

The CMS Level-1 Trigger (L1T) is being upgraded for the High-Luminosity LHC, enabling advanced FPGA-based algorithms capable of identifying rare, unconventional, and beyond-the-Standard-Model (BSM) signatures in real time [1]. **This work** explores a **novel trigger strategy** based on electromagnetic **shower signatures** in the Drift Tube detectors, **targeting** both **high-momentum muons** and the decays of **long-lived particles (LLPs)**.

Shower in DT Chambers?

Localized **bursts of hits** produced by highly energetic muons undergoing **radiative energy losses**, e.g. bremsstrahlung, **or** by the **decays of LLPs** occurring **beyond the inner CMS detector**.

Recovering trigger efficiency

Muon reconstruction in L1T is based on the cross-matching of trigger primitives (TPs) [3]. For **high- p_T muons**, **showers cause ambiguities** in the Analytical Method (AM) resulting in a **faulty muon path** (see), this **degrades reconstruction of kinematics** and leads to **efficiency losses** of up to 10% (Fig. 2) [2]. **early identification of this signature** could help **recover muon reconstruction performance** and improve trigger efficiency.

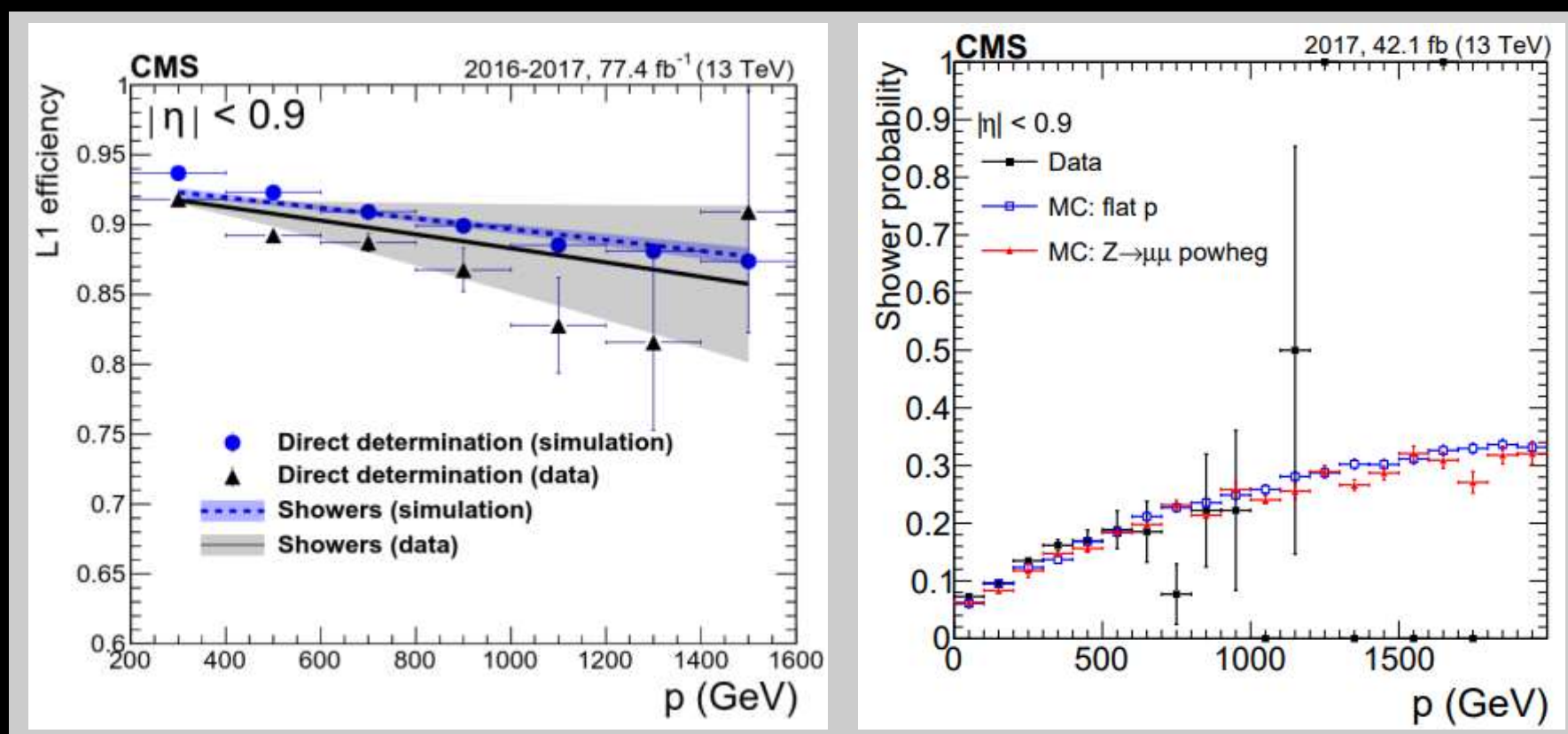


Figure 2. (left) shows how efficiency decreases with increasing muon momentum, this is directly connected with the increase of the number of muon showers, as their production probability (right) grows with momentum. [2]

A **geometrical matching** between AM TPs and SP segment representations was proposed. This approach **flags muon primitives pointing toward shower regions**, providing a tag that downstream track finders can utilize to handle potential track loss [4].

Defining: $\vec{L}_1(u) = \vec{a} + u(\vec{a} - \vec{b})$ and $\vec{L}_2(t) = \vec{p} + t\vec{d}$
There is a **match** if $\{(t, u) \mid \vec{L}_1(u) = \vec{L}_2(t)\}$

That could be **reduced to evaluate**:

$$u = \frac{\det[\vec{v}_2, -\vec{d}]}{\det[\vec{v}_1, -\vec{d}]} \quad \text{and} \quad t = \frac{\det[\vec{v}_1, \vec{v}_2]}{\det[\vec{v}_1, -\vec{d}]}$$

With $\vec{v}_1 = \vec{a} - \vec{b}$, $\vec{v}_2 = \vec{p}_1 - \vec{a}$, and $|\vec{v}_1 - \vec{d}| \neq 0$

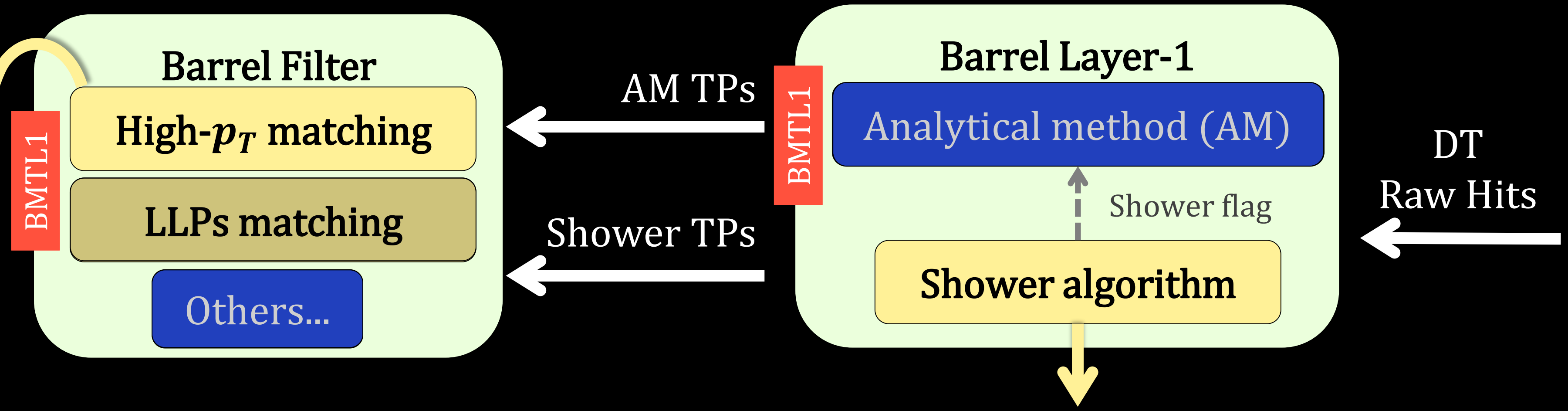
- Simulation studies using only ϕ -plane information show showering-muon tagging **efficiencies above 80%**. Extensions to **include longitudinal (θ)** information are currently under development and are expected to further improve matching performance.
- A **preliminary firmware implementation** achieves **sub-BX latency** using only 4.3k LUTs and 5.6k FFs. **These for a single CMS wheel**; future developments **need extend the design to full detector coverage**.

Future work...

A dedicated **Geant4-based simulation of CMS like Drift Tube detectors** was **developed** to provide a **simplified, controlled and flexible environment** for shower studies. This framework intends enable less ambiguous truth-level definitions and more reliable performance evaluations.

BSM applications of shower primitives are beginning to be investigated. One promising direction is the identification of nearby shower signatures, which could point to a common displaced vertex and potentially reveal the presence of a LLP decay.

Two steps processing



Monitors hit **multiplicities** within a **400 ns time window** (to consider the drift time) and generates compact **shower primitives (SP)** encoding timing and spatial information when predefined **threshold** is exceeded (Fig. 1) [4].

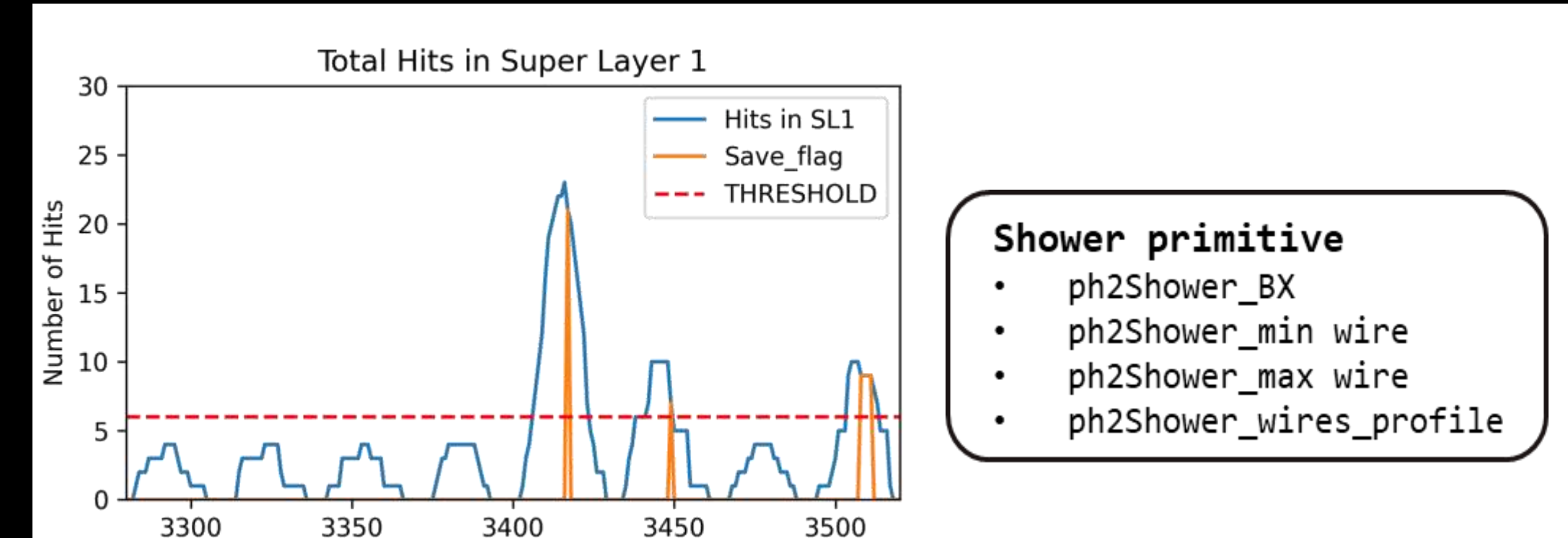


Figure 1. (left) Illustrative examples of hits trending over time, (right) shower primitive payload.

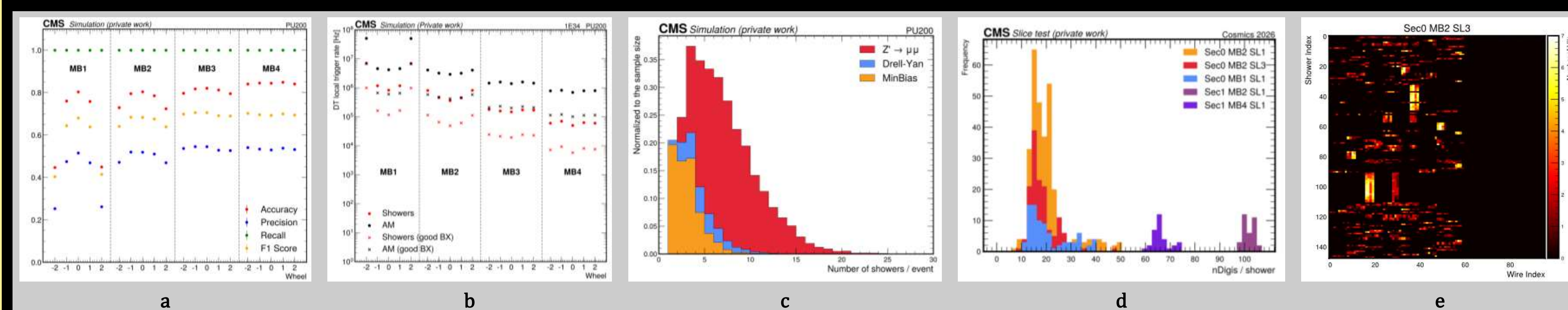


Figure 3. (a) Performance metrics of the shower algorithm: accuracy, precision, recall, and F1 score. (b) DT Local trigger rates. Good BX for these MC samples is 20. (c) Number of showers per event for different physics scenarios. (d) Number of digits of shower primitives produced during CMS slice tests. (e) Wires profile of shower primitives produced during CMS slice tests.

- **Ultra-low resources** consumption: **~2.5k LUTs**, **~2.5k FFs**, and **sub-BX latency**.
- Simulated data studies shown approximately **80% of accuracy** (Fig. 3a) and almost **10 times less** local trigger rate (Fig. 3b) **than** the expected for the **AM algorithm**. Current studies prioritize recall.
- Comparisons across different physics scenarios indicate **lower primitive production rates for low-energy events**, as expected (Fig. 3c).
- The algorithm was **deployed during the 2026 DT Slice tests** to evaluate its performance with real data. Preliminary results are under study, although the currently available statistics remain limited (Figs. 3d-e).

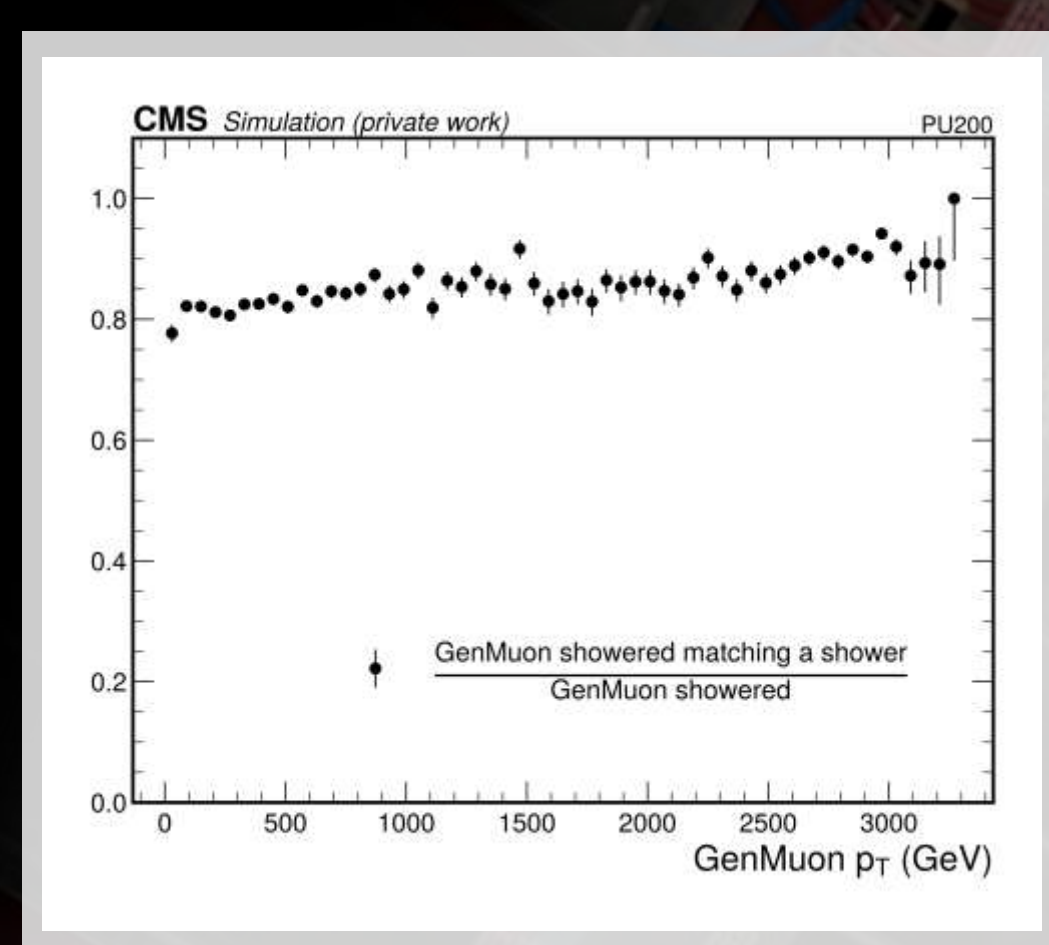
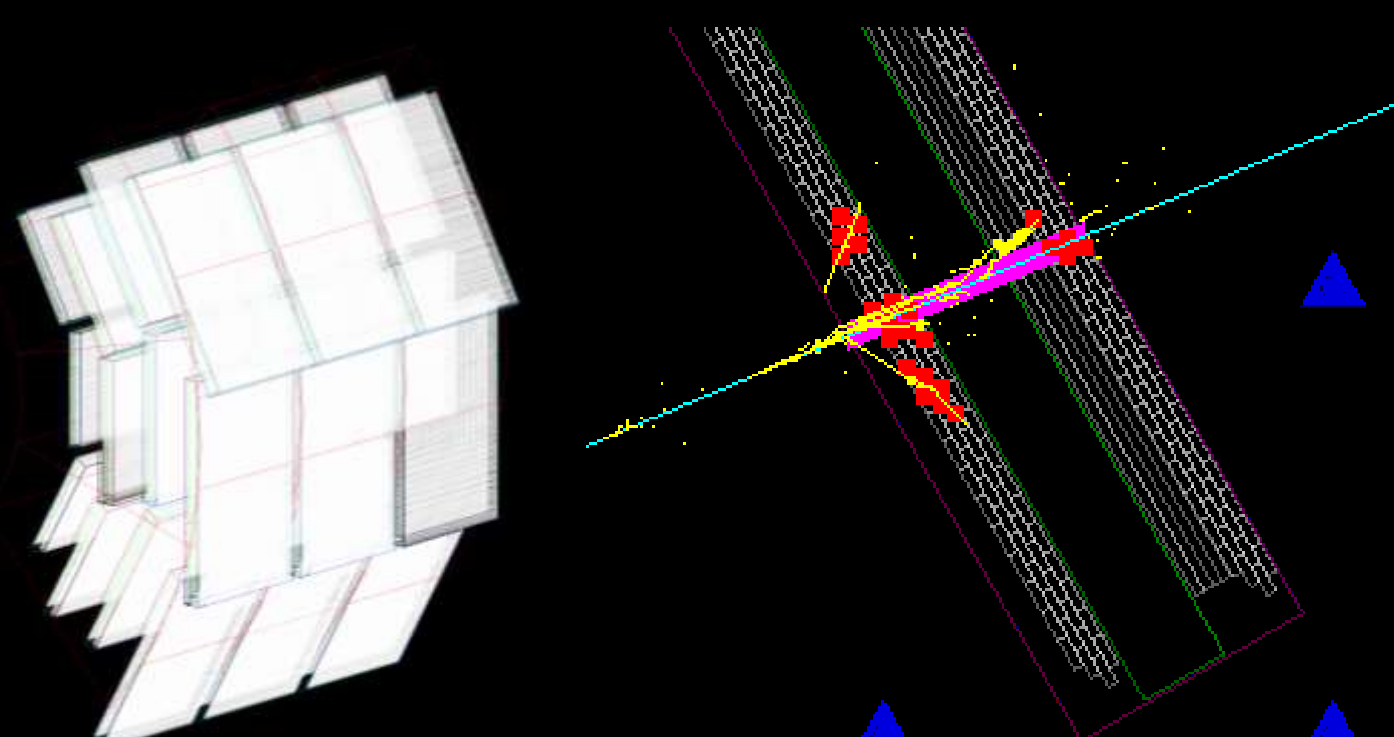


Figure 4. Identification efficiency, defined as the fraction of genmuons that produce a shower signature and are successfully tagged by the algorithm.

Metrics are defined such as:

- Accuracy = $(TP + TN) / (TP + TN + FP + FN)$ - Overall correctness
- Precision = $TP / (TP + FP)$ - of all predicted positive, how many correct?
- Recall = $TP / (TP + FN)$ - of all actual positive, how many found?
- F1 Score = $2 \cdot (Precision \cdot Recall) / (P + R)$ - harmonic mean - balances P and R

TP, FP, TN, and FN means true/false positive/negative cases respectively



Research
Software
Toolkit



References



* Paths illustrations are not real cases of CMS reconstructed trajectories.