

# Deep learning techniques for energy clustering in CMS ECAL

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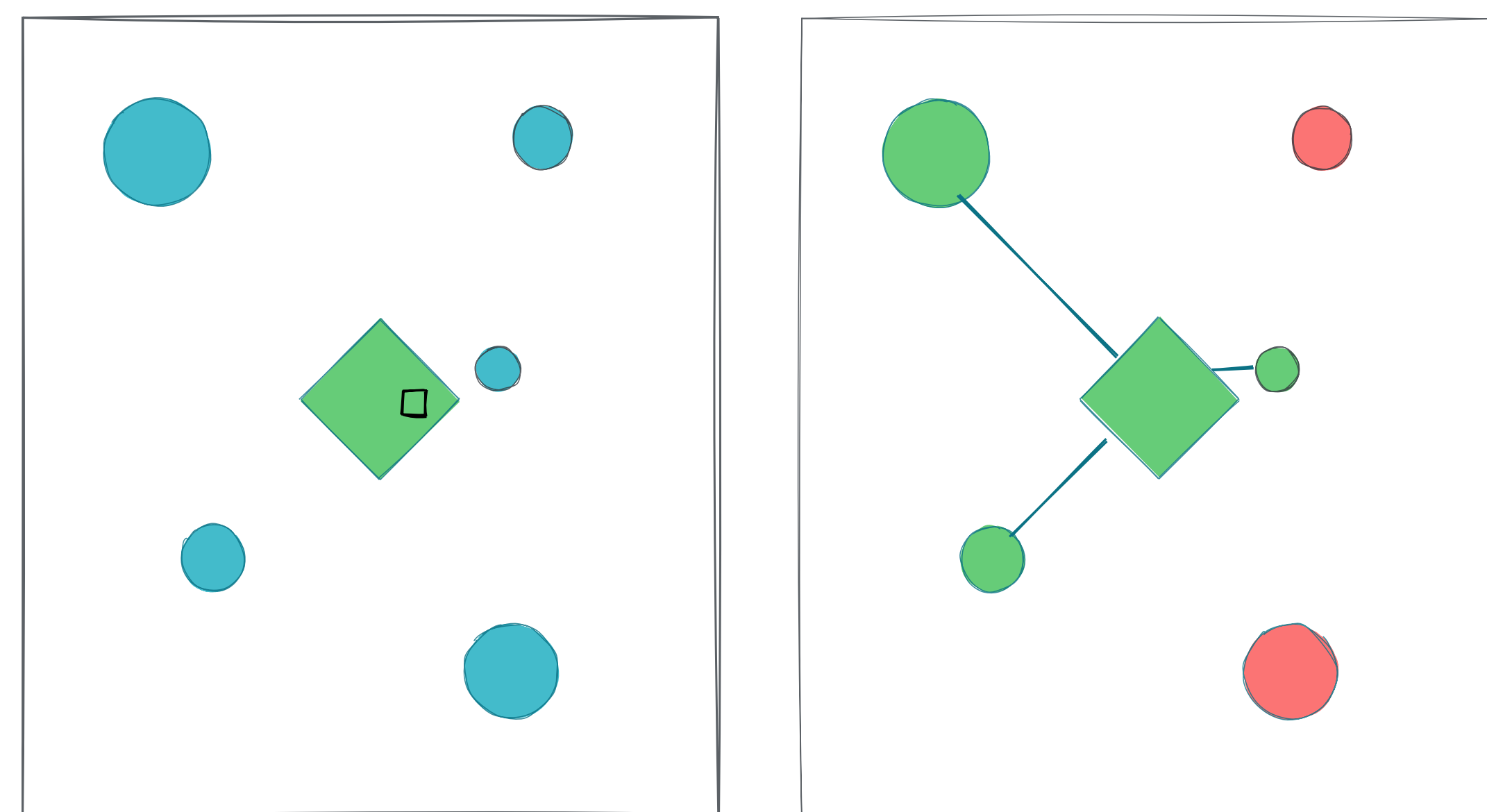


## ECAL local reconstruction



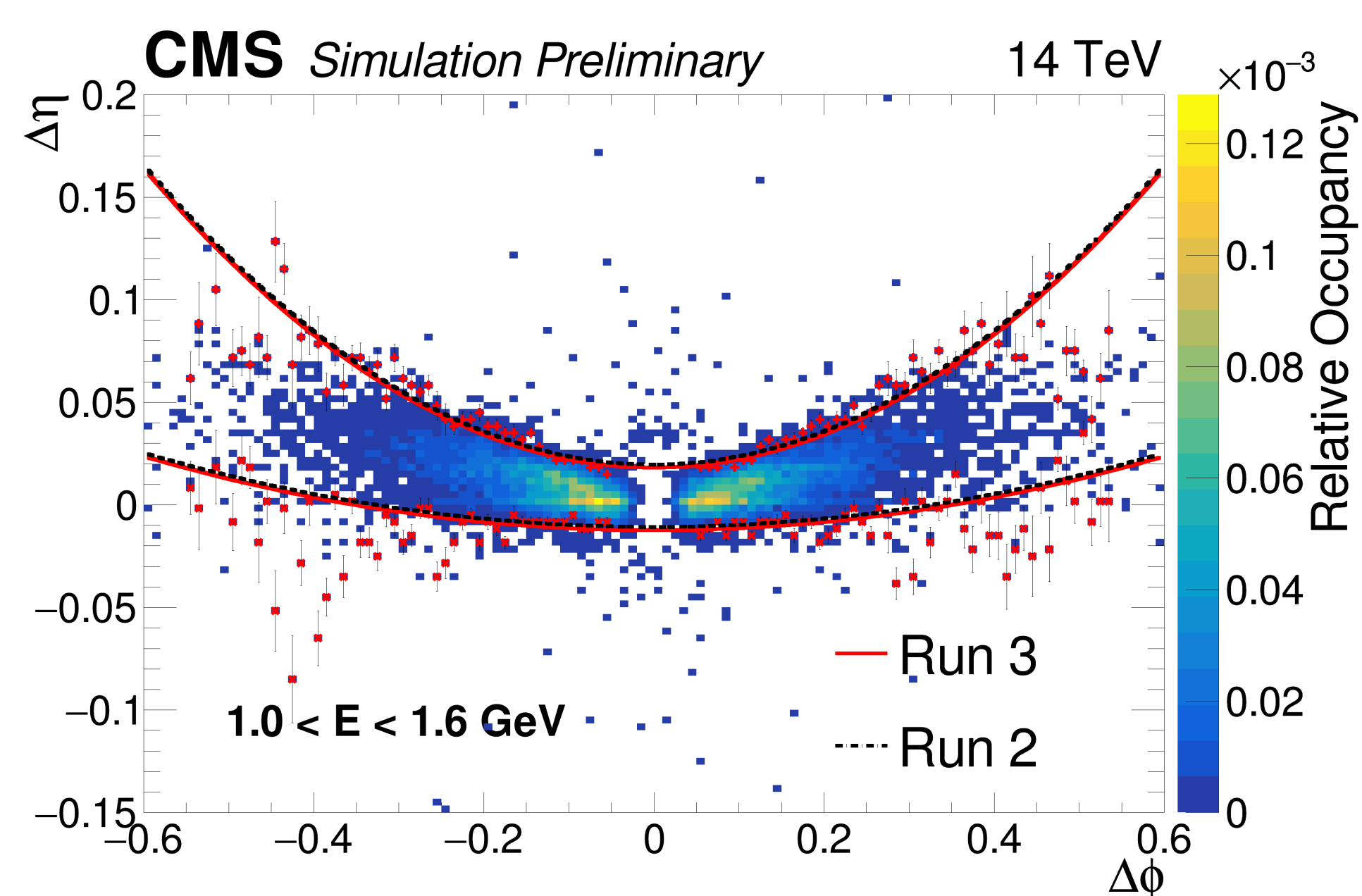
ECAL local energy reconstruction: first step of electron and photon reconstruction in CMS. The energies recorded in the ECAL crystals (**Rechits**) are first gathered together to form **clusters** of neighbouring deposits. CMS strong magnetic field (3.8T) + tracker detector material in front of ECAL = electron and photon fragmentation by bremsstrahlung and  $e^+e^-$  pair production. The **SuperCluster** algorithm gathers together clusters around energetic seeds to restore the optimal energy resolution.

## SuperClustering



Legend: Rechit (square), Seed cluster (diamond), Associated cluster (green circle), Cluster (blue circle), Unassociated cluster (red circle)

## SuperClustering algorithms



**Mustache** = standard CMS SuperClustering algorithm. It selects clusters inside of a  $\Delta\eta$ - $\Delta\phi$  parabolic region defined only by the seed position and the energy of the cluster. Highly efficient for signal, but does not filter pileup\* (PU) and noise contamination.

**DeepSC**: a novel approach based on **Graph Neural Networks** has been developed, exploiting all the available information to improve the energy resolution and make the SuperClustering more robust against PU and noise.

\*pileup = additional low energy p-p interactions overlapping with the hard interaction

## DeepSC - Mustache performance comparison

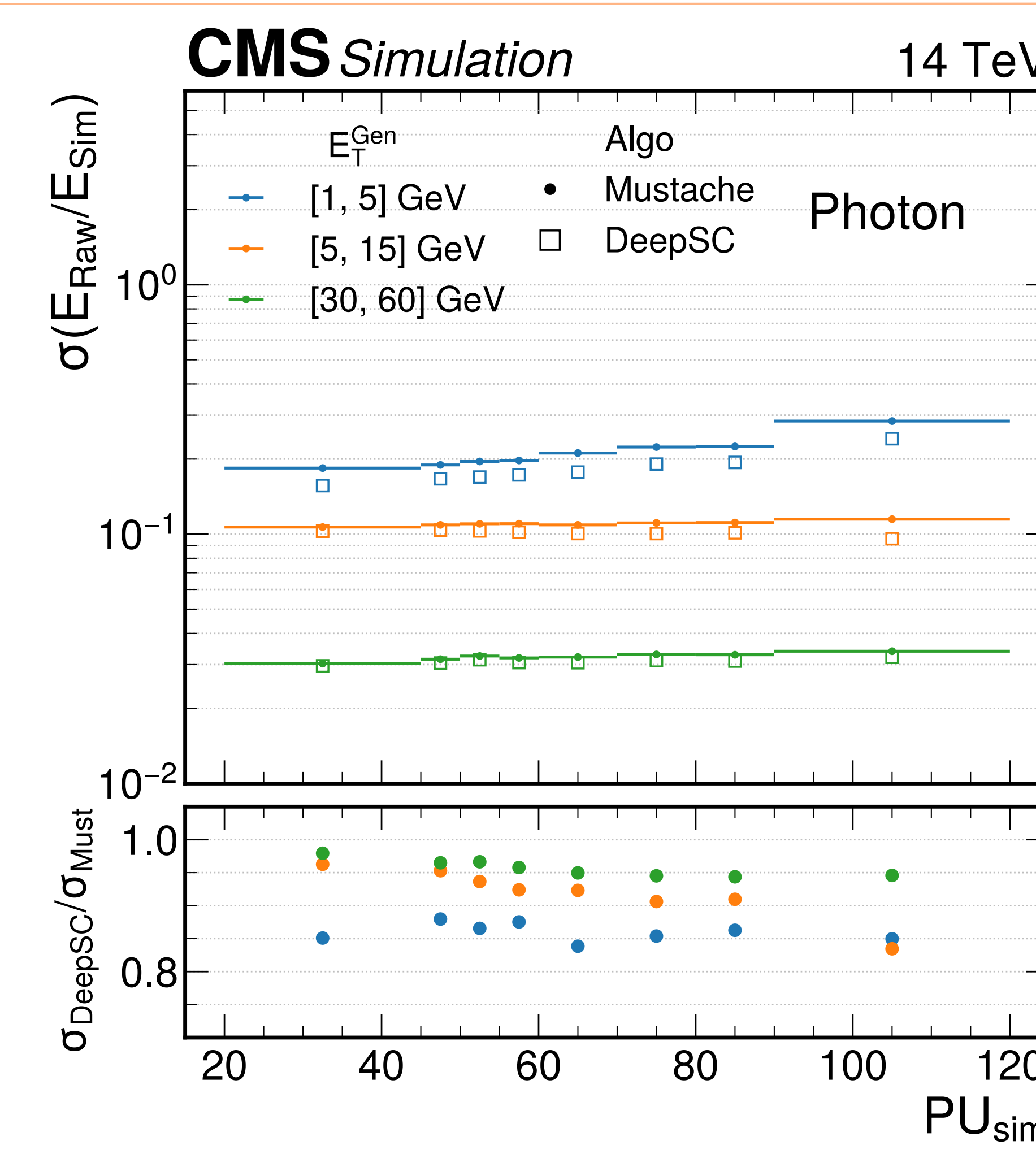
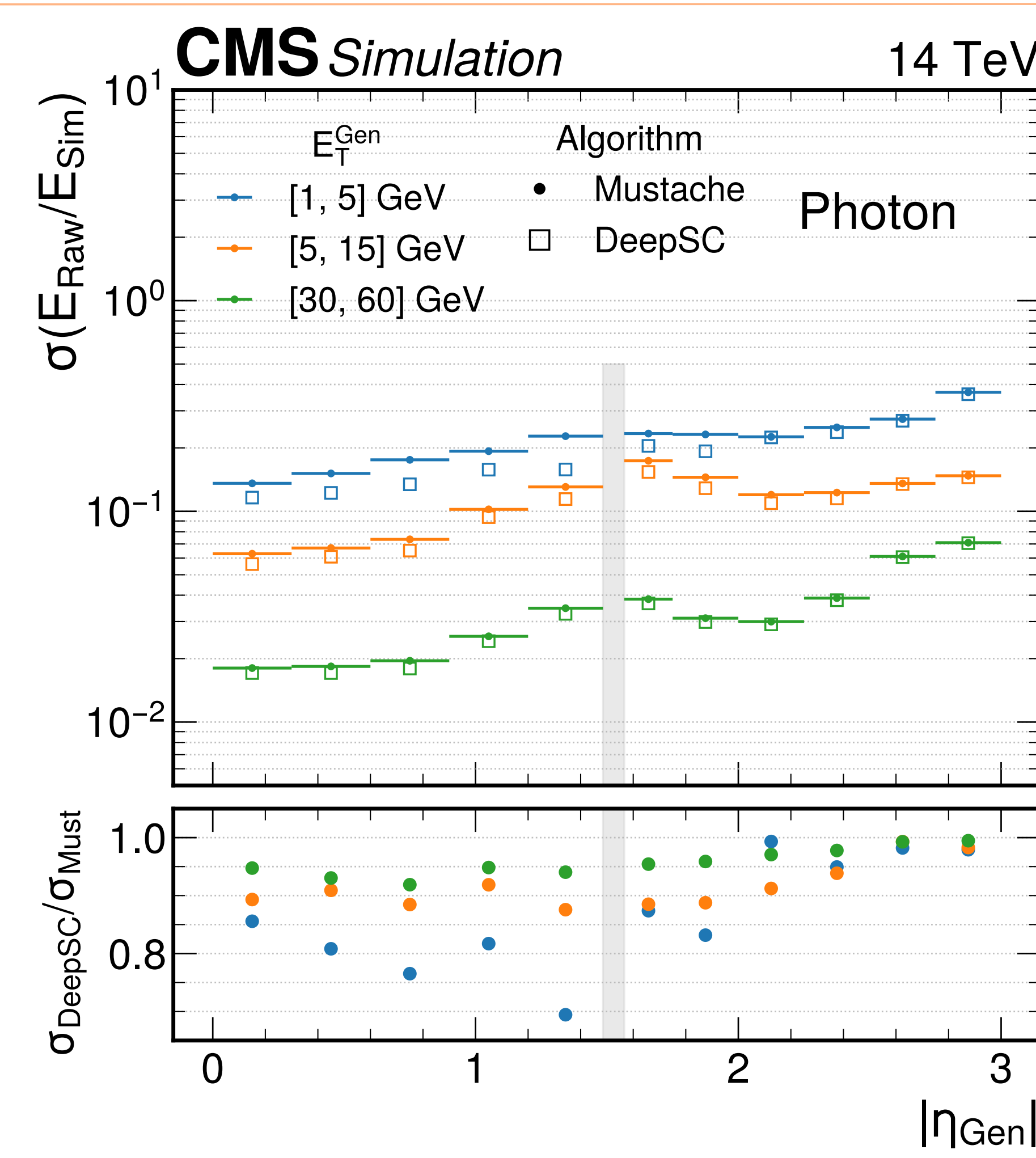
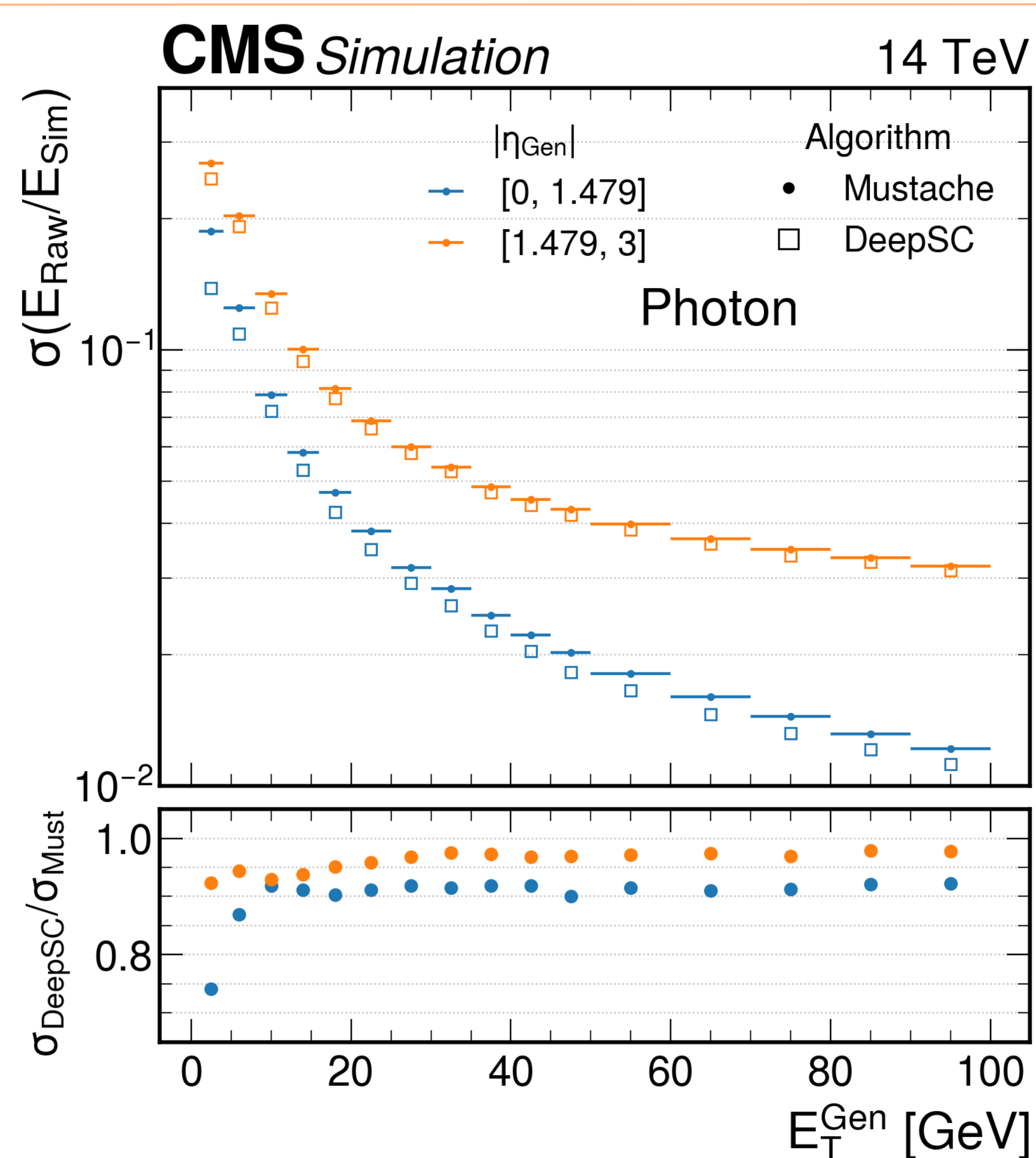
Resolution of the reconstructed uncorrected SuperCluster energy ( $E_{Raw}$ ) divided by the true energy deposits in ECAL ( $E_{Sim}$ ) versus:

- the transverse energy of the gen-level particle  $E_T^{Gen}$  (left)
- the gen-level particle position  $|\eta_{Gen}|$  (center)
- the number of simulated  $PU_{Sim}$  interactions (right)

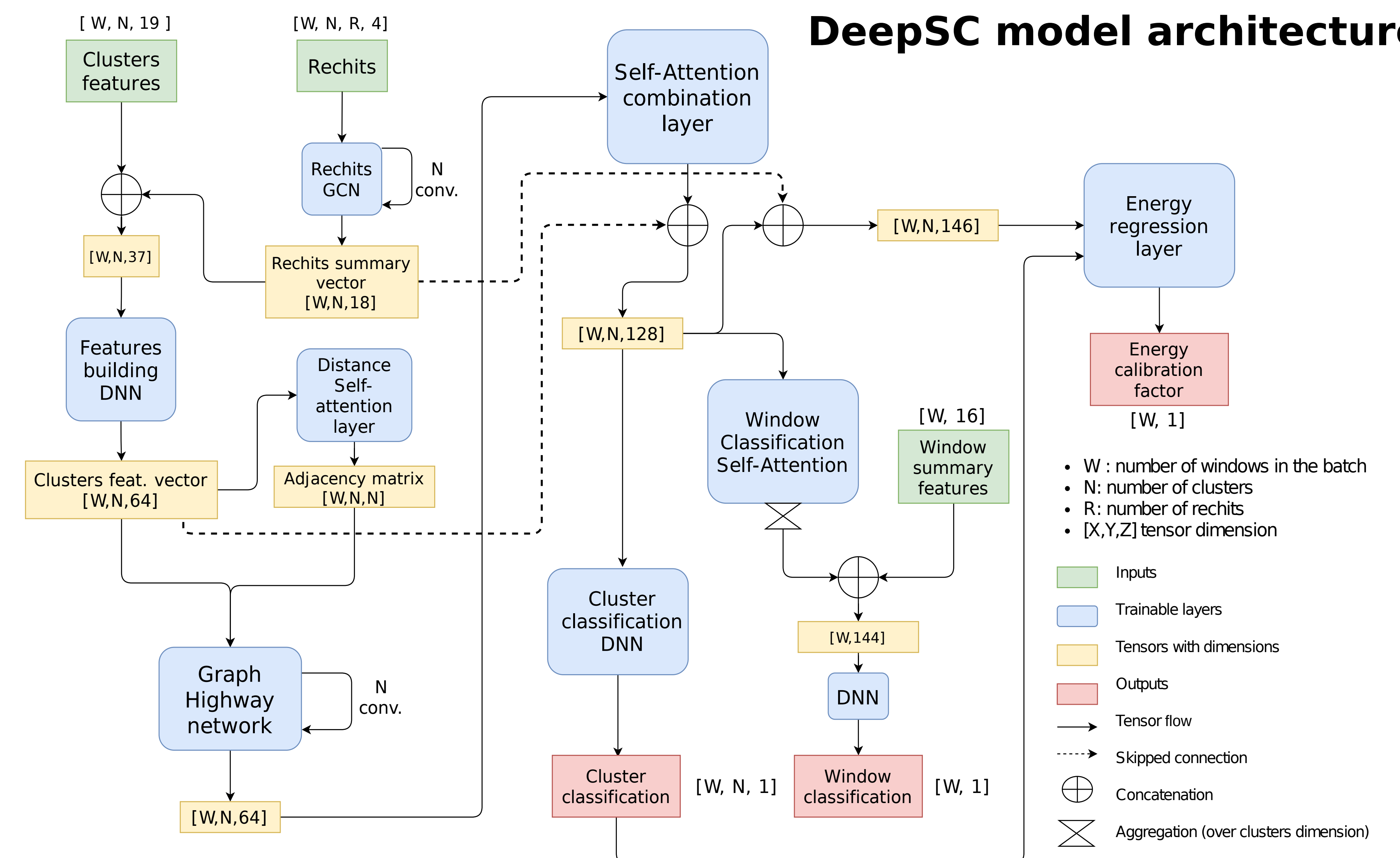
The resolution is computed as half of the difference between the 84% quantile and the 16% quantile of the  $E_{Raw}/E_{Sim}$  distribution in each bin. The lower panel shows the ratio of the resolution of the two algorithms:

$$\sigma_{DeepSC} / \sigma_{Mustache}$$

The DeepSC algorithm shows **significantly improved resolution**, particularly for low  $E_T$  signals and at high PU.



## DeepSC model architecture



Blocks: features encoding, **dynamic graph-building**, **graph convolution** (Graph Highway Network) + **self-attention** layer, and multiple decoding outputs. Optimized to solve three different tasks: **cluster classification**, **window classification** and **energy correction** factor regression. The model is trained on a sample of 2M photons and electrons, generated uniformly in  $\eta$  and  $p_T=[1, 100]$  GeV, with the full CMS Monte-Carlo simulation at 14 TeV. A pileup scenario with the number of true interactions uniformly distributed between [55,75] is used.

- W : number of windows in the batch
  - N : number of clusters
  - R : number of rechits
  - [X,Y,Z] tensor dimension
- Legend: Green box = Inputs, Blue box = Trainable layers, Yellow box = Tensors with dimensions, Red box = Outputs, Arrow = Tensor flow, Dashed arrow = Skipped connection, Circle with plus = Concatenation, Square with X = Aggregation (over clusters dimension)