Online Neural Trigger for Optimizing Data Acquisition During Particle Beam Calibration Tests with Calorimeters

Paulo V. Magacho da Silva, José M. de Seixas,

Denis O. Damazio and Bruno C. Ferreira

Signal Processing Laboratory

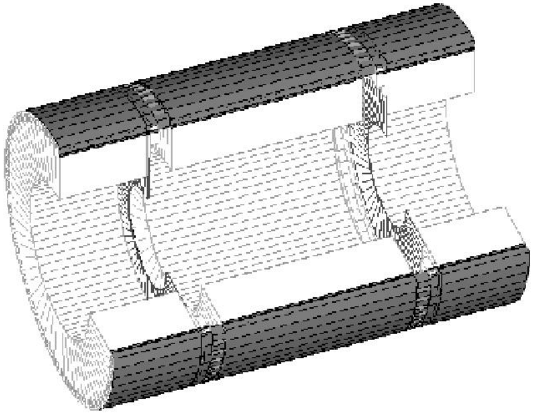
COPPE/EE - Federal University of Rio de Janeiro

Outline

- Introduction
- Motivation
- Integrating Neural processing with DAq system
- Implementation
- Results
- Conclusions

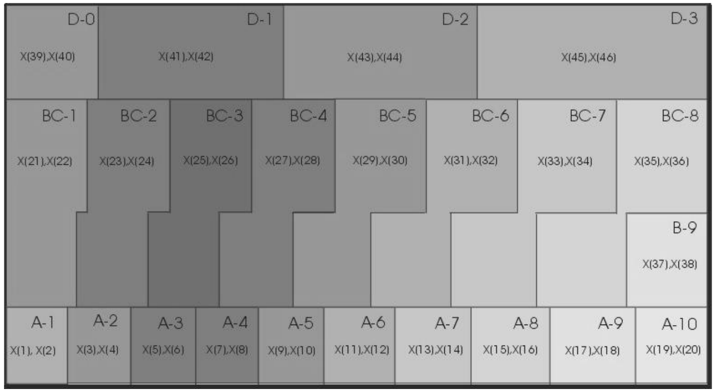
Introduction

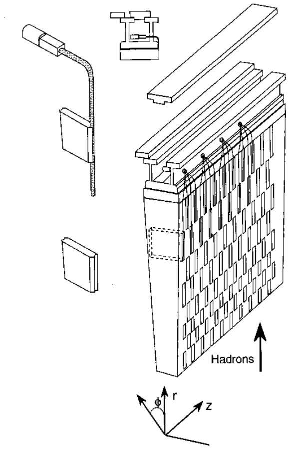
- Work developed in the framework of the ATLAS collaboration for the LHC experiment
- Experimental data were taken during calibration of the ATLAS hadronic calorimeter - Tilecal in the beam line
  - Tilecal is divided into 3 regions (barrel and two extended barrels), 64 modules each
  - Only a fraction of the modules are calibrated using particle beams



Introduction - Tilecal

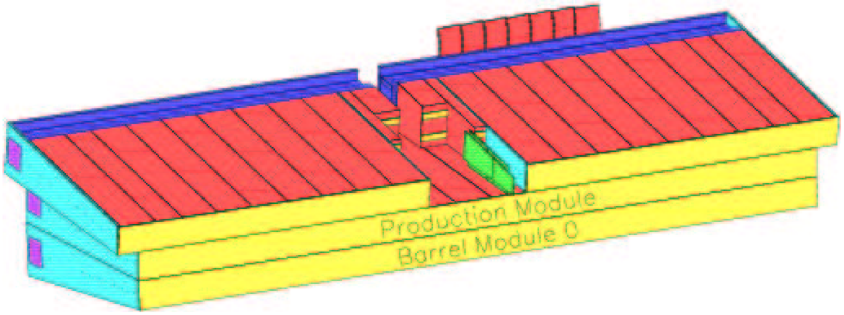
- Calorimeter cells are arranged into three segmentation layers
- A barrel module comprises 45 cells
- Two readouts per cell





Testbeam Setup

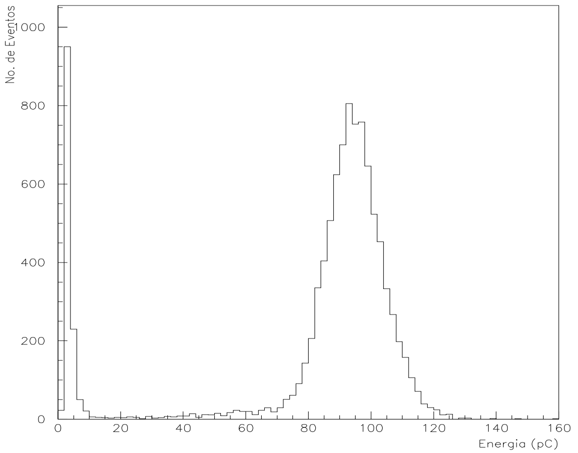
- Typically, during the calibration procedure, muon, pion, and electron beams are used

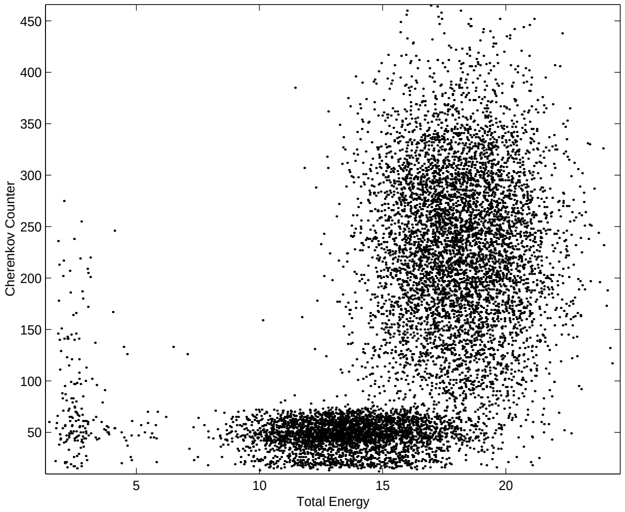


- Auxiliary detectors (Cherenkov counter, beam chambers, scintillating counters, muon wall) are also used for triggering and offline analysis

Objectives

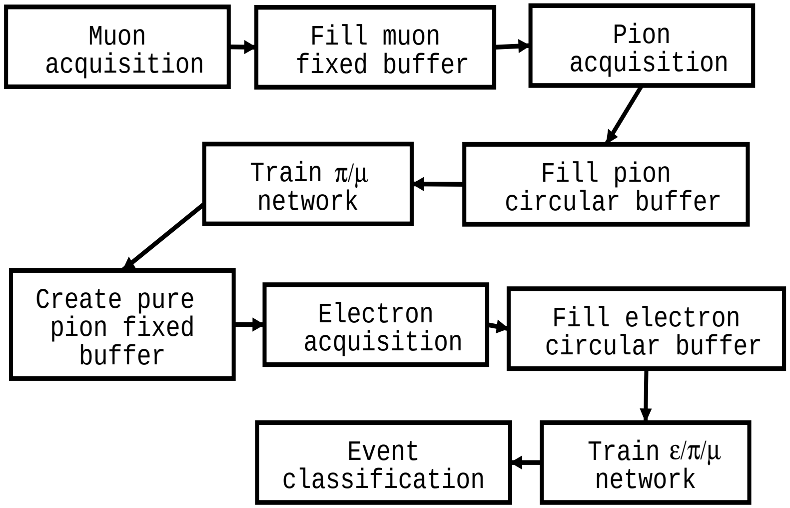
- Despite beam quality, contamination is unavoidable
- Main objective: online detection of contaminations (outsider particles) in the electron beam line
  - presence of different levels of muon and pion contamination
  - online detection reduces the amount of data to be stored
  - offline analysis uses different methodologies for different energy and particle classes





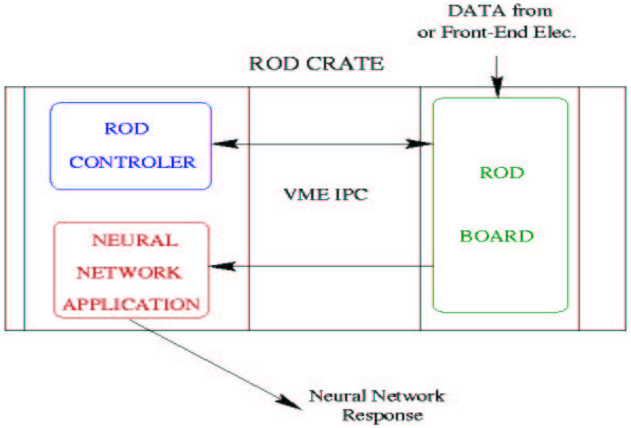
Neural Network

- Neural networks may look attractive to perform online particle identification
  - same methodology used for a wide energy range
  - based on calorimeter information only (may not rely on auxiliary detectors)
  - suitable for online implementation
- A training methodology was developed
- In practice, data from different beam particles may not be readily available during the beam calibration period

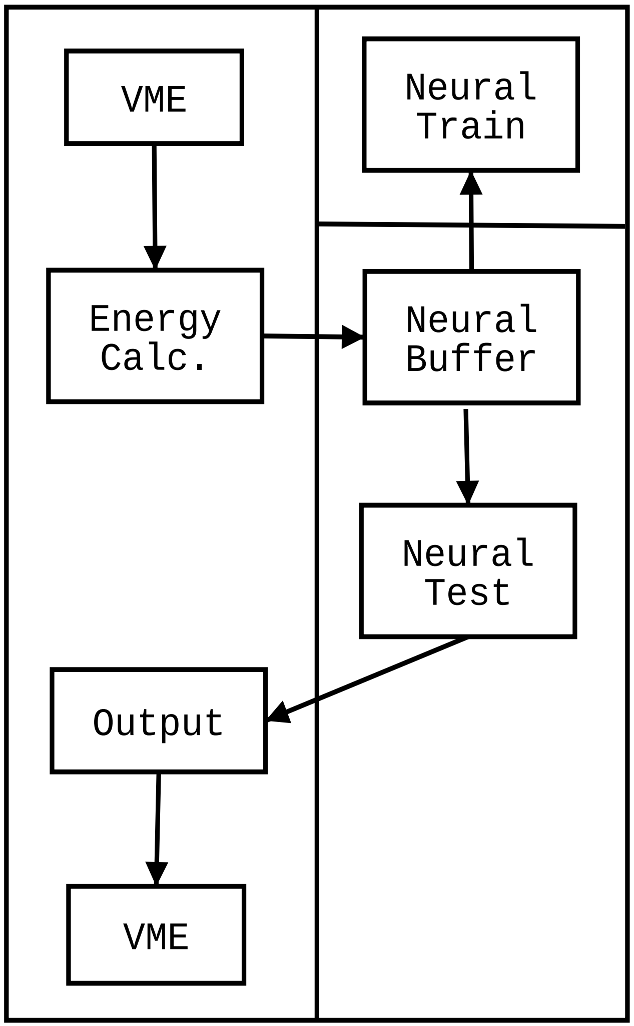


Integration with DAq system

- Neural system was implemented in ROD controller board
- Input data from the detector front-end electronics through VME
- Energy values are computed for half of a barrel module in an event by event basis
  - input data comprises 23 components (single cell readout)
  - speed-up the processing time
- Network output is encoded in data fragment



Implementation



- Two processes are running inside the ROD controller
  - acquire data and compute energy values
  - train the neural network
- Intensive training phase occurs in the beginning of acquisition
- Online network training

Separation in the electron beam

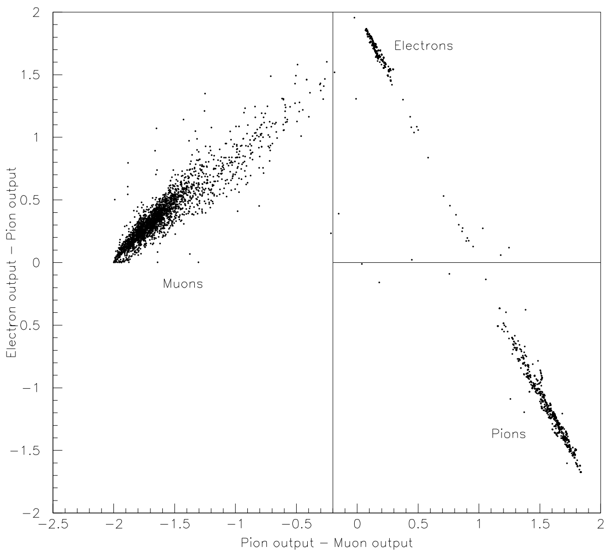
- Data from 180 GeV electron beam (August)
- Muon and pion data from July testbeam period
  - stored muon and pion data come from a different Tilecal module
  - this is due to the absence of specific pion and muon data during this calibration period
  - module to module fluctuations may disturb the network training
- Central module was positioned into the beam’s direction
- Classical cut-based methodology was used to validate the neural particle identification (statistical bias investigation)

Neural network implementation

- Network topology : 23-8-3 (each output neuron assigned to a given particle class)
- Previous acquired muon and pion data (free of contamination by running a similar neural system for pion beams) are stored in a buffer and are used during online training
- Events from the electron beam are stored in a circular buffer
  - despite contamination, all events have the same desired output for network training {-1,-1,+1}

Online Neural Classification

Network response



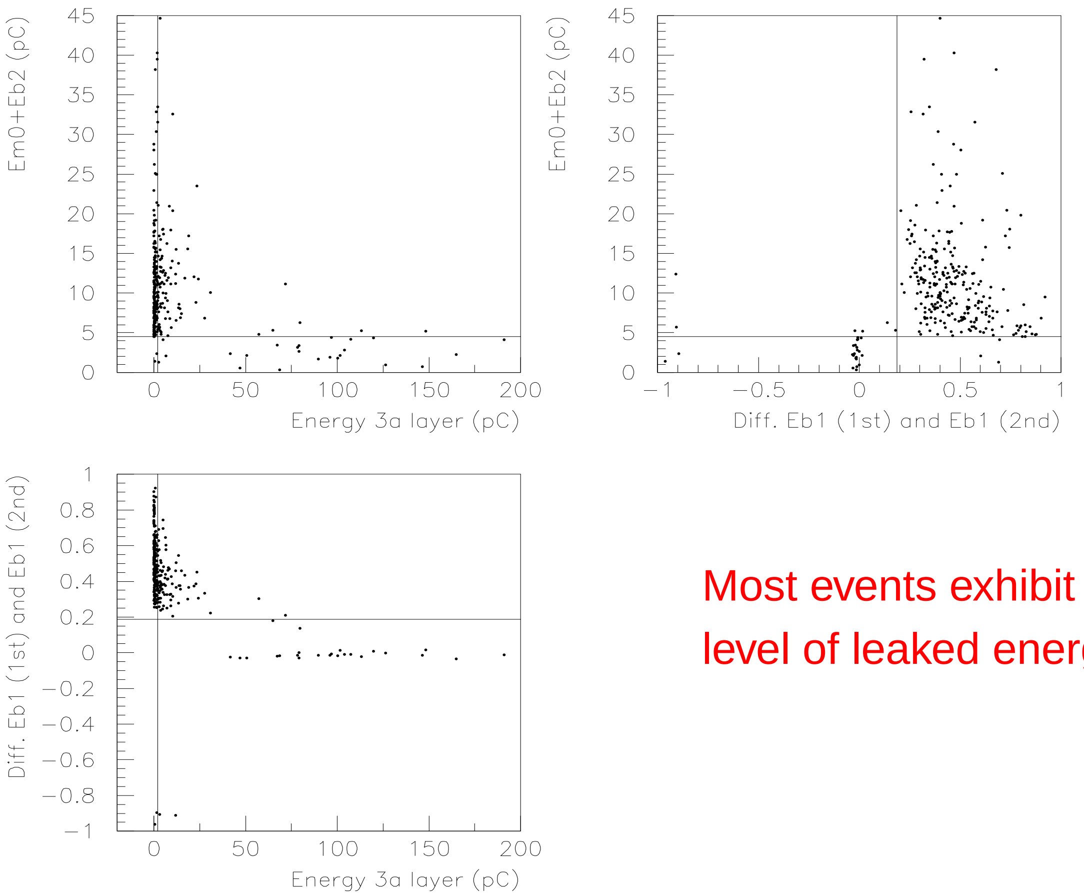
Validation thru classical methodology

η	-0.15	-0.25	-0.35	-0.45	-0.55
Agreement	96.7%	97.4%	97.5%	97.3%	98.4%

$\longrightarrow$ data coming from different modules do not really cause such small disagreement (energy leakage does)

Results

- Correlation for events with classification disagreement between neural and classical cut-based methods



Most events exhibit high level of leaked energy

Improving Performance

- An offline test system was developed for optimizing outsider identification
  - uses <u>recorded</u> online data
  - online code unchanged
  - reproduction of testbeam characteristics
- Learning rate and number of epochs were both optimized
- One more input component was added (leaked energy as measured by outer modules)

Results (optimization)

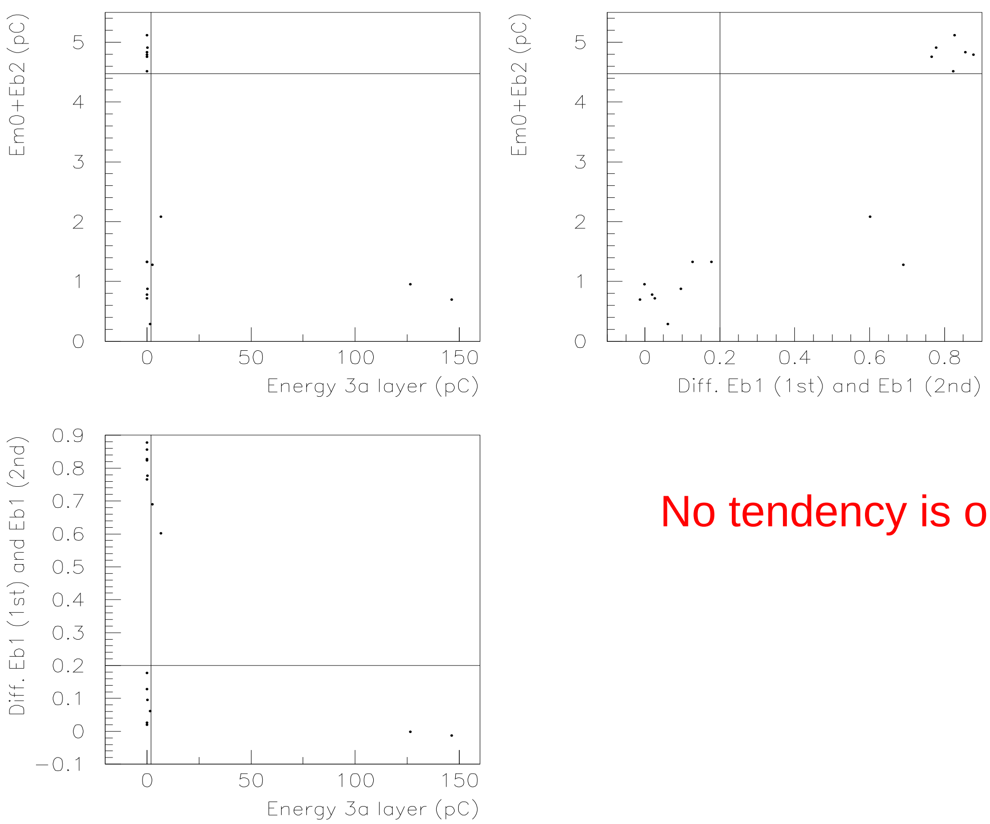
- Agreement between the neural classification and the cut-based methods after optimization

η	-0.15	-0.25	-0.35	-0.45	-0.55
Agreement	99.4%	99.3%	99.3%	99.3%	99.1%

$\rightarrow$ The minimum agreement obtained before the optimizations was 96.7%

Results (optimization)

- Correlation for events with classification disagreement between neural and classical cut-based methods, after optimization



No tendency is observed

Conclusions

- Online neural particle identification was implemented for removing outsiders from the beam-line during calibration of calorimeter modules
- Neural system was integrated with the DAq system
- Data for pions and muons, used to train the neural network, came from a different calorimeter module (system is robust with respect to module to module fluctuations)
- Classification efficiency better than 99.1% using only calorimeter information
- Method is not Tilecal dependent