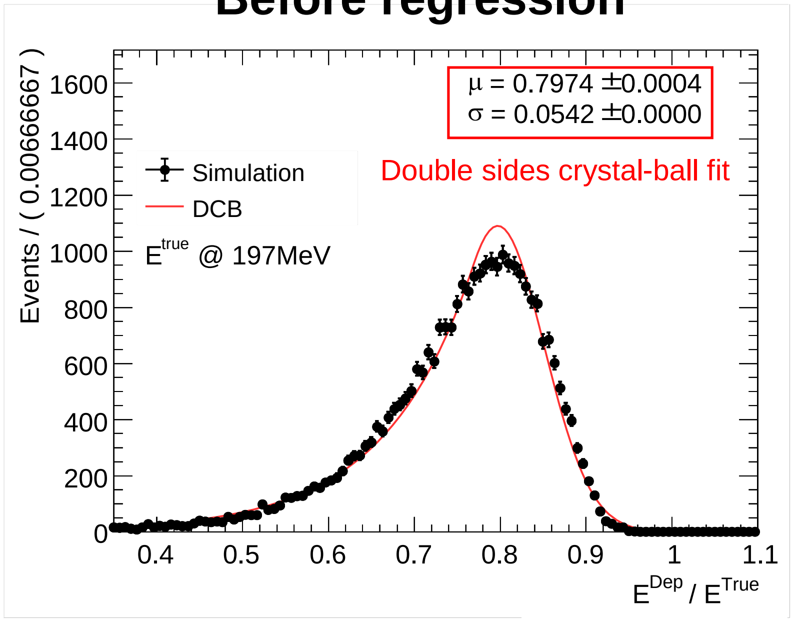
Target = Ebeam/E5x5
uncertainty



- Among all the training variables, E5x5 is the most important one.
- The training output shows reasonable prediction of target variable, Ebeam/E5x5, with less than 5% uncertainty.

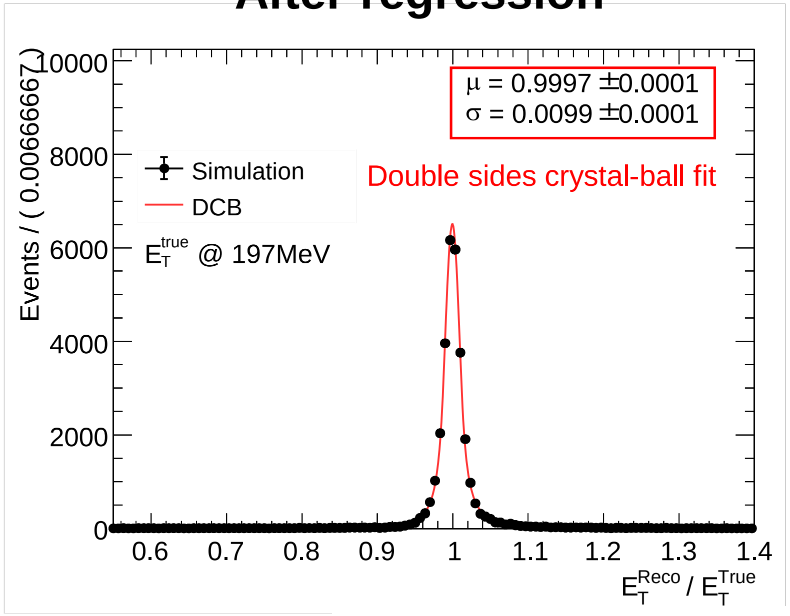
Impact of Energy Regression

Before regression



(E_{5x5}/E_{beam})

After regression

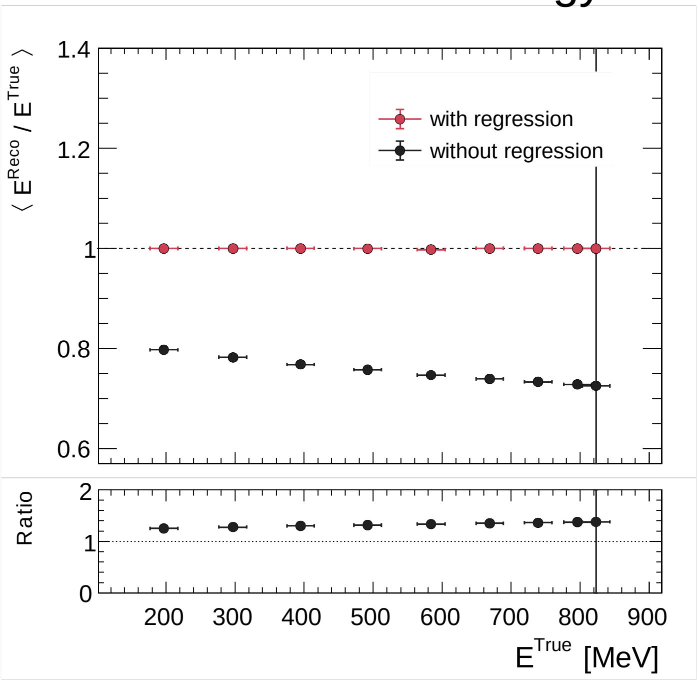


(E_{beam} : $E_{predicted}/E_{true}$)

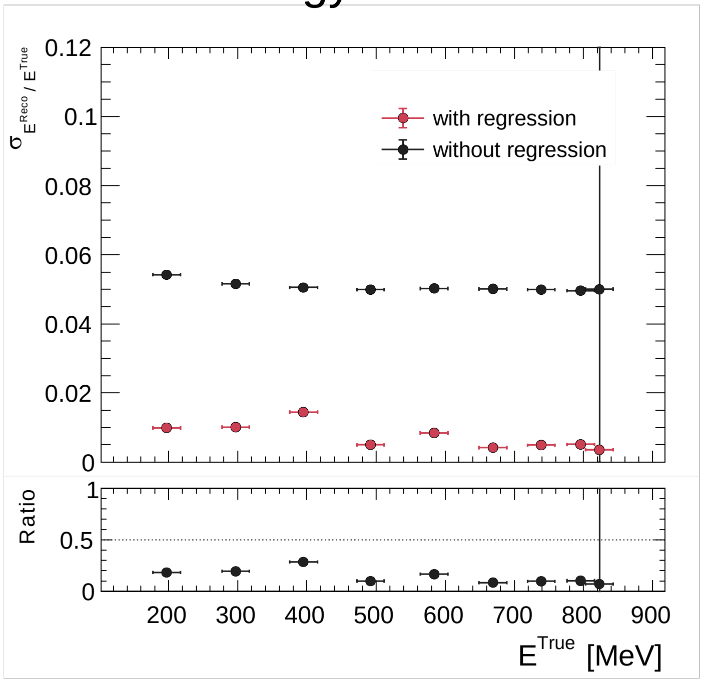
- A **new** MC sample generated w/ 197MeV positron beam w/ 30k events.
- After applying energy regression, the beam energy is will reconstructed by ML model and energy resolution improved from 5% to 1%.

Impact of Energy Regression

Reconstructed energy



Energy resolution



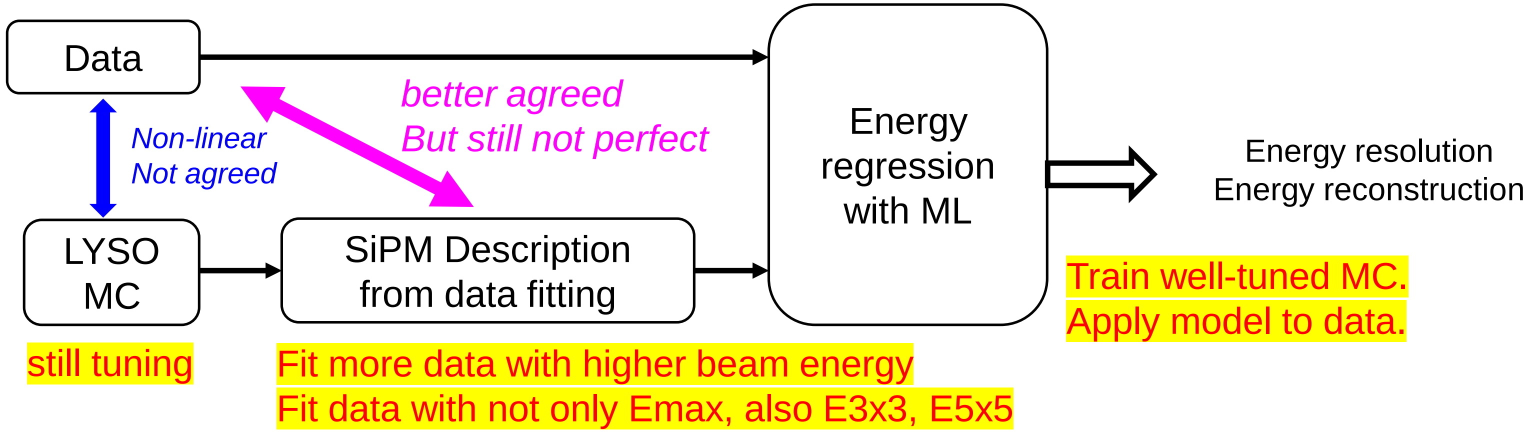
- New MC samples with energy beam = 197MeV to 823 MeV are tested.
- Ebeam is well predicted and energy resolution is also improved after regression regardless the beam energy.

Summary and To Do

- The ZDC ECal has exhibited a non-linear response, and the consistency between data and MC simulations using only LYSO is poor. This discrepancy arises because the SiPM behavior is not accurately modeled in the MC. Following the method from a paper, we characterized the SiPM behavior through data fitting and incorporated this into the MC, resulting in improved data-MC consistency. However, the fit is still not perfect, we need for further fine-tuning of the LYSO MC simulation.

- To achieve better energy resolution and reconstruction, we developed an energy regression method using the XGBoost machine learning technique. The ML regression model has demonstrated excellent performance, improving energy reconstruction by 20% and reducing energy resolution from 5% to 1%. (Attention : Currently, MC samples serve as both the training and test datasets.)

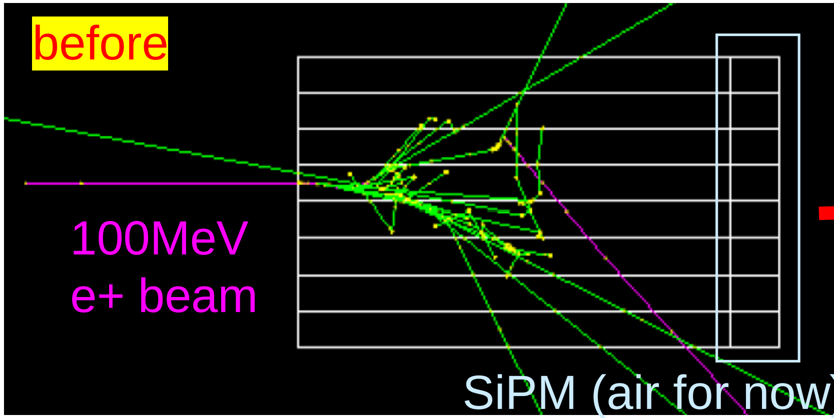
- Next steps include further tuning of the MC simulations to enhance data-MC agreement, particularly at high energies around 800 MeV. Once this is achieved, we will retrain our ML model with the improved MC data and apply energy regression to the experimental data.



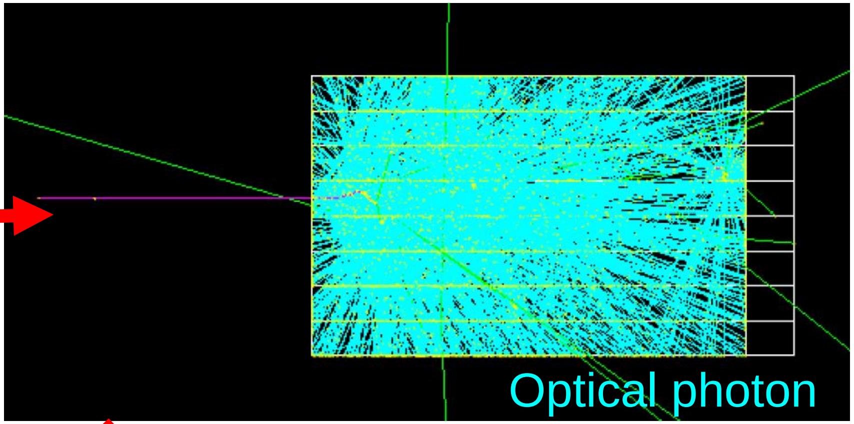
Backup

MC Simulation of standalone ZDC ECal

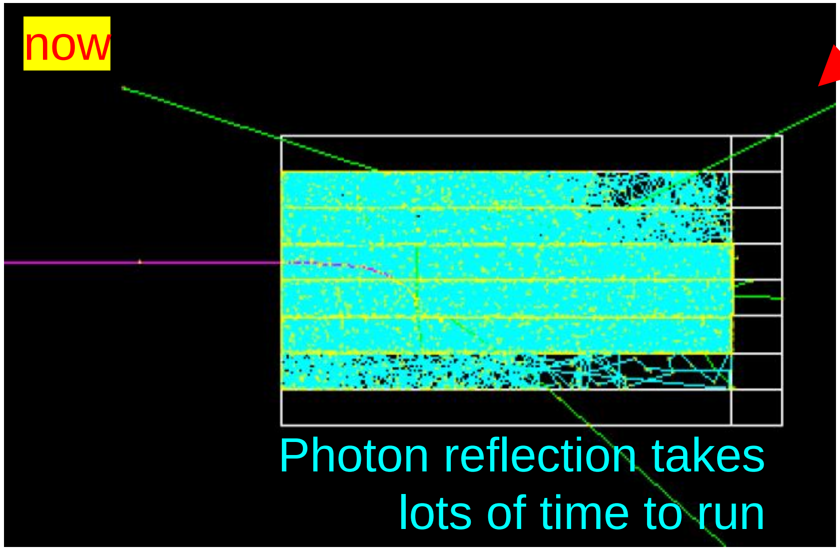
Only LYSO



LYSO + MPT(w/ Birk's)



LYSO + MPT(w/ Birk's) + Reflection Surface



- Positron/Beam(purple)
- Electron(yellow)
- Gamma (green)
- Optical photon (cyan)
  - Scintillation
  - Cherenkov

- Beam energy 50MeV-800MeV simulated.
- MPT and Birk's law are implemented.
- LYSO MC not yet finalized.
- SiPM not simulated.
- More details in backup.

Material Property Table of LYSO

TABLE II
DENSITY, ELEMENTAL COMPOSITION, AND OPTICAL PROPERTIES OF THE LYSO MATERIAL IMPLEMENTED IN THE GEANT4 *In-Silico* TEST PLATFORM

Density (g/cm^3)	Elemental Composition	Refractive Index	Optical Yield, Emission Spectrum, Absorption Length	Optical Decay Time Constants (ns)	Resolution Scale (at 511 keV)	Reference
7.4	$Lu_{1.9}Y_{0.1}Si_1O_5$ (0.5% Ce doping)	See Figure 15	30 Photons per eV, See Figure 15	Fast: 7.1 (7%) Slow: 33.3 (93%)	4.17	[47]

energy dependent

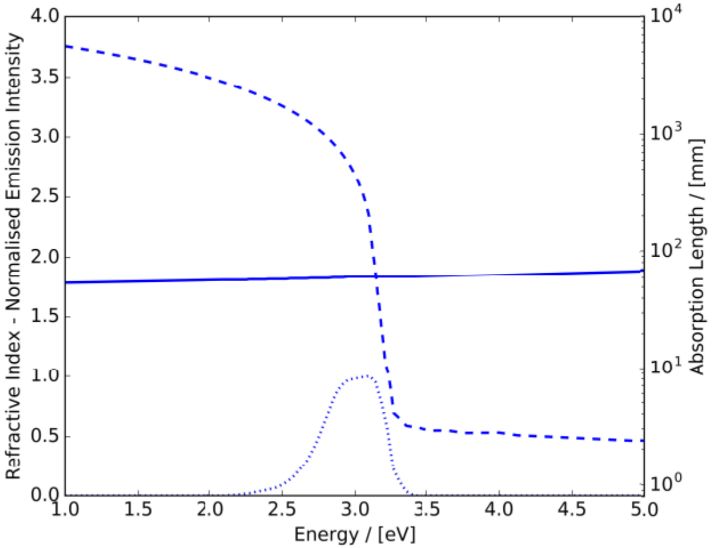


Fig. 15. LYSO scintillator crystal material refractive index (solid line), attenuation length (dashed line), and normalized scintillation photon emission intensity (dotted line) data sets implemented in the Geant4 *in-silico* test platform.

- Reference paper
  https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8876605

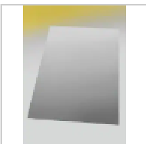
- Reference code
  https://github.com/JunhaoWang511/MLCsimulation/blob/master/src/MLCDetectorConstruction.cc

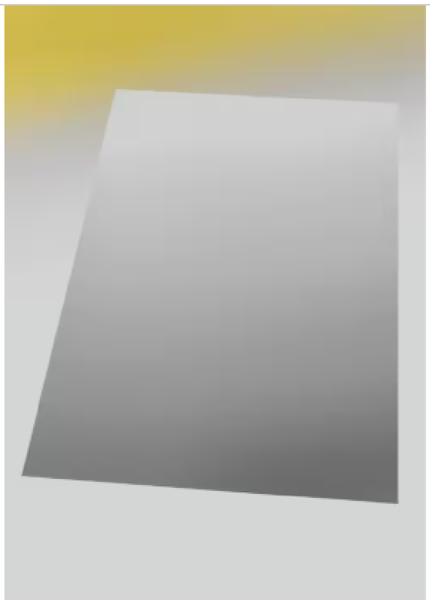
Reflection Surface with 3M ERS

3M™ Enhanced Specular Reflector Film (ESR)

3M ID B5005047091

Details   Typical Properties   Resources





Hover over image to zoom in

Product Description

3M™ Enhanced Specular Reflector Films (ESR) maximize the recycling efficiency of liquid crystal display backlights. 3M ESR is >98% reflective across the visible spectrum and contains no metal.

Construction/Performance

Product	3M ESR 65 Auto	3M ESR 80v2 Auto
Reflectivity (minimum)	98%	98%
Caliper (microns)	65 +/- 4	82 +/- 4
Halogen Free	Yes	Yes

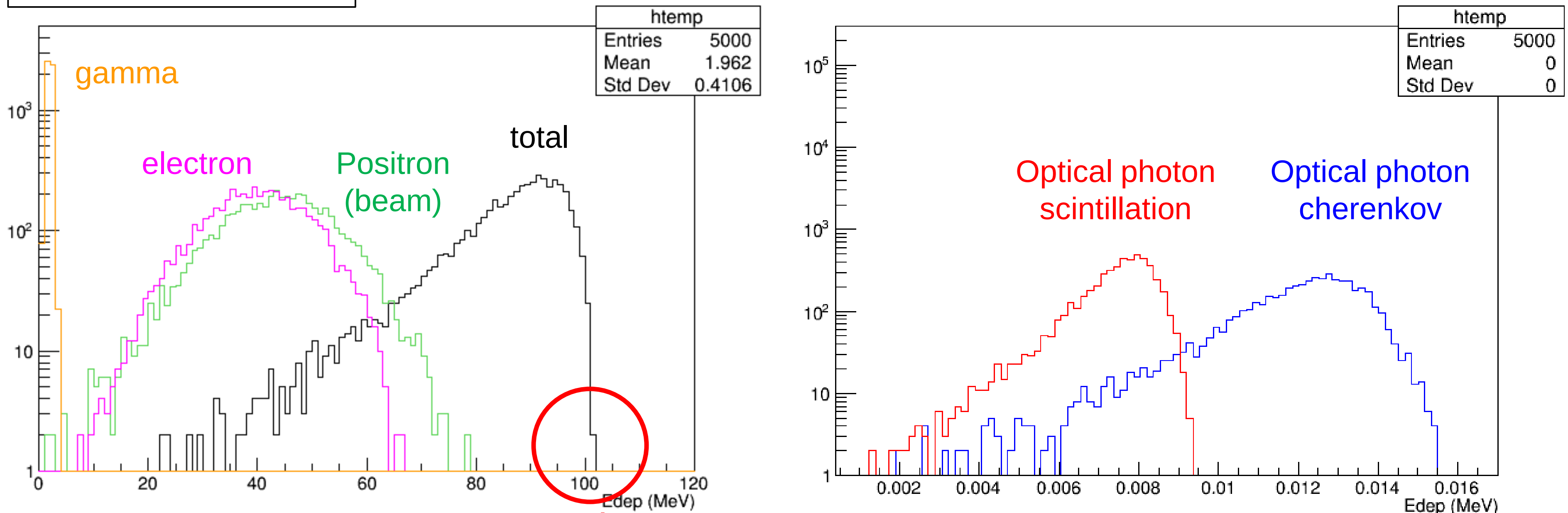
Reflectivity = 0.98

https://www.3m.com/3M/en_US/p/d/b5005047091/

Energy Deposition

100 MeV positron
LY = 50/MeV

Energy deposition <u>per event</u>

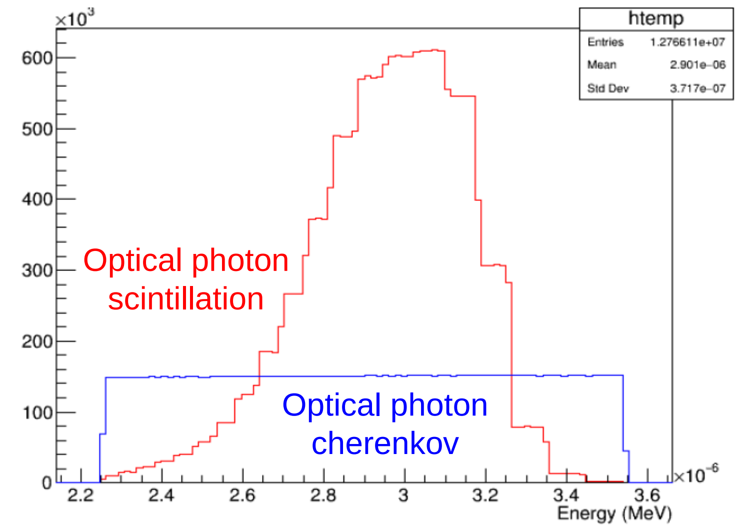


Edep>100MeV, gamma

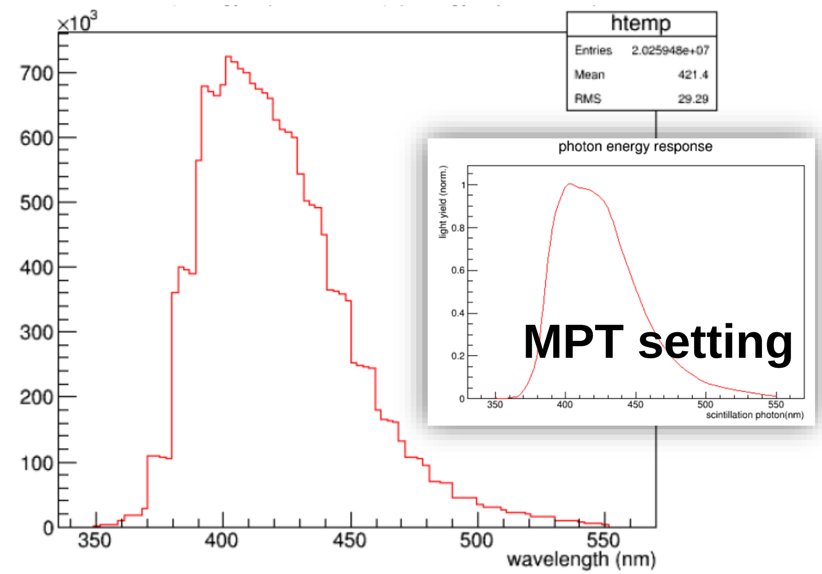
- Most energy are carried by beam and electron.
- Extra energy contribution from gamma.
- Optical photons carry very small amount of energy, ~0.01%.

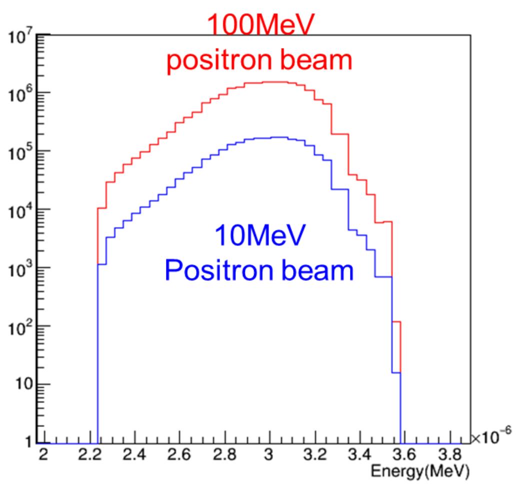
Optical Photons

100 MeV positron, LY = 50/MeV



$$\lambda(nm) = \frac{1240}{E(eV)}$$





- Energy spectrum of scintillation photons is the same as the setup in MPT.
- Energy spectrum of Cherenkov photons is flat.
- Energy spectrum of optical photons doesn’t change w/ the injected beam energy.
- Increase beam energy only increase number of scintillation photons and total energy deposition of scintillation photons, not their energy spectrum.

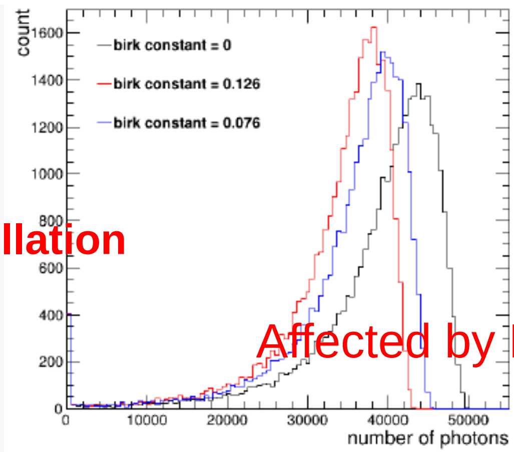
Effects of Light Yield Setting and Birk's Law

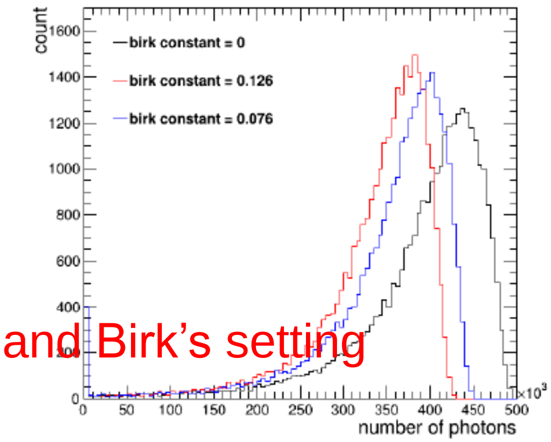
100MeV positron

LY = 500

LY = 5000

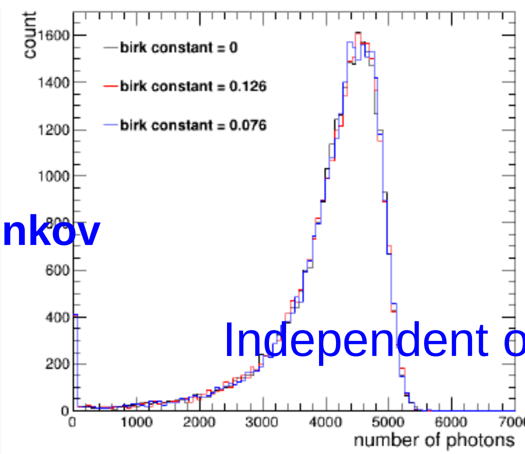
Scintillation

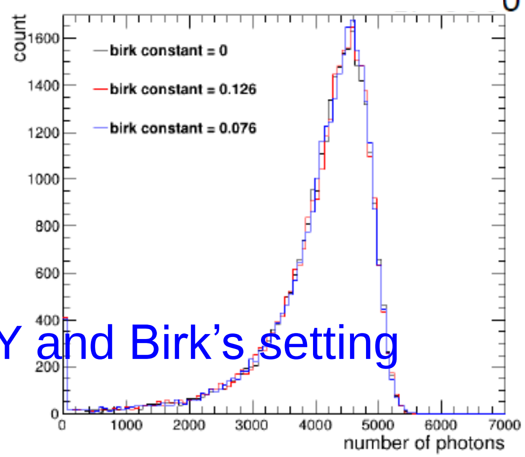




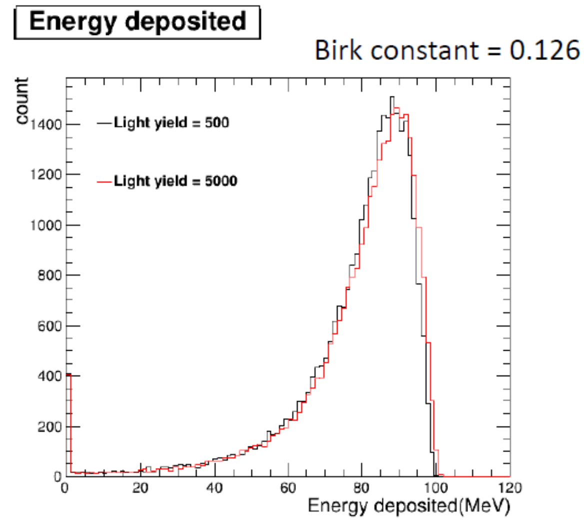
Affected by LY and Birk's setting

Cherenkov





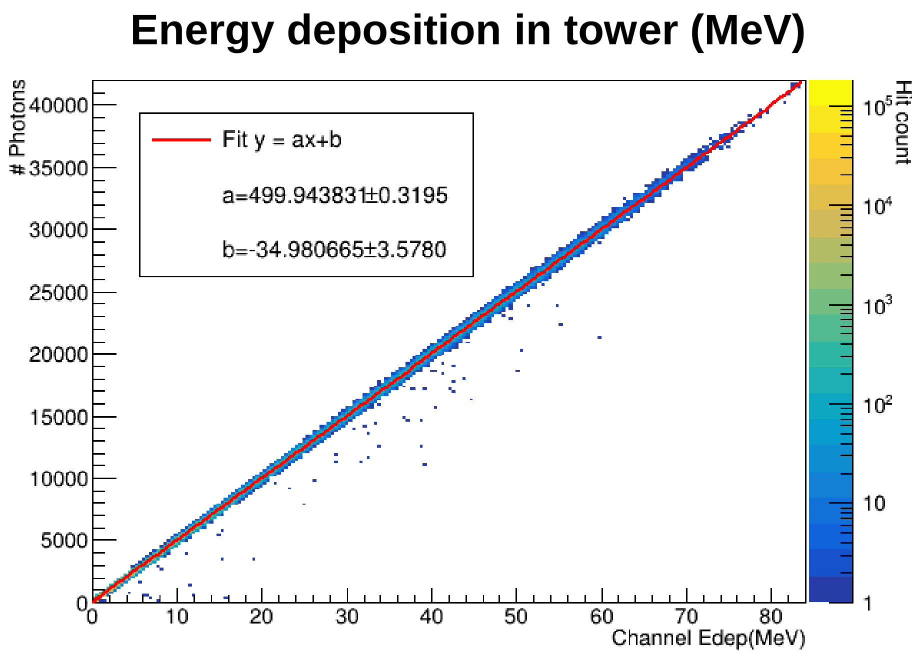
Independent of LY and Birk's setting



- Total energy deposition in crystal doesn't change w/ the setting of LY and Birk's law.
- Currently we were still using the distribution of energy deposition of to fit data. We will switch to optical photons.

Energy and Optical Photons

100 MeV positron, LY = 500/MeV



- Energy deposition in crystal is linear with number of photons generated when E<100MeV.
- Will move to higher energy E = 800MeV and LY = 33,000/MeV.