



# Review of CMS HCAL reconstruction performance

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#### Outline



- Introduction
- Reconstruction algorithms
- Reconstruction performance
- Reconstruction with ML





#### HCAL structure











# Reconstruction algorithms

## HCAL Energy Reconstruction





- Reco input: digitized charge in 8 LHC bunch crossings (BX) in buffer, called time samples
  - Current BX (BX0): 75-100 ns (Time

sample 3) ~60% total charge

- BX+1: ~20% total charge
- First reco algorithm: Method 0
  - Used in Run1 (50 ns bunch spacing)
  - OOT PU almost negligible
  - $(Q_{BX0} + Q_{BX+1})$  x scale factors
- Pulse fitting algorithms
  - In use since Run2 (25 ns bunch spacing)
  - 2016-2017: Method 2 (3) offline (HLT)
  - from 2018: MAHI both offline and HLT



#### Method 2



- M2 estimates the energy of SOI pulse by minimizing  $\chi^2$  using MIGRAD algorithm in Minuit
- Fits up to 3 pulses (SOI 1, SOI and SOI + 1) to QIE digis in 10 TS
- Starts with fitting 1 pulse. If  $\chi^2 > 15$  and charge < 100 fC for HPD or 25000 fC for SiPM (both correspond to ~20 GeV), then switches to 3 pulses





 $A_i$ : QIE digi in ith TS  $\mu_i$ : sum of fitted amplitudes in ith TS  $\sigma_{p,i}^2$ : quadratic sum of uncertainties (pedestals, QIE granularity, and photostatistics)

 $t_j$ : pulse arrival time

ped: floating baseline



#### Method 3



- M3 was developed to meet HLT timing requirment
- Compared to M2, M3:
  - Fits 3 pulses (SOI 1, SOI and SOI + 1) to only 3 TS
  - Drops the arrival time term
  - Uses constant baseline term
  - Fitting  $\rightarrow$  solving linear equations



$$\begin{bmatrix} A_{\text{SOI}-1} \\ A_{\text{SOI}} \\ A_{\text{SOI}+1} \end{bmatrix} = \begin{bmatrix} f_0 & 0 & 0 \\ f_1 & f_0 & 0 \\ f_2 & f_1 & f_0 \end{bmatrix} \begin{bmatrix} \mu_{\text{SOI}-1} \\ \mu_{\text{SOI}} \\ \mu_{\text{SOI}+1} \end{bmatrix} + \begin{bmatrix} B \\ B \\ B \end{bmatrix}$$

#### $A_i$ : QIE digi in ith TS

 $f_{0,1,2}$ : pre-measured fractions of the pulse template in +0, +1 and +2 TS, respectively  $\mu_i$ : amplitudes of ith pulse

B: constant baseline (average of pedestals in

all TS except SOI and SOI+1)



#### MAHI

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- MAHI (Minimization At HCAL, Iteratively) estimates the energy of SOI pulse by minimizing  $\chi^2$  in an iterative approach, using Non-Negative Least Square (NNLS) algorithm instead of MIGRAD in M2
- Reconstruction speed: MAHI is O(10) faster than M2 and O(10) slower than M3



$$\mathbf{V} = \sum_{j=0}^{7} \mu_j^2 \mathbf{D}_j^{\text{pulse}} + \mathbf{D}^{\text{noise}}$$

 $\mu_j$ : amplitudes of jth pulse  $D_j^{pulse}$ : pulse shape uncertainty  $D^{noise}$ : total noise (pedestals, QIE granularity, and photostatistics)

$$\chi^2 = \left[\sum_j \vec{P}_j \mu_j - \vec{d}\right]^T \mathbf{V}^{-1} \left[\sum_j \vec{P}_j \mu_j - \vec{d}\right]$$

 $\overrightarrow{P_j}$ : 8x8 matrix contains pulse template  $\overrightarrow{d}$ : vector contains QIE digis of 8TS





# Reconstruction performance



#### Charged pion resolution in data







- Extrapolate isolated tracks to calorimeter and match to a cone
- Use track momentum ECAL energy in that cone as "truth" HCAL energy
- M0, M2 and MAHI have similar resolutions, but M0 has high response because of OOT-PU



#### Response of pions in MC





- Two MC samples from the same GEN step pion gun
  - One has only OOT-PU
  - The other has no PU
- Extrapolate GEN pion tracks to calorimeter and match to a cone

- Response = cone energy / GEN pion energy
- Plot ratios of responses in OOT-PU sample and no PU sample
- Performance: M2/MAHI better than M0, especially in low energy / high eta regions, because of OOT-PU subtractions







## Reconstruction with ML



### Limitation of analytical algorithms





- Reconstructed energy resolution in each channel
  - MAHI: not fitting pulse arrival time Bad performance at high energy
  - M2: too slow only fits up to 3 pulses
    Bad performance at low energy
- Is there an algorithm that has better resolution at both low and high energy?
- Machine learning can achieve this!



#### DLPHIN





- Deep Learning Processes for HCAL INtegration
- Novel architecture based on 2D CNN
  - Dim. 1: digitized charge in 8 BX
  - Dim. 2: depth → exploit correlations among channels in an HCAL tower
- More than 3 times faster than MAHI
- Better perform from upstream to downstream
  Channel-level → single particle-level → jet-level
- Will benefit almost all physics analyses

#### **DLPHIN** performance









# **Backup Slides**



#### Trigger System and Pileup



- Two-level trigger system
  - Reduce the event rates from 40 MHz to ~1kHz
  - While keeping most of the interesting events
- Level-1 trigger (L1T)
  - Custom ASIC, FPGA, etc
  - Reduce rate to 100 kHz
- High-level trigger (HLT)
  - Commercial CPU + GPU
  - Rate reduce to ~1k Hz





#### pileup (PU)

- In-time PU: current bunch crossing (BX)
- Out-of-time PU: other BX, very important for calorimeter reconstruction



#### **Event Reconstruction**





- Particle Flow (PF) Algorithm
  - Runs on HLT and offline reconstruction
  - Synthesizes information from all subdetectors and reconstructs particles based on their signatures
    - 1. Muon
    - 2. Electron and Photon
    - 3. Charged and Neutral Hadron
- Then PF particles are clustered as jets
  - Usually anti- $k_{\rm T}$  algorithm in CMS
- Last global quantities of an event
  - e.g. missing transverse momentum  $p_T^{miss}$ , aka MET usually a manifest of neutrinos, but may also from BSM :P



#### Parton Shower vs Hadron Shower



r= Molière radius



Parton shower (+ hadronization that form a jet) typically in a cone



Shower length

Hadron shower (interacting with detector material)

typically in a cylinder

- longitudinal development: radiation or interaction length
- lateral development: Molière radius (a cylinder containing on average 90% of the shower's energy deposition)
- Typical Molière radius for a pion is an HCAL tower (0.087 x 0.087 rad.)