

# Workshop on Calorimetry in High-Luminosity Collisions

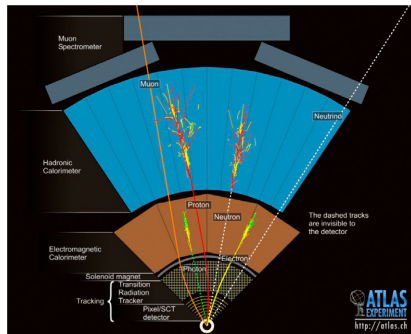
## Open Labs: Energy Estimation

4th October 2023



# Calorimeter systems

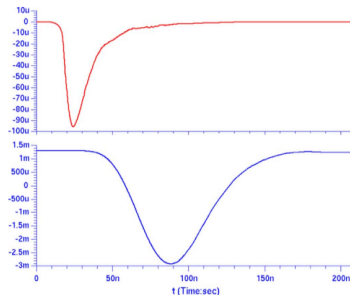
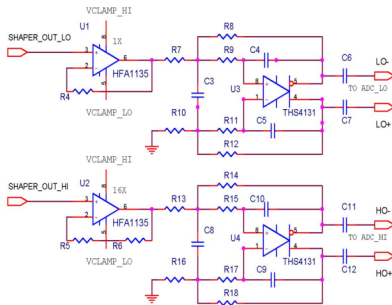
- Measure particle energy by processing readout signals from frontend electronics.
  - How are the calorimeter signals produced?
  - How can we measure the energy from the calorimeter readout signal?
- 
- Design to absorb and sample the energy from different interactions:
    - Electromagnetic
    - Hadronic (strong nuclear force)
  - Highly segmented (thousands of readout channels) providing precise measurements.



# The ATLAS calorimeter system

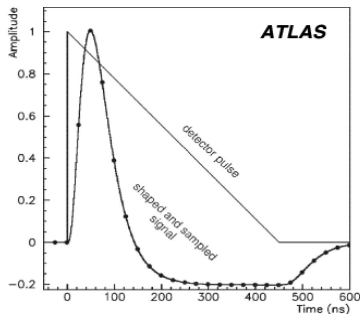
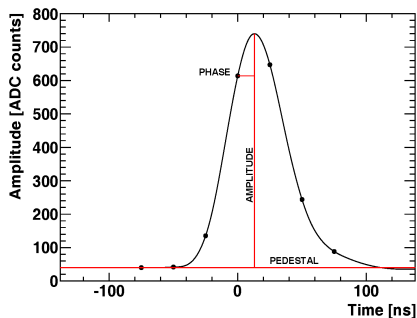
- Example of the front-end electronics design for the ATLAS Tile Calorimeter system.

<https://doi.org/10.1109/TNS.2012.2215053>



# The ATLAS calorimeter system

- The produced detector signal (from a PMT cell or ionization process) 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.

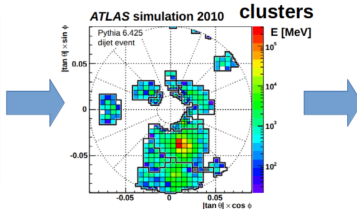
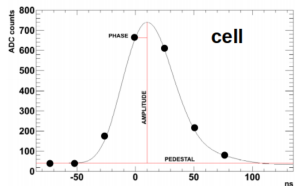


# The Calorimetry Energy Reconstruction Problem

- Calorimeter signals are acquired within a given readout window.
- Pulse parameters are estimated from the received time samples through an Optimal Filtering (OF) procedure:

[https://doi.org/10.1016/0168-9002\(94\)91332-3](https://doi.org/10.1016/0168-9002(94)91332-3)

<https://doi.org/10.1109/TNS.2006.877267>



# Optimal Filter (OF) algorithm

- Calorimeter response signal is modeled as:

$$x[k] = Ag[k - \tau] + n[k] + ped$$

and the signal amplitude (energy) estimation is based on:

$$\hat{A} = \sum_{k=0}^{N-1} x[k]w[k]$$

where the filter coefficients  $\mathbf{w}$  is calculated in order to minimize the variance of the estimation error subject to a set of constraints.

$$\text{i) } \sum_{k=0}^{N-1} w[k]g[k] = 1 \quad \text{ii) } \sum_{k=0}^{N-1} w[k]\dot{g}[k] = 0 \quad \text{iii) } \sum_{k=0}^{N-1} w[k] = 0$$

where  $\mathbf{g}$  and  $\dot{\mathbf{g}}$  represent the reference pulse (shaper) and its derivative, respectively.

# Optimal Filter (OF) algorithm

- Matrix representation of how the set of optimal weights  $\mathbf{w}$  can be computed:

$$\begin{pmatrix} C[1,1] & \cdots & C[1,N] & -g[1] & -\dot{g}[1] & -1 \\ C[2,1] & \cdots & C[2,N] & -g[2] & -\dot{g}[2] & -1 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ C[N,1] & \cdots & C[N,N] & -g[N] & -\dot{g}[N] & -1 \\ g[1] & \cdots & g[N] & 0 & 0 & 0 \\ \dot{g}[1] & \cdots & \dot{g}[N] & 0 & 0 & 0 \\ 1 & \cdots & 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} w[1] \\ w[2] \\ \vdots \\ w[N] \\ \lambda \\ \xi \\ \nu \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ 0 \end{pmatrix}$$

where  $C$  corresponds to the noise covariance matrix, and  $\lambda$ ,  $\xi$  and  $\nu$  are the Lagrange multipliers.

# Optimal Filter (OF) algorithm

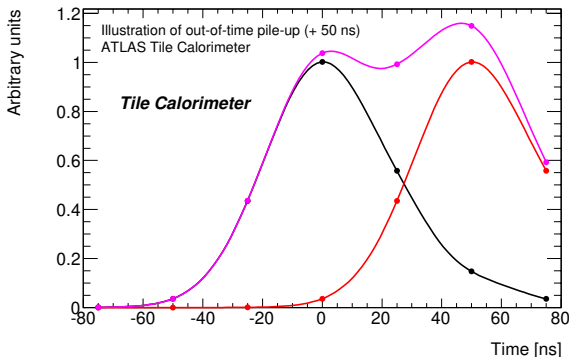
- A few remarks:

- The OF algorithm is efficient and fast (implemented through a FIR filter).
- It operates at its optimum condition if the noise can be described as a gaussian multivariate process.
- However, if the noise presents non-gaussian components (signal pile-up effect, for instance), its performance is degraded.
- It has been used in high-energy calorimeter systems.



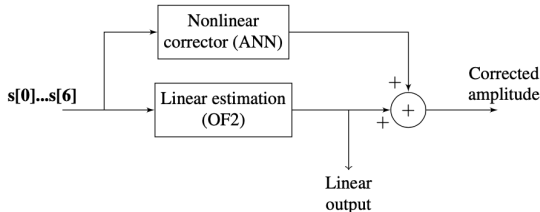
# The Calorimetry Energy Reconstruction Problem

- **Problem:** Increase of luminosity leads to pile-up which distorts the expected pulse shape (calorimeter response is slower than the experiment event rate).
- The pile-up effect degrades the efficiency from typical OF approaches.
- **How can we mitigate the pile-up in the readout signal?**



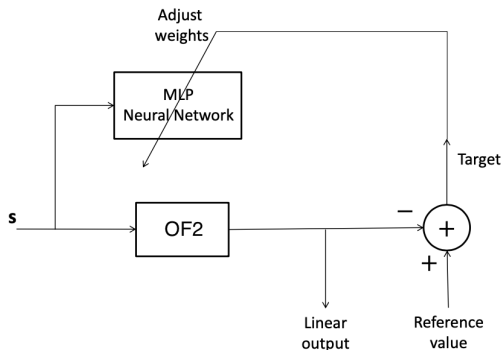
# Energy reconstruction assisted by AI

- 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.



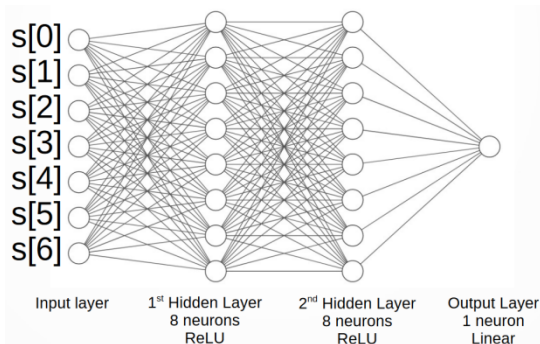
# ANN training strategy

- 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 (or hyperbolic tangent) function can be chosen for the activation function of the hidden layers while a linear function is used for the output neuron.
- For example:



Thank you!