ATLAS Liquid Argon Calorimeter Off-detector Readout Electronics and Machine Learning Algorithms for HL-LHC

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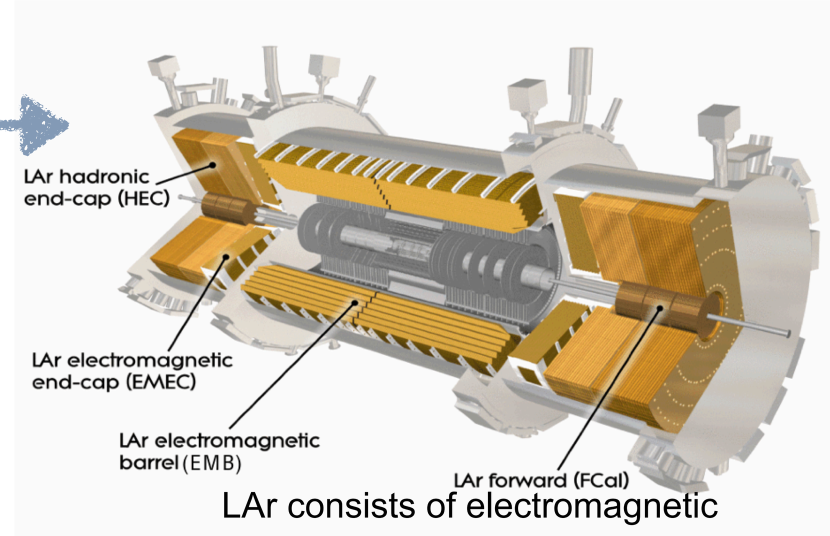
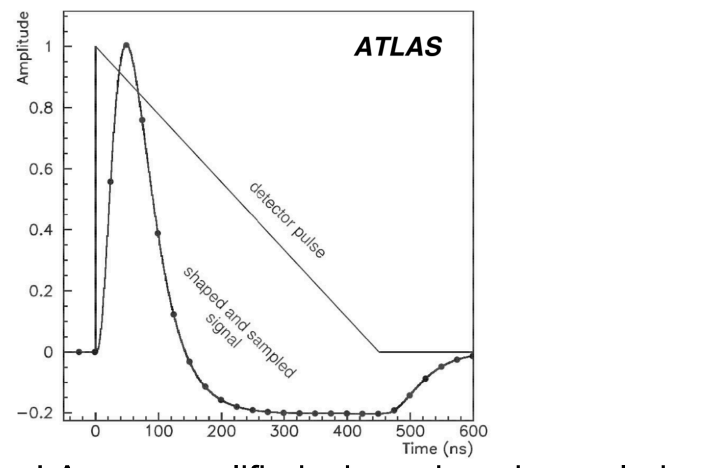
ATLAS EXPERIMENT

1. Liquid Argon Calorimeter (LAr)

- In **ATLAS detector at Large Hadron Collider (LHC)**
- Incoming particles create a shower of lower energy particles → ionization of liquid argon from charged particles in the shower causing electrical current (signal) → measures energy of electrons, photons and hadrons



LAr consists of electromagnetic and hadronic calorimeters

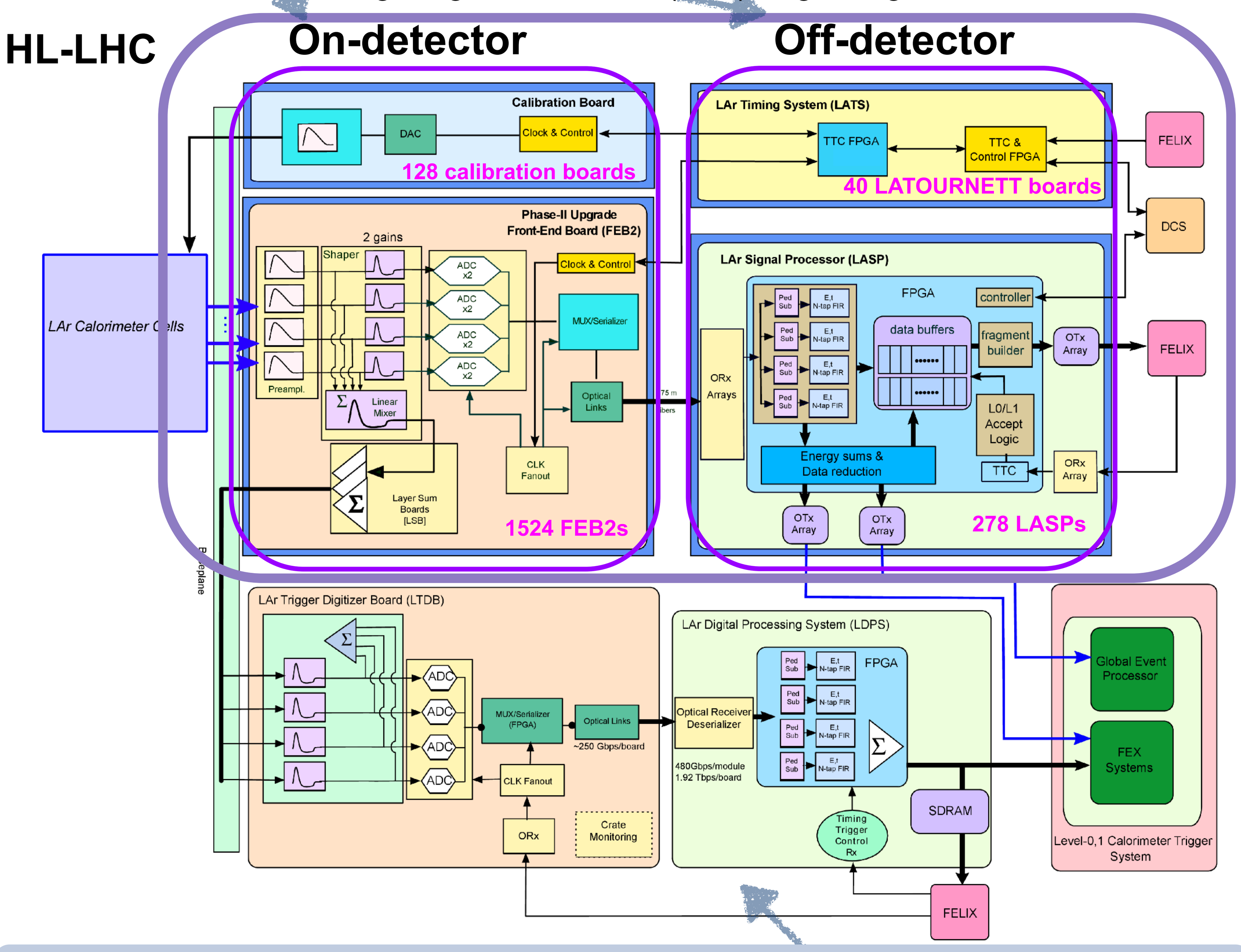


The signals from LAr are amplified, shaped, and sampled every 25 ns at the LHC bunch crossing frequency (40 MHz)

2. Motivation for Upgrade

- **HL-LHC** (High Luminosity LHC) upgrade project:
  - **Increases instantaneous luminosity and data size** (up to ~250 fb^{-1} per year) for more precise measurements or enhanced discovery potential
  - **Increased pileup** (higher # of pp interactions per bunch crossing (BC))

  → Needs Trigger and Data Acquisition (TDAQ) upgrade & **LAr readout electronics upgrade** for compatibility with TDAQ and pileup mitigation
  - On-detector: incl. Front End Board 2 (FEB2) & calibration board
  - Off-detector: incl. LAr Signal Processor Board & LAr Timing System → to be installed during long shut down 3 (LS3) beginning in 2026



3. LAr Signal Processor Board (LASP)

- Runs in parallel with LAr Digital Processing System (LDPS)
- 278 LASP boards receive 345 Tb/s of data
- For each LASP, there will be
  - 1 main board with **2 FPGAs** (Field Programmable Gate Arrays):
    - Receives digitized waveform (pulse) from **6 FEB2s**
    - Computes **energy and timing** of pulse for each calorimetry cell
  - 1 **SRTM** (Smart Rear Transition Module):
    - **Transmits** raw data, energy and timing to trigger at 40 MHz (collision frequency) and Data Acquisition systems at 1 MHz if accepted by trigger
- **Progress**: 4 test boards are tested to be operational and used for integration and performance tests & ongoing efforts to validate that full prototype board design meet specifications

4. Method for computing energy and timing

- **optimal filter** (OF) (e.g. used in LDPS) [1]

$$E = \sum_{i=1}^{n} a_i (s_i - P)$$

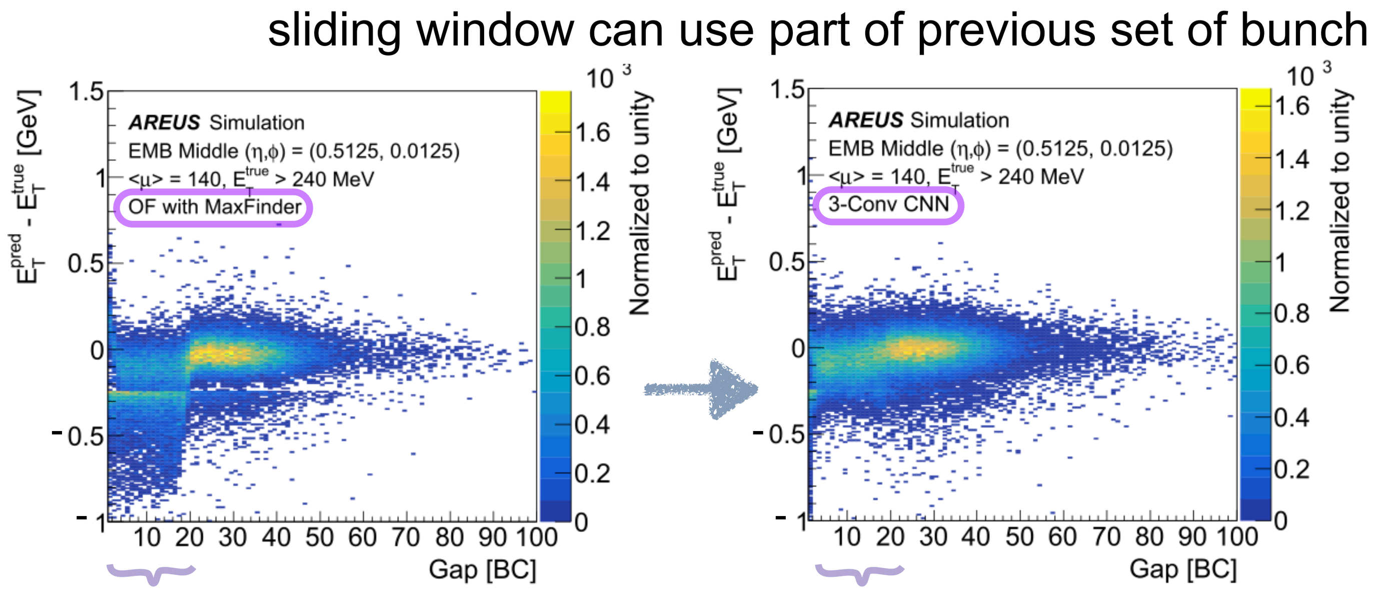
a_i: OFCs ; s_i: samples; P: pedestal of signal from calibration, n: number of samples

  - Assumes the shape of pulse to be known → least square fitting between model and signal data → use optimal filtering coefficients (OFCs)
- Increased **pileup** in HL-LHC → difficult to accurately reconstruct energies of superposing pulses of particles produced from different collisions

  → **solution: use machine learning in LASP**

5. Machine Learning in LASP

- Testing **Convolutional (CNN)** and **recurrent neural network (RNN)** for usage in FPGA in LASP
  - Each FPGA reconstructs energies of 384 calorimeter cells (correp. to 3 FEB2s) at 40 MHz within a latency of 125 ns
  - Both CNN and RNN appropriate for time-ordered data since 1-D CNN recognizes pattern of temporal dependence on samples and RNN with sliding window can use part of previous set of bunch crossings

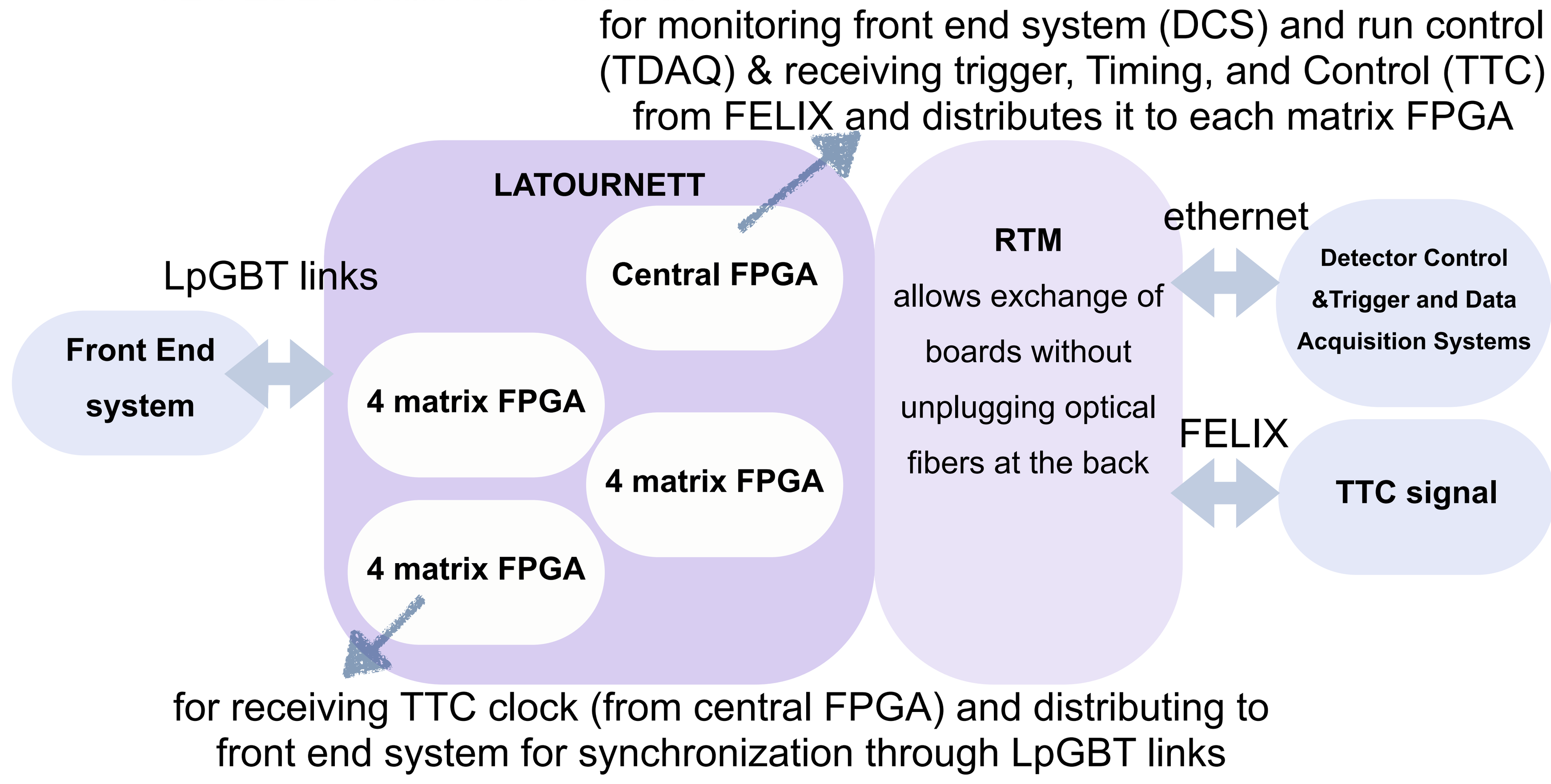


energy resolution overall (for example, for timing gap < 20 BCs) is **less degraded** for using CNN (right) compared to OF (left) even for high average **pile up** condition of <μ>=140

- **Progress**: **CNN & RNN outperform OF (mean and standard deviation of $E_T^{pred} - E_T^{true}$) [2] → ongoing efforts to test with physics performance**
  - firmware: low level implementation meets frequency and latency requirements in a targeted Intel Agilex FPGA [3]

6. LAr Timing System (LATS)

- 40 pairs of LATOURNETT boards
  - One LATOURNETT (Liquid Argon Timing trigger cOntrol distribUtion and fRoNt End moniToring/configuraTion) board can control and monitor up to 72 FEB2s /calibration boards



- **Progress**: ongoing efforts to implement recommendations from hardware preliminary design review (passed in 2024) in recent prototype board design and produce 4 v2 boards in 2025 & prepare for firmware preliminary design review in July, 2024

7. Conclusion

- Testings of both LASP and LATS are in progress and in line with the schedule (production and installation in LS3) ✓
- Machine learning algorithms in LASP outperform OF and firmware meets specifications to prepare for HL-LHC ✓

References

[1] D. O. Damazio, et al. Signal processing for the ATLAS liquid argon calorimeter: studies and implementation. In 2013 IEEE Nuclear Science Symposium and Medical Imaging Conference (2013 NSS/MIC). IEEE, 2013. https://cds.cern.ch/record/1630826/files/ATL-LARG-PROC-2013-015.pdf

[2] G. Aad, et al. Artificial neural networks on FPGAs for real-time energy reconstruction of the ATLAS LAr calorimeters. Computing and Software for Big Science, 5:1–11, 2021. https://link.springer.com/article/10.1007/s41781-021-00066-y

[3] G. Aad, et al. Firmware implementation of a recurrent neural network for the computation of the energy deposited in the liquid argon calorimeter of the ATLAS experiment. Journal of Instrumentation, 18(05):P05017, 2023. https://arxiv.org/pdf/2302.07555

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