Perspectivas para a Estimação de Energia do Calorímetro de Telhas do ATLAS no HL-LHC

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ATLAS EXPERIMENT

UERJ — Universidade do Estado do Rio de Janeiro

lps — COPPE/Poli/UFRJ — Laboratório de Processamento de Sinais — Inteligência Computacional. Inovação

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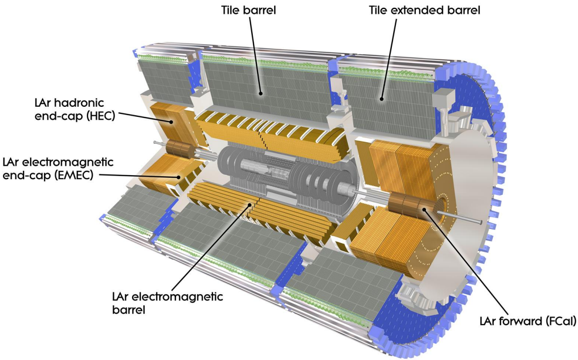
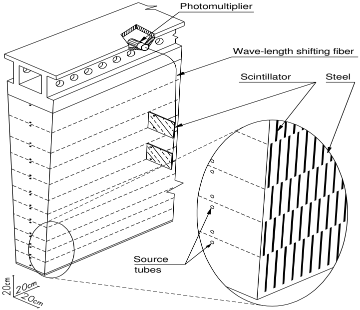
ATLAS calorimeter system

- The ATLAS calorimeter system at LHC:
  - It comprises two systems: the Liquid Argon and Tile calorimeters.
  - It is divided into three sections: two extended barrels and one central barrel.



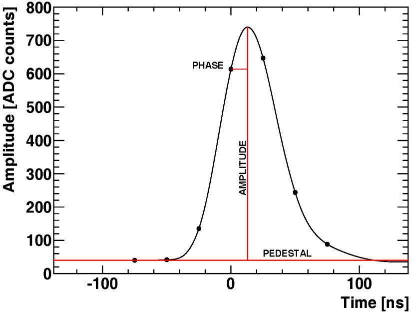
The ATLAS calorimeter system

- In the Tile calorimeter (TileCal), the particle energy is absorbed (steel) and sampled by scintillating tiles.



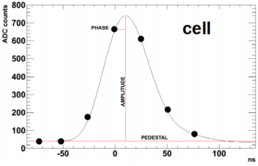
The ATLAS calorimeter system

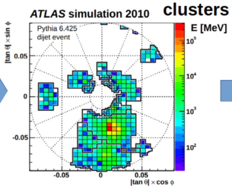
- The produced detector signal (from a PMT cell) is conditioned in such a way that the amplitude is proportional to the energy.
- Energy is reconstructed by estimating the parameters (amplitude, phase, pedestal) of the digitized pulse within a readout window.

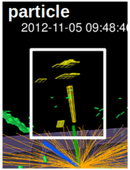


The energy estimation problem

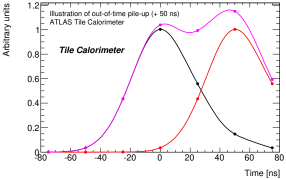
- Currently, the response signals are acquired within a given readout window (around 150 ns).
- The parameters are estimated from the received time samples through an optimal filtering technique.





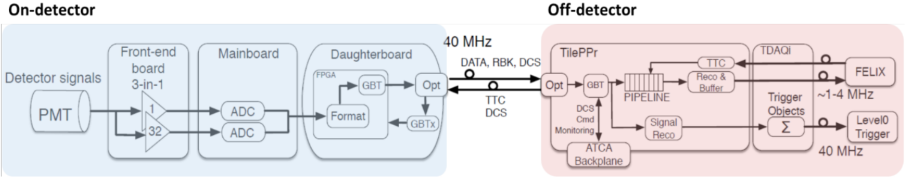


- Problem: In high-luminosity conditions, the signal pile-up degrades the energy estimation efficiency.



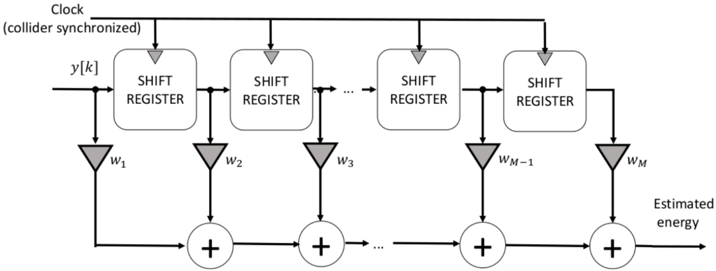
TileCal Energy reconstruction for HL-LHC

- Linear methods were extensively tested and are currently employed.
- Considering the signal conditions at HL-LHC, advanced algorithms can be evaluated, profiting from new electronics that will be employed (pipelined times samples triggered by L0)
- Wiener Filtering, as well as Neural Networks and Deep Learning strategies are particularly interesting.



Energy Estimation per bunch crossing

- Free-running estimation are usually implemented using FIR filters;
- Lasted M samples are stored in *shift registers*;
- Filter taps are linearly combined ($\boldsymbol{w}$ coeficients) in order to estimate the amplitude of the central signal (peak at $M/2$).



Energy Estimation per bunch crossing

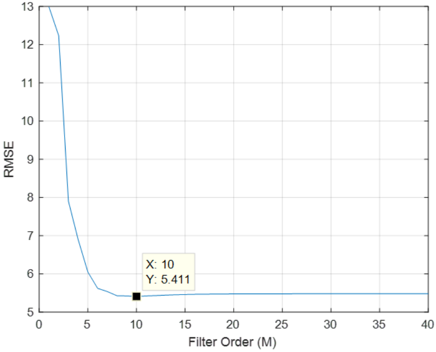
- **Least Mean Squares (LMS)** filtering algorithm is proposed to adjust the weigths of the FIR filter;
  - Minimizes the squared error between the estimated energy value $\hat{a}$ generated by the filter and the target a value, given the observed input matrix Y. The weights of the FIR filter are defined by equation:

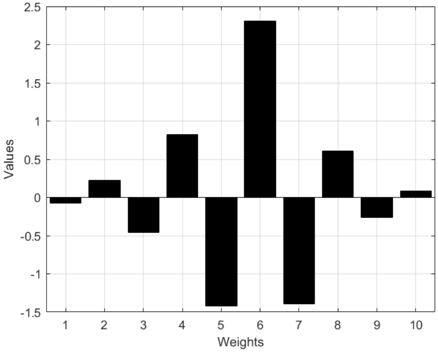
$$\boldsymbol{w} = (\boldsymbol{Y^T Y})^{-1} \boldsymbol{Y^T a} \tag{1}$$

Note: The LMS solution converges to the **Wiener** solution.

Energy Estimation per buch crossing

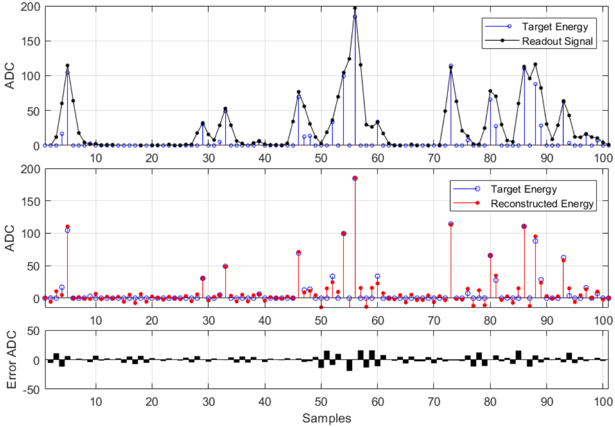
- **Preliminary test**: An occupancy of 30% is considered, and the energy amplitude is defined by a uniform distribution for training and exponential distribution (average 30) for test.
- Filter Order Definition based on the estimation error RMS value.





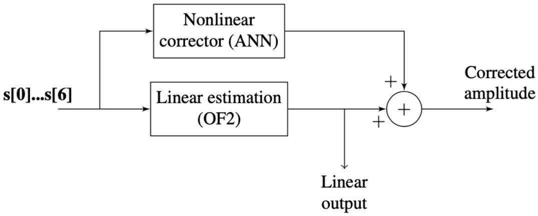
Energy Estimation per bunch crossing

- **Preliminary test:**



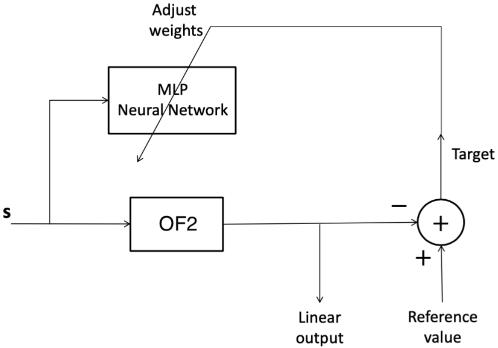
Energy reconstruction assisted by ANN

- Artificial Neural Networks (ANN) and deep learning strategies can be tested to cope with the signal pile-up harsh conditions.
- Here, considering that a linear approach provides a reasonable solution for the problem, we look into a simple Multi-layer Perceptron (MLP) as a nonlinear corrector that assists the OF2 estimates
- The ANN does not estimate the energy, but it provides a fine tuning to the linear estimate.
- The linear estimate is preserved and the nonlinear correction is applied upon user decision.



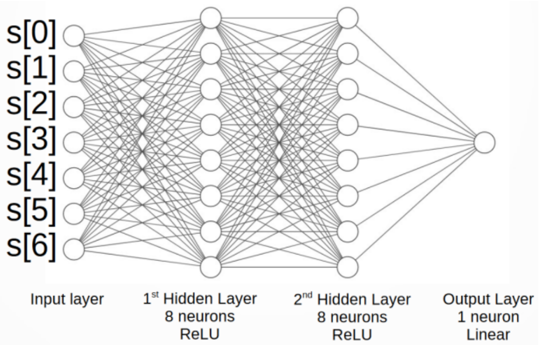
ANN training strategy

- For training the ANN, a simulation data set is needed, where the reference signal amplitude value is used.
- The ANN is trained in such a way that it compensates for the nonlinear component due to the noise (pile-up+electronic).
- Therefore, the target is the difference between the linear estimate and the reference value.



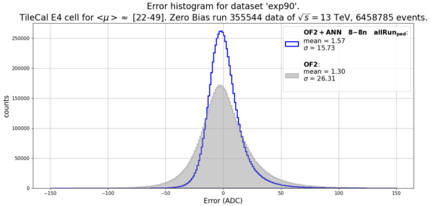
ANN design

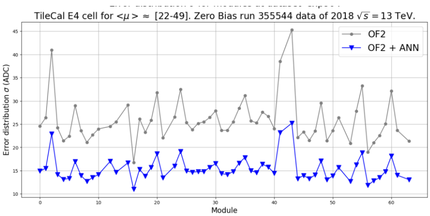
- The signal time samples are fed into the ANN structure.
- Two hidden layers are selected based on the energy estimation efficiency.
- A relu function was chosen for the activation function of the hidden layers while a linear function is used for the output neuron.

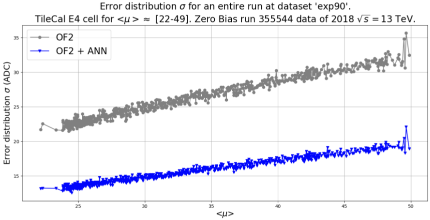


Application to TileCal signals

- The combined strategy has been applied to TileCal signals.
- Estimation error used as a performance metric.

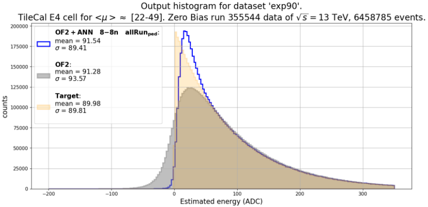


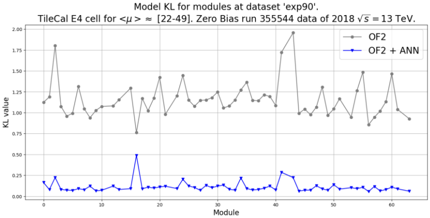


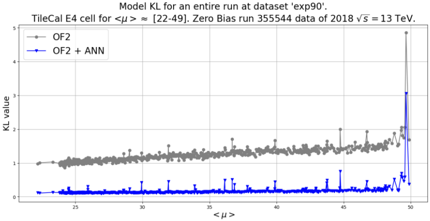


Application to TileCal signals

- Additionally, the Kullback-Leibler (KL) divergence was tested as a measure of how well the estimated and expected distributions agree.
- It's a non-symmetric measure of the difference between two probability distributions.







Conclusions

- The HL-LHC will introduce new challenges to the energy estimation task.
- Online and offline opeartion may profit from different strategies.
- The use of neural networks and alternative linear approaches are being considered.
- The combined method is currently being incorporated within the TileCal reconstruction software for offline use.
- Tests considering severe pile-up conditions expected for HL-LHC are being carried out.
- Deep neural network structures will be evaluated.