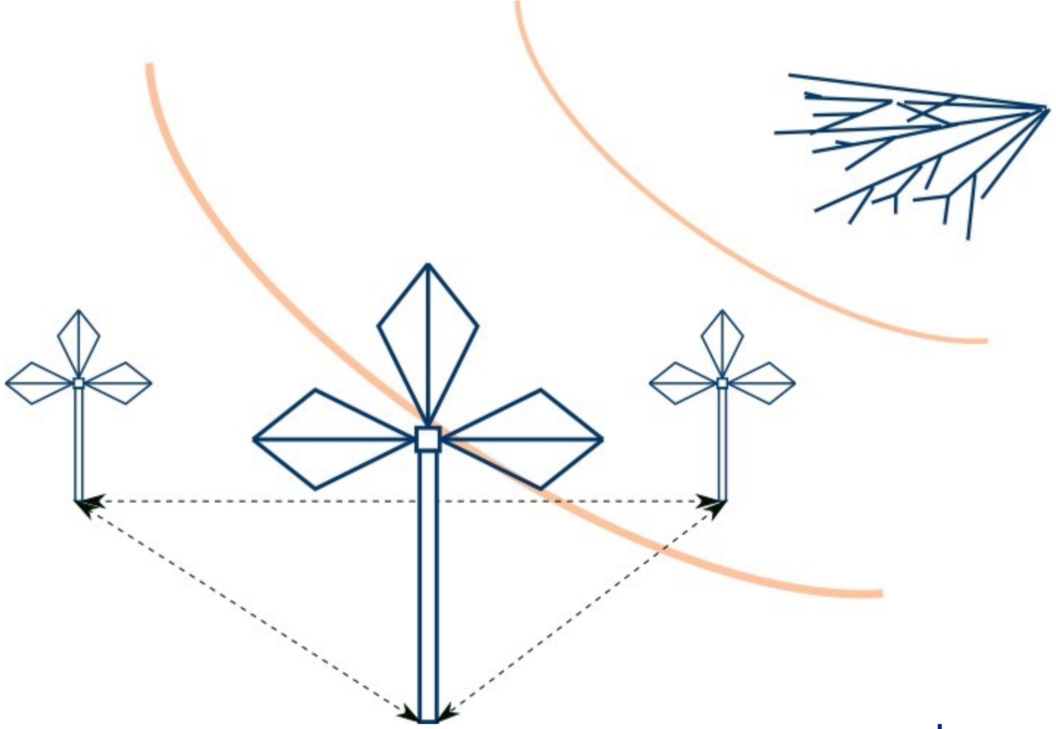


Development of an Autonomous Detection-Unit Self-Trigger for GRAND

Pablo Correa
for the GRAND collaboration

CHICAGO 2024

10th ARENA Workshop | 14 June 2024

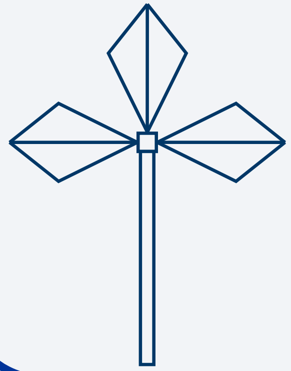
GRAND LPNHE PARIS anr DFG cnrs

The NUTRIG Project

GRAND overview:
Kumiko Kotera's talk

- GRAND requires **autonomous radio trigger**
  - Maximum **purity**
  - Maximum signal selection **efficiency**
  - Minimum **SNR threshold**
- Trigger must be **scalable** to GRAND10k arrays
  - Minimum **cost**
  - Minimum **data bandwidth**
- **NUTRIG**: Develop scalable radio trigger
  - **First level trigger** (FLT): **this talk**
  - **Second level trigger** (SLT): Jelena Köhler's talk
  - **Air-shower emission model:** Lukas Külzow's talk

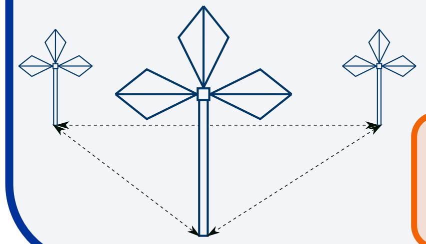
Single detection unit (DU) trigger rate



GP300 nominal:
1kHz

**NUTRIG FLT target:
100 Hz**

Array of DUs trigger rate



GP300 nominal:
10 Hz

**NUTRIG SLT target:
1 Hz**

GRAND Trigger Scheme

NUTRIG project

L1
FLT-0
on FPGA
Threshold trigger on trace/wavelet

1 kHz →

L2
FLT-1
on CPU
Template fitting vs CNN

100 Hz →

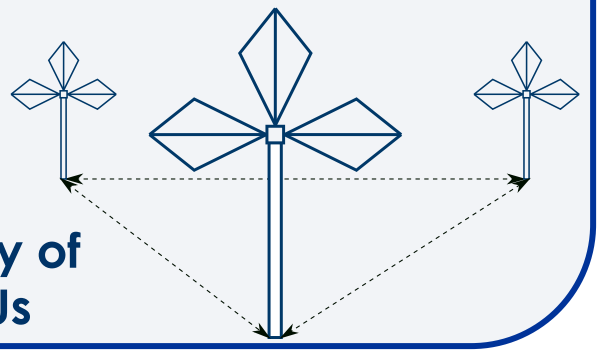
L3
SLT
on central DAQ
Crude reconstruction with FLT-1 data

Currently on hardware

This talk
Sandra Le Coz,
Jean-Marc Colley, PC

Single DU

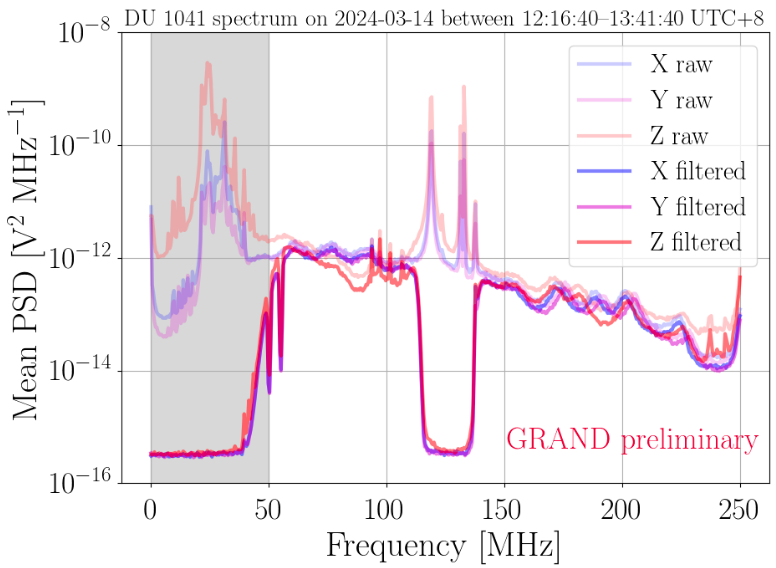
Jelena Köhler's talk



Array of DUs

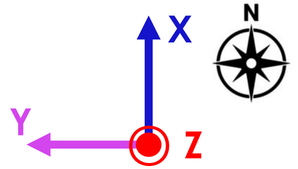
Offline FLT-1 Database: Background

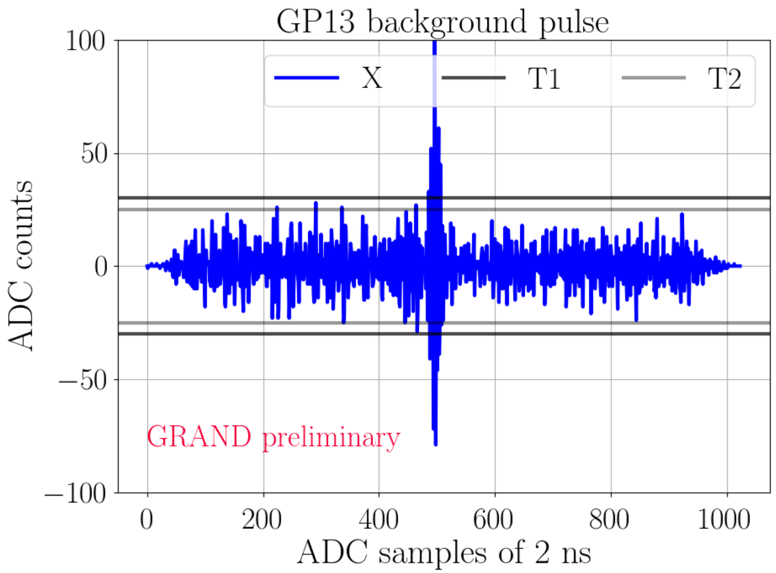
- **GRANDProto13** minimum-bias data
  - **Period**: 16 January 2024 – 24 April 2024
  - Traces of ~2 μs recorded **every 10 seconds**
- Offline **digital filters**
  - **Shortwaves**: <50 MHz
  - **Aeronautic communications**: 113.5–139.5 MHz
- Offline **double-threshold** FLT-0
  - **Similar** to current trigger on hardware
  - Only applied on **channels X & Y**
  - First T1 crossing is **FLT-0 trigger time t_0**
  - T1 & T2 **not representative** of GP300 trigger rate!



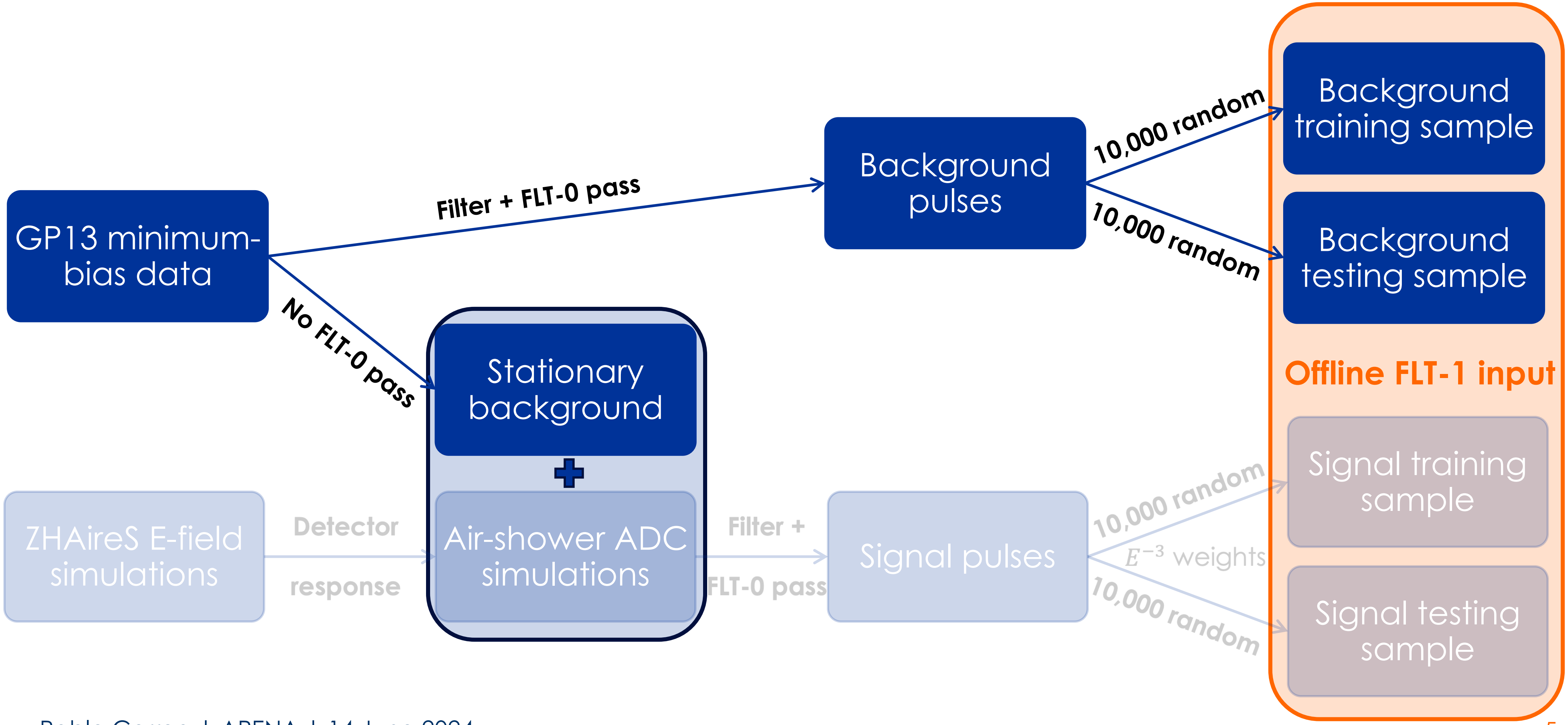
GP300 details:
Simon Chiche's talk

14-bit ADC @ 500 Msps
1 ADC count = 109.86 μV
1 ADC sample = 2 ns





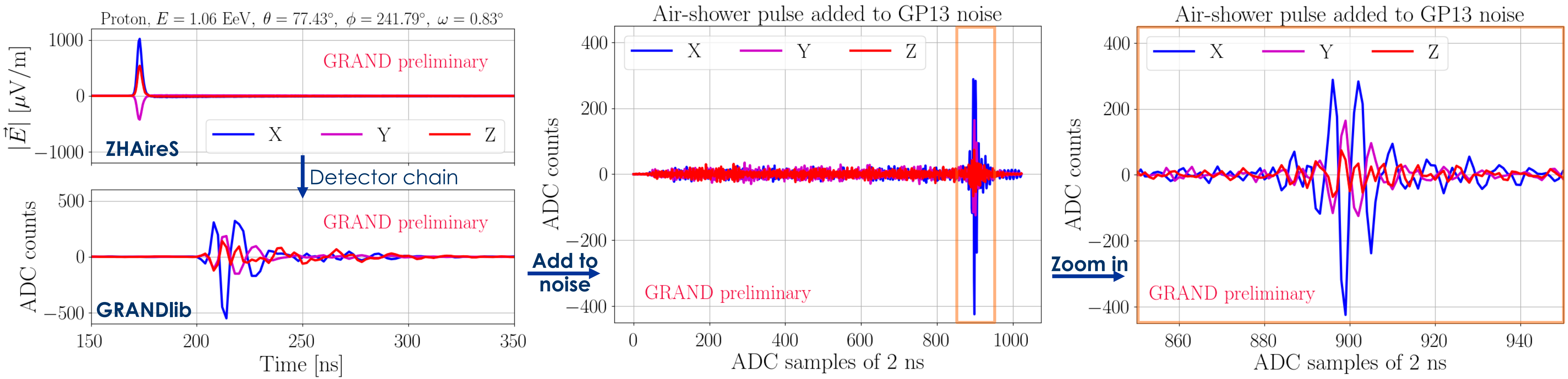
Offline FLT-1 Database Construction



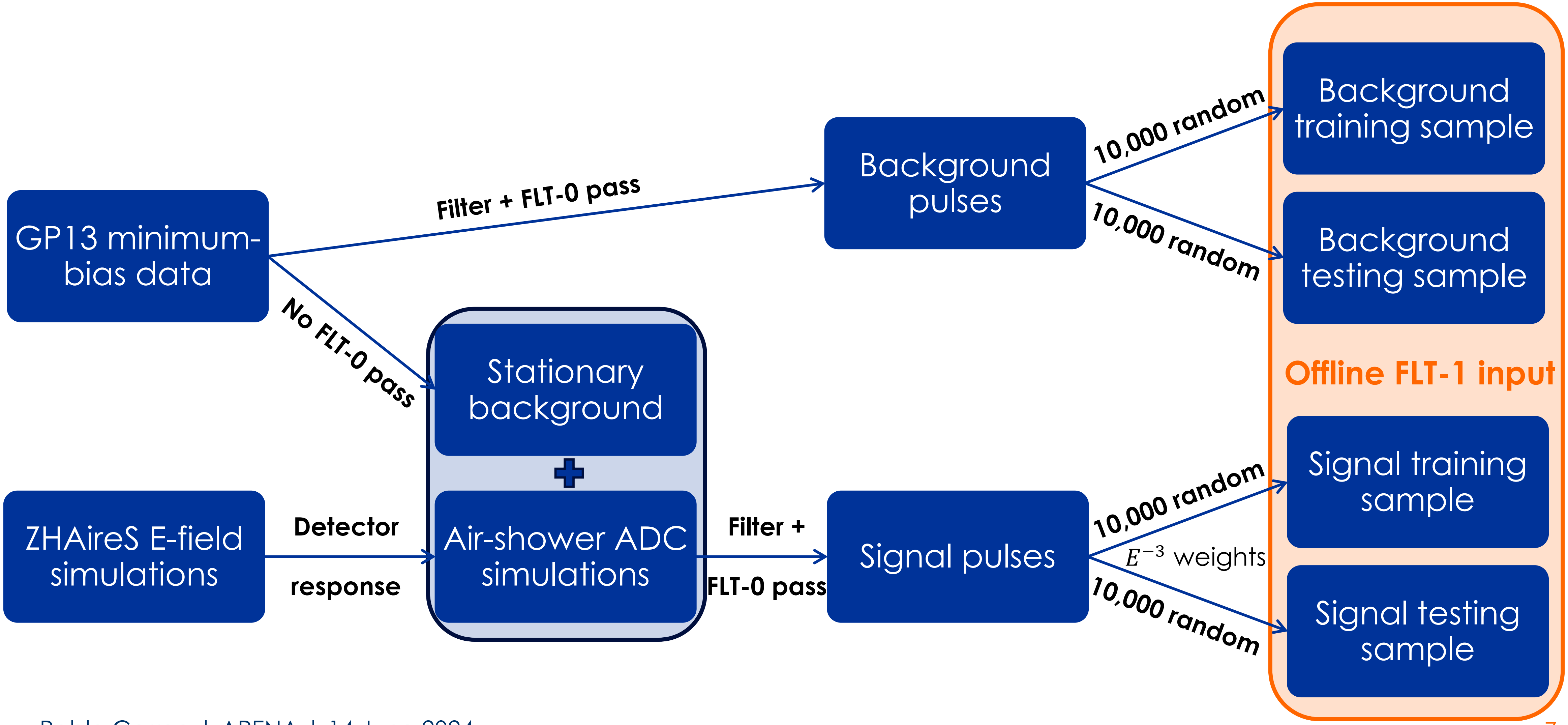
Offline FLT-1 Database: Signal

- 12,500 **ZHAireS** E-field simulations
- Process E-fields with **GRANDlib**
  - Realistic simulation of **GRAND detector pipeline**
  - Antenna response + RF chain **up to ADC**
- **Add to stationary noise** from GP13 data
  - **Apply digital filters** after adding signal to noise

ZHAireS simulations
Proton primary
$\log_{10}(E/\mathrm{eV}) \in [16.5, 18.5]$
$\theta \in [30.6°, 87.3°], \phi \in [0°, 360°]$



Offline FLT-1 Database Construction



FLT-1: Template Fitting

Template library (X+Y)
ZHAireS + GRANDlib simulations
Sampled for different θ and ω

- Step 1: **Fit pulse-peak time** t_p
  - **Maximum correlation** between trace V and template T [Henrichs+ PoS ICRC2023 259]

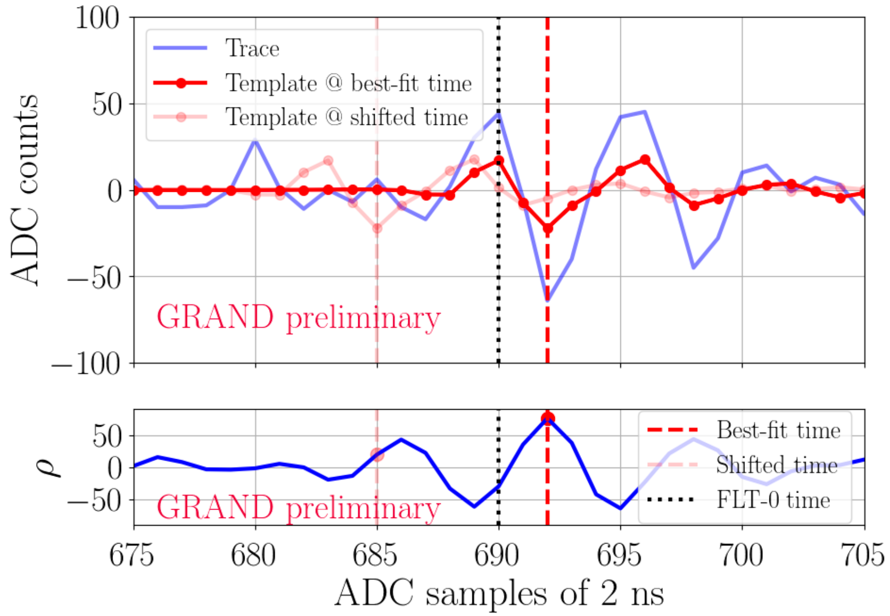
$$\rho(\tau) = \int T(t)\, V(t+\tau)\, \mathrm{d}t$$

$$\hat{t}_p = \mathrm{argmax}_\tau\, |\rho(\tau)|$$

- Step 2: **Fit amplitude** κ
  - **Least-squares fit** of template amplitude to trace

$$\chi^2_T = \Sigma_i\, |V(t_i) - \kappa T(t_i)|^2/\sigma_i^2, \quad \sigma_i = \mathrm{RMS}^2/V(t_i)$$

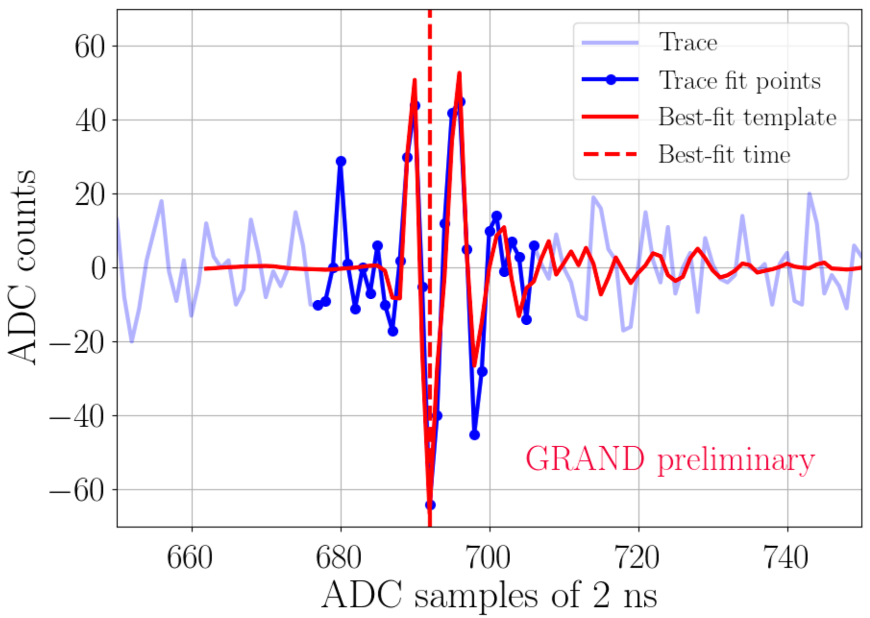
$$\hat{\kappa} = \mathrm{argmin}_\kappa\, \chi^2_T$$



Repeat steps 1 & 2 for 96 templates

Find **best-fit template**
$$T_b = \mathrm{argmin}_T\, \chi^2_T$$

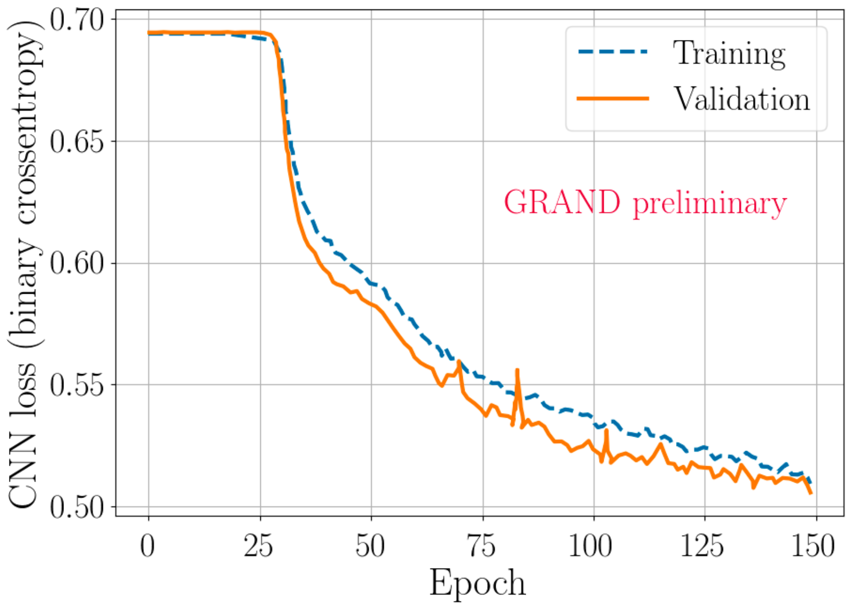
Compute **test statistic**
$$\mathrm{TS} = \log_{10} |\hat{\kappa}\rho(\hat{t}_p)|$$



FLT-1: Neural Network

Developers
Sandra Le Coz (LPNHE)
Jean-Marc Colley (LPNHE)

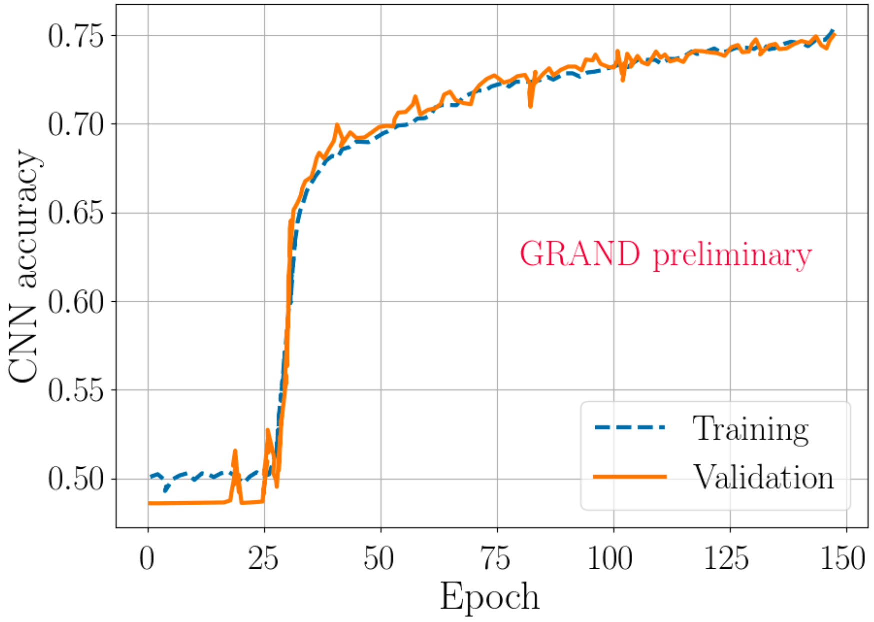
- **Convolutional neural network** (CNN)
  - Keras/**Tensorflow** framework (Lite for online)
  - **2 convolution layers** (3 @ ICRC 2023)
    [Le Coz PoS ICRC2023 224]
- **Training** sample: 2 x 10,000 traces (S+B)
  - **Validation** subsample: 10% of training sample
- Minimization of **loss function**
  - **Gradient descent** over 150 epochs
- **Accuracy** of CNN
  - Proportion of **well-classified traces**
    - **Background** classification: score < 0.5
    - **Signal** classification: score > 0.5



CNN
Input: trace (X+Y+Z)

Filters per layer: 32
Kernel size: 11
Padding: "same"
Max-pooling: 4
Dropout: 0.3
Weights: ~14,000

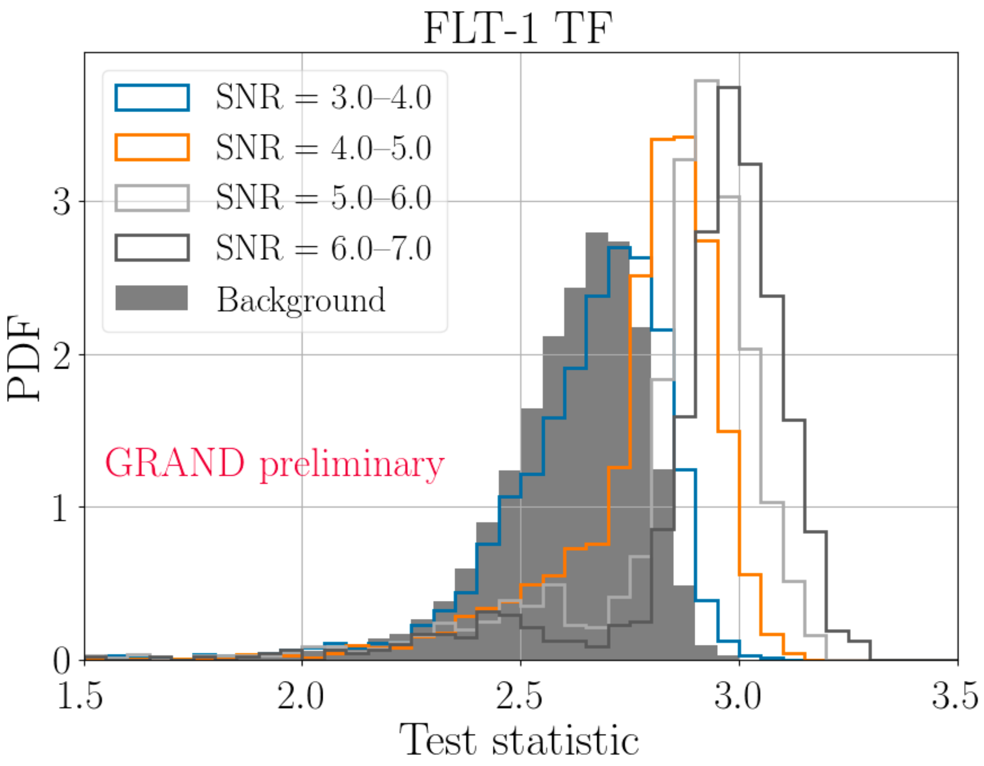
Output: **score** ∈ [0,1]



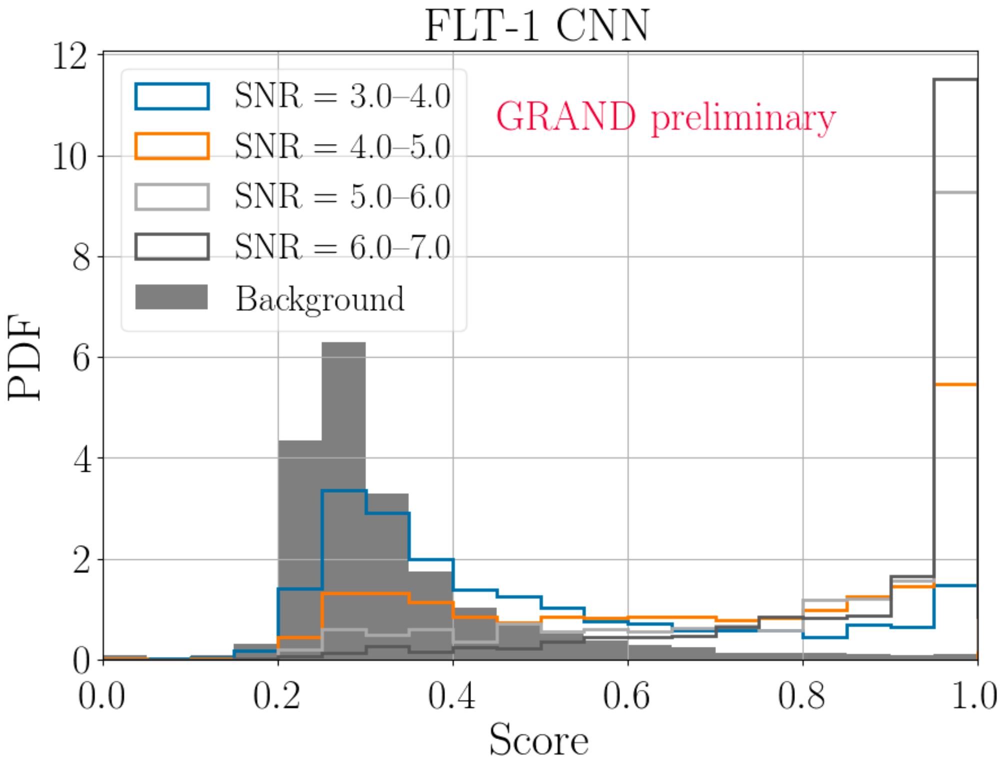
Offline FLT-1 Performance

Results
Testing data samples
2 x 10,000 traces

- CNN has better **signal-background** (S-B) **separation**
- Template fitting (TF) still in **early stages**!



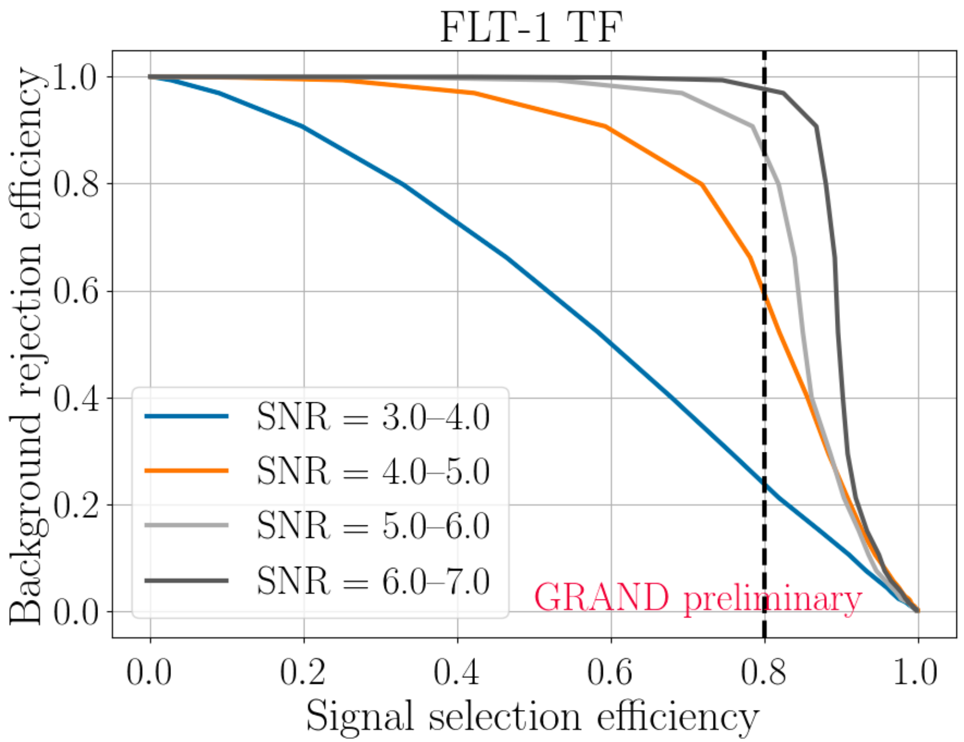
SNR
Max. shower pulse
/ noise RMS



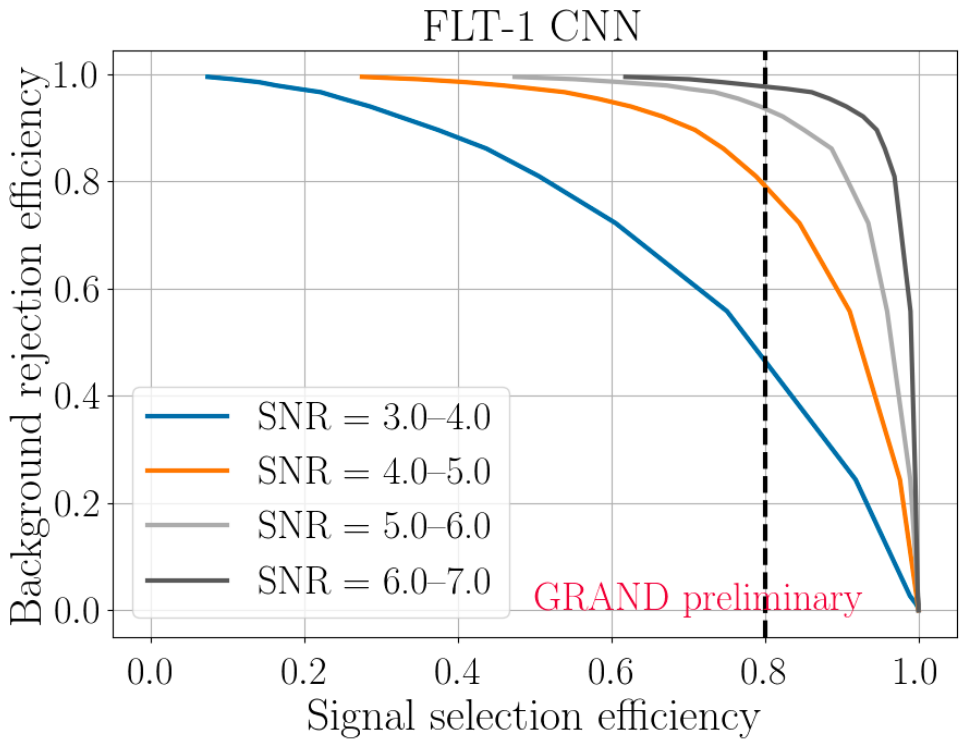
Offline FLT-1 Performance

Results
Testing data samples
2 x 10,000 traces

- FLT-1 results looks **promising** for both methods
- If we **select 80% of signal at 5σ**, we can **reject 80-90% of background**



SNR
Max. shower pulse
/ noise RMS



Conclusions and Outlook

Summary

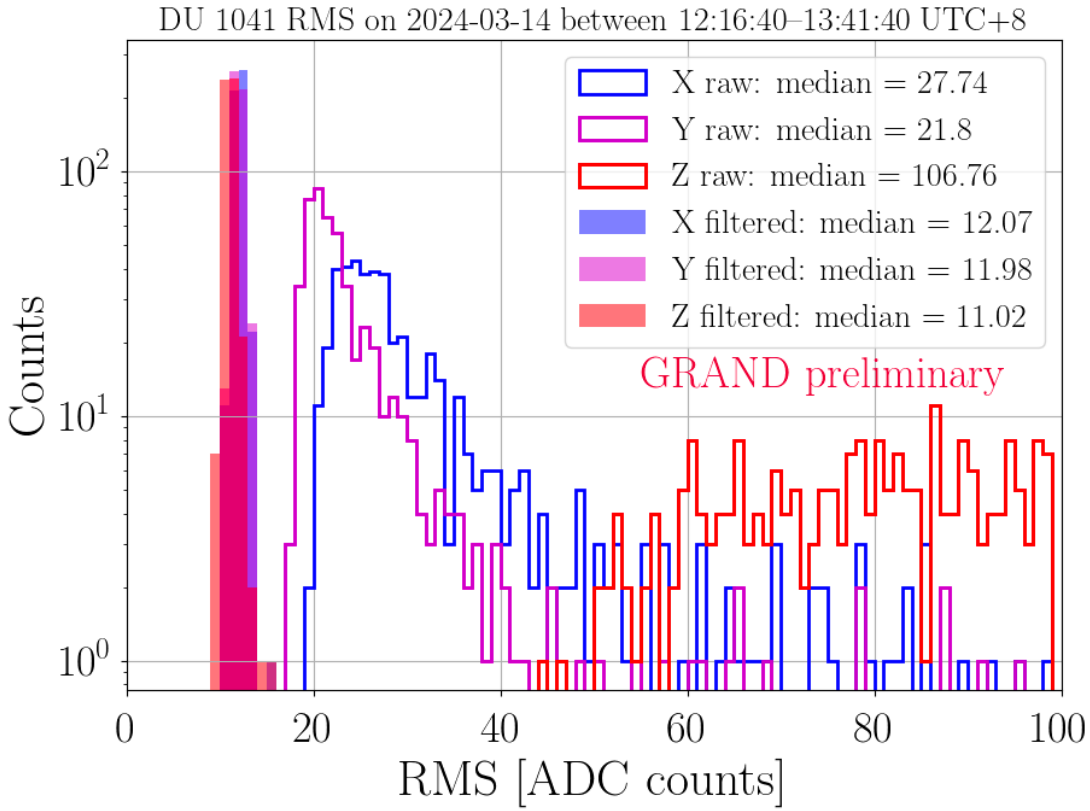
- Constructed **database** for NUTRIG
  - Background from **GP13 data**
  - Signal from **ZHAireS simulations**
- Considered two **FLT-1 algorithms**
  - **Template fitting** (PC)
  - **CNN** (J.M. Colley, S. Le Coz)
- Offline **FLT-1 results promising**
  - **CNN** currently better S-B separation than TF
  - **80–90% B rejection for 80% S selection @5σ**

Outlook

- **Optimize** FLT-1 algorithms
  - Reduce templates, **computation time**,…
- Perform **online tests** of FLT-1 methods
  - **Port** to CPU on front-end board
  - Controlled tests at **LPNHE test bench**
- Test FLT-1 at **GRAND@Nançay**
  - **Dedicated prototype** for NUTRIG
  - Tests in **realistic conditions** [PC PoS ICRC2023 990]

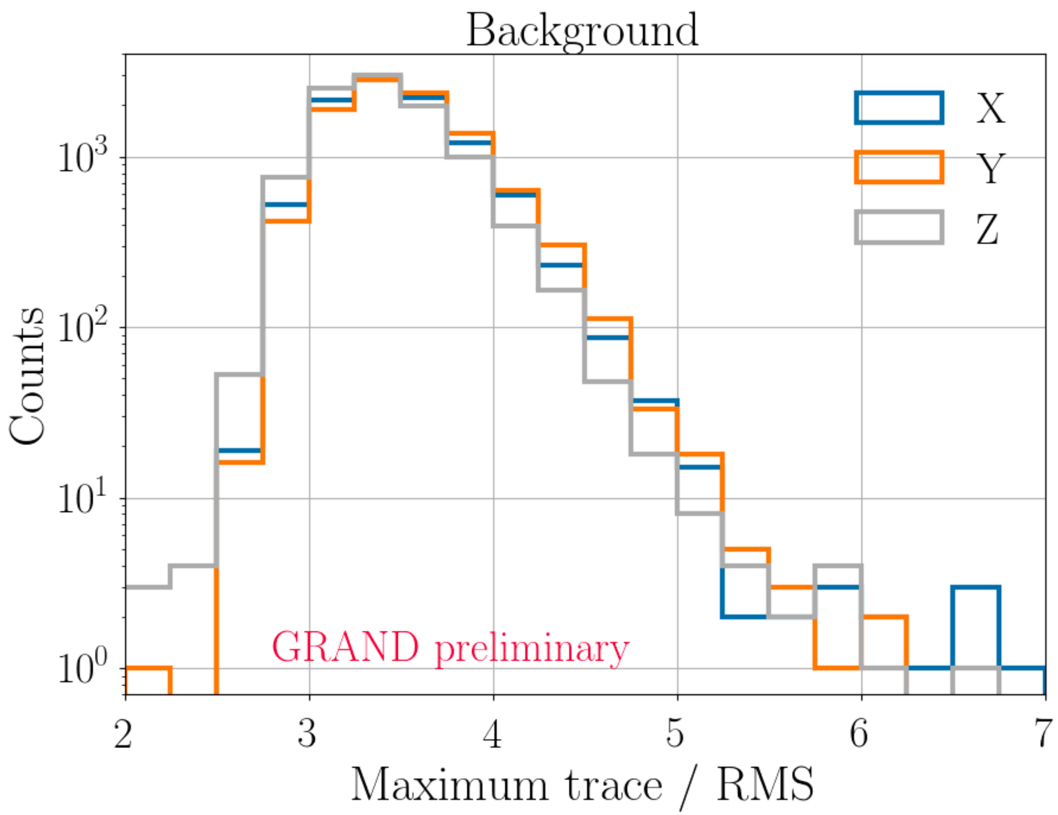
BACKUP

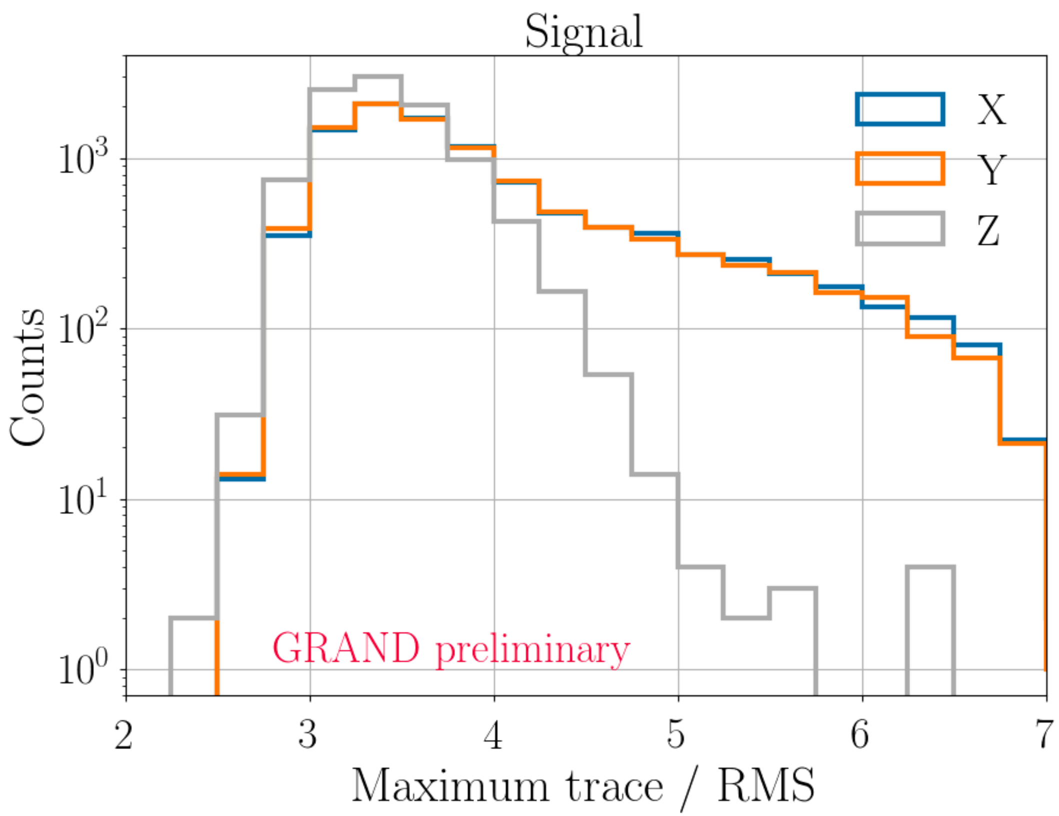
Effect of Filters on RMS @ GP13



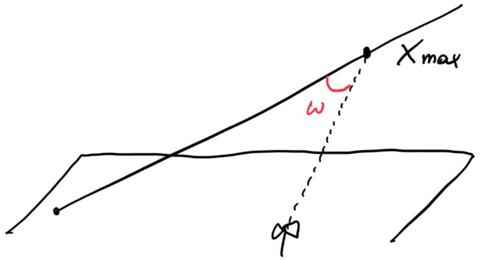
Database Properties

Training samples

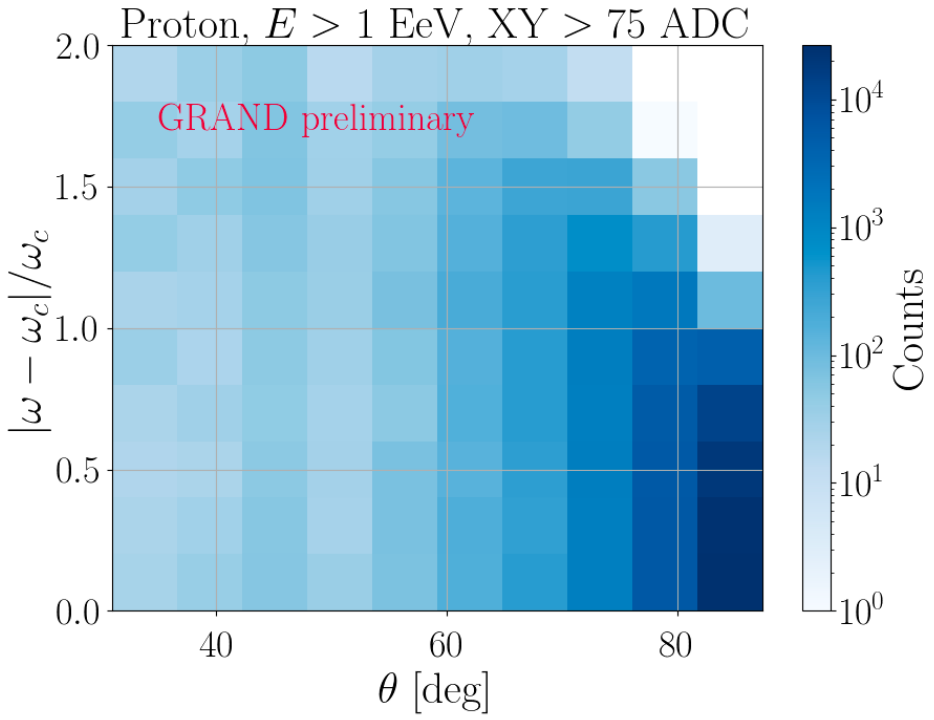


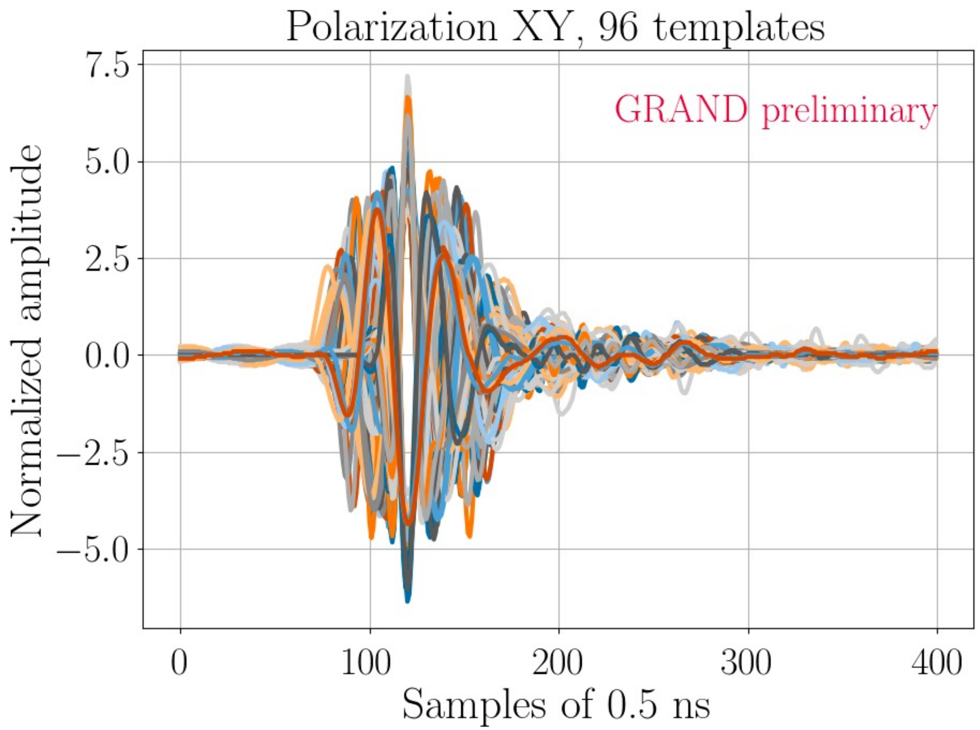


Template FLT-1: Library



- Same **air-shower simulations** as DB
  - Keep **0.5 ns sampling**
  - Focus on $E > 1$ EeV
  - **Bin** air-shower pulses in θ and ω
- **Randomly pick** one template per bin
  - **96 templates** for X+Y
  - 96 templates for Z (not considered in this work)





Template FLT-1: Algorithm

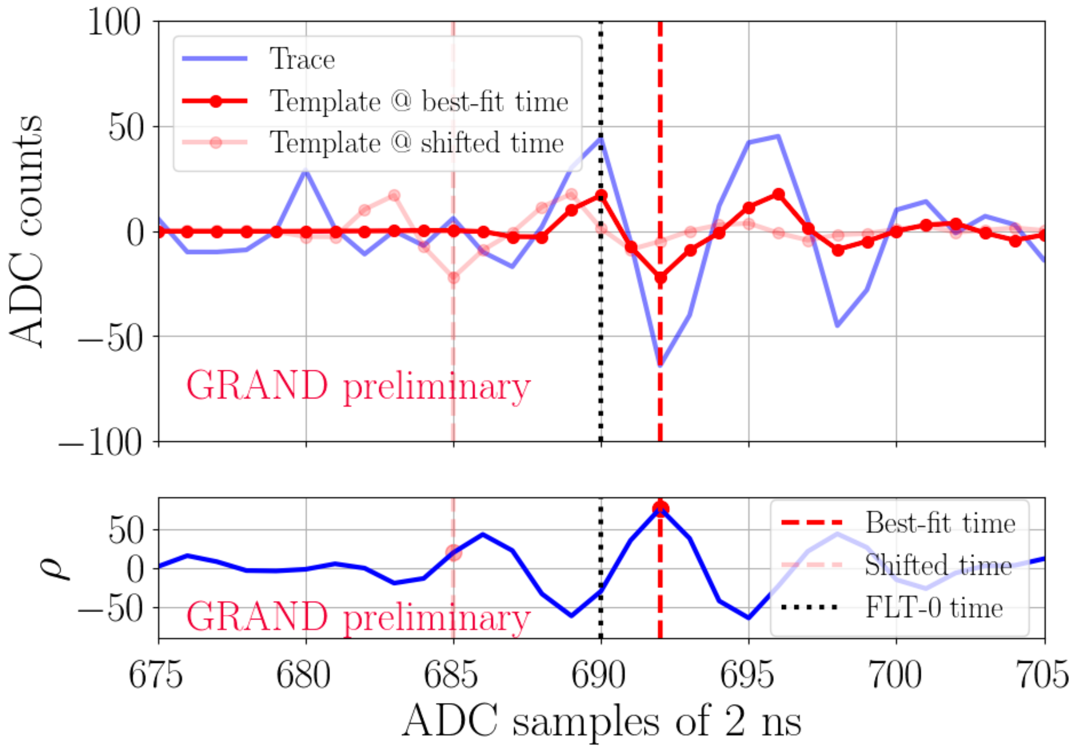
Step 1: Fit template time

- Take **scan window** around FLT-0 time t_0
  - $\tau \in [t_0 - 15 \text{ ADC samples}, t_0 + 15 \text{ ADC samples}]$
- Compute template-trace **cross correlation** for each time in window [Henrichs+ PoS ICRC2023 259]

$$\rho_T(\tau) = \int T(t)\, V(t+\tau)\, \mathrm{d}t$$

- **Maximum correlation** yields "best-fit" time

$$\hat{t}_{FLT} = \mathrm{argmax}\, |\rho_T(\tau)|$$



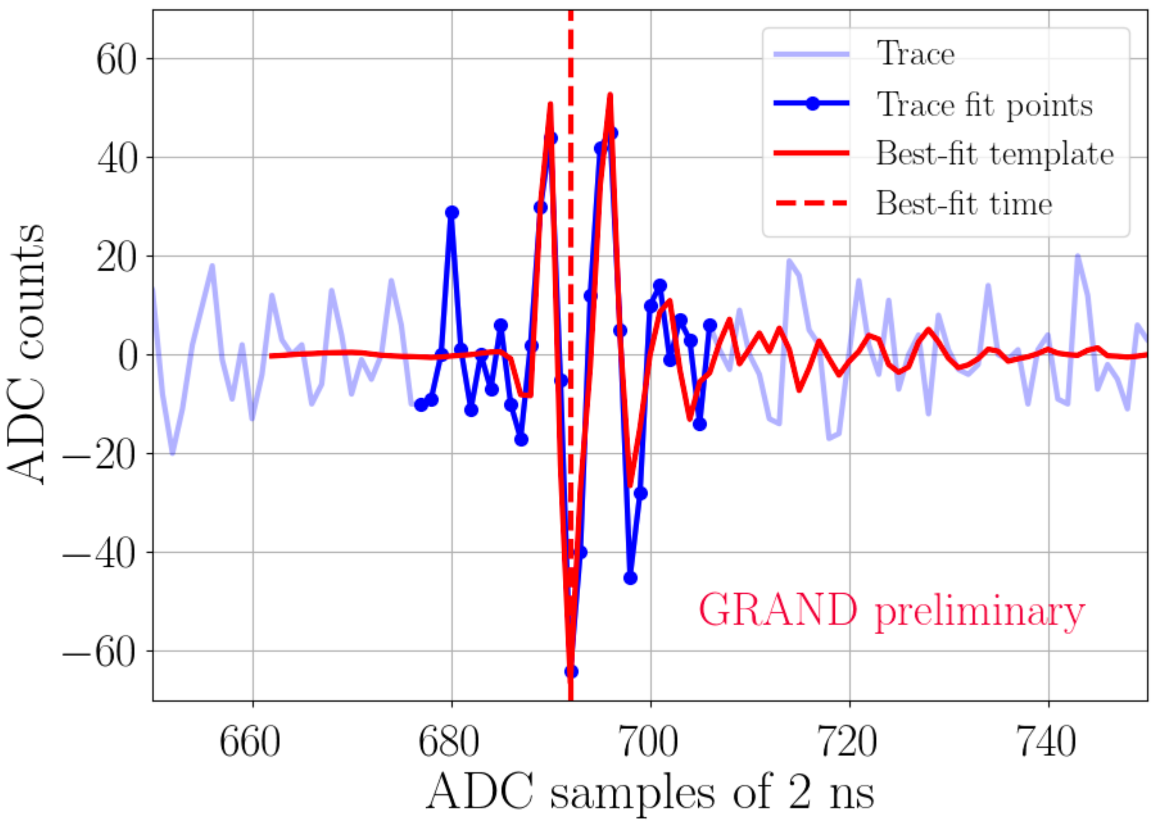
Template FLT-1: Algorithm

Step 2: Fit template amplitude

- Take **fit window** around best-fit time $\hat{t}_{FLT}$
  - $t_i \in [\hat{t}_{FLT} - 10 \text{ ADC samples}, \hat{t}_{FLT} + 15 \text{ ADC samples}]$
- **Weight** fit points with $\sigma_i = \mathrm{RMS}^2 / V(t_i)$
- Perform a **least-squares fit**

$$\chi_T^2 = \min_{\kappa_T} \sum_i \frac{|V(t_i) - \kappa_T T(t_i)|^2}{\sigma_i^2}$$

- **Minimum** χ_T^2 yields best-fit amplitude $\hat{\kappa}_T$



Template FLT-1: Algorithm

Step 3: Compute test statistic

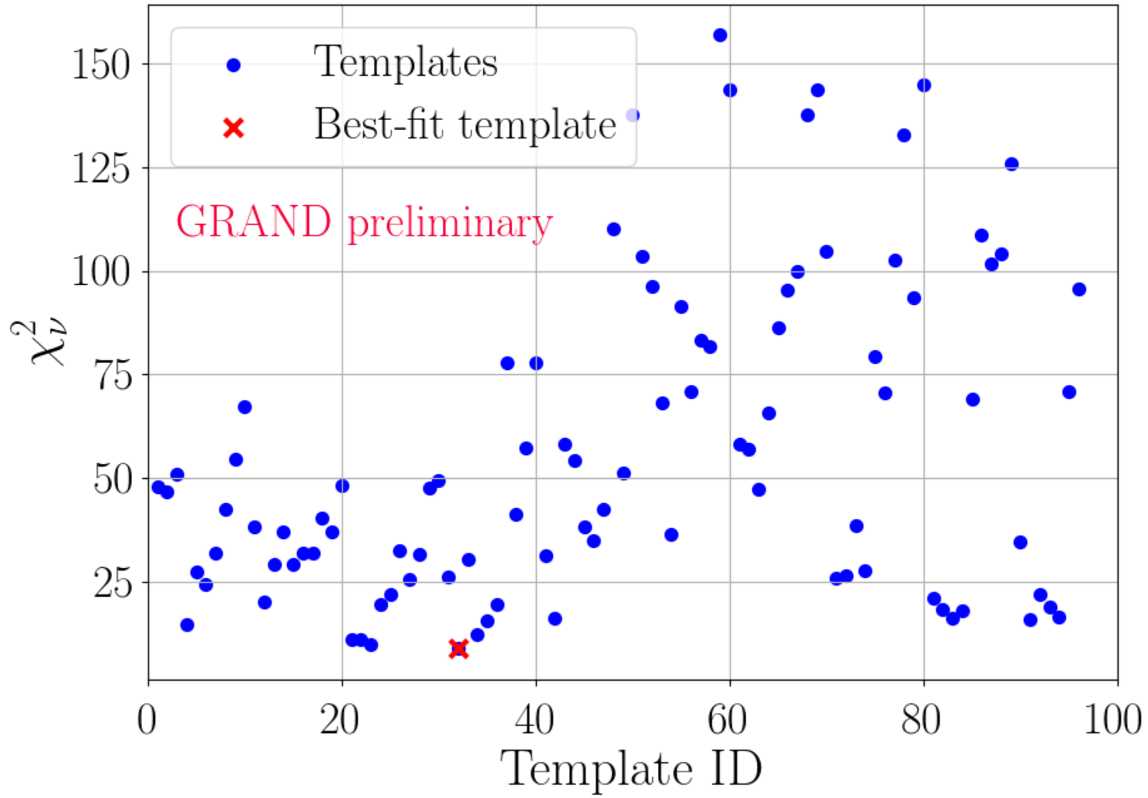
- **Repeat** steps 1 & 2 for all templates
- Find the **best-fit template**

$$T_b = \mathrm{argmin}_T\, \chi^2_T$$

- Compute a **test statistic** as

$$\mathrm{TS} = \log_{10} |\hat{\kappa}_b \rho_{T_b}(\hat{t}_{s,b})|$$

- **TS threshold** defines FLT-1 pass condition



FLT-1 Selection Efficiency