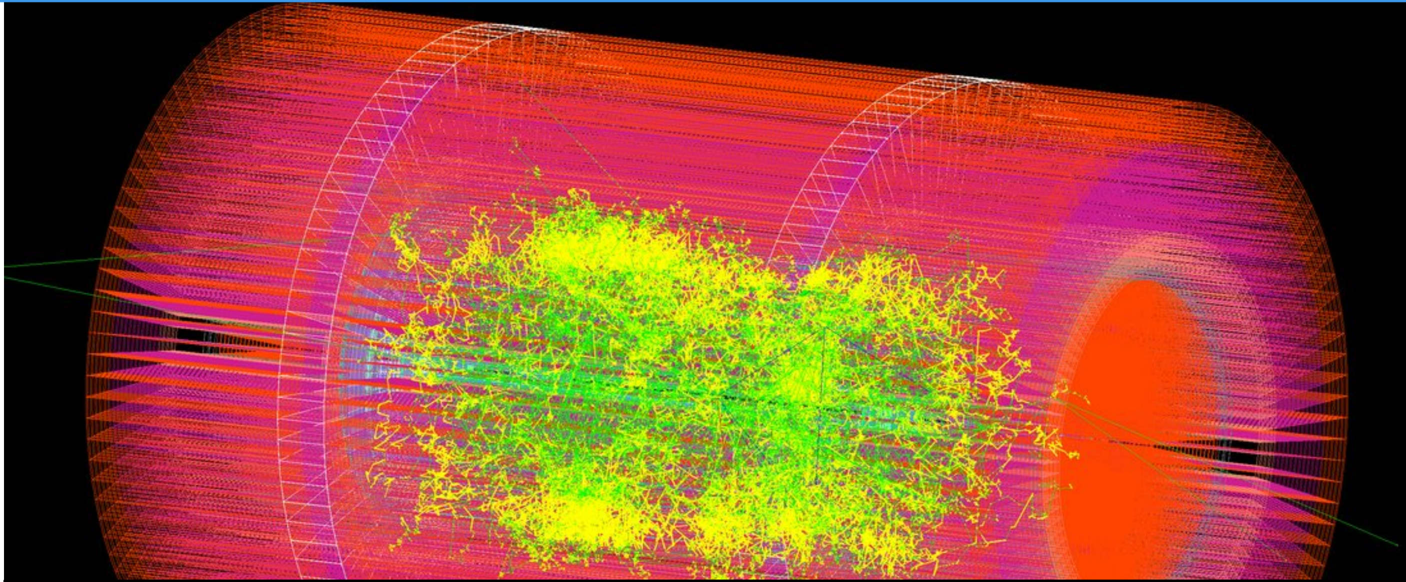
Simulação e Processamento de Sinais para Futuros Desenvolvimentos em Calorimetria de Altas Energias

Workshop RENAFAE 2022
25 a 28 de março



M. V. Araújo[a] , M. Begalli[b] , W. S. Freund[a] , Philipp Gaspar[a], G. I. Gonçalves[b] , M. Khandoga[c] , B. Laforge[c], A. Leopold[d] , J. L. Marin[e] , B. S-M Peralva[b] , J. V. F. Pinto[a] , M. S. Santos[e] , J. M. Seixas[a] , **E. F. Simas Filho**[e], E. E. P. Souza[c,e]

[a] LPS - COPPE/Poli – UFRJ // [b] UERJ // [c] LPNHE - Sorbonne Universitté,
[d] KTH, Stockholm, Sweden // [e] LSD – PPGEE - UFBA

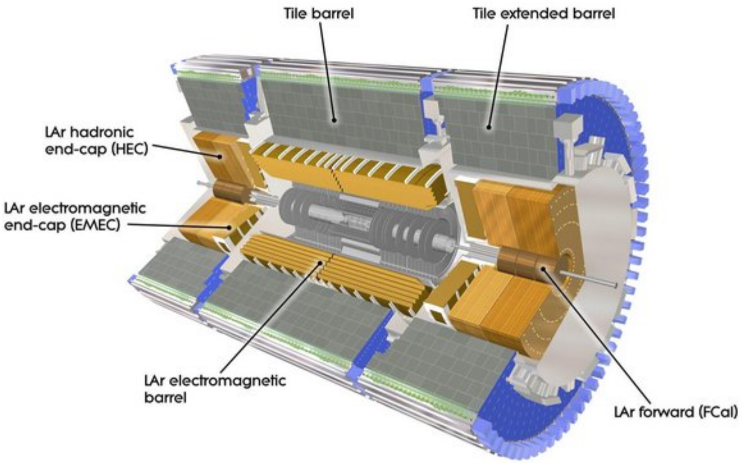
Outline

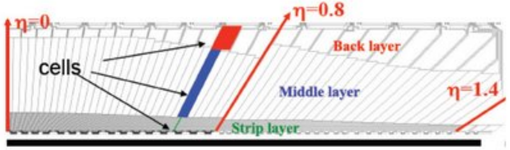
- Introduction
- Proposed Simulation Framework
  - Simulator features
  - Case-study results for a general purpose sampling calorimeter
- The Crosstalk Problem in Calorimeters
  - Crosstalk reduction using machine learning (ongoing work)
- Accessing Multi-Anode PMT with Machine Learning
- Conclusions and Perspectives

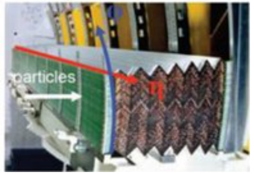
Introduction

- Calorimeters play an important role in high-energy physics experiments:
  - extremely fast response;
  - essential for online trigger and offline analysis.
- Their design include:
  - electronic instrumentation;
  - signal processing chain;
  - computing infrastructure;
  - response to particle showers.
- This work presents combined efforts for simulation and signal processing in calorimeters.

ATLAS Calorimeter

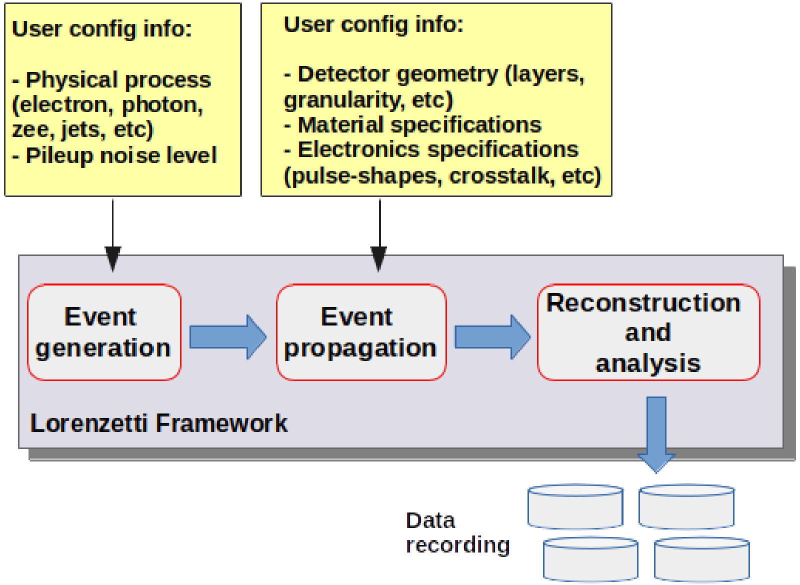






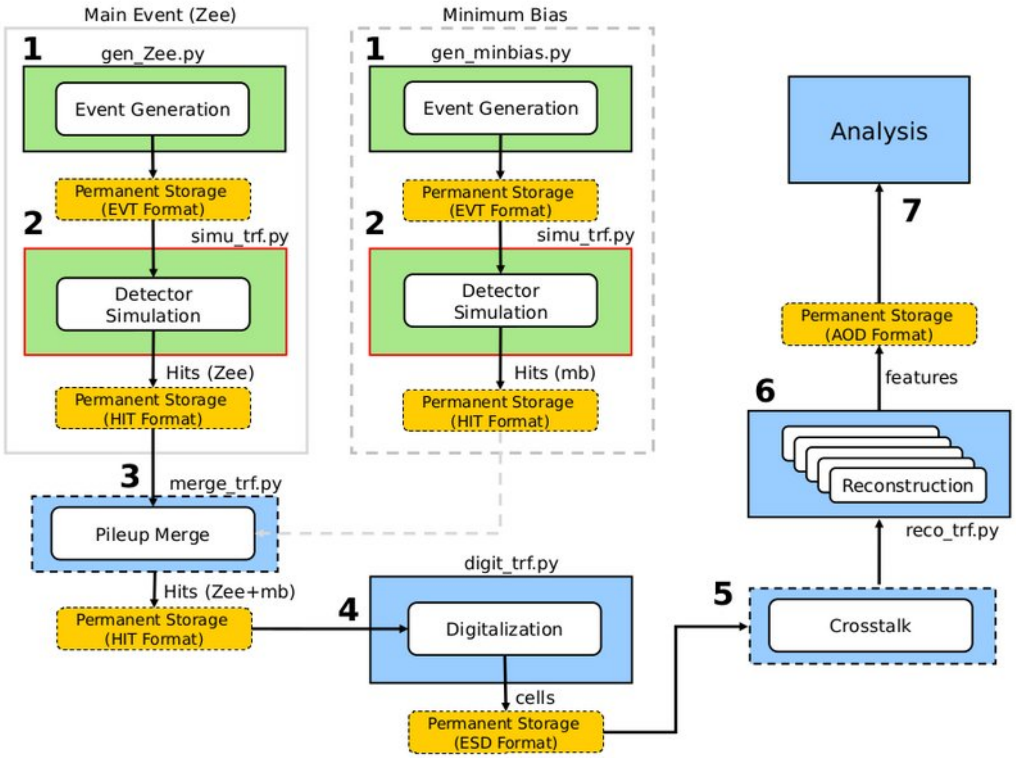
Proposed Calorimeter Simulator

- Main framework features:
  - ready for a ‘‘non-expert’’ user on HEP simulation (preconfigured software structure);
  - user-configurable calorimeter structure (different designs are allowed);
  - provides low-level (cells) information for signal processing studies;
  - energy estimation module (Optimum Filter + Constrained OF are implemented);
  - crosstalk module.

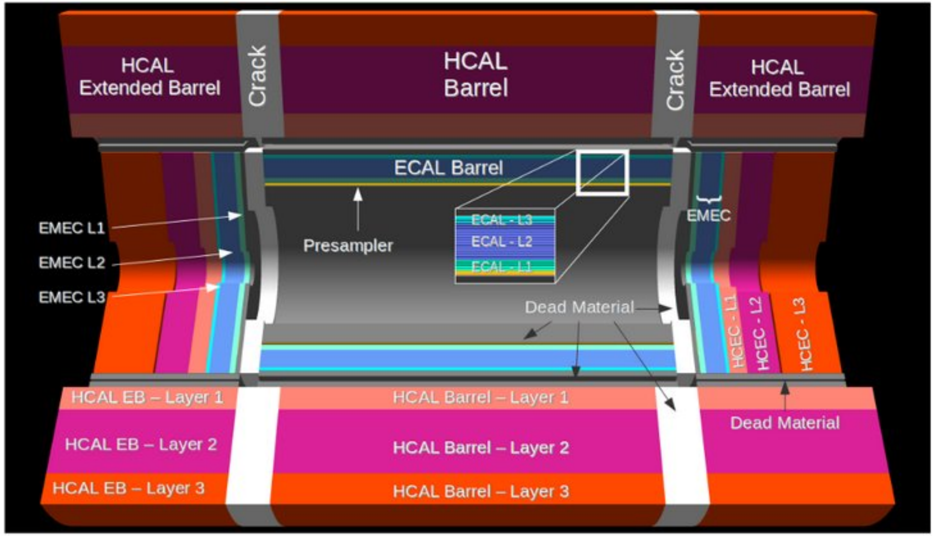


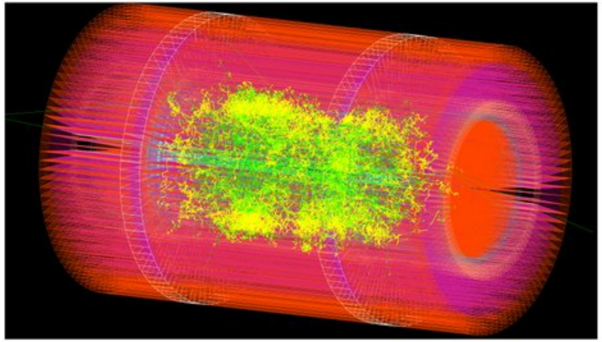
Simulation chain summary

- The simulation framework is user-configurable and provides from low-level (cells) to high-level (shower-variables) information.
- Dashed boxes (minbias generation, pileup merge and crosstalk) are optional blocks that may be turned on/off by the user.
- "Partial" simulation files are saved to allow reuse of previously produced data.
- Instructions for framework installation and running are provided.



Case-study: General-purpose sampling calorimeter simulation





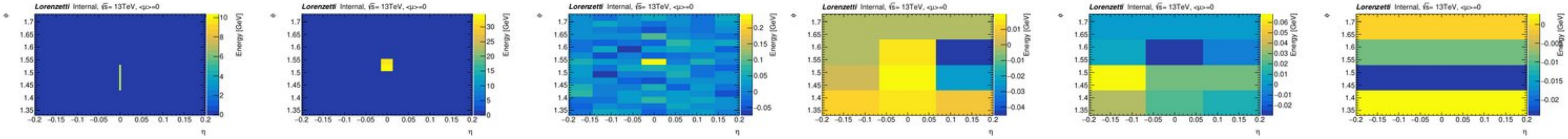
pp event propagation

Specifications

Layer	Sampling	Coverage	Granularity ($\Delta\eta \times \Delta\phi$)
Presampler	Barrel	$0.00 < \|\eta\| < 1.58$	0.025×0.1
	End-Cap	$1.50 < \|\eta\| < 1.80$	0.025×0.1
Electromagnetic Calorimeter			
Layer 1	Barrel	$0.00 < \|\eta\| < 1.55$	0.003×0.1
	End-Cap	$1.37 < \|\eta\| < 1.80$	0.003×0.1
		$1.80 < \|\eta\| < 2.00$	0.025×0.1
		$2.00 < \|\eta\| < 2.37$	0.006×0.1
		$2.37 < \|\eta\| < 3.20$	0.1×0.1
Layer 2	Barrel	$0.00 < \|\eta\| < 1.50$	0.025×0.025
	End-Cap	$1.35 < \|\eta\| < 2.50$	0.025×0.025
		$2.50 < \|\eta\| < 3.20$	0.1×0.1
Layer 3	Barrel	$0.00 < \|\eta\| < 1.58$	0.05×0.1
	End-Cap	$1.35 < \|\eta\| < 2.50$	0.05×0.025
		$2.50 < \|\eta\| < 3.20$	0.1×0.1
Hadronic Calorimeter			
Layer 1	Barrel	$0.00 < \|\eta\| < 1.09$	0.1×0.1
	Extended Barrel	$0.94 < \|\eta\| < 1.77$	0.1×0.1
	End-Cap	$1.50 < \|\eta\| < 2.50$	0.1×0.1
		$2.50 < \|\eta\| < 3.20$	0.2×0.2
Layer 2	Barrel	$0.00 < \|\eta\| < 1.09$	0.1×0.1
	Extended Barrel	$0.85 < \|\eta\| < 1.41$	0.1×0.1
	End-Cap	$1.50 < \|\eta\| < 2.50$	0.1×0.1
		$2.50 < \|\eta\| < 3.20$	0.2×0.2
Layer 3	Barrel	$0.85 < \|\eta\| < 0.72$	0.2×0.1
	Extended Barrel	$0.85 < \|\eta\| < 1.41$	0.2×0.1
	End-Cap	$1.50 < \|\eta\| < 2.50$	0.1×0.1
		$2.50 < \|\eta\| < 3.20$	0.2×0.2

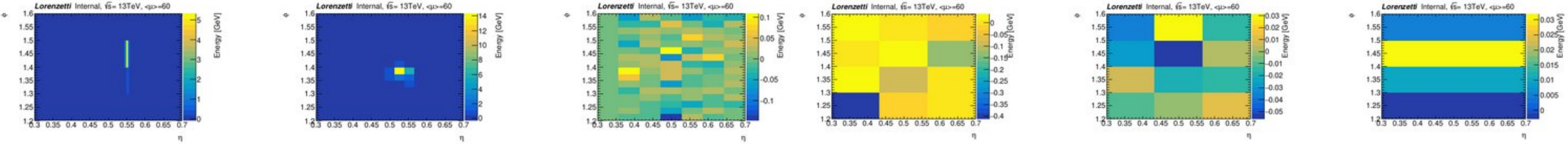
Results – Energy Deposition

pp → Z → e^-e^+ – no pileup



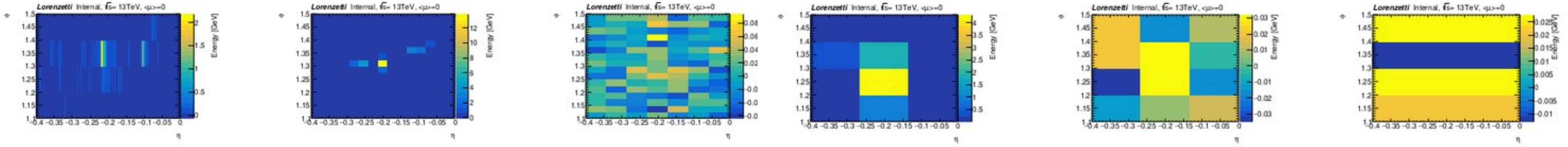
(a) EM1 (b) EM2 (c) EM3 (d) HAD1 (e) HAD2 (f) HAD3

pp → Z → e^-e^+ – with pileup: <mu> = 60



(a) EM1 (b) EM2 (c) EM3 (d) HAD1 (e) HAD2 (f) HAD3

pp → jets – no pileup



(a) EM1 (b) EM2 (c) EM3 (d) HAD1 (e) HAD2 (f) HAD3

Results

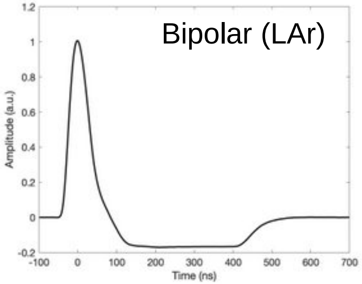
Simulated Events:

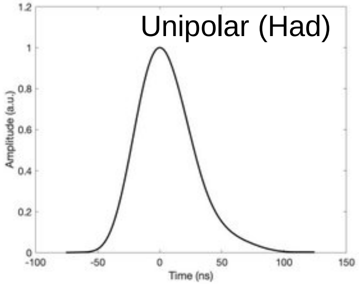
- pp → Z → e^-e^+
- pp → Jets

For validation:

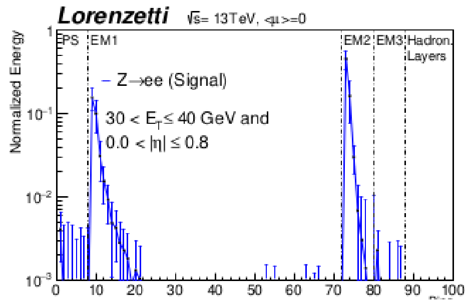
- Shower-shapes
- Ring sums

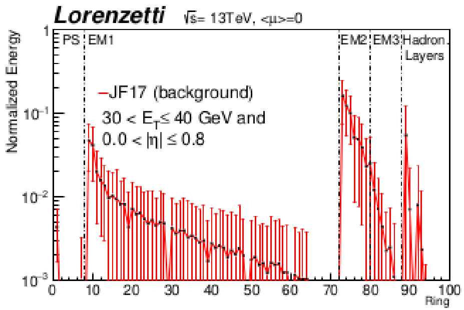
CaloCells Pulse-shapes



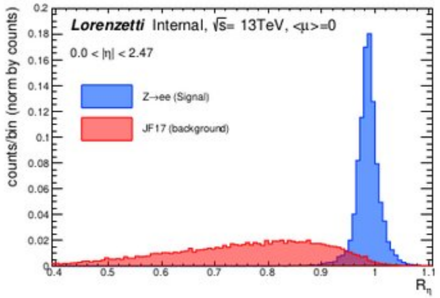


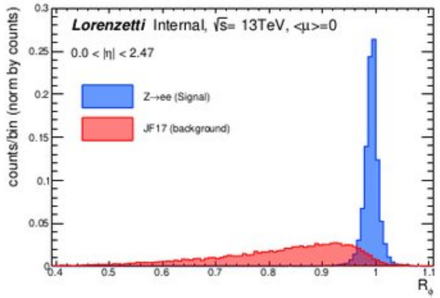
Ring-Sums

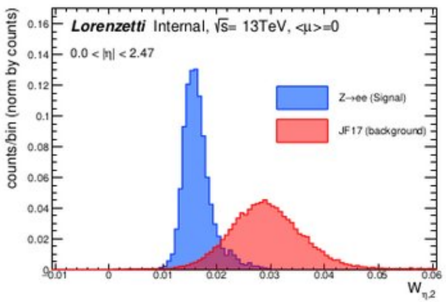


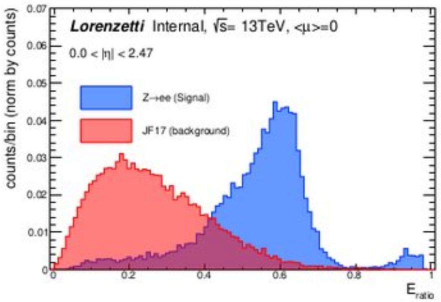


Shower-shapes







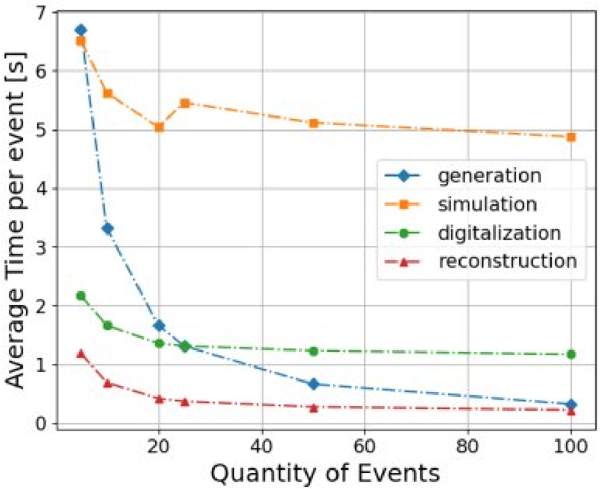


Results – Simulation time analysis

- The relative amount of time required for each computational step varies for the different main events;

- MinBias events are simulated separately from the main events, recorded, and used to produce combined (merged) simulations.

- In this way, pileup simulation time may be reduced if different main event types are used.



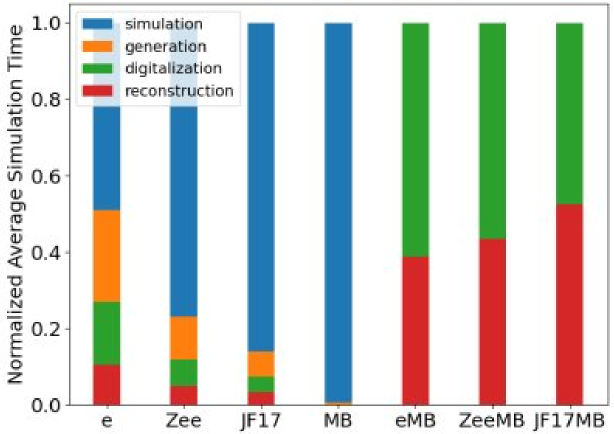
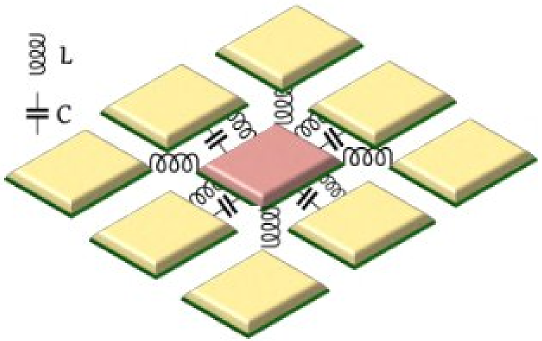


Table 3: Average production times (in seconds) for simulation of 10 events from different physics processes of interest.

Electrons	Zee	Jets	MinBias (MB)	Elect.+MB	Zee+MB	Jets+MB
101.9 ± 5.4	174.2 ± 18.0	260.8 ± 29.8	15311.0 ± 356.0	20.1 ± 0.1	21.3 ± 0.1	23.6 ± 0.1

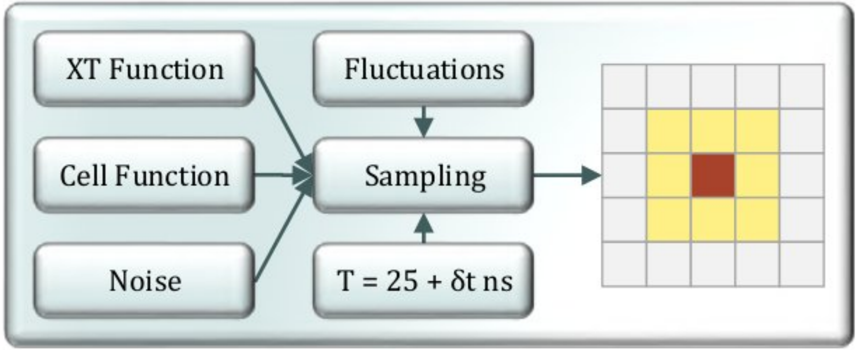
The Crosstalk Problem in Calorimeters

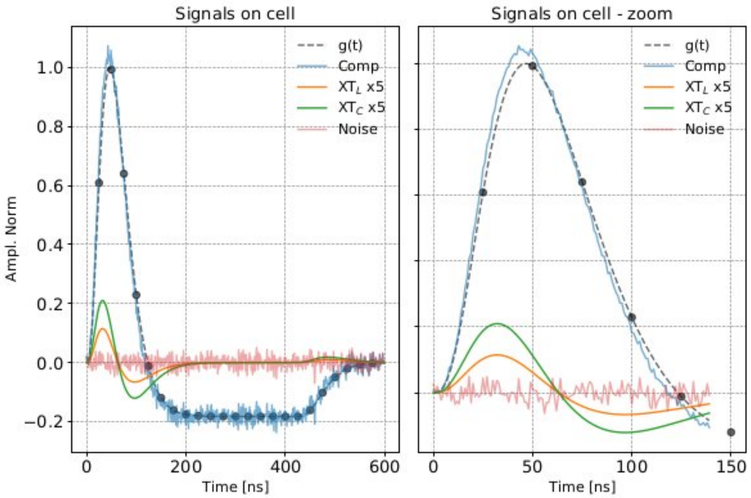
- Due to the LAr calorimeter geometry and high-granularity neighboring cells may produce cross interference (crosstalk).



- For ATLAS, the main crosstalk sources are from inductive (L) and capacitive (C) natures.

- The crosstalk is not perfectly modeled in ATLAS MC and, in this study, a stand-alone simulation was developed:



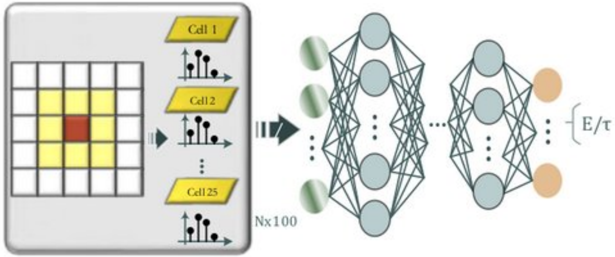


Ongoing work: Crosstalk Reduction Strategy

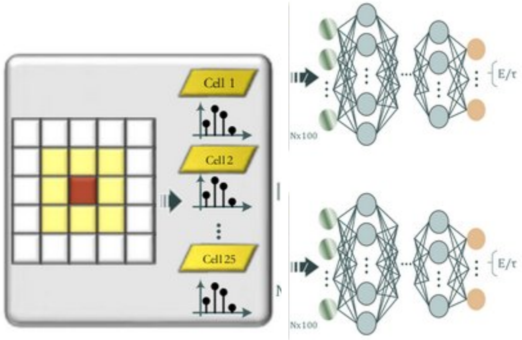
- Lar calo uses the Optimal Filter and crosstalk interference may affect the estimation of both, energy and time of flight.

- Machine learning methods are being used to reduce the crosstalk effects:

  – Cluster-level approach →



  – Cell-level approach →



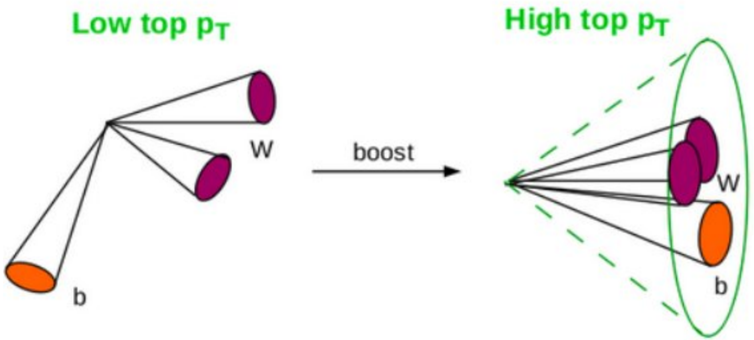
Perspectives:

- Incorporate the crosstalk simulation module to ATLAS MC samples.

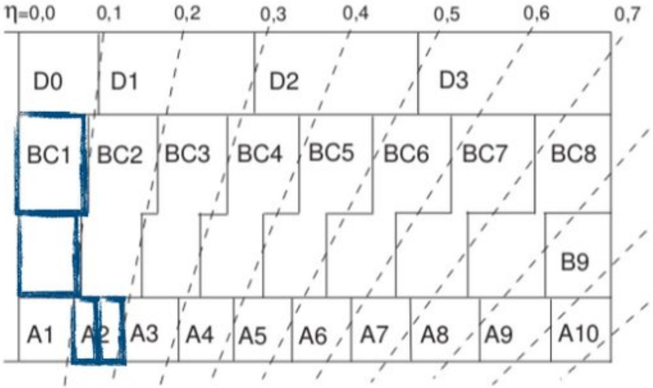
- Evaluate the proposed crosstalk reduction strategies using ATLAS MC.

Accessing Multi-Anode PMT information using Machine Learning

- Increase Tilecal granularity by using Multi Anode PMT without changing the detector mechanical structure.
- The detection of Boosted Jets in HL-LHC may benefit from such finer granularity in Tilecal
- Proposed solution: application of machine learning methods.

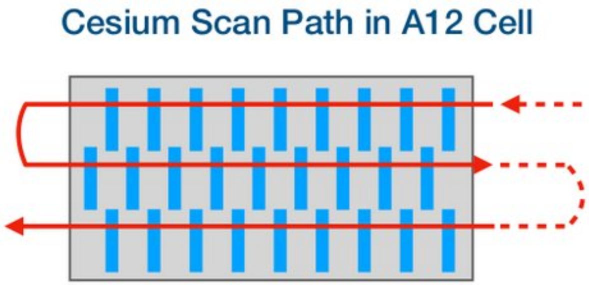


Tilecal segmentation

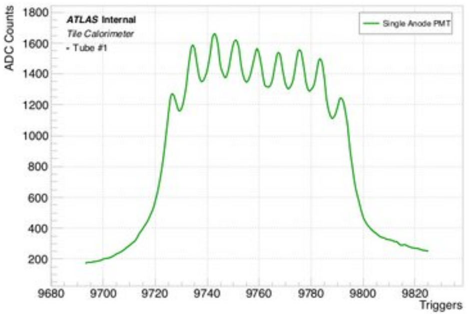


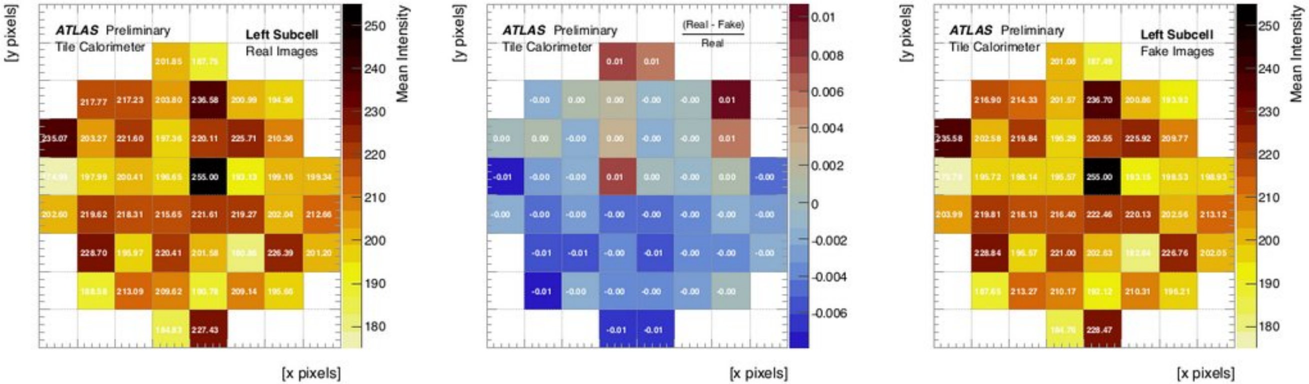
Accessing Multi-Anode PMT information using Machine Learning

- Calibration data obtained from a cesium source was used to access the typical response of the multi-anode cells.
- A convolutional neural network was used to map the single anode readout to an emulated multi-anode response.



Typical calibration signal





Conclusions and Perspectives

- To deal with the stringent experimental conditions expected in modern high-energy calorimeters, accurate simulation is required to develop signal processing and machine learning methods.

- This work presents a framework for detailed, accurate, and user-configurable simulation of high-energy calorimeters.

- The proposed environment produces EM and hadronic shower profiles, including adjustable pile-up levels, different pulse-shapes, energy estimation algorithms for cell readout, and signal crosstalk modeling between neighboring calorimeter cells.

- Results for a machine-learning approach for generating multi-anode calorimeter information also indicate that it is possible to increase the granularity accurately using emulated signals.