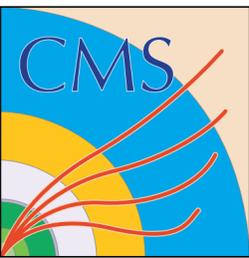
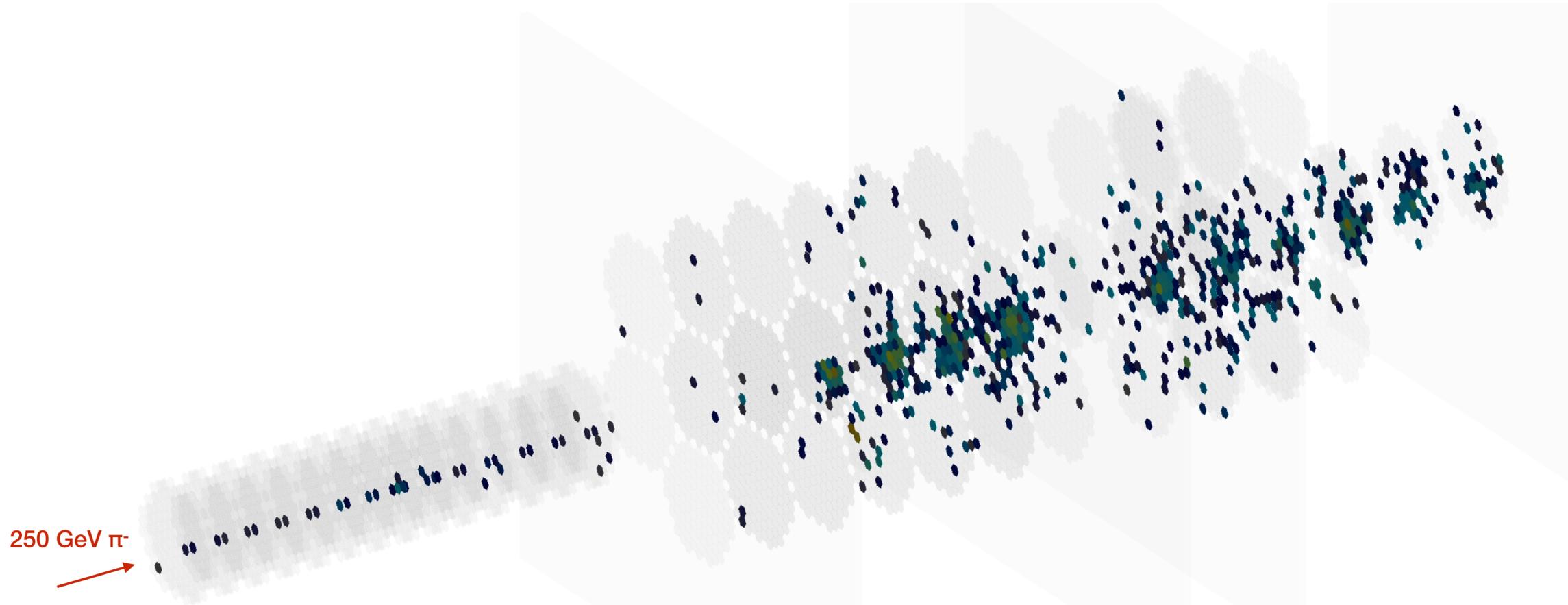


# Qualification, Performance Validation and Fast Generative Modelling of Beam Test Calorimeter Prototypes for the CMS Calorimeter Endcap Upgrade

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M. Sc. RWTH



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 654168



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für Bildung  
und Forschung



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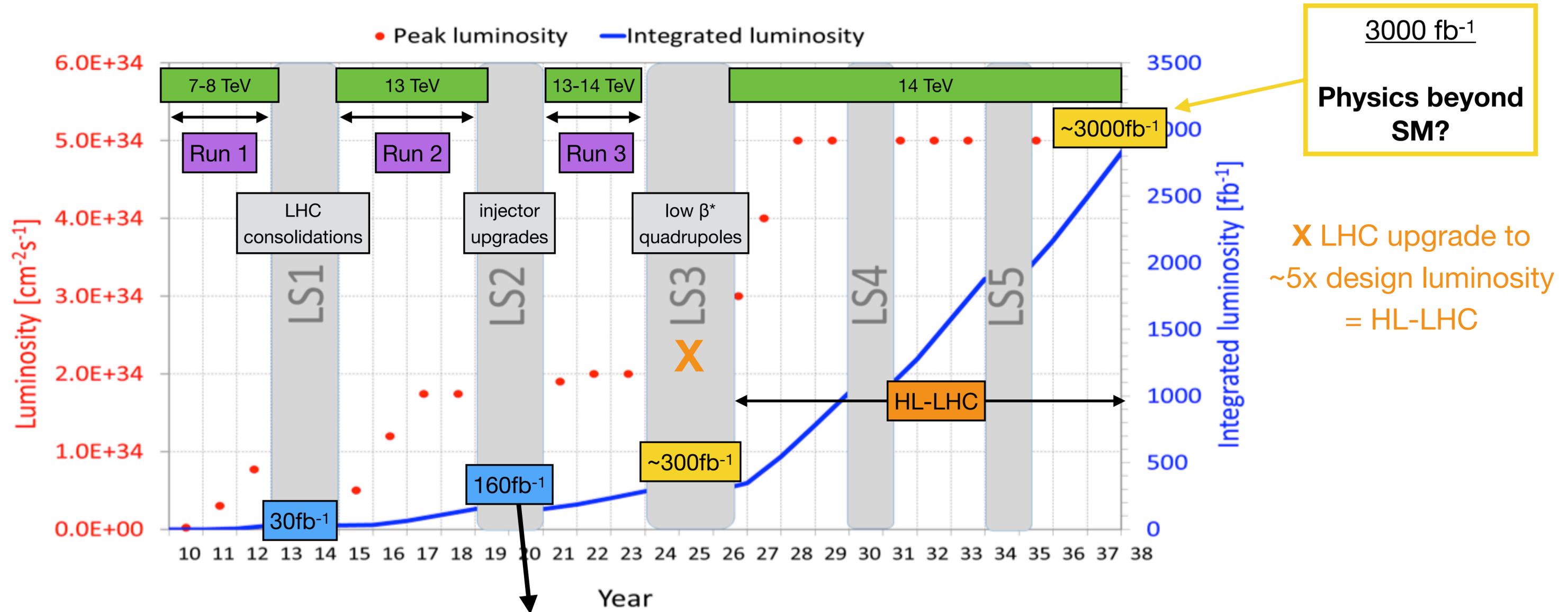


# The midterm future at CERN: High Luminosity LHC

**Standard Model of Particle Physics (SM):** Theory of matter and interactions at smallest scale.

**Decisive deficits**, e.g. dark matter, matter-antimatter asymmetry, incorporation of gravity, ...

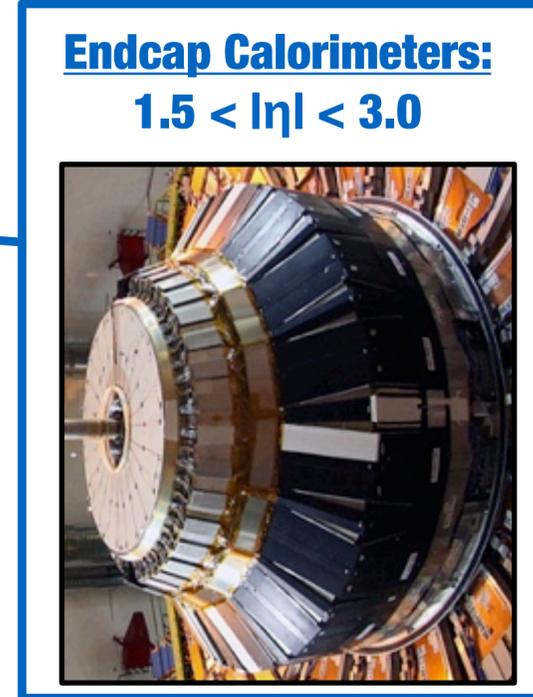
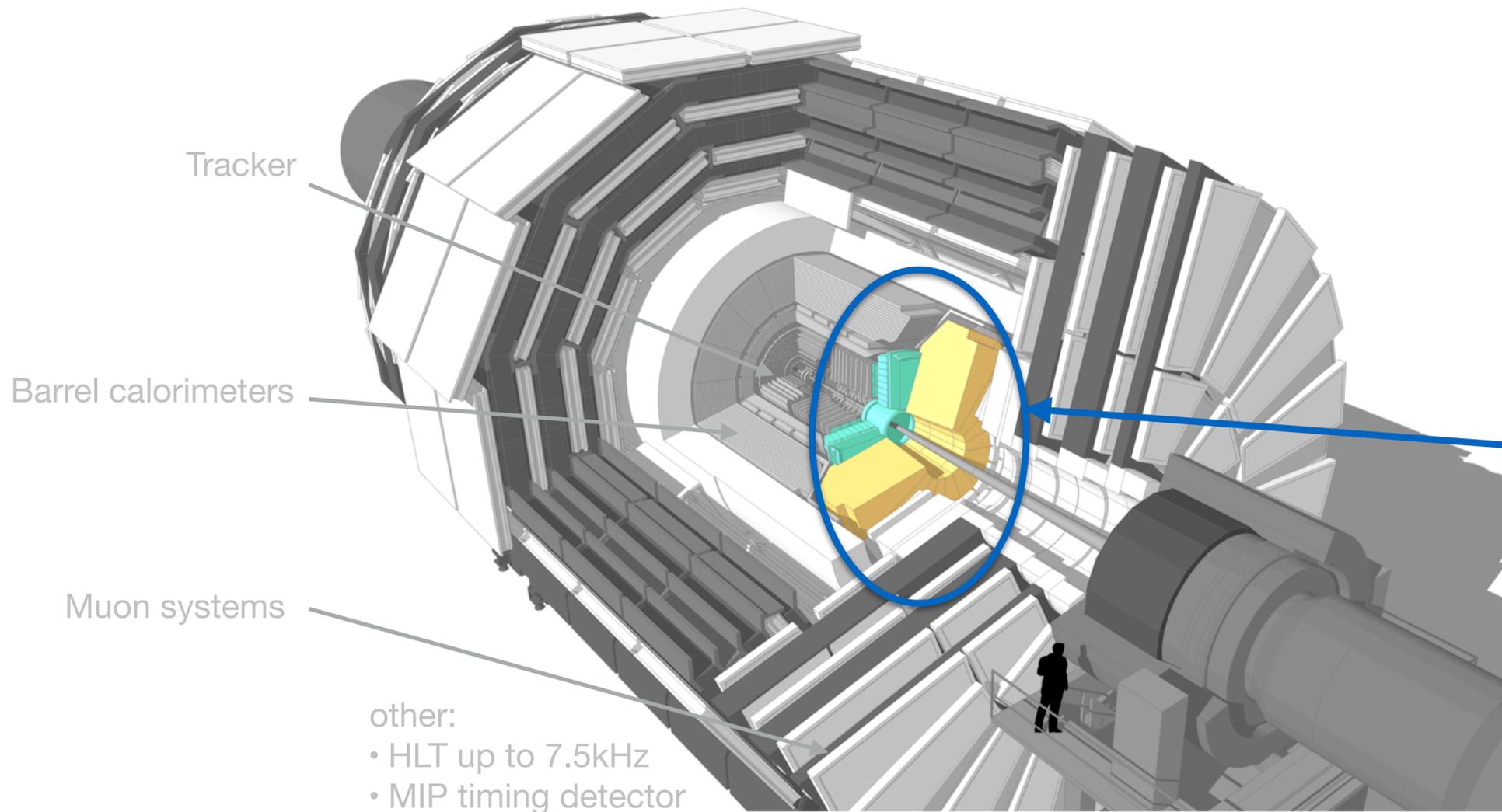
Exp. testing via high-energy particle collisions: **Large Hadron Collider (LHC)** @ CERN.



➔ LHC Runs 1+2: **Robustness of SM consolidated. No new physics.**

Experimental challenges	LHC	HL-LHC	Mitigation strategy
<ul style="list-style-type: none"> <li>• inst. luminosity</li> <li>• detector irradiation</li> <li>• pile-up interactions</li> </ul>	$2 \times 10^{34} \text{ s}^{-1} \text{ cm}^{-2}$ $O(10^{14} \text{ neq/cm}^2)$ $O(40)$	$\rightarrow$ up to $7.5 \times 10^{34} \text{ s}^{-1} \text{ cm}^{-2}$ $>O(10^{15} \text{ neq/cm}^2)$ $140-200$	<ul style="list-style-type: none"> <li>▸ improved trigger &amp; computing</li> <li>▸ irradiation-hard sensors &amp; electronics</li> <li>▸ 4D granularity</li> </ul>

Compact Muon Solenoid (CMS)  
HL-LHC Upgrades



## HGCAL = Sampling calorimeter

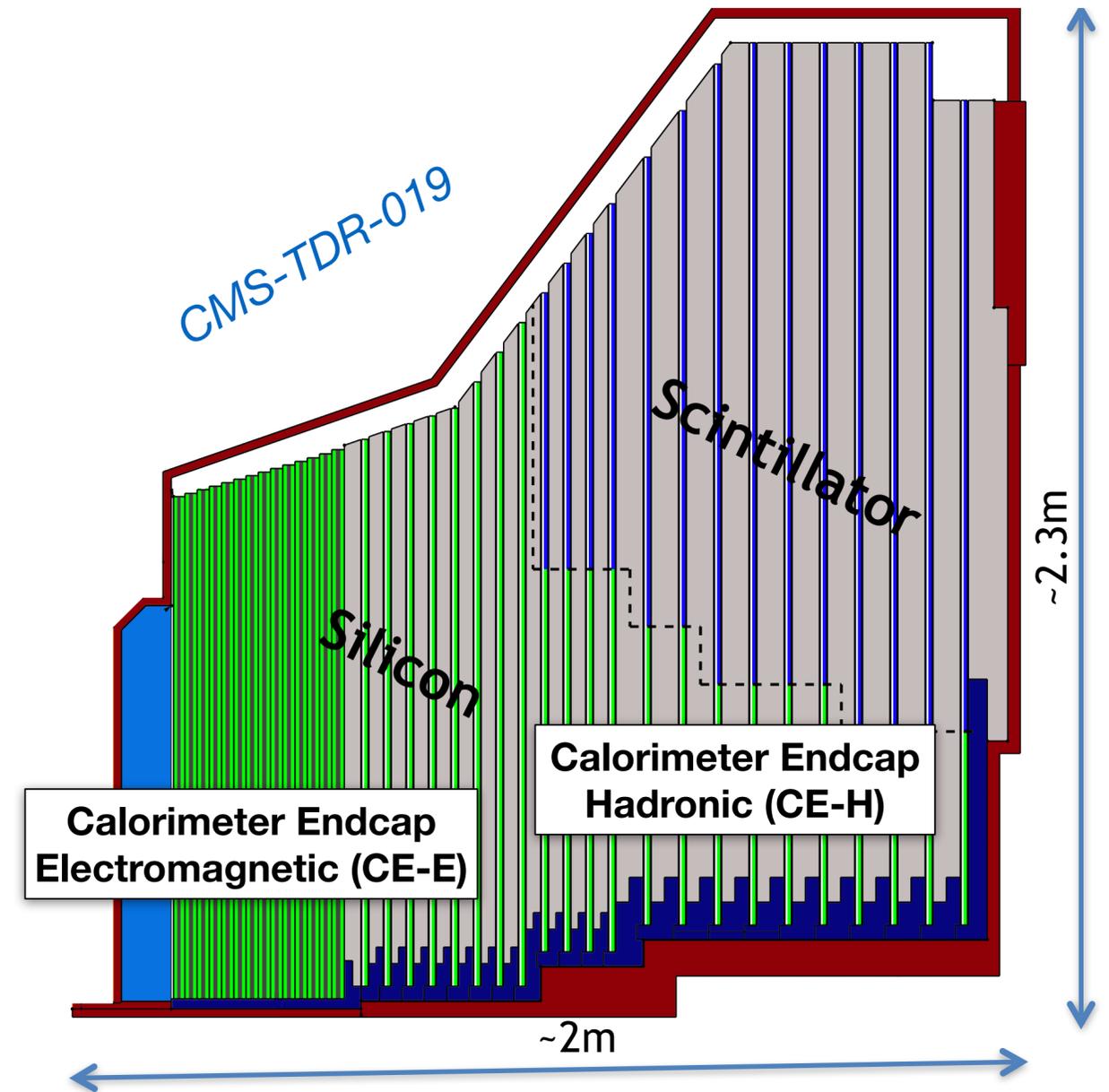
- **Silicon sensors** in CE-E and high radiation regions of CE-H.

Active material

Both endcaps	Silicon	Scintillators
Area	>600m <sup>2</sup>	400m <sup>2</sup>
#Modules	~30000	~4000
Channel size	0.5 - 1 cm <sup>2</sup>	4-30 cm <sup>2</sup>
#Channels	~6 M	~240k
Op. temp.	-35 ° C	-35 ° C

Passive material

Per endcap	CE-E	CE-H (Si)	CE-H
Absorber	Pb, CuW, Cu	Stainless steel, Cu	
Depth	25 X <sub>0</sub> , 1.3 λ	~8.5 λ	
Layers	28	8	14
Weight		215t / endcap	



**Does the silicon-based HGICAL design meet the expectation?**

- **Core elements functional? Operation and calibration?**
- **Proper performance for electromagnetic and for hadronic showers?**
- **Exploitation of granularity?**

Problem 1:

All-new HGICAL:  
Design based on simulation and R&D.

Problem 2:

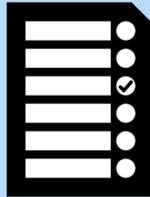
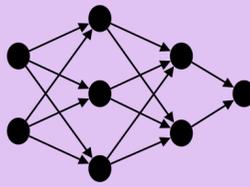
Computing for calorimeter simulation a limited resource soon.



Nov 2016

**Time-efficient calorimeter simulation without reducing the dimensionality of the data?**

- Characterise components.
- Build prototypes.
- Tests with real particles.
- Calibrate the detector & analyse data.
- Compare results to simulation.
- Apply machine learning.

Experimental aspects	<p><u>1. CMS HGCAL Prototype Construction</u> Silicon sensors &amp; FE electronics - Module assembly - Prototype mechanics</p> <p><u>2. HGCAL Test Beams 2018</u> Setups at DESY and CERN - Beam characterisation - Developed test beam infrastructure - Signal reconstruction</p>	 
Test beam results	<p><u>3. Qualification of Prototype Silicon Modules</u> MIP detection efficiency - MIP calibration - Timing calibration &amp; resolution</p> <p><u>4. Performance Validation of Calorimeter Prototypes</u> EM showers: Longitudinal shower profile - Energy linearity &amp; resolution - Positioning resolution - HAD showers: Shower start identification - Energy reconstruction</p>	  <i>Selected Highlights</i>
ML-based fast sim.	<p><u>5. Fast Generative Modelling of Calorimeter Data</u> Towards faster simulation - Wasserstein Generative Adversarial Networks - Proof-of-concept - Application to 2018 test beam prototype</p>	
<p><u>6. Conclusions</u></p>		



# 1. CMS HGCAL Prototype Construction

- 4.5 “Prototype Assembly in 2018”
- 8.1 “Electrical Properties of 6” Silicon Sensors”

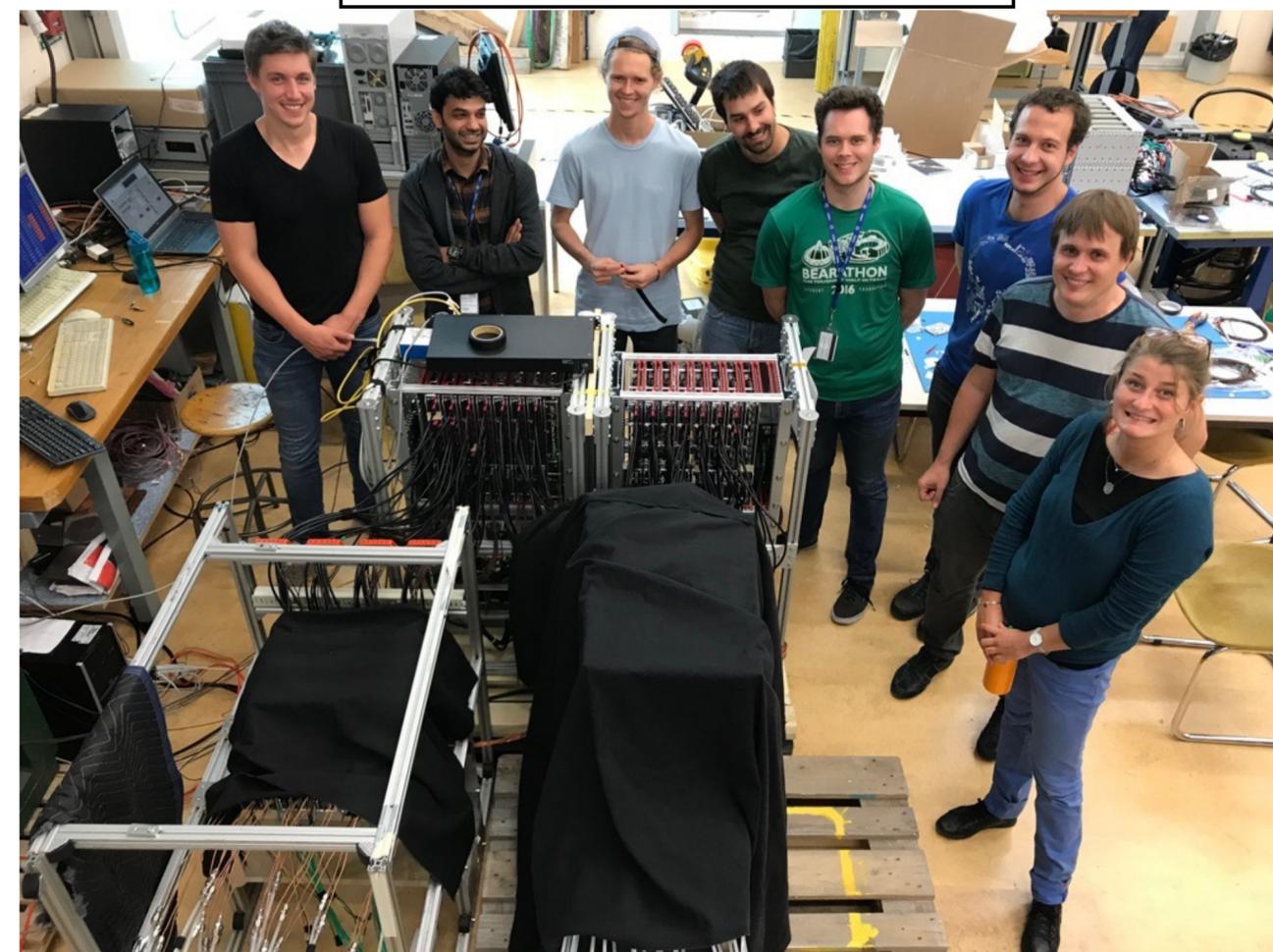
Electrical characterisation of 6” silicon sensors



Mounting of silicon prototype modules on HGCAL prototype detector planes



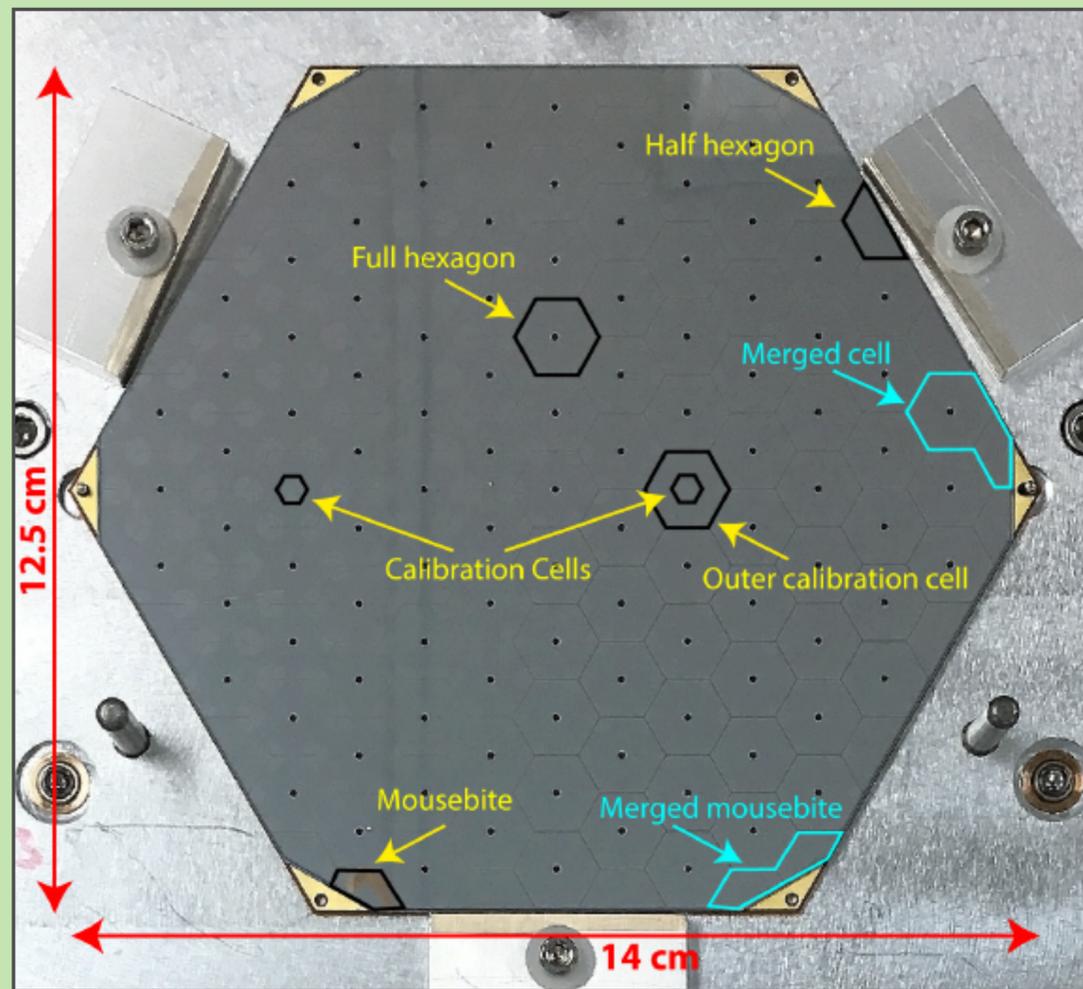
After assembly and first pedestal runs before the final beam test





## HGCAL prototype silicon sensor for beam tests

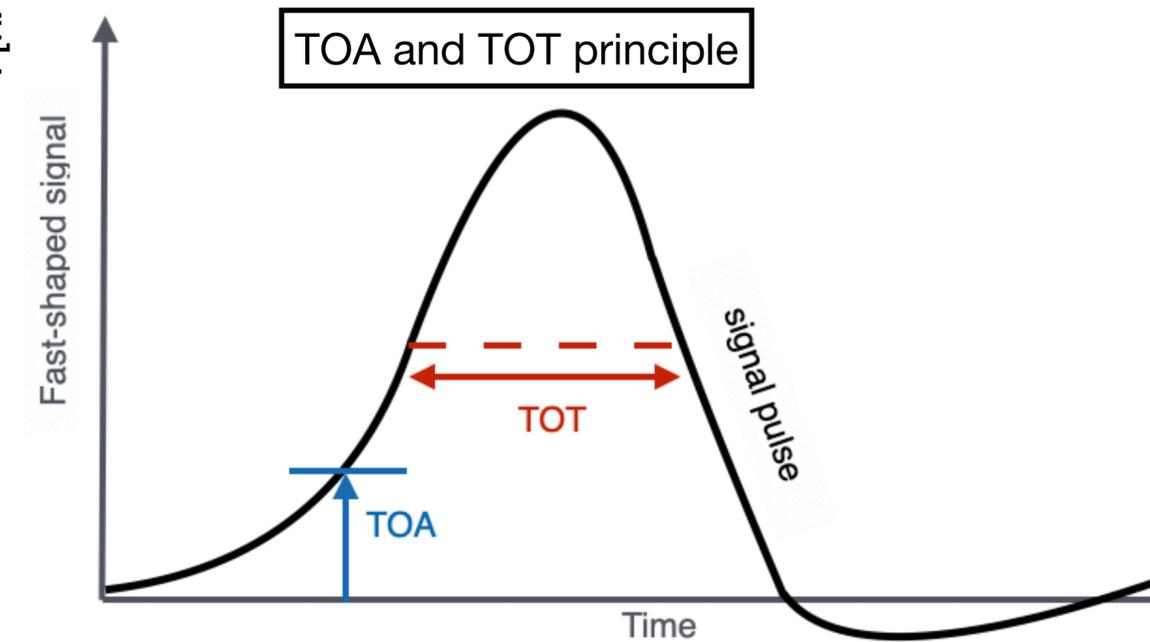
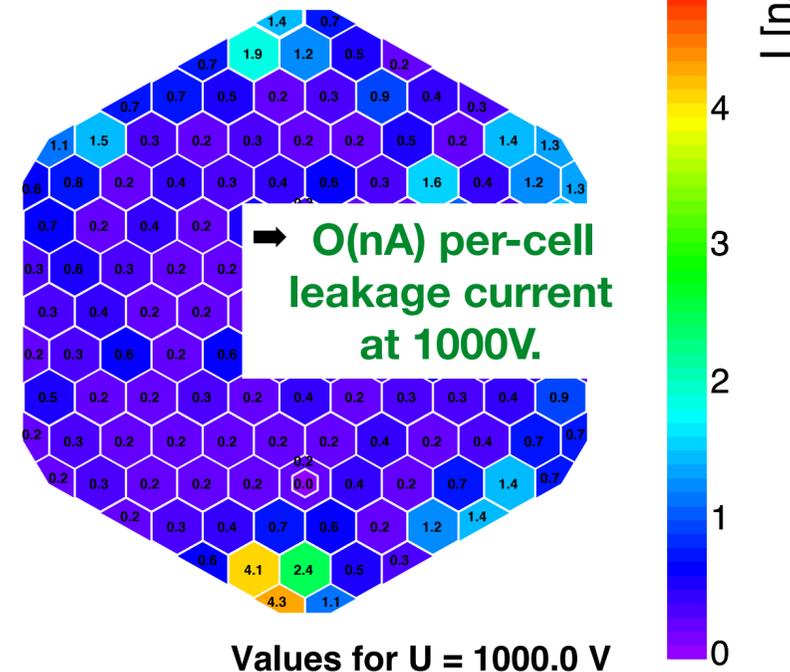
- 6" hexagonal wafer, n-type bulk.
- 135 cells, 5 different geometries, "full cell" ~1cm<sup>2</sup>.
- Non-irradiated → small leakage current.



## Prototype readout ASIC: SKIROC2-CMS

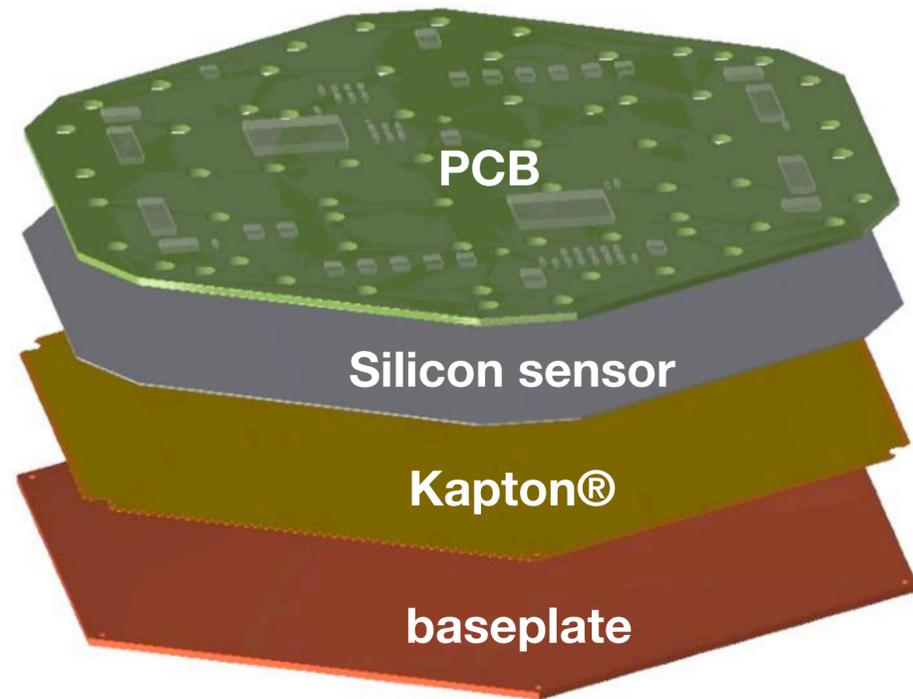
- Shapes, amplifies and digitises signals from the silicon sensors.
- Operated at 40 MHz, 13-deep memory with slow shaped signal (**high & low gain**).
- Fast shaped signal: Time-of-arrival (**TOA**) and time-over-threshold (**TOT**).

HPK 6" 135ch - 1083



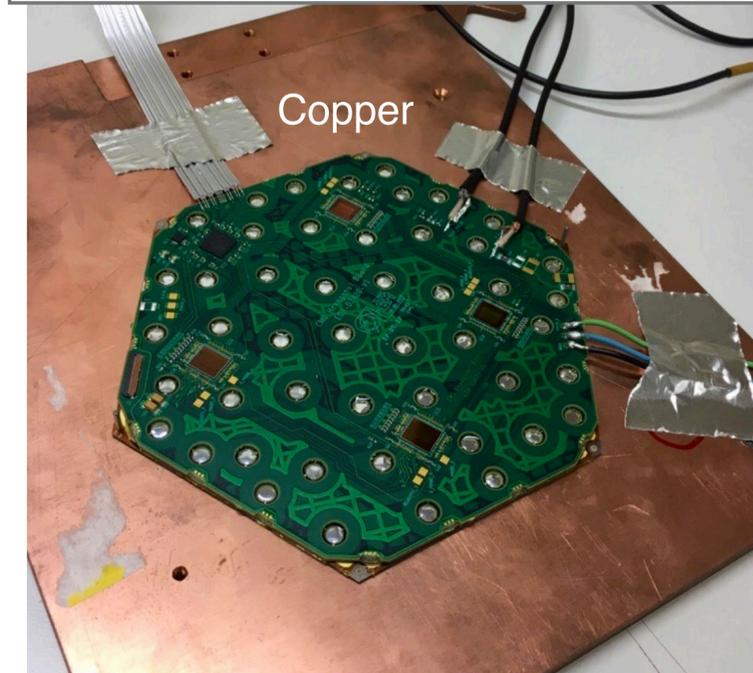


Modules assembled as glued stack of **baseplate**, **Kapton®**, **Si sensor** and **PCB**:

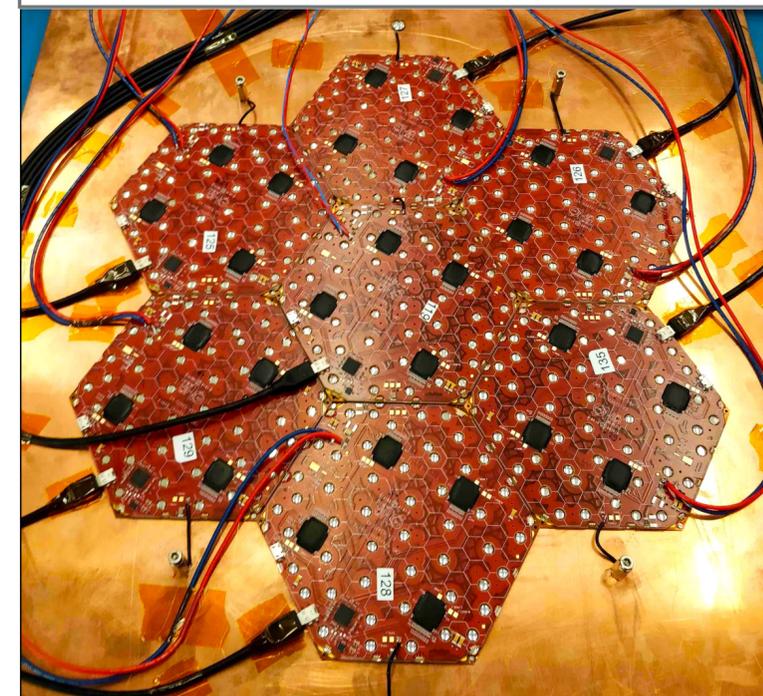


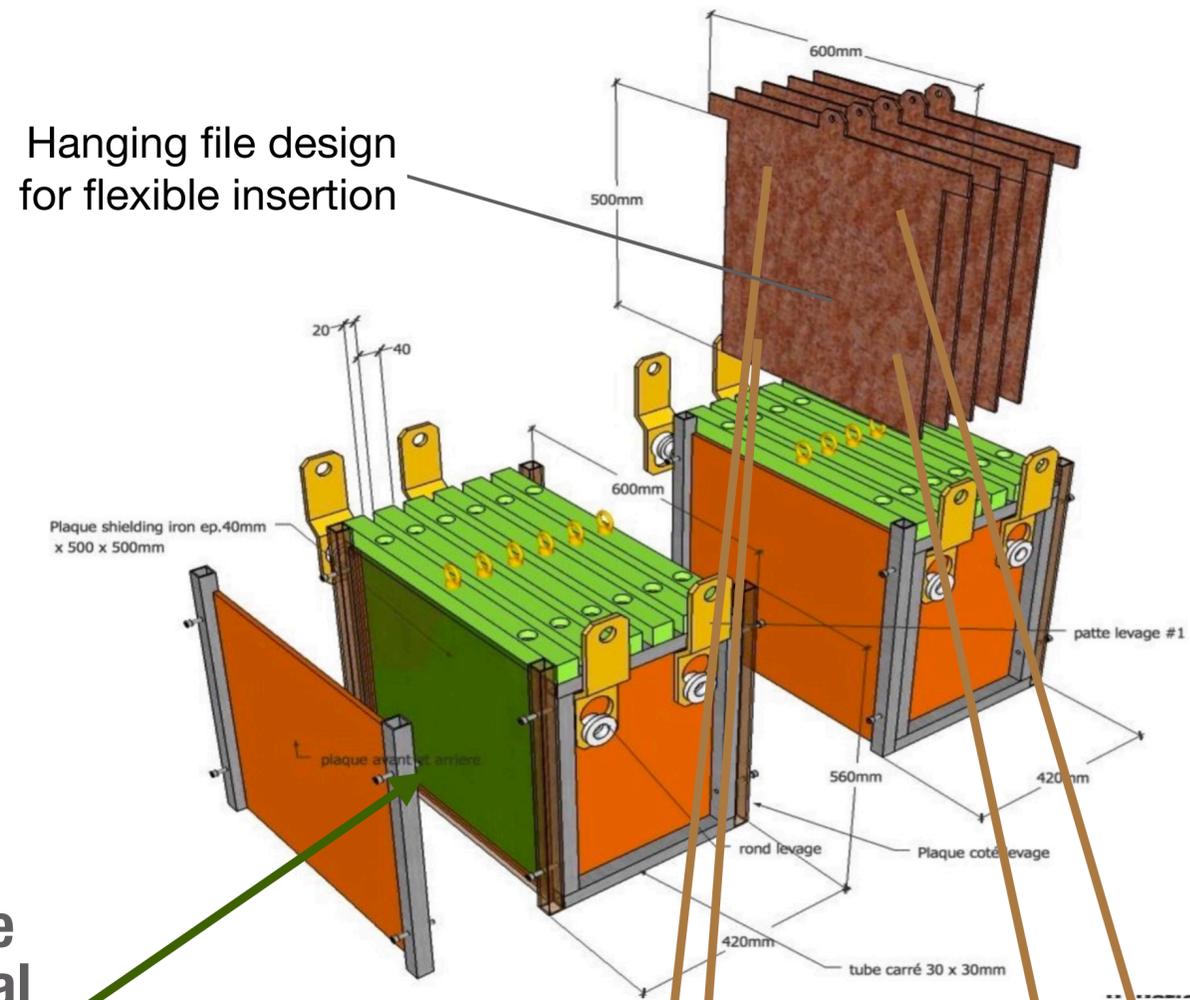
*gluing*  
➔  
*wire bonding*

1-module layer in electromagnetic part



7-module "daisy" layer in hadronic part

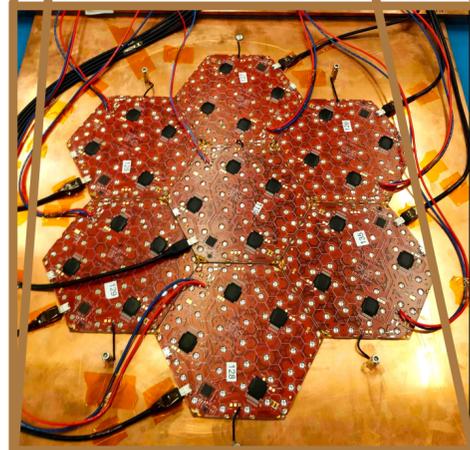




## Passive material

- **CE-E:**  
material: Pb, W, Cu  
thickness: 5-6 mm
- **CE-H-Si:**  
material: Fe  
thickness: 4 cm  
weight: O(1000kg)

Active material

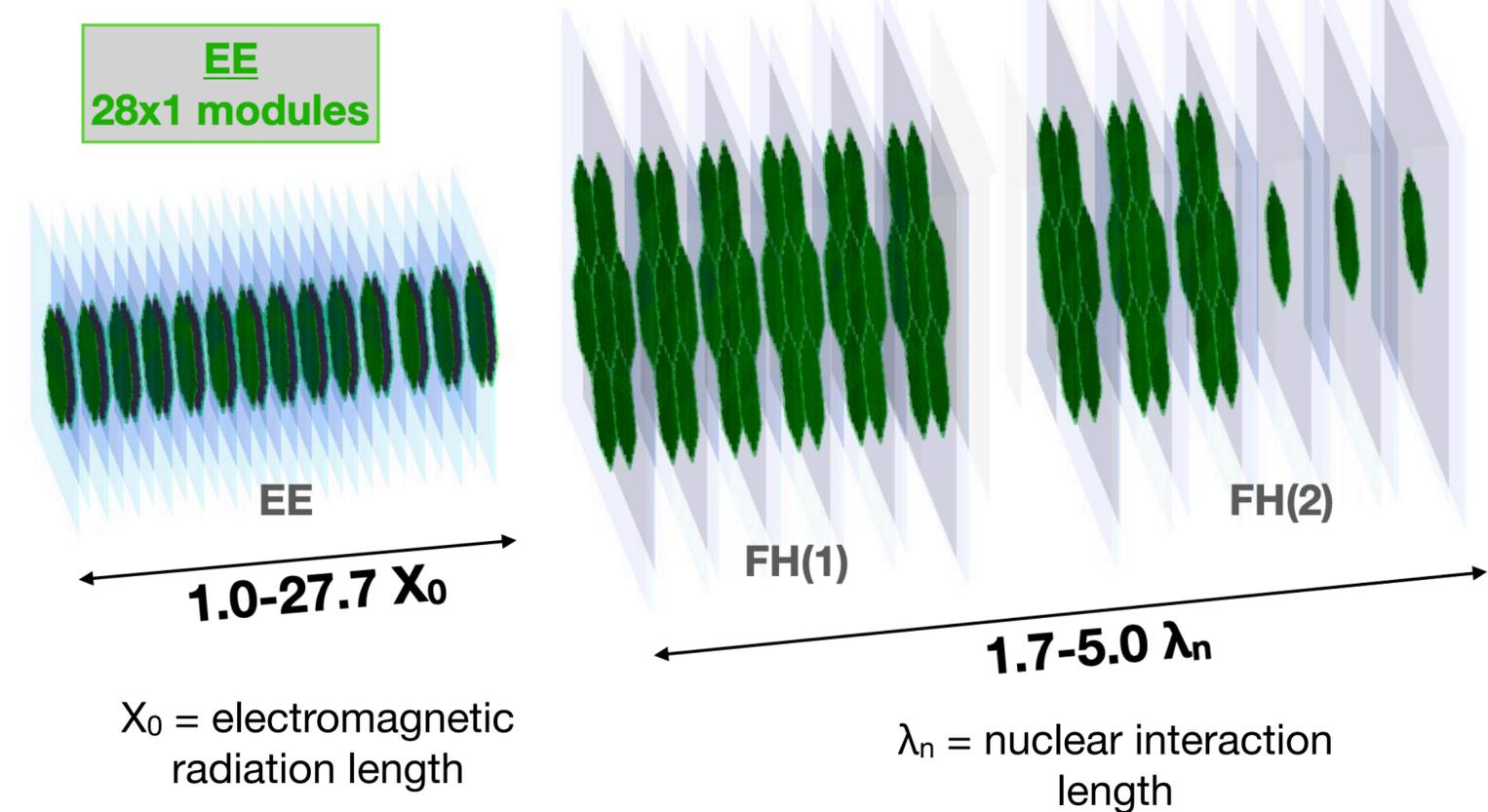


- 94 prototype modules assembled by October 2018.
- Full CE-E prototype with 28 layers.
- Half-equipped CE-H(Si) prototype with 12 layers.

## Configuration 1 11 Oct - 18 Oct 2018

**EE**  
28x1 modules

**FH**  
9x7 + 3x1 modules



→ ~12,000 readout channels.



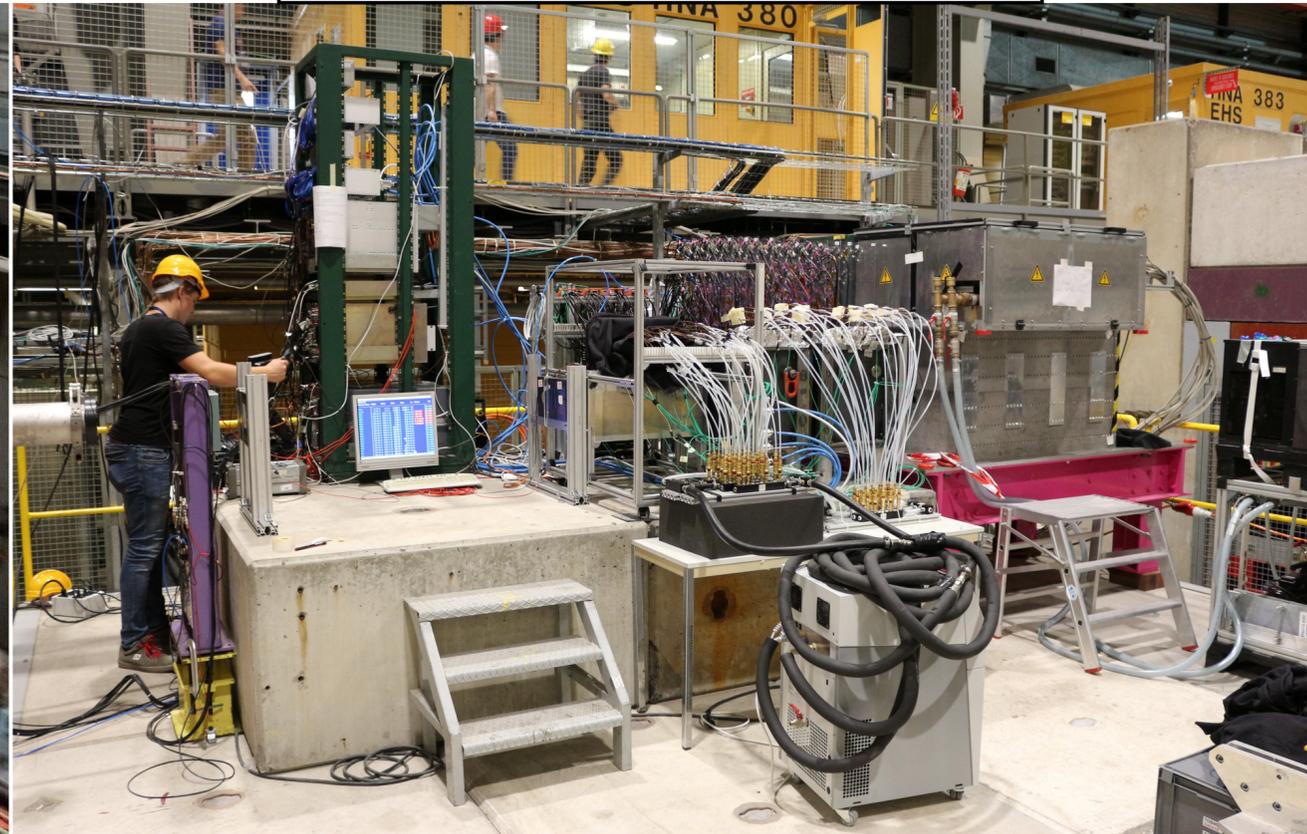
## 2. HGICAL Test Beams 2018

- 6. "Experimental Infrastructure"
- 7. "Data Reconstruction Algorithms"
- 8.2 "Tomography of the Prototype PCB"

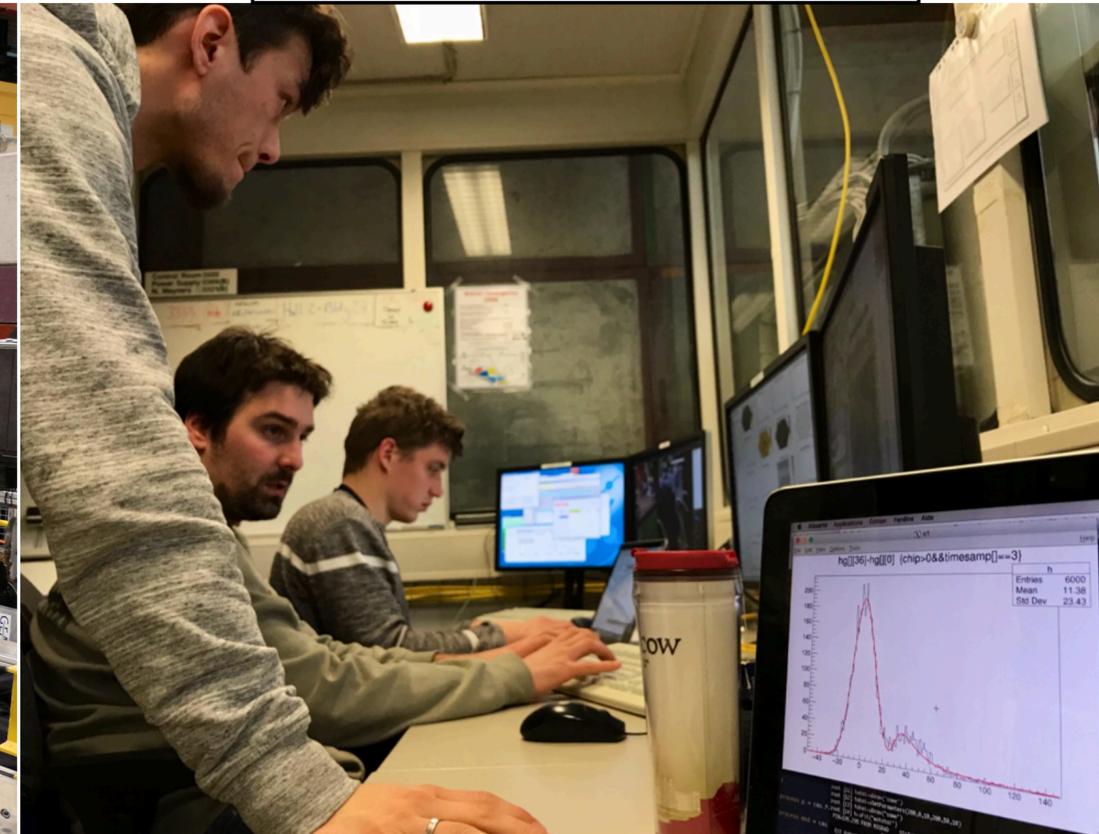
Installation of delay wire chambers in the CERN SPS H2 area



Ultimate HGICAL prototype beam test setup in H2 in October 2018



Prompt data reconstruction and monitoring in the control room





March 2018 @DESY II (T21)

October 2018 @CERN SPS (H2)

1 + 2 HGCAL modules:  
1 module: mounted on moving stage

**Setup**

94 HGCAL modules:  
28-layer EE setup + 12-layer FH setup

1.6 - 6 GeV/c  $e^-$

**Particles**

$e^+$ ,  $\mu^-$ ,  $\pi^-$  up to 300 GeV/c

silicon module design qualification

**Goal**

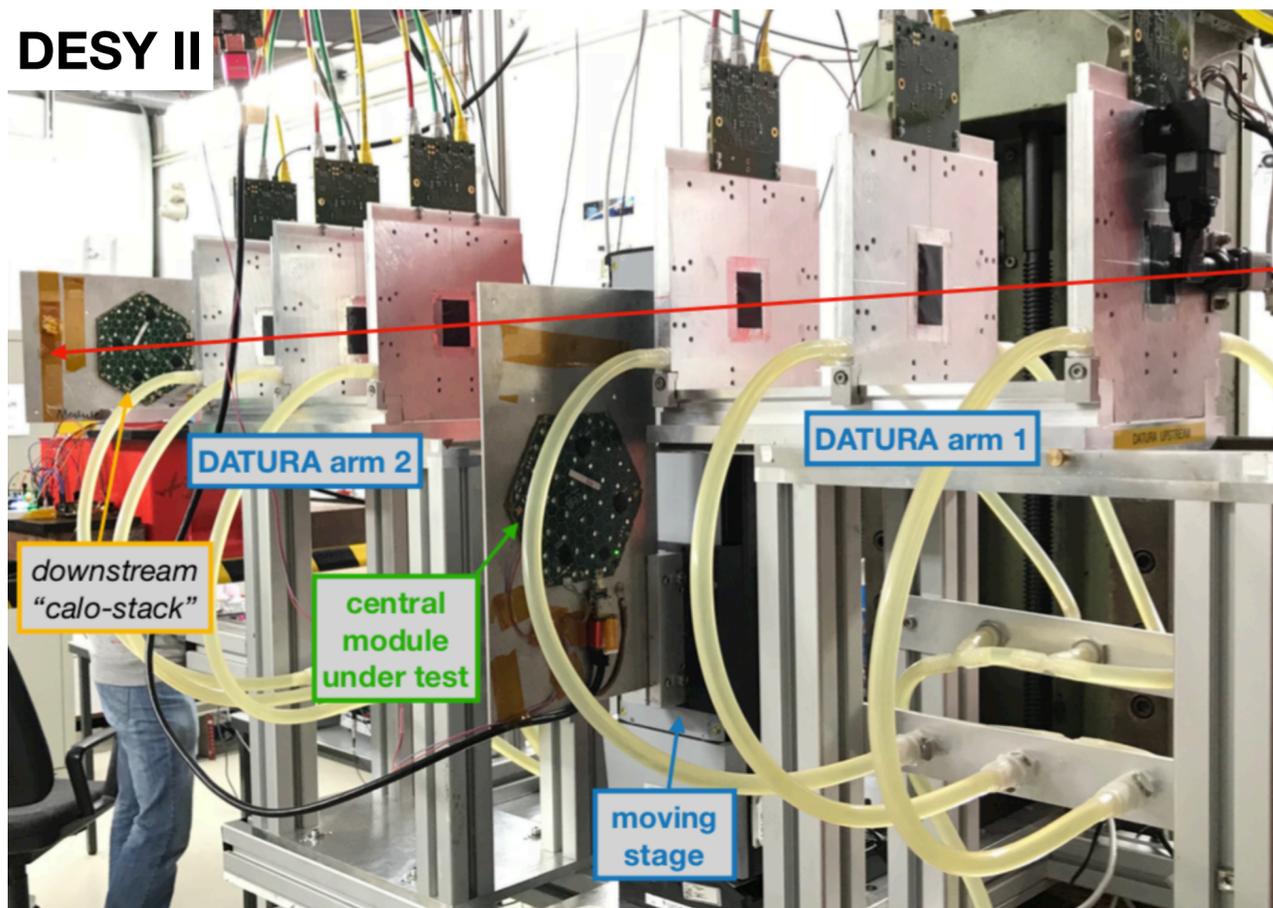
full in-situ calibration, performance+comparison to simulation

DATURA beam telescope

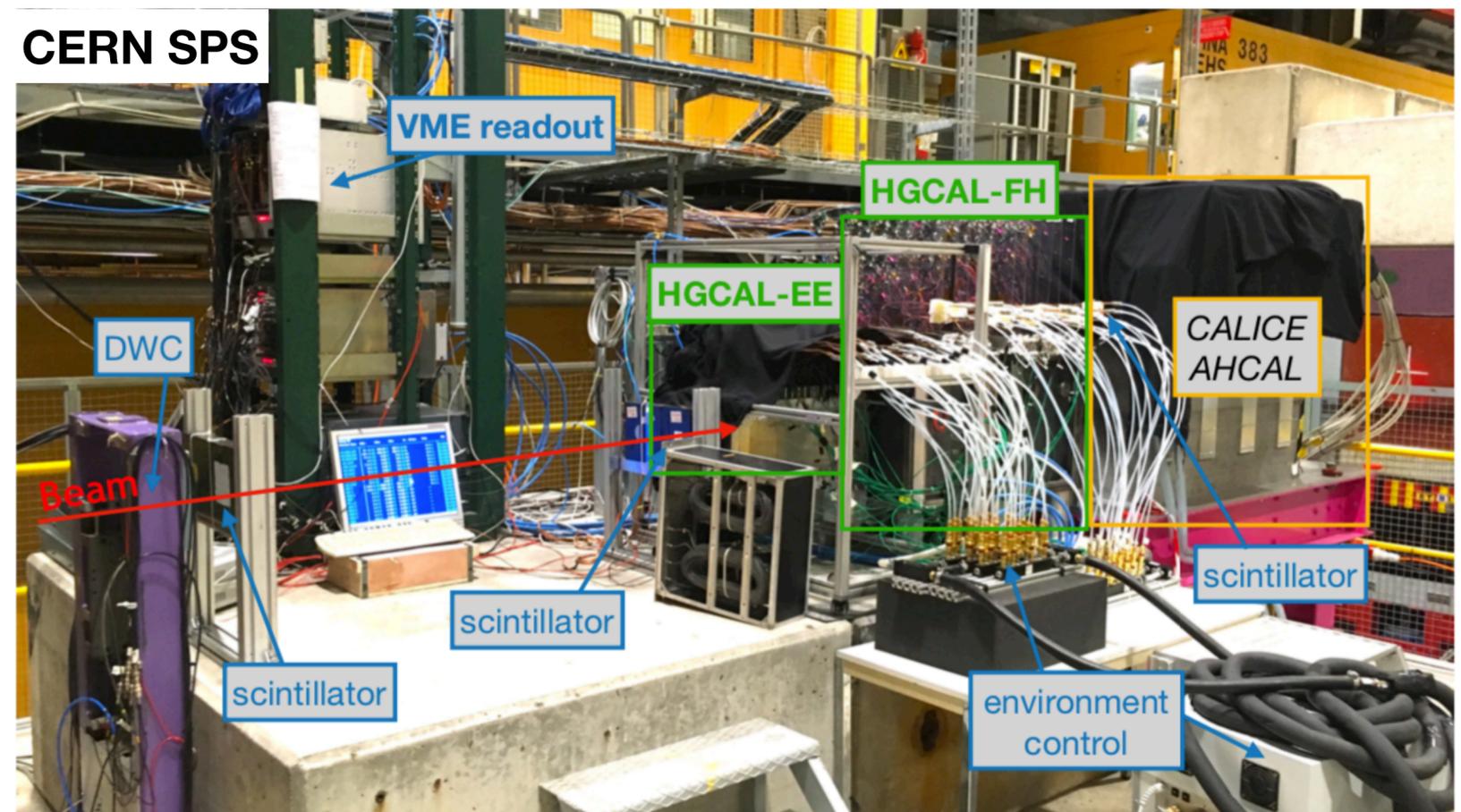
**Aux. detectors**

delay wire chambers (DWC), microchannel plates, threshold Cherenkov detectors

DESY II



CERN SPS





Beam detectors are essential.

## DATURA Beam Telescope @DESY

Tracking of up-/downstream e<sup>-</sup>.

➔ **Impact position and kink angles.**

✓ Pointing resolution of ~10 μm, limited by multiple scattering.

- **Used:** PCB material tomography and MIP detection efficiency.

## MicroChannel Plate (MCP) @CERN

Charged particles → fast signal.

➔ **Time of particle incidence.**

✓ MCP timing resolutions down to ~30 ps.

- **Used:** TOA calibration and prototype's timing performance.

## Delay Wire Chambers (DWCs) @CERN

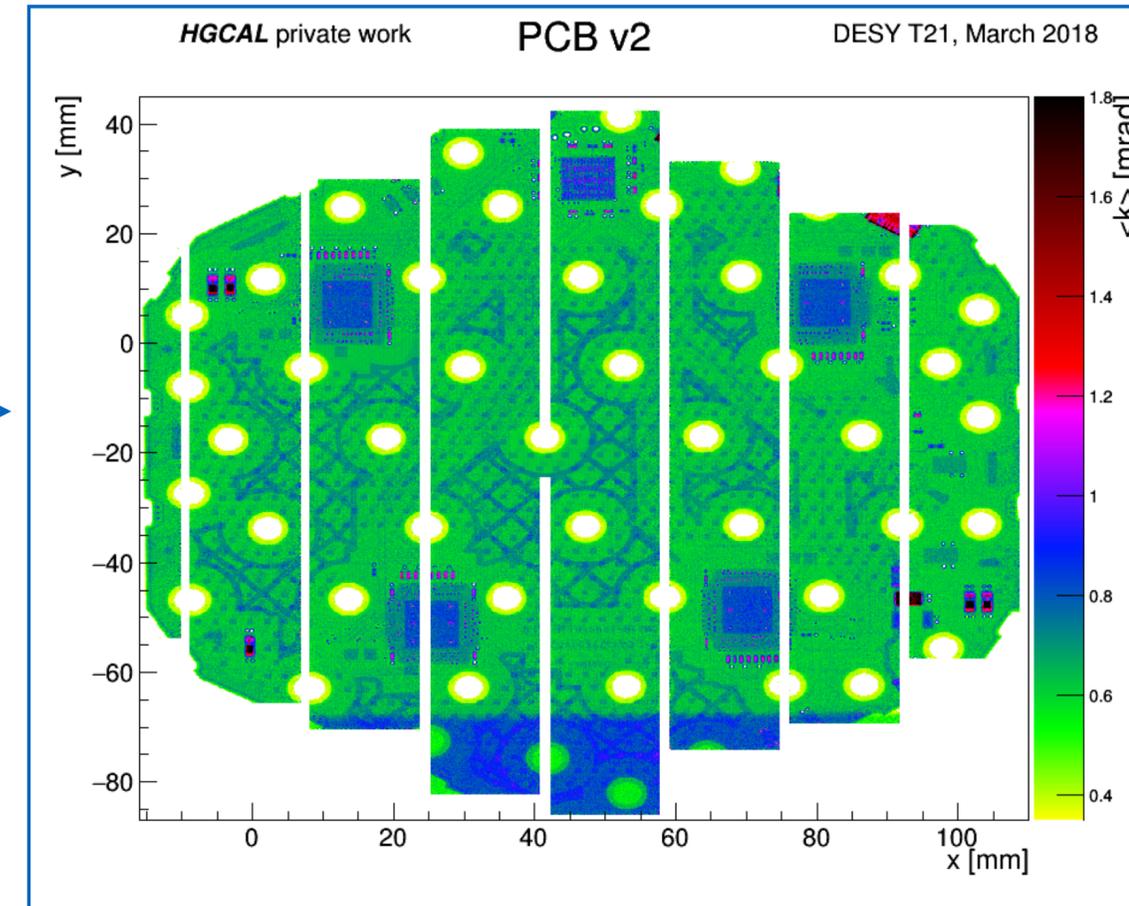
Tracking of upstream particles.

➔ **Impact position.**

✓ Pointing resolution of ~0.5 mm, limited by intrinsic DWC resolution.

- **Used:** MIP detection efficiency & purification, pointing & angular resolution, beam profile for sim.

HGCAL prototype printed circuit board





## 1. Data acquisition system (DAQ)

- Custom made electronics for HGAL prototype readout.
- Off-the-shelf electronics for beam detectors.
- Integration into EUDAQ framework.

*Published: JINST 15 (2020) P01038*

- Event synchronisation: trigger and timestamp.

*Publication in collaboration review soon.*

## 2. Data quality monitoring (DQM)

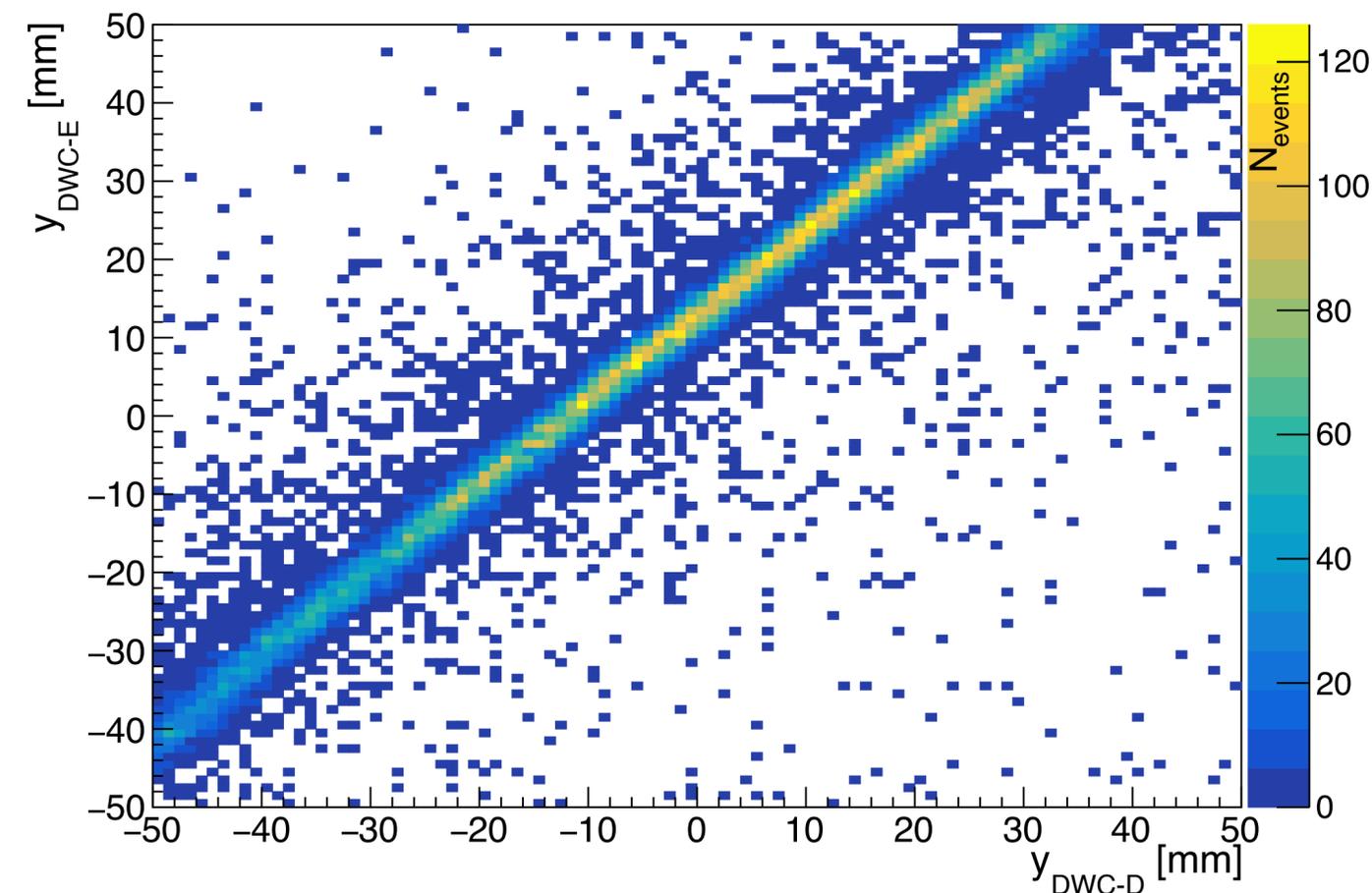
- Online reconstruction & visualisation of the data.

## 3. Event reconstruction

- Algorithms & workflow largely implemented from scratch.
  - DWCs: position ~ time difference, alignment.
  - MCP: waveform analysis.
  - Beam telescope (DESY): multi-step track reconstruction.
  - **HGAL prototype: next.**

## DQM: DWC-correlations

Online DQM HGAL Beam Test Run 718, CERN H2, October 2018





Raw data from SKIROC2-CMS for every channel:

- Slow-shaped signal waveform, 13 samples, two gains (HG/LG).
- TOT and TOA.

Reconstruction: "Hits"

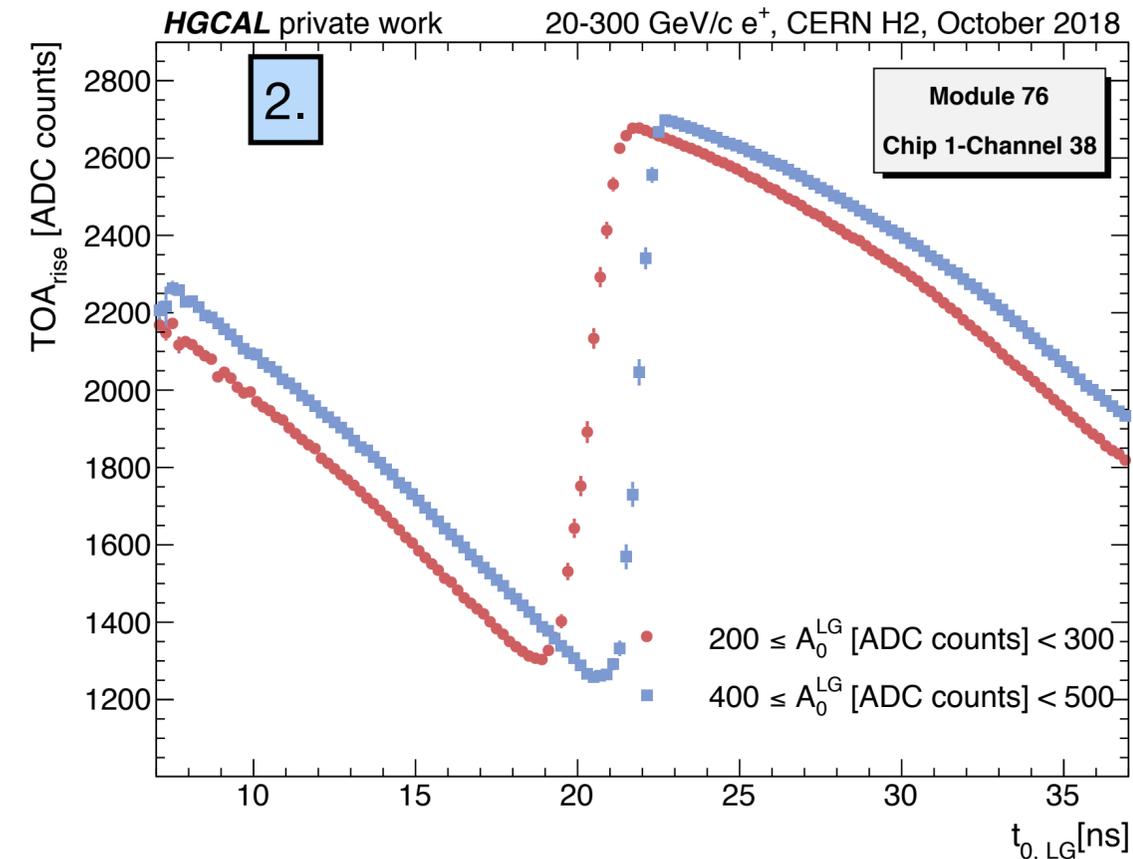
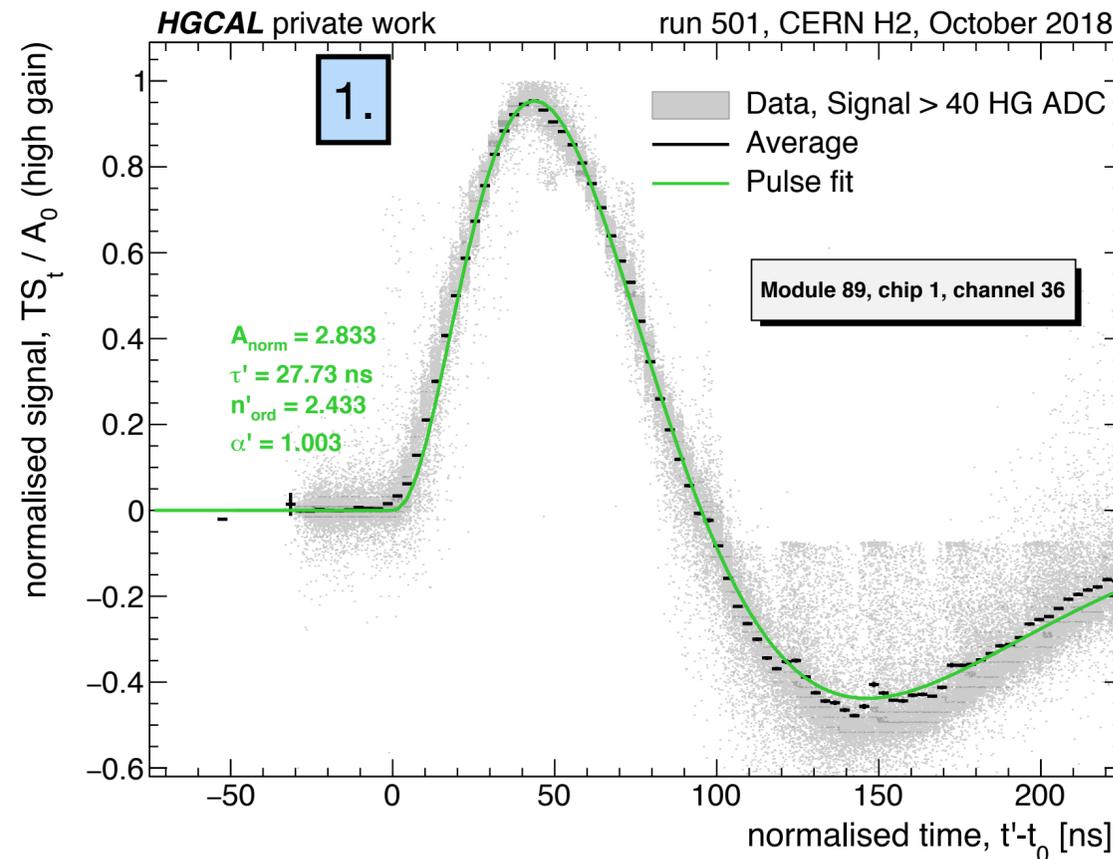
Deposited **energy** and **timestamp** for every channel.

**Time, 2-steps:** 2.

- TOA - time nonlinearity.
- Fixed threshold discriminator → time walk.

**Energy, 5-steps:**

1. Pedestal assessment and subtraction.
2. Common-mode noise subtraction.
  - Based on common baseline shift in a module.
3. Signal amplitude from waveform fits. 1.
  - Avoid 0-signal-fitting: Preselection criteria.
4. Gain linearisation.
  - Use most-sensitive, non-saturated gain.
5. Conversion to physical energy.
  - Defined by minimum ionising particle.

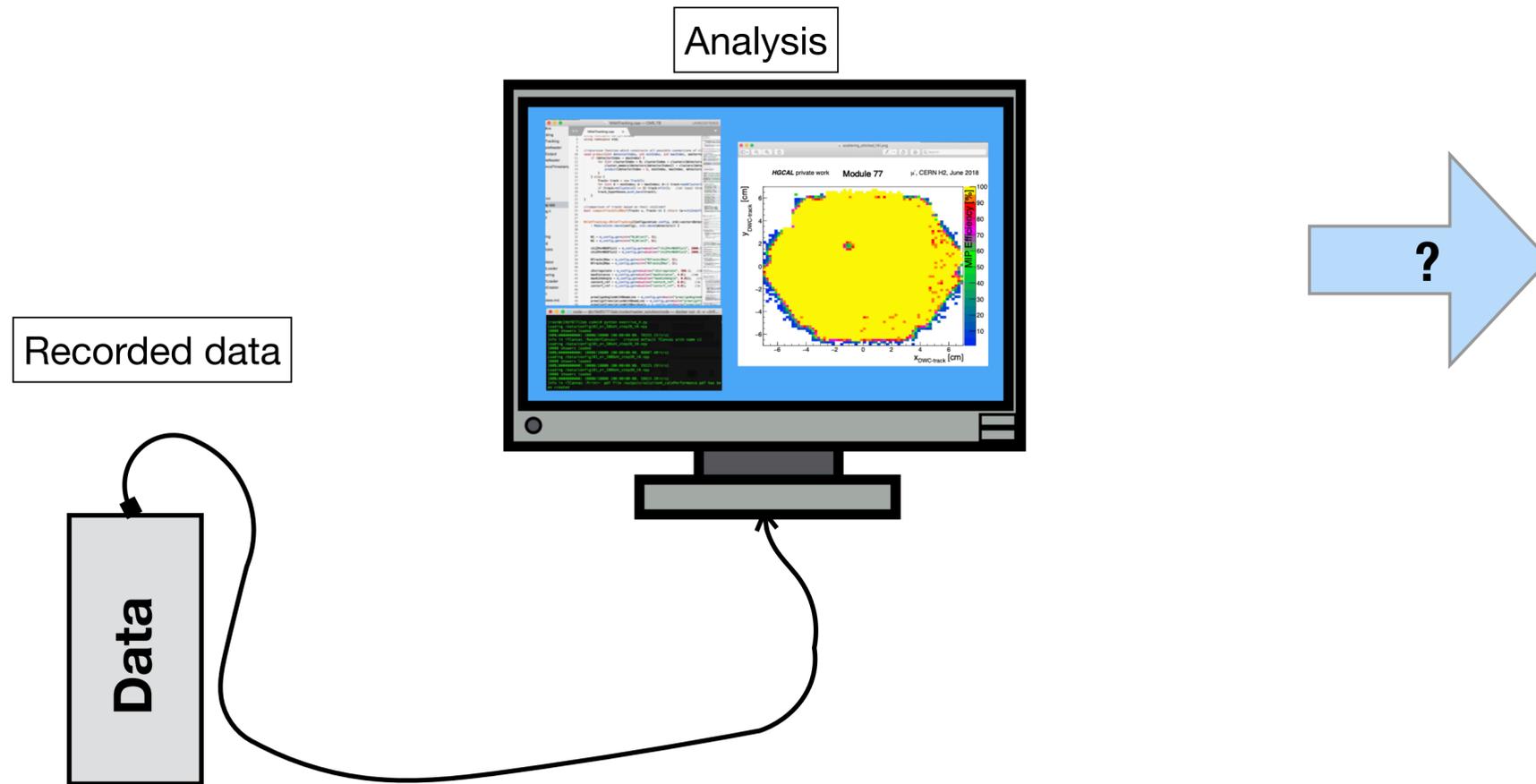




# 3. Qualification of Prototype Silicon Modules

**Selected Highlights**

- 8.4 “Module Qualification with Minimum Ionising Particles”
- 9.1 “Energy Response to Minimum Ionising Particles”
- 9.3 “Calibration and Resolution of the Time-of-Arrival”



Prototype modules functional



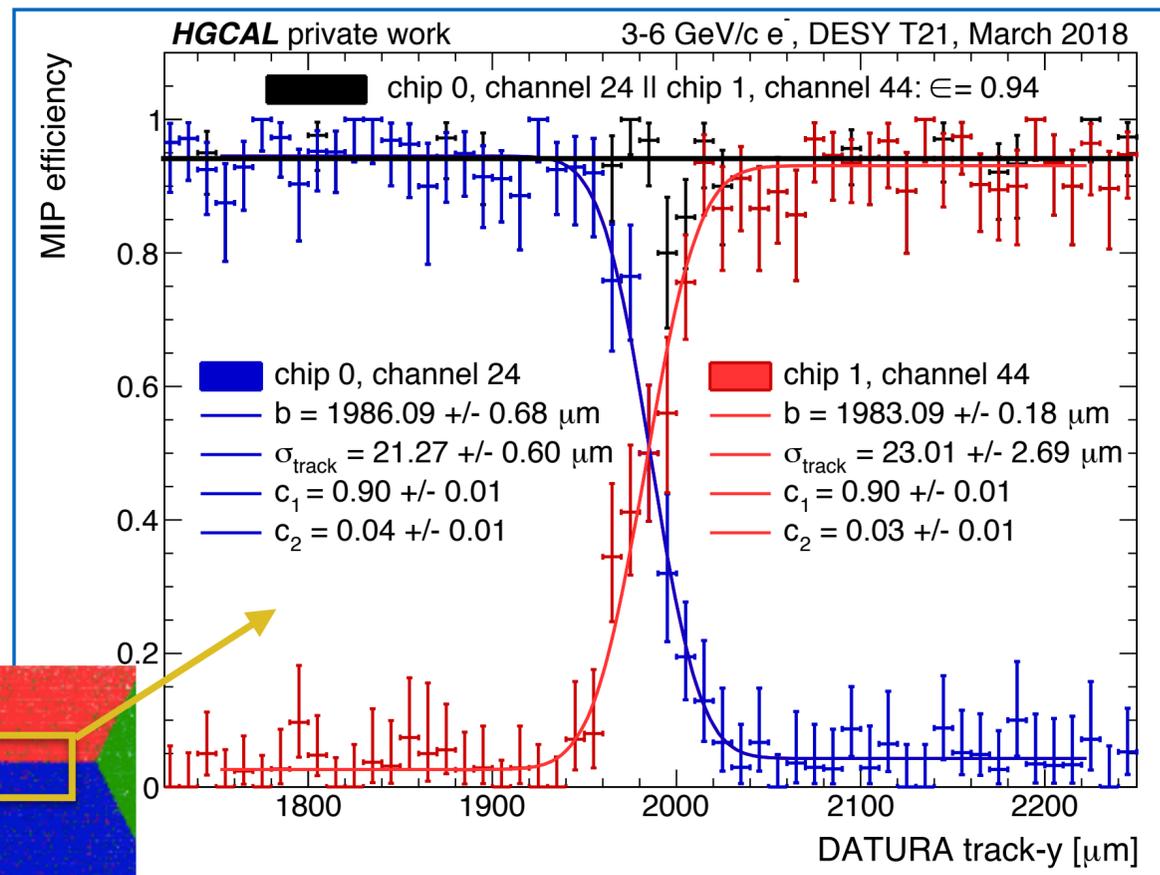
*Publication in collaboration review: "Construction, Commissioning and Calibration of CMS CE prototype silicon modules"*



## MIP efficiency at cell-cell boundary

Efficiency to detect electron-MIPs measured at DESY.  
Integral component: Precise tracking with DATURA beam telescope.

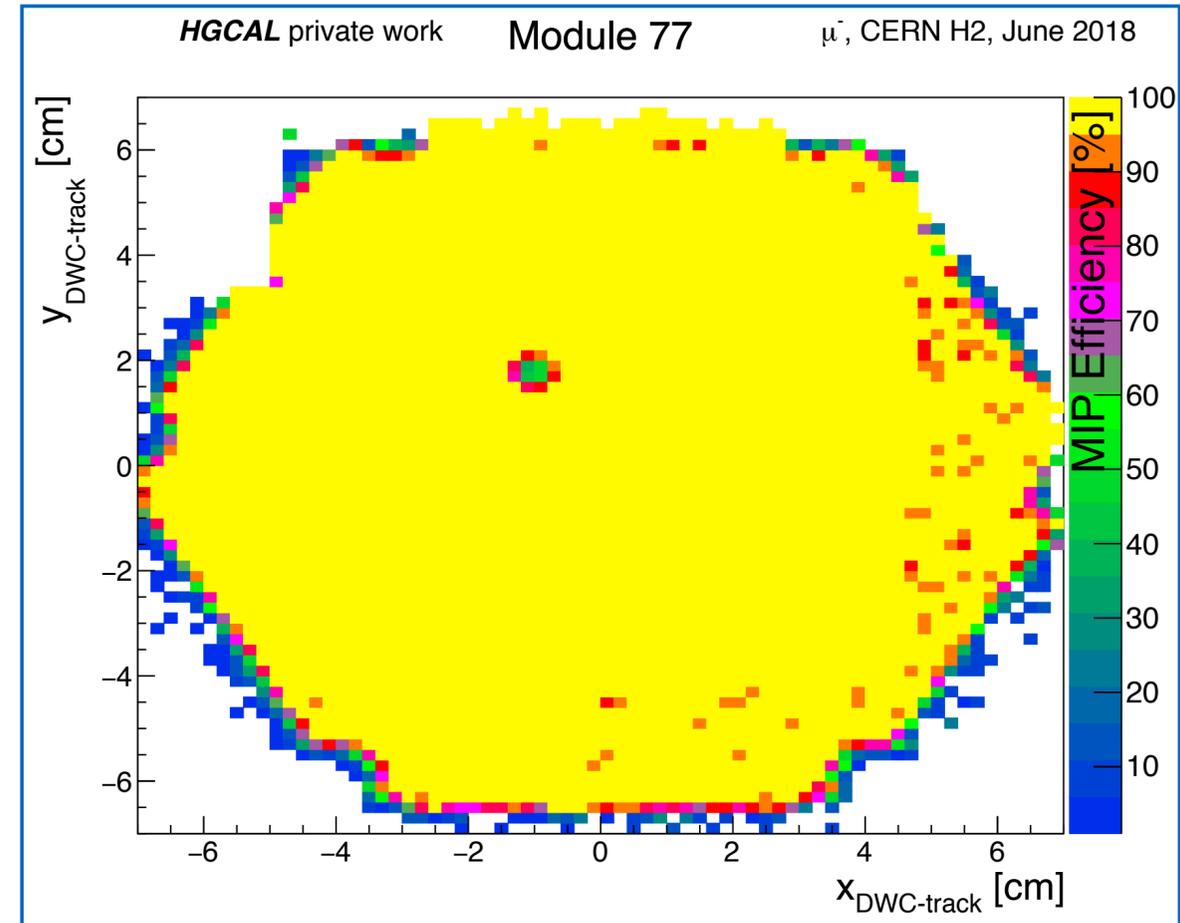
- ▶ Close to 100% for exposed cells.
- ▶ Per-cell MIP efficiency falling quickly at cell boundary.
- ▶ No efficiency gap between cells.



➔ MIP signals confined to single cells: Good.

## Full module MIP efficiency maps

1. Denominator: Extrapolate  $\mu$ -track from DWC.
  2. Numerator: Check if active cell is in vicinity.
- ▶ Integrated efficiency close to 100% for most modules.
  - ▶ 5 / 28 modules with areas of reduced efficiency.
    - 1x bad ASIC, 1x high leakage current, 3x insufficient pad-chip bonding.



➔ MIP efficiency: Good.



## MIP calibration strategy

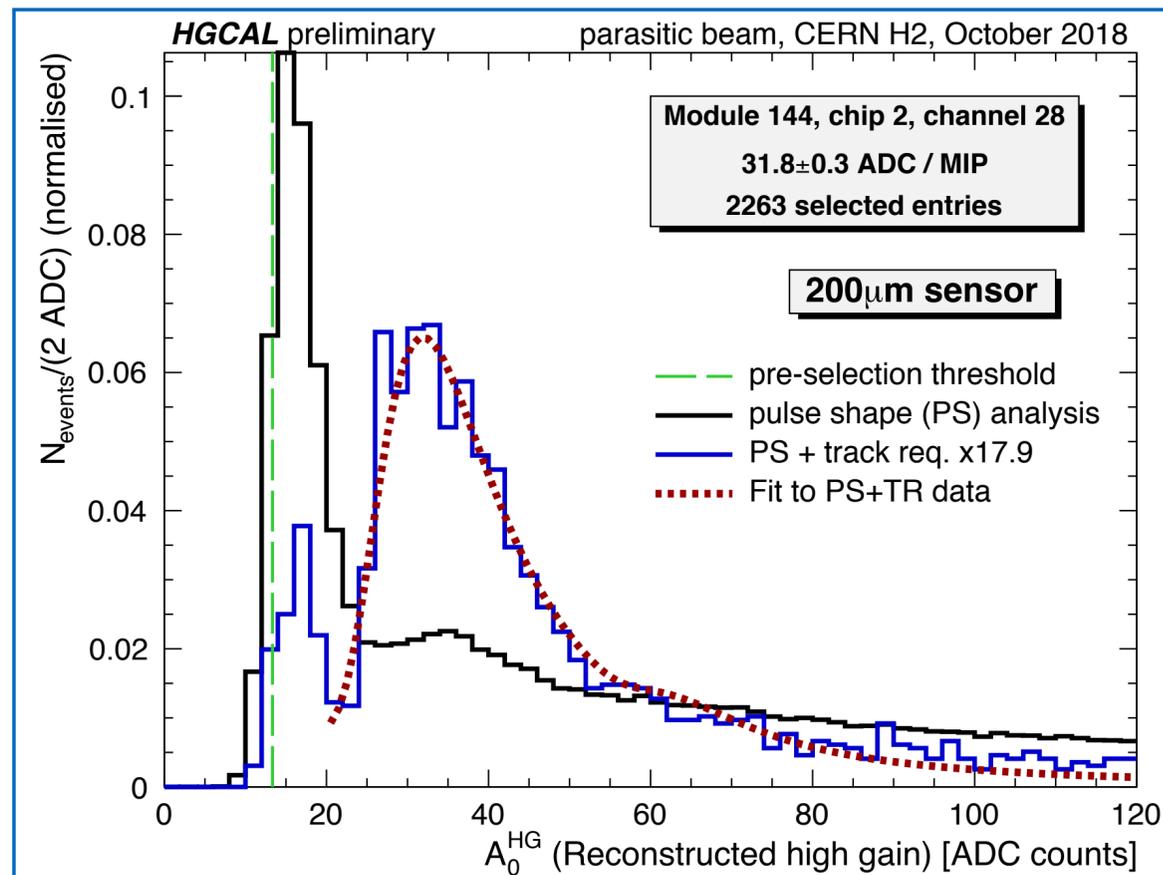
Signal spectrum induced by MIPs.  
Calibration = maximum of Landau x Gaussian fit.

- Tracking of MIPs with HGCAL prototype:
  - > Signal purification.
- Muon beam and parasitic (undefined) beam.

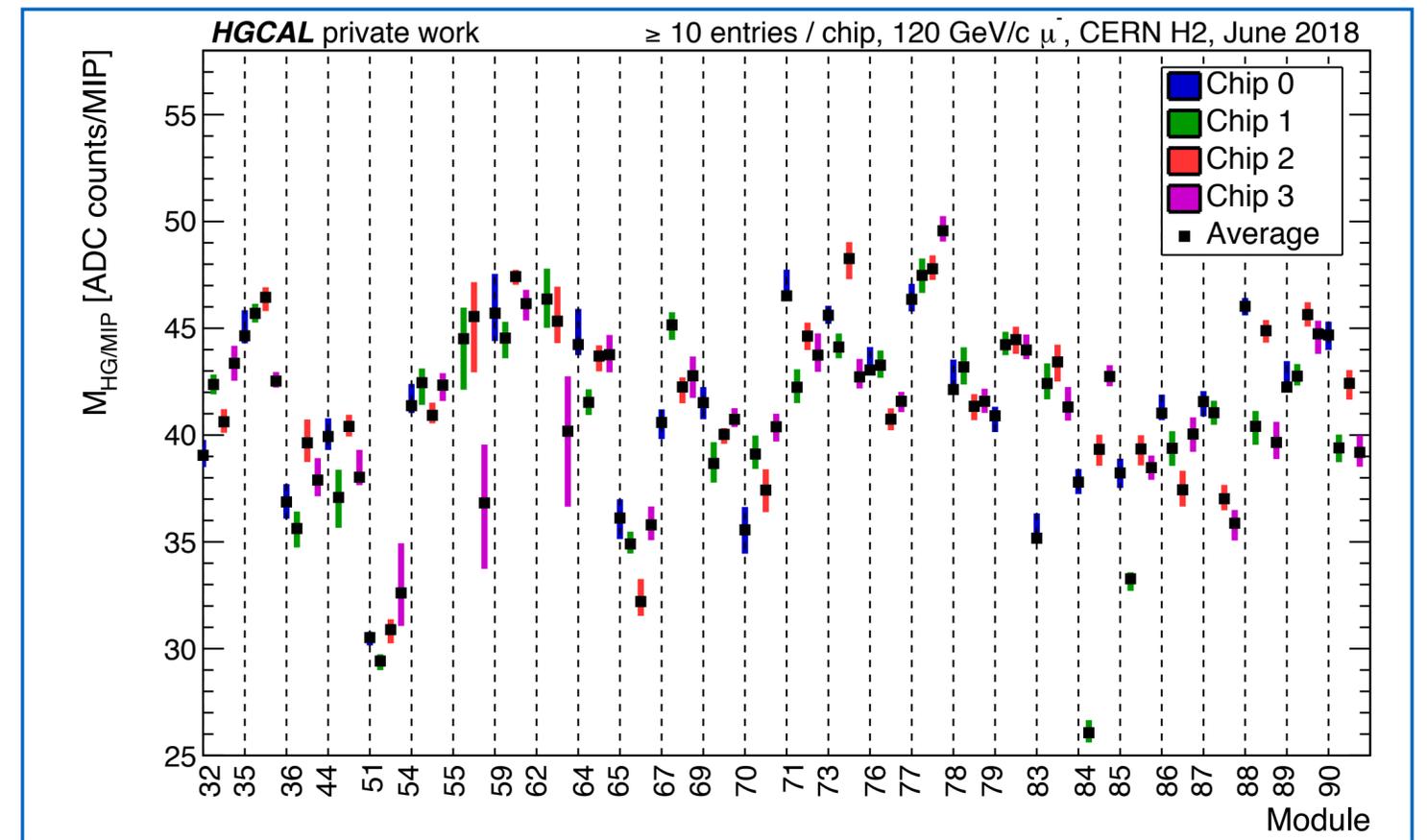


## MIP calibration results

- ✓ >10,000 channels (~85%) calibrated.
- ~3% variations within channels of same chip.
- Chip-chip variations sizeable.
- Scaling with sensor thickness as expected.
- Dependence on cell geometry.



➔ **HGCAL as MIP-tracking device: Good.**



➔ **MIP calibration feasible - and mandatory.**



## Timing calibration

**Timing important for HGCAL: pile-up rejection & clustering.**

2 calibration ingredients:

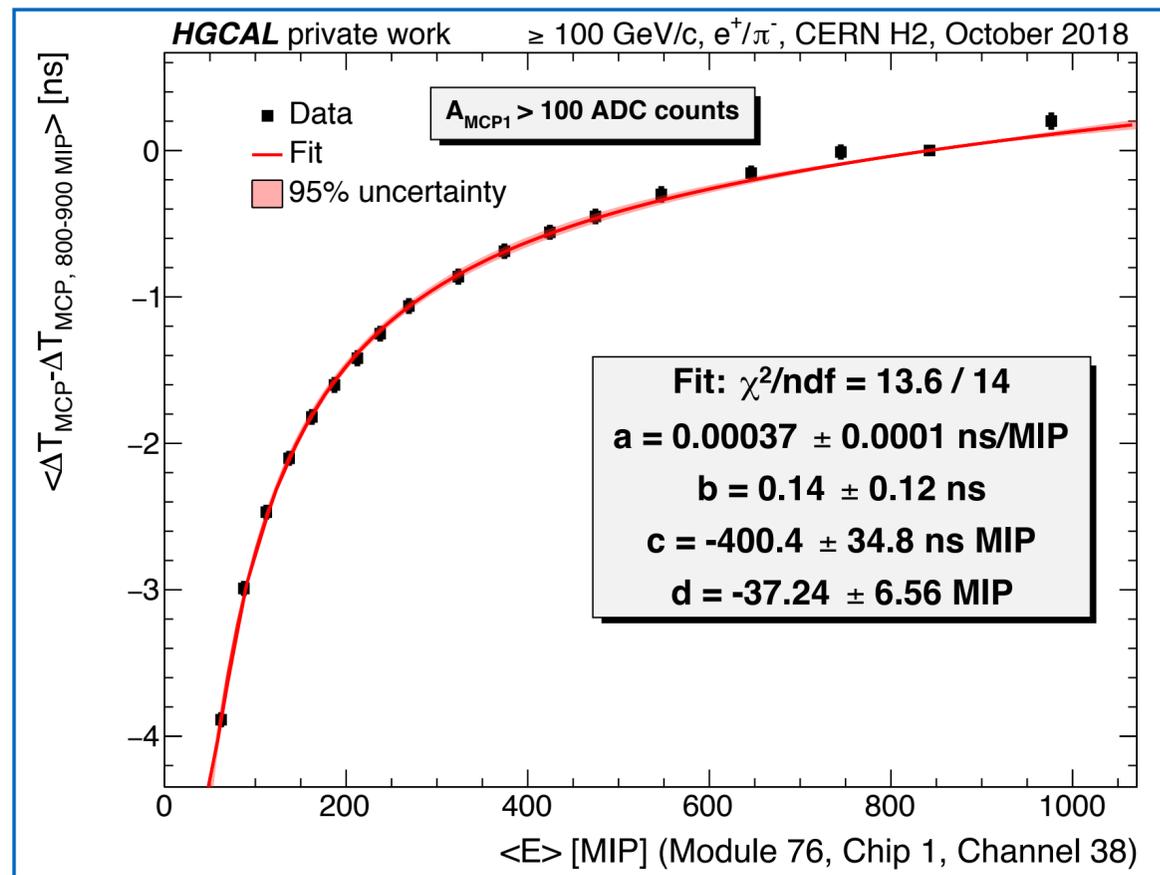
- TOA-nonlinearity.
- Time walk due to fixed threshold discriminator.



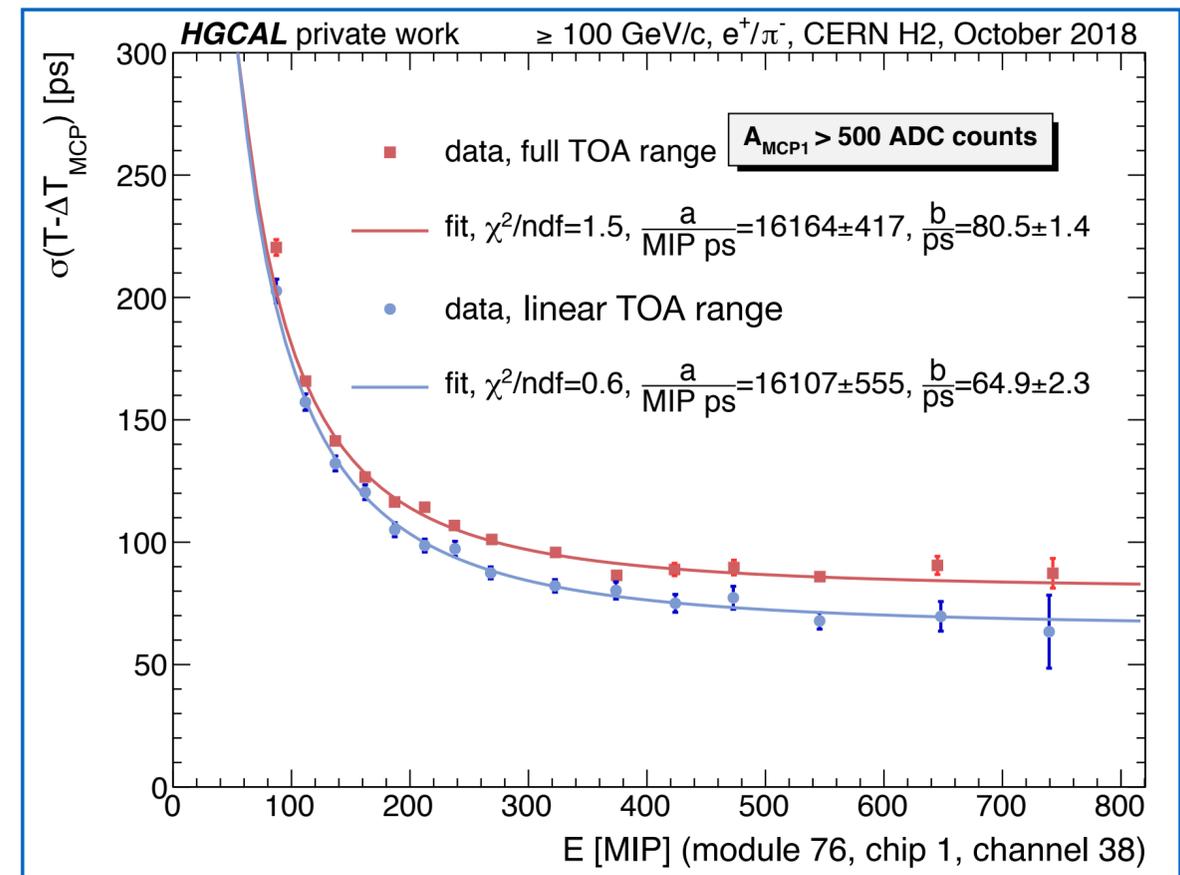
## Timing performance

✓ Handful of central channels calibrated → proof-of-principle.

- Compare calibrated timestamp to reference time from MCP.
- Better performance for linear region of the TOA.
- E-dependent resolution. Constant ~65ps.



➔ **Timing calibration (with ext. time reference): Feasible.**



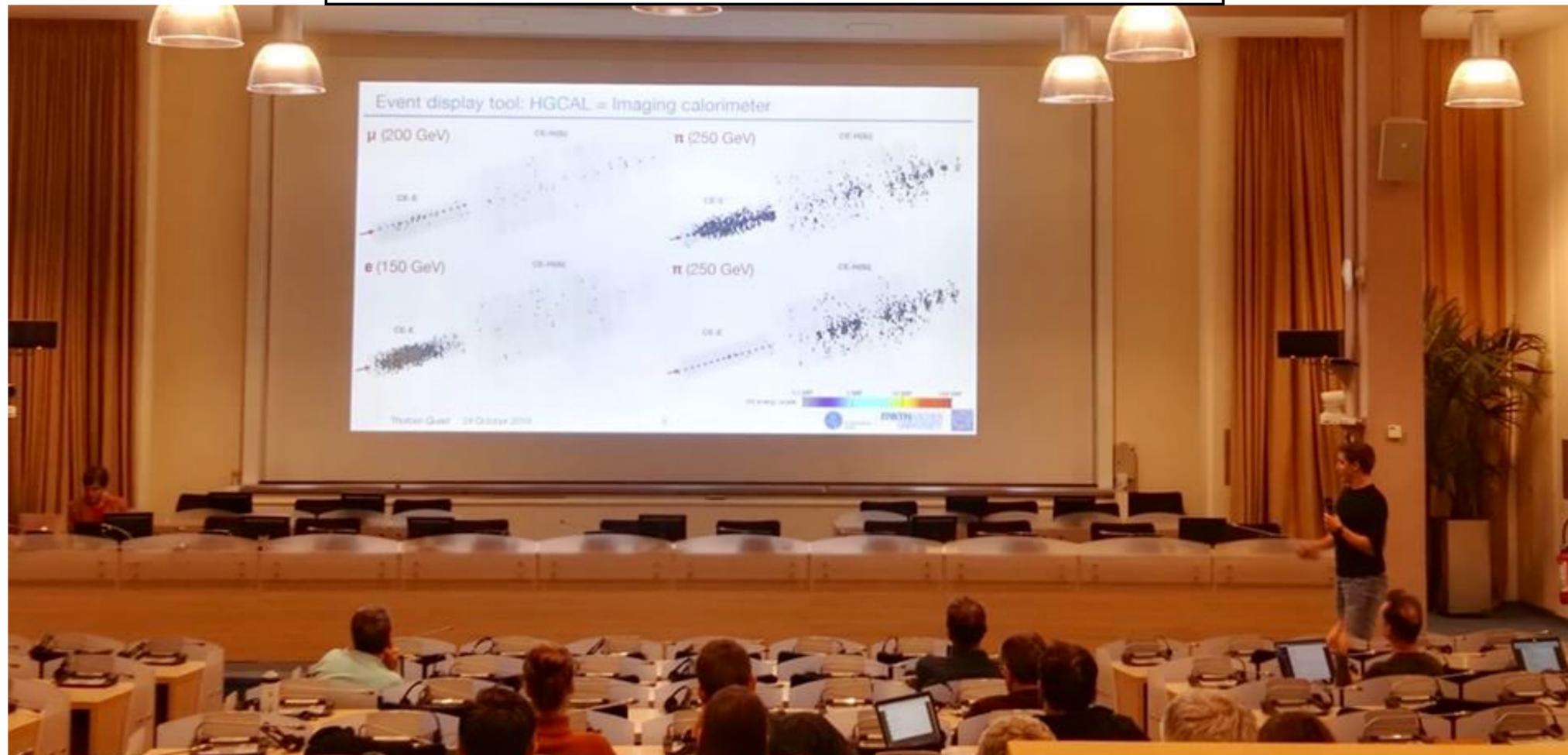
➔  **$\sigma_T$  close to 60 ps for high-E: Good.**



**Selected Highlights**

- 10.2 “Studies with Electromagnetic Showers”
- 10.3 “Studies with Hadronic Showers”

Showing event displays at the 2019 EP R&D Day at CERN  
“HGAL = Imaging calorimeter”



*Publication in collaboration review soon:*

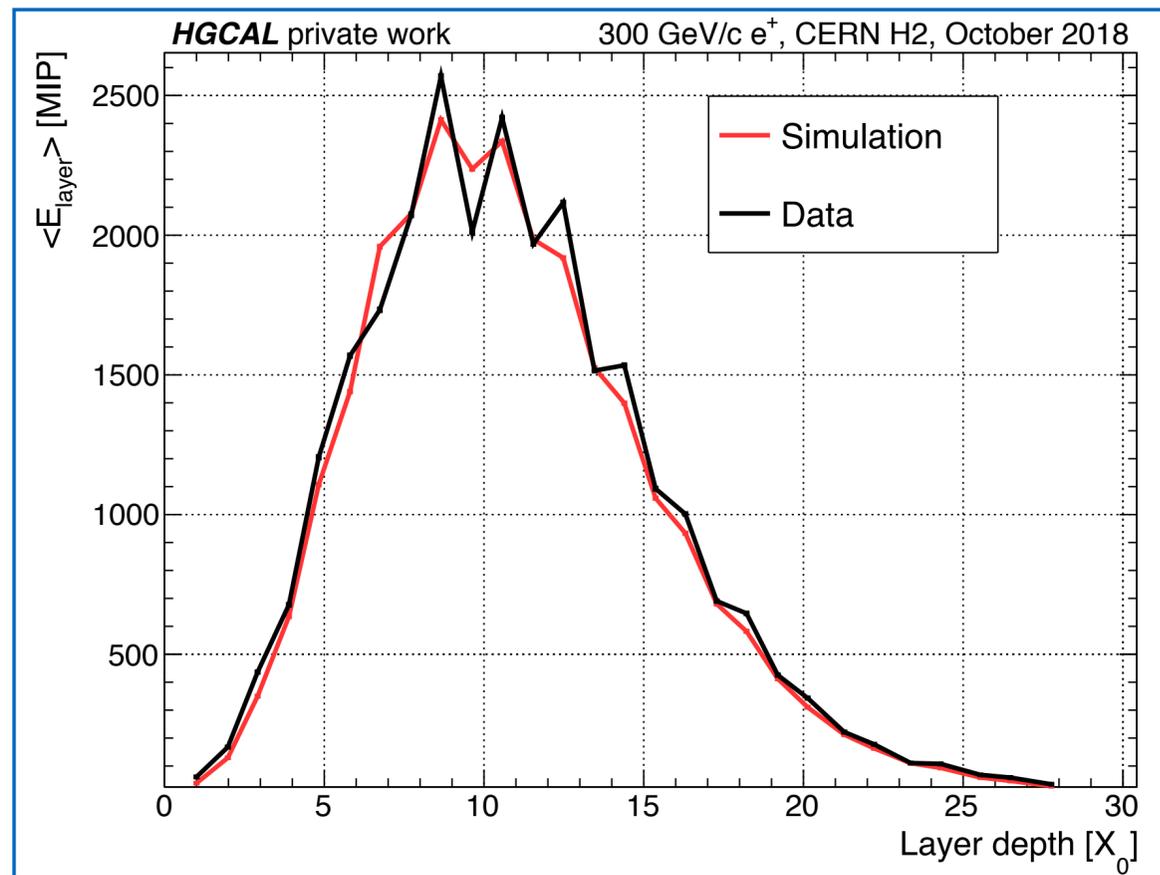
*“Measurement of the response of a CMS HGAL silicon-pad calorimeter prototype to electrons at the 2018 beam tests”*



## EM: Longitudinal shower profile

:= mean energy deposit in a layer vs. depth

- EM showers fully contained.
- Overall good agreement to simulation.



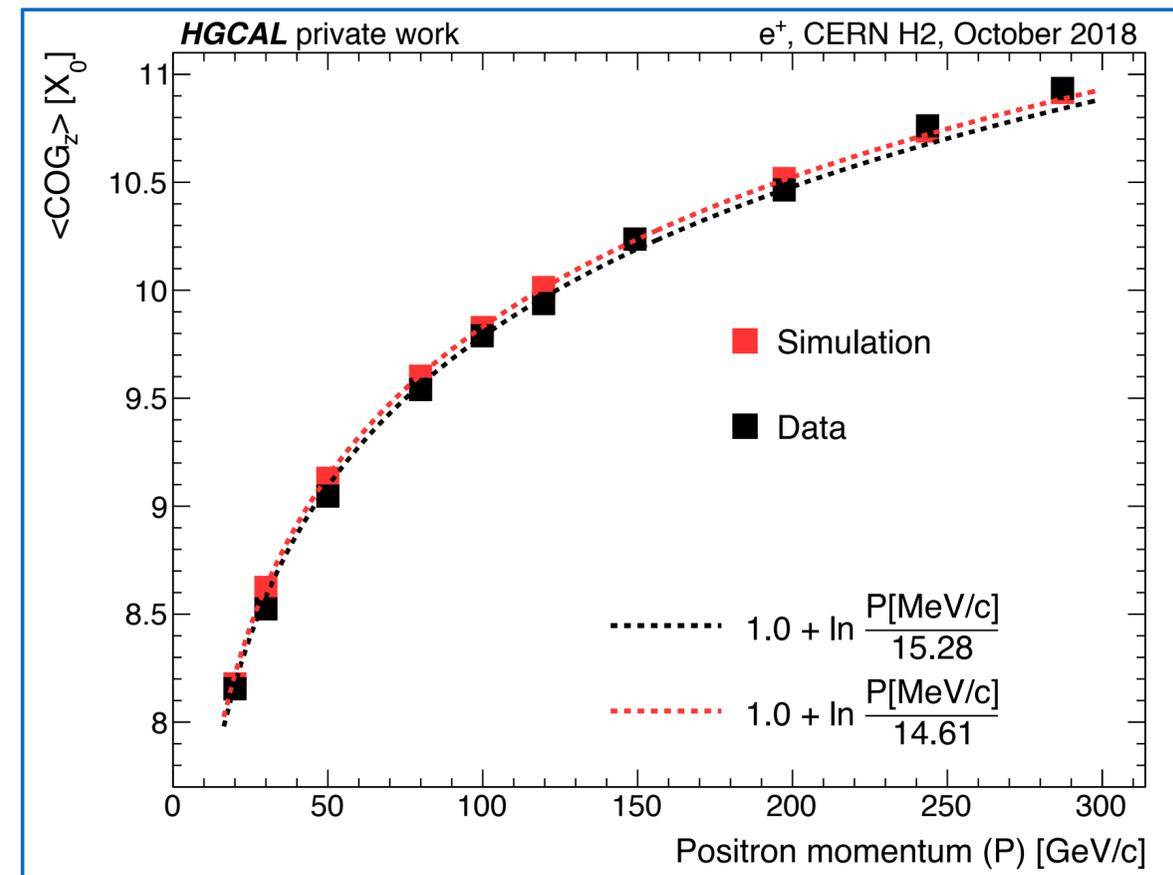
➔ Longitudinal shower evolution: Good.

## EM: Shower depth

:=  $E_{\text{layer}}$ -weighted center-of-gravity

Expect: Depth  $\sim \log(\#\text{particles}) \sim \log(E)$

- Log-scaling.
- Data = Simulation.



➔ Depth scaling with energy: Good.



## EM: Energy linearity and resolution

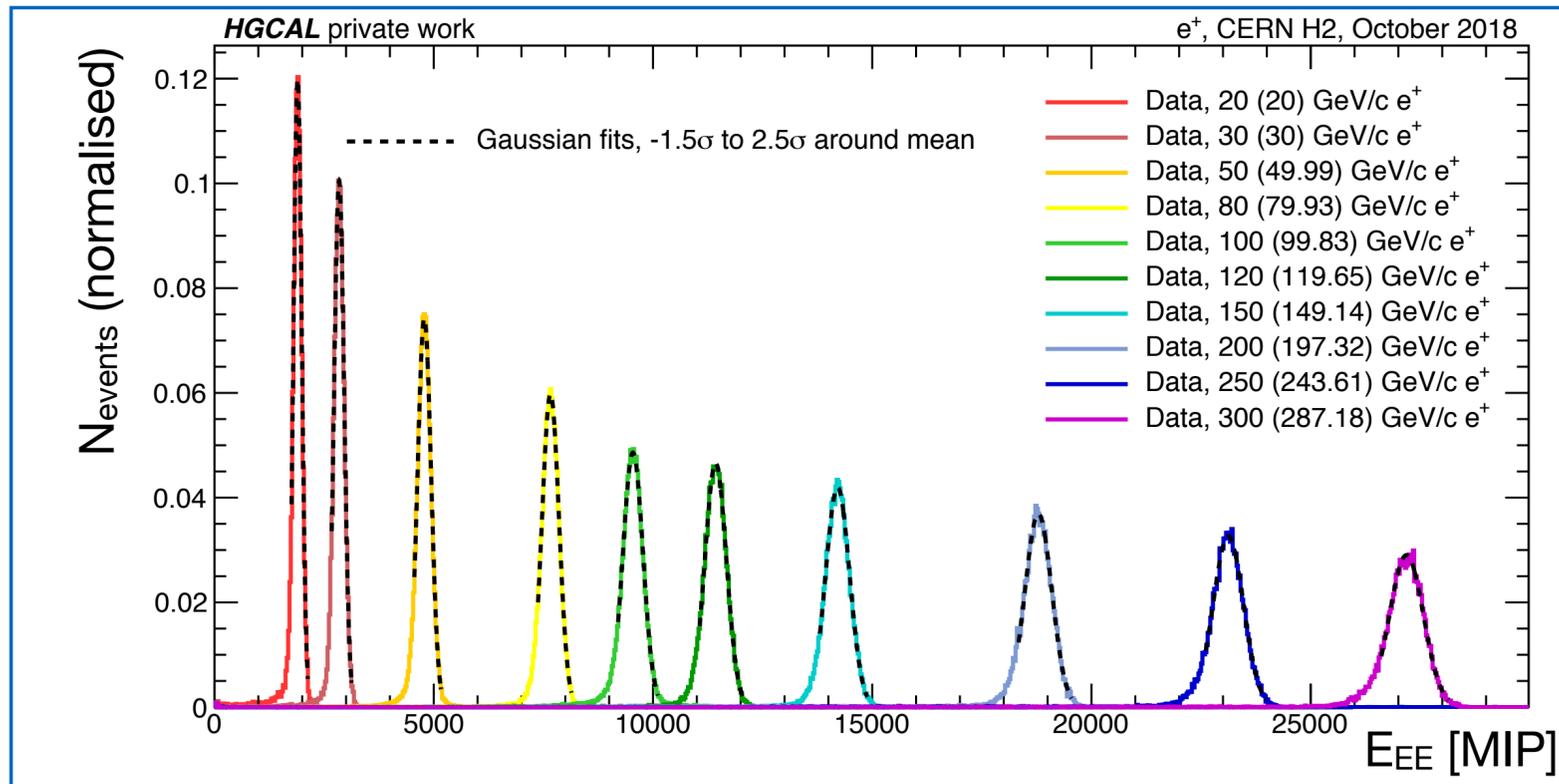
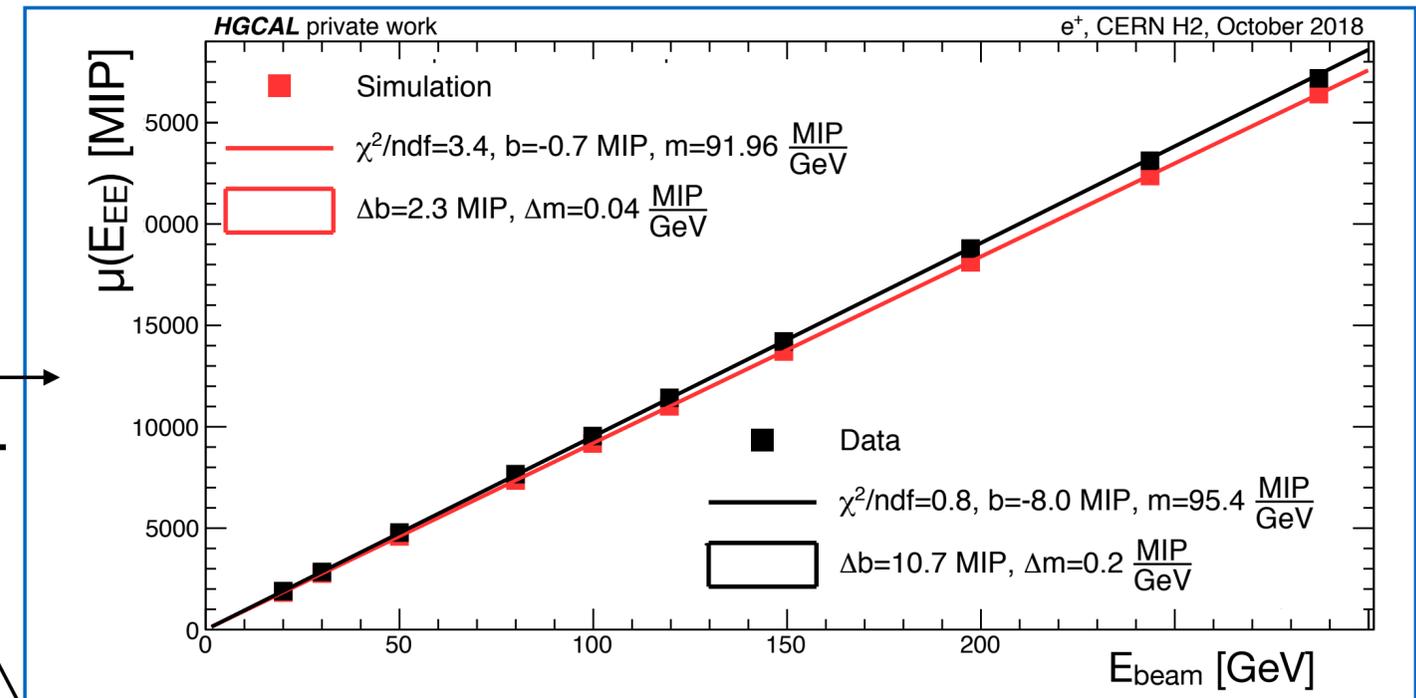
**Most important calorimeter quantity!**

Equal layer distancing  $\rightarrow$  Energy  $\sim E_{EE} := \sum_{EE} E_{hit}$ .

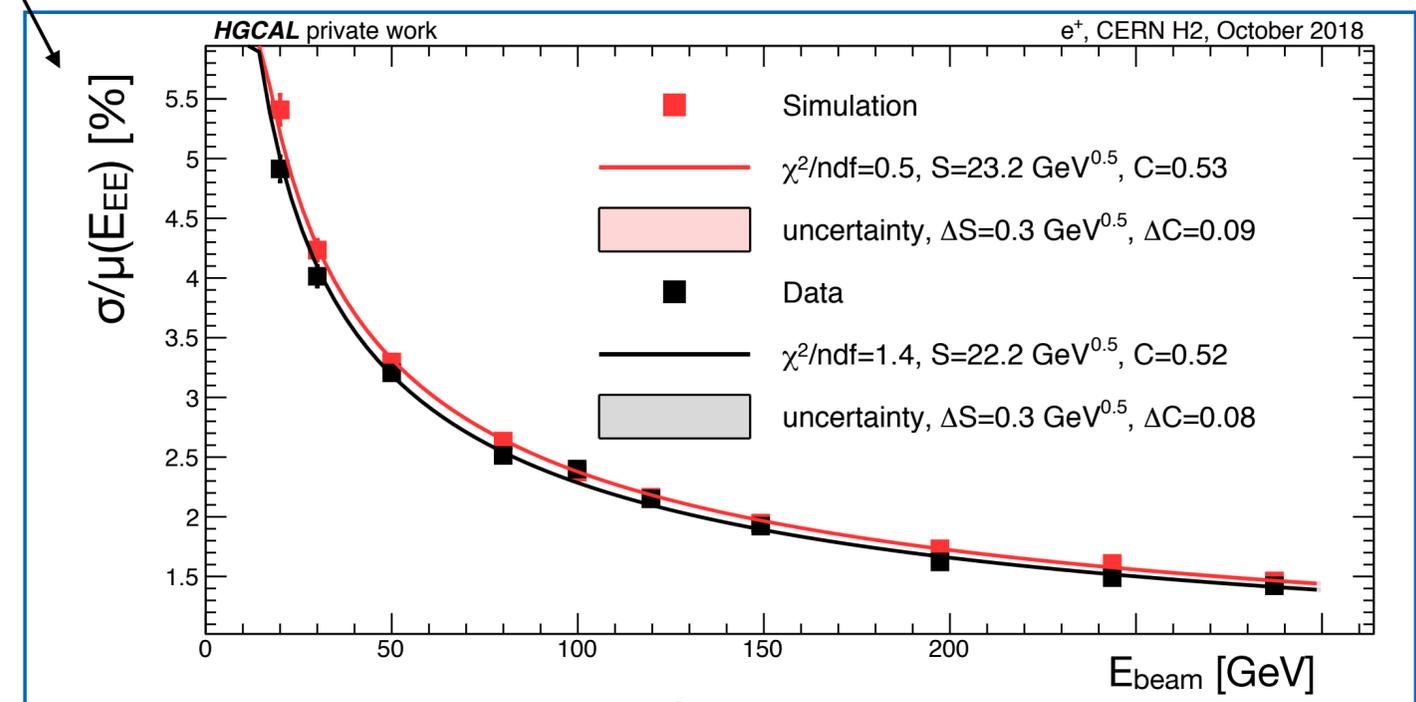
► Gaussian distribution of  $E_{EE}$ .

► **Linearity** :=  $\mu(E_{EE})$  vs.  $E_{beam}$ .

► **Resolution** :=  $\sigma/\mu(E_{EE})$  vs.  $E_{beam}$ .



► **The HGCAL prototype is a calorimeter: Very good.**



► **Linear response: Good.**

► **EM resolution as simulated: Good.**

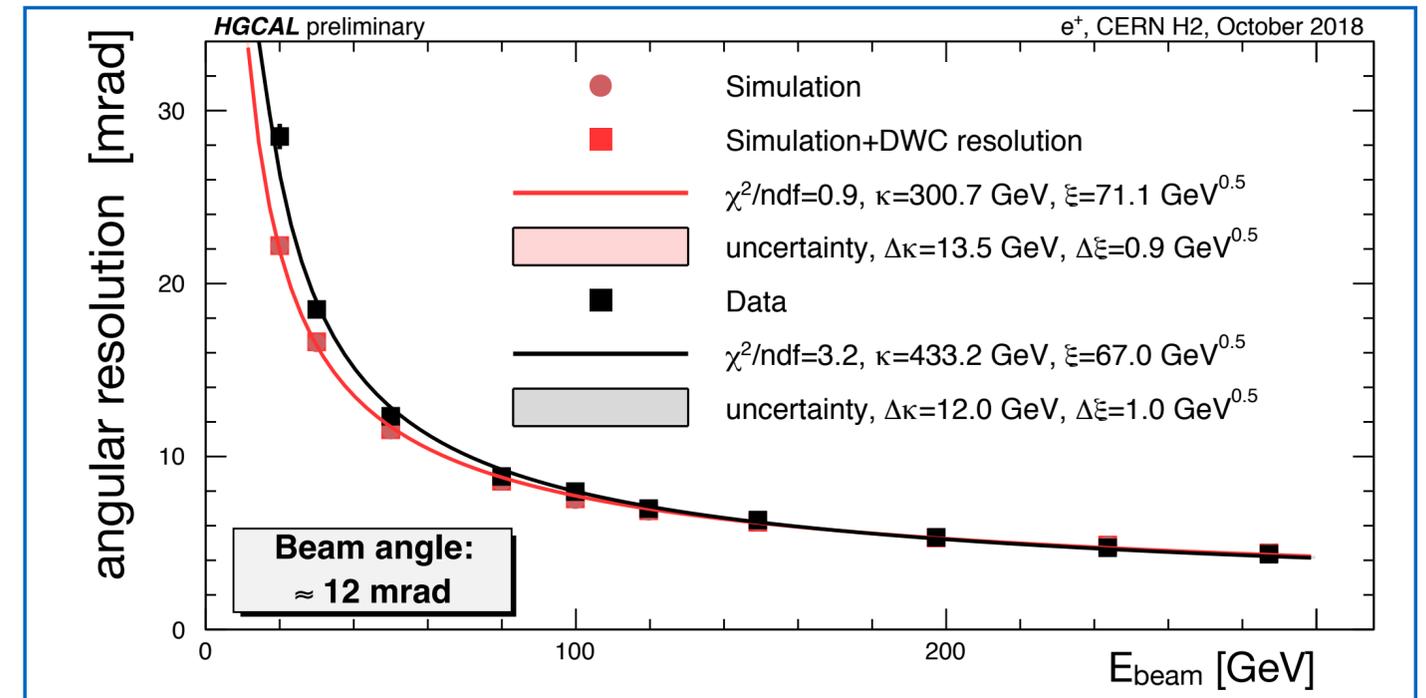
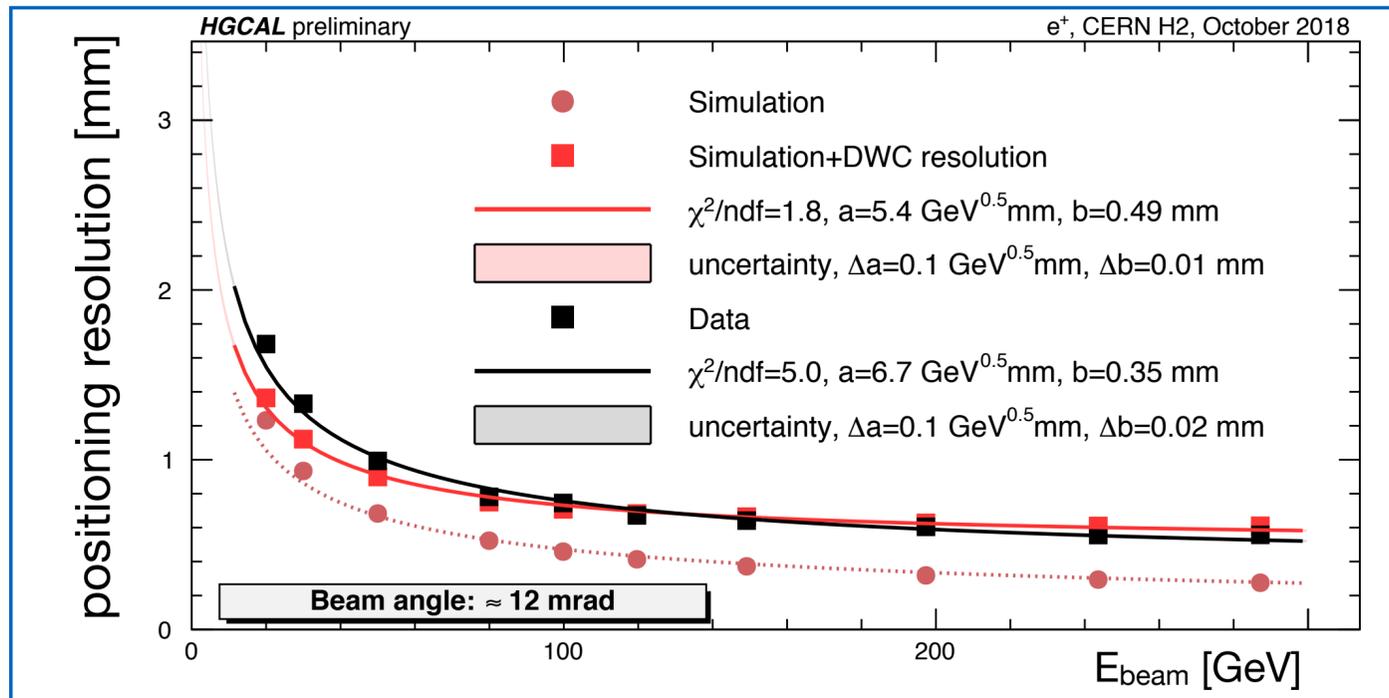
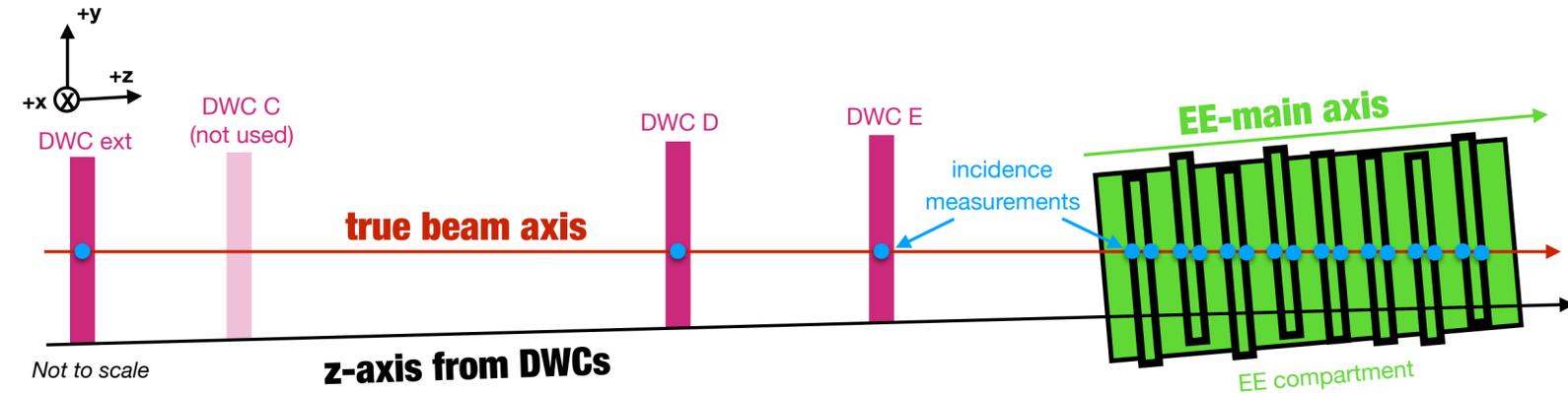


## EM: Shower axis positioning & angular resolution

Important quantity for particle flow calorimetry.

3-step procedure:

1. Compute impact position at each EE layer using logarithmic weighting. *Published: JINST 13 (2018) P10023*
2. Combine EE layers to shower axis.
3. Compare position and angle to upstream DWCs.



➔ Positioning resolution —> 0.6 mm.

➔ Angular resolution —> 5 mrad.

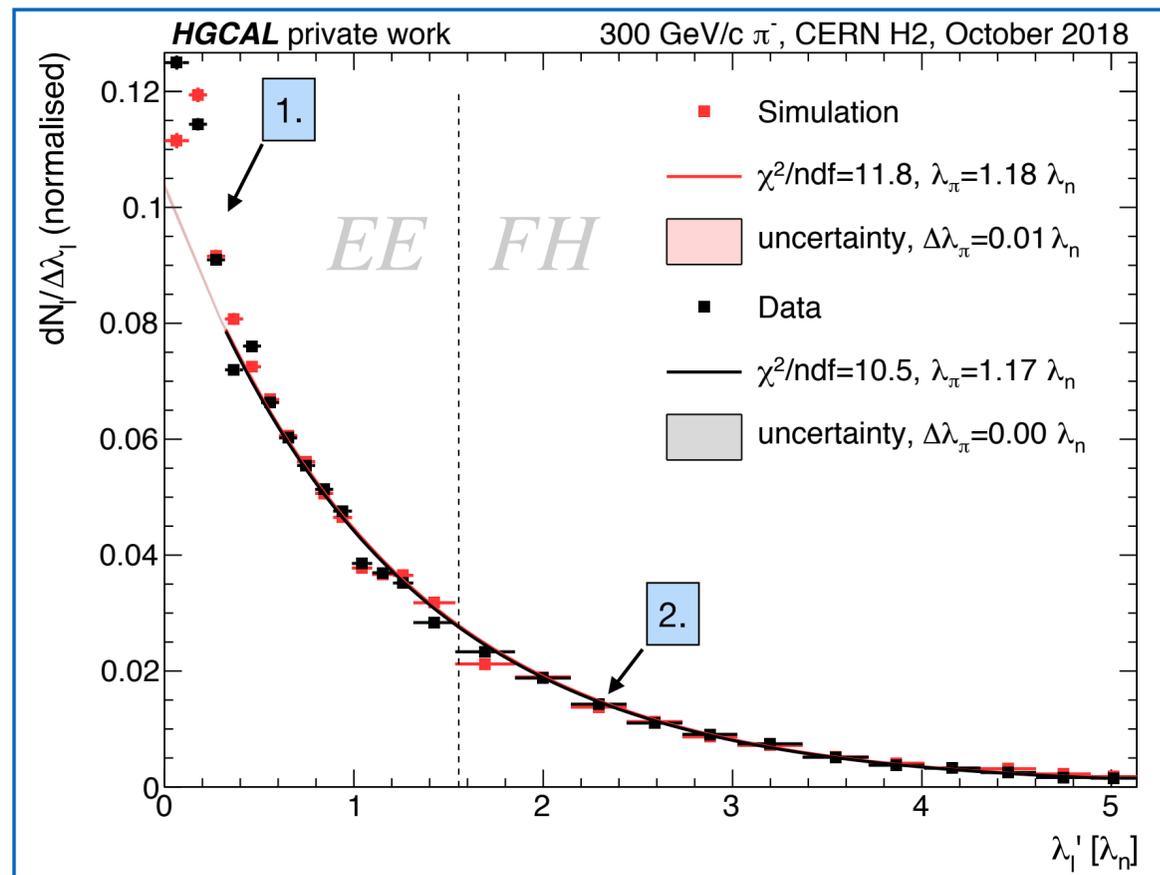
➔ The HGCAL prototype is suitable for particle flow: Very good.



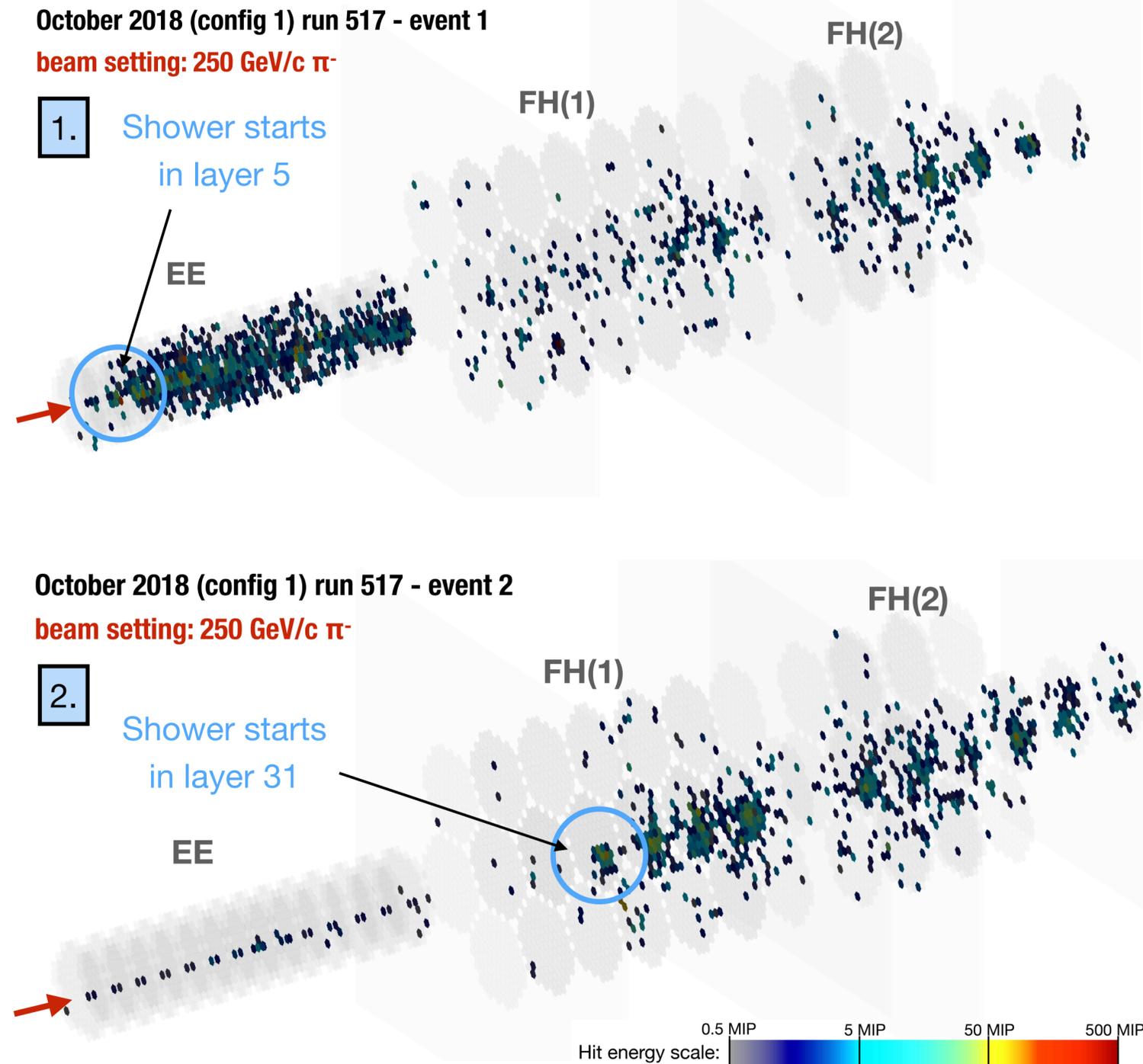
## HAD: Shower start depth

Use longitudinal segmentation to identify shower start depth.  
Shower start := significant increase in energy density.

- Exponential decay function.
- $\lambda_\pi \sim 1.17 \lambda_n$ , consistent with passive material properties.



➔ Shower start ID: Good.



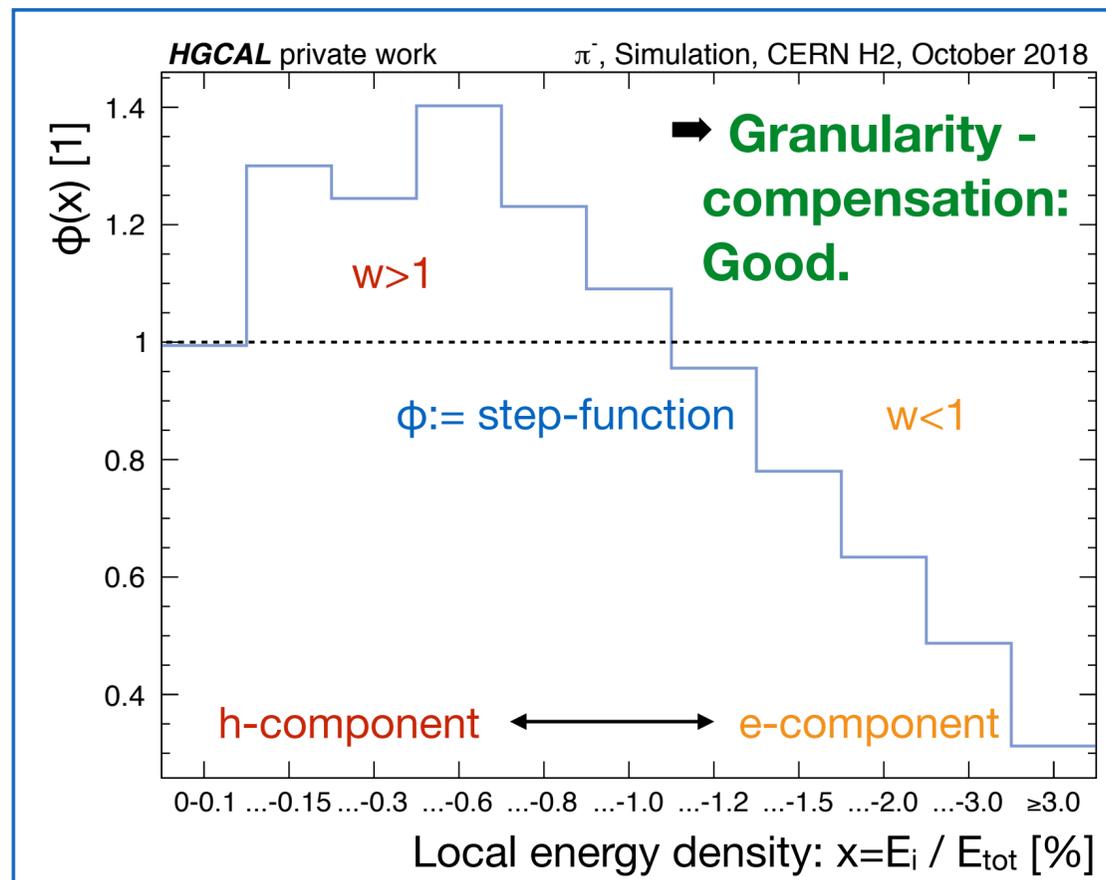
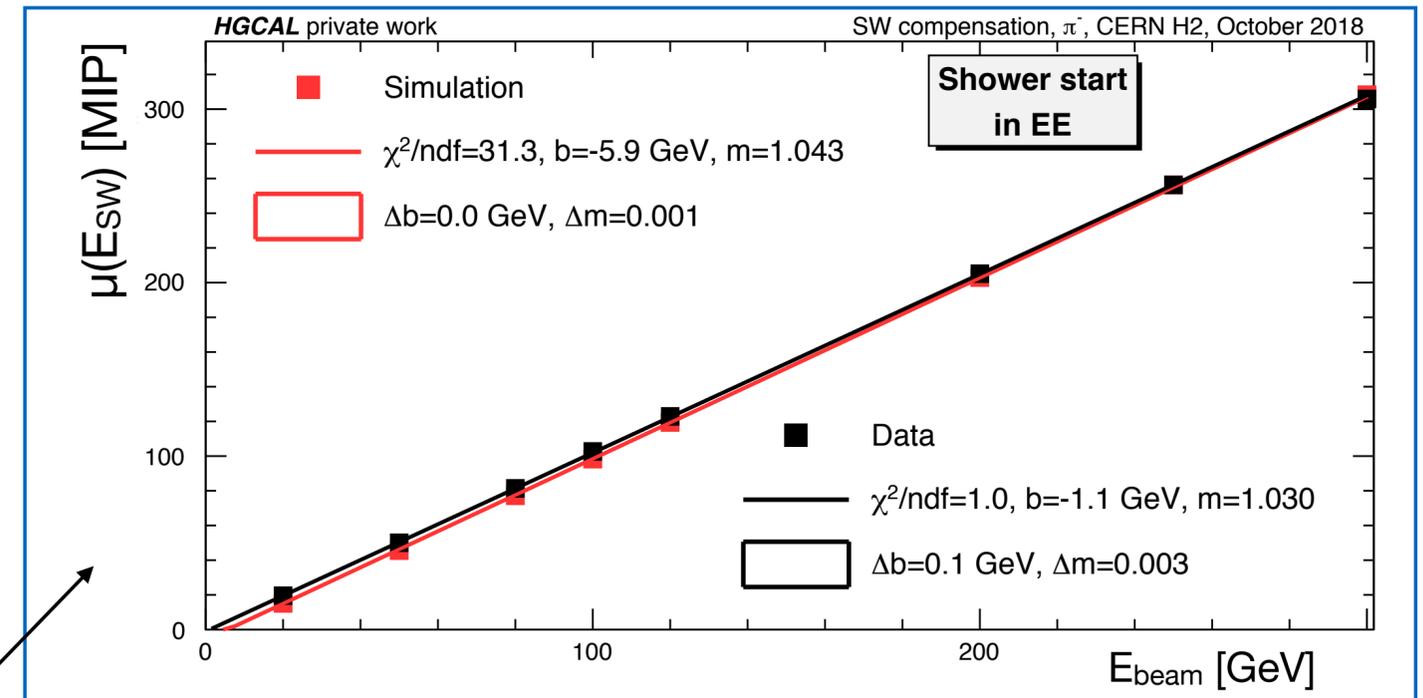


## HAD: Advanced shower reconstruction

- a) Different sampler configurations in EE and FH.
  - Compartment weights  $w_{EE}$  and  $w_{FH}$ .
- b) Non-compensation:  $h/e < 1$ .
  - Treat hadronic and electromagnetic constituents differently: Weights  $\phi(x)$ .
  - $x :=$  energy density as a proxy. **Relies on granularity.**

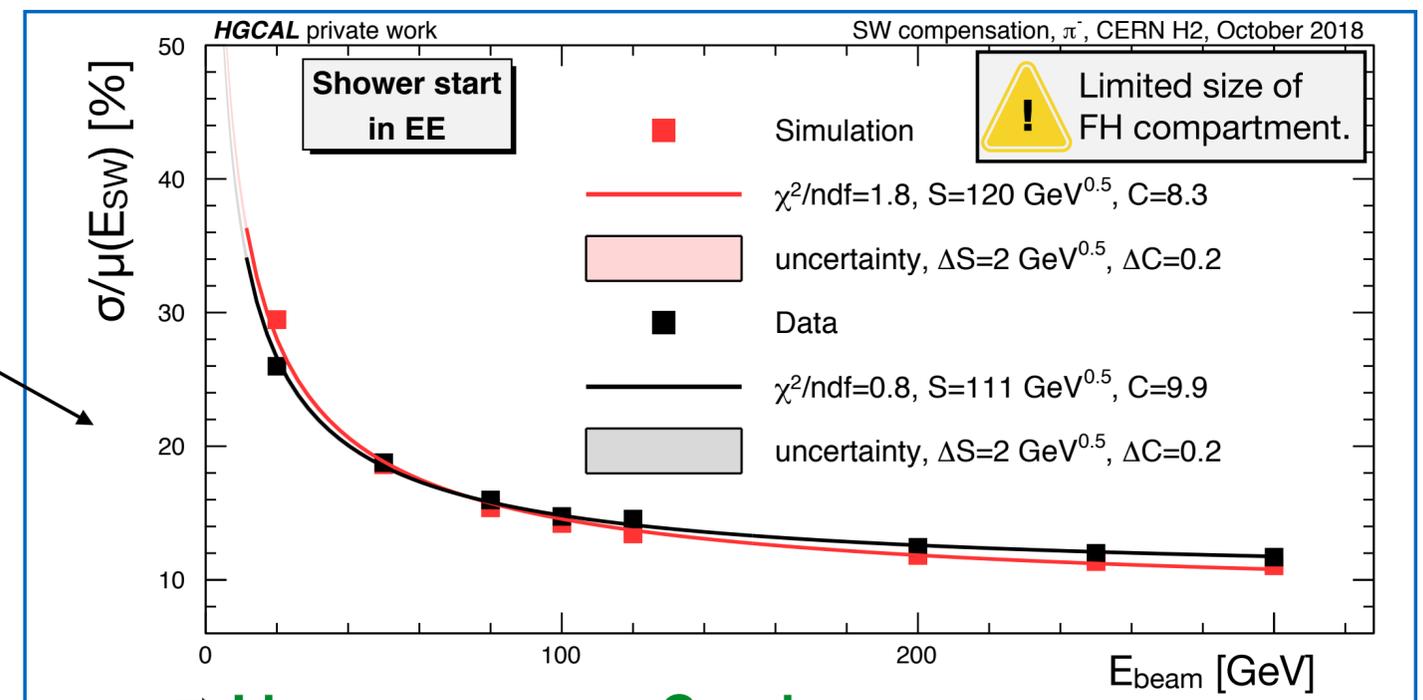
### → "Software compensation"

$$E_{SW} := w_{EE} \times [\sum_{EE} E_i \times \phi(E_i/E_{tot})] + w_{FH} \times [\sum_{FH} E_i \times \phi(E_i/E_{tot})]$$



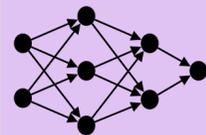
→ **Linearity** :=  $\mu(E_{sw})$  vs.  $E_{beam}$ .

→ **Resolution** :=  $\sigma/\mu(E_{sw})$  vs.  $E_{beam}$ .



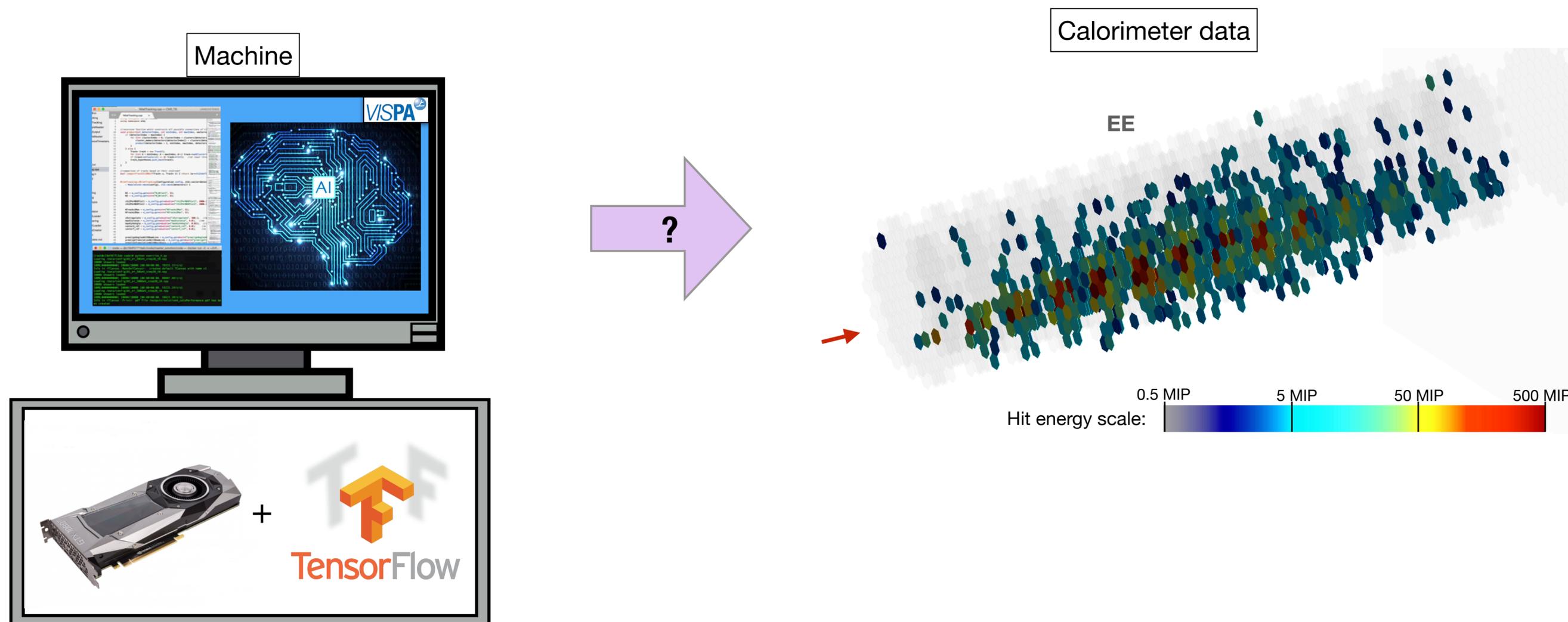
→ **Linear response: Good.**

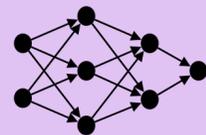
→ **HAD resolution as simulated: Good.**



# 5. Fast Generative Modelling of Calorimeter Data

▸ 11. “Fast Generative Modelling of Electromagnetic Calorimeter Showers”





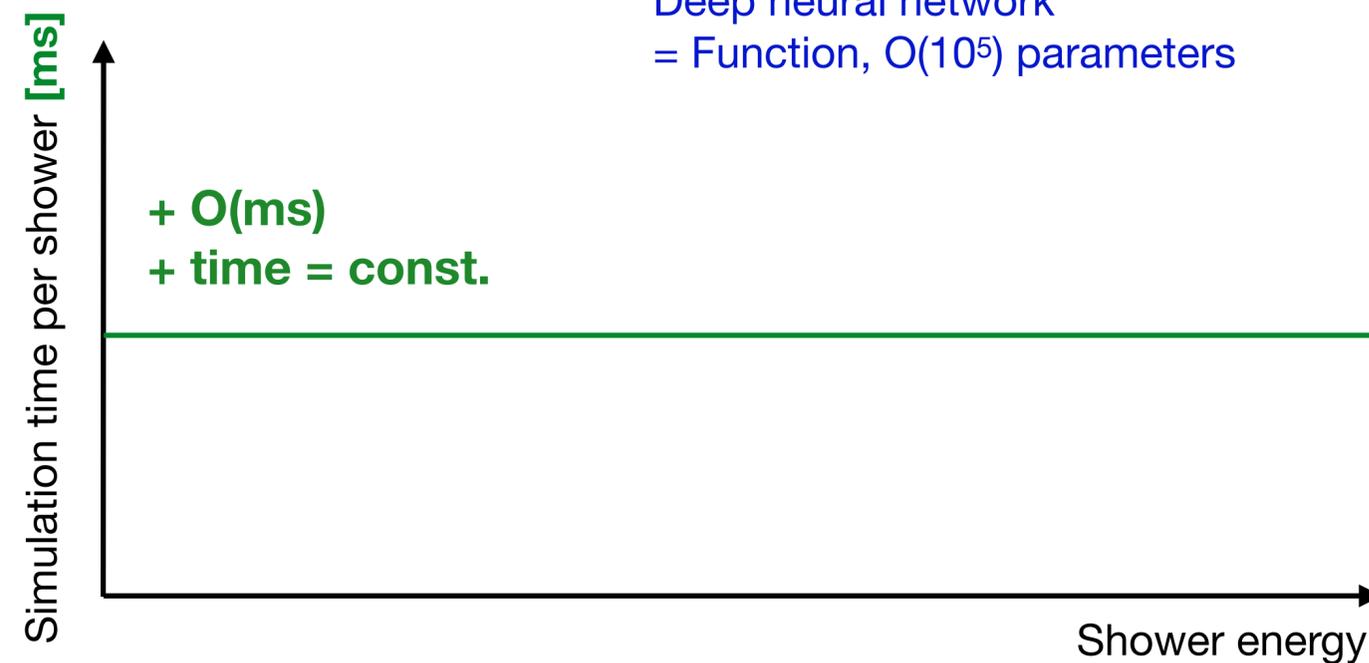
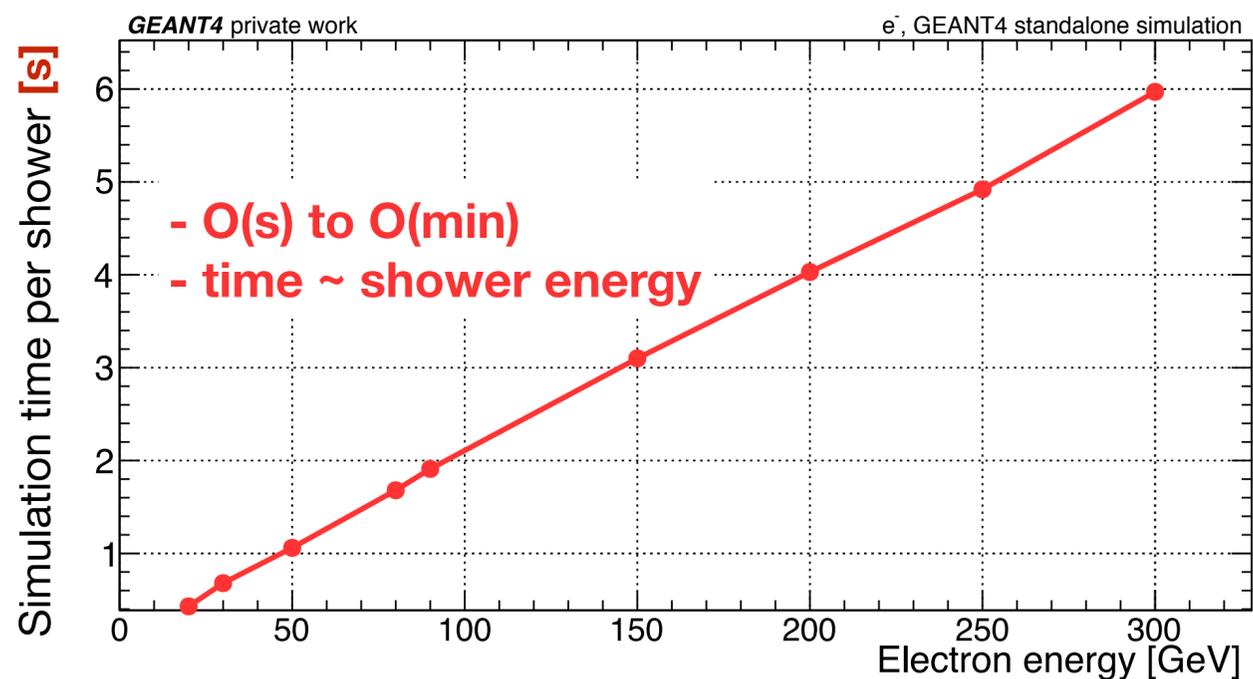
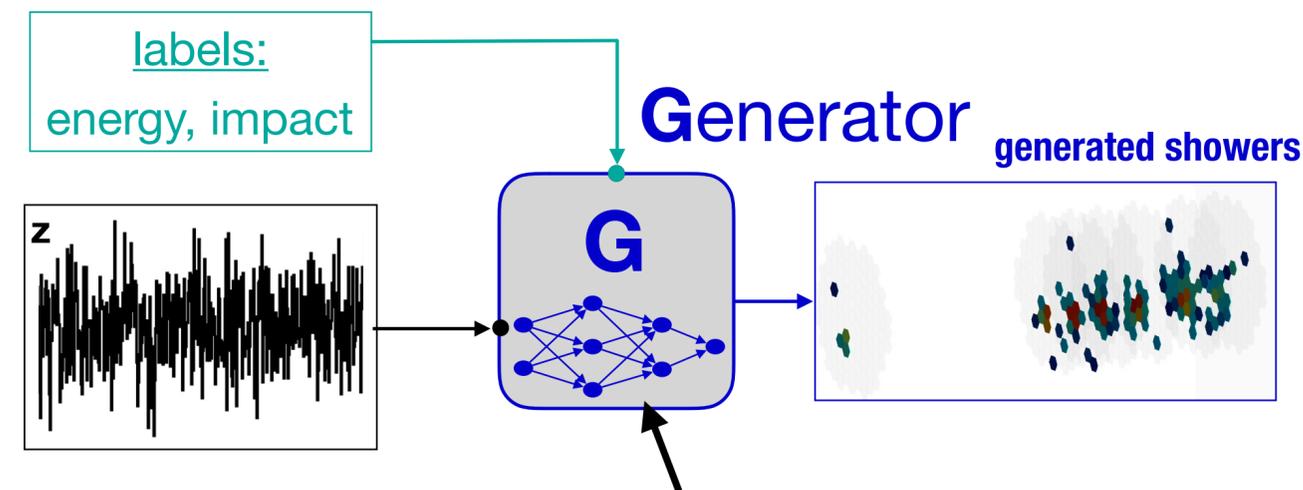
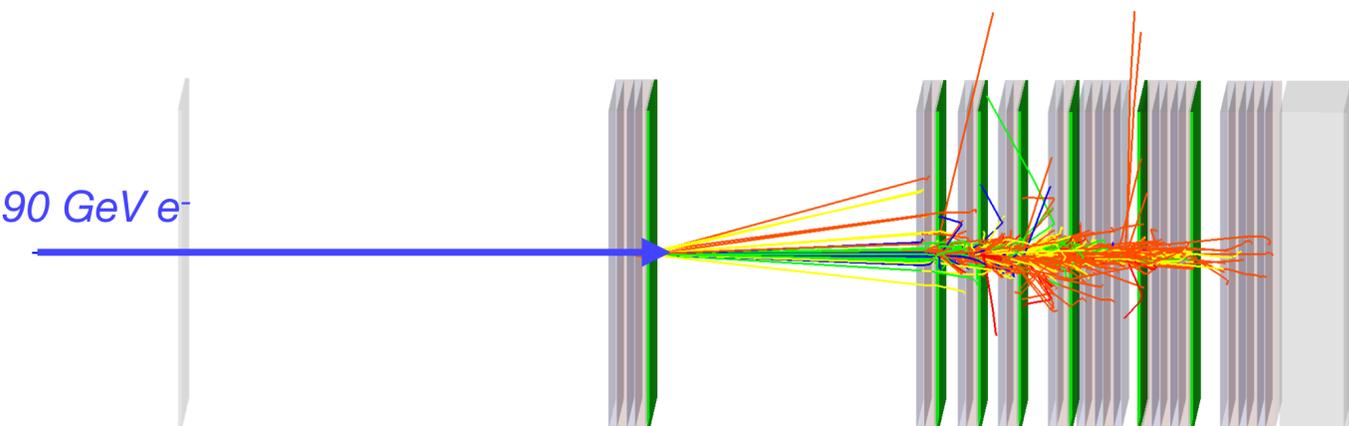
## State-of-the-art: *GEANT4*

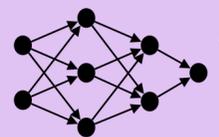
- Sequential simulation of shower particles and their interaction with material.
- Physics lists: High accuracy achievable (+).



## Deep Learning

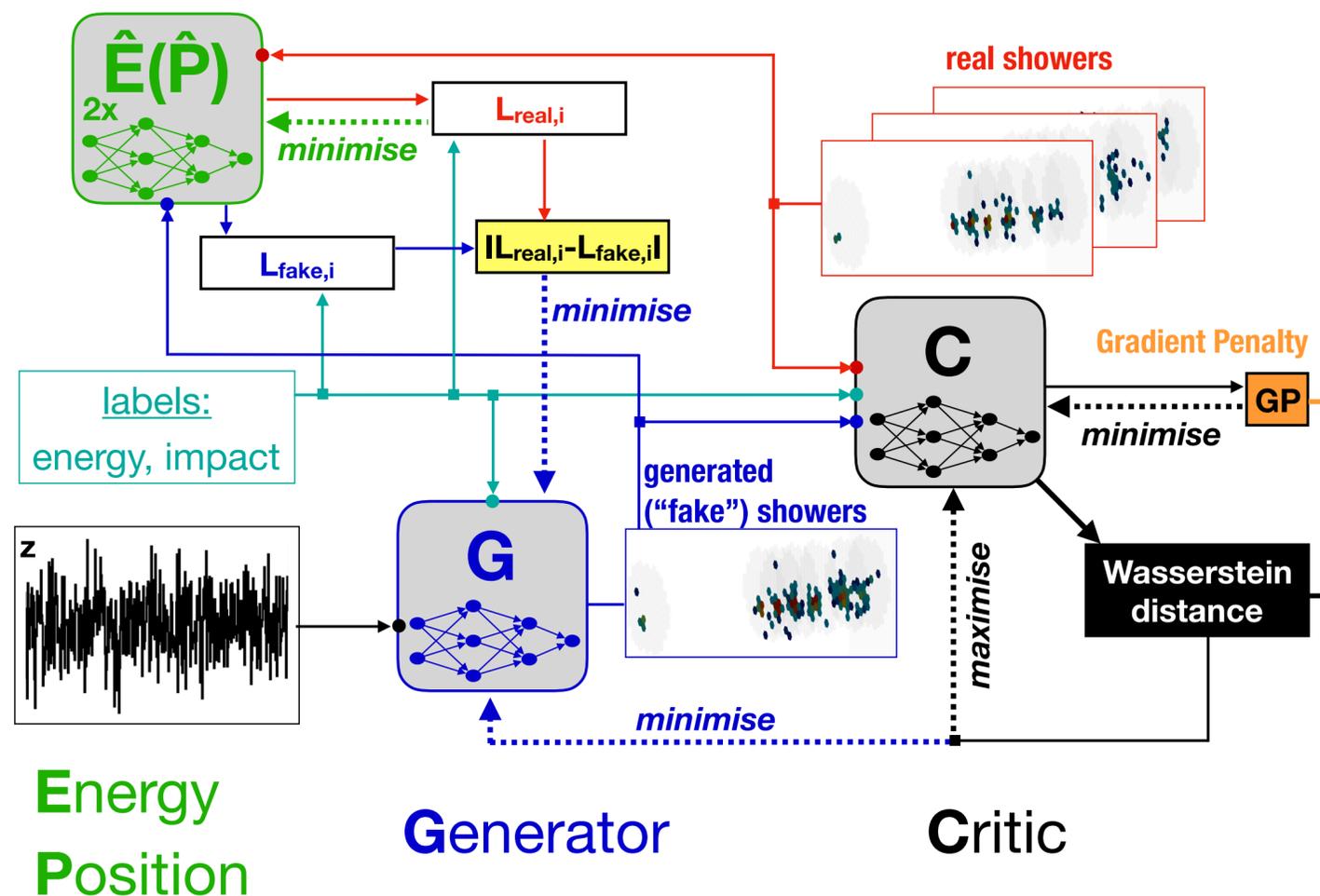
- Shower simulation = evaluation of a powerful NN.



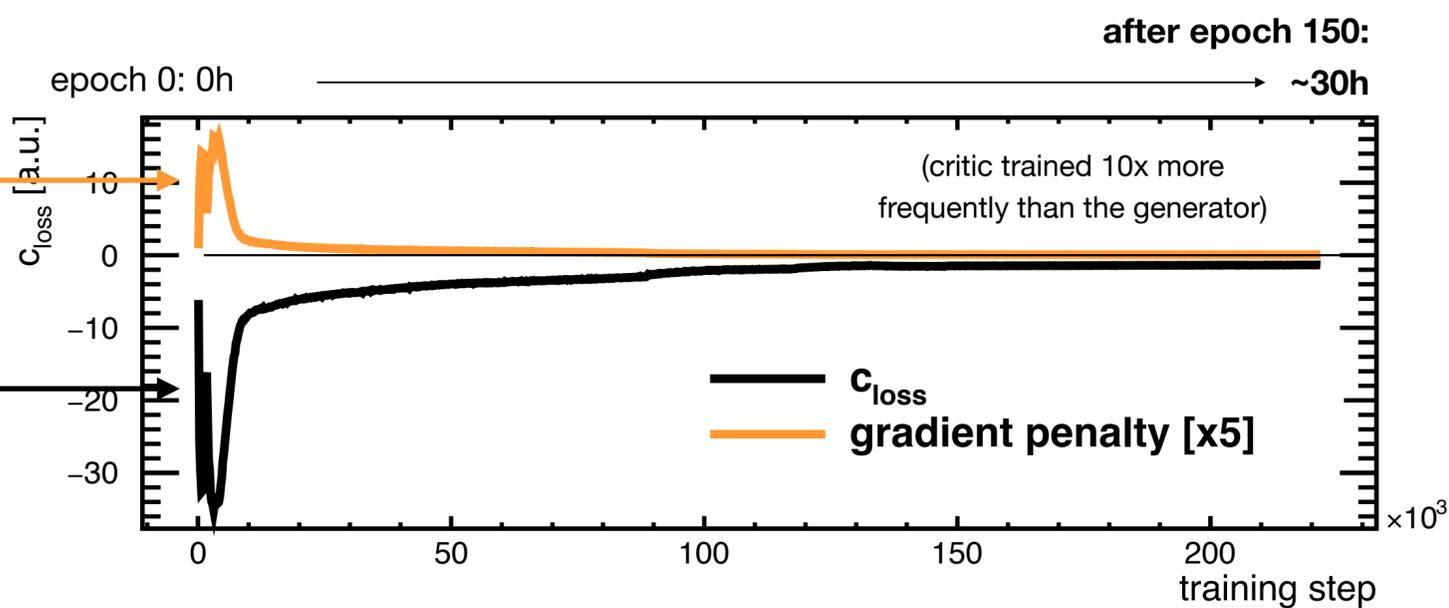


## Generator accuracy through adversarial training:

Key metric: Wasserstein (EM) distance real vs. generated images.



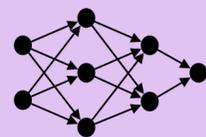
## Loss monitoring during the training



➔ **Critic loss (~EM distance) → 0: Good.**

### Deployed training scheme with 4 networks:

- EM distance approximated by critic network.
- EM distance minimised by generator network.
- Critic regularisation with gradient penalty.
- Label conditioning with 2 regressors networks.



## "Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network"

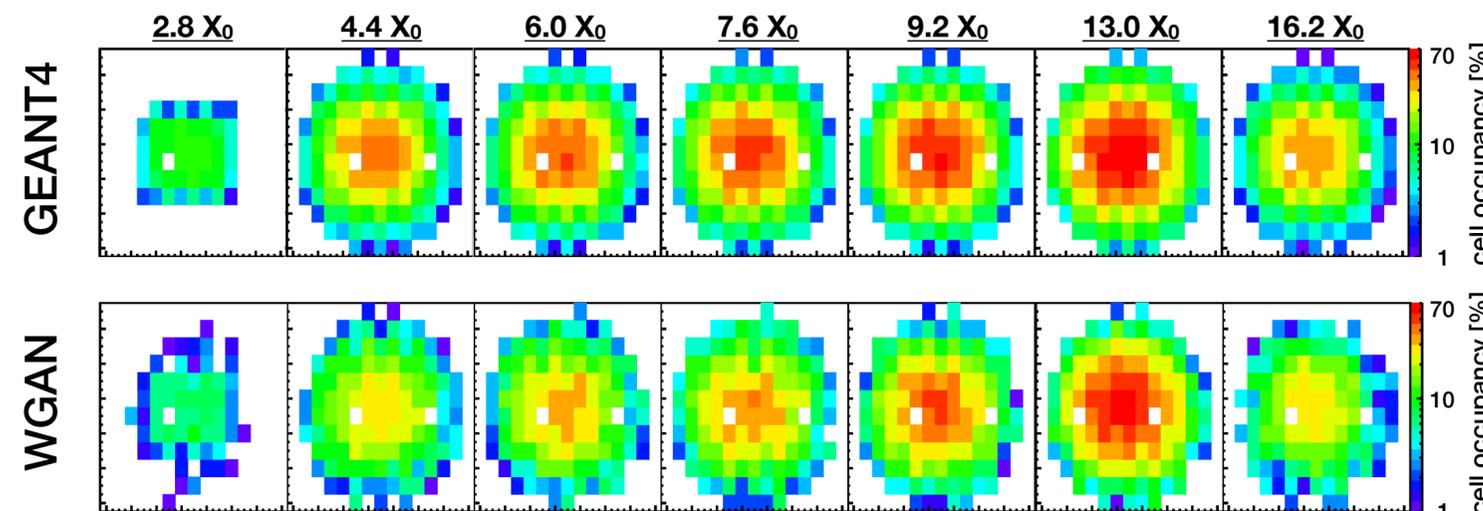
Published: *Comput Softw Big Sci* (2019) 3: 4

"Real data" = simulated 7-layer EE prototype from 2017.

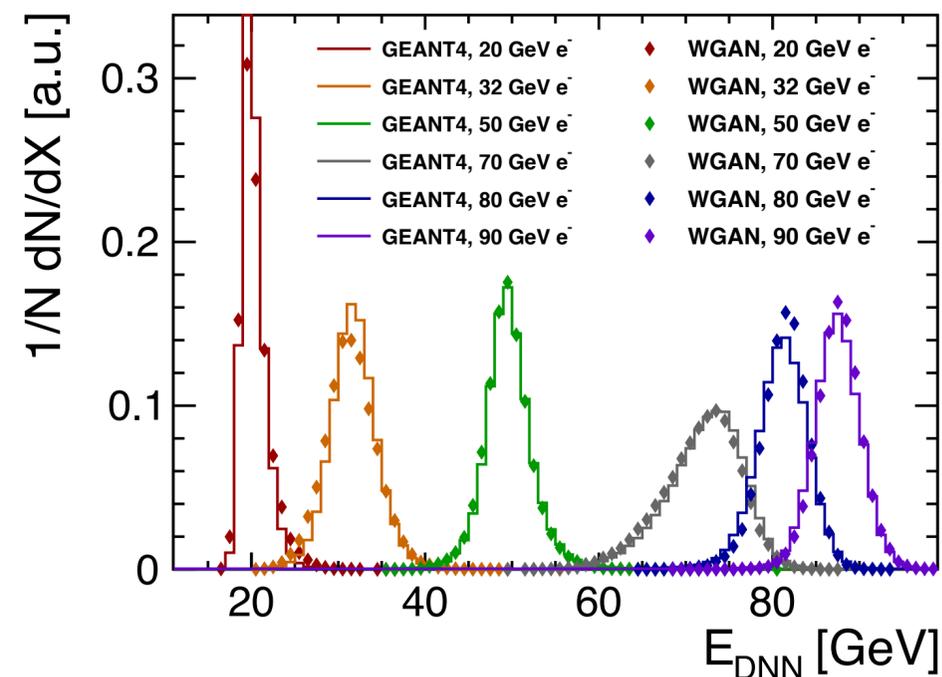
### → WGAN vs. GEANT4

- ▶ O(1000x) **faster**
- ▶ showers **similar**
- ▶ labels **respected**
- ▶ **x low-energy density**

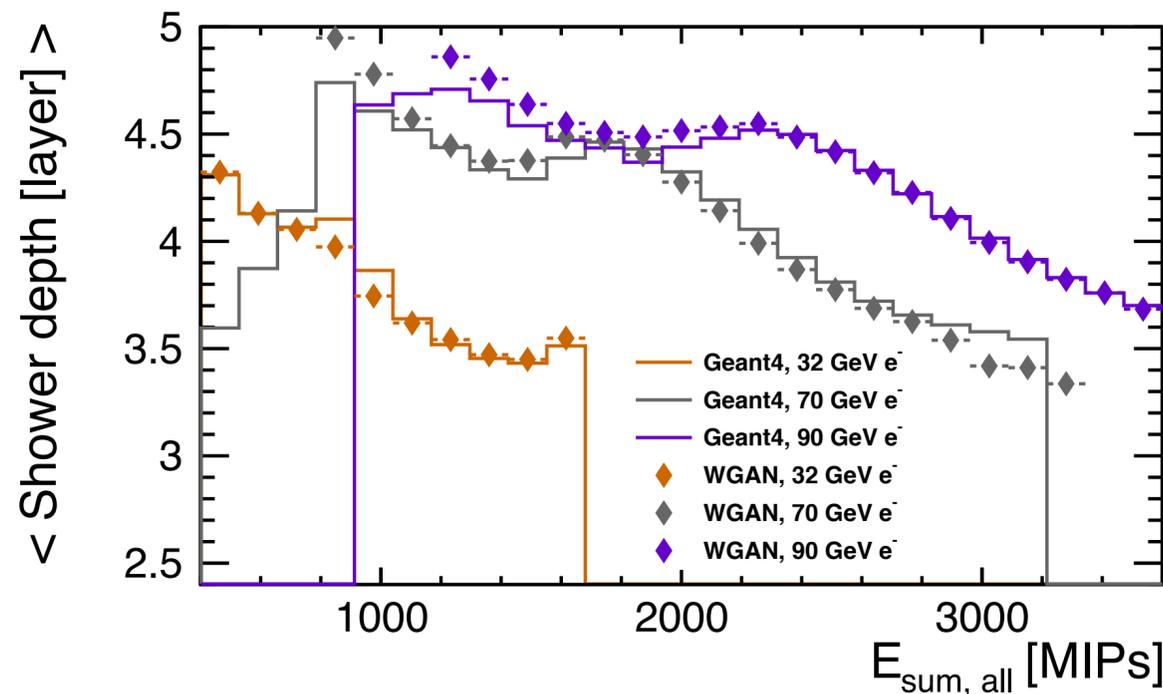
### → Average event display: Good.



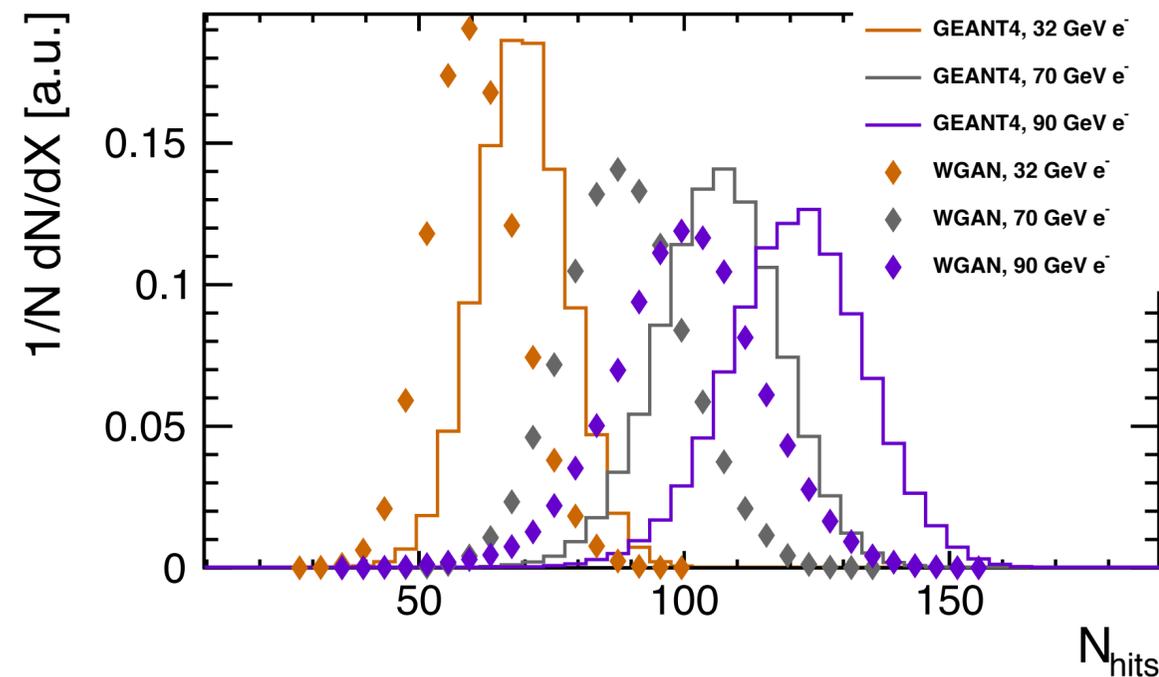
### → Observables: Good.

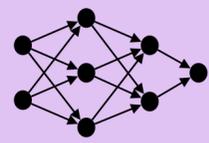


### → Correlations: Good.



### x Cell occupancy.





## Generative modelling of real test beam data

Developed WGAN training scheme re-applied...

- ... on **28-layer EE** prototype and ...

▸ Works!

➔ **Geometry-agnostic approach.**

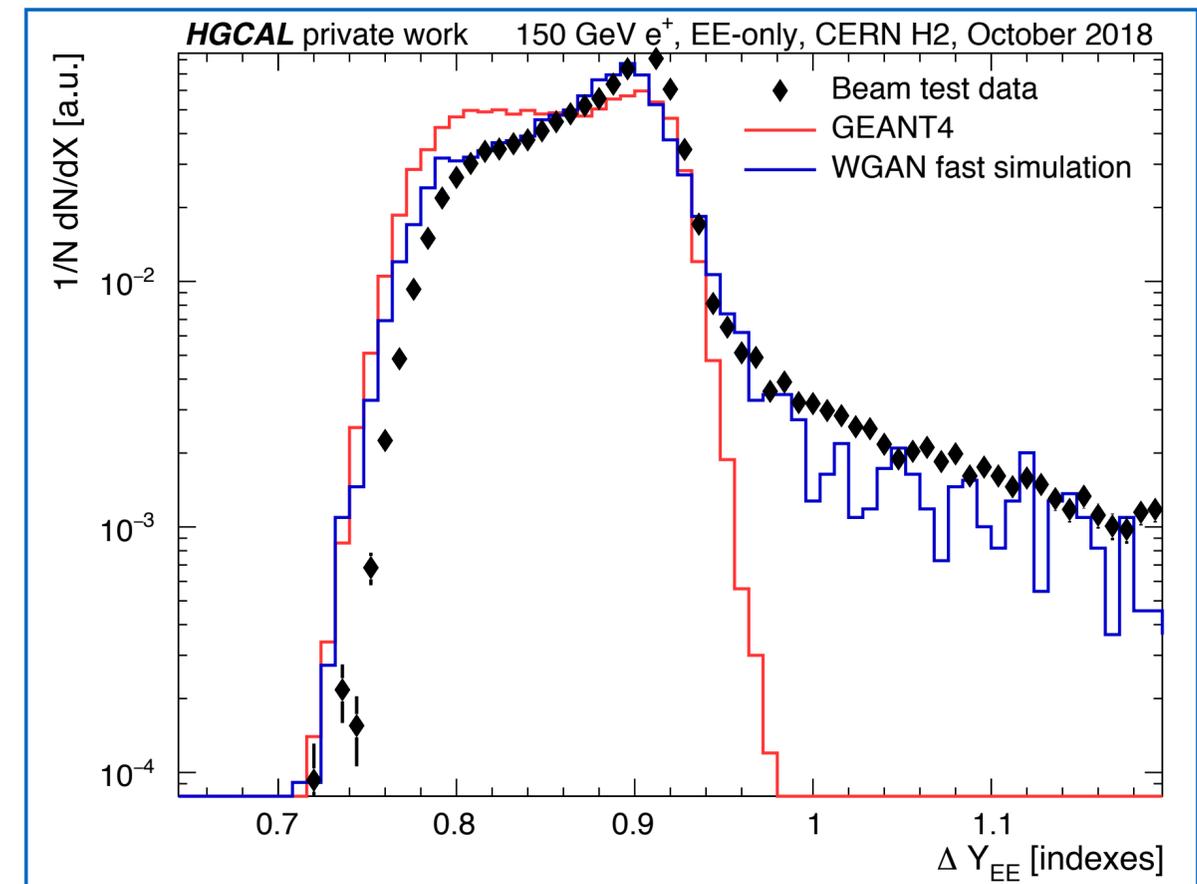
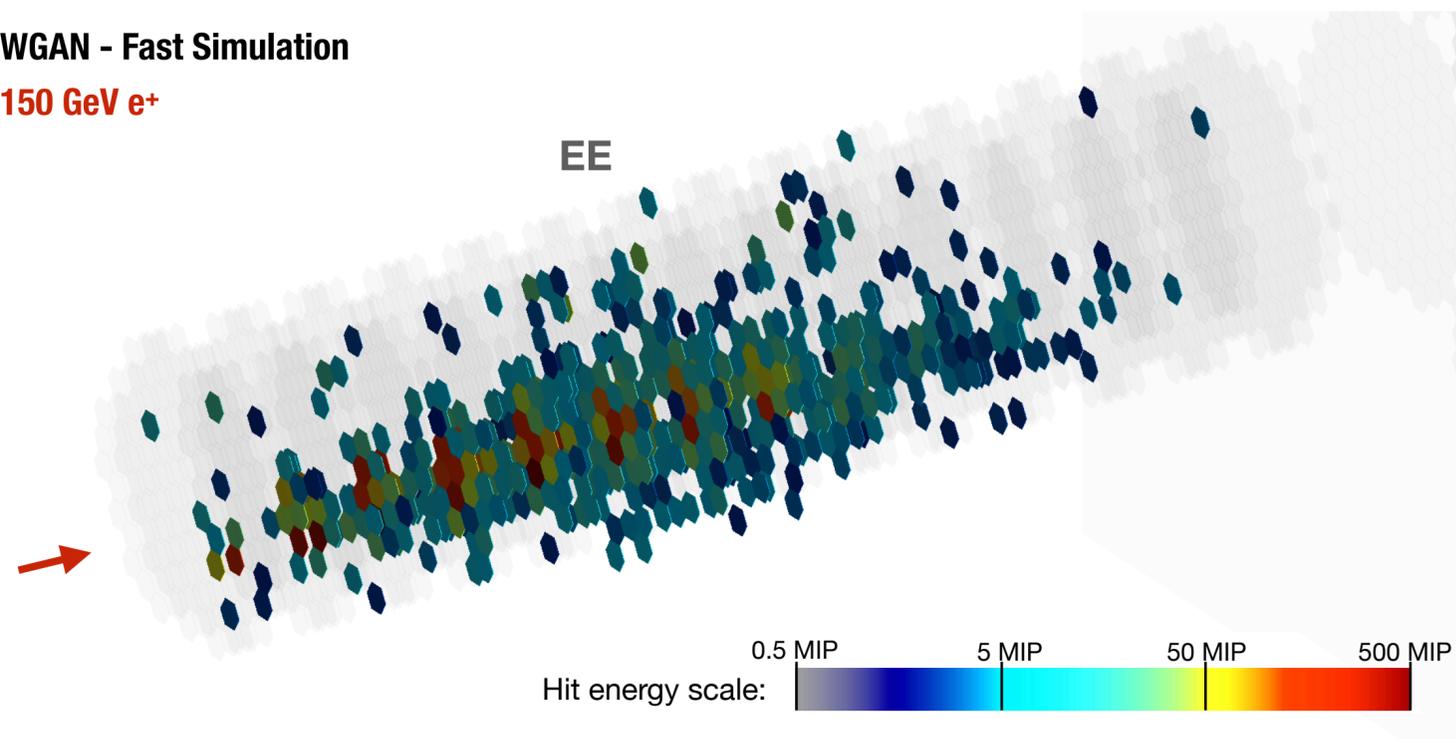
- ... with **real shower data.**

▸ Data vs. **GEANT4** vs. **WGAN**

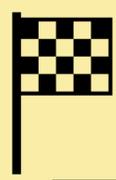
➔ **Evidence: WGAN > GEANT4.**

WGAN - Fast Simulation

150 GeV e<sup>+</sup>



Transverse shower spread.



## Prototype Testing in Particle Beam

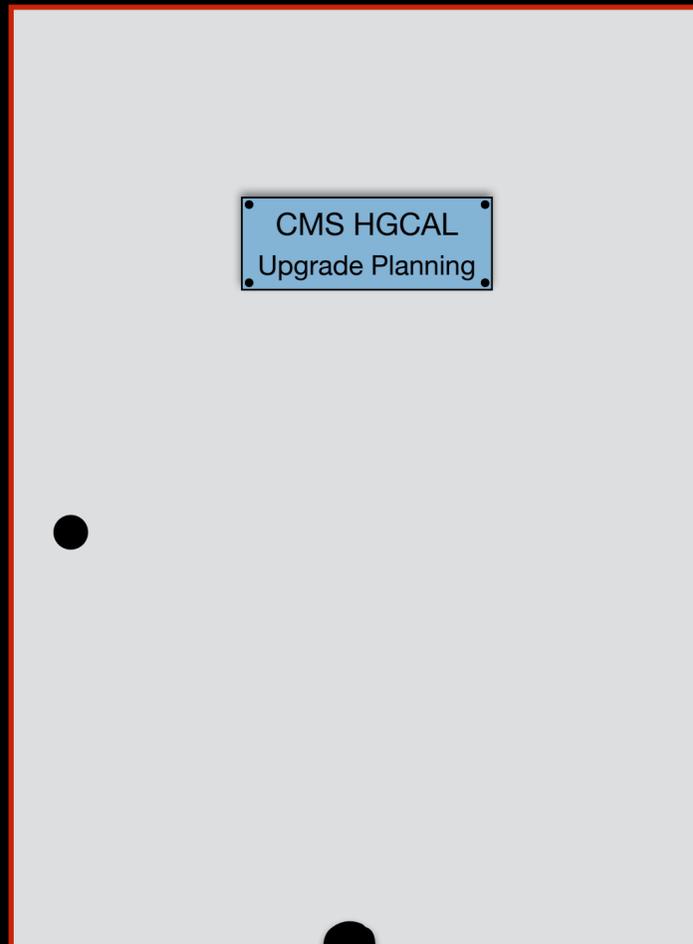
▸ Test results in **agreement** with HGCAL **design**:

a) **Modules are functional.**

- ✓ Proper detection of MIPs.
- ✓ Energy calibration in-situ.
- ✓ Timing capabilities.

b) **Performance as expected.**

- ✓ Longitudinal shower evolution.
- ✓ Energy linearity & resolution.
- ✓ Positioning capabilities for Particle Flow.
- ✓ Granularity helpful.



## Generative Modelling of HGCAL Data

- **Wasserstein** distance **suitable** for generative modelling of calorimeter data. HGCAL studied as one example.
- Orders of magnitude **speed-up**.
- Generated showers mostly appear to be **well-modelled**.

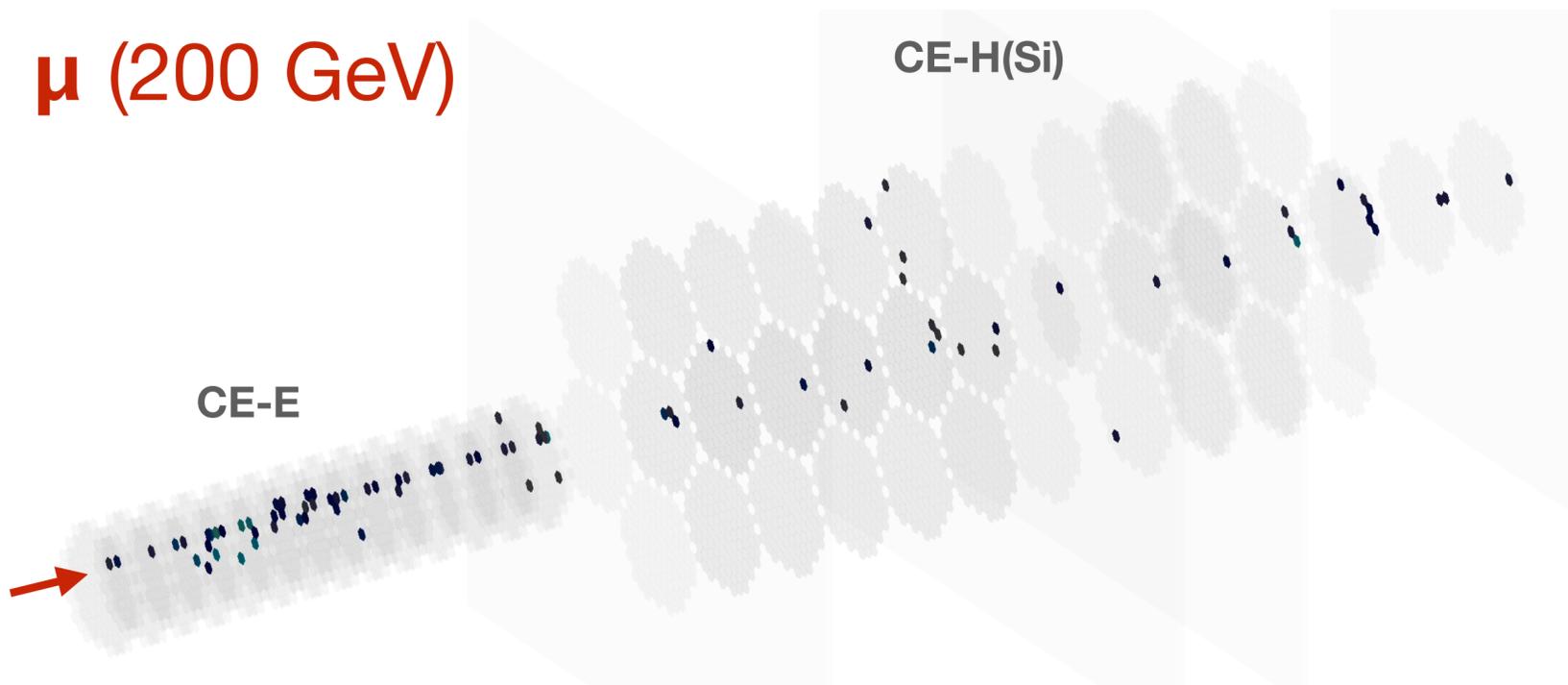
- ✓ Characterise components.
- ✓ Build prototypes.
- ✓ Tests with particles.
- ✓ Calibrate the detector & analyse data.
- ✓ Compare results to simulation.
- ✓ Apply machine learning.



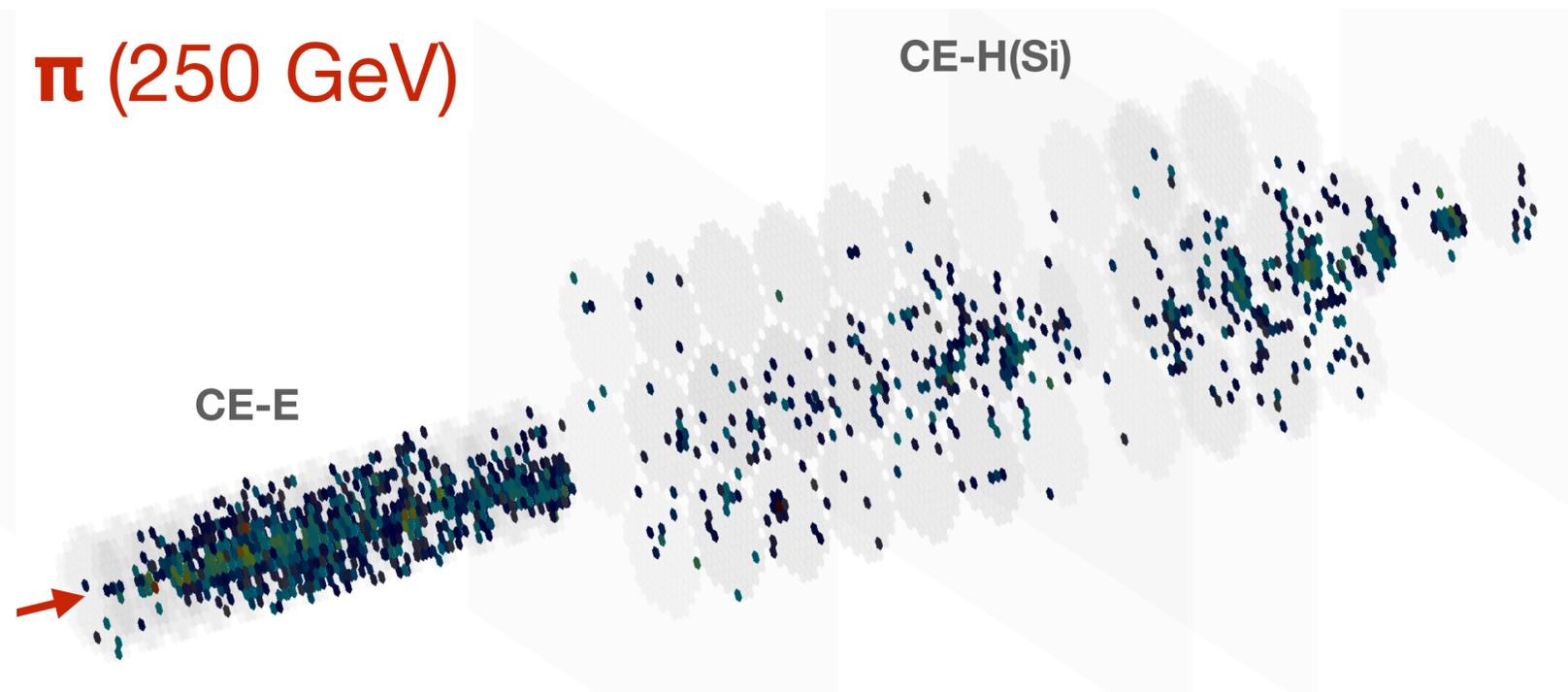
**Now**



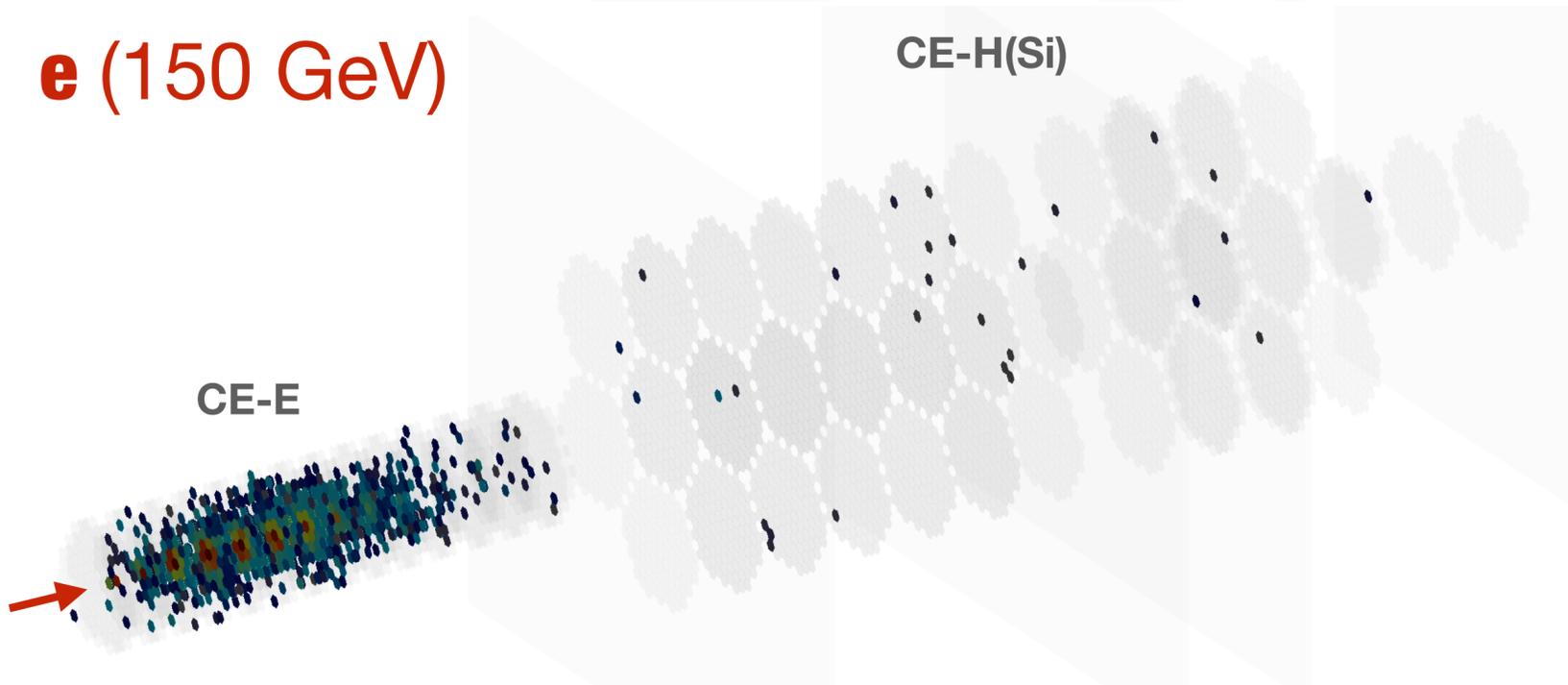
$\mu$  (200 GeV)



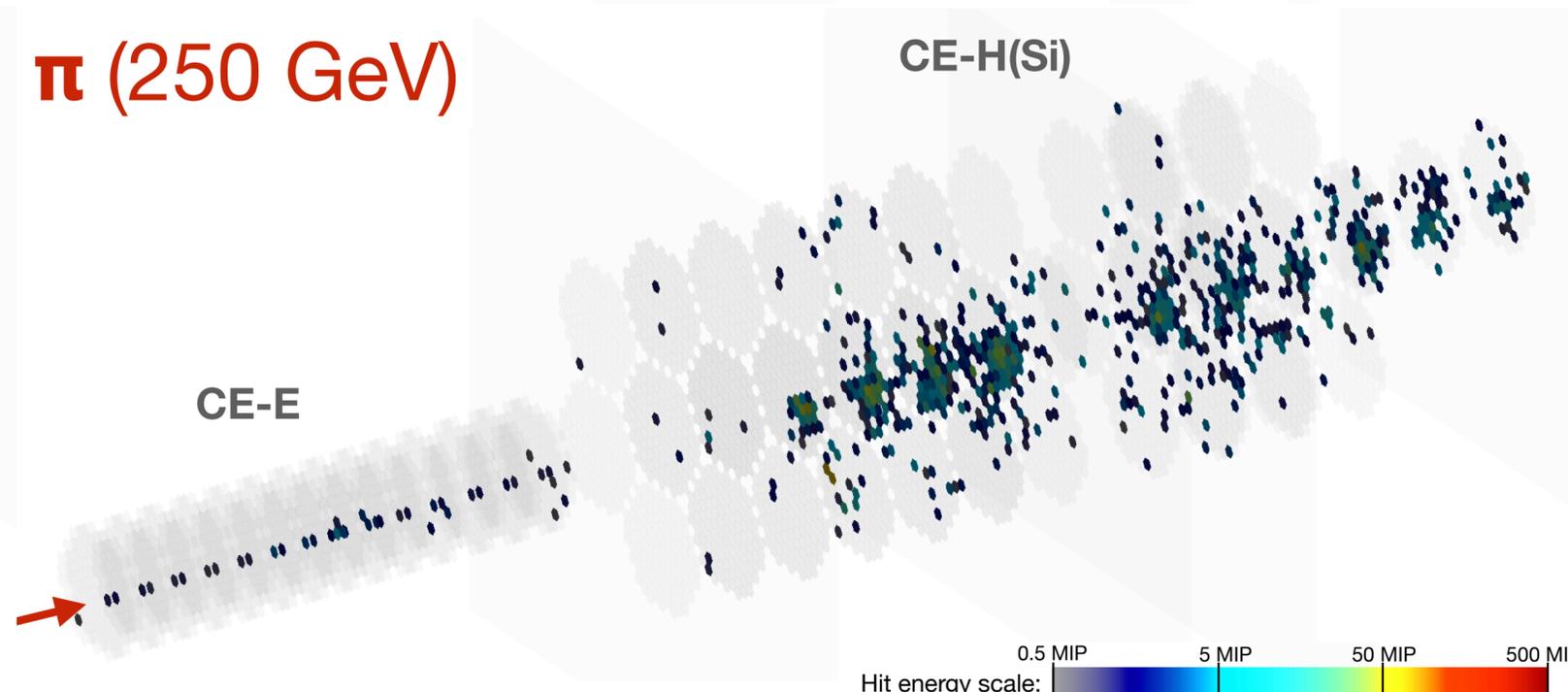
$\pi$  (250 GeV)



$e$  (150 GeV)



$\pi$  (250 GeV)





## Charged particles

- Ionisation (Bethe-Bloch) and multiple scattering.
- **Minimum ionising** for  $\beta\gamma = 3$  and  $E < E_{crit}$ :  $dE/dX = O(1 \text{ MeV cm}^2/\text{g})$ .

MIPs

## Particle showers

### $e^{+/-}$

- Bremsstrahlung dominant loss above  $O(50 \text{ MeV})$ :  $e^{+/-} \rightarrow e^{+/-} \gamma$ .
- Positron annihilation:  $e^+ e^- \rightarrow \gamma \gamma$ .

### $\gamma$

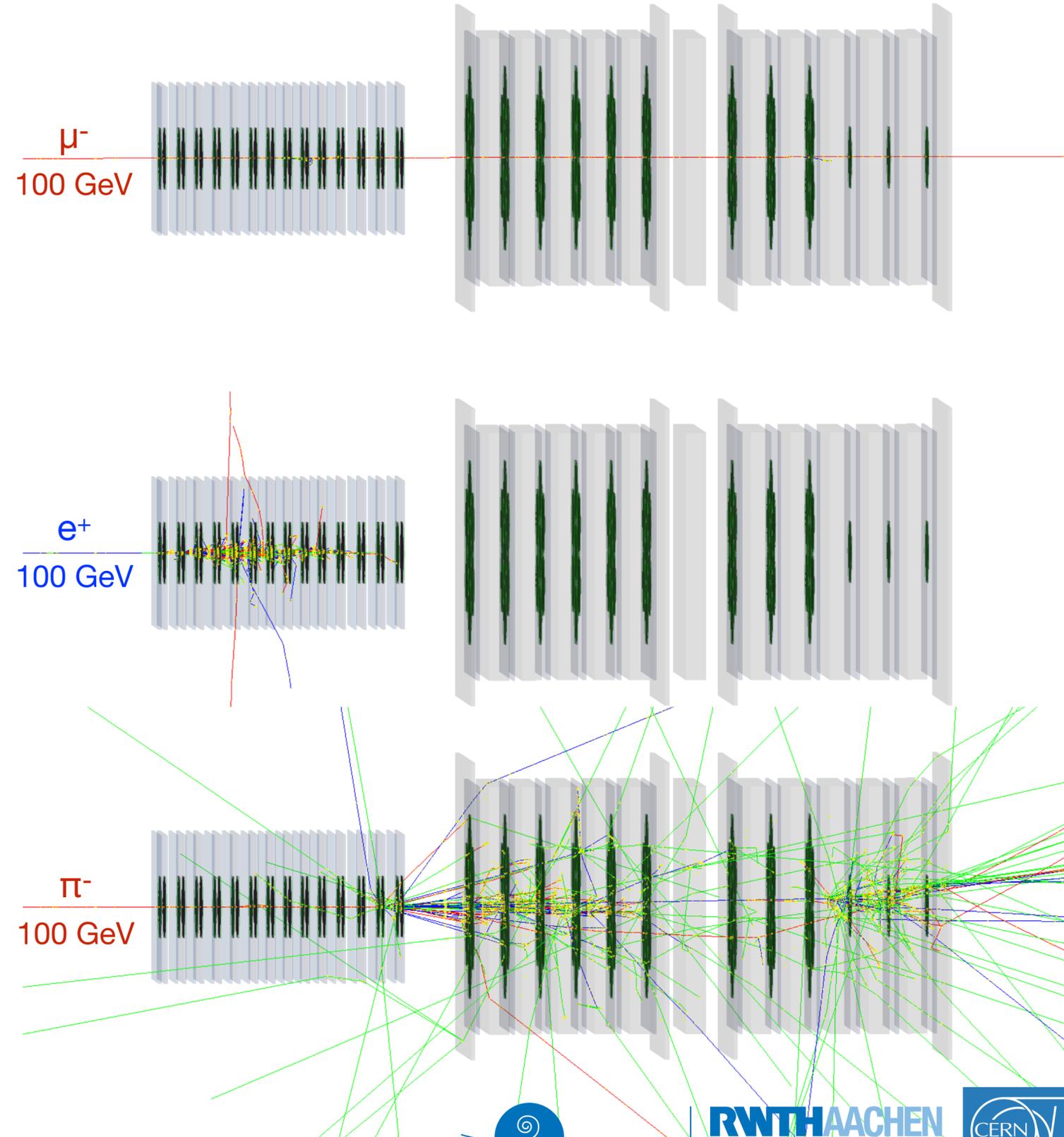
- Photo effect and Compton scattering for  $E < O(1 \text{ MeV})$ .
- Pair production dominant for high energies.
- **EM showers**: Compact. Scale:  $X_0$ .

electromagnetic (EM)

### Hadrons

- Nuclear reactions with target material and de-excitation processes.
- Only phenomenological descriptions available.
- **HAD showers**: Scale =  $\lambda_n > X_0$ . Sparser, wider, deeper than EM showers.
- $\pi_0 \rightarrow \gamma \gamma$ : EM component in hadronic showers.

hadronic (HAD)





## Noise

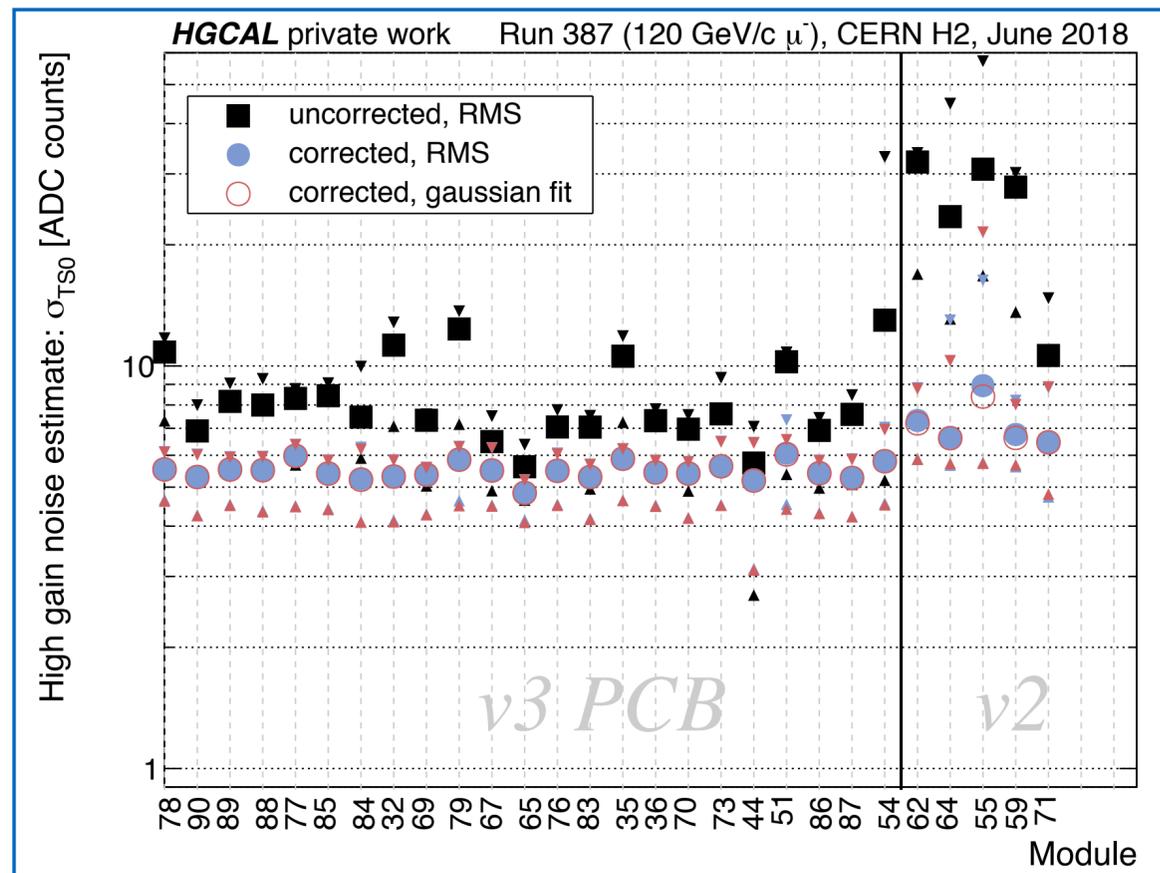
Noise from signal-free pedestal distributions.

- Total noise below 30 HG ADC counts.
- Common mode noise can be subtracted for each event  
—> noise reduction.
- Corrected noise ~ gaussian.
- Level below 10 HG ADC.

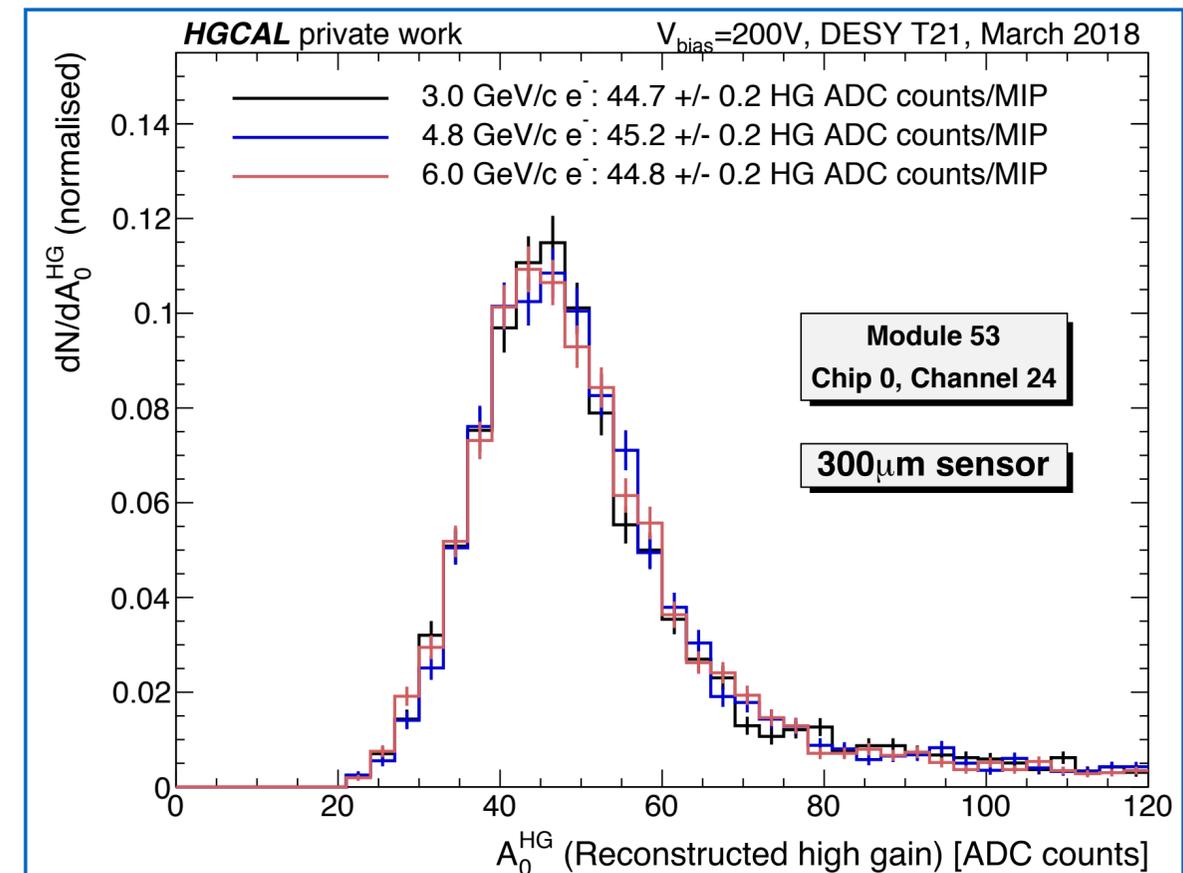
## Signals by minimum ionising particles

MIP = smallest relevant energy deposit

- Detectable in both gains.
- 1 MIP ~ 45 HG ADC counts.
  - MIP signal independent on energy for  $\beta\gamma > 100$ .
  - Scales with applied bias voltage.



➔ **Noise: Good.**



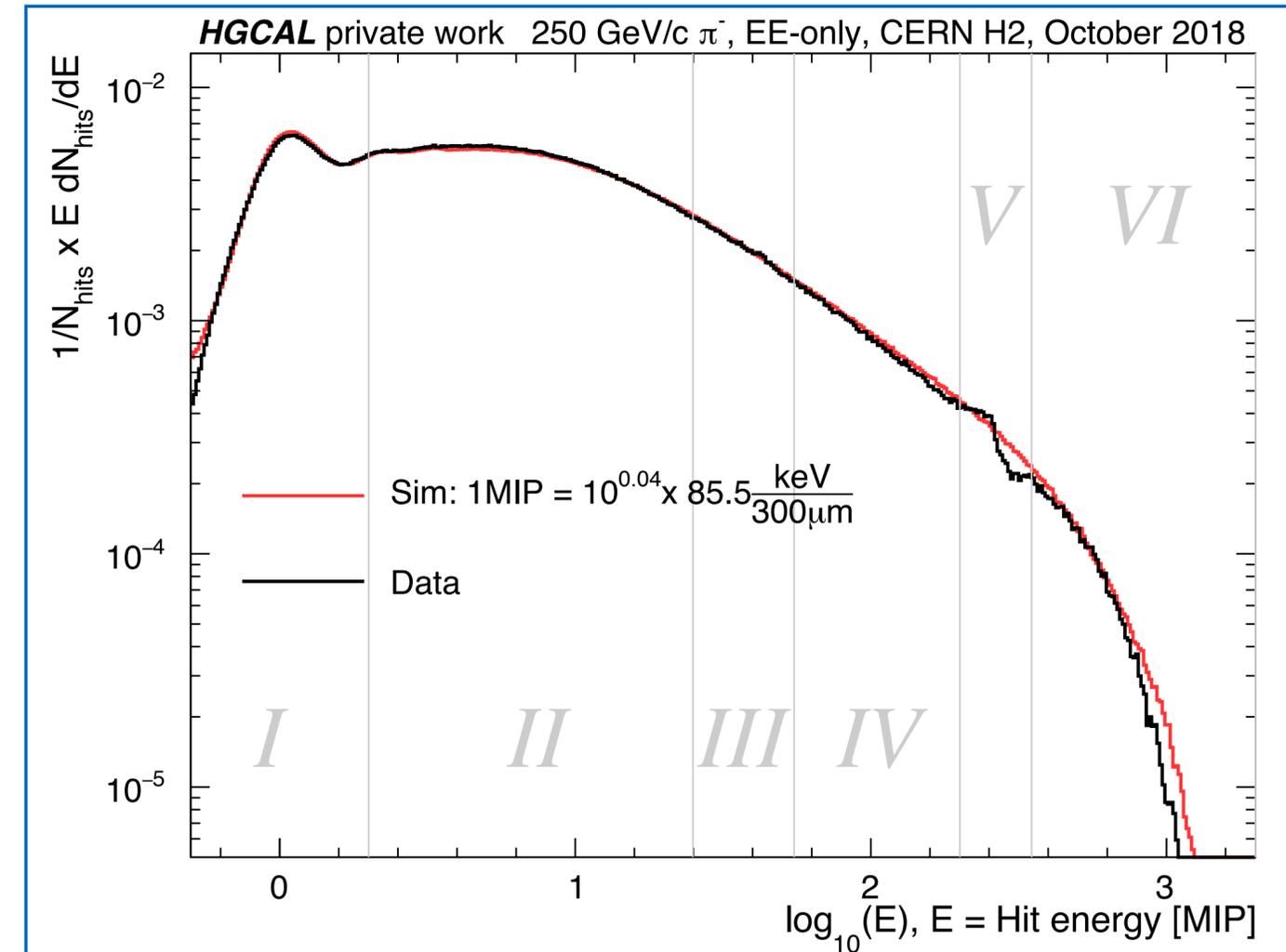
➔ **MIP signals expected: Good.**



- ✓ Gain linearisation.
- ✓ Scale calibration with MIPs.

### Hit energy spectrum: Data vs. simulation

- 6 interesting ranges: MIPs → TOT.
  - Allows for tuning of keV/MIP in simulation.
- *I* - MIP signal: good.
  - *II* - High gain usage: good.
  - *III* - HG/LG transition: no discontinuity = good.
  - *IV* - Low gain usage: good.
  - *V* - LG/TOT transition: ok.
  - *VI* - TOT usage: good.



➔ Energy calibration of EE and FH: Reasonable.

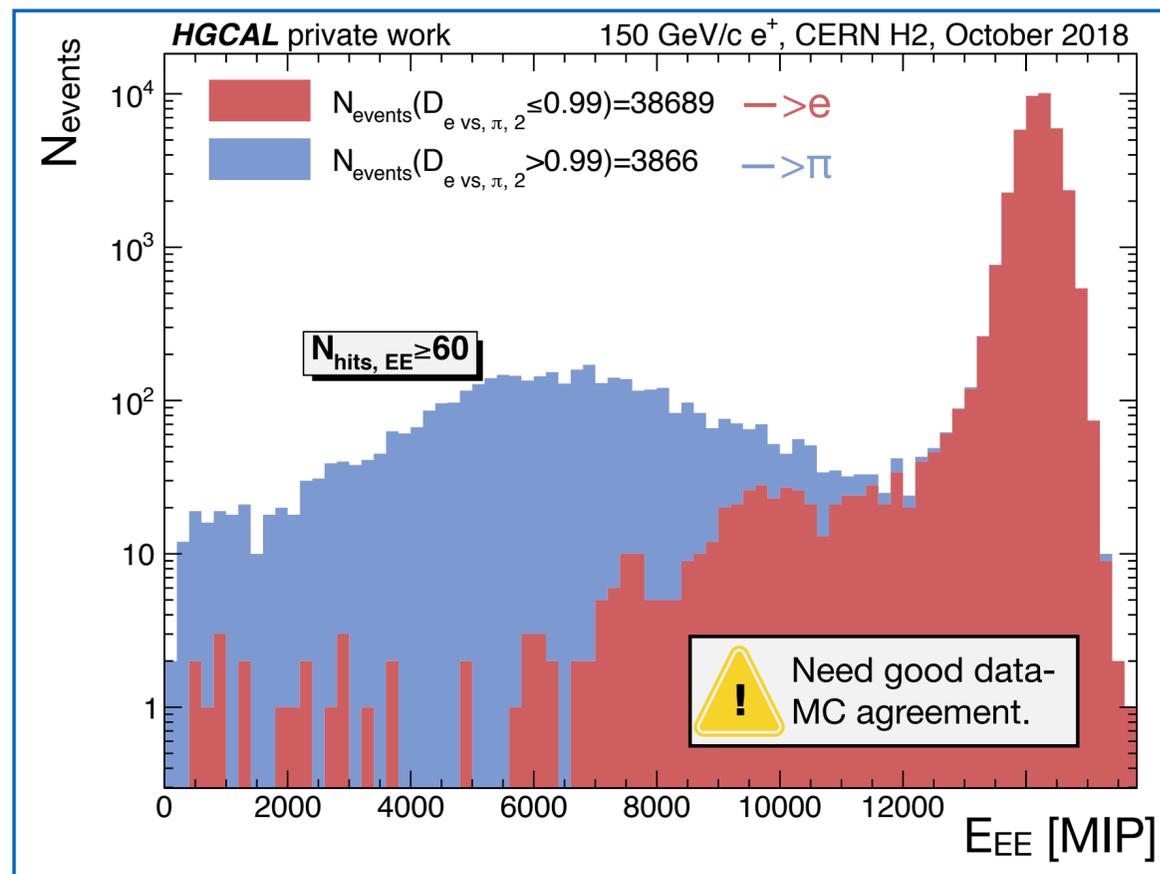


## e/ $\pi$ separation

Granularity for sophisticated task beyond classic calorimetry?

Shower “image” = input to convolutional neural network (CNN).

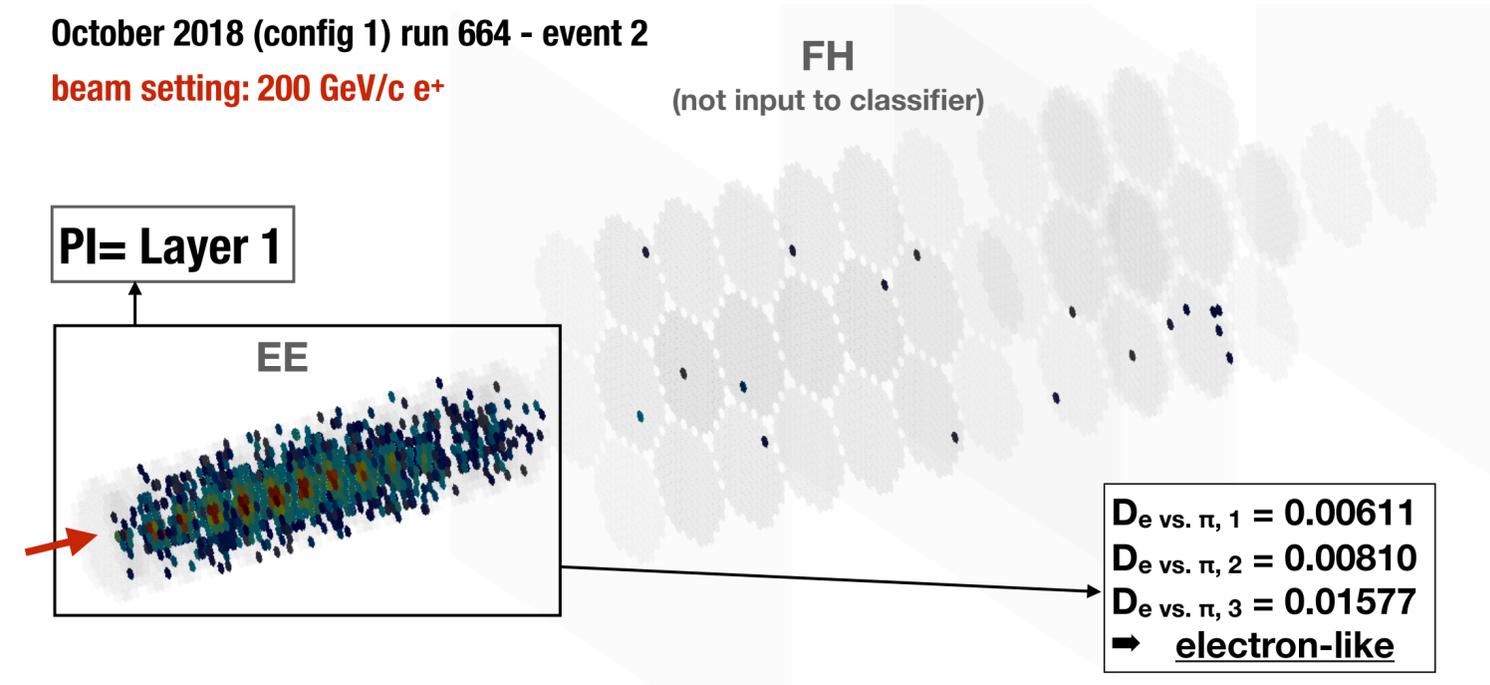
- $D_{e \text{ vs } \pi}(e) \rightarrow 0, D_{e \text{ vs } \pi}(\pi) \rightarrow 1$ . Training on simulated data.
- As expected: CNN-discriminator correlated to shower start.
- **Proof-of-principle demonstrated on test beam data.**



➔ Granularity exploitable for e/ $\pi$  separation: Good.

➔ Machine learning a suitable tool.

October 2018 (config 1) run 664 - event 2  
beam setting: 200 GeV/c e<sup>+</sup>



October 2018 (config 1) run 664 - event 2363  
beam setting: 200 GeV/c e<sup>+</sup>

