# Longitudinal structure optimization for the high density electromagnetic calorimeter

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LUXE

**The 2024 International Workshop on Future Linear Colliders (LCWS2024)**

Calorimetry, Muon detectors session

July 10, 2024

**Outline:**

1. Motivation
2. Configuration scan
3. Monte Carlo approach
4. Genetic algorithm
5. Multi-objective optimization
6. Conclusions

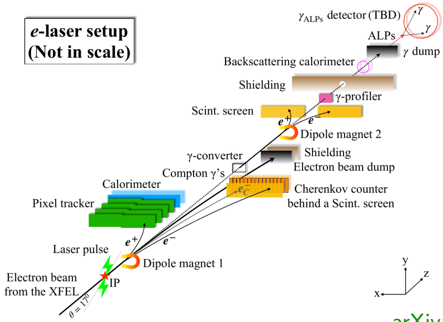
**Outline:**

# Motivation

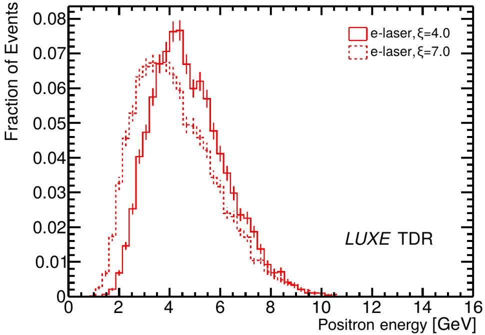
## LUXE experiment at DESY

for more details see contribution by Ruth Jacobs

Unique high precision experiment dedicated to study of Strong Field QED (SFQED) with use use of 16.5 GeV electron beam of Eu.XFEL colliding with intense optical laser.




arXiv:2102.02032




High rate of $e^+e$ pair production expected due to non-linear effects (multi-photon scattering).

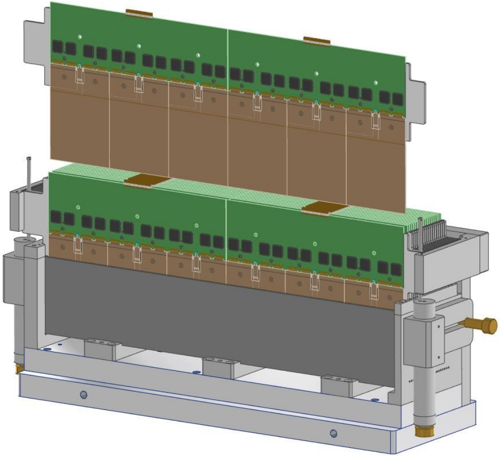
# Motivation

## ECALp - high density positron calorimeter for LUXE

arXiv:2308.00515

High density calorimeter for precise energy and position measurement (small Molière radius)

- 21 tungsten absorber plates, 3.5 mm thick (1 $X_0$)
- (15) 20 layers of 320 $\mu$m silicon sensors
  - active layers 780$\mu$m thick put in 1 mm gaps
  - six CALICE silicon sensors in each layer
  - each sensor: 16 $\times$ 16 pads of 5.5$\times$5.5 mm$^2$
  - total active area: 54$\times$9 cm$^2$



Mechanical prototype under construction at the University of Warsaw.

For sensor test results see contribution by Yan Benhammou

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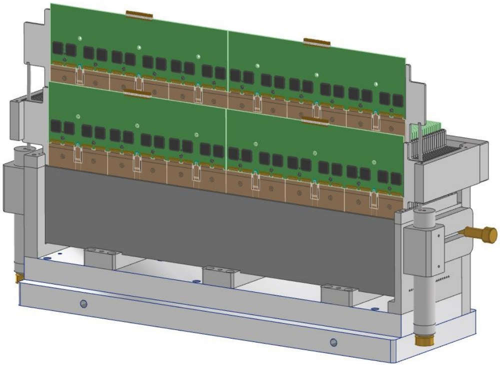

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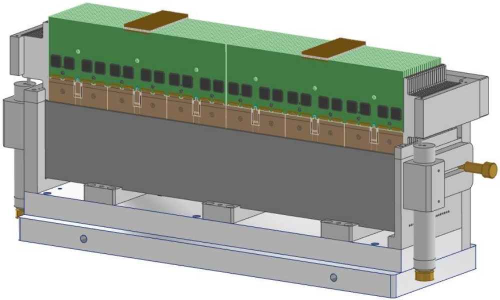

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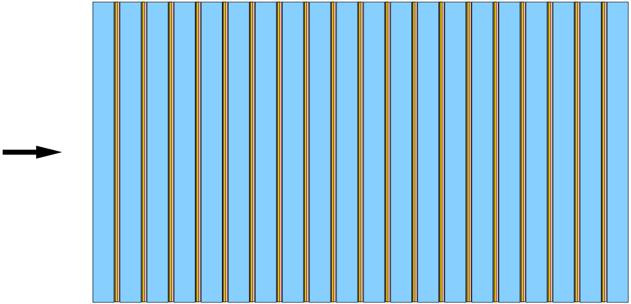
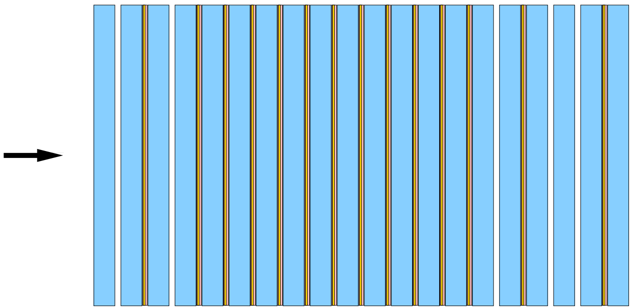
## ECALp longitudinal structure optimization



not to scale

Best solution is always to instrument all calorimeter gaps.

## ECALp longitudinal structure optimization



not to scale

Best solution is always to instrument all calorimeter gaps.

However, only 15 layers likely to be instrumented in LUXE phase I.

- how much will performance of the calorimeter be affected?
- how to choose empty layers to minimize the effect?

⇒ need for a dedicated study

**Outline:**

# Configuration scan

## Approach

Analytical procedure has been developed, allowing for very fast calibration optimization and energy/position measurement precision estimate for arbitrary configuration of active layers.

Layers can be easily "deactivated" in MC by forcing their calibration factors to zero.

Analytical procedure can be easily repeated for multiple configurations...

With $N = 20$ gaps in ECALp, the total number of possible layer configurations is

$$N_{\mathrm{comb}} = 2^{20} - 1 = 1'048'575$$

(1 to 20 layers instrumented) which can be checked in $\mathcal{O}(1\mathrm{h})$ (energy scan 2.5 – 15 GeV).

We can then look for the optimal configuration for given number of instrumented layers...

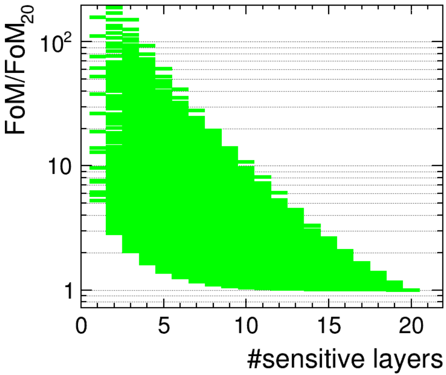
Energy or position resolution shown relative to that of fully instrumented calorimeter

# Configuration scan

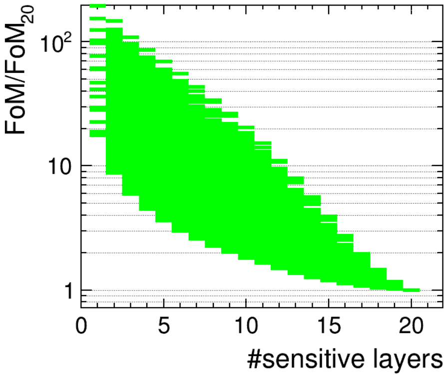
**Scan results** 1 to 20 layers instrumented

Figure of merit change as a function of the number of active layers, for $E = 2.5 - 15$ GeV

Position resolution optimization




Energy resolution optimization



# Configuration scan

## Optimization

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

Indicated configurations:

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

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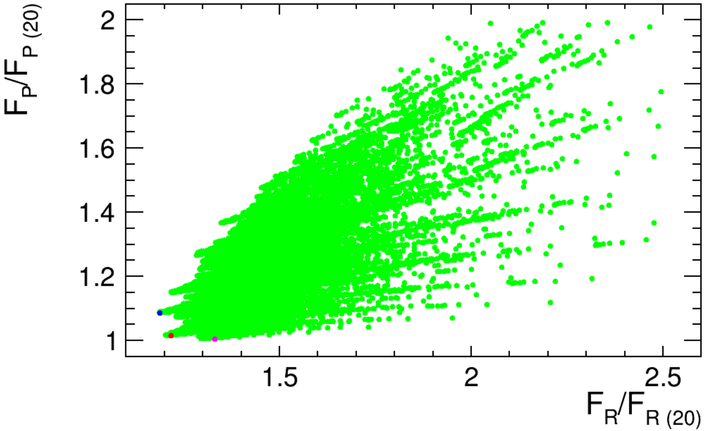


# Configuration scan

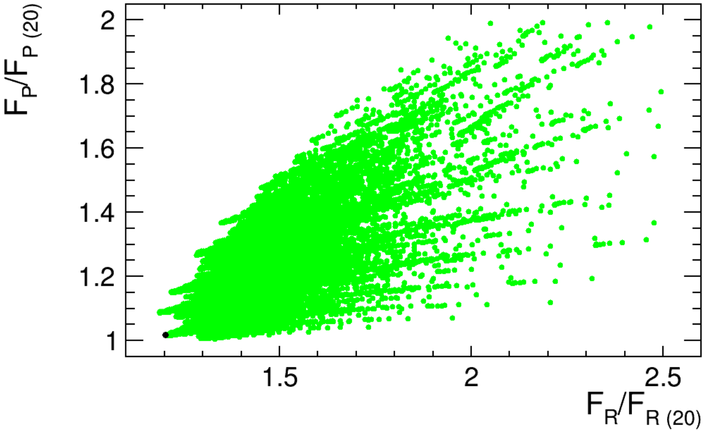
## Optimization

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

Indicated configurations:

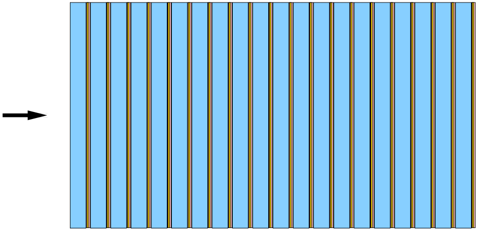
. | | | | | | | | | | | | | . | | . . .

**Optimal !?...**



**Outline:**

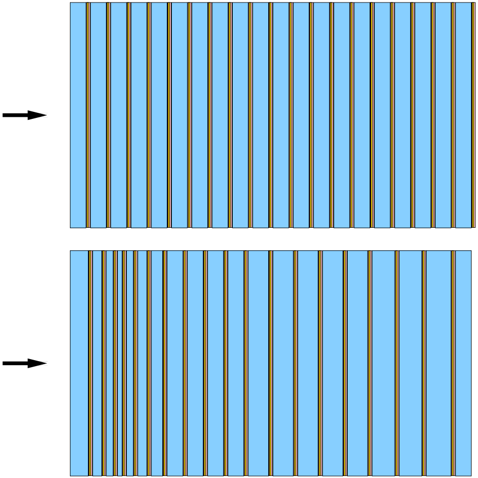
## Extended detector model



Geant 4 simulation of ECALp:

- 21 tungsten plates of 1 $X_0$ each
- 21 active layers with 320 $\mu$m silicon and 460 $\mu$m support/kapton in 1 mm gap (one extra layer to simplify the model)

## Extended detector model



Geant 4 simulation of ECALp:

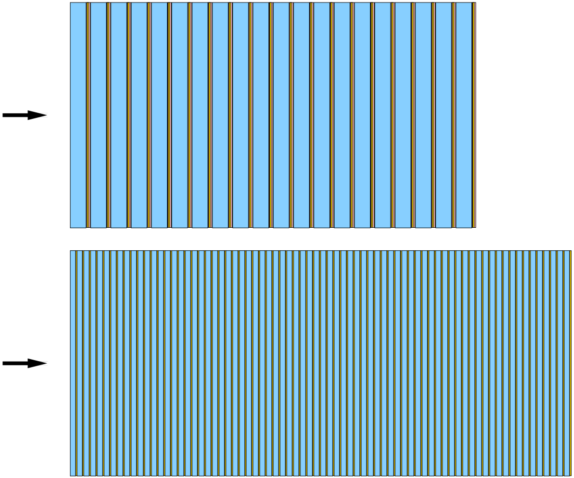
- 21 tungsten plates of 1 $X_0$ each
- 21 active layers with 320 $\mu$m silicon and 460 $\mu$m support/kapton in 1 mm gap (one extra layer to simplify the model)

When looking for optimal solution, one should also allow for non-uniform structures.

$\Rightarrow$ better energy and position resolution results can be obtained with optimized calibration for the same number of layers

# Monte Carlo approach

## Extended detector model



Geant 4 simulation of ECALp:

- 21 tungsten plates of 1 $X_0$ each
- 21 active layers with 320 $\mu$m silicon and 460 $\mu$m support/kapton in 1 mm gap (one extra layer to simplify the model)

Model used for non-uniform configurations:

- 75 tungsten plates of $\frac{1}{3}X_0$ each
- 75 active layers with 320 $\mu$m silicon in $\frac{1}{3}$ mm gap

Same sensor, almost the same average density, extended to 25 $X_0$

# Monte Carlo approach

**Test case** Look for optimal configuration for calorimeter with 15 active layers.

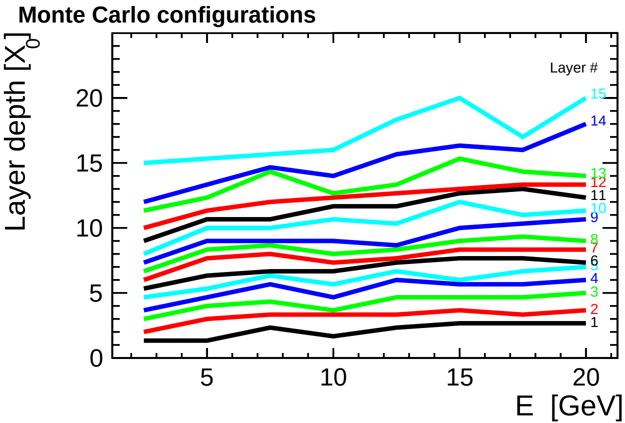
$2.28 \cdot 10^{15}$ possible configurations $\Rightarrow$ direct scan over all not realistic

Easiest solution: generate configurations at random and select the best one

Example result: 1'000'000 random configurations per energy $\Rightarrow$

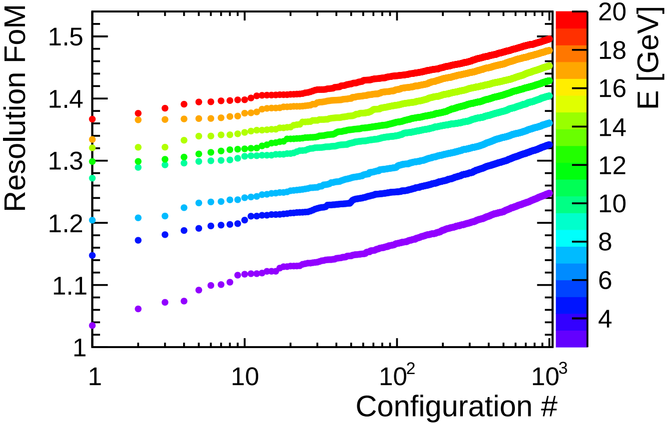
Large fluctuations visible!

Low probability to find the optimal one...



## Results

Energy resolution figure-of-merit for the 1000 best configurations (out of $10^6$) for each energy

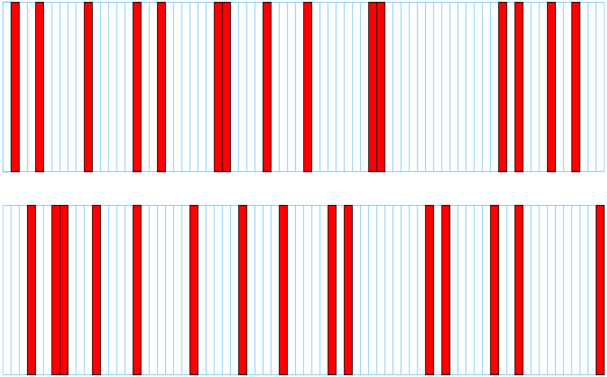



Large differences between best configurations - result not stable

**Outline:**

**Concept** generation of new "children" configurations

Take random "parent" pair from the collection of best configurations found so far.



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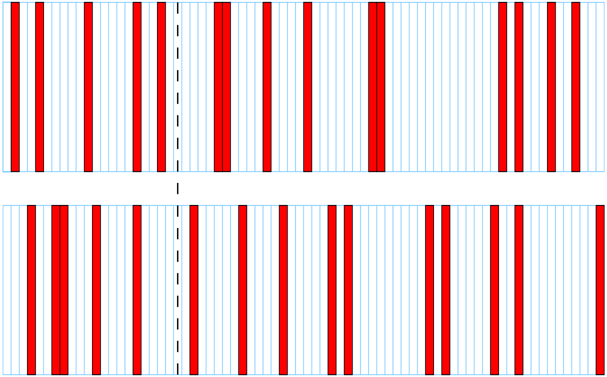

- Select random cut in the layer sequence

# Genetic algorithm

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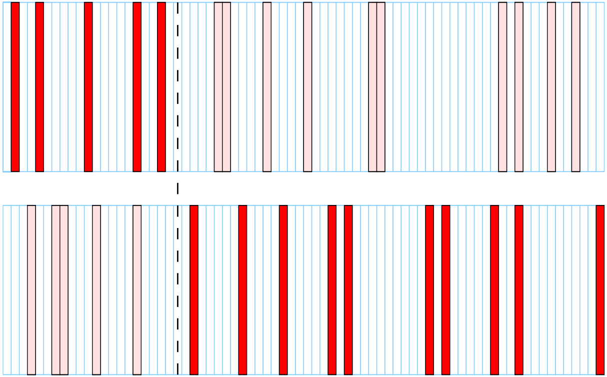

- Select random cut in the layer sequence
- Combine the first part of the first with the second part of the second configuration

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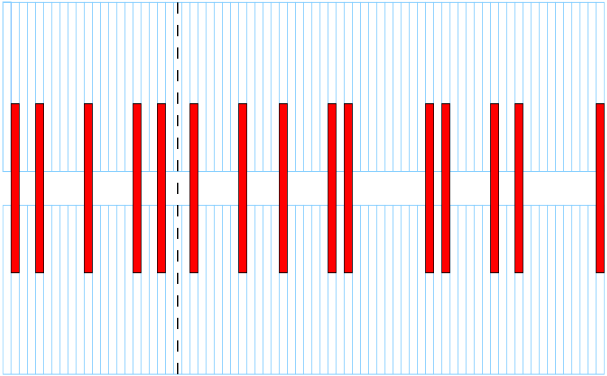

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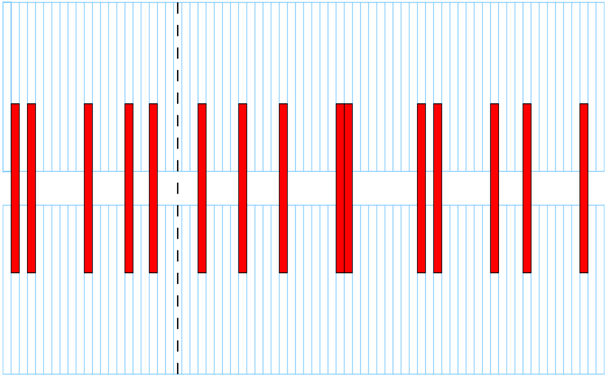

- Select random cut in the layer sequence
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- Add random mutations
  mutation probability decreases with time

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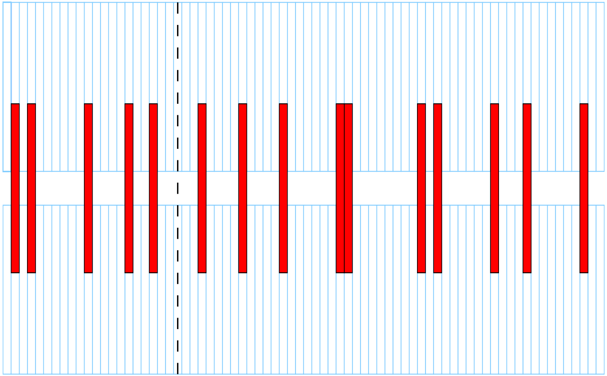


- Select random cut in the layer sequence
- Combine the first part of the first with the second part of the second configuration
- Add random mutations
  mutation probability decreases with time

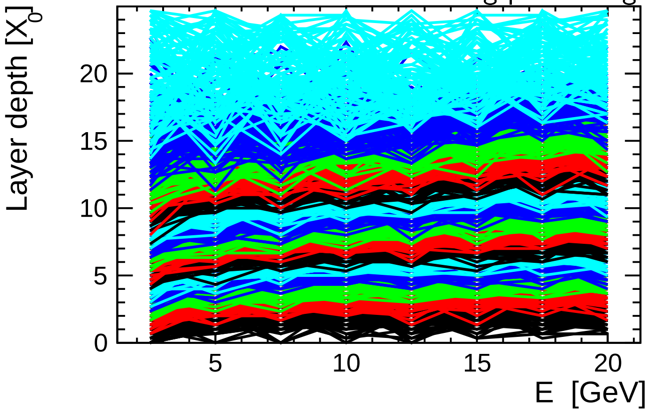
Use this procedure to generate large population of children.

Select the best ones as the next generation.

**Results** procedure applied separately for each energy

Layer positions for 100 best configurations (with best energy resolution) in each generation.

**Monte Carlo configurations** - starting point for genetic algorithm



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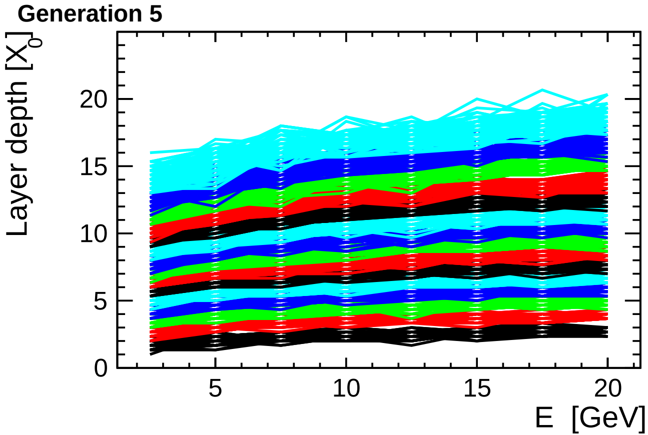

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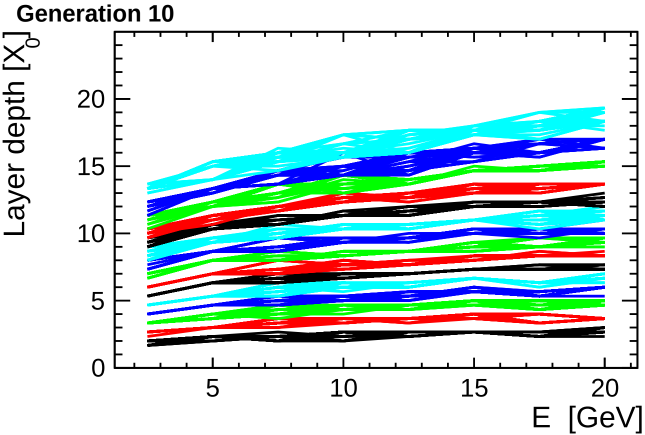

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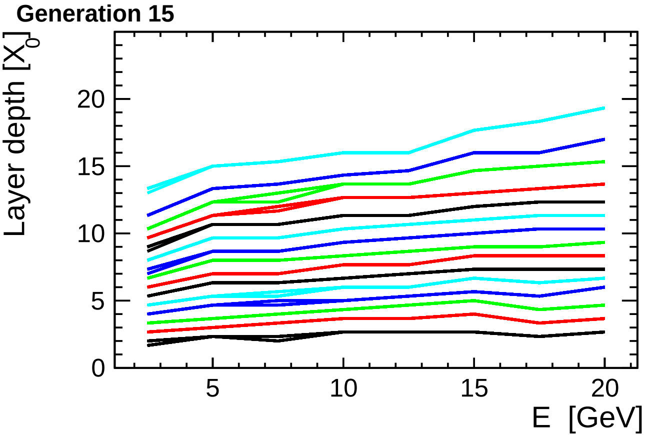

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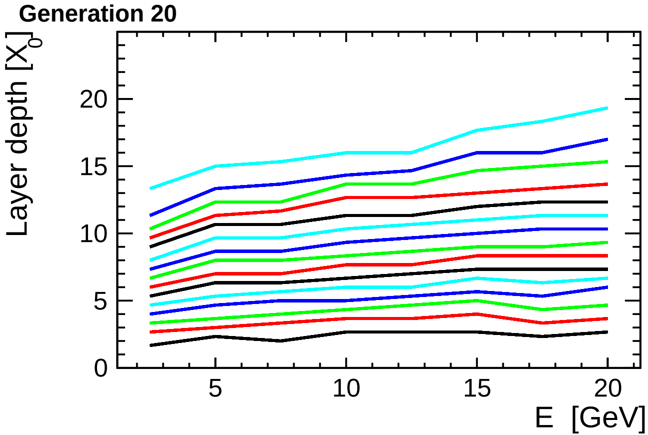
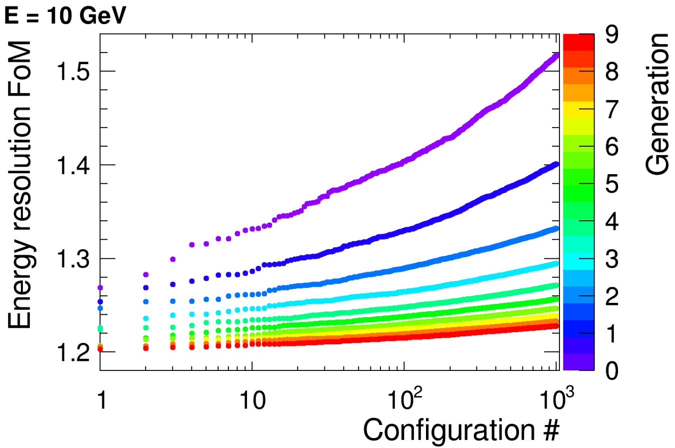


**Results** for example energy

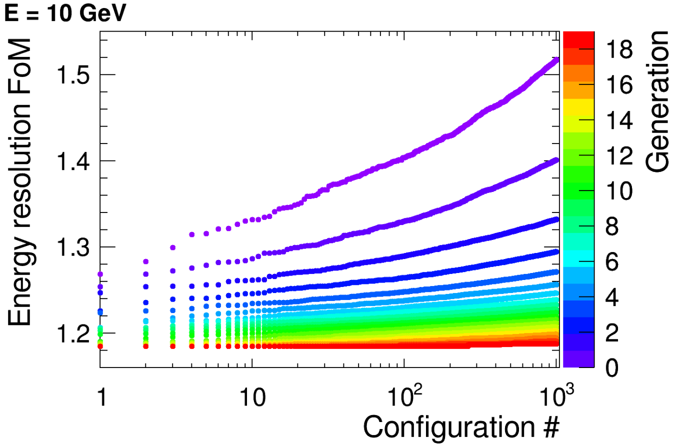
Best 1000 results of energy resolution optimization, first 10 generations



# Genetic algorithm

**Results** for example energy

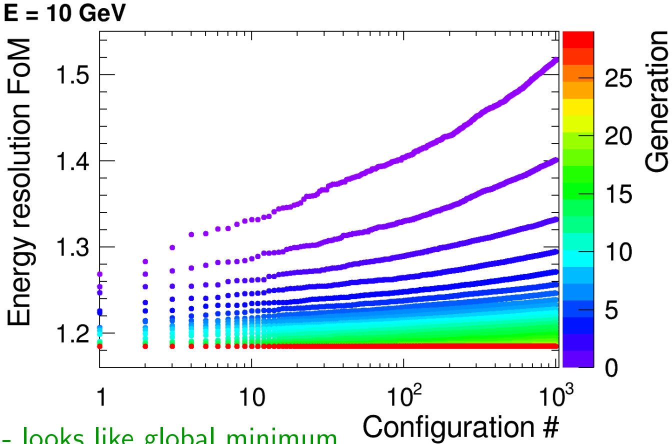
Best 1000 results of energy resolution optimization, first 20 generations



# Genetic algorithm

**Results** for example energy

Best 1000 results of energy resolution optimization, first 30 generations



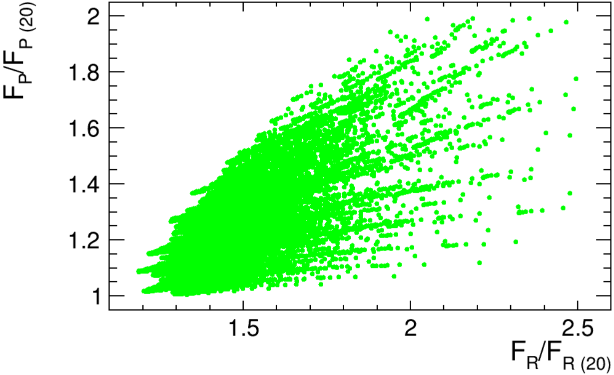

Very stable solution - looks like global minimum

**Outline:**

# Multi-objective optimization

## Problem

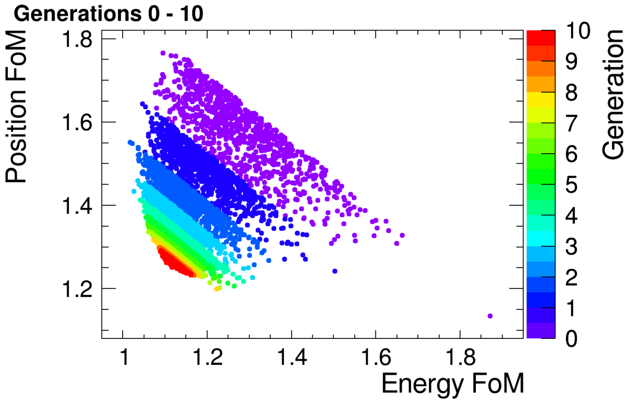
As shown with the configuration scan, optimization result depends on the optimization goal.




How to define the goal, if we need to optimize both energy and position measurement?

## Combined FoM

Simplest solution: combine (add) energy and resolution figures of merit:



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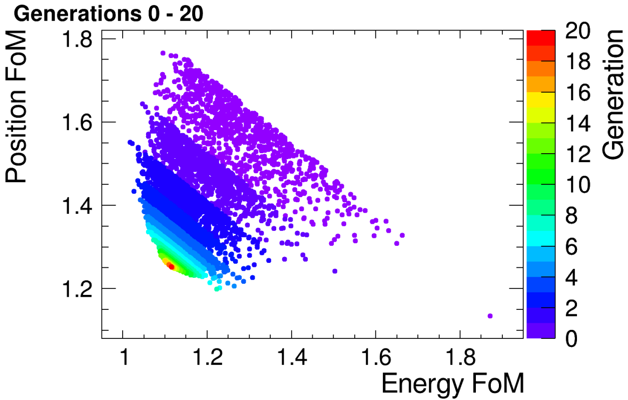


Procedure converges well to single solution.

## Non dominated sorting

idea taken from arXiv:2103.00522

When configuration A gives better energy resolution and better position resolution than configuration B, we can clearly state that A is better (more optimal) than B.

We can say that A dominates B

However, if only one resolution is better and the other one is worse, we can not decide which configuration is better (without considering particular measurement goal).

They are equivalent, they belong to the same "Pareto front"

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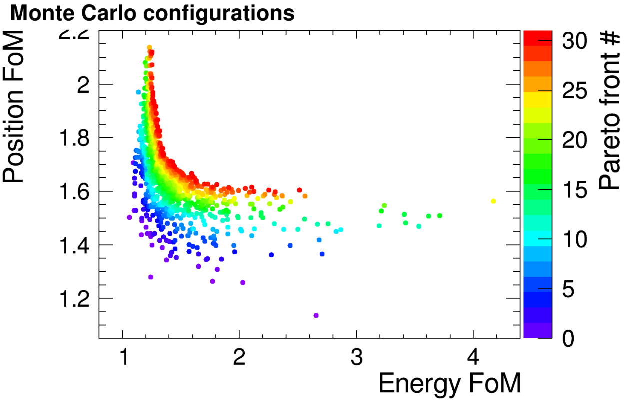
They are equivalent, they belong to the same "Pareto front"

By grouping population of configurations in Pareto fronts, we can (partially) sort all configuration and select the best performing ones (by selecting best performing fronts), without any additional assumptions!

pygmo library was used for the results presented here

## Non dominated sorting

Configurations from the best Pareto fronts (best 1000 configurations)



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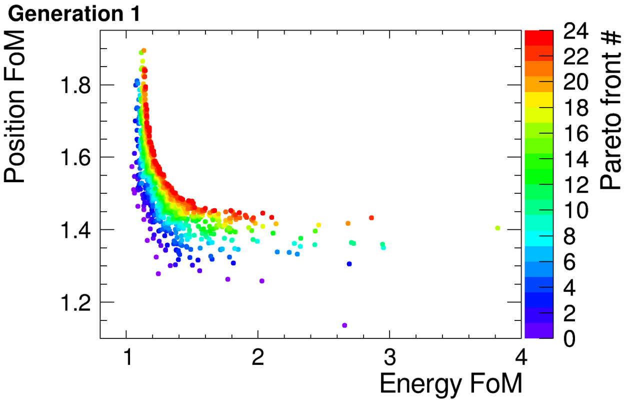

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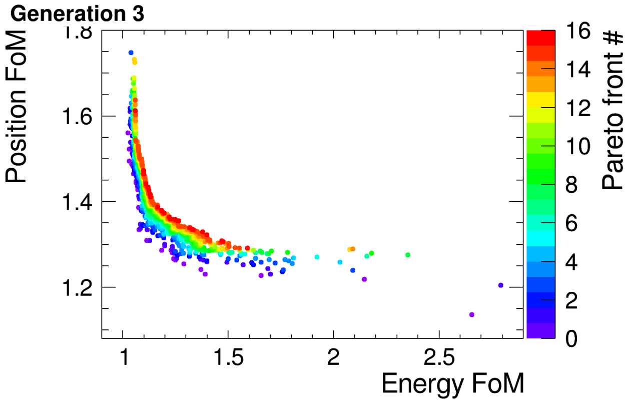

# Multi-objective optimization

## Non dominated sorting

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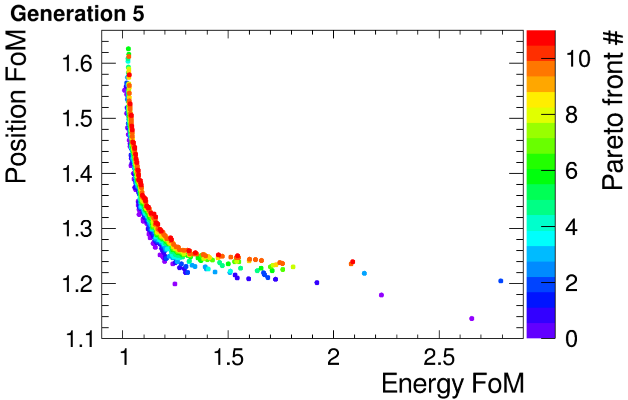

# Multi-objective optimization

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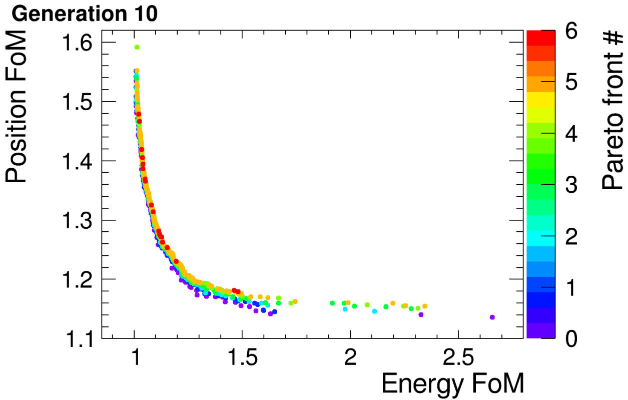

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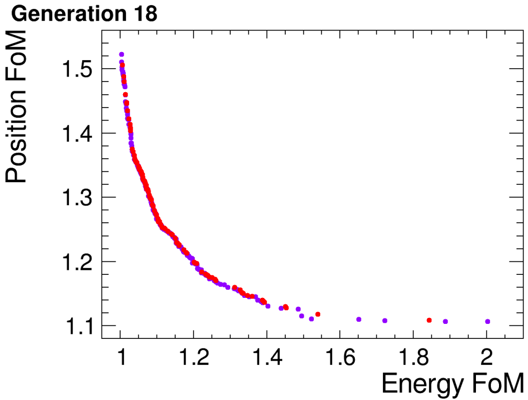
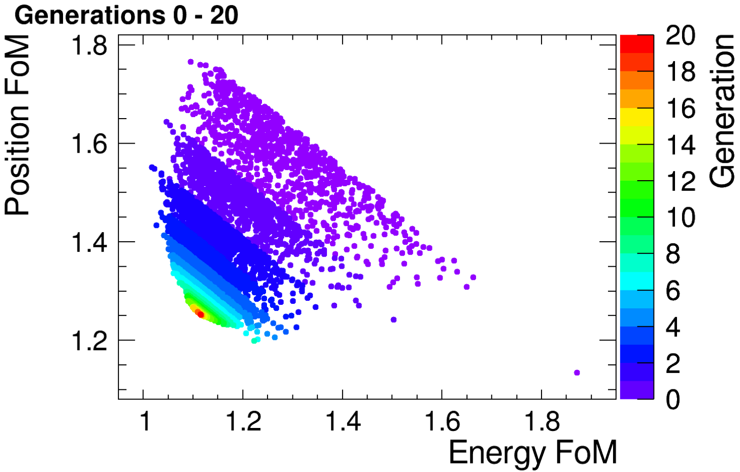



We find Pareto optimal set of configurations, which can be tested for the particular problem

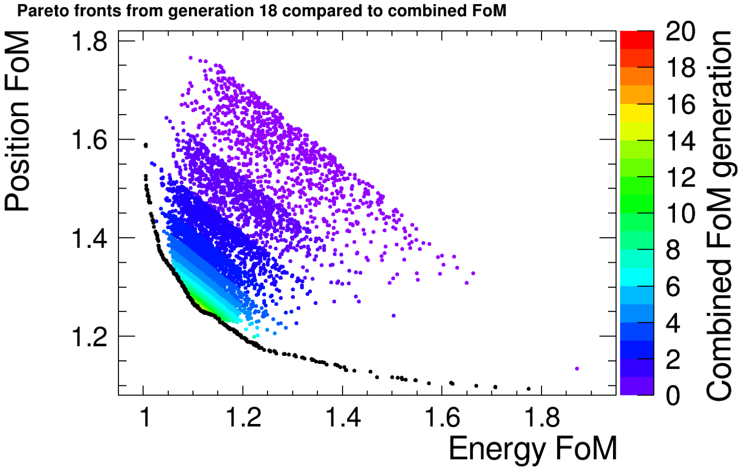
## Result

Results of the combined FoM optimization: (reminder)



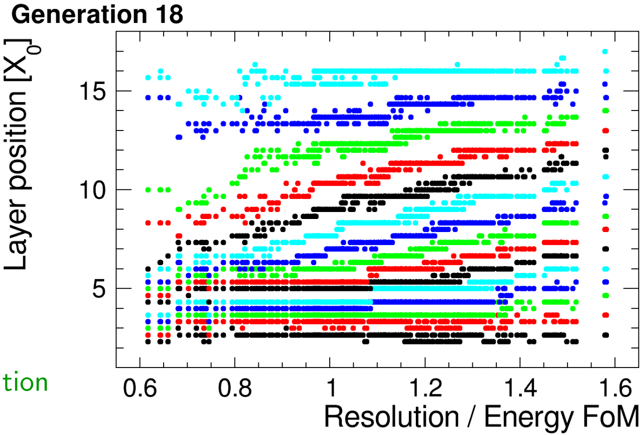
## Result

Optimized Pareto front corresponds to the envelope of the targeted optimization results



## Result

We can see how the preferred longitudinal structure changes with the optimization goal




⟸ position resolution    energy resolution ⟹

**Outline:**

# Conclusions

General framework proposed for calorimeter response calibration and optimization.
Including response linearity, energy resolution and position resolution goals.
Different calorimeter configurations can be very efficiently compared.

The framework built for the LUXE ECALp optimization studies
extended to the more general case of high density electromagnetic calorimeter.

Genetic algorithm looks like an efficient tool for finding the optimal calorimeter configuration.

Optimization results strongly depend on the optimization goal selected.

Non dominated sorting based on Pareto frontiers can be used to find a larger set of optimal configuration, which can then be considered in more details, for particular measurement.

The approach is very general, can be used also for other experiments and calorimeter concepts.

Presented are just the first results, we clearly plan to continue...

# Backup slides

## Energy/position reconstruction

We assume that the calorimeter response (positron energy estimate) is calculated as a weighted sum of signals from $N$ individual calorimeter layers:

$$E_{meas} = \sum_{i=1}^{N} c_i \cdot s_i$$

## Energy/position reconstruction

We assume that the calorimeter response (positron energy estimate) is calculated as a weighted sum of signals from $N$ individual calorimeter layers:

$$E_{meas} \quad = \quad \sum_{i=1}^{N} c_i \cdot s_i$$

Similar formula can also be used when reconstructing particle position in the calorimeter:

$$X_{meas} \quad = \quad \frac{1}{E_{meas}} \sum_{i=1}^{N} c_i' \cdot x_i \cdot s_i$$

where $x_i$ is energy-weighted average position of the energy deposit $s_i$ in layer $i$.
This is a simplified picture, but adequate for the approach presented here.

# Calibration framework

## Relative energy resolution

To compare detector response at different incident energies $E_0$ we introduce

$$\delta_R \;=\; \frac{\sigma_E}{\langle E \rangle} \cdot \frac{\sqrt{E_0}}{a} \quad \rightarrow 1 \quad \text{for expected resolution} \;\; (a \approx 20\%)$$

## Figure of merit for combined measurements at different energies

Figure of merit for energy resolution:

$$F_R \;=\; \sum_E \delta_R^2(E) \;=\; \sum_E \frac{1}{a^2 E} \sum_{i,j} c_i \, c_j \left( \langle s_i s_j \rangle - \langle s_i \rangle \langle s_j \rangle \right)$$

Figure of merit for position resolution:

$$F_P \;=\; \sum_E \sigma_X^2(E) \;=\; \sum_E \frac{\sum_{i,j} c_i \, c_j \left( \langle x_i x_j s_i s_j \rangle - \langle x_i s_i \rangle \langle x_j s_j \rangle \right)}{\left( \sum_i c_i \, \langle s_i \rangle \right)^2}$$

## Analytic optimization

Optimal calibration factors are those which minimize variance of $E_{meas}$ or $X_{meas}$.

To avoid calibration bias, energy normalization constraint can be added:
implemented using Lagrange multiplier

$$\sum_E \sum_i c_i \langle s_i \rangle \;=\; \sum_E E$$

## Analytic optimization

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Calibration factors for all layers, $c_i$, can be found by solving a set of linear equations:

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

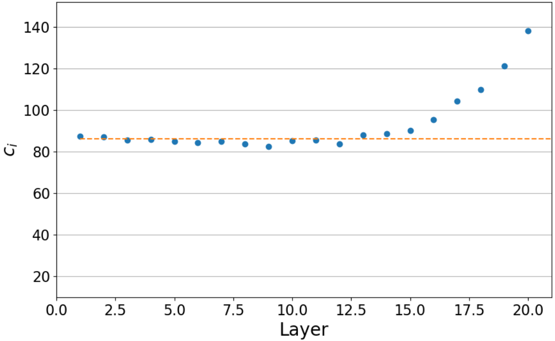
where matrix $\mathbb{A}$ and vector $\vec{B}$ can be calculated from single layer averages: $\langle s_i \rangle$ and $\langle s_i s_j \rangle$ for energy measurement optimization or $\langle x_i s_i \rangle$ and $\langle x_i x_j s_i s_j \rangle$ for position measurement

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

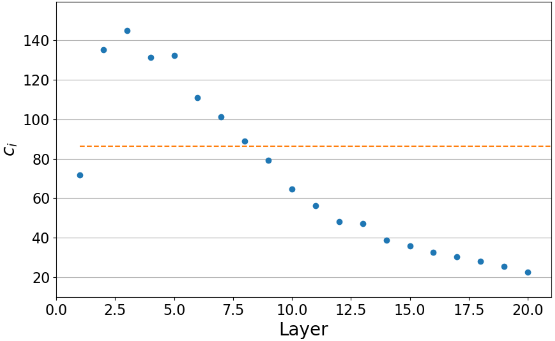
## Full calorimeter calibration

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

Energy resolution




Position resolution

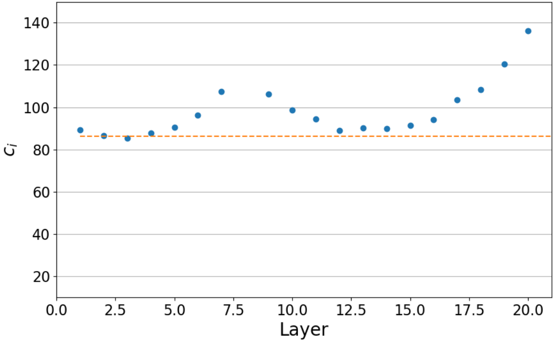



Calibration factors clearly depend on the optimization goal!

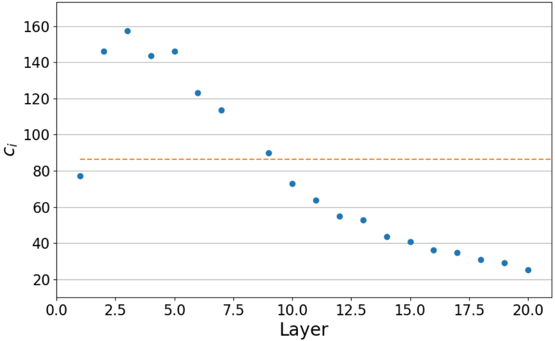
## Full calorimeter calibration

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

Energy resolution




Position resolution




Very flexible procedure: calibration factors for configuration with $8^{th}$ layer removed

# Configuration scan

**Best energy resolution**

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 scan

## Best position resolution

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 | . . . . | . . . . . . . . . . . . . . .
```