Karlsruhe Institute of Technology

PIERRE AUGER OBSERVATORY

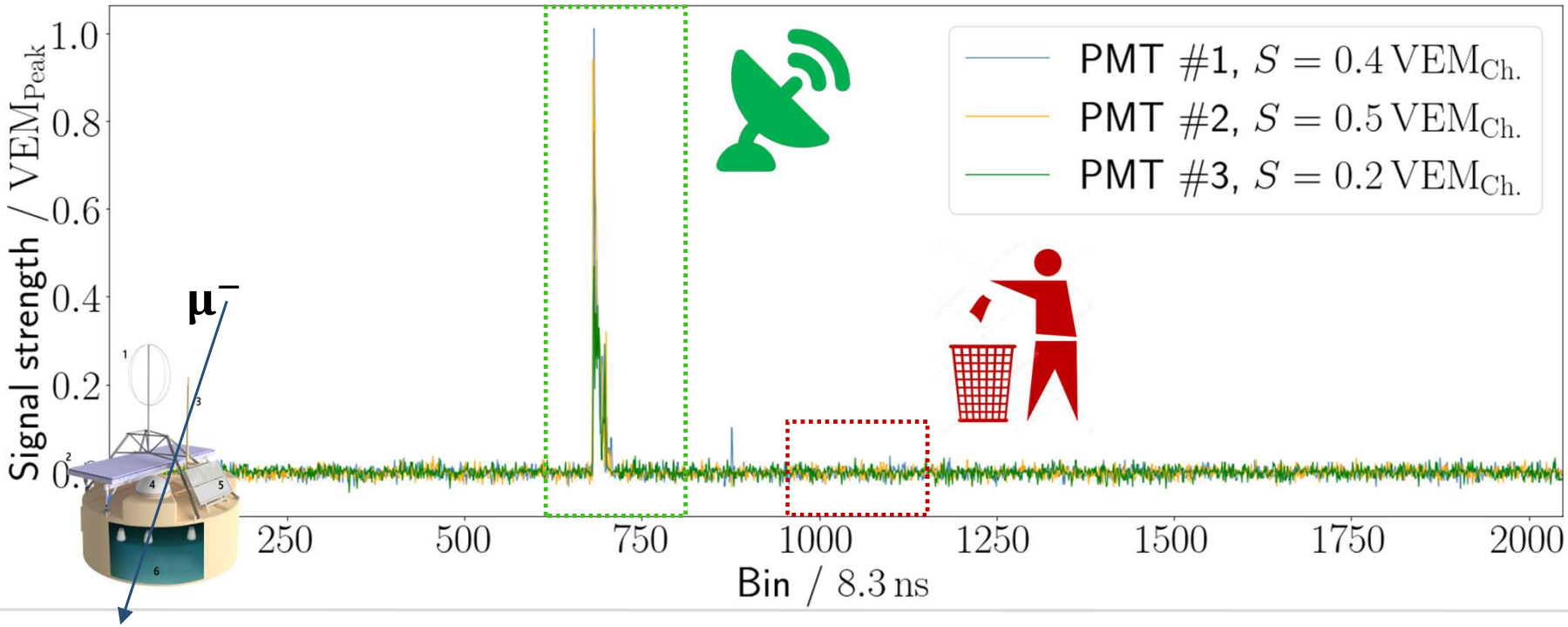
Potential of neural network triggers for the Water-Cherenkov detector array of the Pierre Auger Observatory

Triggers session 14.11.23

Paul Filip, David Schmidt

Strategy

- Feed labelled subset of trace to neural network architecture
- Teach it to distinguish between Signal / Background



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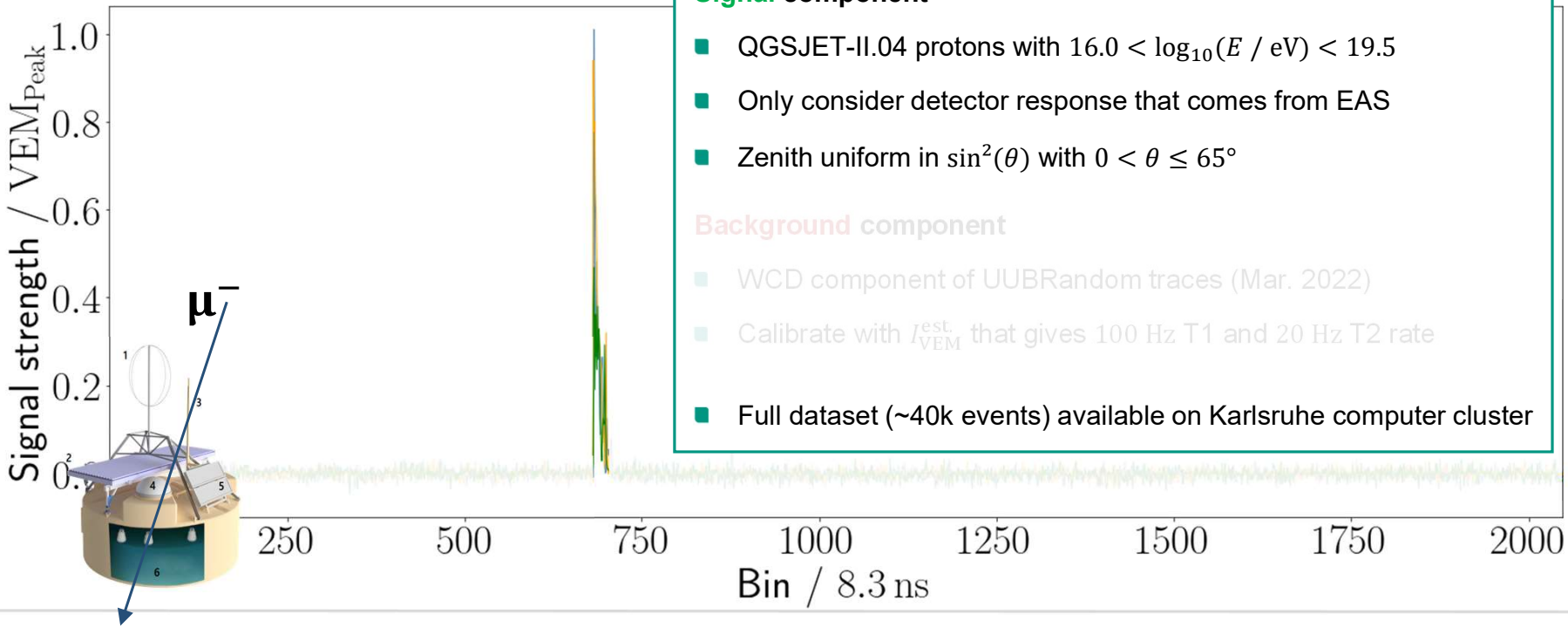

Signal component

- QGSJET-II.04 protons with $16.0 < \log_{10}(E \,/\, \mathrm{eV}) < 19.5$
- Only consider detector response that comes from EAS
- Zenith uniform in $\sin^2(\theta)$ with $0 < \theta \leq 65°$

Background component

- WCD component of UUBRandom traces (Mar. 2022)
- Calibrate with $I_{\mathrm{VEM}}^{\mathrm{est.}}$ that gives 100 Hz T1 and 20 Hz T2 rate

- Full dataset (~40k events) available on Karlsruhe computer cluster

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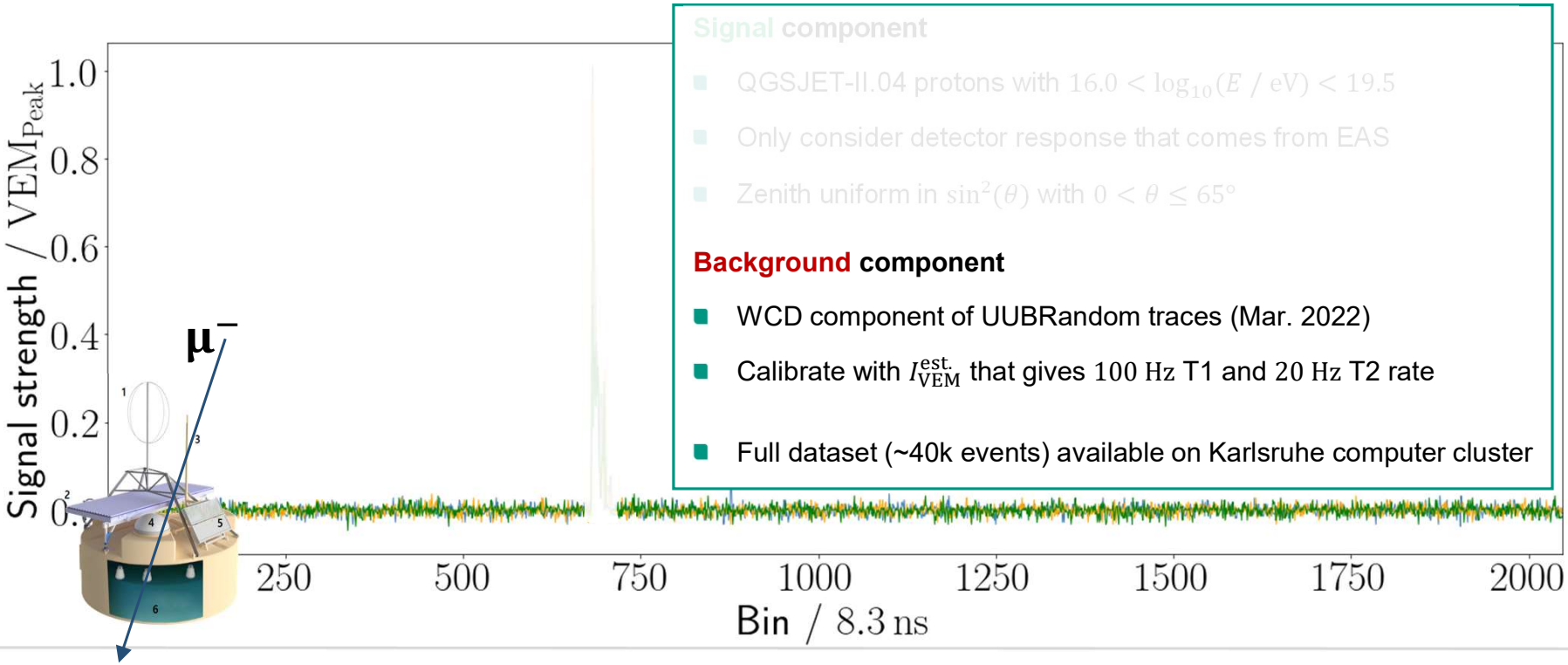
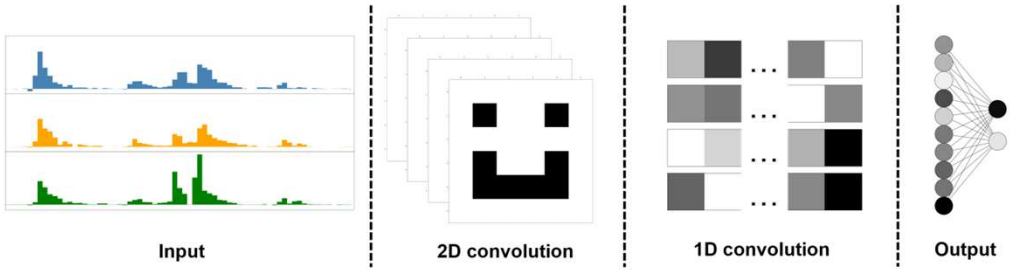


Network architectures

- 120 bins $\times$ 3 PMTs $=$ 360 input values ➡ 1 binary output $\{0, 1\}$ (1 = Signal, 0 = Background)

Convolutional neural networks (CNNs)

- Good at recognizing objects in images
- Treat input data as 3×120 pixel image
- Output independent of signal position in window
- 1-2 convolutional layers with dense final layer
- 84 to 890 free trainable parameters



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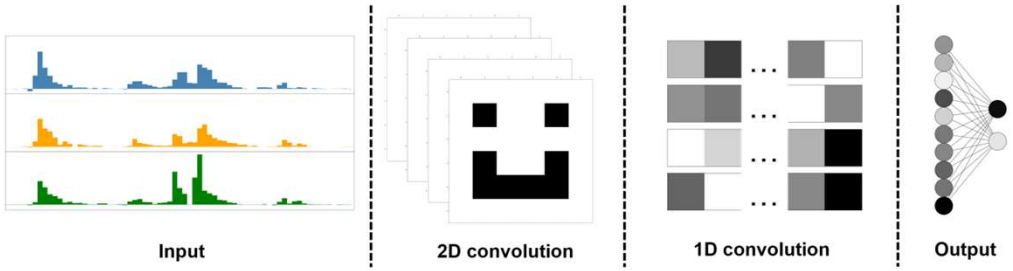
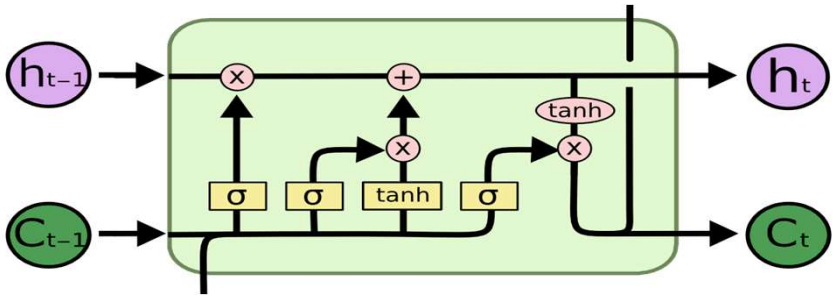


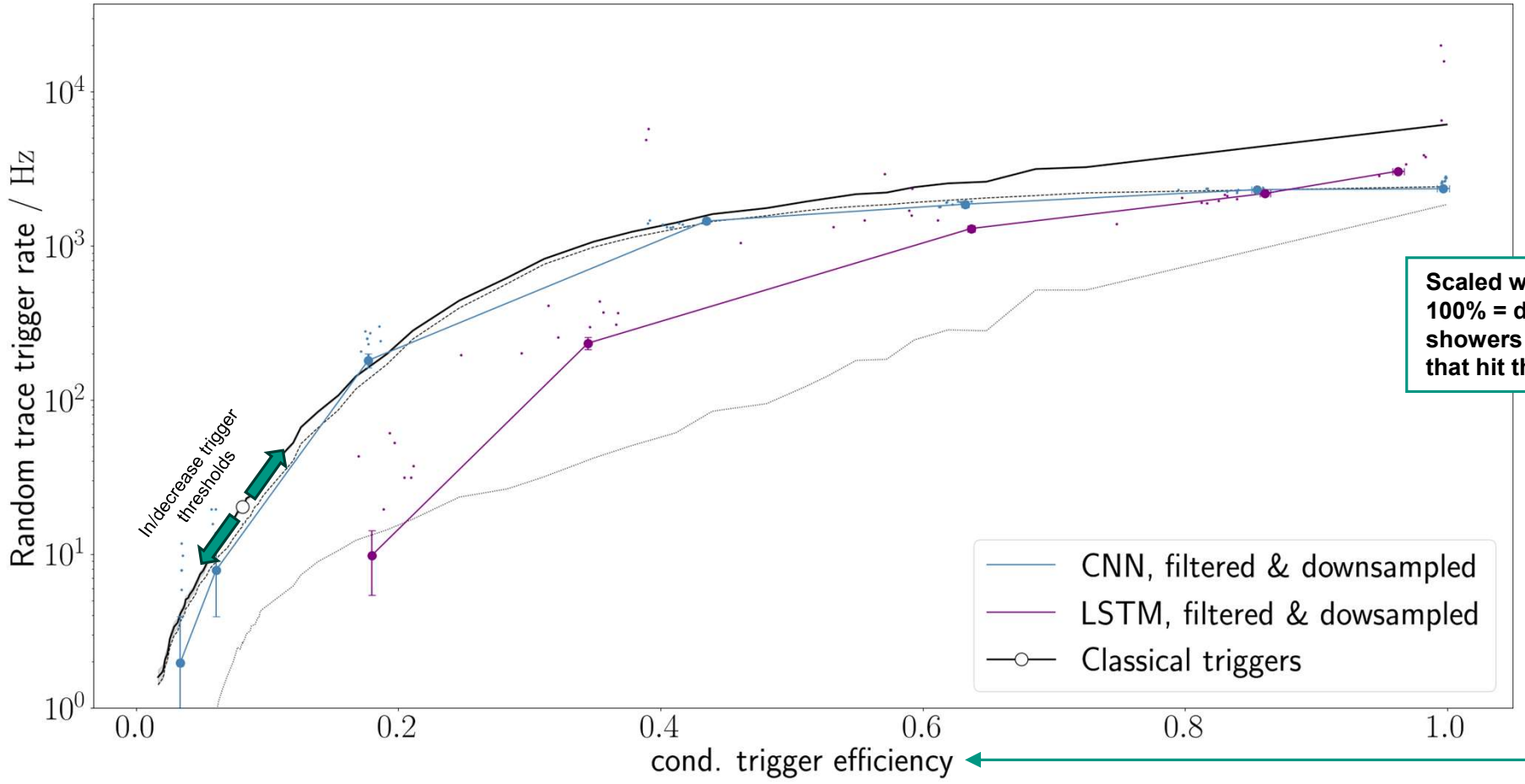
Recurrent neural networks (LSTMs)

- Good at recognizing patterns sequential data
- Basic LSTM receives 1-dimensional input
- Implement 1 distinct LSTM for each PMT
- 12 to 44 free trainable parameters



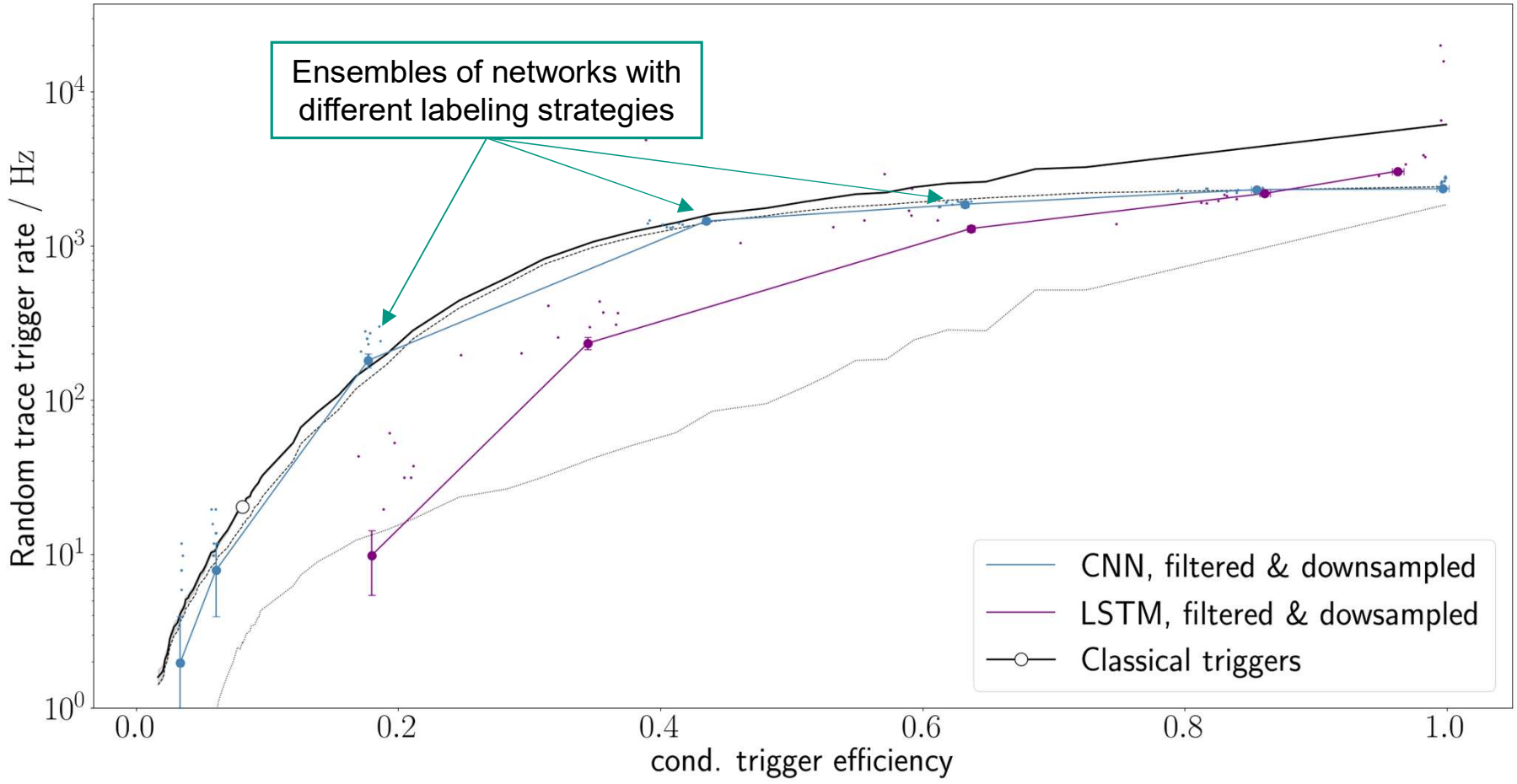
From https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Training results

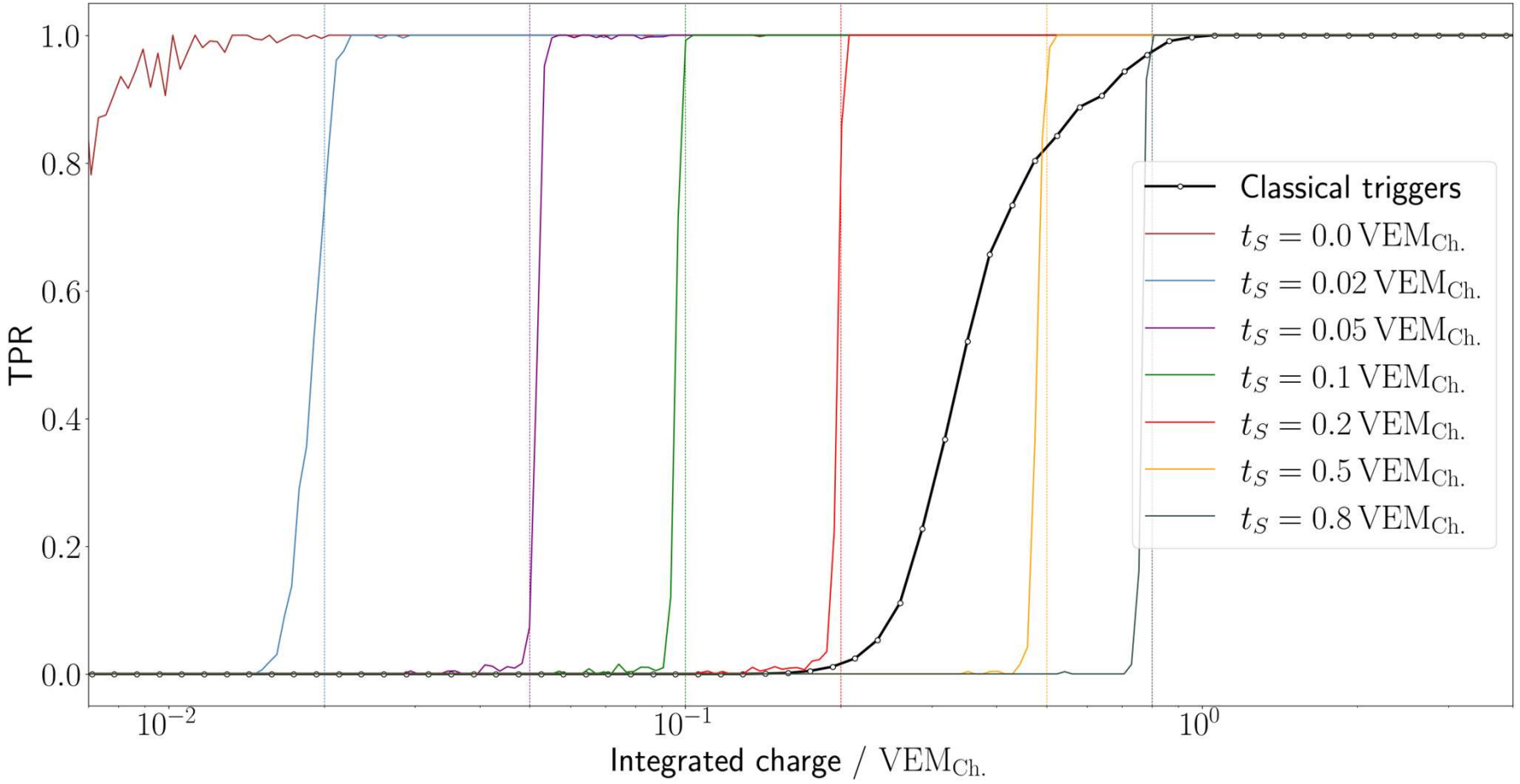


Scaled with LDF
100% = detect all showers (T2-level) that hit the array

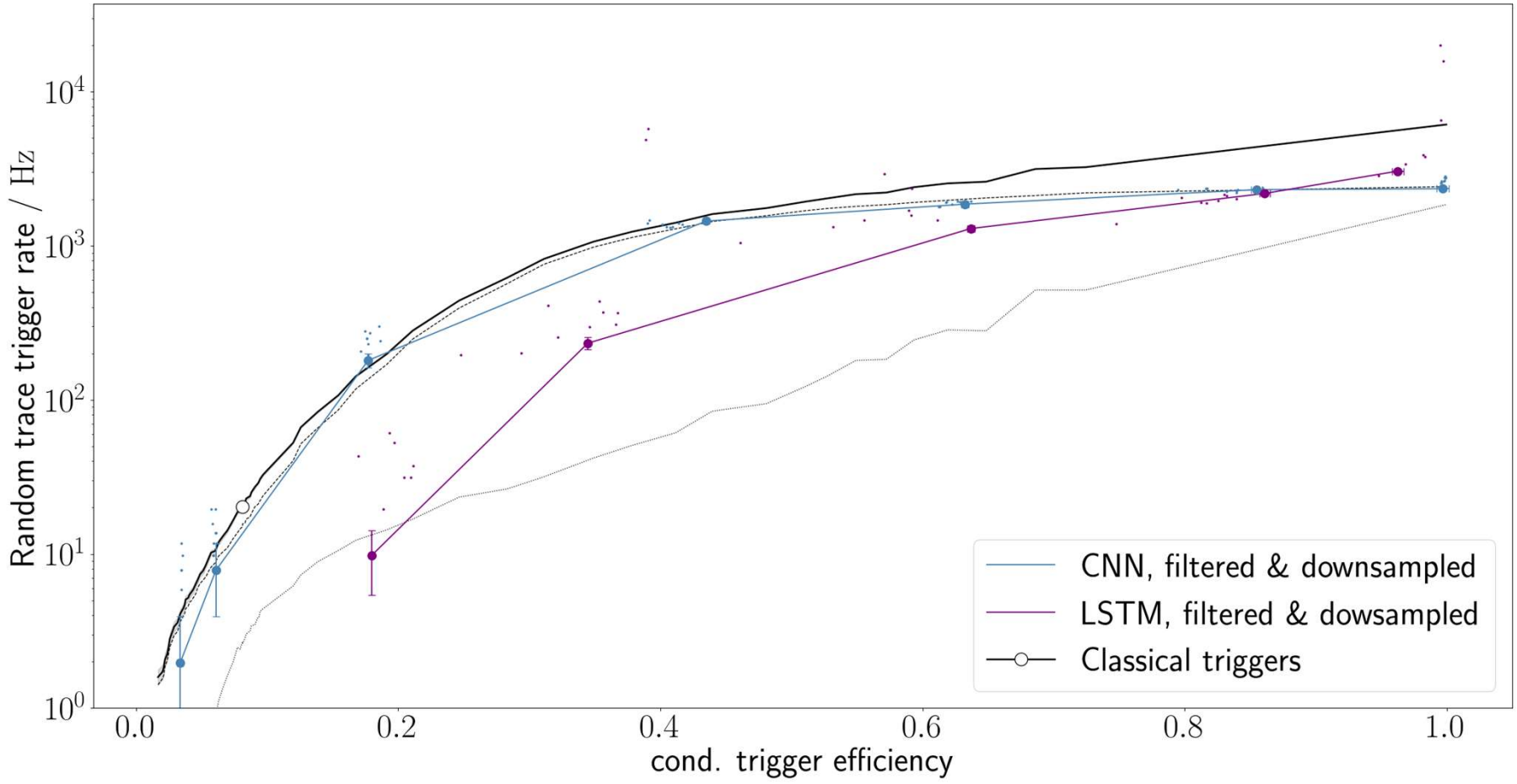
Training results



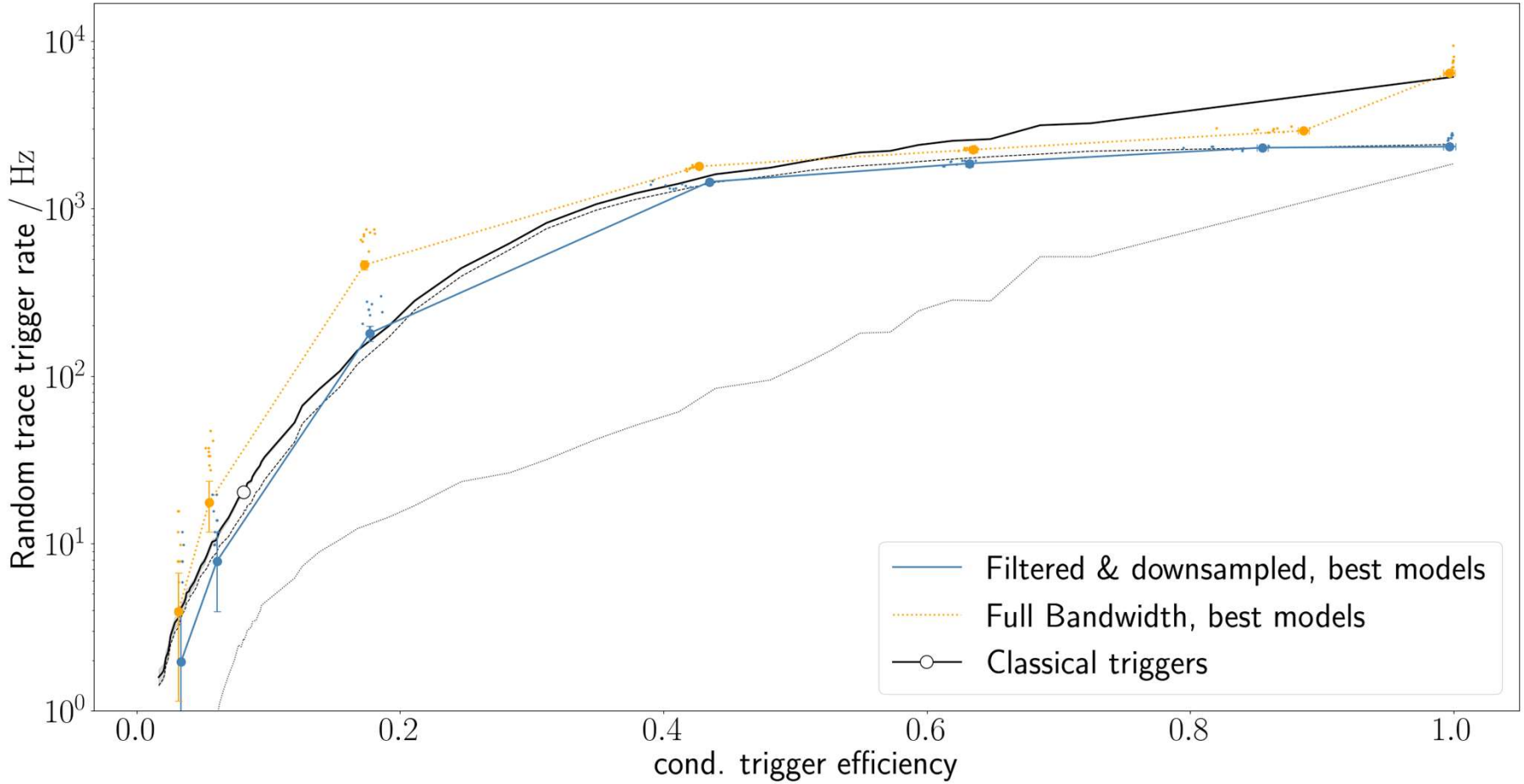
Training results



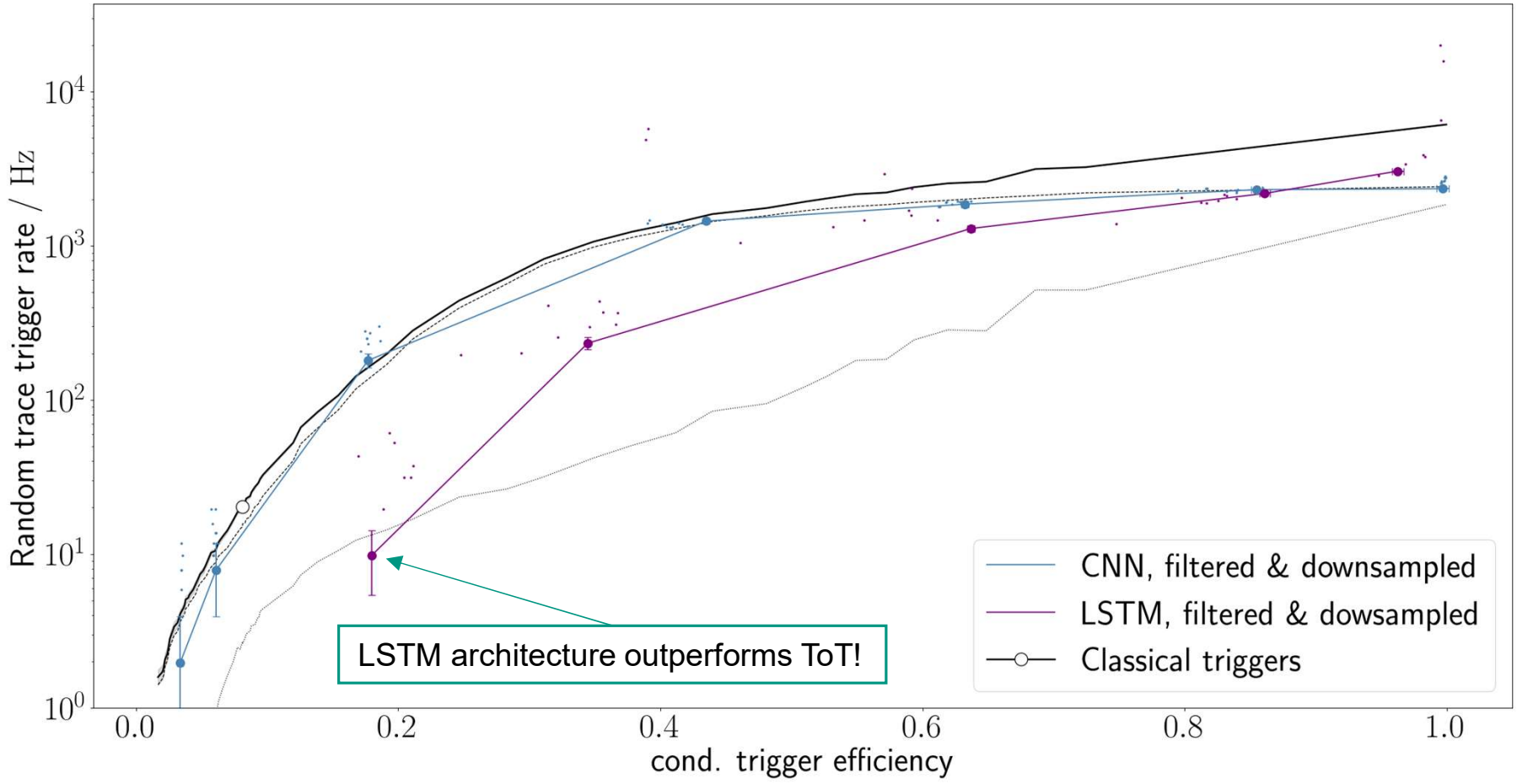
Training results



Training results

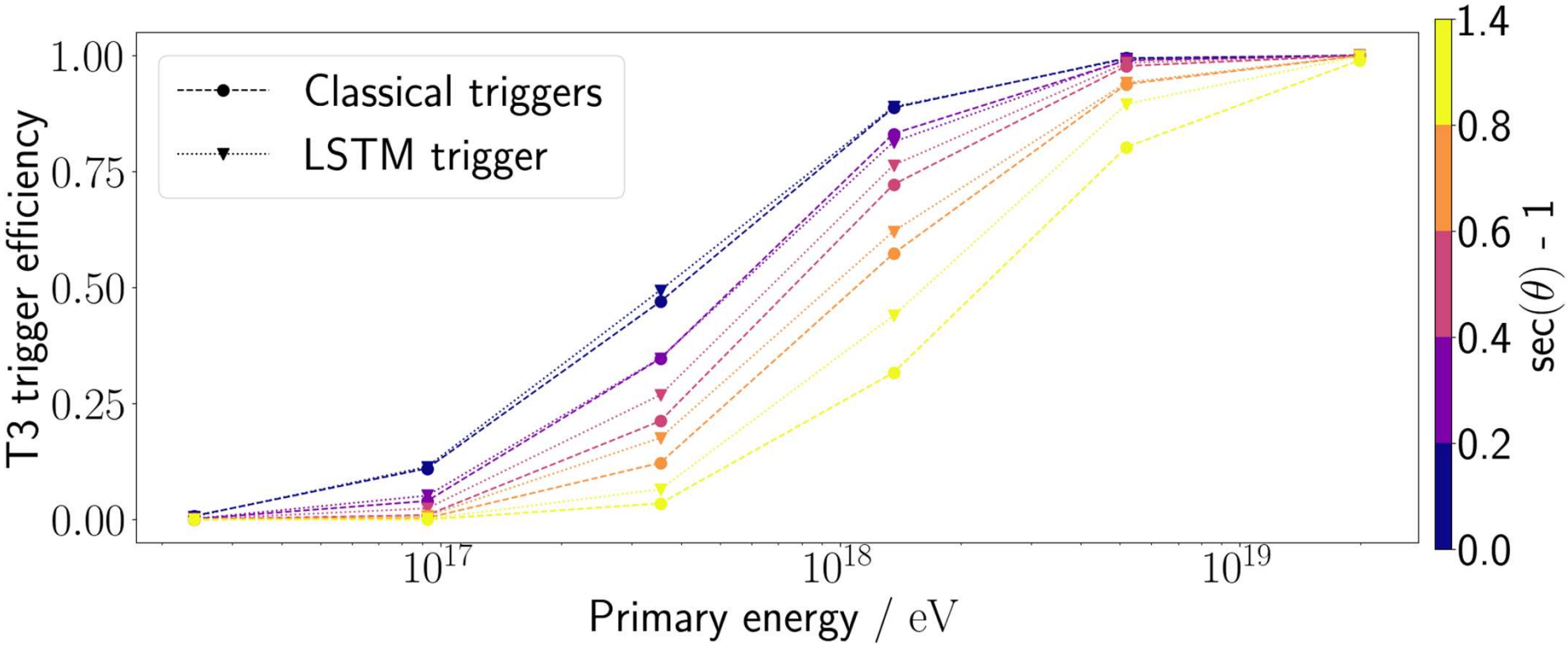


Training results



Resulting T3 efficiencies

- **Most drastic gains at high inclinations, $\theta \approx 60°$**
- **Possibly higher gains at $\theta \geq 65°$**



Summary / Outlook

- Test data-driven, machine learning concepts
  - Neural networks work out of the box but „too efficient“
  - Control trigger rate by implementing charge cut
- Convolutional neural networks
  - Performance of simple CNN architectures on par with Th-Trigger
  - Filtered & downsampled data preferred over full bandwidth input
- LSTM / recurrent neural networks
  - First results indicate better performance than ToT
  - Large gains in event detection efficiency at high shower angles

Summary / Outlook

- Lot of work needed until prototyping stage is left
  - Presented results stem from simulations only
  - No primary distinction, only data from protons considered
  - Only one hadronic interaction model (QGSJET-II.04)
- Ground work is completed
  - Key assumptions have been tested and verified to hold true
  - Analysis chain is implemented and ready to run
  - Neural networks show a lot of potential as SD triggers

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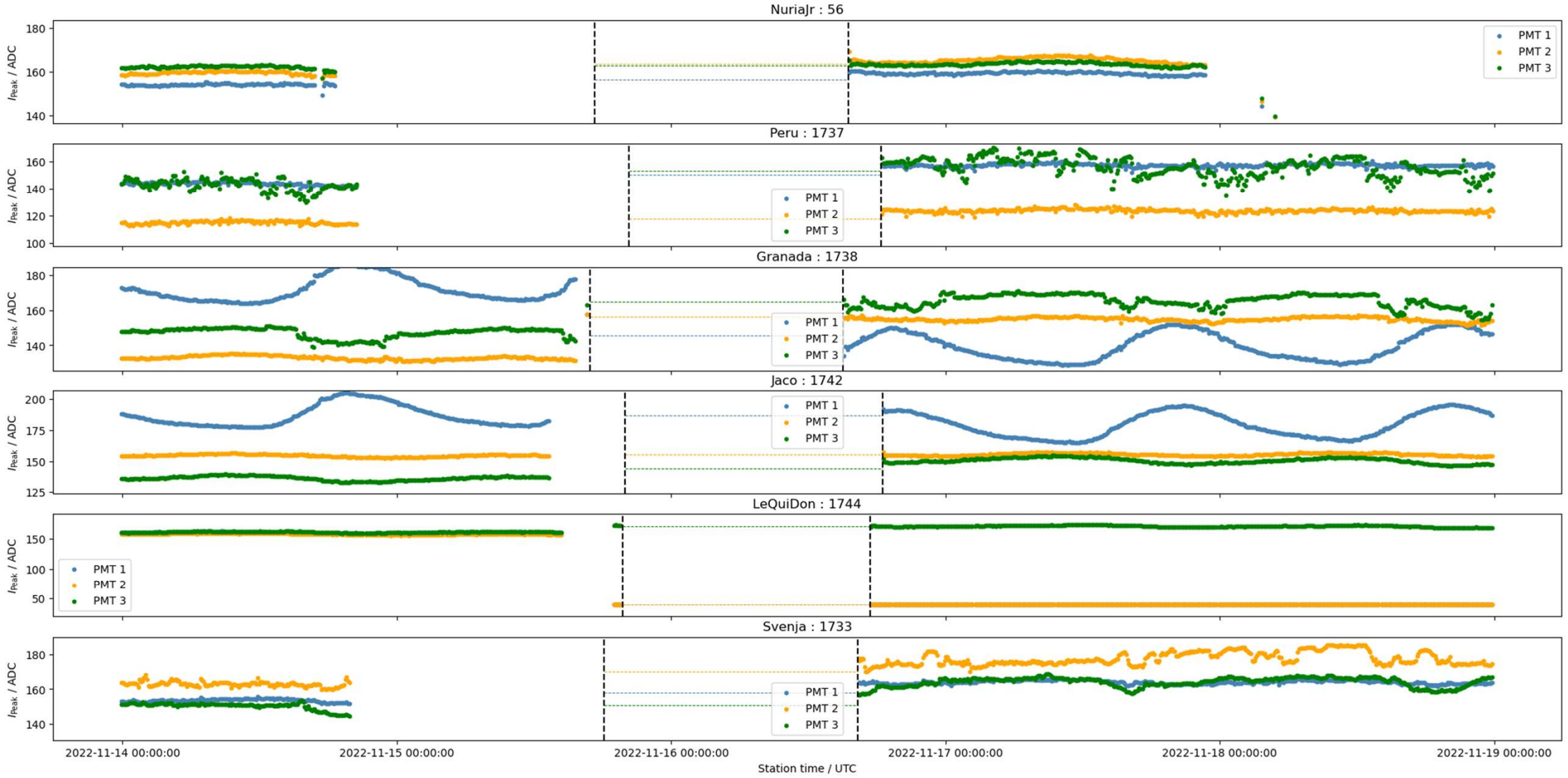
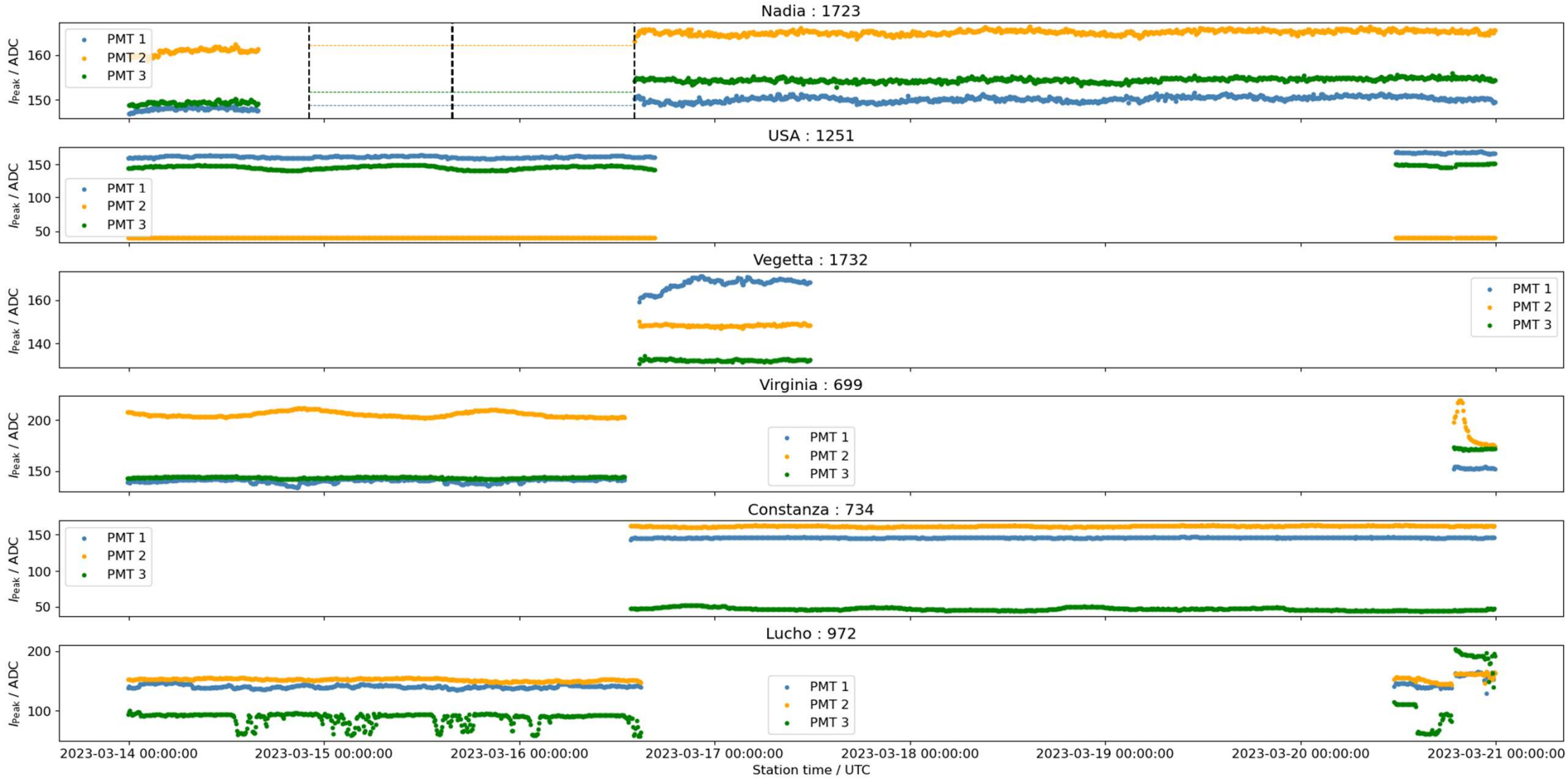
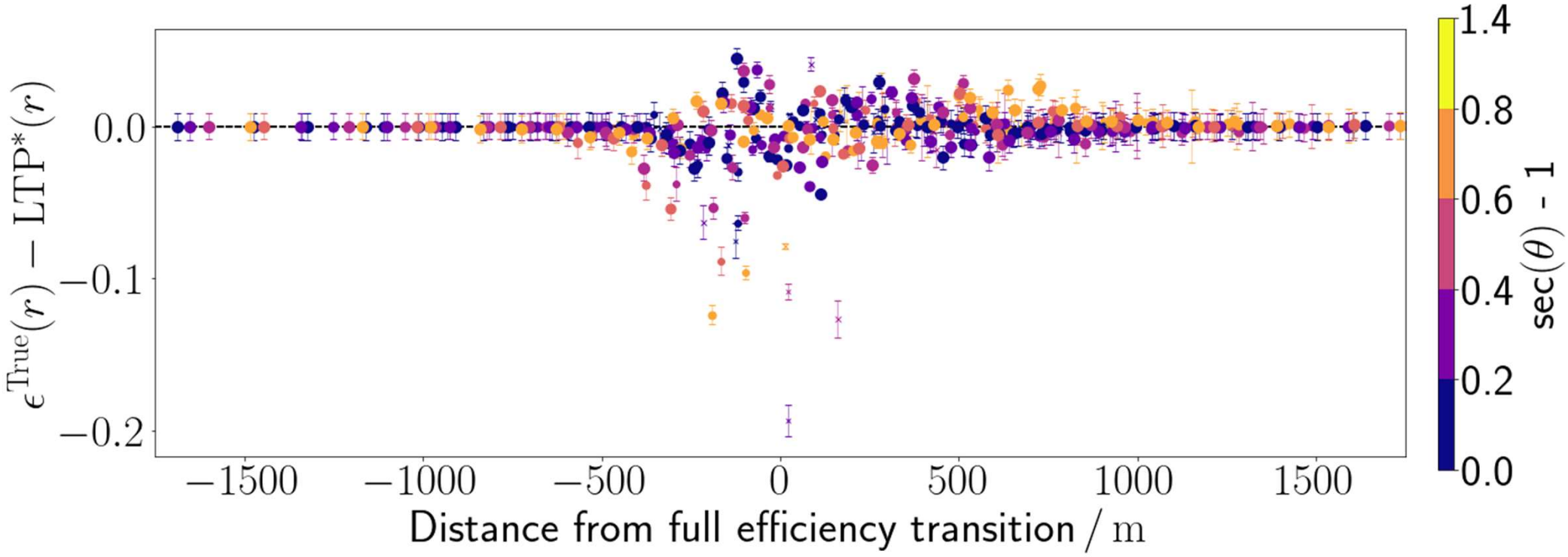
Backup

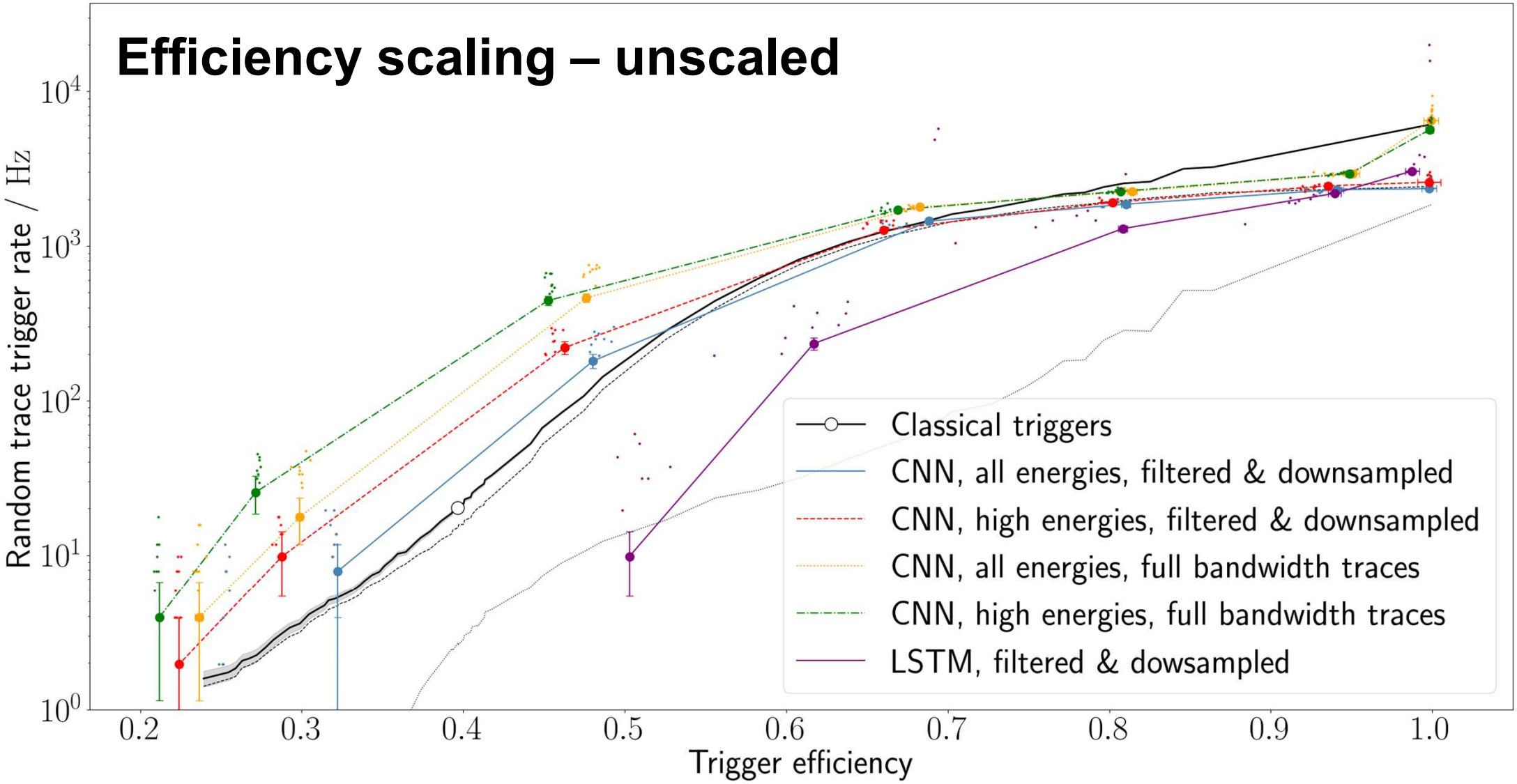

NuriaJr : 56
Peru : 1737
Granada : 1738
Jaco : 1742
LeQuiDon : 1744
Svenja : 1733
PMT 1
PMT 2
PMT 3
I_{Peak} / ADC
2022-11-14 00:00:00
2022-11-15 00:00:00
2022-11-16 00:00:00
2022-11-17 00:00:00
2022-11-18 00:00:00
2022-11-19 00:00:00
Station time / UTC


Nadia : 1723
USA : 1251
Vegetta : 1732
Virginia : 699
Constanza : 734
Lucho : 972
PMT 1
PMT 2
PMT 3
I_{Peak} / ADC
2023-03-14 00:00:00
2023-03-15 00:00:00
2023-03-16 00:00:00
2023-03-17 00:00:00
2023-03-18 00:00:00
2023-03-19 00:00:00
2023-03-20 00:00:00
2023-03-21 00:00:00
Station time / UTC

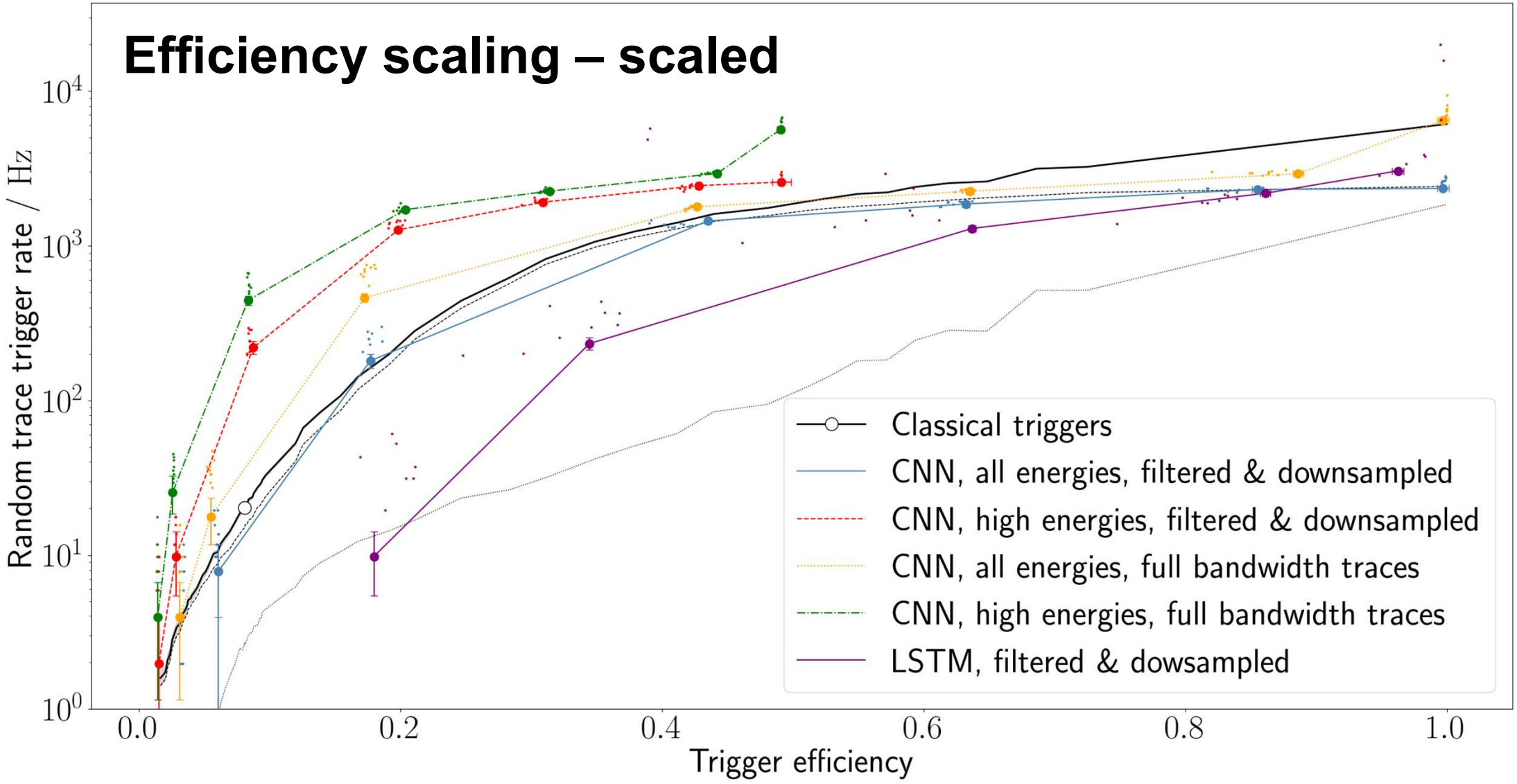
Residuals – LTP fitfunction



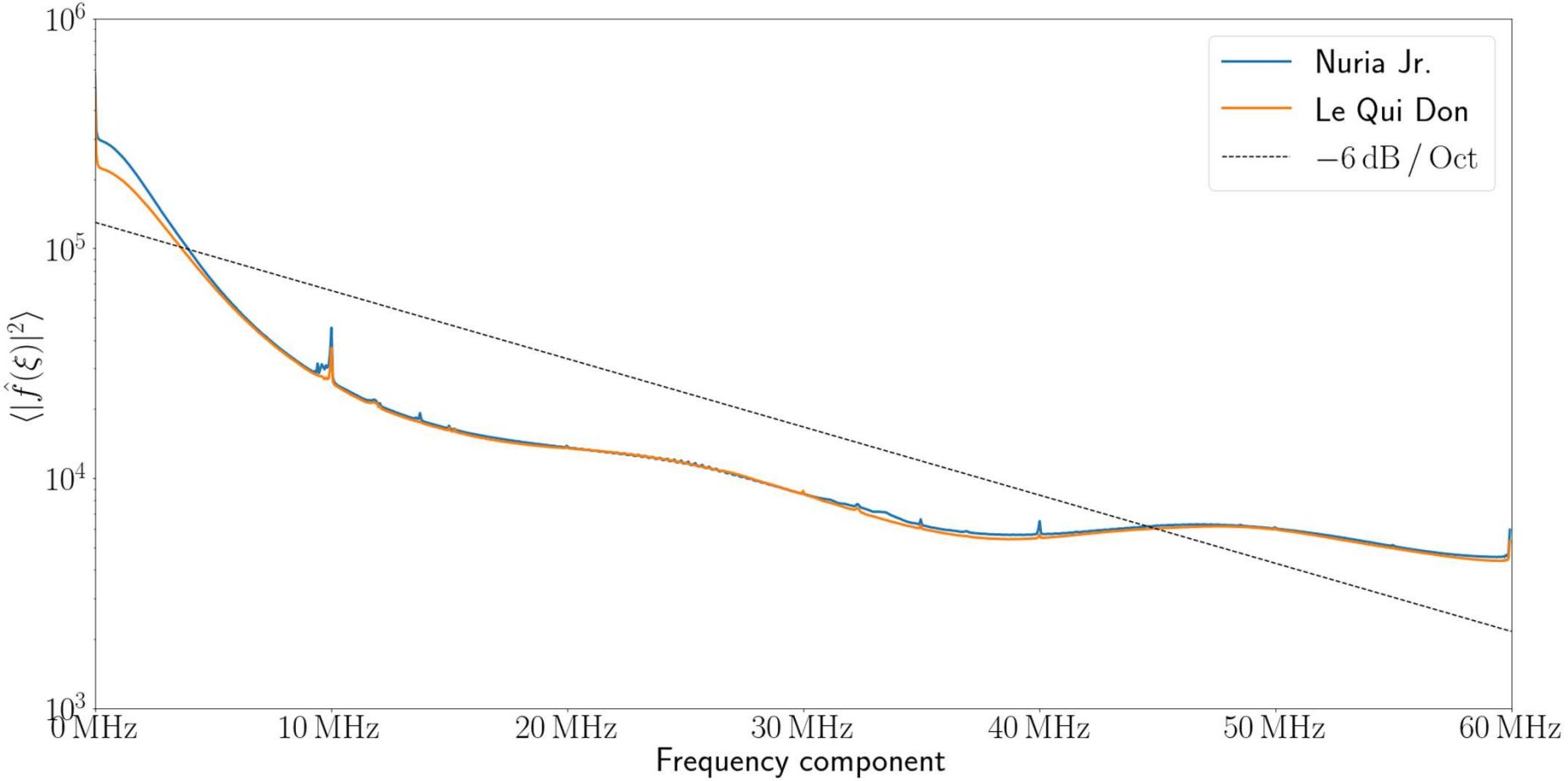
Efficiency scaling – unscaled



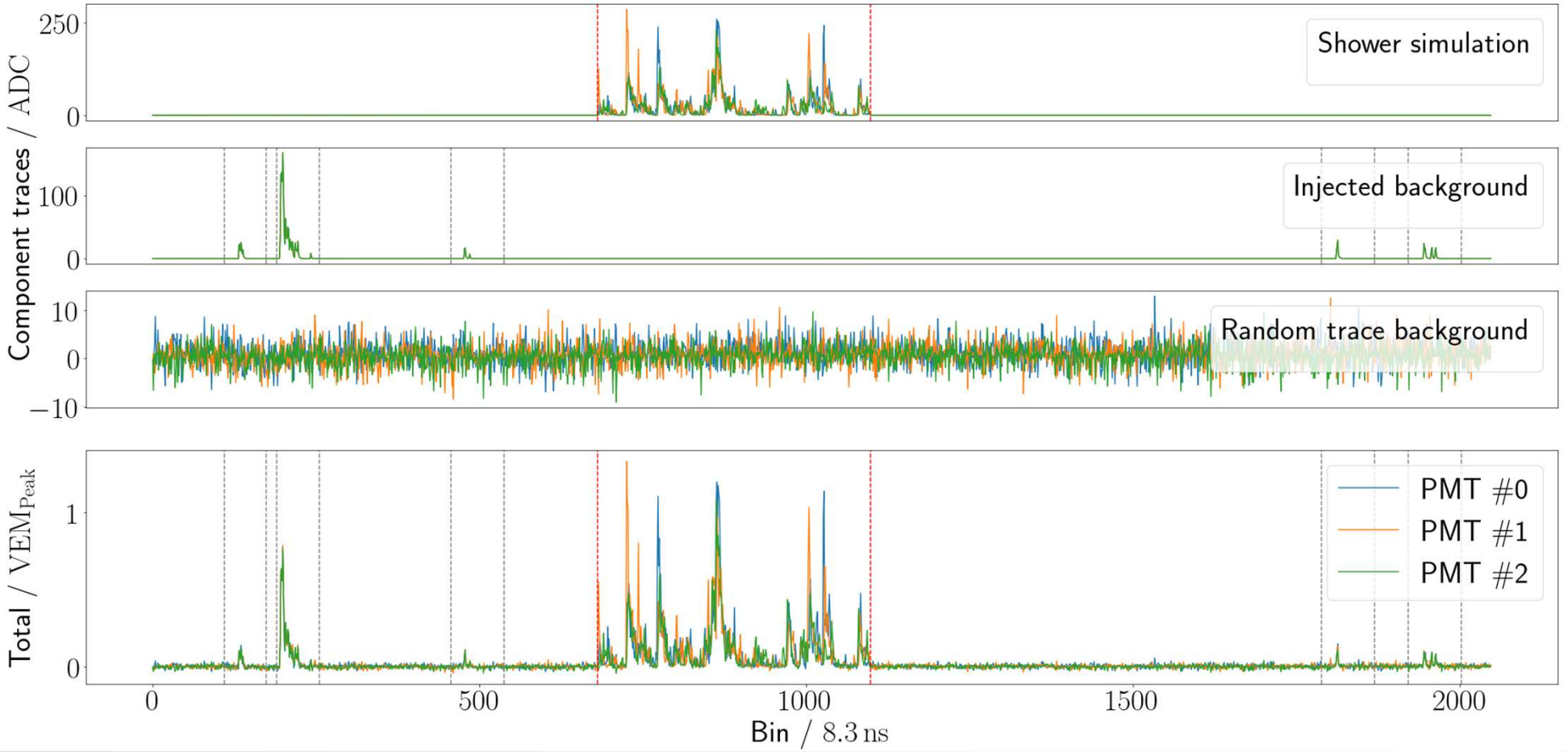
Efficiency scaling – scaled



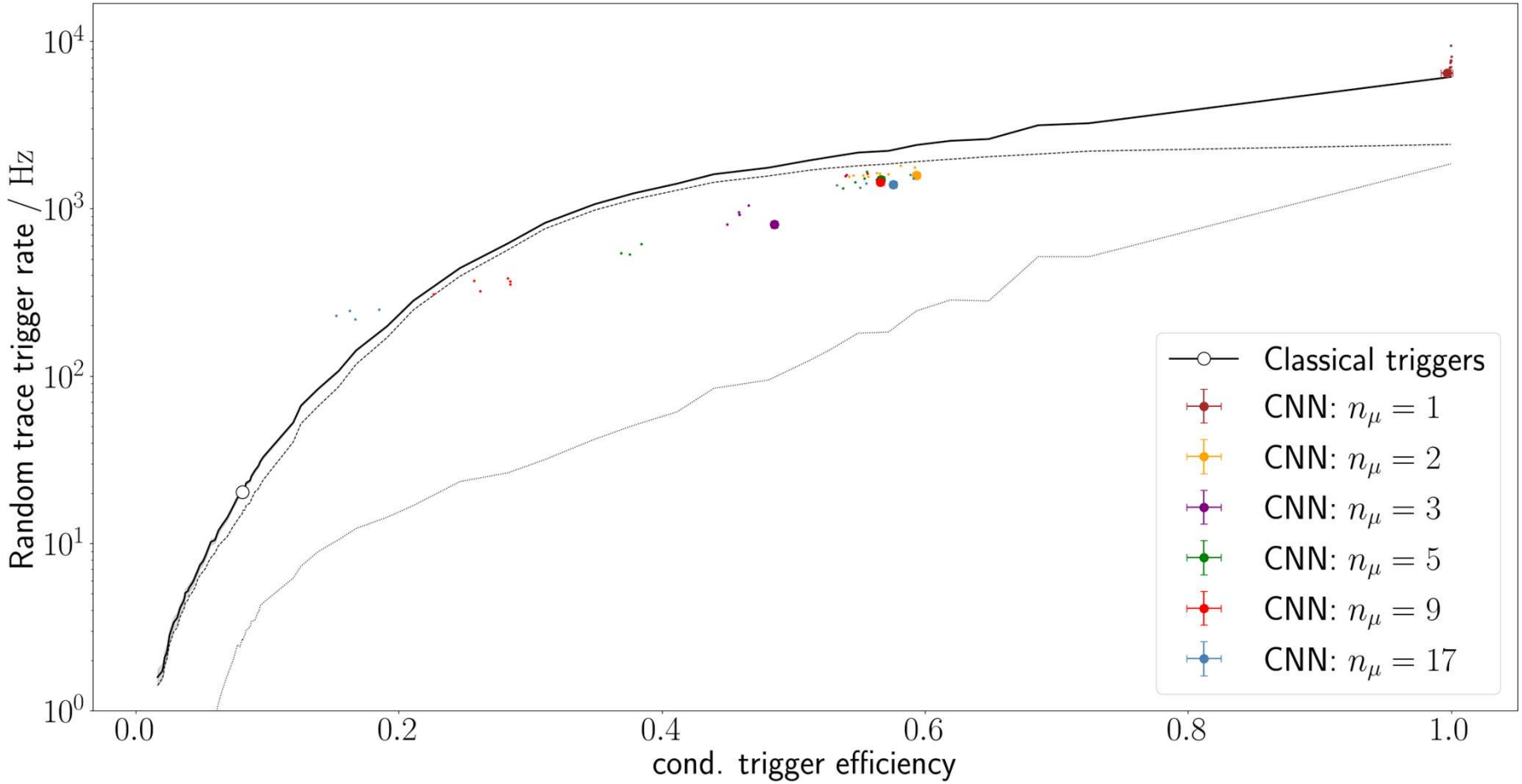
Random traces – Power spectrum



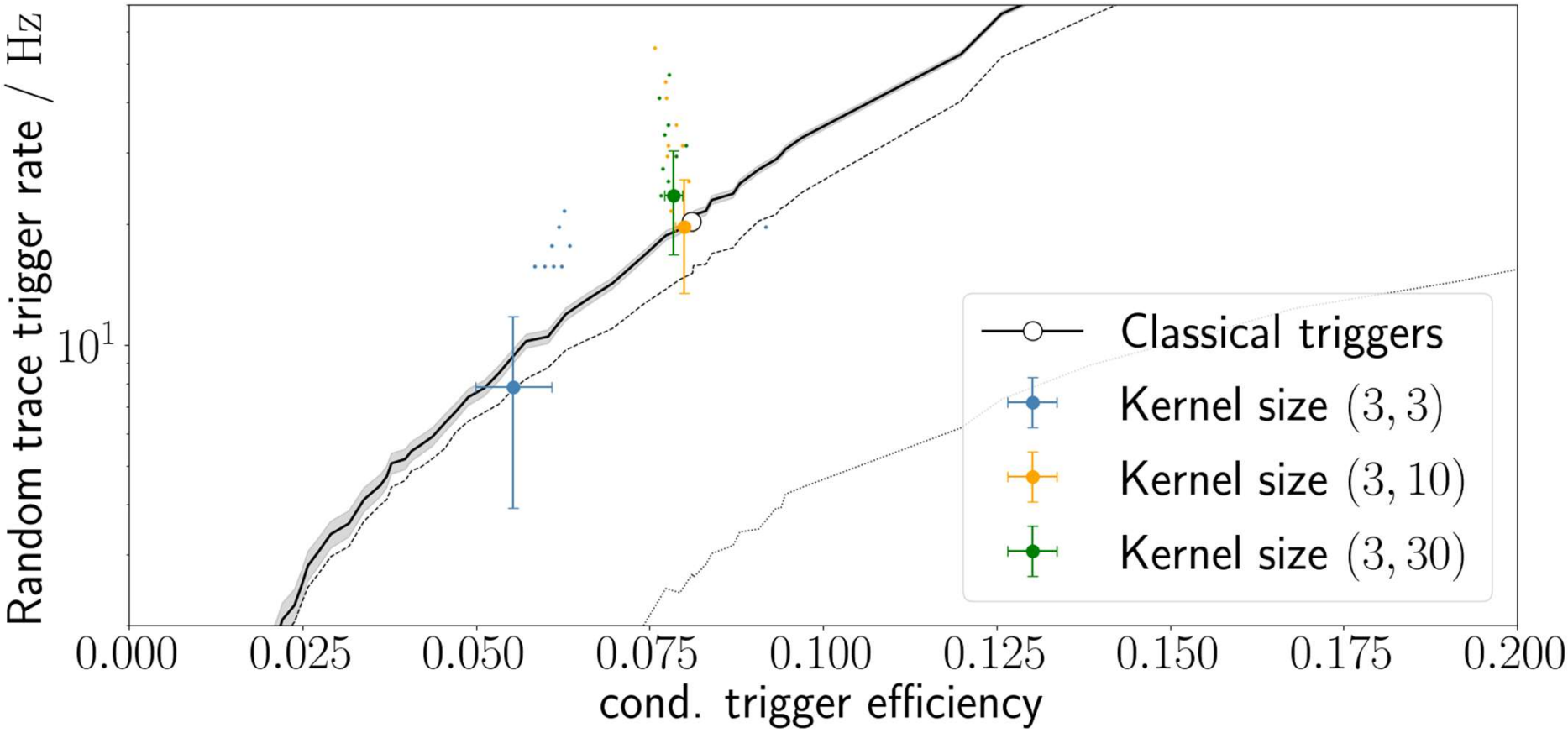
Trace building



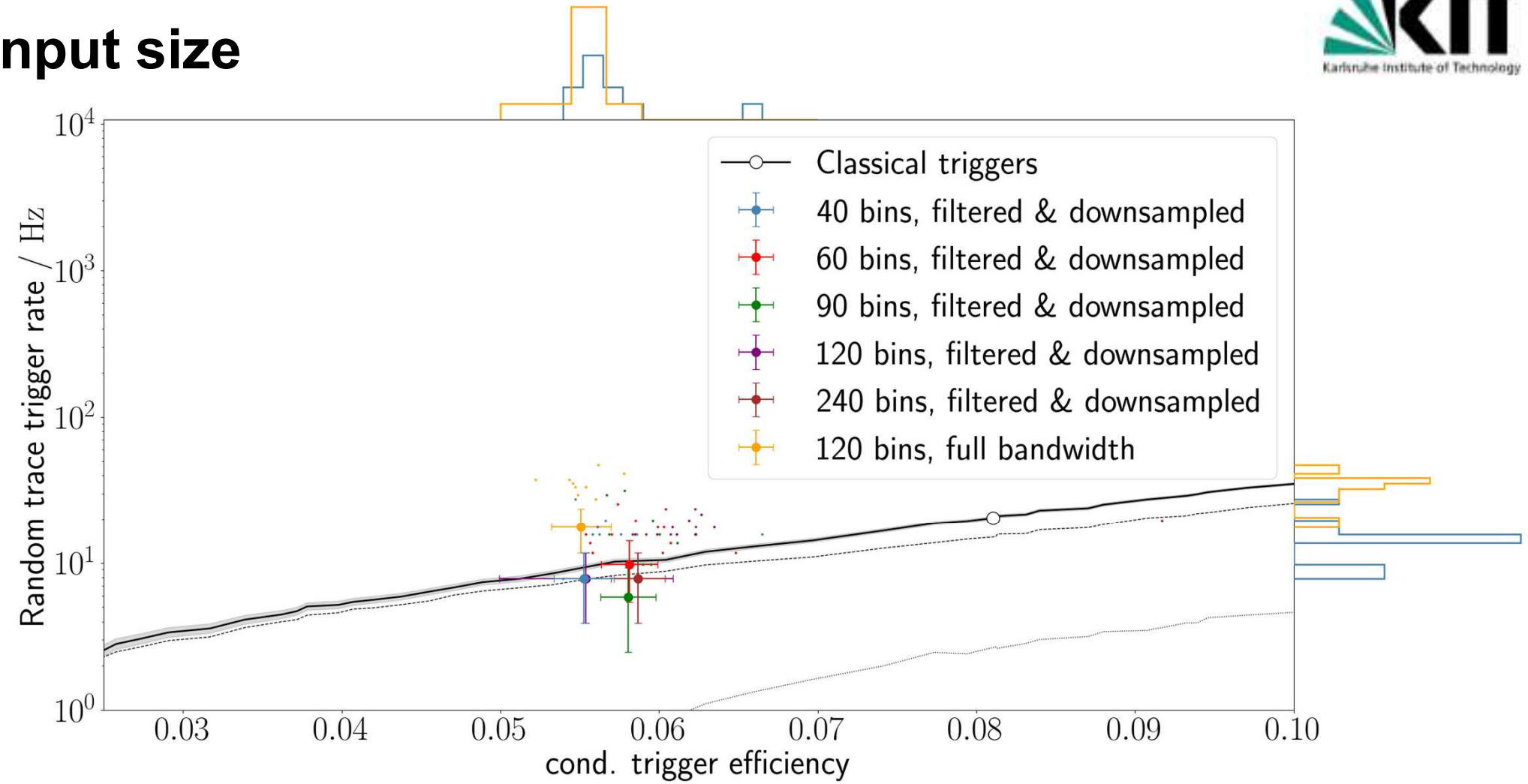
Muon cut


Random trace trigger rate / Hz
10^4
10^3
10^2
10^1
10^0
0.0
0.2
0.4
0.6
0.8
1.0
cond. trigger efficiency
Classical triggers
CNN: $n_\mu = 1$
CNN: $n_\mu = 2$
CNN: $n_\mu = 3$
CNN: $n_\mu = 5$
CNN: $n_\mu = 9$
CNN: $n_\mu = 17$

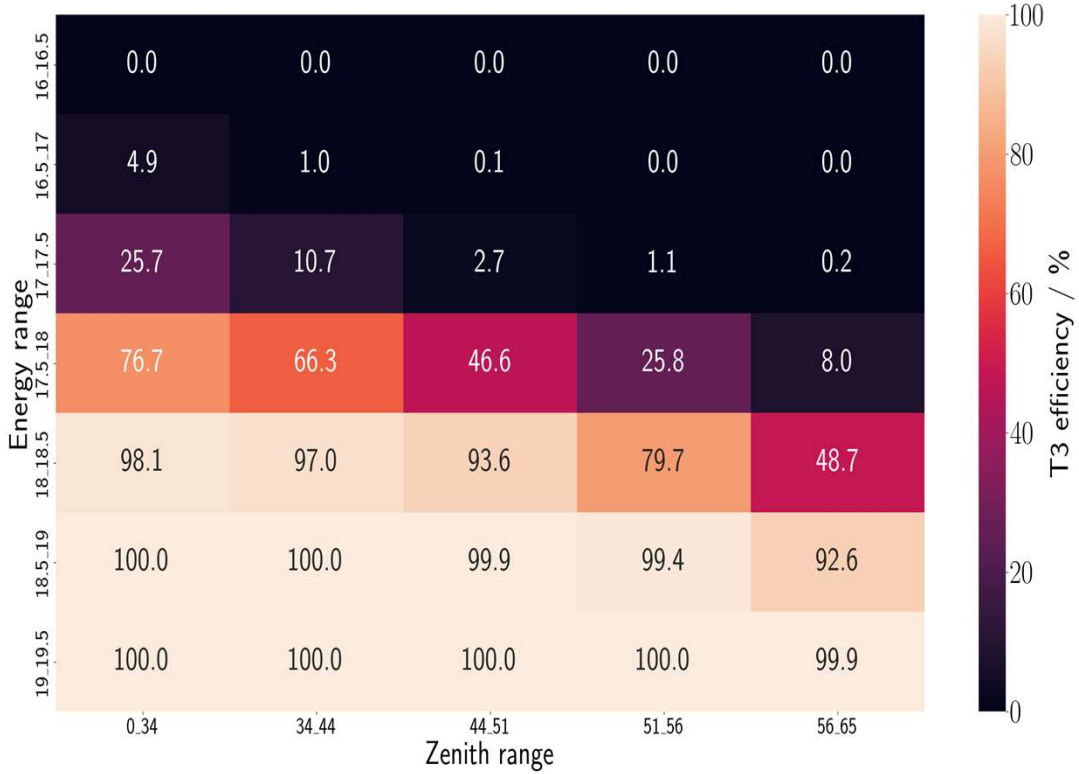
Kernel size


Random trace trigger rate / Hz
10^1
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
cond. trigger efficiency
Classical triggers
Kernel size $(3, 3)$
Kernel size $(3, 10)$
Kernel size $(3, 30)$

Input size


Classical triggers
40 bins, filtered & downsampled
60 bins, filtered & downsampled
90 bins, filtered & downsampled
120 bins, filtered & downsampled
240 bins, filtered & downsampled
120 bins, full bandwidth
Random trace trigger rate / Hz
cond. trigger efficiency
10^0
10^1
10^2
10^3
10^4
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10

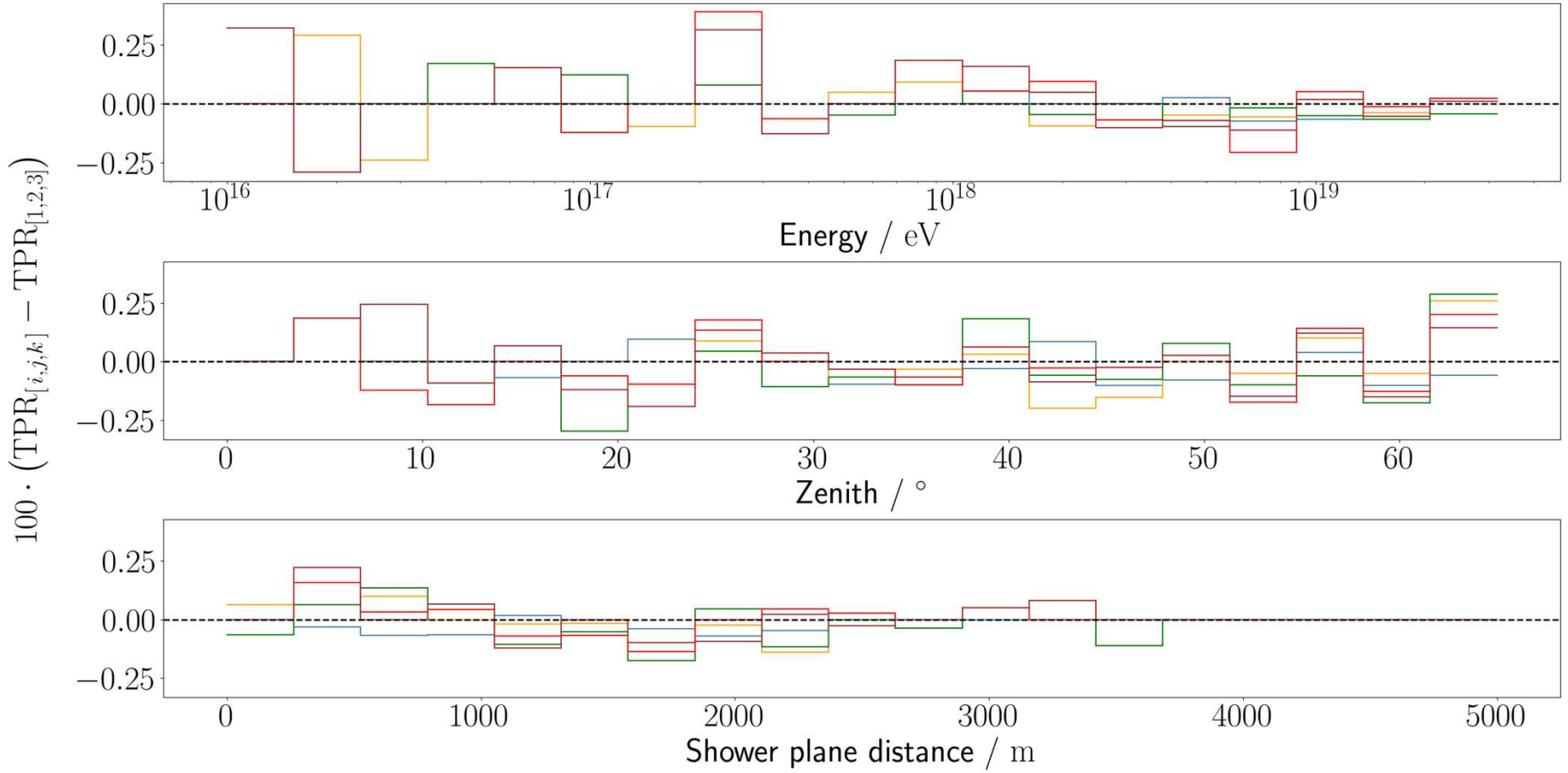
T3 efficiency calculation



Offline approach

Bayesian folding

LSTM permutations



Network parameters

Type	Input size	Kernel size	n_{train}	w/ dense extension
CNN	(3, 120)	(3, 3)	**140**	**834**
CNN	(3, 120)	(3, 10)	**216**	**534**
CNN	(3, 120)	(3, 30)	**444**	**714**
CNN	(3, 40)	(3, 3)	**84**	**210**
CNN	(3, 60)	(3, 3)	**100**	**290**
CNN	(3, 90)	(3, 3)	**120**	**390**
CNN	(3, 240)	(3, 3)	**220**	**890**
LSTM	(3, 120)	–	**12**	(single layer)
LSTM	(3, 120)	–	(three layers)	**44**

Sample headline: Arial 24pt bold

Subline: Arial 20pt bold

- Lorem ipsum dolor sit amet, consetetur sadipscing
- …
  - …
  - …

Subline: Arial 20pt bold

Sample headline: Arial 24pt bold

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- Lorem ipsum dolor sit amet, consetetur sadipscing
- …
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Subline: Arial 20pt bold

Sample headline: Arial 24pt bold

- Lorem ipsum dolor sit amet, consetetur sadipscing elitr, sed diam nonumy eirmod
  - At vero eos et accusam et justo duo dolores et ea rebum. Stet clita kasd gubergren
    - No sea takimata sanctus est Lorem ipsum dolor sit amet.
- Lorem ipsum dolor sit amet, consetetur sadipscing elitr, sed diam nonumy eirmod tempor invidunt
- …
- …

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  - …

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Lorem ipsum dolor sit amet, consetetur sadipscing elitr, sed diam nonumy eirmod tempor invidunt ut labore et dolore magna aliquyam erat, sed diam voluptua.

At vero eos et accusam et justo duo dolores et ea rebum. Stet clita kasd gubergren.

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