MC studies of the ECAL-p performance

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Outline

1. Longitudinal leakage (Kamil)
2. Gaps between sensors (Kamil)
3. Readout optimization (WIS'2023)
4. Energy reconstruction with ML

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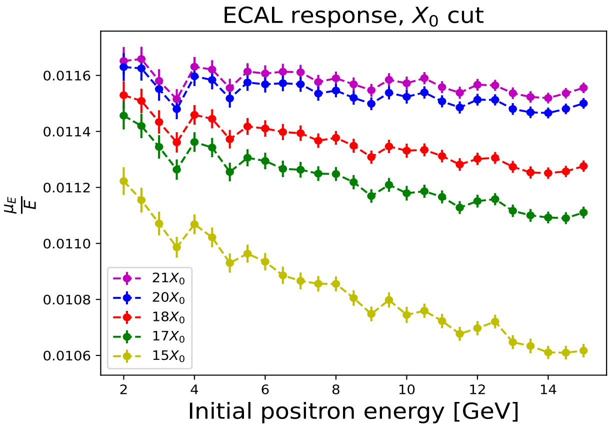
ECAL-P response with reduced number of X_0

In order to check how the thickness of ECAL-P impacts the linearity of its response, sum of deposits from different number of layers were used. μ_E is an average of energies deposited in each event.



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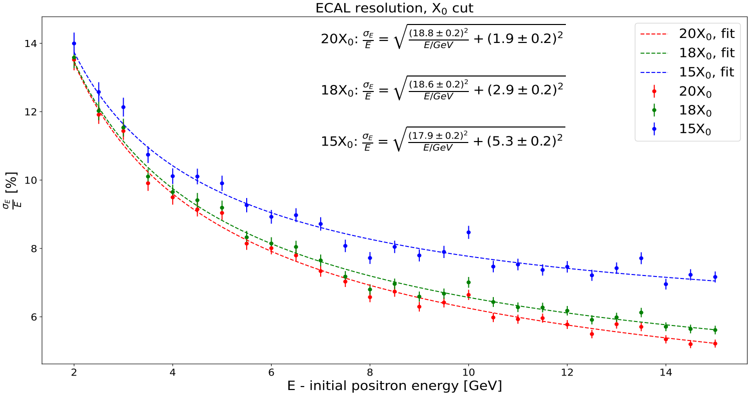


Average cascade profile - fit results

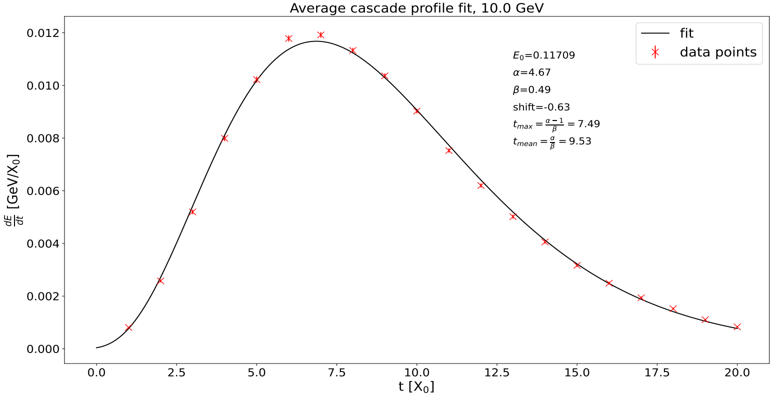


Figure: Gamma distribution fit to average cascade profile, 10GeV

Results of correction for leakage

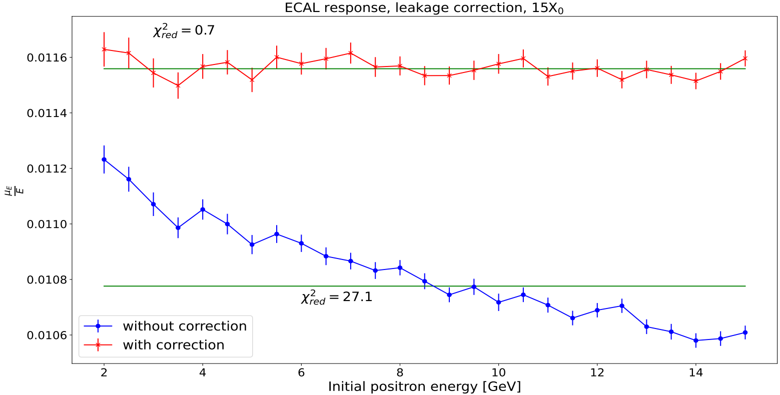


Figure: Leakage correction results for $15X_0$, ECAL-P response plot

Results of correction for leakage

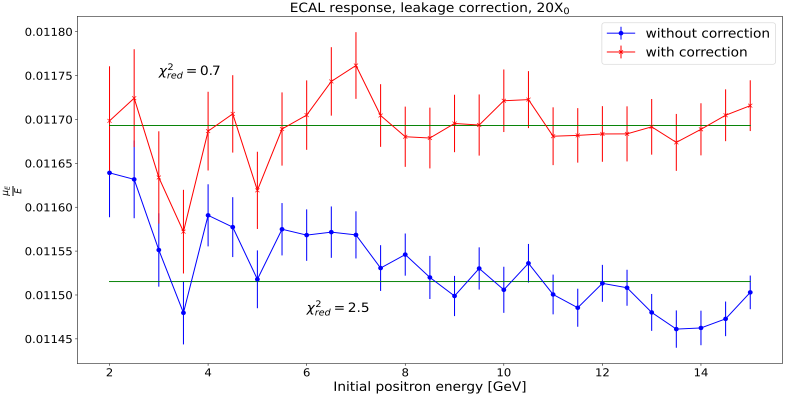
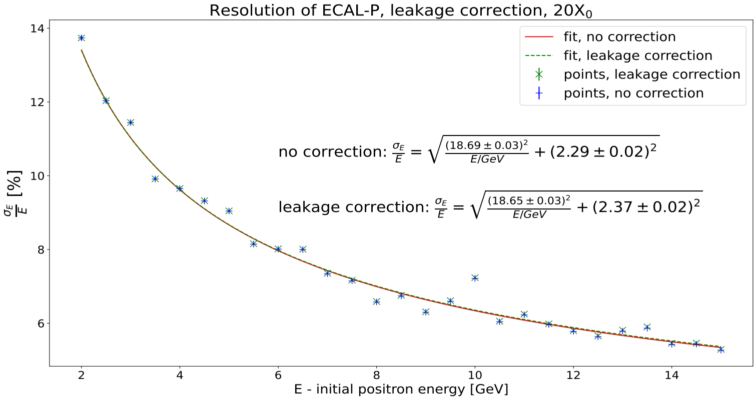


Figure: Leakage correction results for $20X_0$, ECAL-P response plot

Positron Calorimeter: ECAL-P, energy resolution

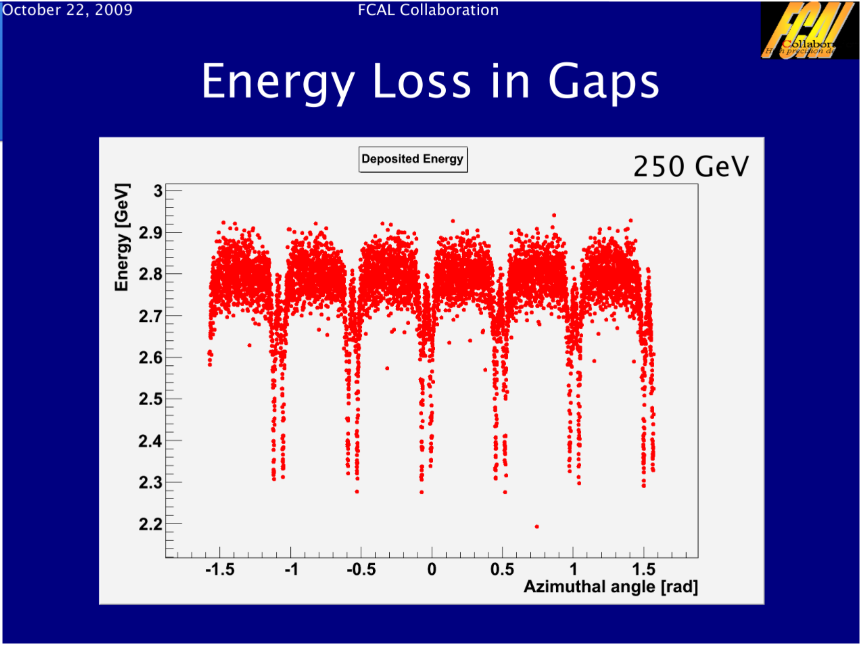


- energy resolution, before and after leakage correction
- two scenarios: $15 \times 1X_0$ and $20 \times 1X_0$ layers (this page)
- **Using longitudinal profile fit, leakage can be corrected for**

Outline

LumiCal results

Slide from
“Tile gaps and energy resolution in LumiCal” by Jonathan Aguilar and Bogdan Pawlik IFJ-PAN, Krakow



Gaps between sensors

HAMAMATSU

HAMAMATSU PHOTONICS K.K.

(P. 3 / 8)

Type No. S12834(X)	Doc .No. K30-B70125

2.Product outline

- PIXEL detector
- Chip size 89.7x89.7mm, 5020 μ m pitch , 16x16ch
- Bare chip shipment

3. Ratings and Characteristics

■ General Ratings

Parameter	Rating	Unit
Device type	P+ PIXEL on N substrate	
Chip size	89700 ± 40 x 89700 ± 40	μ m
Active area	88480 x 88480	μ m
Chip thickness	320±15	μ m
Number of PIXELs	256(16 x 16)	ch
PIXEL pitch	5530 x 5530	μ m
PIXEL GAP	10	μ m

$\Rightarrow$ 1.22 mm gap

Gaps between sensors

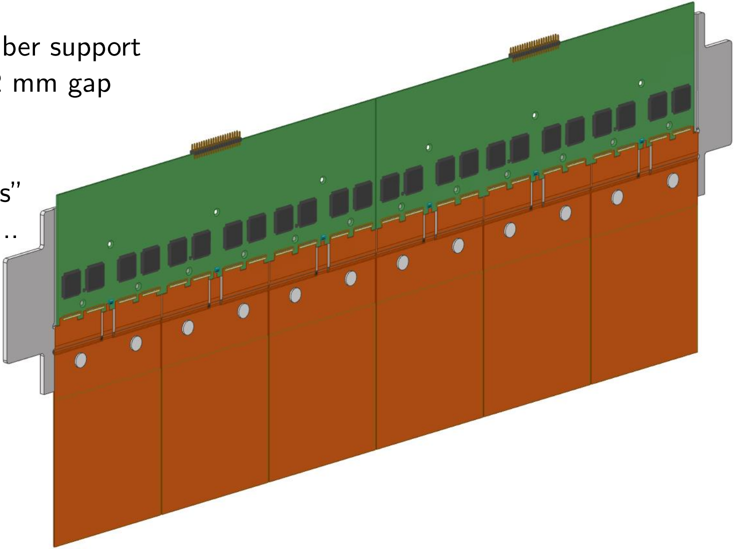
90 mm width assumed for carbon fiber support

$\Rightarrow$ additional 0.3 mm $\Rightarrow$ 1.52 mm gap

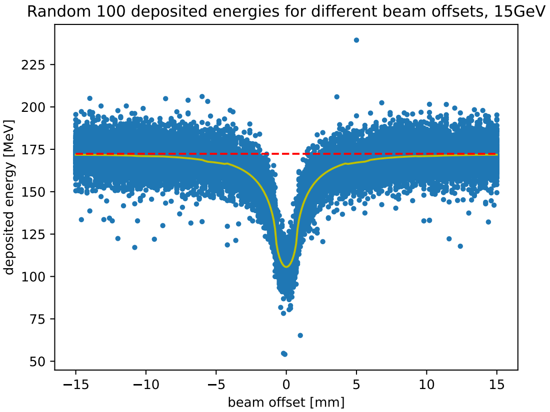
Finite mechanical tolerance

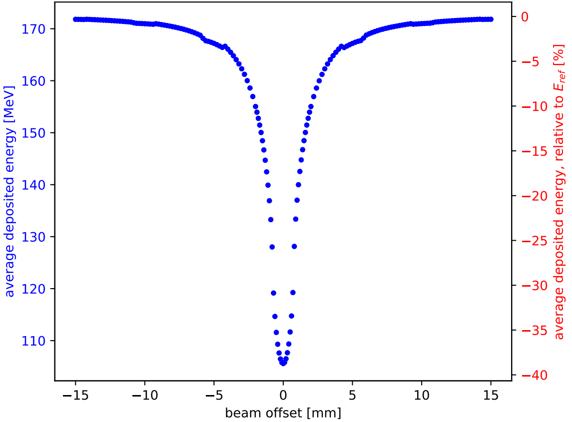
$\Rightarrow$ gaps between sensor “sandwiches”

$\Rightarrow$ additional 0.3 to 0.5 mm ...

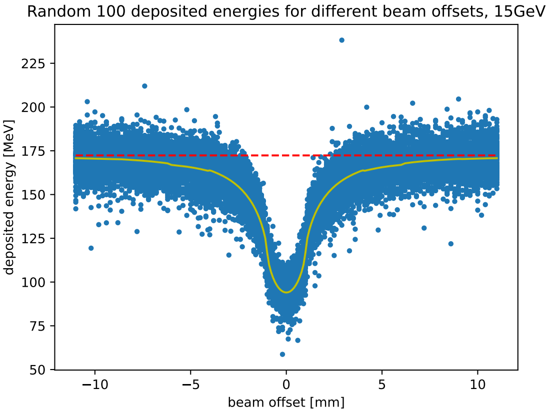


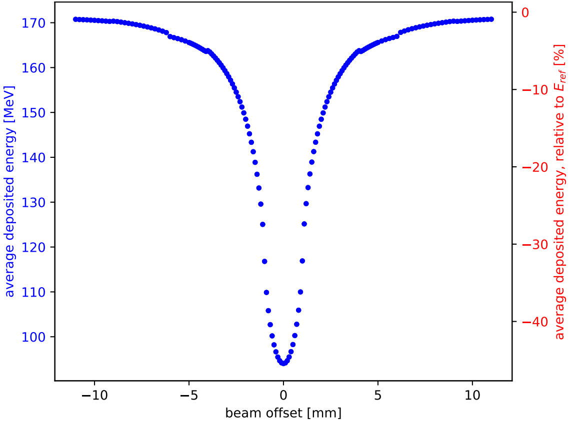
Results for 1.52mm gap
gun position vs energy





Results for 2.02mm gap
gun position vs energy

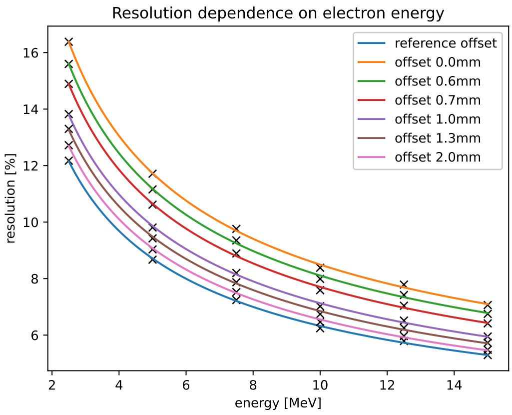




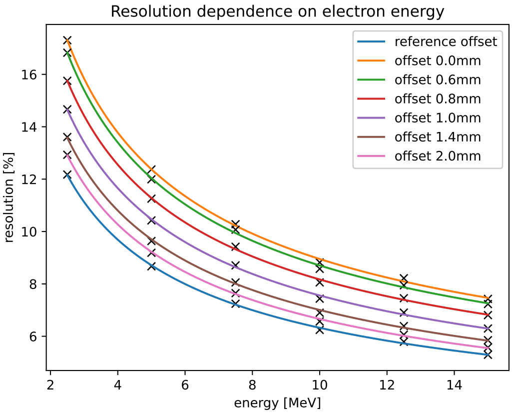
Energy vs resolution

For 1.22mm and 1.52mm gap

1.22mm gap

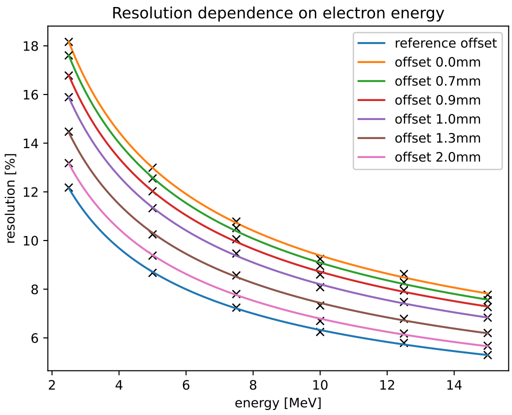


1.52mm gap

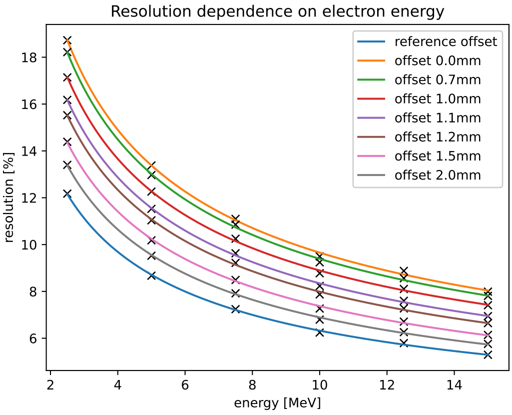


Energy vs resolution
For 1.82mm and 2.02mm gap

1.82mm gap

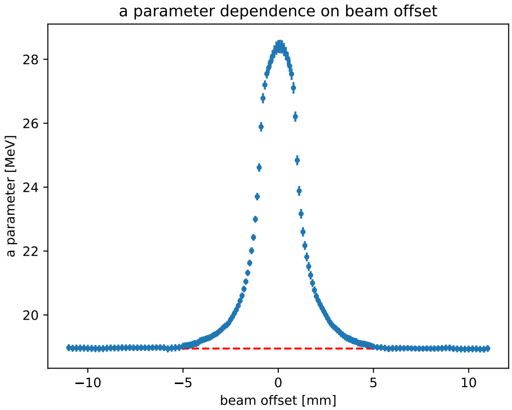


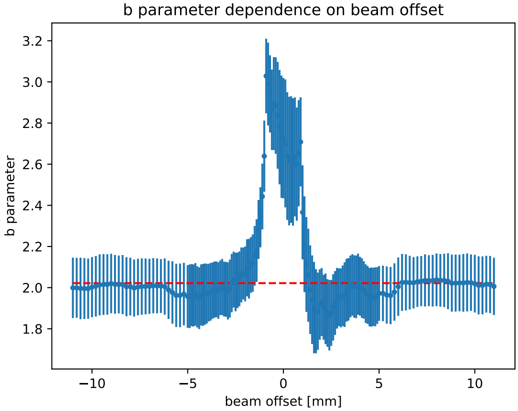
2.02mm gap



Gun position vs a and b

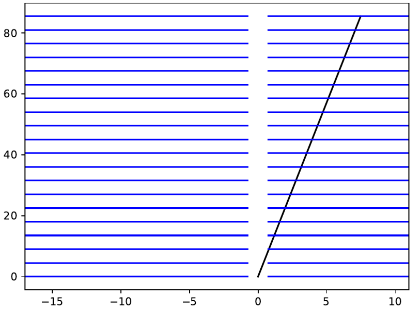
For 1.82mm gap





Approximation of tilted beam

- No MC with positrons hitting ECAL-P at an angle
- Inclined trajectory of a positron can be approximated by small shift of each layer



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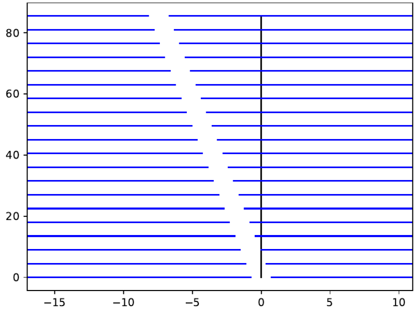
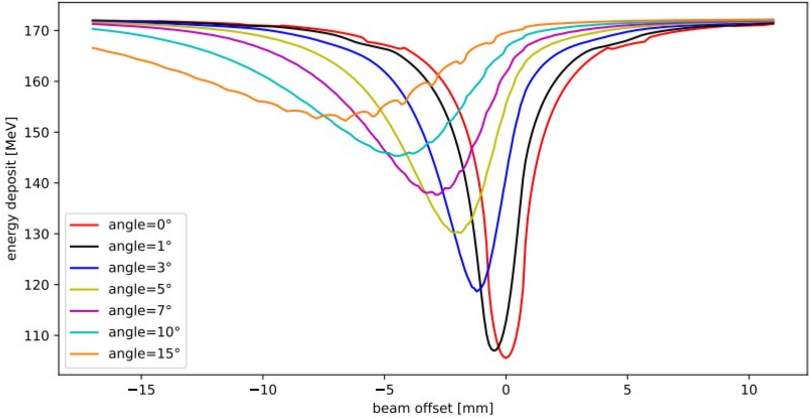
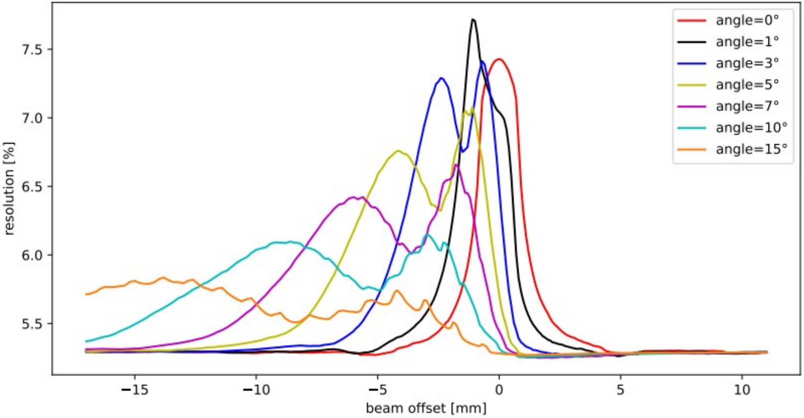


Deposited energy vs position, 15GeV

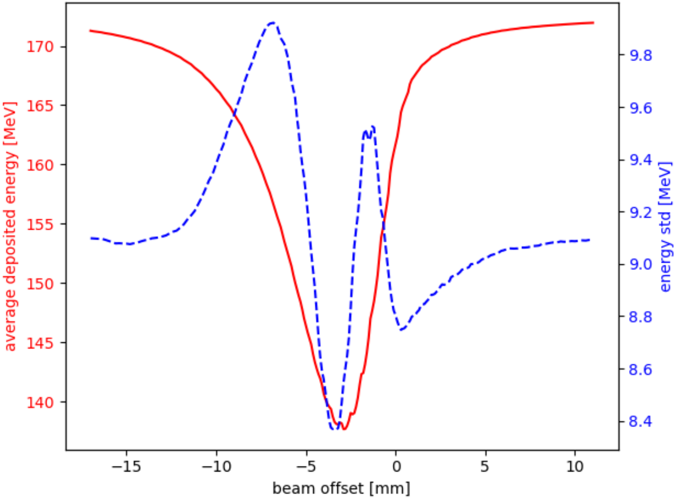


Resolution vs position, 15GeV



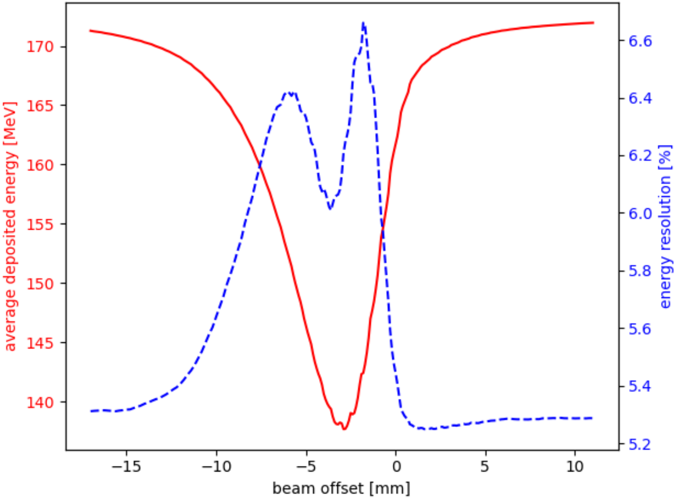
Deposit and std vs position, 15GeV

θ=7°

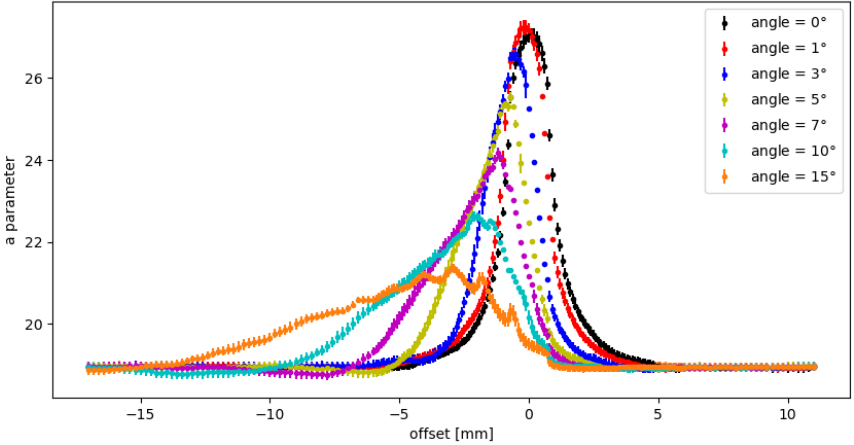


Deposit and resolution vs position, 15GeV

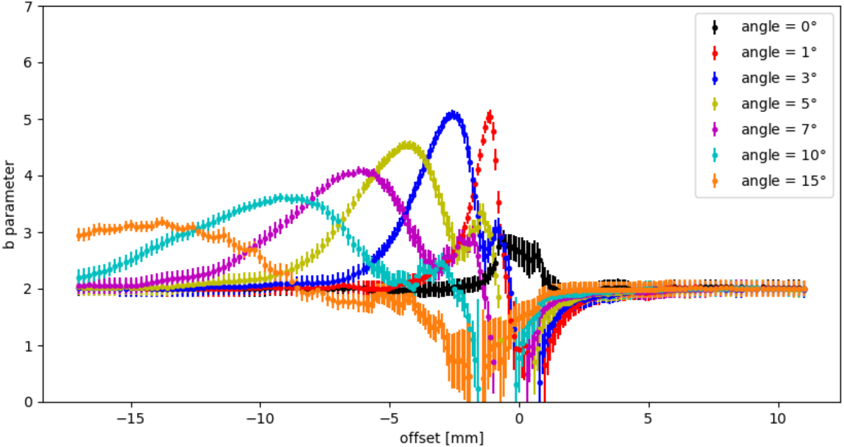
θ=7°



a parameter vs position



b parameter vs position



Conclusions

- Effect of the presence of the gap **is not negligible** even for larger angles (10°-15°)
- Thus it has to be taken into consideration in positron's spectrum reconstruction
- Our current understanding:
  two main factors affecting resolution:
  - Energy loss in gap → smaller number of deposits
    → larger Poisson fluctuations (reflected in a parameter)
  - Transverse profile fluctuations → gap loss fluctuations
    (reflected in b parameter)

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Analytic optimization

see backup slides for more details

Calibration factors for all layers, c_i, can be found by solving a set of linear equations.
One can write it in a symbolic form:

$$\mathbb{A} \cdot \vec{c} \;=\; \vec{B}$$

where matrix $\mathbb{A}$ and vector $\vec{B}$ can be calculated from single layer averages, $\langle s_i^E \rangle$ and $\langle s_i^E s_j^E \rangle$.

These averages can be calculated only once (from MC event samples)
and then use to test different optimization strategies $\Rightarrow$ extremely fast!

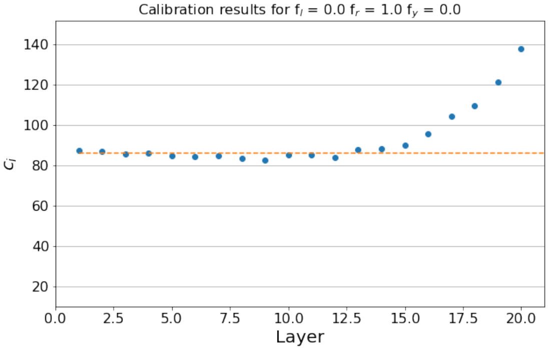
When only resolution is considered (for $f_l = 0$), additional constraint has to be added:
implemented using Lagrange multiplier

$$\sum_E \left(\sum_i c_i \langle s_i^E \rangle \;-\; E \right) \;=\; 0$$

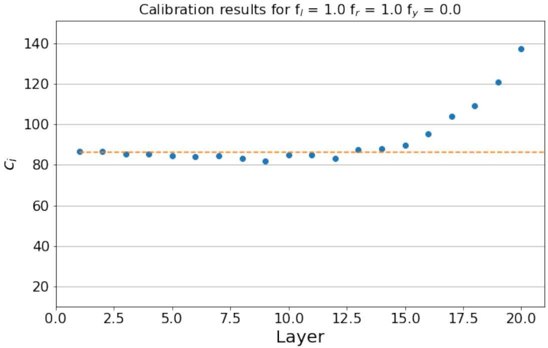
Full calorimeter calibration new samples

Calibration factors from optimization in the positron energy range from 2.5 to 15 GeV

Resolution only



Resolution + linearity



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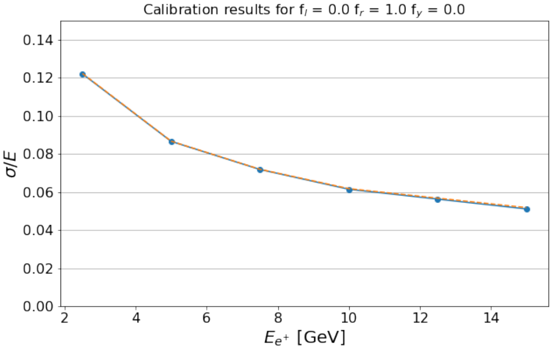

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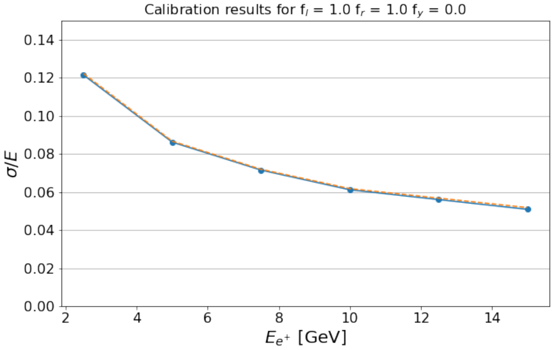
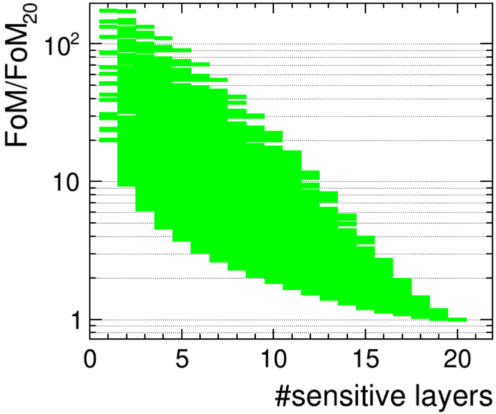
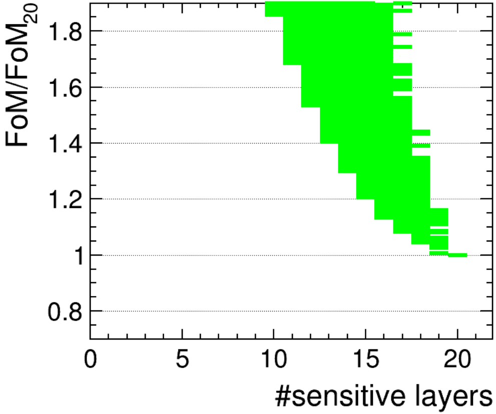


Configuration scan

Figure of merit $(\sim \sigma_E^2)$ change as a function of the number of active layers, for $E = 15$ GeV





Configuration optimization

Results

Optimal configurations
for the decreasing number of active sensor layers

$E = 2.5 - 15$ GeV

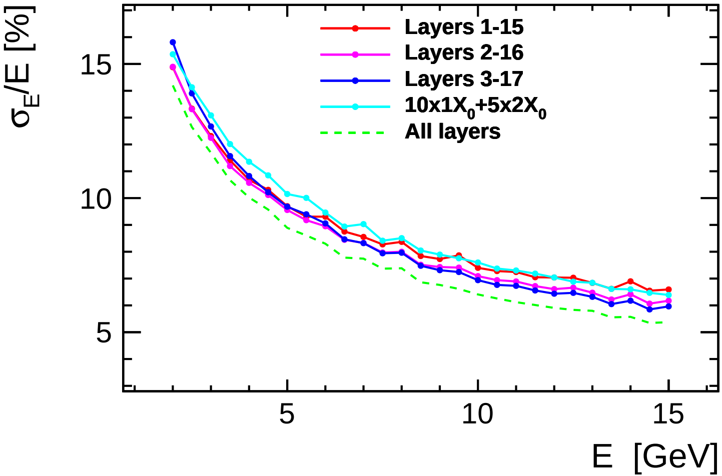
| - active layer
. - empty slot

```
N_L | Best option
----+----------------------------------------
 20 | | | | | | | | | | | | | | | | | | | | |
 19 | . | | | | | | | | | | | | | | | | | | |
 18 | . | | | | | | | | | | | | | | | | | | .
 17 | . | | | | | | | | | | | | | | | | . | .
 16 | . | | | | | | | | | | | | | | . | | . .
 15 | . . | | | | | | | | | | | | | | | . . .
 14 | . . | | | | | | | | | | | | . | | . . .
 13 | . . | | | | | | | | | . | | . | | . . .
 12 | . . | | | | | | | | | . | . | | . . . .
 11 | . . | | . | | | | | | . | . | . | . . .
 10 | . . | . | | | | . | | . | | . | . . . .
  9 | . . | . | | | . | | . | . | . | . . . .
  8 | . . . | | . | | . | | . | . . | . . . .
  7 | . . . | . | | . | . | . | . | . . . . .
  6 | . . . | . | . | . | . . | . | . . . . .
  5 | . . . | . | . | . . | . | . . . . . . .
  4 | . . . | . . | . . | . . | . . . . . . .
  3 | . . . . | . . . | . . . | . . . . . . .
  2 | . . . . . | . . . . | . . . . . . . . .
  1 | . . . . . . . | . . . . . . . . . . . .
```

Configuration optimization

Result summary

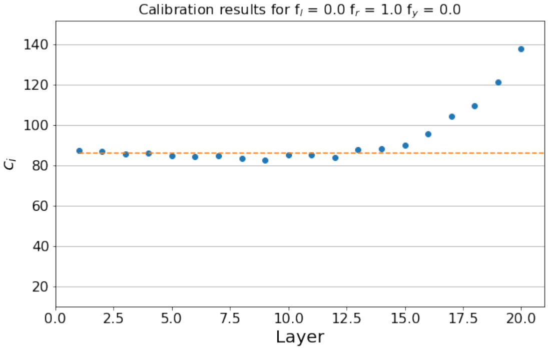
calibration optimized for best energy resolution in 2–15 GeV range



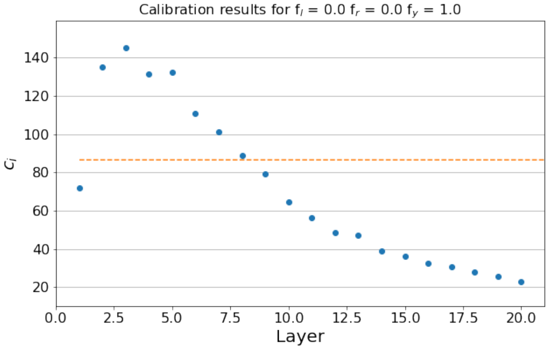
Optimization

Optimal calibration factors for full calorimeter, calibration for 2.5 to 15 GeV

Energy reconstruction



Position reconstruction (weighted average)



Position reconstruction

Configuration scan

Optimal configurations
looking at the Y position spread only
position calculated as weighted average

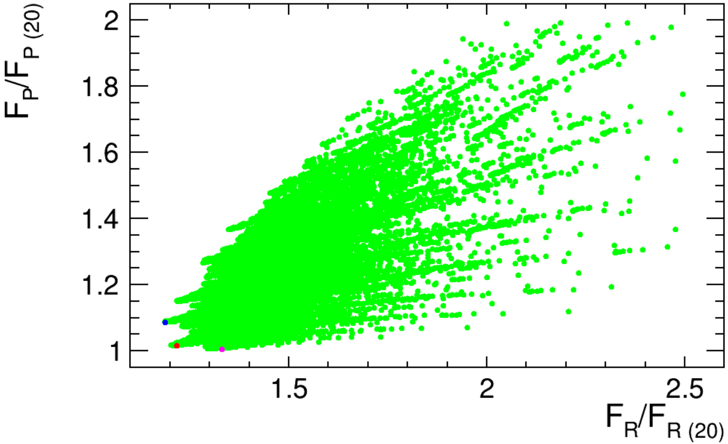
E = 2.5 – 15 GeV

| - active layer
. - empty slot

```
N_L | Best option
20  | | | | | | | | | | | | | | | | | | | | |
19  | | | | | | | | | | | | | | | | | | | | .
18  | | | | | | | | | | | | | | | | | | | . .
17  | | | | | | | | | | | | | | | | | | . . .
16  | | | | | | | | | | | | | | | | | . . . .
15  | | | | | | | | | | | | | | | | . . . . .
14  | | | | | | | | | | | | | | | . . . . . .
13  | | | | | | | | | | | | | | . . . . . . .
12  | | | | | | | | | | | | | . . . . . . . .
11  | | | | | | | | | | | | . . . . . . . . .
10  . | | | | | | | | | | . . . . . . . . .
9   . | | | | | | | | | . . . . . . . . . .
8   . | | | | | | | | . . . . . . . . . . .
7   . | | | | | | | . . . . . . . . . . . .
6   . . | | | | | | . . . . . . . . . . . .
5   . . | | | | | . . . . . . . . . . . . .
4   . . | | | | . . . . . . . . . . . . . .
3   . . . | | | . . . . . . . . . . . . . .
2   . . . | | . . . . . . . . . . . . . . .
1   . . . . | . . . . . . . . . . . . . . .
```

Optimization

Position vs resolution optimization results for N=15 hardware configurations   2.5–15 GeV



Indicated configurations:

. . | | | | | | | | | | | | | | | . . .

. | | | | | | | | | | | | | | | . . . .

| | | | | | | | | | | | | | | . . . . .

Outline

Motivation

We consider ML approach for positron flux reconstruction
based on 4-D energy distribution in the calorimeter

What is the expected performance?

Academic exercise, just to understand the problem better:
try to use ML to reconstruct single shower energy
$\Rightarrow$ can we do better than with the "standard" approach ?

Motivation

We consider ML approach for positron flux reconstruction
based on 4-D energy distribution in the calorimeter

What is the expected performance?

Academic exercise, just to understand the problem better:
try to use ML to reconstruct single shower energy
$\Rightarrow$ can we do better than with the "standard" approach ?

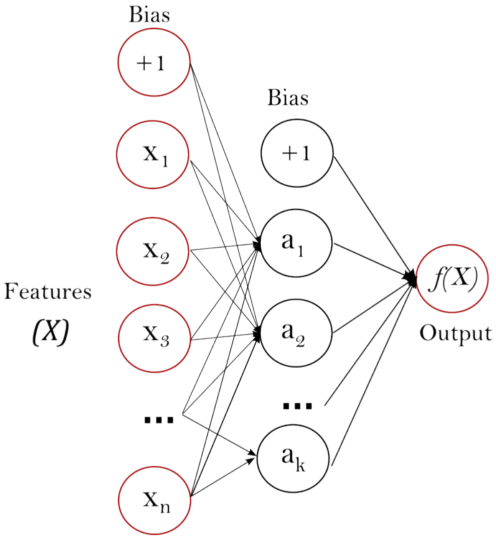
I had no experience with ML regression before...
Neural networks look like natural solution, but clearly not the only option...

Framework

I use Multi-layer Perceptron (MLP) algorithm as implemented in scikit-learn package

Class MLPRegressor used for regression is very similar to the "standard" neural network used for classification (trained using backpropagation of errors), but with no activation function in the output node.

The final result is just the linear combination of the last hidden layer output values.



Energy reconstruction with ML

Data

I used the most recent Geant 4 production from Sasha:

main files: `glaser_positron_step/luxe_ecalp_*gev_cv11qgsphp_tv33_hv1.root`

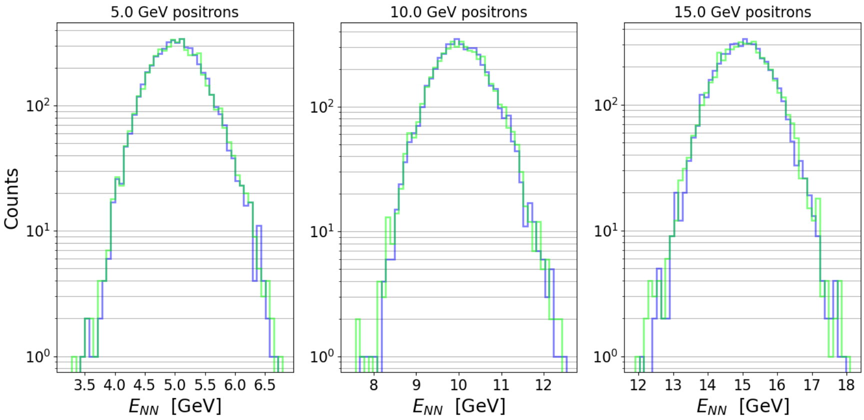
- positron gun at calorimeter face
- positron energy range: from 3 GeV to 20.0 GeV, with 1 GeV step
- 25 000 events per file

additional files:
`glaser_positron_step/angle_0/luxe_ecalp_*gev_0deg_cv11qgsphp_tv33_hv1.root`

- positron gun at calorimeter face
- positron energy range: from 2.5 GeV to 15.0 GeV, with 2.5 GeV step
- 25 000 events per file

Energy reconstruction with ML

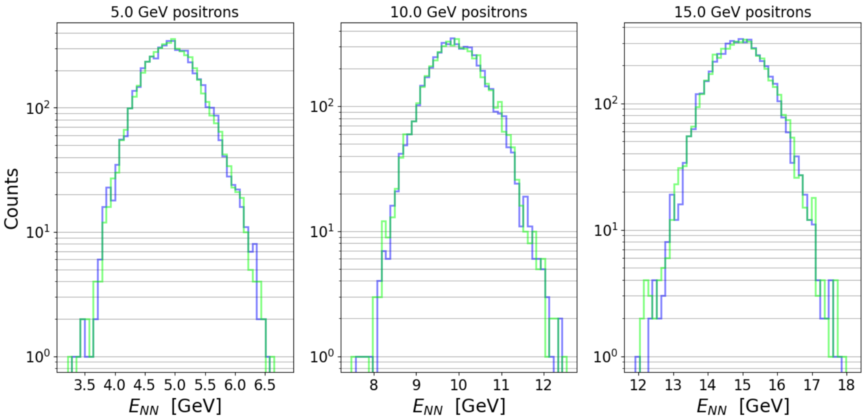
NN response distribution for test events (20% of sample) compared with sum of deposits



Good agreement already with one hidden layer (100 nodes)

Energy reconstruction with ML

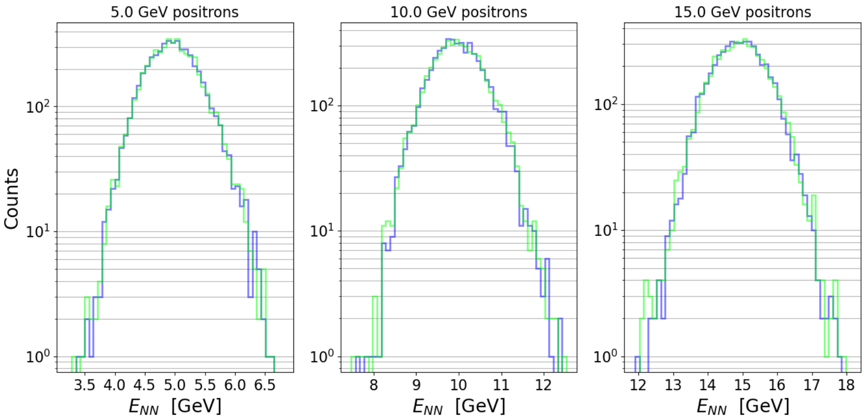
NN response distribution for test events (20% of sample) compared with sum of deposits



No visible improvement for two hidden layers (100+20 nodes)

Energy reconstruction with ML

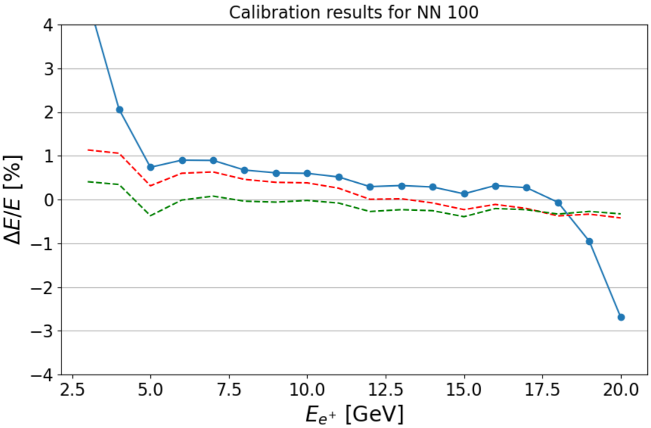
NN response distribution for test events (20% of sample) compared with sum of deposits



Consistent results for three hidden layers (50+50+50 nodes)

Energy reconstruction with ML

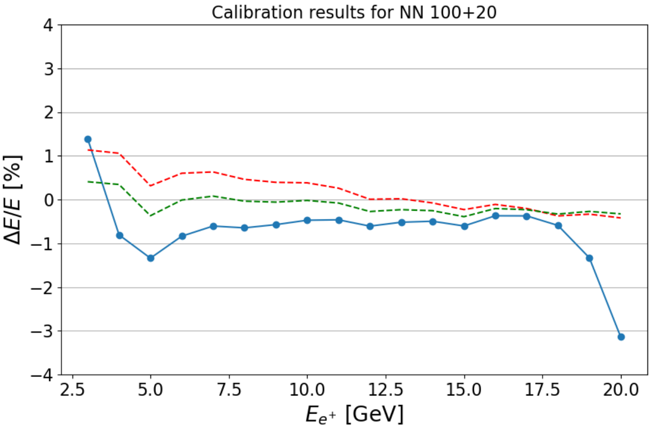
NN response linearity compared with optimized calibration and plain sum of deposits



Clear problem at lowest and highest energies (100 nodes)

Energy reconstruction with ML

NN response linearity compared with optimized calibration and plain sum of deposits



Clear problem at lowest and highest energies (100+20 nodes)

Energy reconstruction with ML

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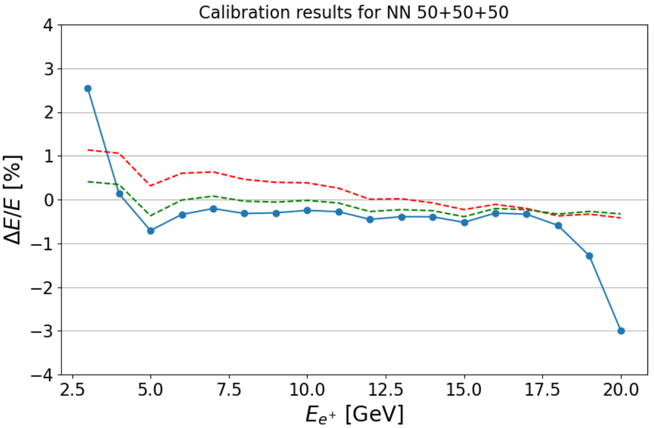
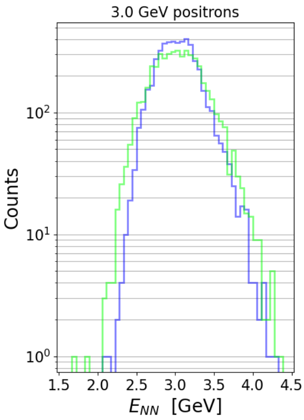


Good linearity, but only from 6 to 17 GeV! (50+50+50 nodes)

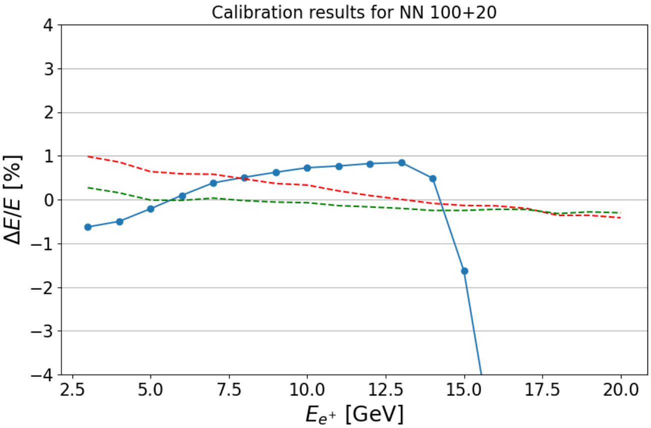
NN response distribution for test events (20% of sample) compared with sum of deposits



Distributions narrower at lowest and highest energies (100+20 nodes)

Energy reconstruction with ML

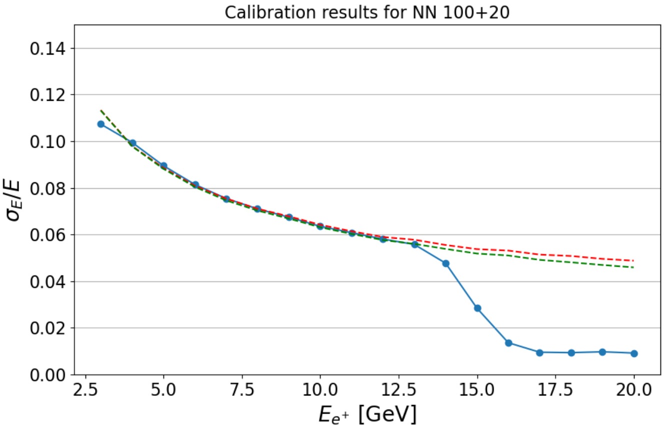
NN response linearity when trained with 2.5 GeV to 15.0 GeV files



Clear problem at highest energies (100+20 nodes; similar for other)

Energy reconstruction with ML

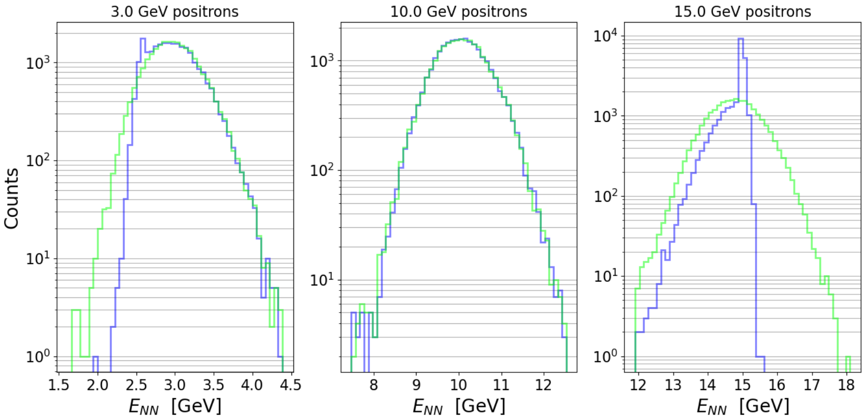
Energy resolution from NN response when trained with 2.5 GeV to 15.0 GeV files



Clear problem at highest energies (100+20 nodes; similar for other)

Energy reconstruction with ML

NN response distribution for test events, when trained with 2.5 GeV to 15.0 GeV files



NN learned that true energies are always between 2.5 and 15 GeV (100+20 nodes)

Conclusions

Regression with neural network quite efficient in positron energy reconstruction.

However, it needs to be trained on a significantly wider energy range.

It can not do better than what we obtain the optimized calibration...

Very preliminary results. The subject clearly deserves much deeper studies...