CMS ECAL TECHNIQUES, CALIBRATION AND PERFORMANCE TOWARDS RUN 3

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ON BEHALF OF THE CMS COLLABORATION
Outline

- Dedicated legacy calibration of Run 2 CMS Electromagnetic Calorimeter (ECAL)
- Developments for Run 3
  - Online (rate stability etc)
  - Automated calibration workflow
  - ML based super-clustering
  - ML based energy correction
- End-to-end mass regression for merged electromagnetic showers
  - Application in reconstruction of ‘a’ in H→aa→4γ decays
CMS Electromagnetic Calorimeter (ECAL)

- Lead tungstate crystal (PBWO$_4$)
- Barrel: 61200 crystals read by Avalanche Photo-Diodes (APDs)
- Endcaps: 14648 crystals read by Vacuum Photo-Triodes (VPTs)
- Preshower: 3X$_0$ of Pb/Si strips to discriminate between prompt photons and photons from pi0 decay

- **High resolution**: for precision physics
- **High granularity**: relevant for position measurement and enabled merged photon searches
- **Compact**:
  - Small Molière radius = 2.19 cm
  - High density = 8.28 g/cm$^3$
  - Short radiation length (X$_0$) = 0.89 cm
- Excellent timing resolution (~150 ps) for high energy showers - widened long-lived particle searches
Importance of the ECAL in Higgs physics

- Conception of the CMS ECAL was driven by $H \rightarrow \gamma\gamma$ search
- Excellent energy resolution, and position reconstruction led to the discovery of Higgs in $H \rightarrow \gamma\gamma$ and $H \rightarrow ZZ \rightarrow 4l$ decay modes
Challenges in energy measurement - Laser corrections

- **Detector ageing:** Significant reduction in crystal transparency and increased APD noise
- **Dedicated laser system** to monitor each channel every 40 minutes.
- Crucial to **maintain stable ECAL energy scale and resolution** over time.
High pile-up during Run 2

Dedicated **multi-fit method to subtract the contributions from pile-up** in the ECAL pulse shape fit for energy estimation
Calibration and performance in Run 2

- Similar performance achieved as in Run 1 in spite of harsher environment in terms of radiation level (and hence detector ageing) and pile-up
- Calibration of the ECAL is achieved via dedicated methods (Z→ee etc) that ensure
  - stable energy scale with time
  - equilization of the ECAL response in $\eta$ and $\phi$
- Refined calibration done at the end of Run 2
- Largest source of uncertainties in H→$\gamma\gamma$
  - Electron energy scale/resolution: 0.1 GeV
  - Residual pT dependence of the photon energy scale: 0.11 GeV
  - Non-uniformity of the light collection: 0.11 GeV
For Run 3, at L1/HLT **frequency of laser updates has been increased** from twice-per-week (Run 2) to once-per-fill** (Run 3) (frequency of offline update is 40 minutes - used in refined calibration)

- Checked on Run 2 data with Run 2 and Run 3 conditions applied and compared with the refined calibration
- Faster processing of laser data enabled frequent updates
- **Improved HLT electron rates and resolution**

**In 2022, a fill is 10 hrs long on an average**
Towards Run 3: Offline calibration - Quick delivery via automation

- **Constant monitoring and fine time granularity** is needed for calibration to mitigate radiation damage effects and achieve improvement at the level of Legacy calibration at the end of Run 2

- Tracking the response evolution over time is the main challenge

- Automated calibration framework developed during Run 3 using a framework of finite state machine through **Jenkins** and **influxdb** + **Grafana** for monitoring

- Timing calibration (timing of ECAL shifts due to irradiation), pulse shape updates, various steps in energy calibrations, alignment …
Run 3 future: ECAL super-clustering using GNN

Performance in Run 2 after regression

- **Run 2 (a.k.a Mustache super-clustering):** Purely geometrical approach of hit collection within a certain window motivated by the spread of shower along $\phi$
  - High efficiency - gathers even low energy clusters
  - Downside: suffers from pileup (PU) and noise contamination
  - Dedicated regression is applied to correct for these effects on an average

Approach for Run 3: Graph Neural Network

- New development ongoing for **Run 3** based on **Graph Neural Network**
  - **Input features** include information from clusters and its crystals (rechits)
  - **Multiple outputs:** cluster classification (whether in/out of SC), object identification (electron/photon/jet), and energy regression
Run 3 future: ECAL super-clustering using GNN

- Response estimated by fitting the calibrated electron/photon energy divided by the true energy with a Cruijff function
- Resolution better in most of the cases compared to the current algorithm developed during Run 2
Run 3 future: Energy regression using Dynamic Reduction Network

- Dedicated energy regression for electrons and photons
  - Loss in tracker, modular gaps
  - Pile-up and noise
  - Thresholds to discard noisy crystals
- Run 2: semi-parameteric BDT based regression
  - uses ~30 high-level input features that describe the electromagnetic shower
  - Used for all the electron/photon objects within CMS
- New developments ongoing using graph-based Dynamic Reduction Network (DRN)

![Approach for Run 3: DRN](image)
Improved per-object energy resolution by ~10% for both electrons and photons

Leads to a 5% improvement in the invariant mass - confirmed in Run 2 data

In the process of being deployed for Run 3
Particle flow algorithm used in CMS is based on “engineered” shower-shape inputs.

Not optimum for very merged signatures in the ECAL produced by the decay of highly boosted particles (e.g. $\Gamma \rightarrow \gamma\gamma$ where $\tau$ is any resonant particle)

Developed a technique ‘end-to-end’ ML. Bypasses feature engineering and uses detector hits directly as input to the ML network

- **Train convolutional neural network** to estimate parent ‘$\Gamma$’ mass of merged photons using ECAL detector deposits to reconstruct “instrumentally merged” $\Gamma \rightarrow \gamma\gamma$ decays

- Input: images of energy deposit pattern of $\Gamma \rightarrow \gamma\gamma$ inside the ECAL

- This way, subtle and crystal-level variations in shower pattern is learnt across the merging scale
- No significant excess observed over SM-only
- Improves indirect constraints from $\text{Br}(\text{SM } H \rightarrow \gamma\gamma)$ for $m_\alpha < 1.2 \text{ GeV}$

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CMS-HIG-21-016
Outstanding performance of the CMS ECAL in Run 2 as in Run 1 in spite of harsher environment

Developments done for Run 3 at both online and offline levels

- Stable rates, better resolution
- Automated calibration workflow - fast and continuous tracking of detector calibration with time
- ML based super-clustering and energy methods show improvement and more resistance towards pile-up and noise

End-to-end ML methods enabled merged photon searches at very low resonance masses for the first time

ECAL will keep playing crucial role in Run 3 and future HL-LHC searches
THANK YOU
BACKUP
- Systematics due to pT dependence

- Systematics due to non-uniformity of light collection
Towards Run 3: ECAL super-clustering using GNN

- **Run 2 (a.k.a Mustache super-clustering):** Purely geometrical approach of hit collection within a certain window motivated by the spread of shower along $\phi$
  - High efficiency - gathers even low energy clusters
  - Downside: suffers from pileup (PU) and noise contamination
  - Dedicated regression is applied to correct for these effects on an average
- New development ongoing for Run 3 based on Graph Neural Network

- **Input features** include information from clusters and its crystals (rechits):
  - $E$, $E_T$, $\eta$, $\phi$, $z$, number of crystals, relative to seed: $\Delta \eta$, $\Delta \phi$, $\Delta E$, $\Delta E_T$
  - List of rechits for each cluster
  - Summary window features: max, min, mean of the crystal variables: $E_T$, $E$, $\Delta \eta$, $\Delta \phi$, $\Delta E$, $\Delta E_T$
- **Multiple outputs:** cluster classification (whether in/out of SC), object identification (energy/photon/jet), and energy regression
GNN Architecture

- W: number of windows in the batch
- N: number of clusters
- R: number of rechts
- [X,Y,Z] tensor dimension

Diagram:

- Clusters features
- Higher dim rep
- Concatenate
- Features building DNN
- Clusters feat. vector
- Clusters classification DNN
- Graph Highway network
- N conv.
- Self-Attention combination layer
- Rechts
- Rechts summary vector
- GCN
- N conv.
- Distance Self-attention layer
- Adjacency matrix
- Flow of info between diff clusters
- Window Classification Self-Attention
- Window summary features
- [W,144]
- DNN
- Cluster classification
- Window classification
- [W,1]
- Energy regression layer
- Energy calibration factor
- [W,146]
- [W,N,128]
- [W,N,18]
- [W,N,37]
- [W,N,19]

Legend:
- Inputs
- Trainable layers
- Tensors with dimensions
- Outputs
- Tensor flow
- Skipped connection
- Concatenation
- Aggregation (sum over clusters dimension)
Detector windows are built around each cluster with $ET > 1$ GeV called seed.

The seed is connected to all the clusters in each window to form a graph.

Input features are computed for each cluster from basic quantities. The list of the position and energy deposited in each crystal forming the clusters (rechit) is also retrieved and used as input.

The TensorFlow model is evaluated on batches of detector windows: the output is the probability of each edge between the seed and the nearby clusters.

The complete graph is traversed, starting from the highest energy seed, to solve overimpositions and collect the final supercluster.

A final cut of $ET > 4$ GeV is applied to remove super cluster formed mainly by detector noise and very low energy PU.
Higgs $\rightarrow$aa$\rightarrow$4$\gamma$ using “end-to-end mass regression” technique

- Possible to apply this strategy to highly merged analyses

- H$\rightarrow$aa$\rightarrow$4$\gamma$, a is light (pseudo) scalar
  - Well motivated in BSM extensions of Higgs sector (2HDM, NMSSM, ALP)
  - $a\rightarrow\gamma\gamma$ decay mode important below production threshold of heavier states: $m_a < 2m_\mu$, $m(3n^0)$, $m(J/\psi) \sim 0.2, 0.4, 3$ GeV
  - Smaller $m_a$ $\rightarrow$ larger Lorentz boost ($\gamma_L = 60$ to 600 for $m_a = 1.2$ to 0.1 GeV, resp.)
  - Experimentally challenging at the LHC for $m_a < 1$ GeV
    - $m_a \sim 0.1$ GeV, $a\rightarrow\gamma\gamma$ deposits within one ECAL crystal!

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CMS-EVM-20-001

CMS-HIG-21-016
Cruijff fit

\[ Cruijff(x, \mu, \sigma_L, \sigma_R, \alpha_L, \alpha_R) = \begin{cases} 
\frac{(x - \mu)^2}{e^{-\frac{2\sigma_L^2 + \alpha_L(x - \mu)^2}{2}} + (x - \mu)^2} 
& \text{if } x - \mu < 0 \\
\frac{(x - \mu)^2}{e^{-\frac{2\sigma_R^2 + \alpha_R(x - \mu)^2}{2}} + (x - \mu)^2} 
& \text{if } x - \mu > 0 
\end{cases} \]
End-to-end ML to reconstruct merged signatures

- Particle flow algorithm used in CMS is based on “engineered” shower-shape inputs.
  - Not optimum for very merged signatures in the ECAL produced by the decay of highly boosted particles (e.g. $\Gamma \rightarrow \gamma \gamma$ where $\tau$ is any resonant particle)
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  - This way, subtle and crystal-level variations in shower pattern is learnt across the merging scale
End-to-End ML can clearly reconstruct the mass peak for very low masses

No significant excess observed over SM-only

- Improves indirect constraints from \( \text{Br}(\text{SM H} \rightarrow \gamma\gamma) \) for \( m_a < 1.2 \text{ GeV} \)
- First CMS \( H \rightarrow aa \) limits below \( a \rightarrow \mu\mu \) threshold (\( m_a < 210 \text{ MeV} \))