Detector layout optimization
for task Highly Compact Calo

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study done withing the LUXE ECAL-P group

LUXE

DRD6 Collaboration Meeting ay CERN

Software and Analysis session

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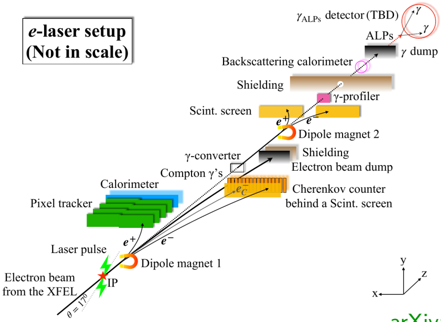
Detector layout optimization

Outline:

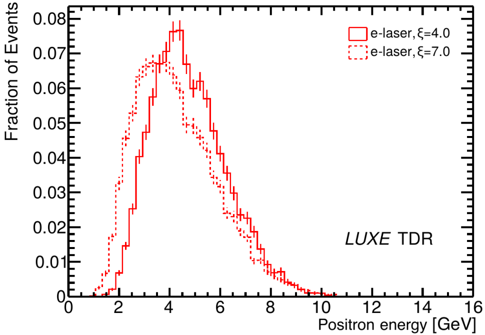
For more details see arXiv:2409.19654

LUXE experiment at DESY

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



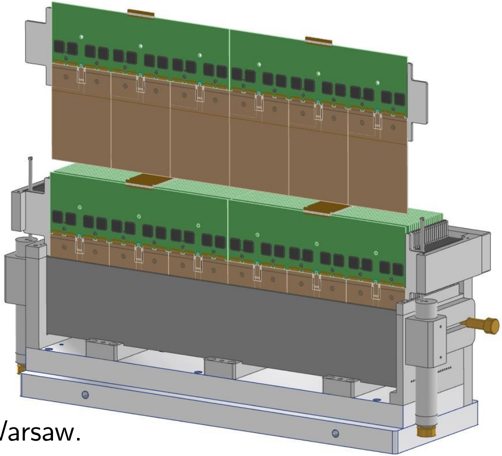
High rate of e^+e^- **pair** production expected due to non-linear effects (multi-photon scattering)

ECAL-P - 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)
- 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 × 16 pads of 5.5×5.5 mm^2
  - total active area: 54×9 cm^2



Mechanical prototype under tests at the University of Warsaw.

ECAL-P longitudinal structure optimization

Analytical procedure developed for (very fast) calibration optimization and energy/position measurement precision estimate for arbitrary configuration of active layers.

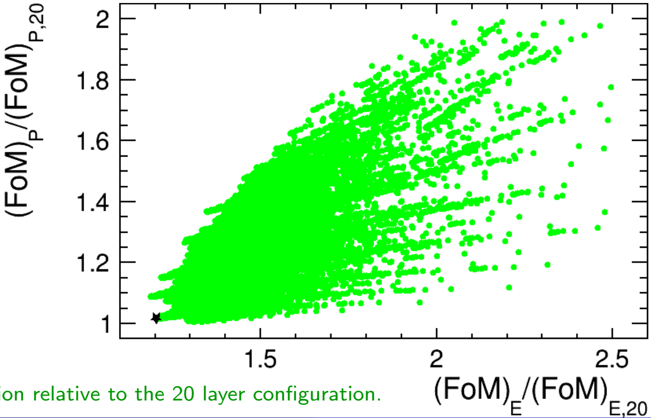
How to choose optimal configuration, if we have are only able to instrument 15 layers?

Position vs energy resolution FoM (figure of merit) for all possible choices of 15 out of 20 sensor gaps.

Indicated configuration:

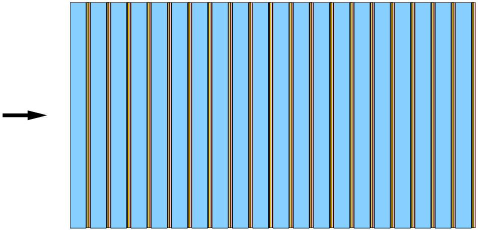
.|||||||||||||.||...

Optimal !?...



FoM: expected RMS of energy/position distribution relative to the 20 layer configuration.

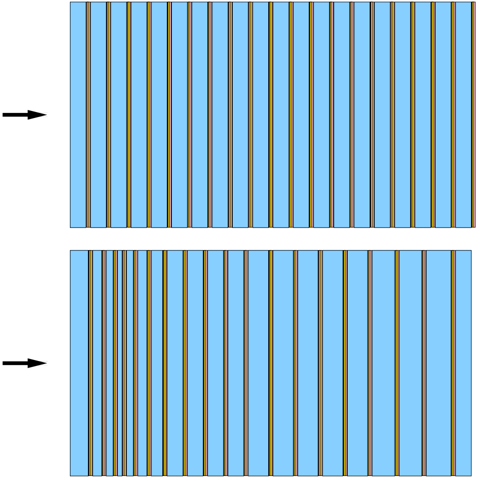
Extended detector model



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



Geant 4 simulation of ECALp:

- 21 tungsten plates of 1 X_0 each
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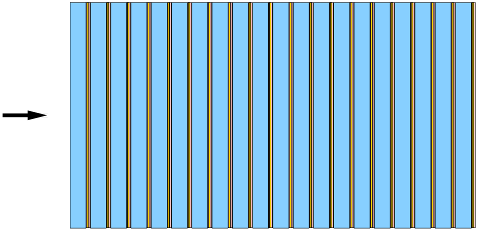
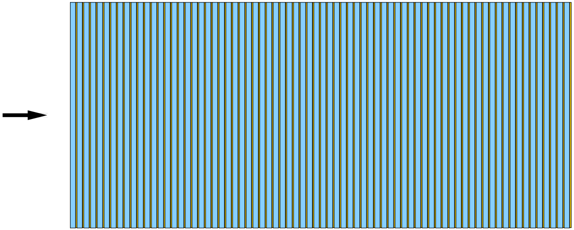
When looking for optimal solution, one should also allow for non-uniform structures.

⇒ 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
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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, almost the same average density, extended to 25 X_0

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

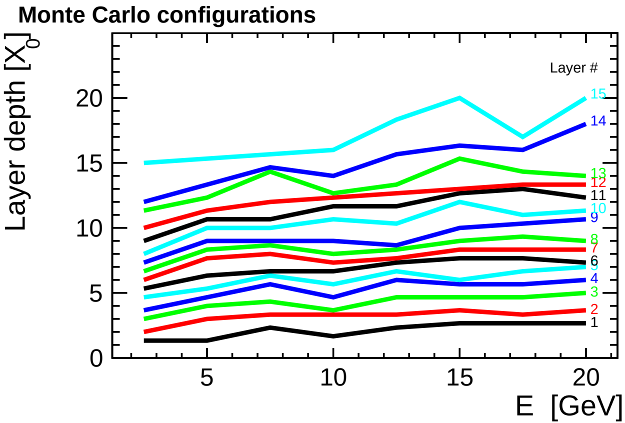
$2.28 \cdot 10^{15}$ possible configurations ⇒ direct scan over all not realistic

Easiest solution: generate configurations at random and select the one with the **best energy resolution**

Example result: 1'000'000 random configurations per energy ⇒

Large fluctuations visible!

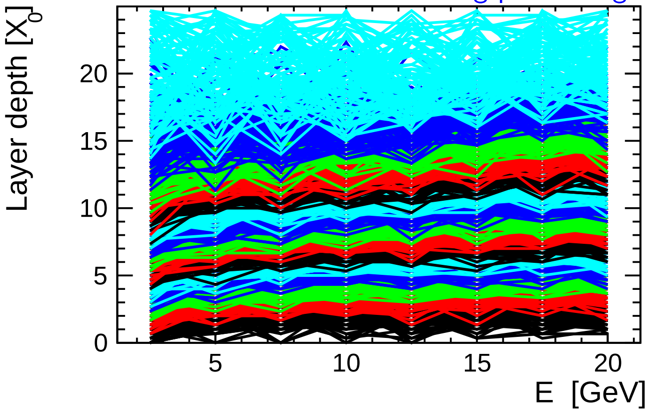
Low probability to find the optimal one...



Optimization results procedure applied separately for each positron 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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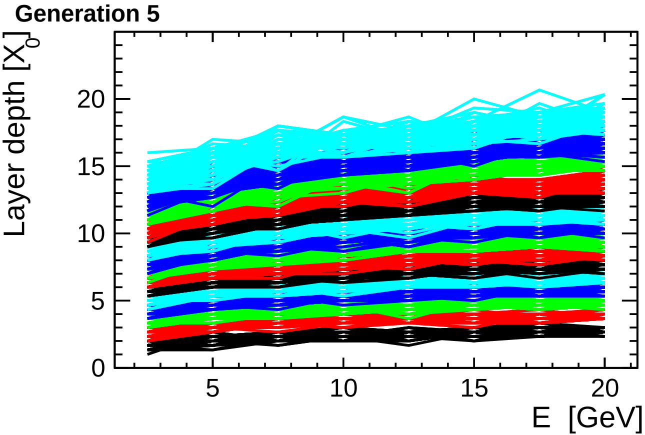

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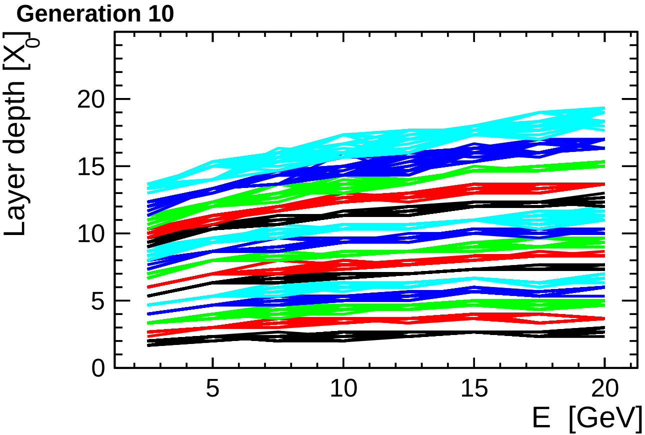

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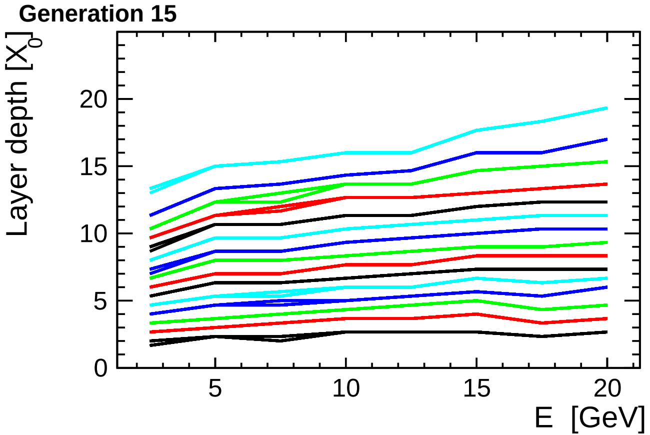

Genetic algorithm

Optimization results procedure applied separately for each positron energy

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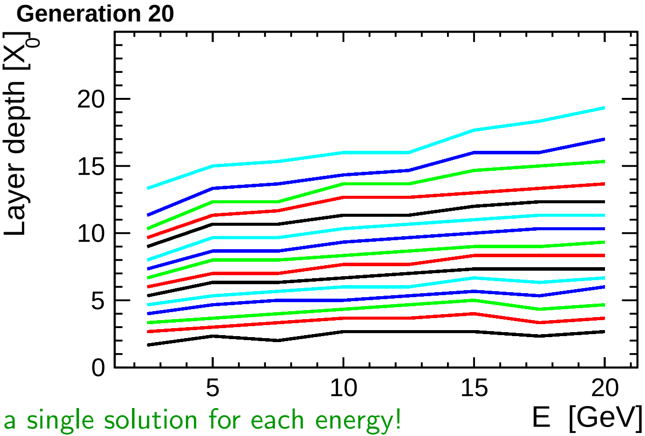
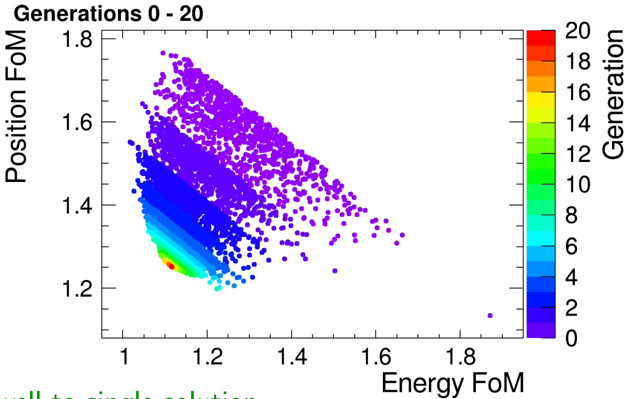


Converging fast to a single solution for each energy!

Combined FoM

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

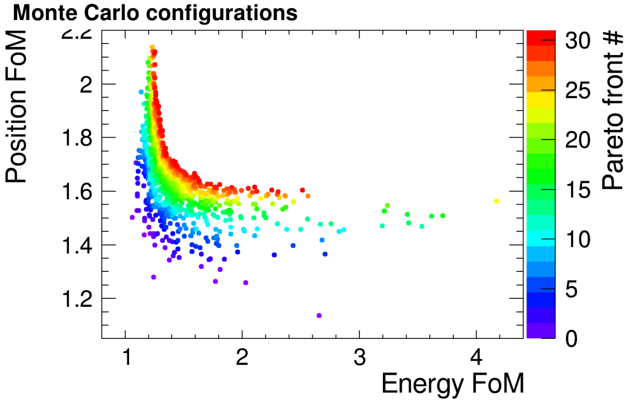


Procedure converges well to single solution.

But how to make sure it is the one optimal for our problem?

Non dominated sorting for energy and position resolution idea taken from arXiv:2103.00522

Configurations from the best Pareto fronts (best 1000 configurations)



Multi-objective optimization

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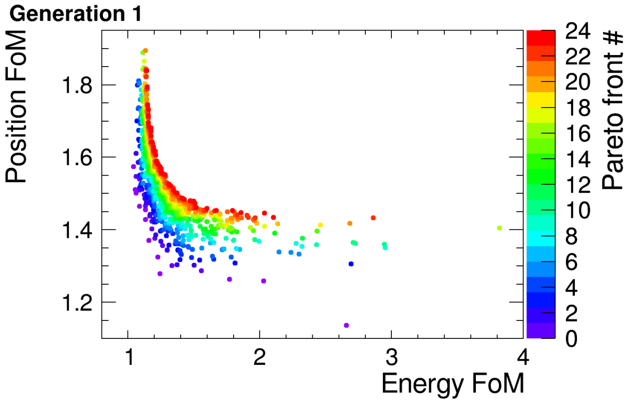

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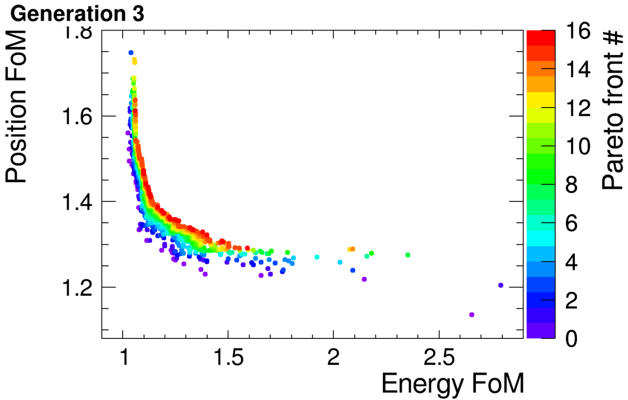

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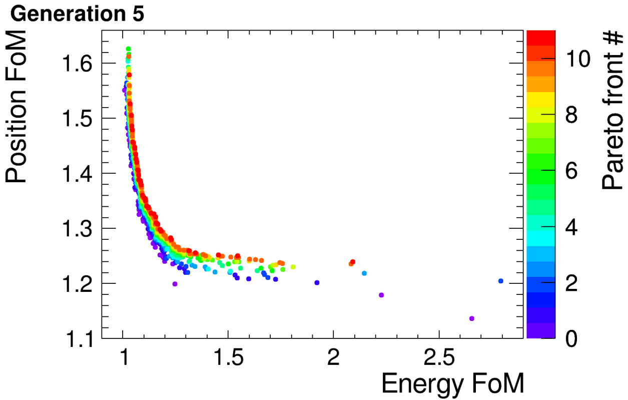

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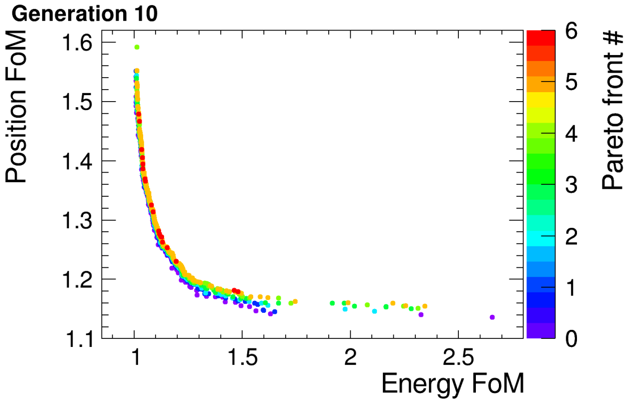

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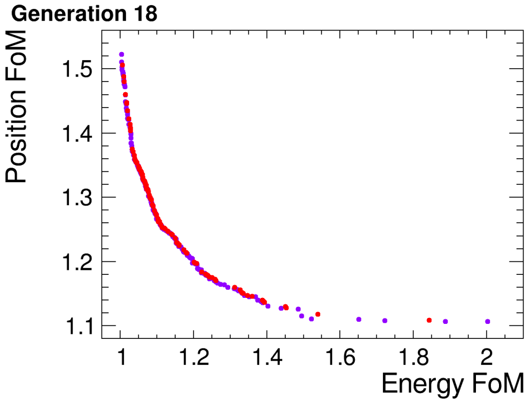
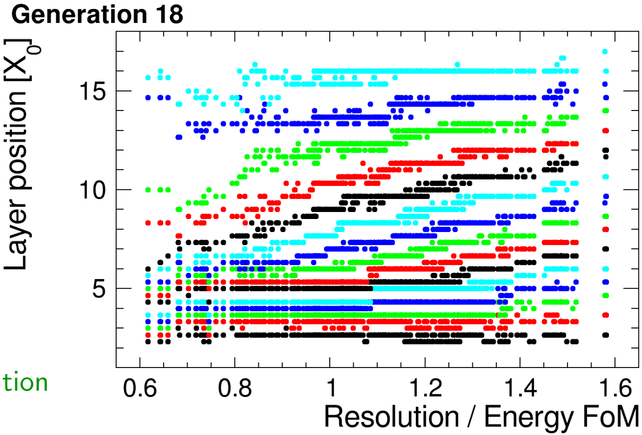


We find Pareto optimal set of configurations, which can be tested for the particular problem

Result

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



⟸ position resolution   energy resolution ⟹

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.

Plans

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

Targets for the near future:

- increase simulation granularity for more precise results (0.1 X_0 ?)
- include shower direction determination as optimization goal
- include readout segmentation in the optimization procedure

Funding application submitted in June, waiting for the decision...

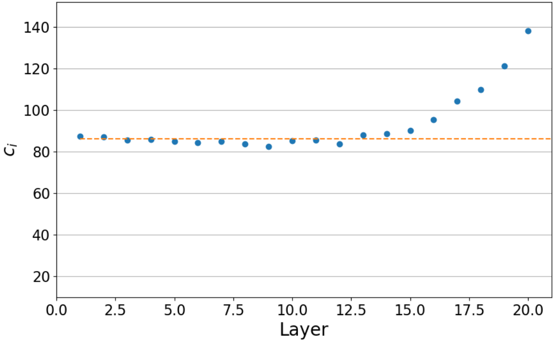
For more details see arXiv:2409.19654

Backup slides

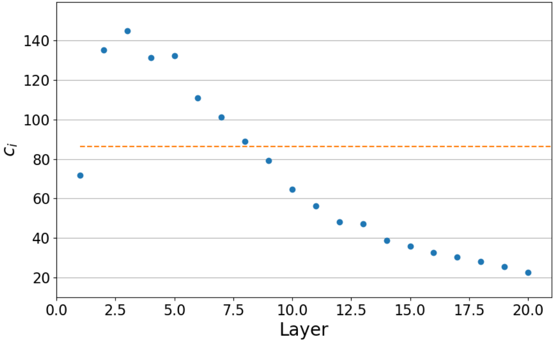
Full calorimeter calibration

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

Energy resolution



Position resolution

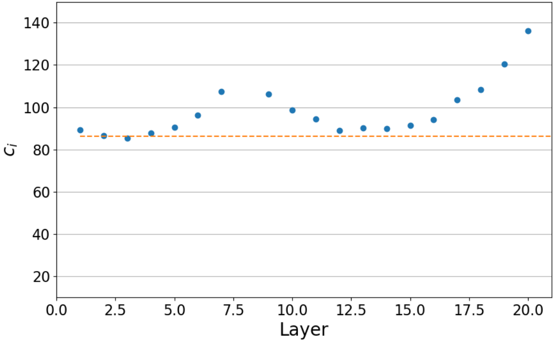


Calibration factors clearly depend on the optimization goal!

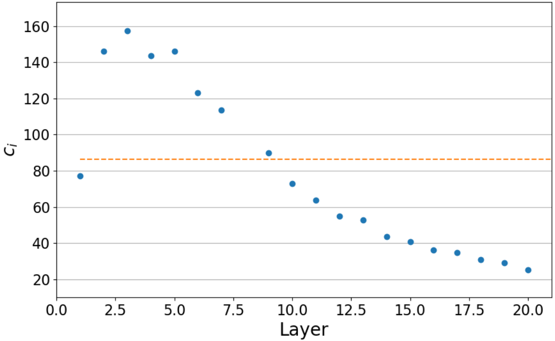
Full calorimeter calibration

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

Energy resolution



Position resolution

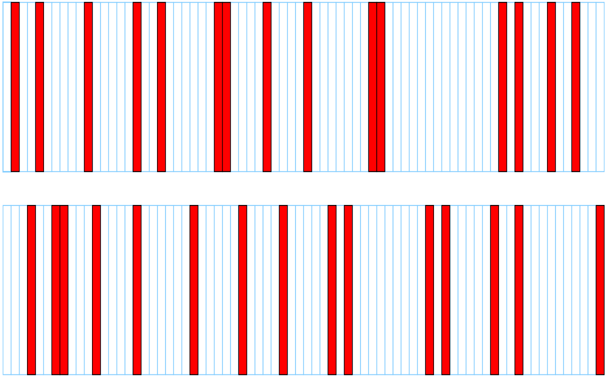


Very flexible procedure: calibration factors for configuration with 8^{th} layer removed

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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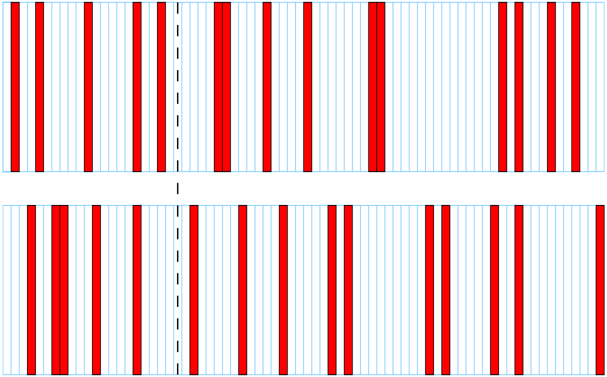

- Select random cut in the layer sequence

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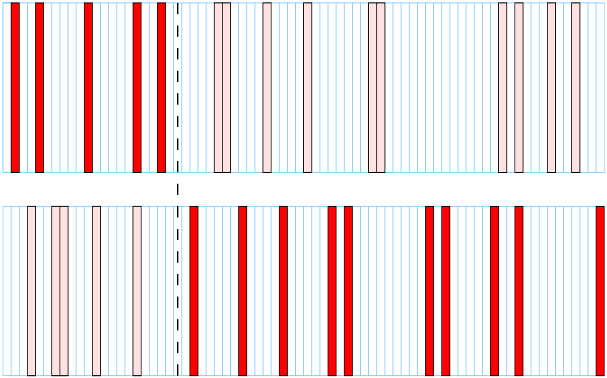

- Select random cut in the layer sequence
- Combine the first part of the first with the second part of the second configuration

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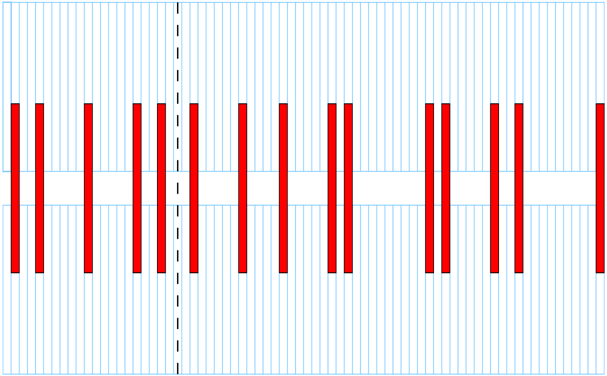

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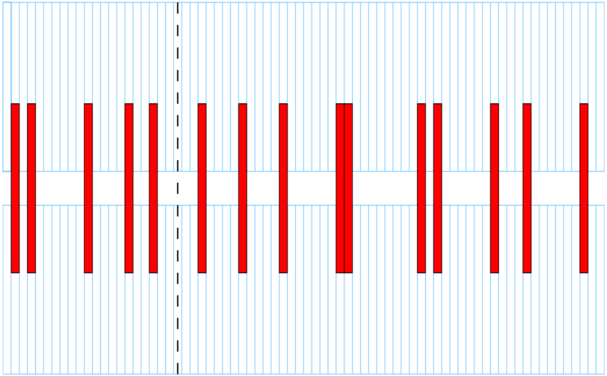

- Select random cut in the layer sequence
- Combine the first part of the first with the second part of the second configuration
- Add random mutations
  mutation probability decreases with time

Genetic algorithm

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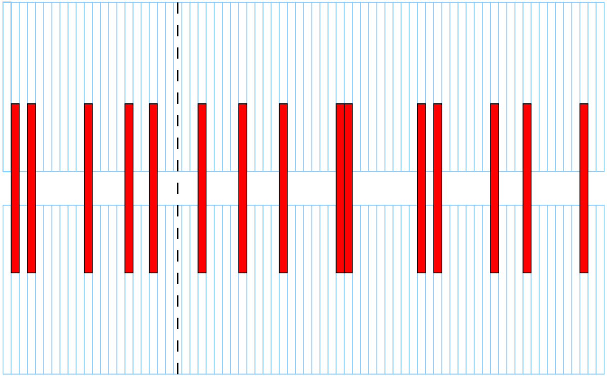

- Select random cut in the layer sequence
- Combine the first part of the first with the second part of the second configuration
- Add random mutations
  mutation probability decreases with time

Use this procedure to generate large population of children.

Select the best ones as the next generation.

Multi-objective optimization

Non dominated sorting

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”

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