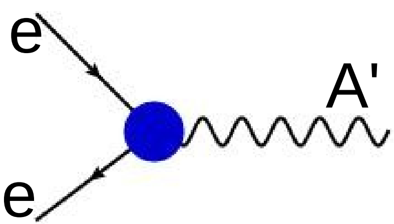
Machine learning assisted reconstruction of positron-on-target annihilation events

Kalina Dimitrova
Faculty of Physics, Sofia University

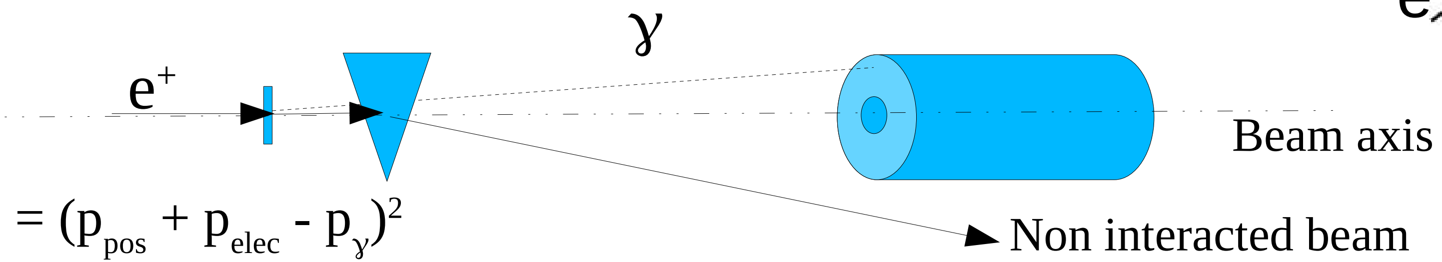
National Forum on Contemporary Space Research (NAFSKI 2023)
20.10.2023

** partially supported by **BNSF: KP-06-D002_4/15.12.2020** within **MUCCA, CHIST-ERA-19-XAI-009** and by the **European Union - NextGenerationEU**, through the National Recovery and Resilience Plan of the Republic of Bulgaria, project **SUMMIT BG-RRP-2.004-0008-C01***

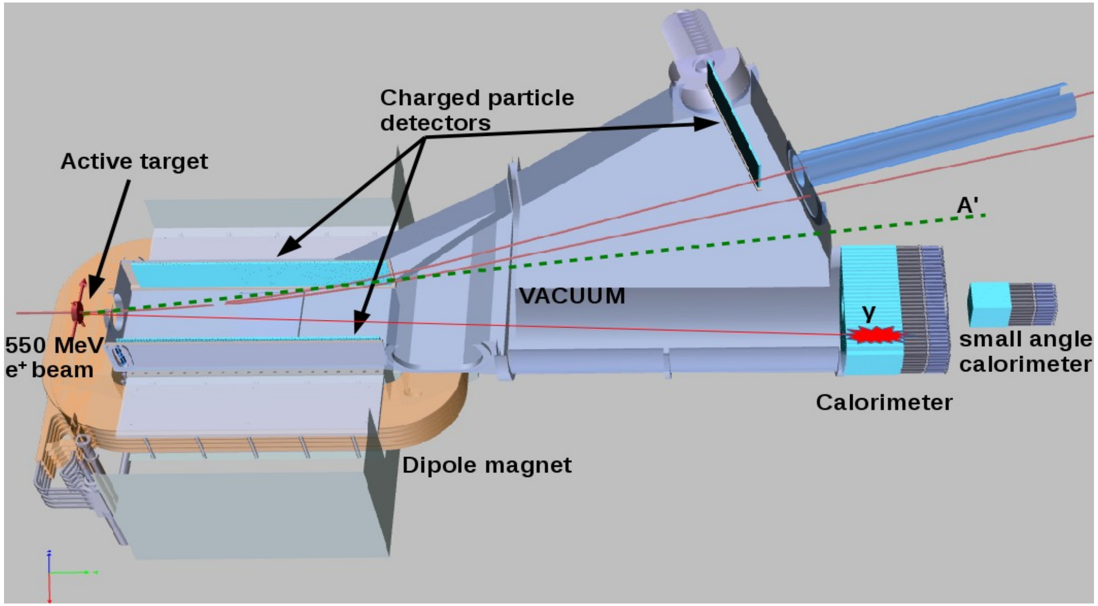
The PADME Experiment



Positron Annihilation into Dark Matter Experiment

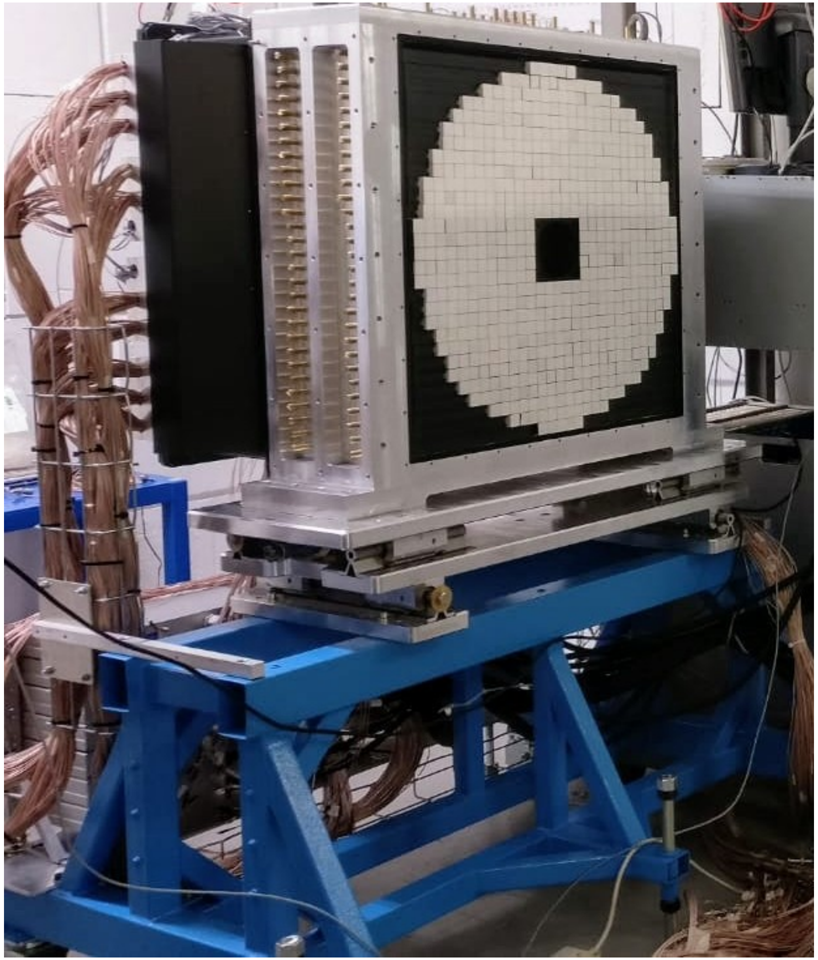


$$M_{miss}^2 = (p_{pos} + p_{elec} - p_{\gamma})^2$$

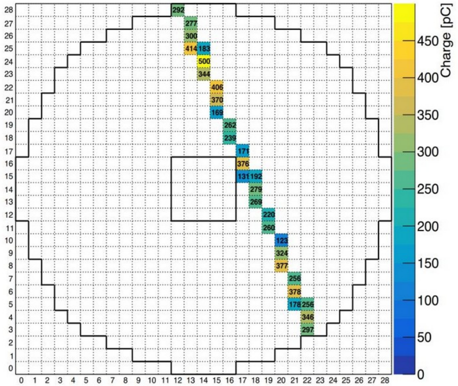


- Small scale fixed target experiment
  - e^+ @ Frascati Beam Test Facility
  - Solid state target
  - Charged particles detectors: PVeto, HEPVeto, EVeto
  - Calorimeters: ECal and SAC
  - Beam monitoring system

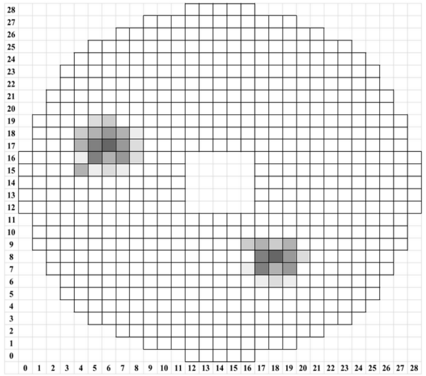
The PADME electromagnetic calorimeter



Muon track

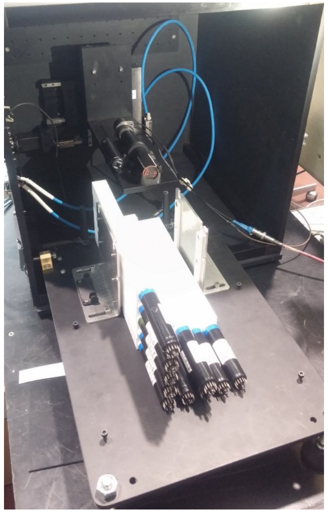


Two photon showers

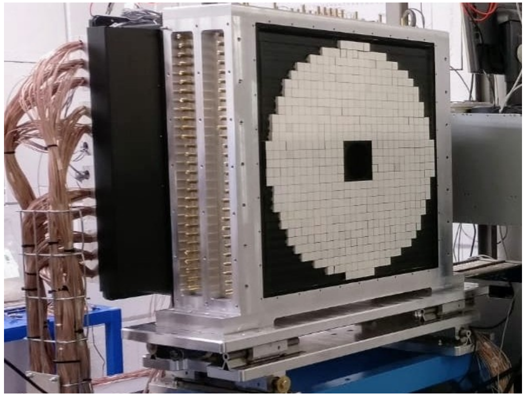


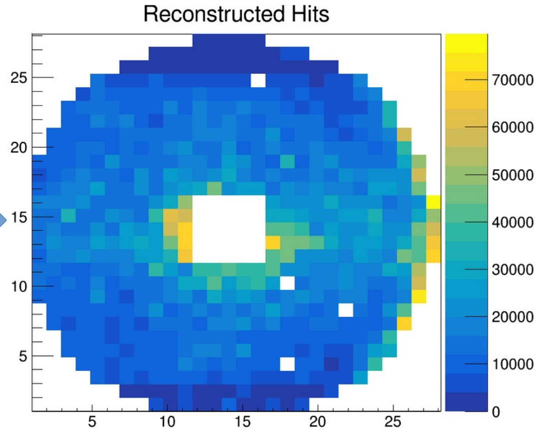
ECAL: The heart of PADME

- 616 BGO crystals, 2.1 x 2.1 x 23 cm^3
- BGO covered with diffuse reflective TiO_2 paint
  - additional optical isolation: 50 – 100 µm black tedlar foils
- Scintillation light decay time – O(300 ns)



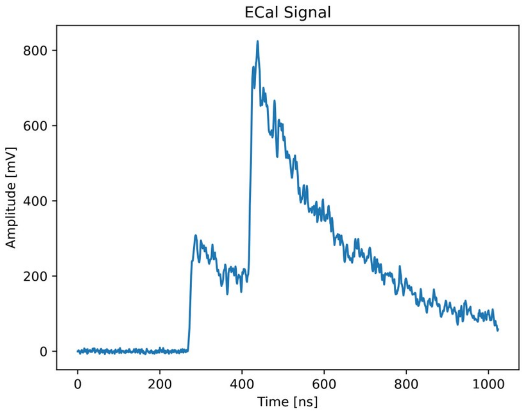
Reconstruction of signals from the ECal

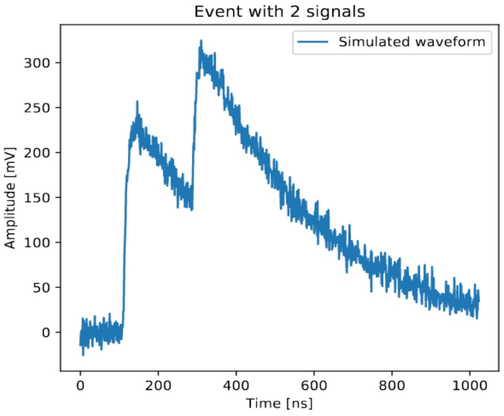


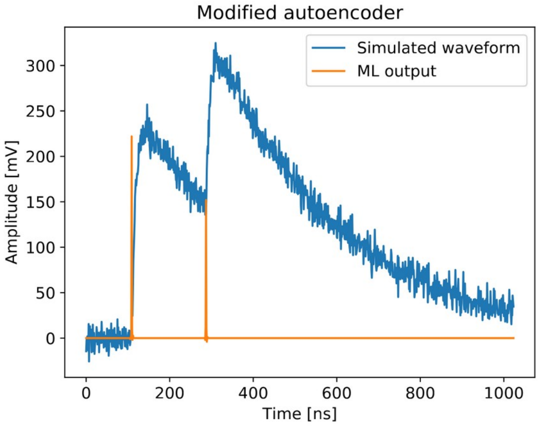


- The large number of close-in-time signals require a reliable method for separating them, capable of:
  - Reconstruction of the arrival time of each individual signal
  - Accurate reconstruction of the signal amplitude

- One possible method includes developing and testing neural networks with different architecture and purposes: classification and regression
- For the training of all networks were developed additional algorithms for signal simulation

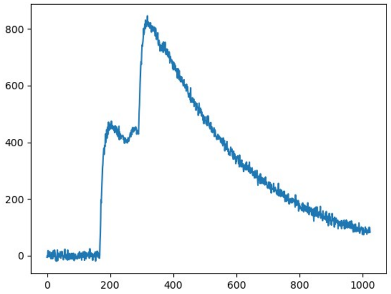




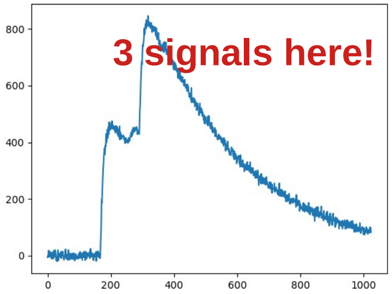


The machine learning approach to PADME data: a summary

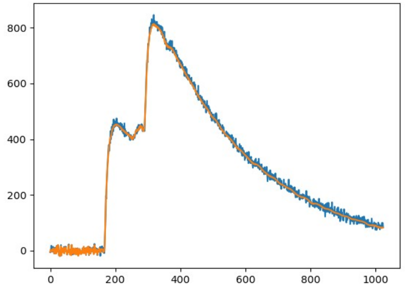
Signal simulation → Simple CNN for counting → Autoencoder → Modified autoencoder



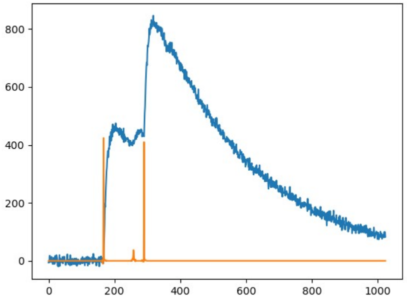
- Generation of noise + several waveforms
- Predefined signal shape
    - Difference between two exponents
    - Calorimeter response function
    - Fixed rise and fall time
- Random number of signals (between 0 and 4)
- Random amplitude and arrival time for each signal



- Classification task to identify the number of pulses in a waveform
- Trained on 100 000 events
- 100% signal discrimination above 50 ns difference, 90% above 30 ns



- Convolutional autoencoder for signal and noise description
- Unsupervised learning – both input and desired output are the waveform arrays
- The waveforms are successfully replicated with the noise in the signal regions significantly suppressed

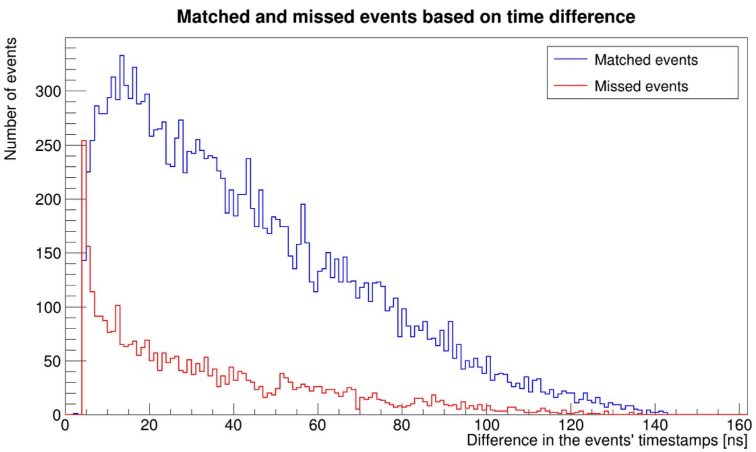


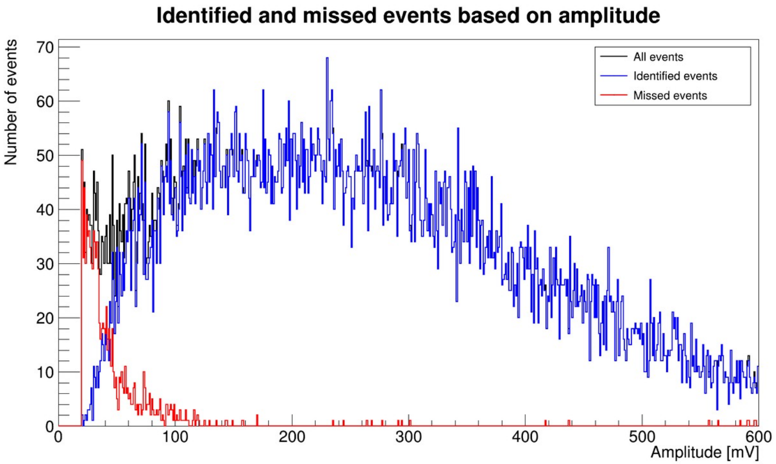
- Same architecture as autoencoder network
- Supervised learning –desired output contains information about the time and amplitude
- Efficiency for time and amplitude thoroughly investigated:
    - Excellent arrival time determination
    - Problems with amplitude reconstruction

Main properties of the modified autoencoder reconstruction

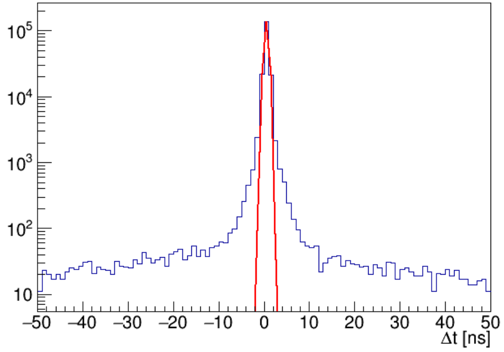
Pulse identification

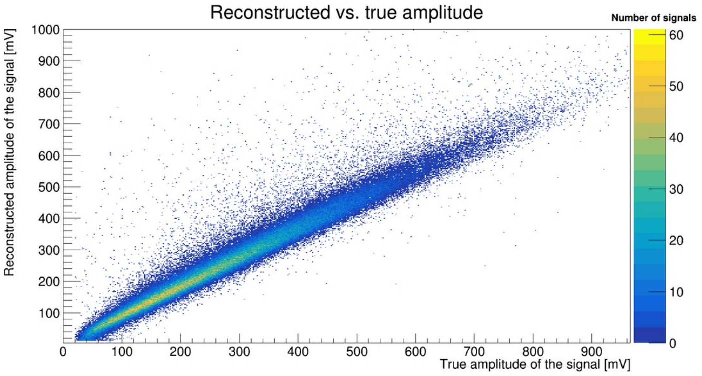
- Efficiency for lower numbers of signals are higher because of unrecognized signals from events with higher numbers
- For closely located signals: Most of the missed events are with dt < 10 ns
- Most of the events with amplitudes < 50mV are not identified





Arrival time and amplitude determination

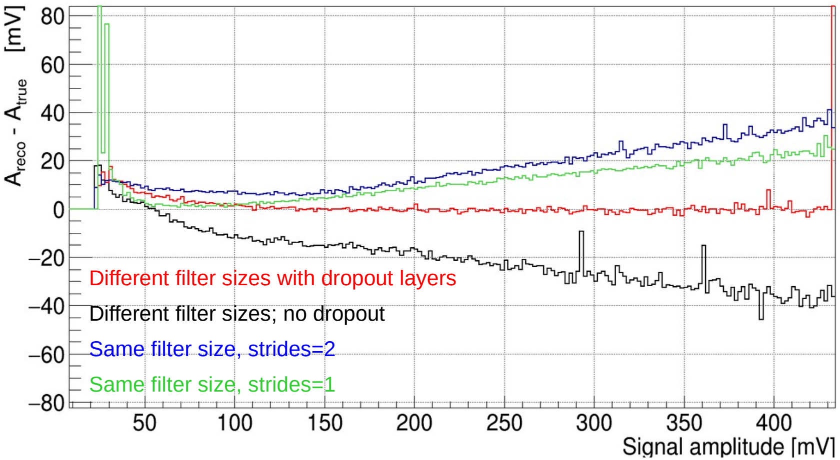


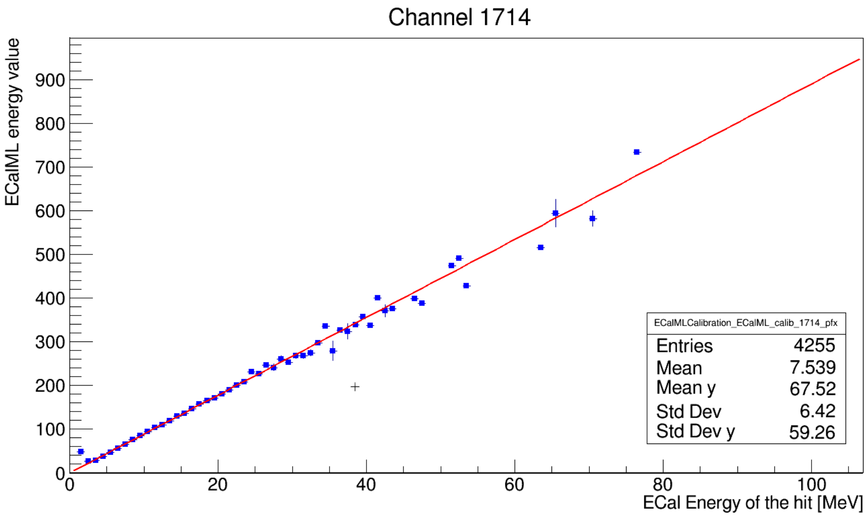


- Δt distribution is symmetric, non-gaussian tails exist
- σ ~ 520 ps, RMS ~ 3.2 ns
- Strong correlation between real and reconstructed amplitude
- Worse reconstruction for the small amplitudes

Moving from simulations to real data: calibration

- Different models were trained and the best performing one was introduced to the experiment software
- All the ML methods were originally developed in Python; applying the model was made possible using the TensorFlow C API
- ML reconstruction for the ECal can be performed simultaneously with the conventional reconstruction.



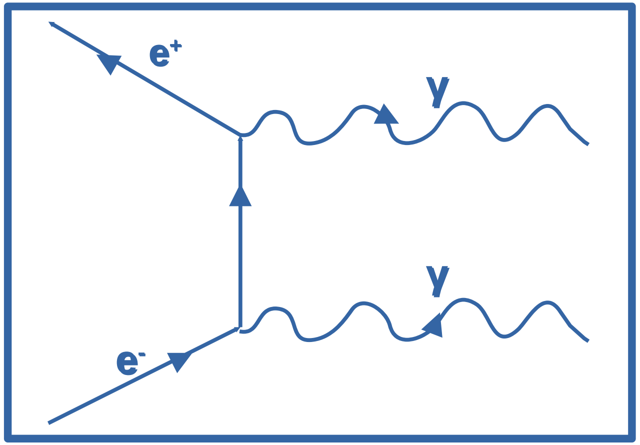


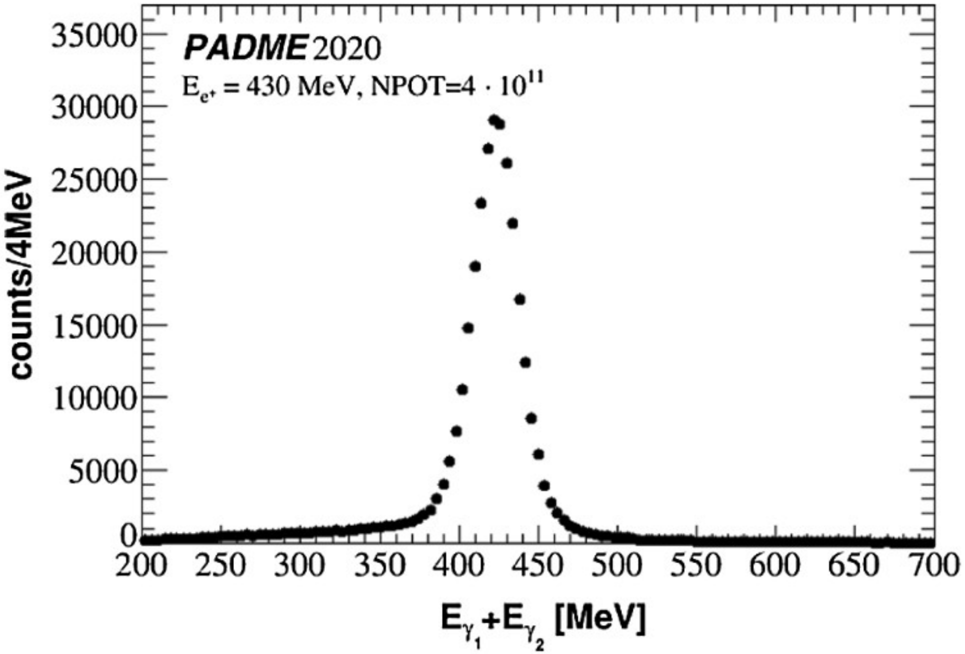
Calibration: from amplitude values to energy

- For each channel were filtered and plotted only the matching signals – the ones found both by the ML and conventional reconstruction
- A calibration equation was obtained for 612 of the 616 channels

e+e- → γγ events at PADME

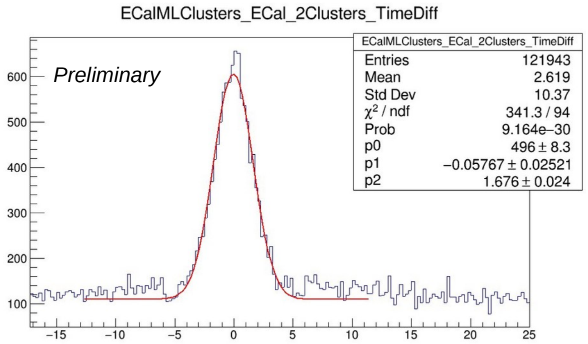
- **Theoretically well-known process**, used for understanding the ECal performance
- Measurement of this cross section is important for:
  - Calibration of the photon reconstruction
  - Monitoring of the beam intensity



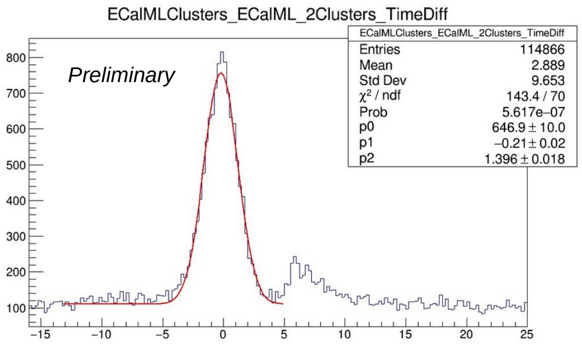


- Measurements of the cross section for the annihilation of 430 MeV positrons and electrons at rest already performed and published (Phys. Rev. D 107, 012008 (2023))
- The process can be used for evaluation of the performance of any new ECal reconstruction methods developed

First try of clusterisation



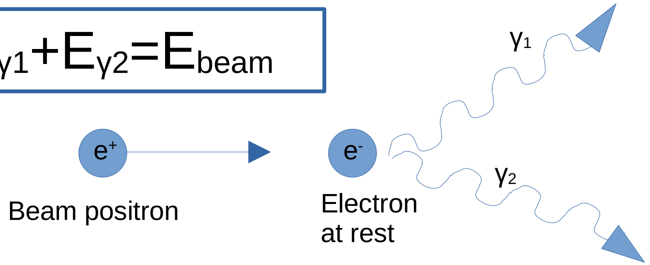
Time difference between two clusters, **ECal**



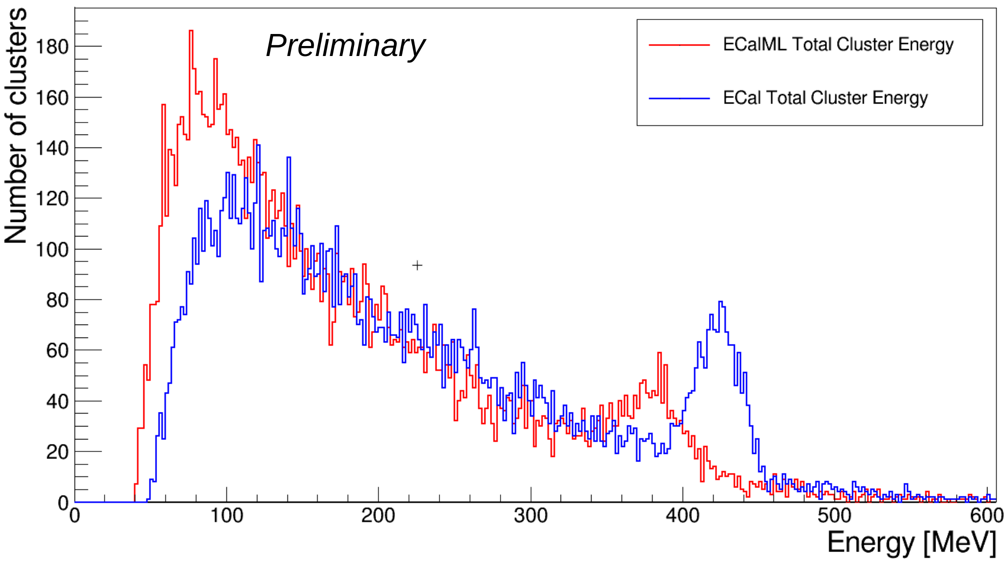
Time difference between two clusters, **ECalML**

- All of the channels are calibrated with their corresponding equations
- Standard clusterisation is performed and events with two clusters with less than 5ns difference are analyzed.

$$E_{\gamma 1}+E_{\gamma 2}=E_{beam}$$

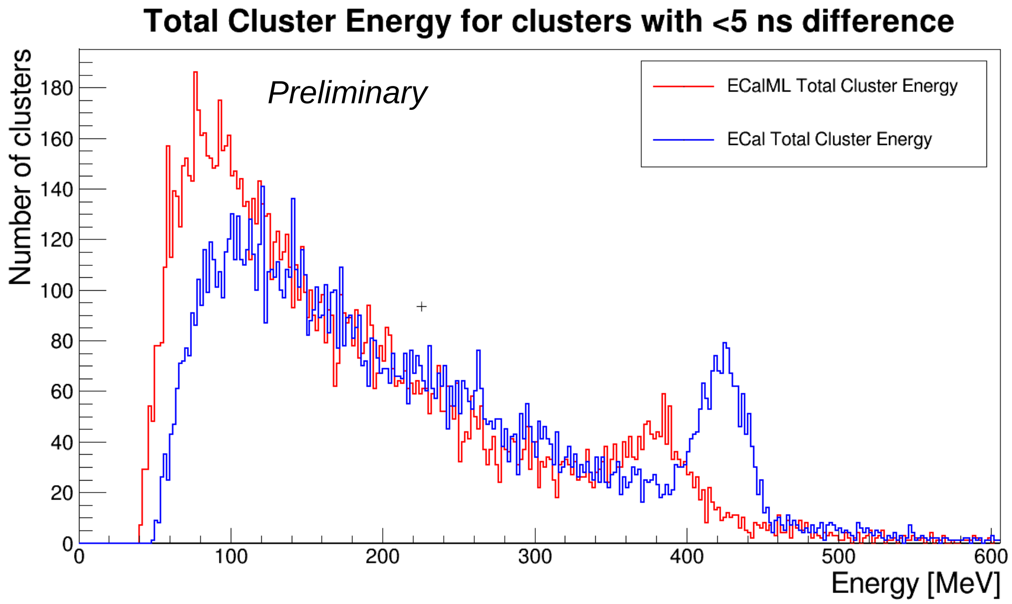


- Evaluation of the time difference between the two clusters shows that the ML reconstruction provides better time resolution
- The total cluster energy for those events shows a clear peak at around 400 MeV
- Compared to the original reconstruction, the peak is at a lower energy, which indicates a problem with the calibration → more precise calibration is needed

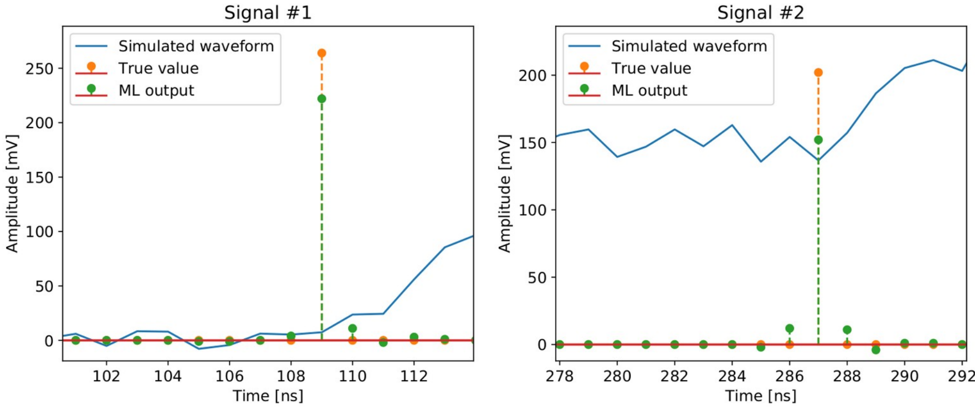


Investigation of the effect of the MINDIST parameter using e+e-→γγ events

- Looking for the reason for the smaller value of the total cluster energy for e+e-→γγ events when using the ML reconstruction
- **Hypothesis:** a smaller value of MINDIST may result in losing energy which the channel-by-channel calibration cannot deal with



MINDIST is the amount of neighboring position values added to the main signal amplitude when constructing the ML results

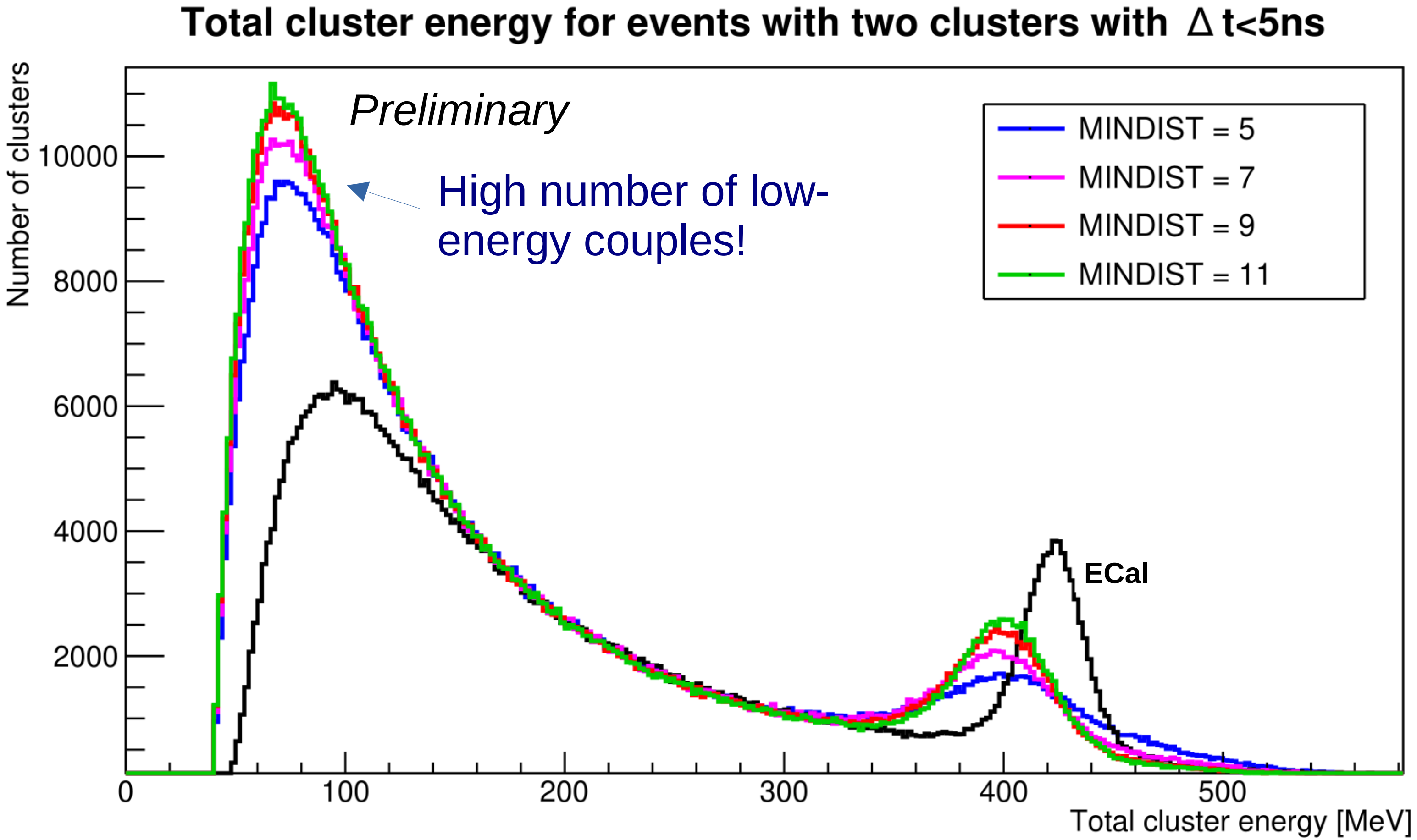


- Reconstruction performed on the same dataset for 4 values of MINDIST without calibration
- For each value new calibration files for the channel-by-channel calibration were produced and used for reconstucting the data a second time

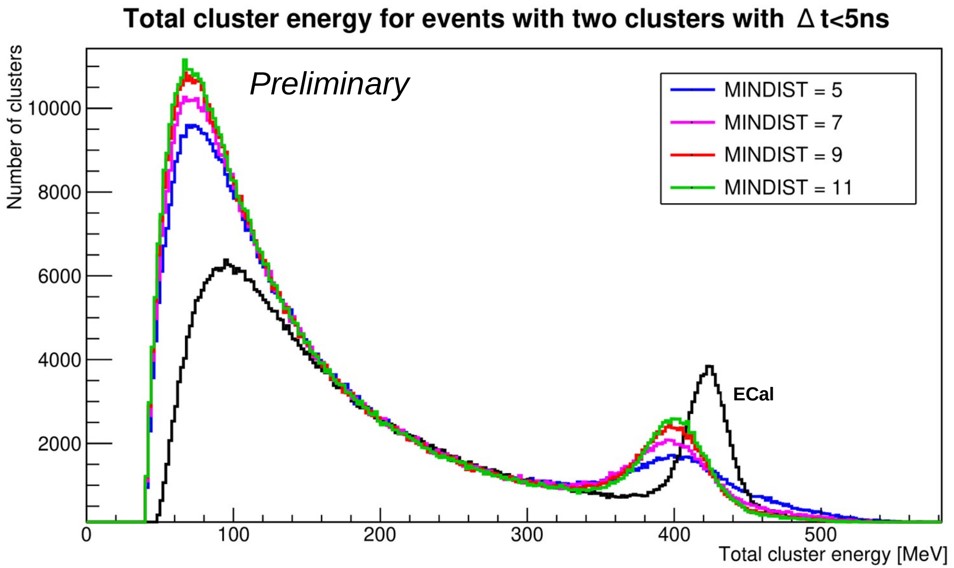
Investigation of the effect of the MINDIST parameter using e+e- → γγ events

- The value of the total cluster energy does not change with the variation of MINDIST
- However, the higher MINDIST is, the narrower the peak is → perhaps it's better to use a higher value

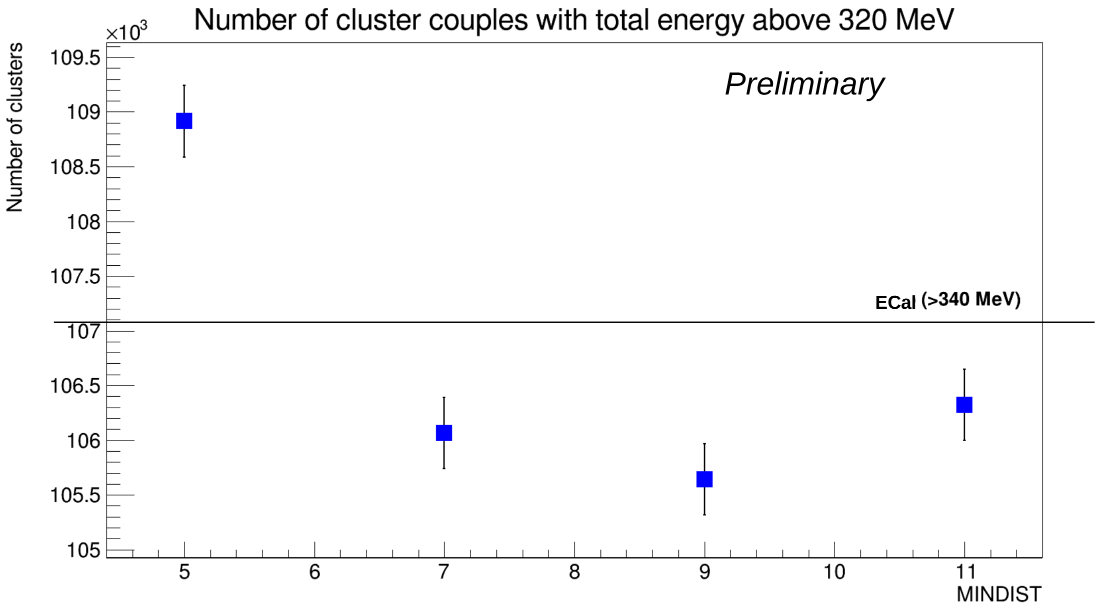
(As long as it doesn't interfere with the limit for separating individual signals)



Investigation of the effect of the MINDIST parameter using e+e- → γγ events



- The total number of clusters was integrated taking into account the difference in the peak positions
  - For **ECal**, cluster couples with **E_{tot}>340 MeV** were taken (peak is at 425 MeV)
  - For the **ECalML**, cluster couples with **E_{tot}>320 MeV** were taken (peak is at 400 MeV)

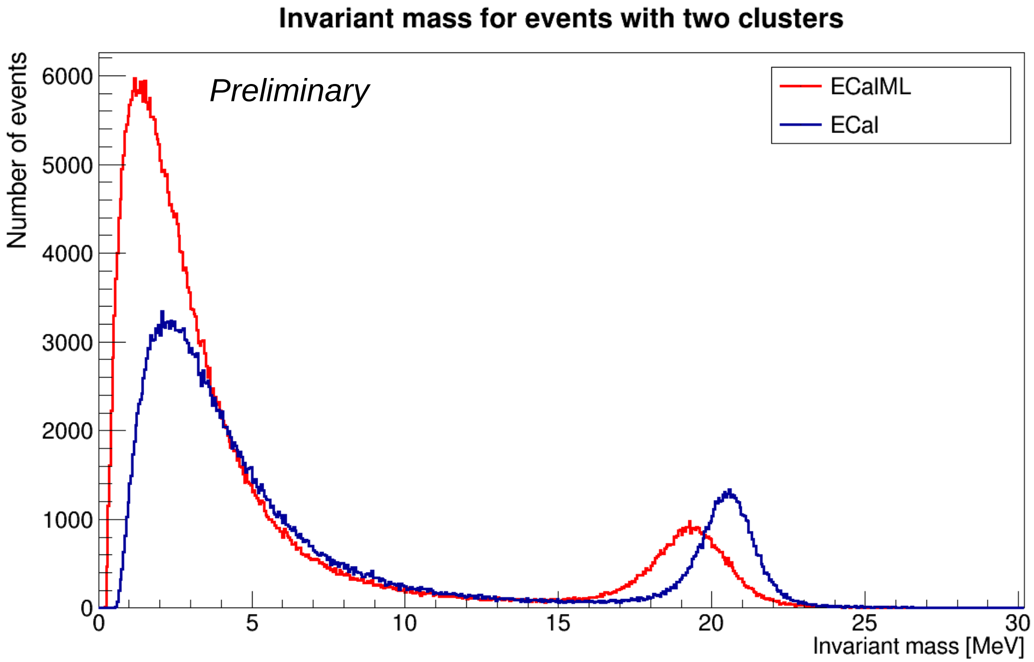


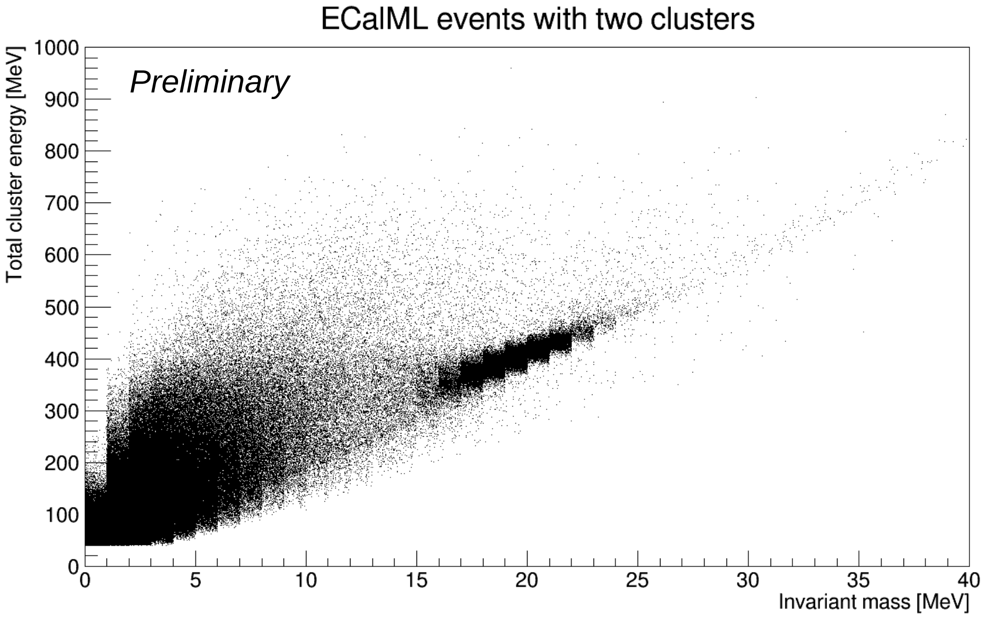
- **The total number of clusters for the original reconstruction and for the various ML cases is similar** despite the wider peak
- Higher number of cluster couples for MINDIST=5
  - Possible cluster splitting in single-cluster events?

Calculating the invariant mass for e+e-→γγ events

- The cluster energies were used to calculate the invariant mass for the two photons:

  $M^2=E_1E_2R^2/Z^2$ where R is the distance between the clusters and Z is the distance between the target and the calorimeter





Correlation between the invariant mass an the total cluster energy → allows for more precise filtering of the events

Conclusions

- A machine learning method, specifically developed for the PADME electromagnetic calorimeter was **successfully implemented in the experiment software**, simultaneously with the conventional method for reconstruction
- Applying ML techniques provides **better time resolution**
- The combined energy of the cluster couples at small Δt shows a **clear peak at an energy around 400 MeV**, close to the expected position for $e^+e^- \rightarrow \gamma\gamma$ events
- **The energy given by the ML reconstruction differs** from the one given by the conventional method and the results were used for investigation of the significance of one of the reconstruction parameters
- From simulation to **actual physics results**: successfully obtained total cluster energy and invariant mass values for $e^+e^- \rightarrow \gamma\gamma$ events