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

Longitudinal structure optimization...

Outline:

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

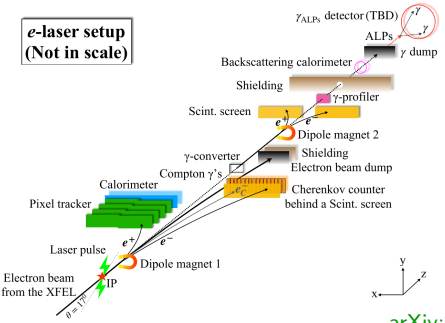
Longitudinal structure optimization...

Outline:

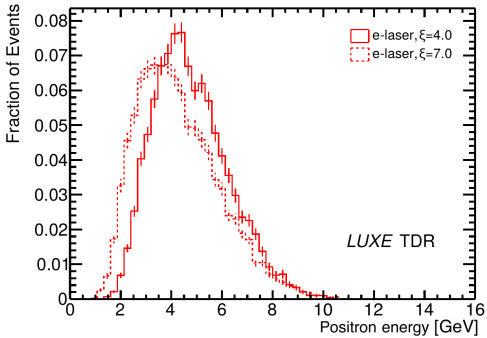
LUXE experiment at DESY

for more details see contribution by Ruth Jacobs

Unique high precision experiment dedicated to study of Strong Field QED (SFQED) with use use of 17.5 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).

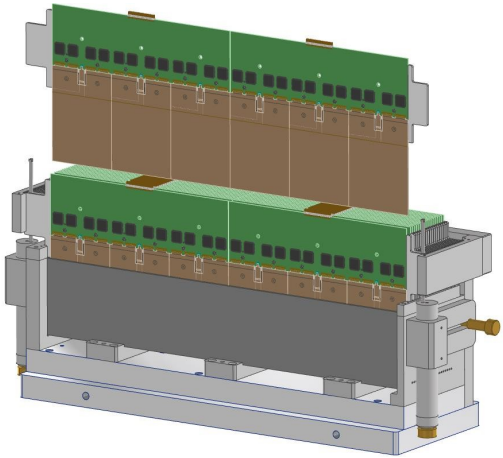
ECALp - high density positron calorimeter for LUXE

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 μm silicon sensors
  - active layers 780μm 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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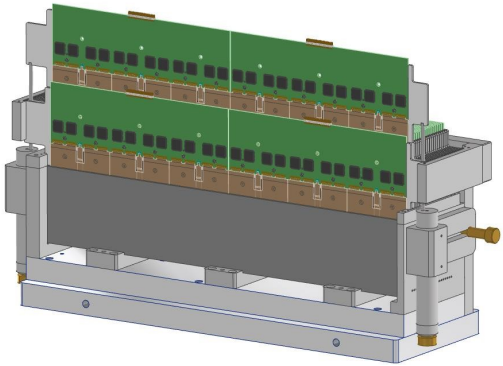

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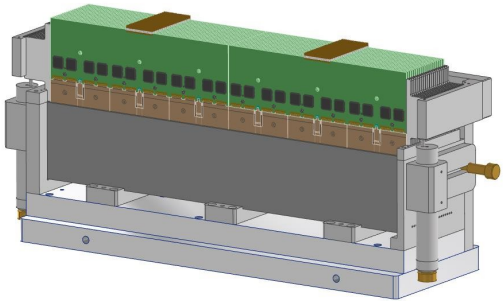

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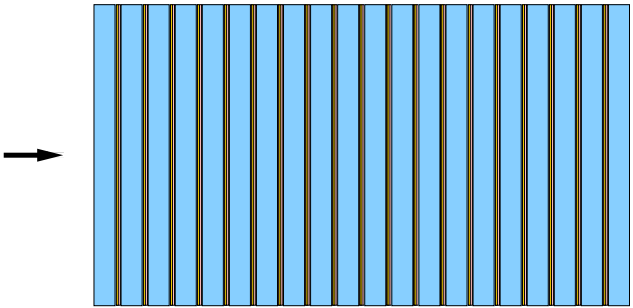
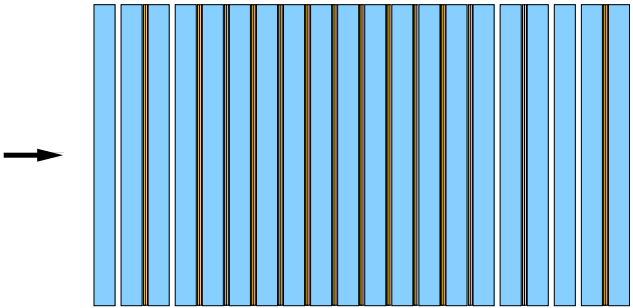
ECALp longitudinal structure optimization



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?

$\Rightarrow$ need for a dedicated study

Longitudinal structure optimization...

Outline:

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 we have total of just

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

possible layer configurations, which can be checked in $\mathcal{O}(1\text{h})$ (energy scan 2.5 – 15 GeV).

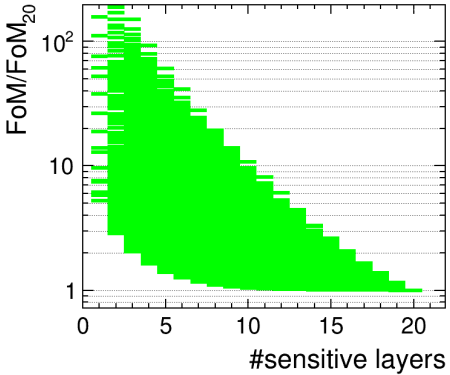
We can then look for the optimal configuration for given number of instrumented layers...

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

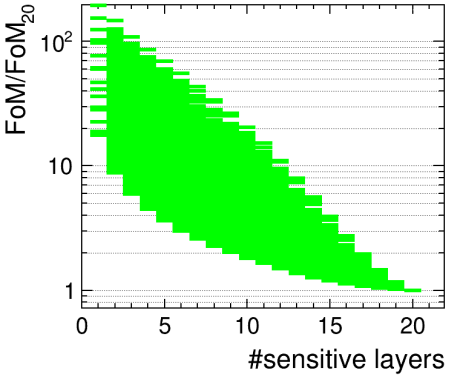
Scan results

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

Position resolution optimization



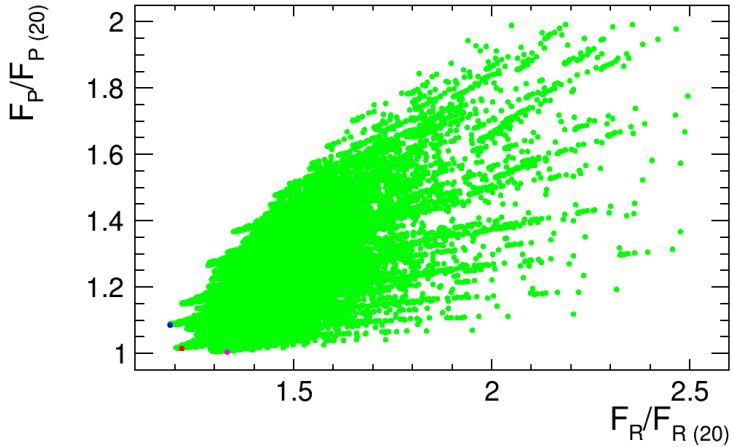
Energy resolution optimization



Optimization

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

Indicated configurations:



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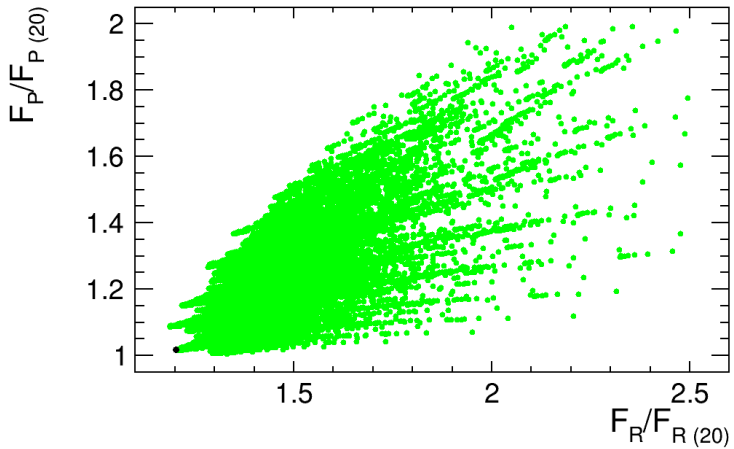
Indicated configurations:

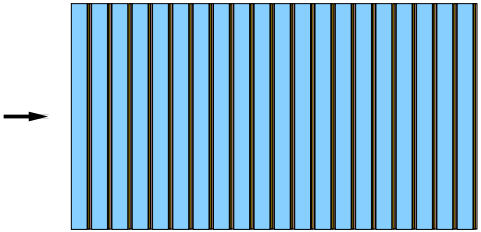
.!!!!!!!!!!!!!!.!!...

Optimal !?...



Outline:

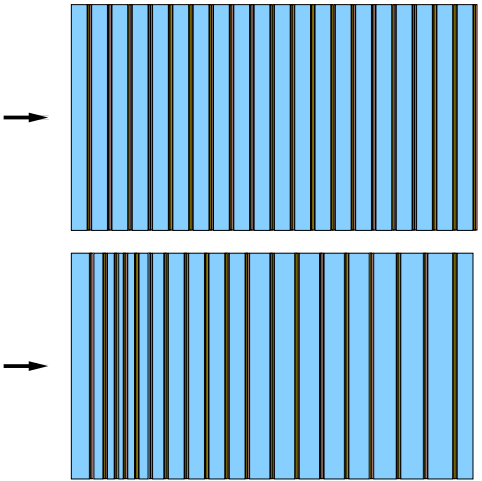
Extended detector model



Geant 4 simulation of ECALp:

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

Extended detector model



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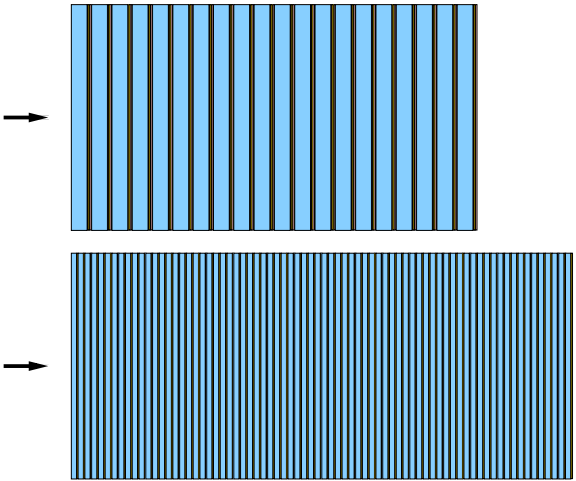
When looking for optimal solution, one should also allow for non-uniform structures.

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

Extended detector model



Geant 4 simulation of ECALp:

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Model used for non-uniform configurations:

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

Same sensor, same sampling fraction, same average density, extended to 25 X_0

Monte Carlo approach

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

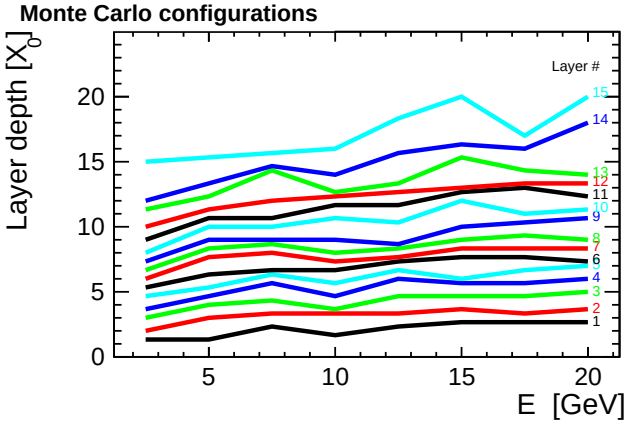
$2.28 \cdot 10^{15}$ possible configurations $\Rightarrow$ direct scan over all not realistic

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

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

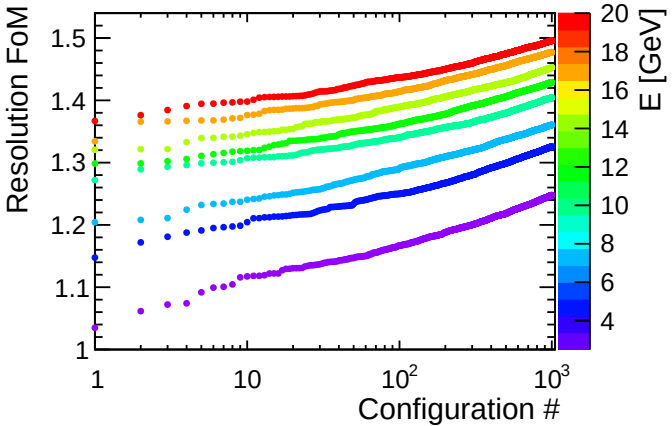
Large fluctuations visible!

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



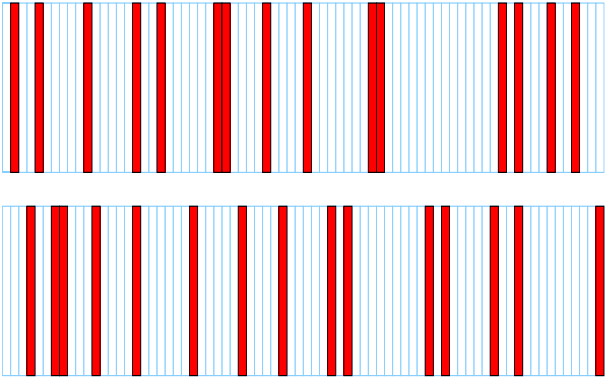
Large differences between best configurations - result not stable

Outline:

Genetic algorithm

Concept generation of new "children" configurations

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



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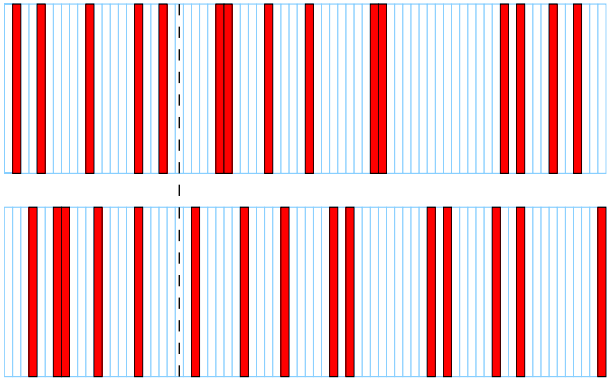

- Select random cut in the layer sequence

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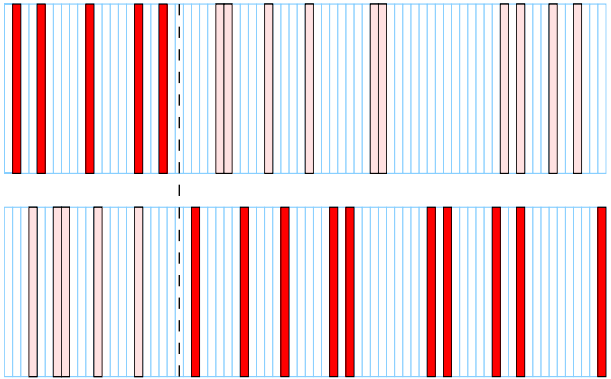

- Select random cut in the layer sequence
- Combine the first part of the first with the second part of the second configuration

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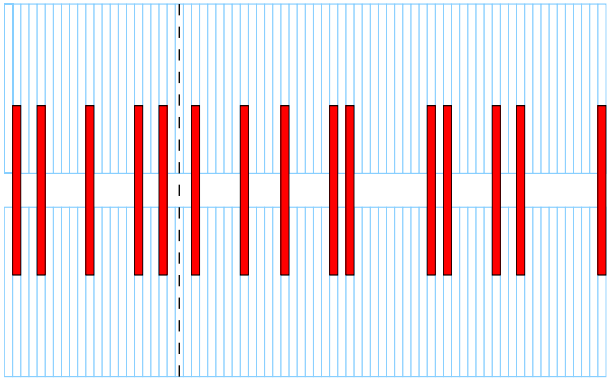

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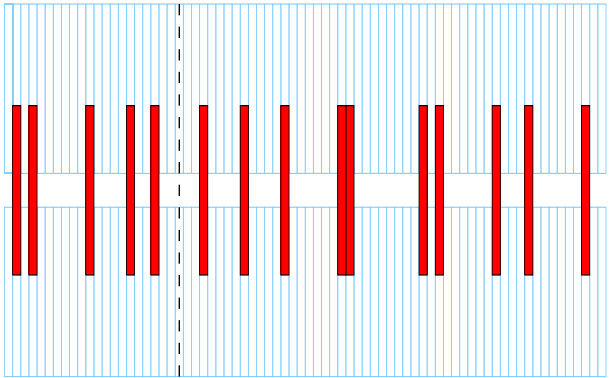

- Select random cut in the layer sequence
- Combine the first part of the first with the second part of the second configuration
- Add random mutations
  mutation probability decreases with time

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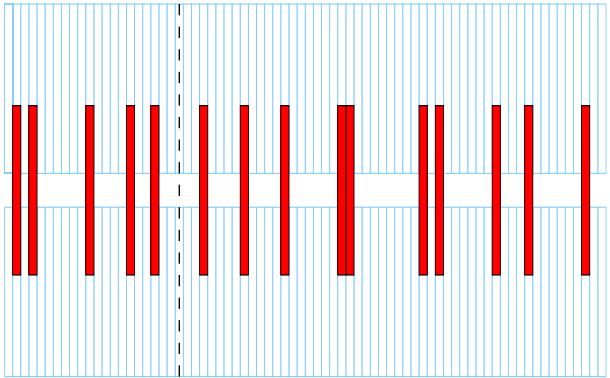


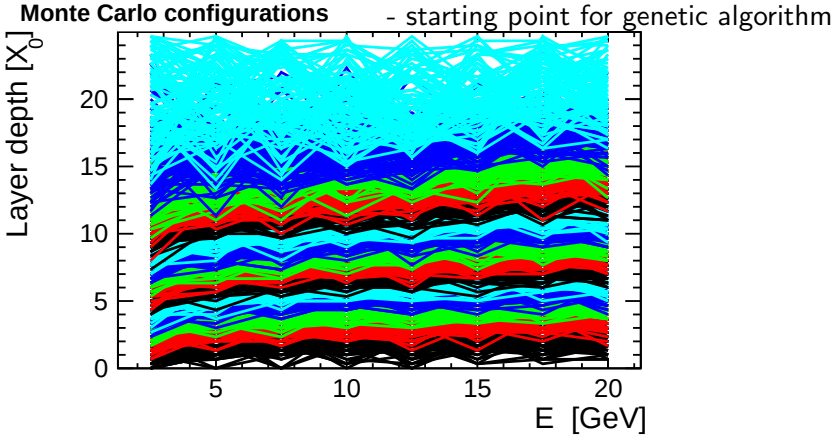
- Select random cut in the layer sequence
- Combine the first part of the first with the second part of the second configuration
- Add random mutations
  mutation probability decreases with time

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.



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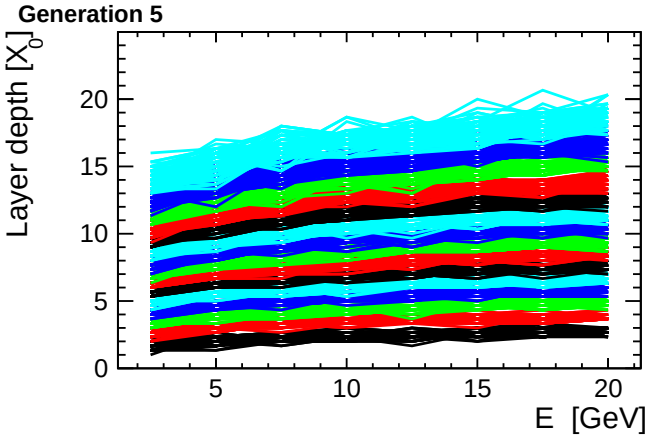

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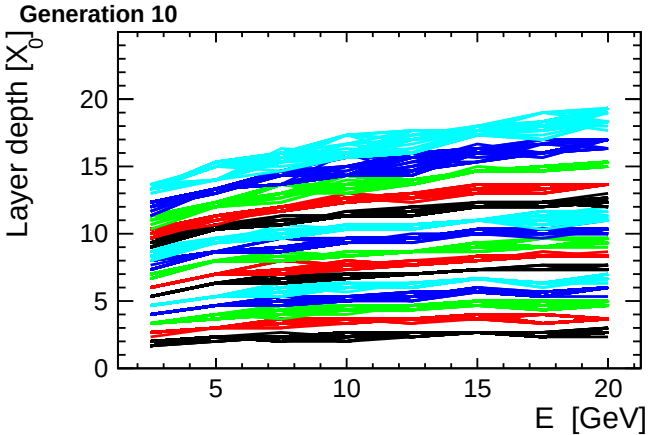

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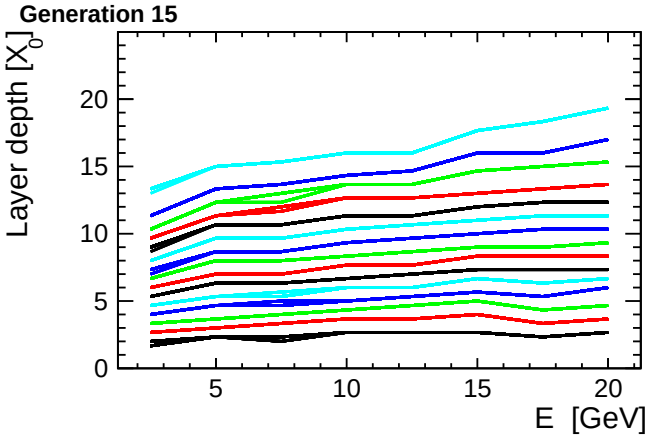

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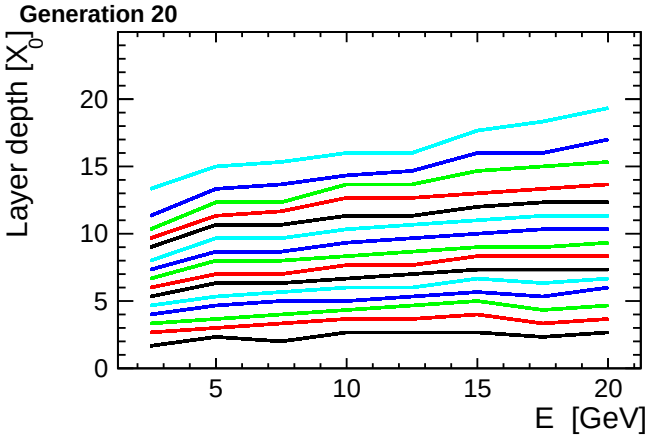
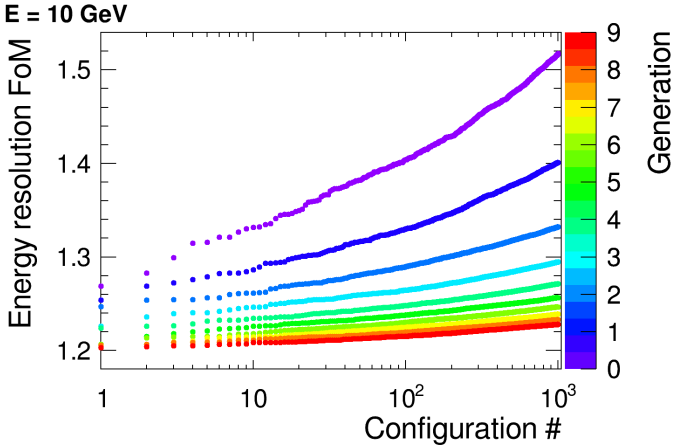


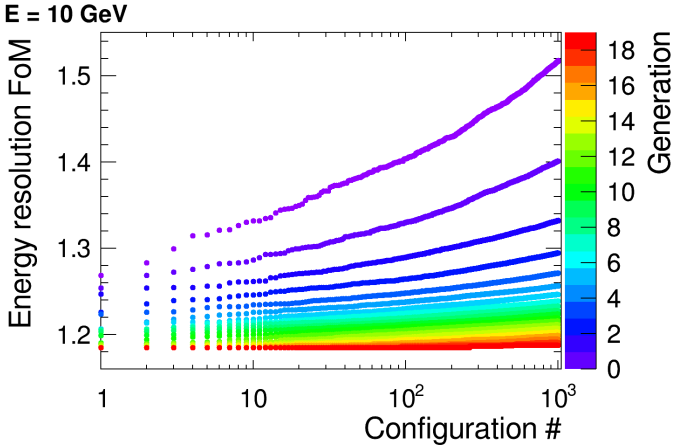
Results for example energy

Best 1000 results of energy resolution optimization, first 10 generations



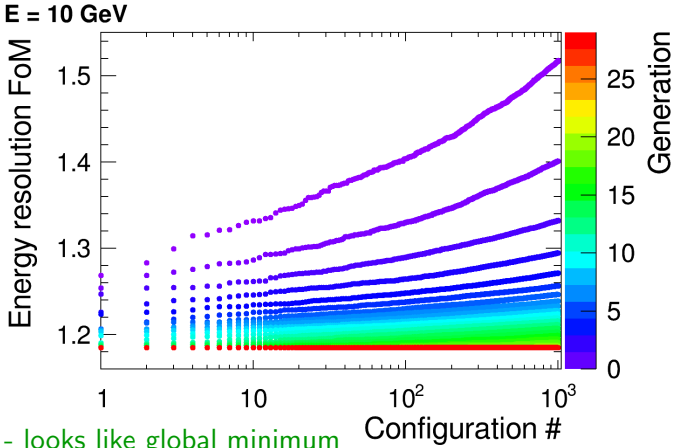
Results for example energy

Best 1000 results of energy resolution optimization, first 20 generations



Results for example energy

Best 1000 results of energy resolution optimization, first 30 generations



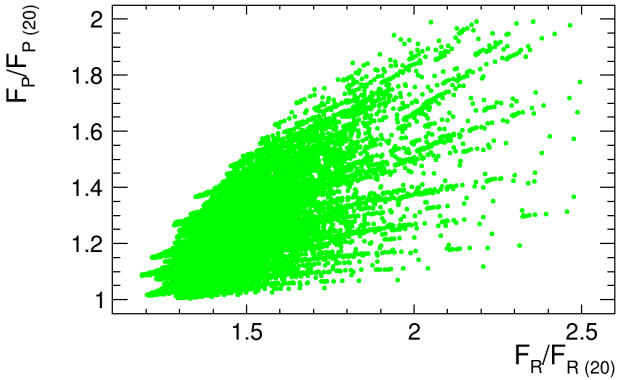
Very stable solution - looks like global minimum

Longitudinal structure optimization...

Outline:

Problem

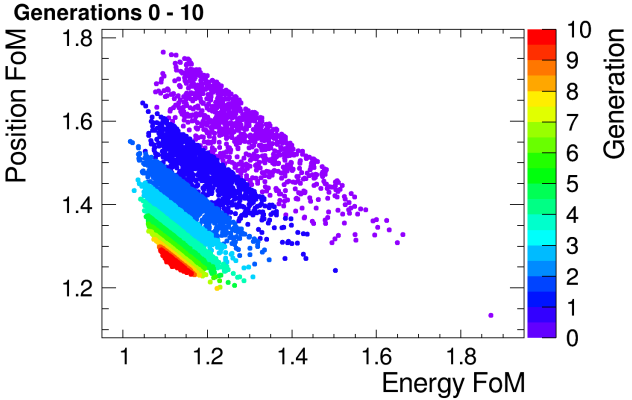
As shown with the configuration scan, optimization result depends on the optimization goal.



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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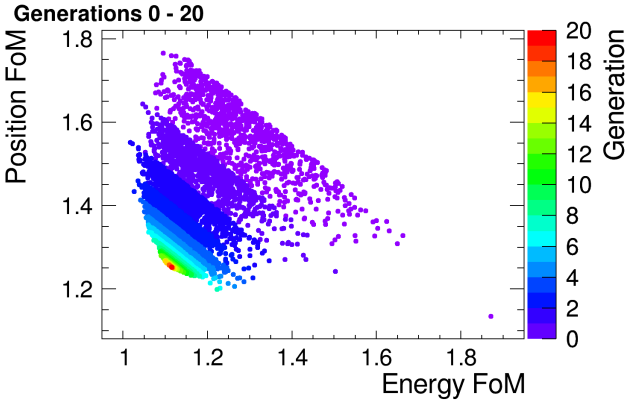

Procedure converges well to single solution.

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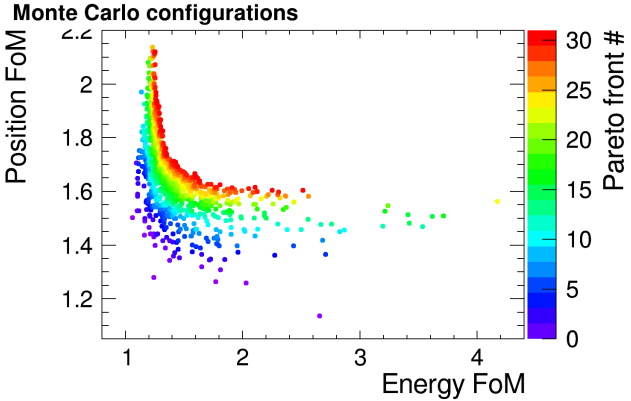
By grouping population of configurations in Pareto fronts, we can (partially) sort all configuration and select the best performing ones (by selecting best performing fronts), without any additional assumptions!

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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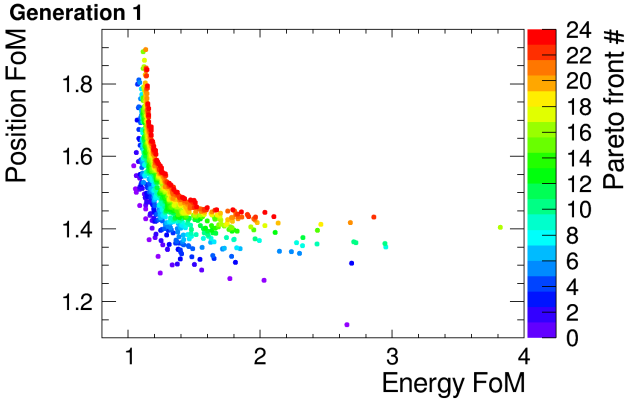

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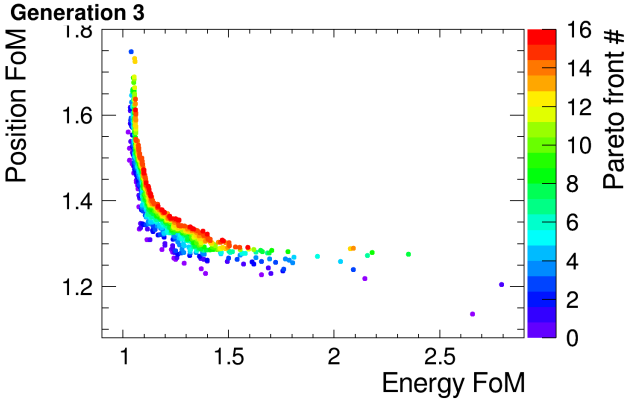

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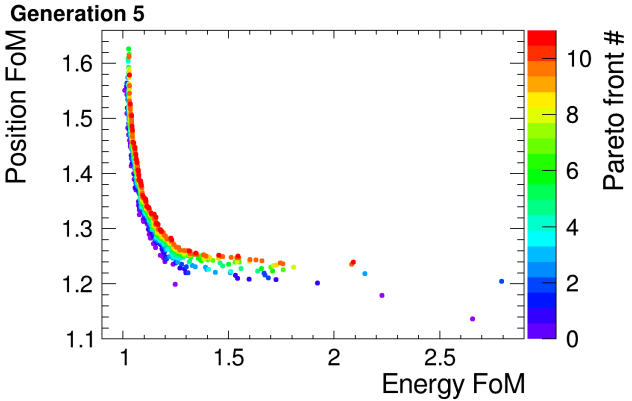

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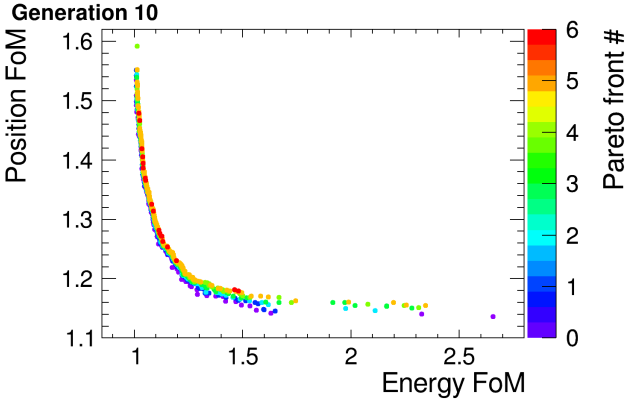

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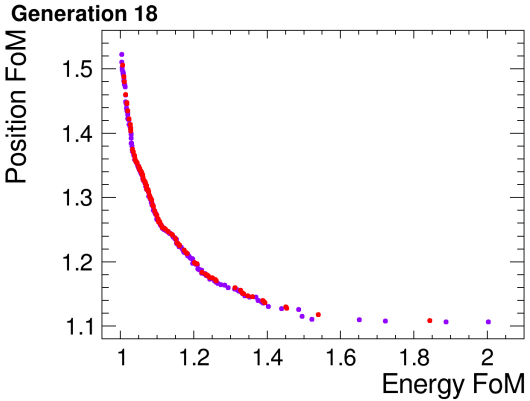
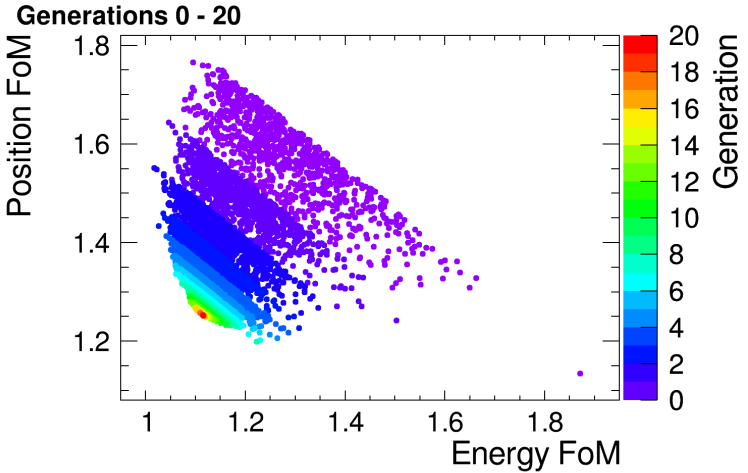


We find Pareto optimal set of configurations, which can be tested for the particular problem

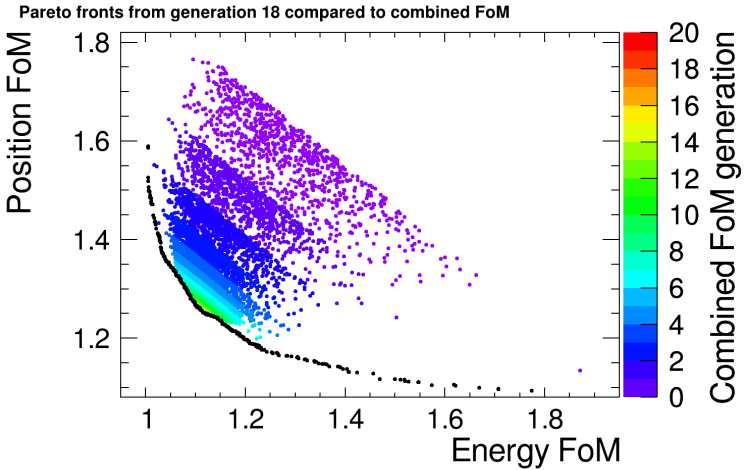
Result

Results of the combined FoM optimization: (reminder)



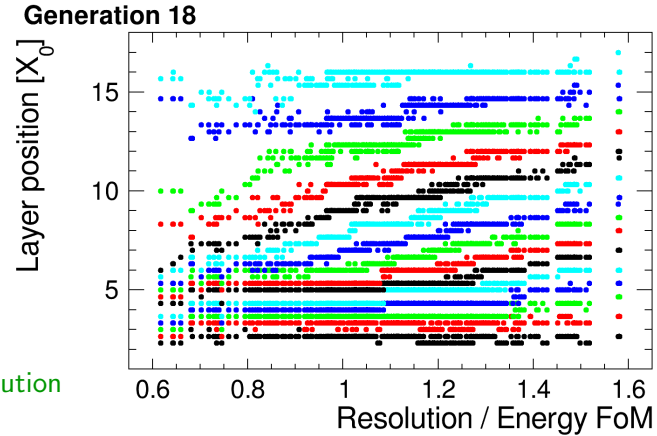
Result

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

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

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

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

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.

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

$$\sum_i c_i \langle s_i \rangle \quad = \quad E$$

Analytic optimization

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

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

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

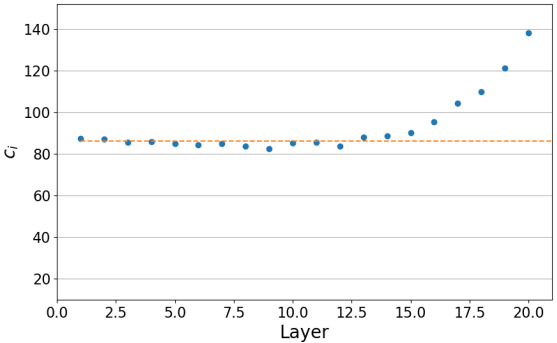
where matrix $\mathbb{A}$ and vector $\vec{B}$ can be calculated from single layer averages: $\langle s_i \rangle$ and $\langle s_i s_j \rangle$ for energy measurement optimization or $\langle x_i s_i \rangle$ and $\langle x_i x_j s_i s_j \rangle$ for position measurement

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

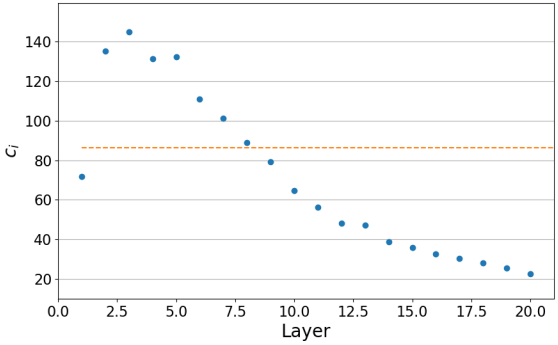
Full calorimeter calibration

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

Energy resolution



Position resolution

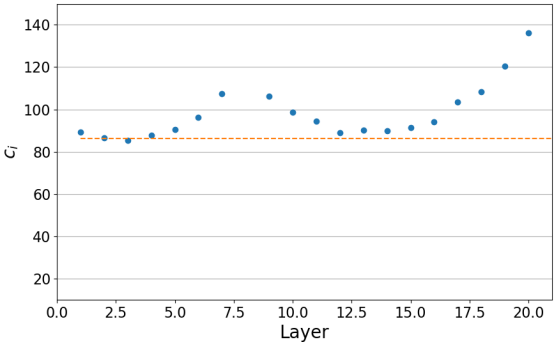


Calibration factors clearly depend on the optimization goal!

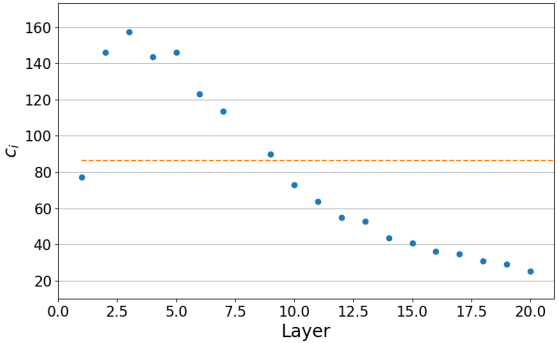
Full calorimeter calibration

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

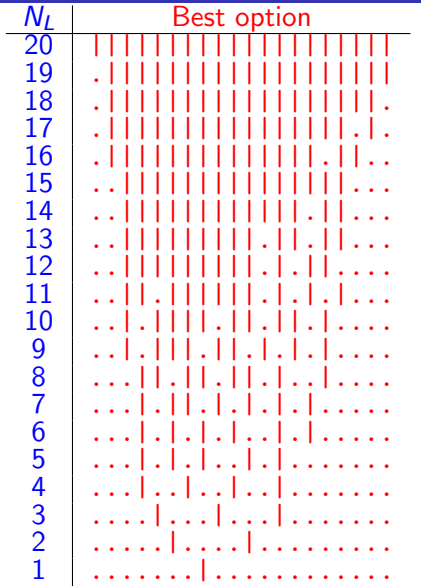
Configuration scan

Best energy resolution

Optimal configurations
for the decreasing number of active sensor layers

E = 2.5 – 15 GeV

| - active layer
. - empty slot



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
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