dRICH Data Reduction system: last updates

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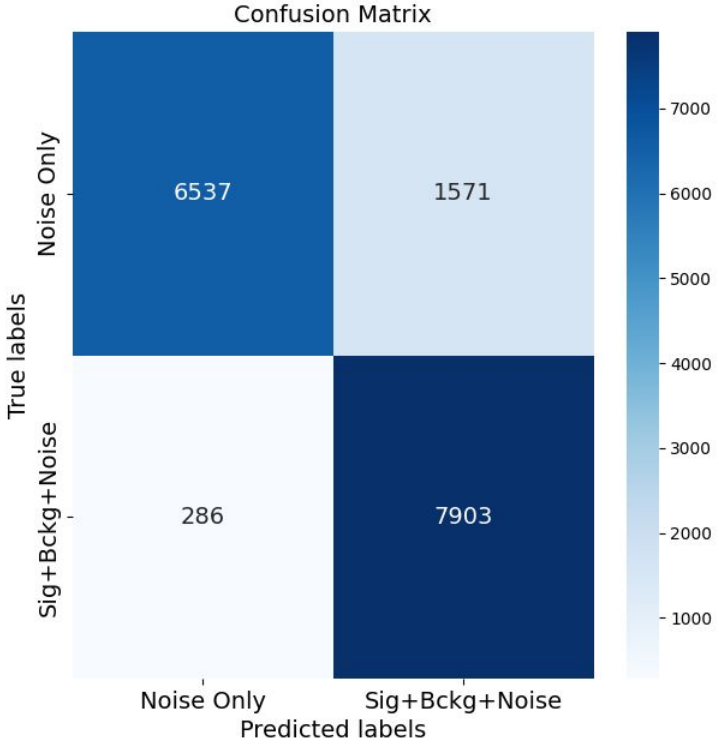
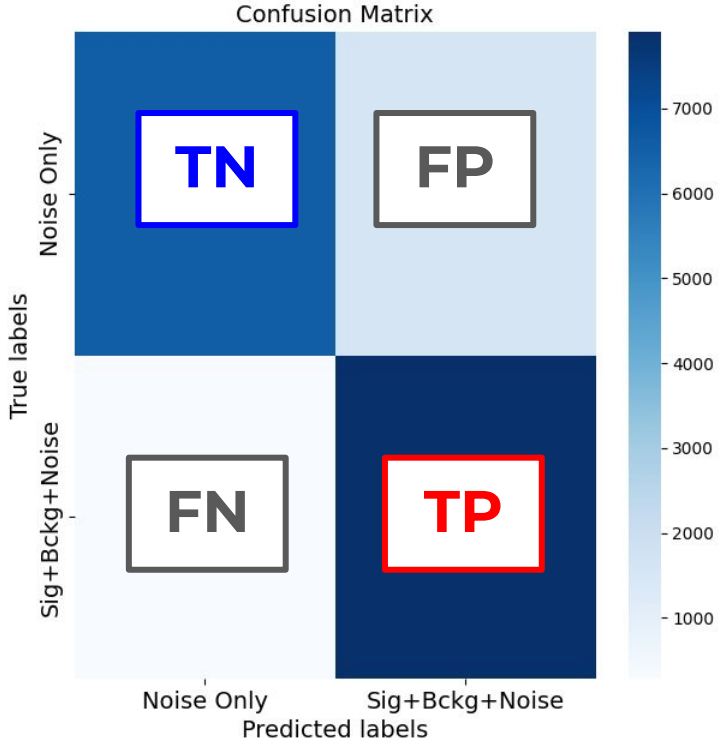
ePIC DAQ meeting
13/03/2026

Positive (P) ⇒ Signal // Negative(N)⇒Noise



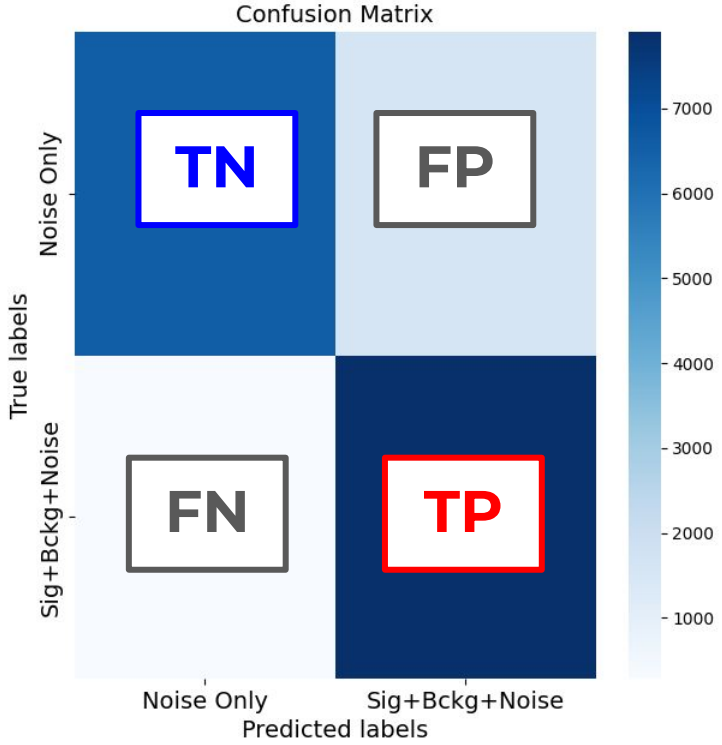


Performance evaluation and targets

- In this change of paradigm, to evaluate the model performance, we introduce:
  - **True Positive Rate (TPR):** percentage of correctly classified true-labeled Signal+Background+Noise events
  - **True Negative Rate(TNR):** percentage of correctly classified true-labeled Noise-Only events

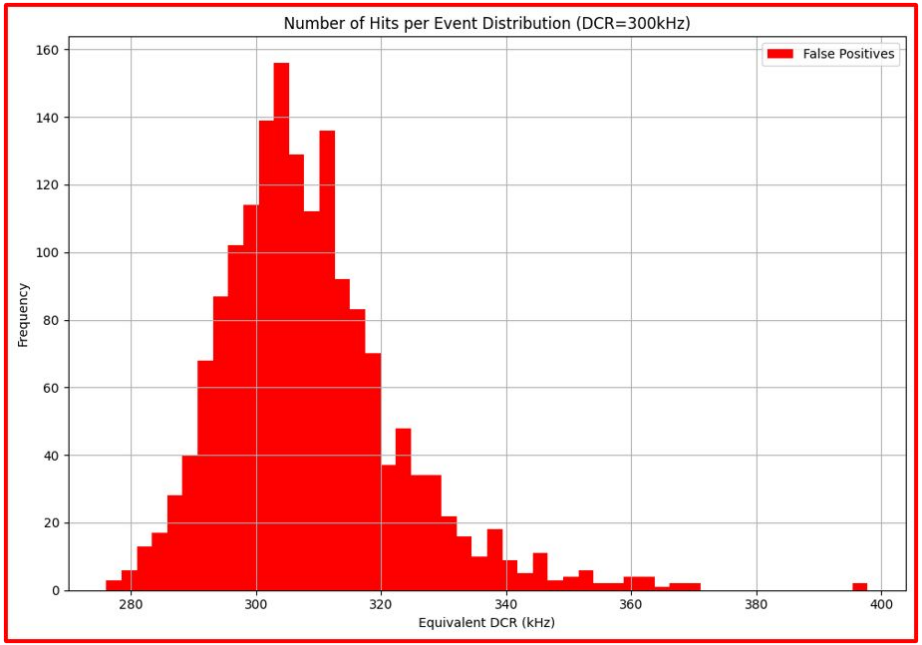
$$TPR = \frac{TP}{TP + FN}$$ as high as possible

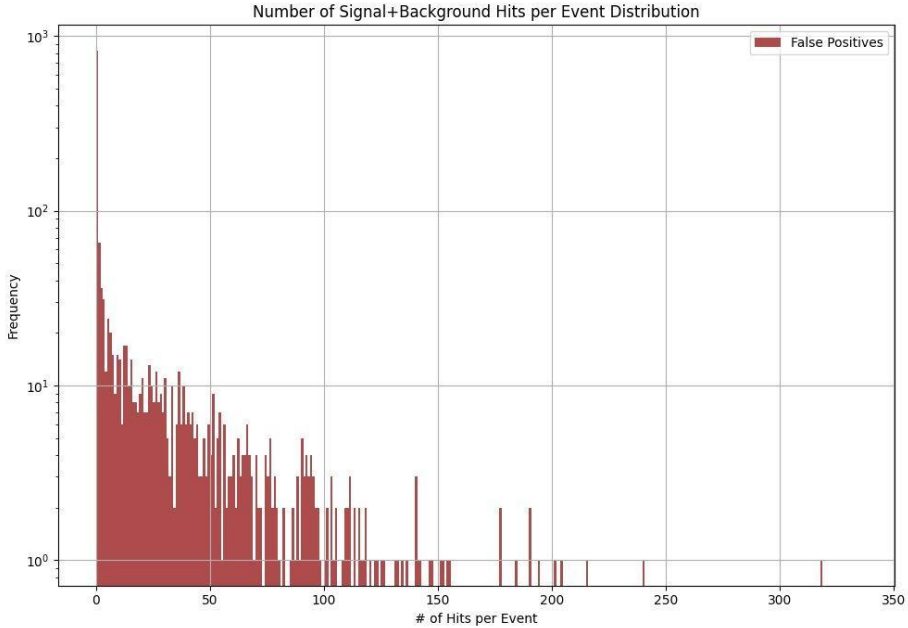
$$TNR = \frac{TN}{TN + FP}$$ >= 80% [⇒ reduction factor >=5]



False Negative (FN) Analysis

False Negative events —same indexes→ Source Sig+Bckg reconstructed events



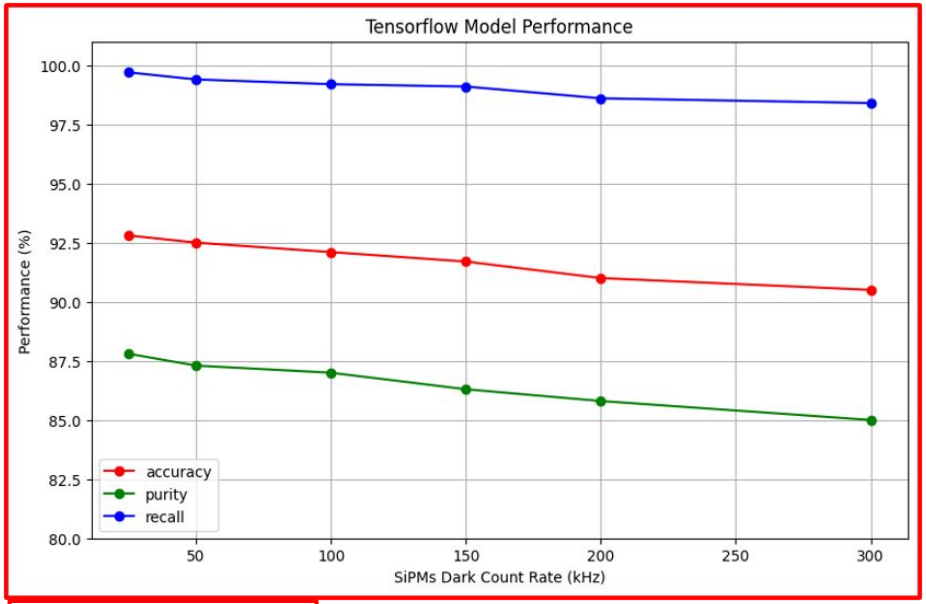


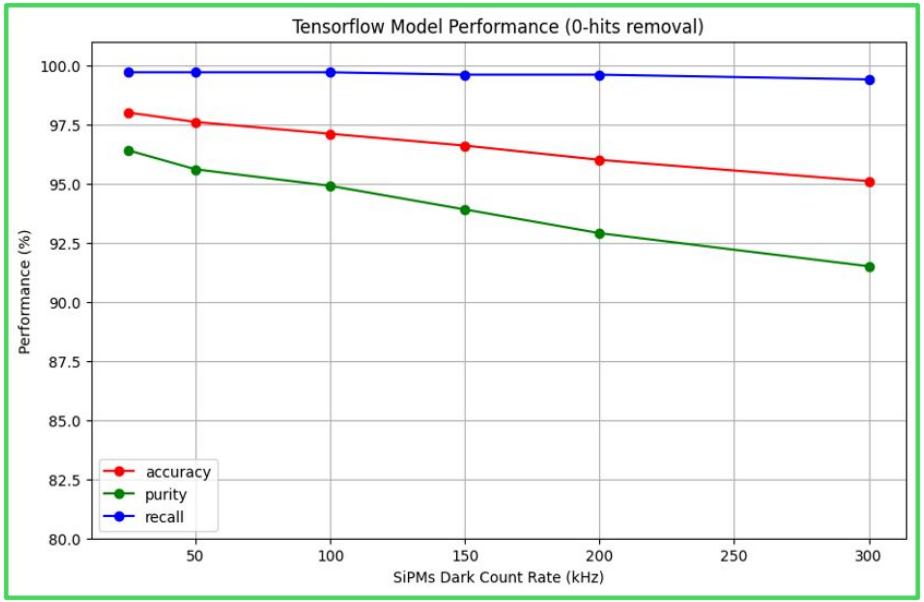
FN = signal events mis-predicted as noise by the model ➜ cause!

False Positive (FN) ⇒ 0-hits removal (⇒ “nozeros” dataset)

0-hits removal

⇒ purity enhanced by ~6.5%



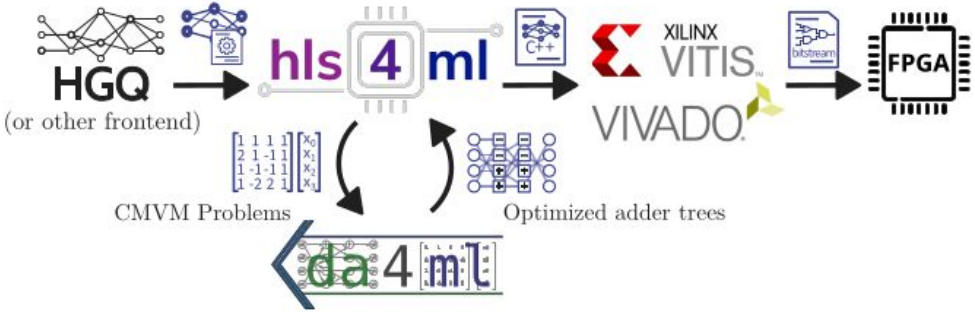


RICH2025 performance

FN = signal events mis-predicted as noise by the model ➜ possible solution

HGQ for quantization step

- To solve the **quantization issue occurred with DCR >=150 kHz**, we aligned our system with the new state-of-the-art libraries for FPGA ML model implementation:

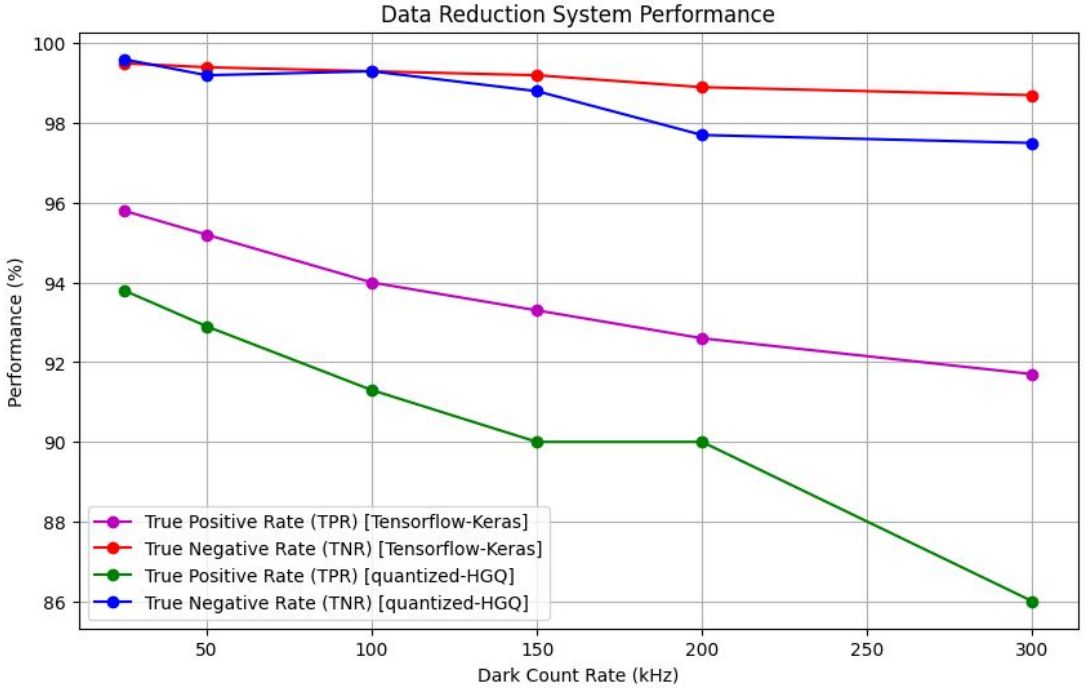


  - ❏ **da4ml** is a library implementing neural networks on FPGAs with DA (**D**istributed **A**rithmetic). There are two main components:
    - ➢ CMVM optimizer with graph-based pre-optimization and common sub-expressions elimination (CSE) to **reduce the firmware footprint for the CMVM operation**.
    - ➢ Low-level symbolic tracing utility for generating combinational/fully pipelined network/sub-network in HDL or HLS code.

  - ❏ **HGQ**2 (**H**igh **G**ranularity **Q**uantization 2) is a **quantization-aware training** framework built on Keras v3, targeting real-time deep learning applications on edge devices like FPGAs.
    - ➢ HGQ2 implements an **gradient-based automatic bitwidth optimization** and quantization-aware training algorithm. By leveraging gradients, it allows for **bitwidth optimization** at arbitrary granularity, up to per-weight and per-activation level.

HGQ performance (⇒ “nozeros” dataset)

P = signal+background+noise
N = noise-only
TPR = TP / (TP + FN)
TNR = TN / (TN + FP)



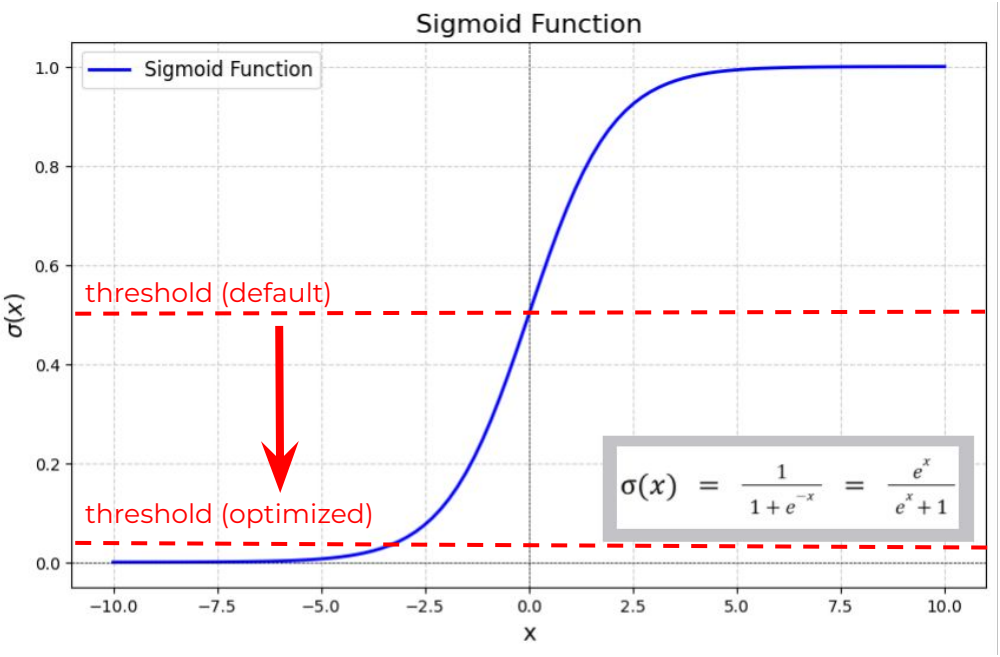
Optimized threshold for TPR maximizing

Binary Classifier Output (Sigmoid Activation)

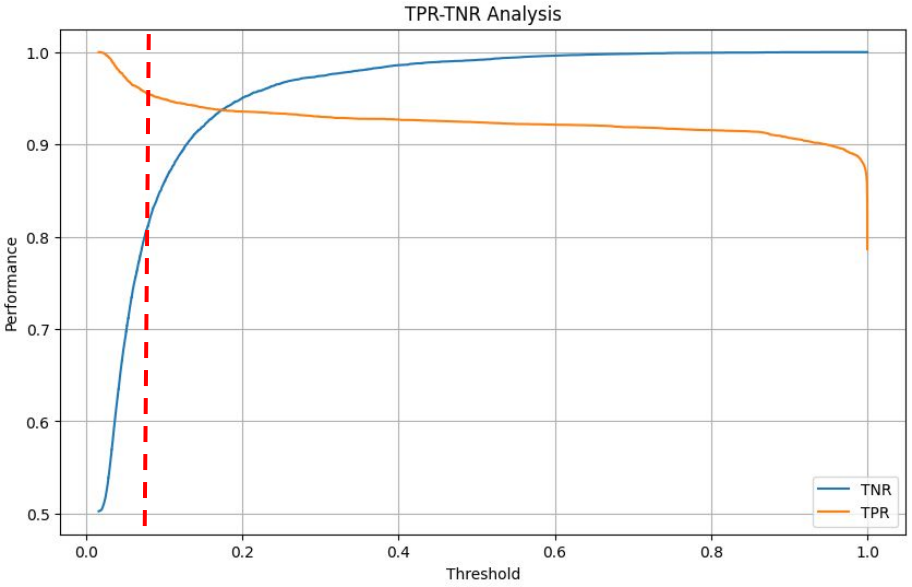
- The final layer uses a **sigmoid activation function**, producing an output in the range **[0, 1]**, interpreted as the **probability of belonging to the positive class**.
- A **decision threshold t** is applied to obtain a binary prediction:
  - *output* ≥ *t* ⇒ **positive class**
  - *output* < *t* ⇒ **negative class**
- The default choice is **t=0.5**, but the threshold can be **adjusted depending on the analysis goals**.

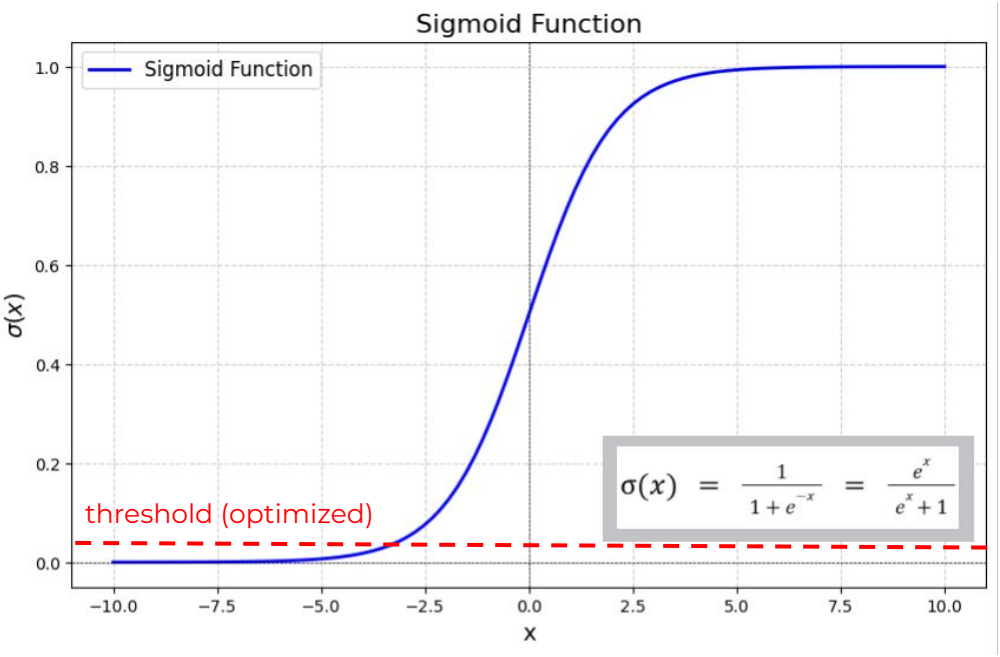
Effect of changing the threshold

- **Lower threshold** → more events classified as positive ⇒ higher **sensitivity/recall for positives**, but more **false positives** ⇒ higher **TPR**, lower **TNR**
- **Higher threshold** → stricter positive classification ⇒ higher **specificity for negatives**, but more **false negatives**.
  ⇒ higher **TNR**, lower **TPR**



Optimized threshold for TPR maximizing

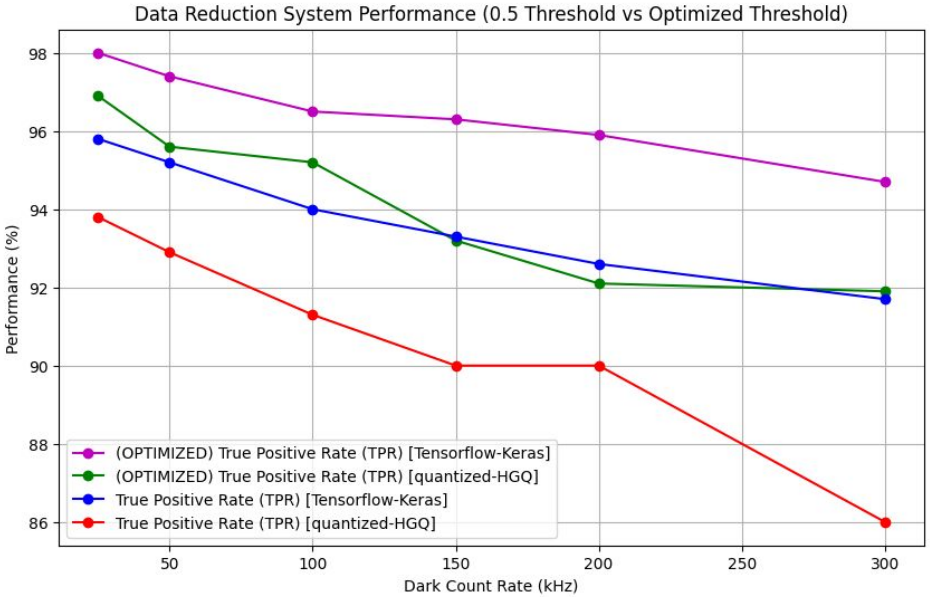


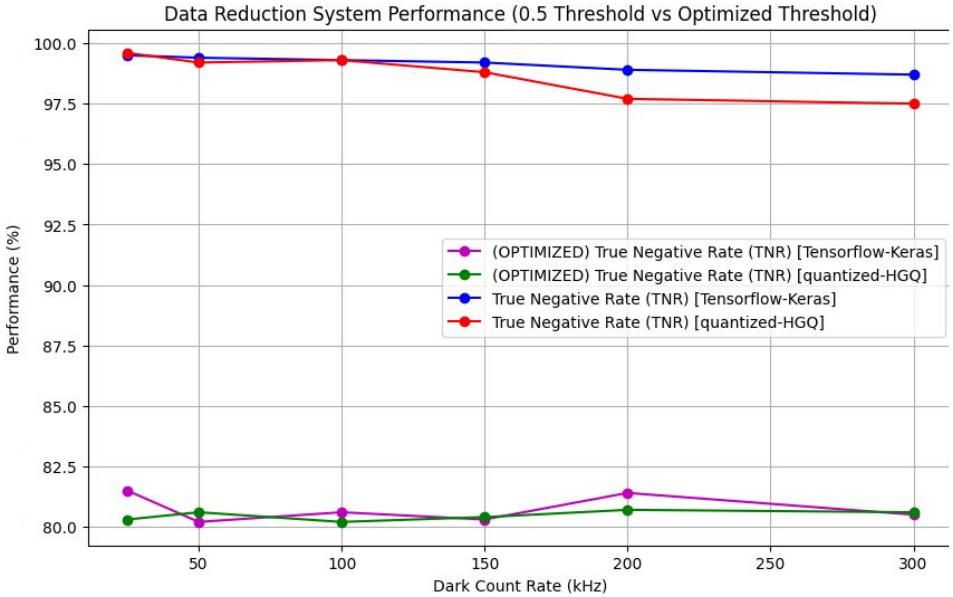


$$\text{TNR} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad >= 80\% \; [\Rightarrow \text{reduction factor} >= 5]$$

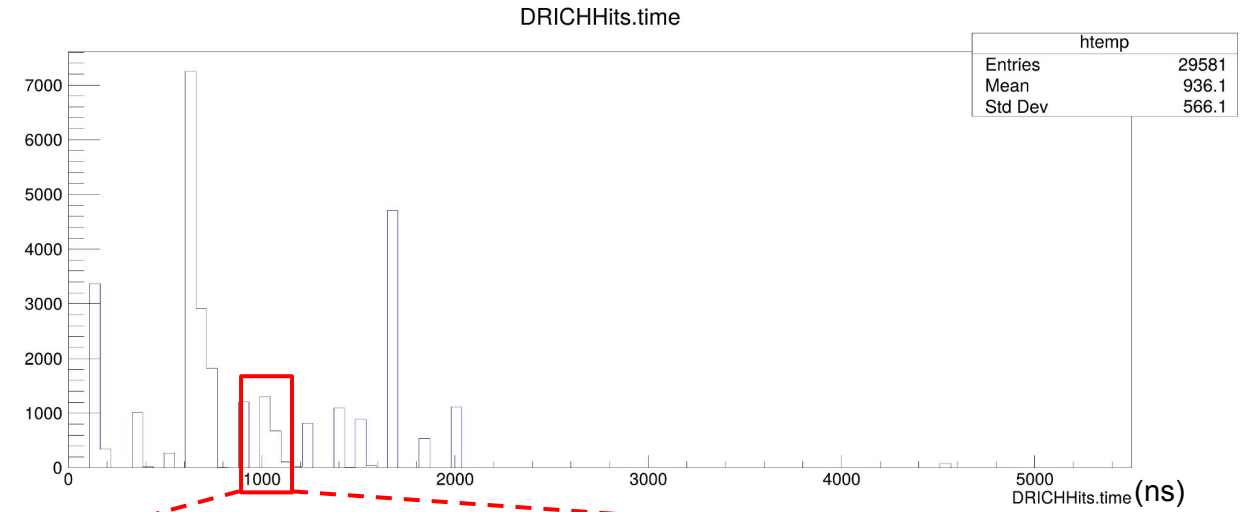
TPR maximizing

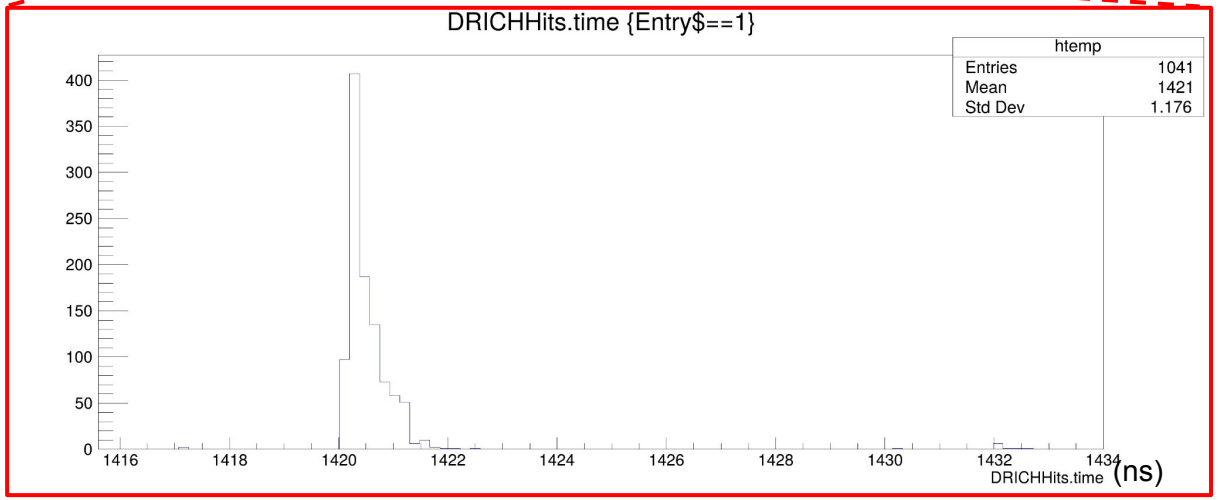
P = signal+background+noise
N = noise-only
TPR = TP / (TP + FN)
TNR = TN / (TN + FP)





Time-Information Input for Multi MLP model





Signal+Background Simulated Events

⇒ **ROOT File TBranch**: DRICHHits

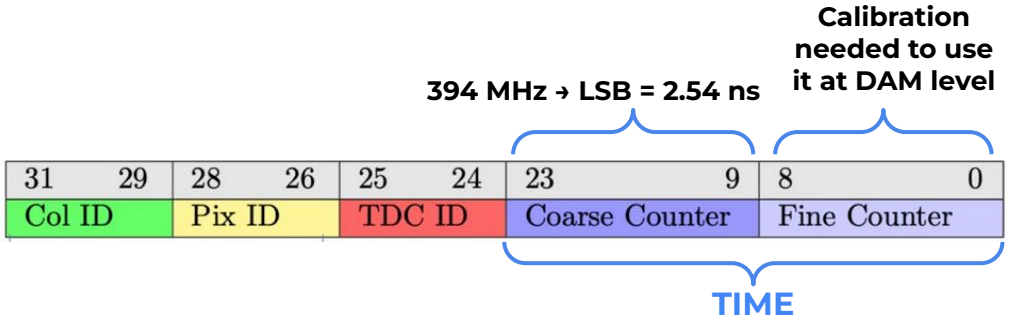
⇒ **Entry**: DRICHHits.time

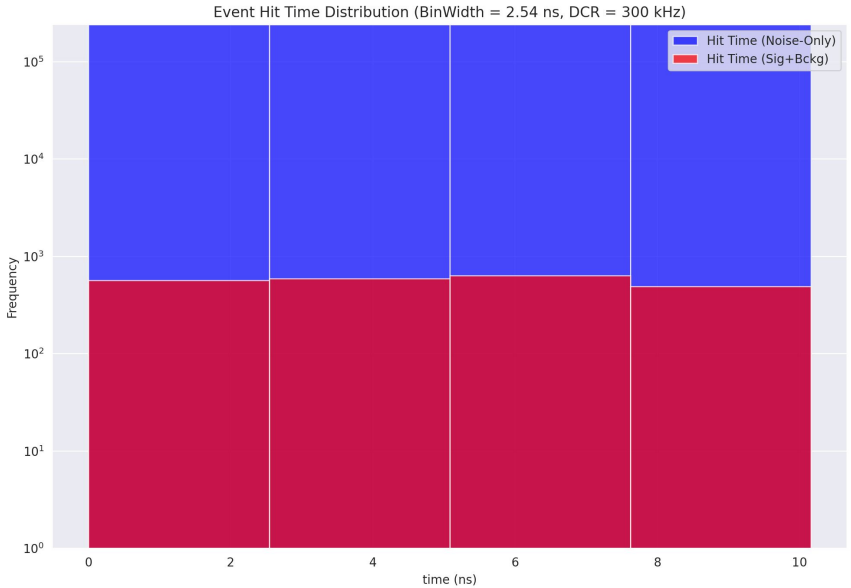
Focus on a single event time distribution

⇒ ~2ns wide time distribution (as expected)

Timing Distribution

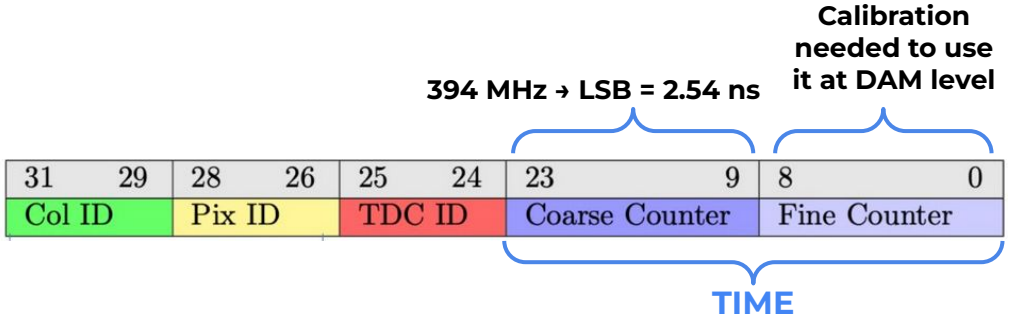
- We start to evaluate how to implement the **timing information** to enhance the performance of the data reduction system.
- Thus, we started to look at the **timing distribution** of the datasets generated for the MLP NN model training and validation

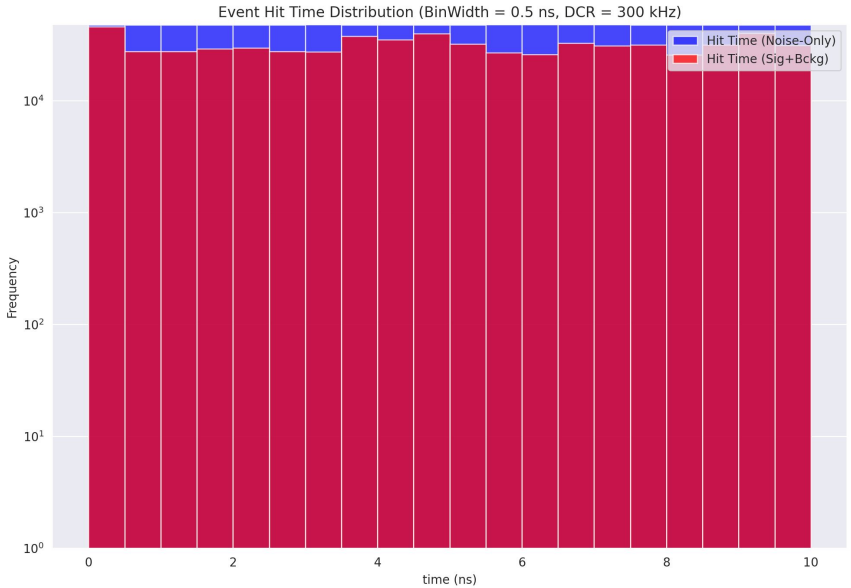




Timing Distribution

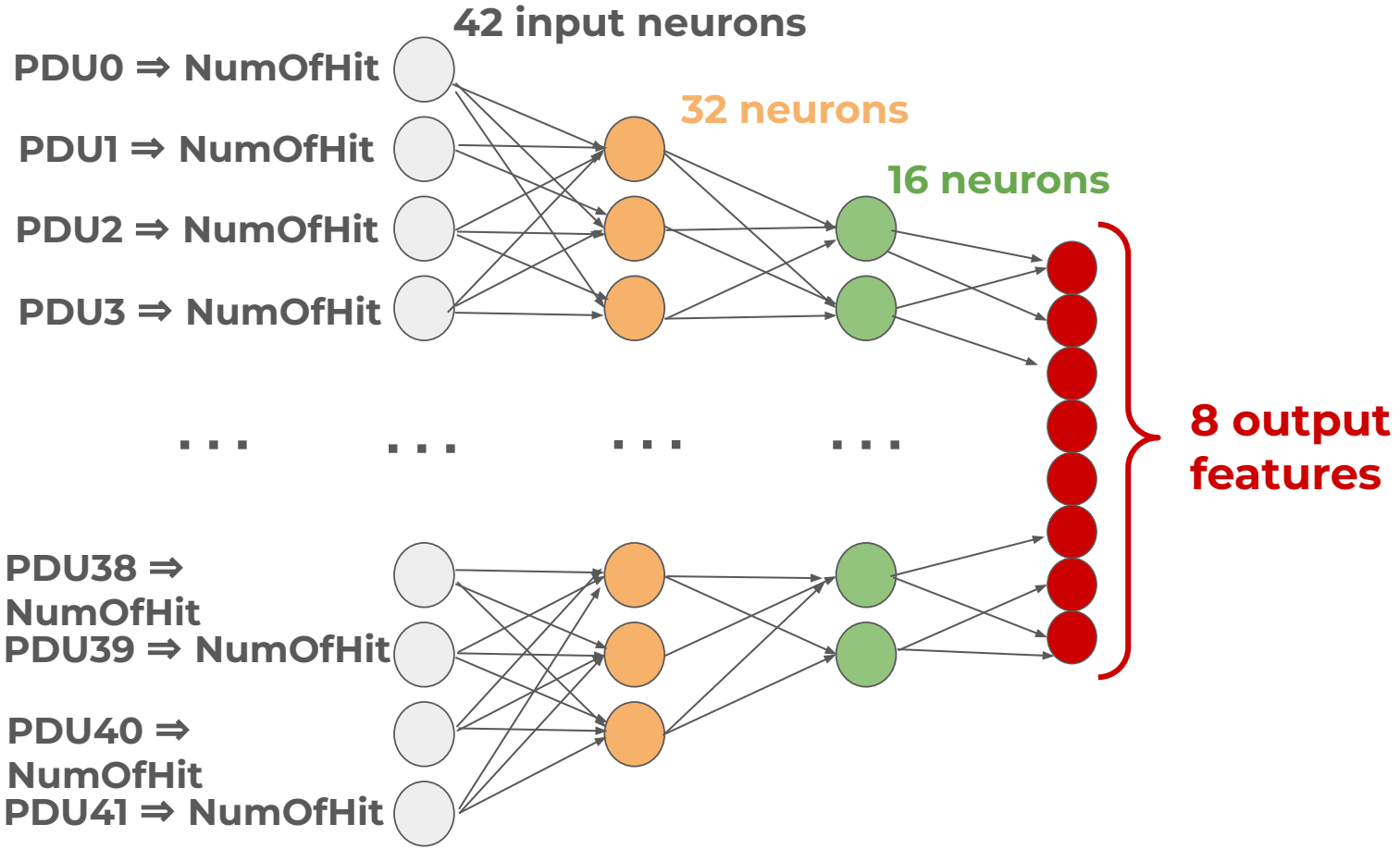
- We start to evaluate how to implement the **timing information** to enhance the performance of the data reduction system.
- Thus, we started to look at the **timing distribution** of the datasets generated for the MLP NN model training and validation ⇒ **binwidth** connected to the bit resolution available from **Coarse Counter** and **Fine Counter**



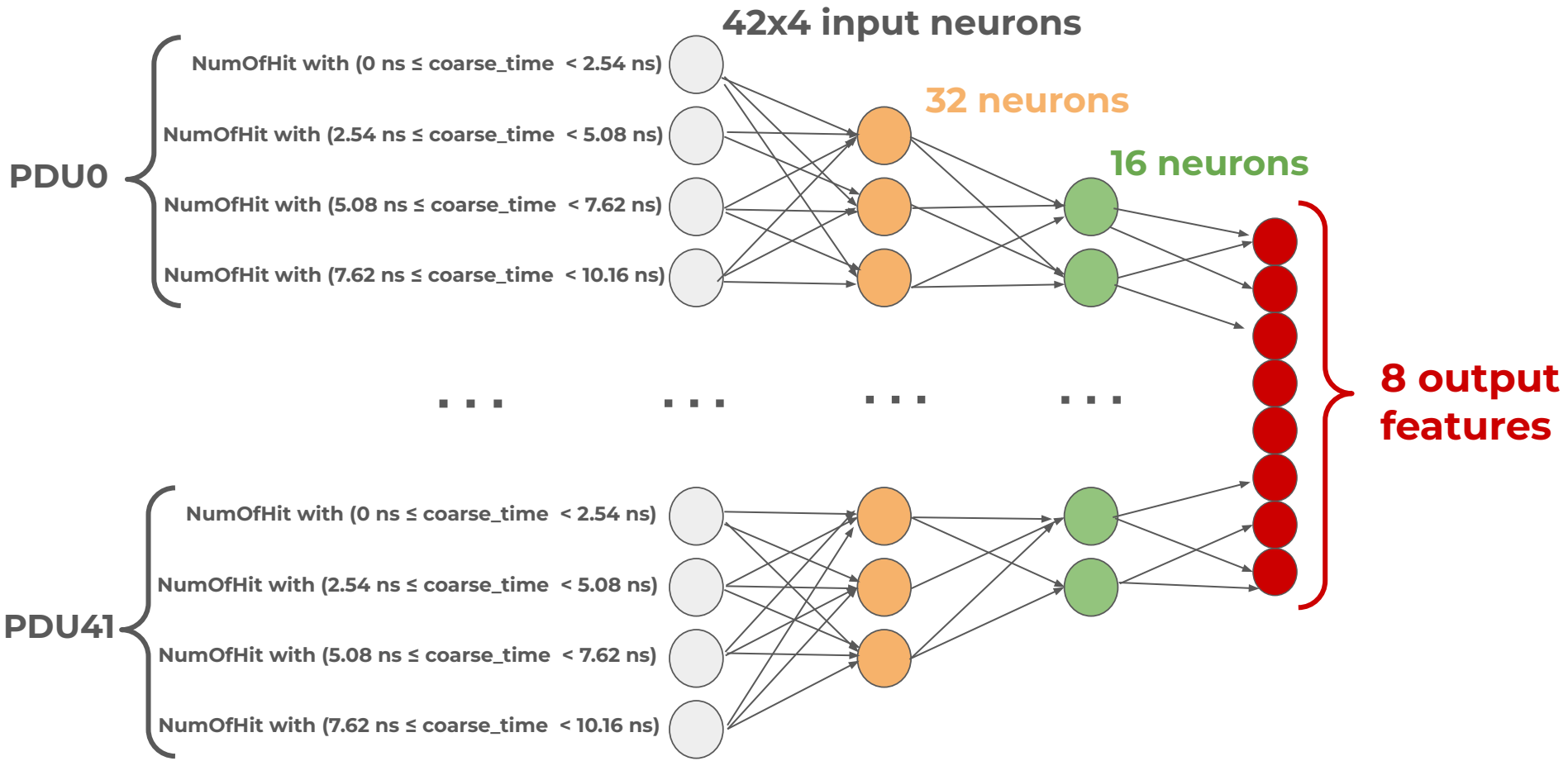


Multi-MLP model with timing information
⇒ Keras/HGQ2 evaluation

DAM input ⇒ Subsector PDU Number Of Hit

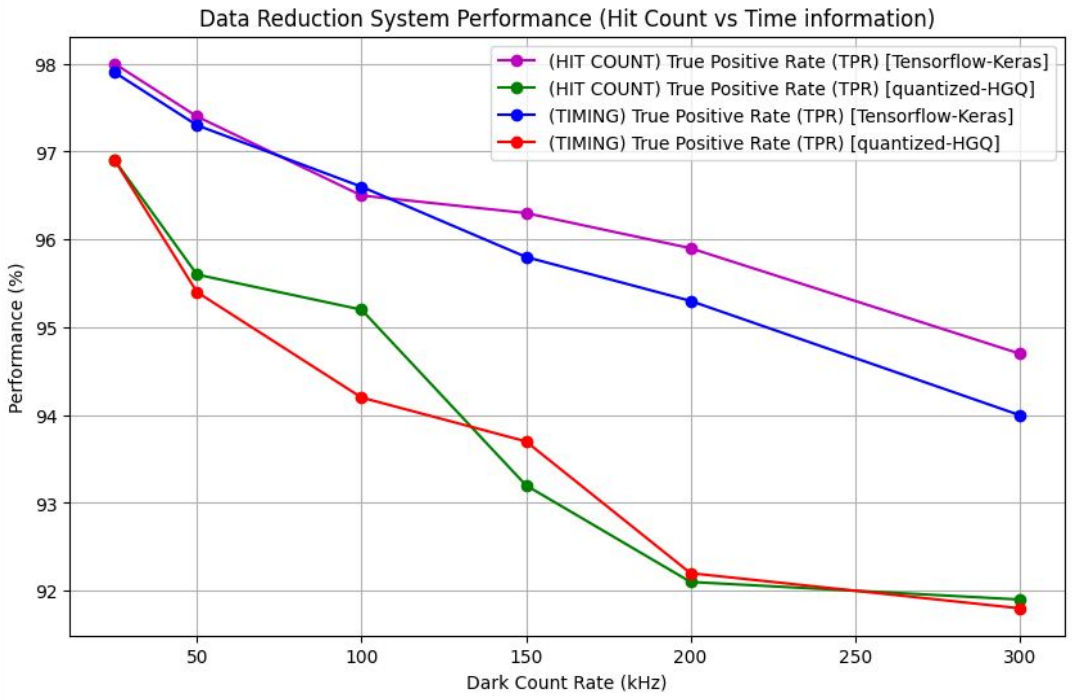


4 bin time-histogram (2.54ns binwidth) ⇒ DAM input



TPR comparison

P = signal+background+noise
N = noise-only
TPR = TP / (TP + FN)
TNR = TN / (TN + FP)



- :(

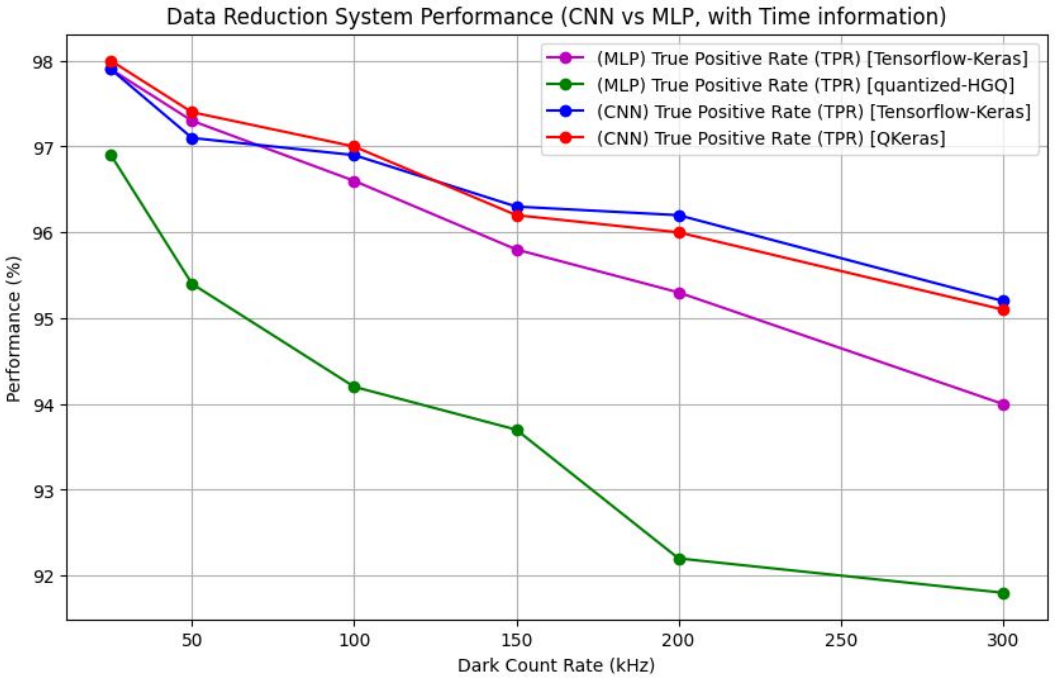
Can we switch to another model?
⇒ CNN alternative

P = signal+background+noise
N = noise-only
TPR = TP / (TP + FN)
TNR = TN / (TN + FP)

- Since the unexpected loss in performance when using the time information as input the MLP model, we tried to evaluate a different model
  ⇒ **CNN input layers** for DAM models, SectorMLPs remain the same

- **TPR** increases wrt the MLP one, however...
  ⇒ **CNN *`hls4ml`* istantiation interval:**
  II ~ 4 clock cycles
  ⇒ throughput ~ 50 MHz (@200MHz clock) < 100 MHz (EIC rate)

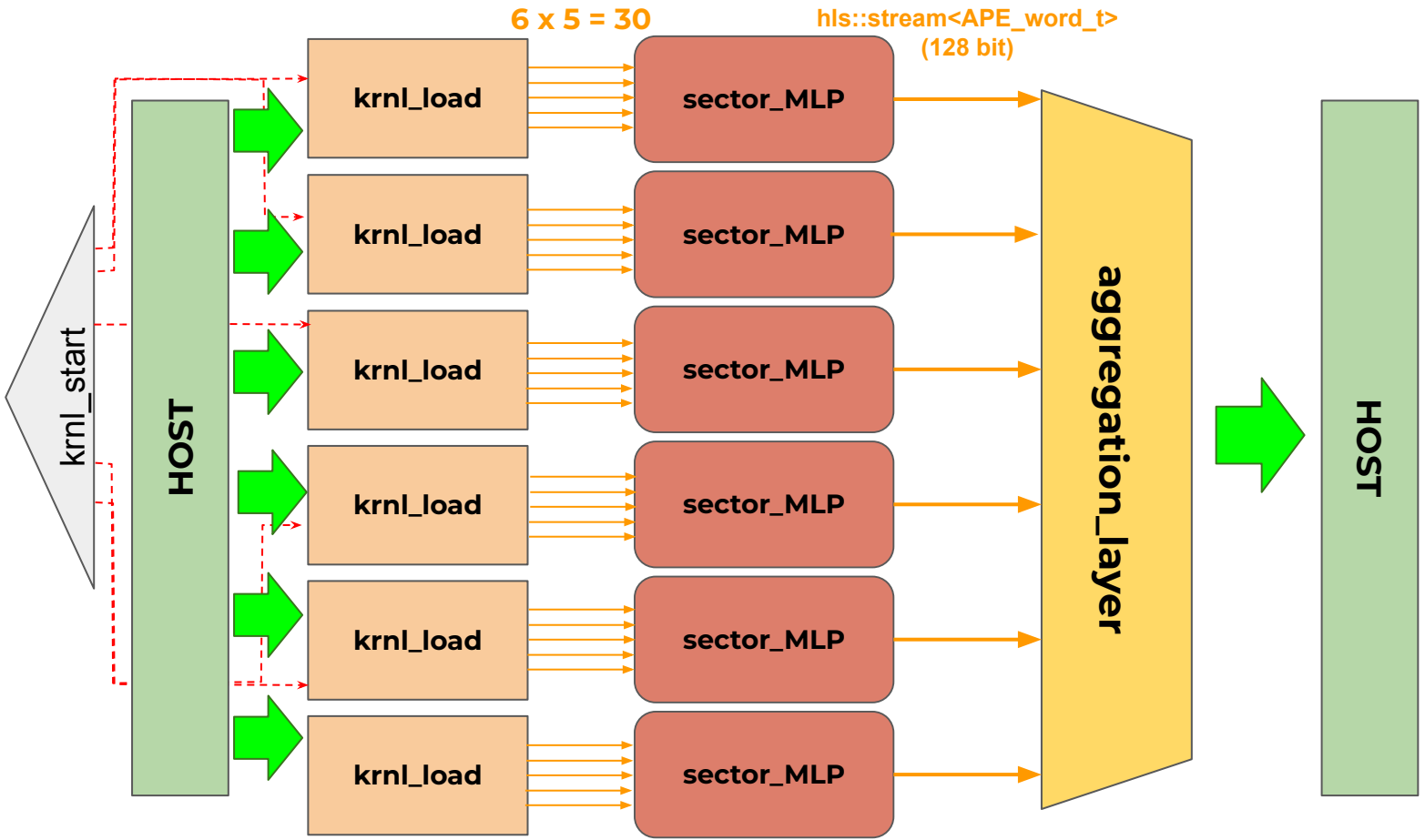
- **:(**



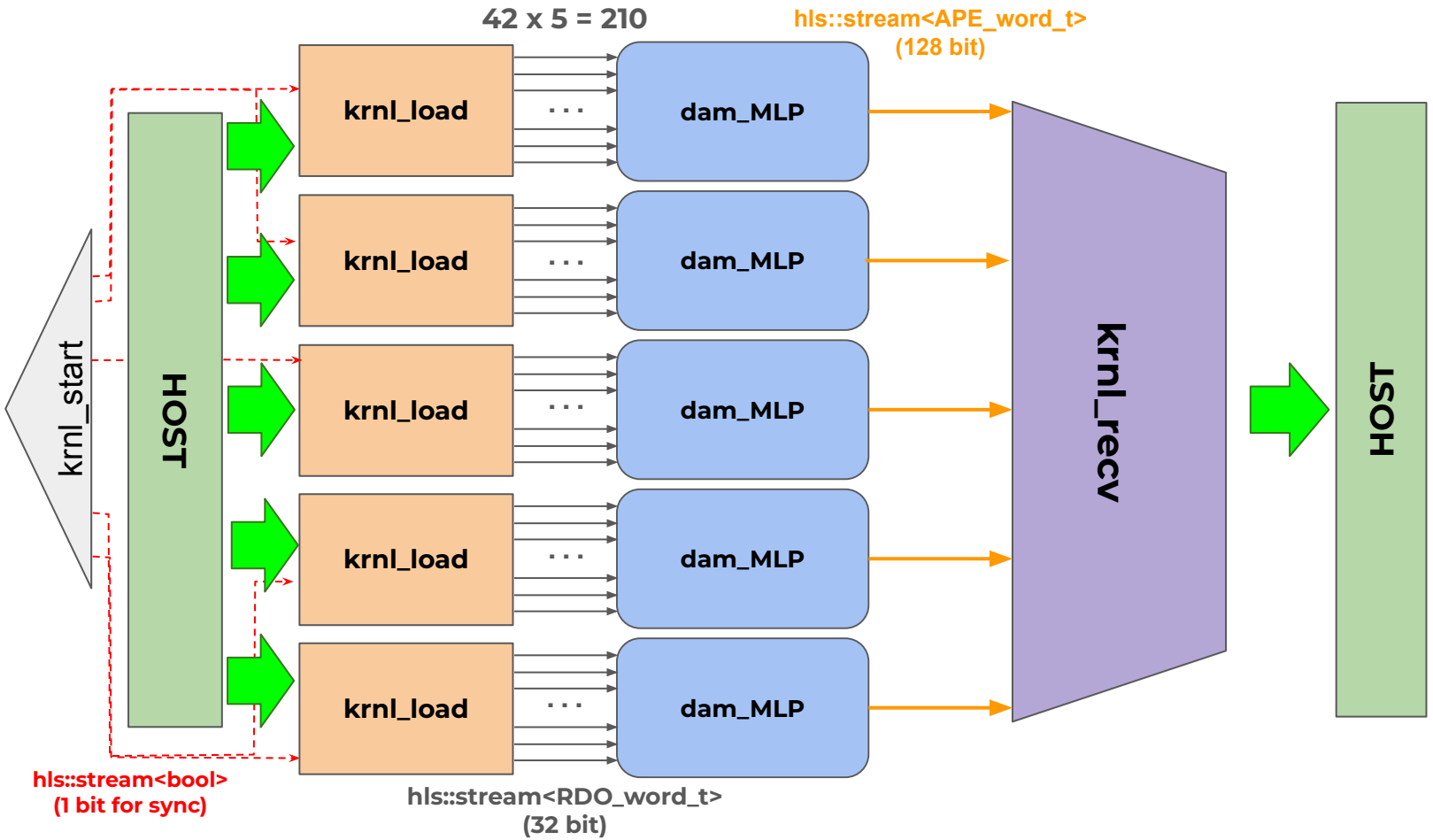
HW Multi-MLP model implementation

⇒ DAM to TP Communication testbed (preparation for RT2026 and possibile IEEE publication)

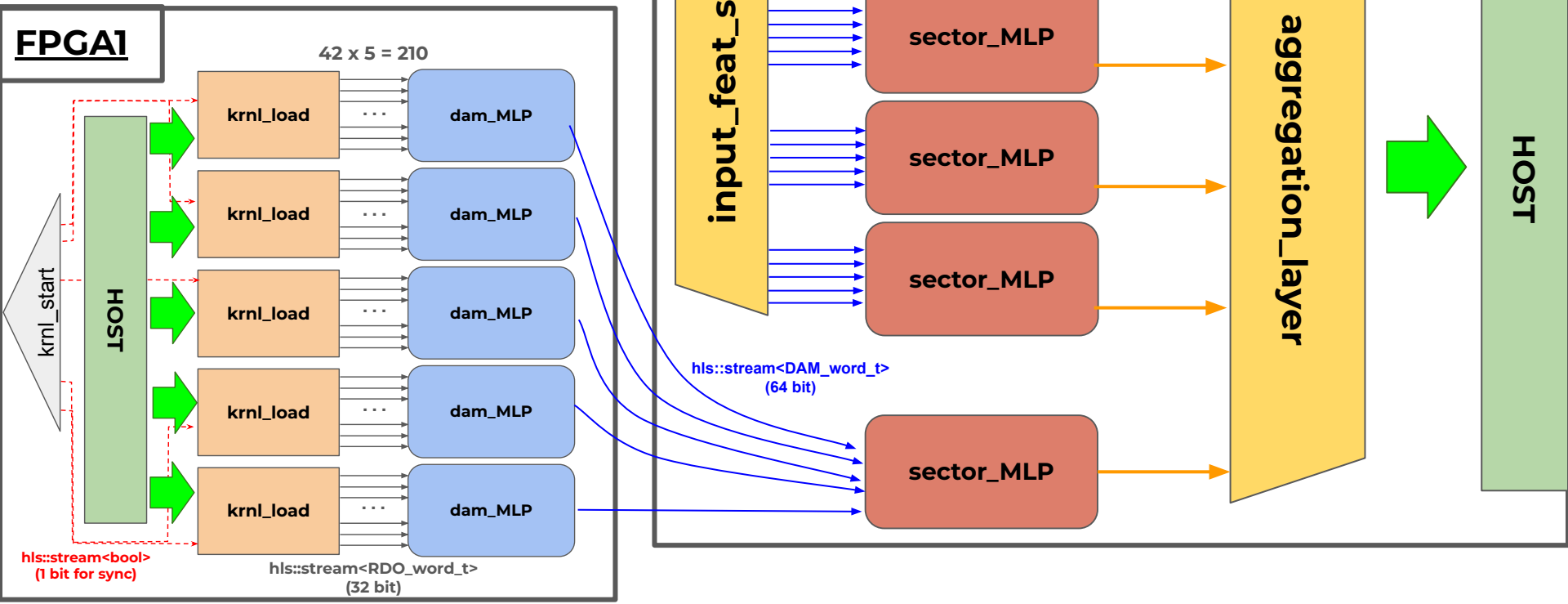
Single FPGA setup ⇒ TP architecture



Single FPGA setup ⇒ Sector architecture (5 DAMs)

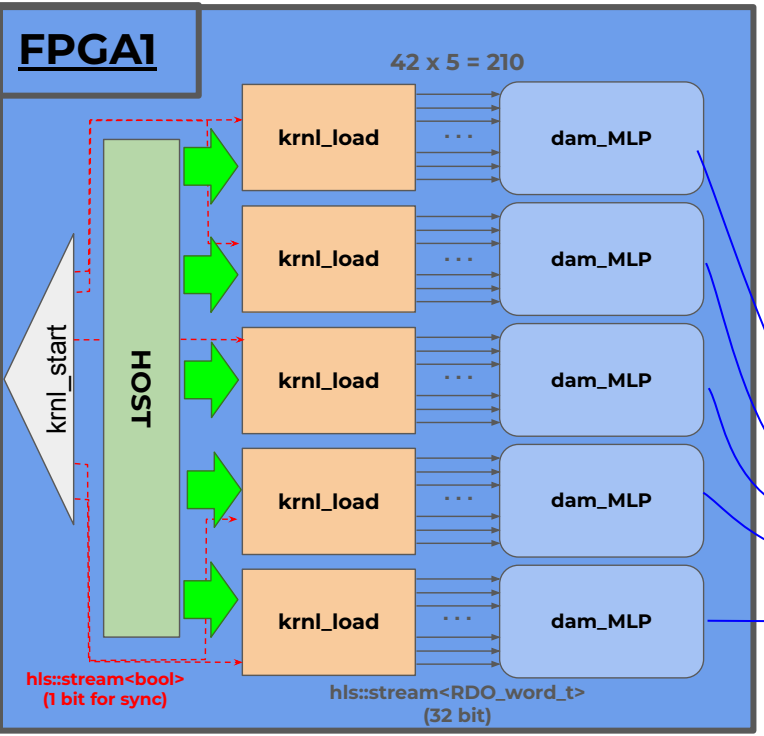


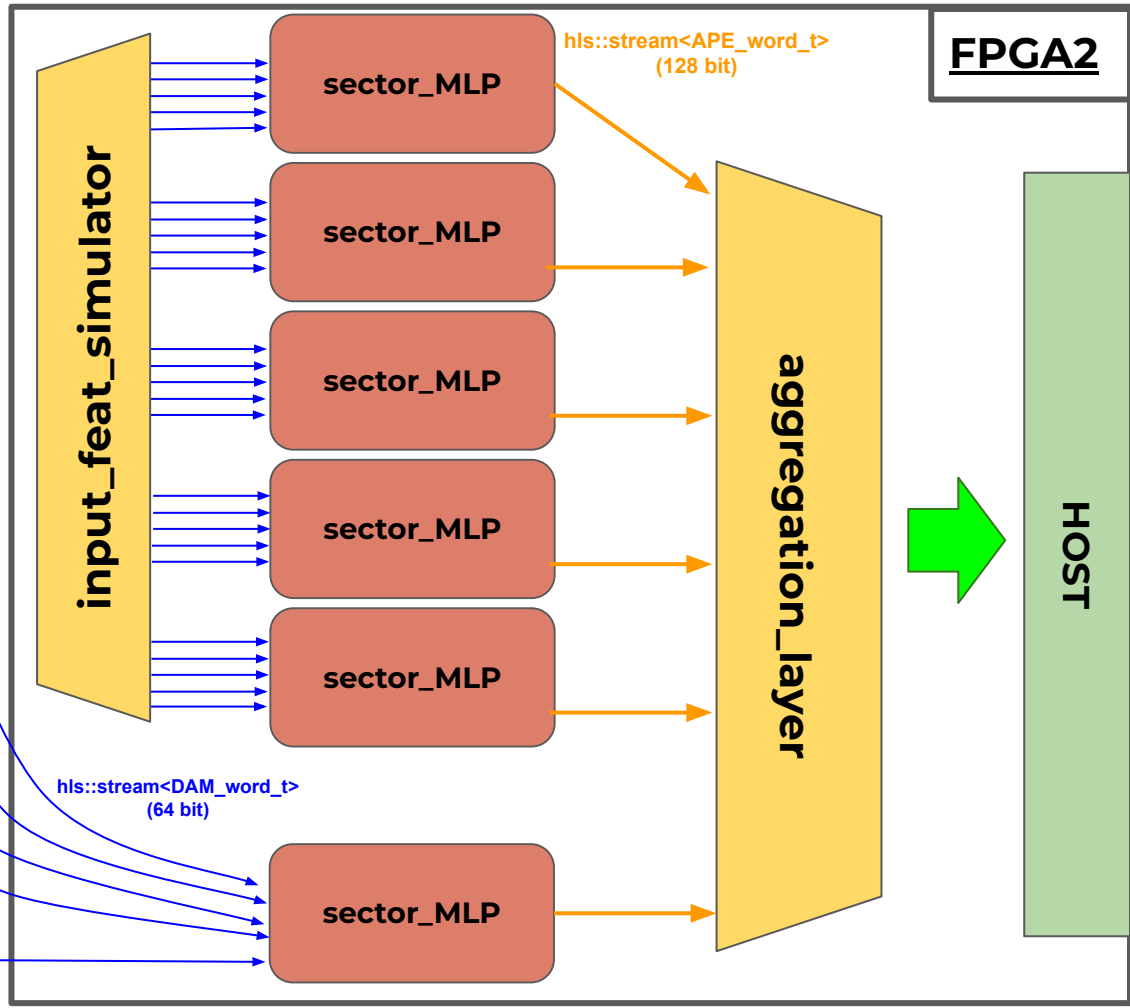
Multi FPGA setup



Multi FPGA setup

FPGA1
⇒ datastream simulation of an entire sector (5 DAMs)
⇒ ALINX AXAU15

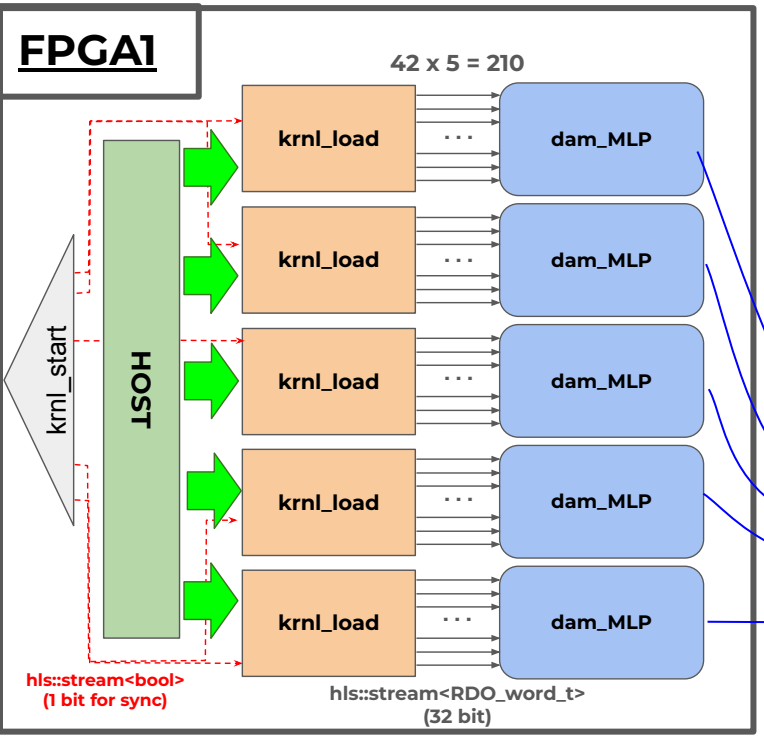


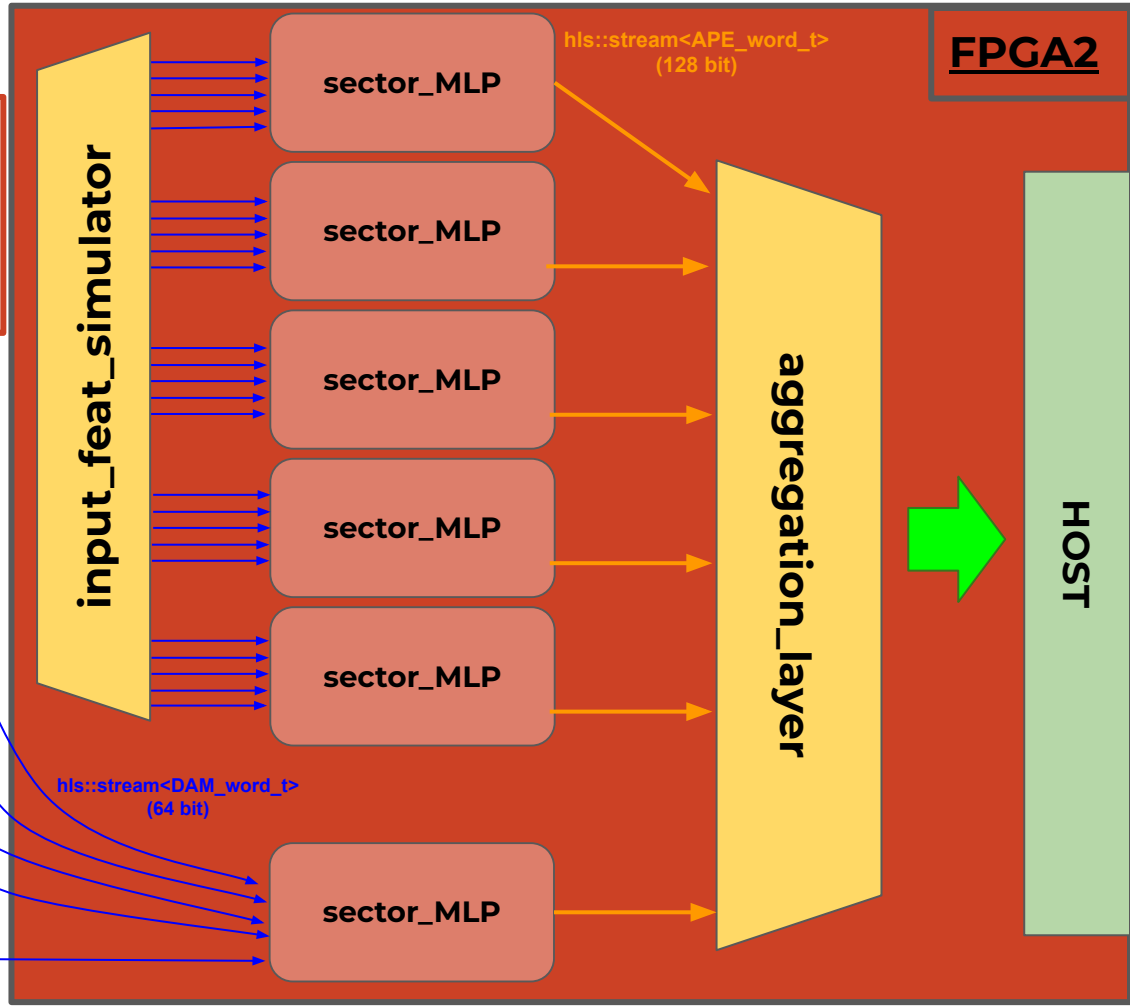


Multi FPGA setup

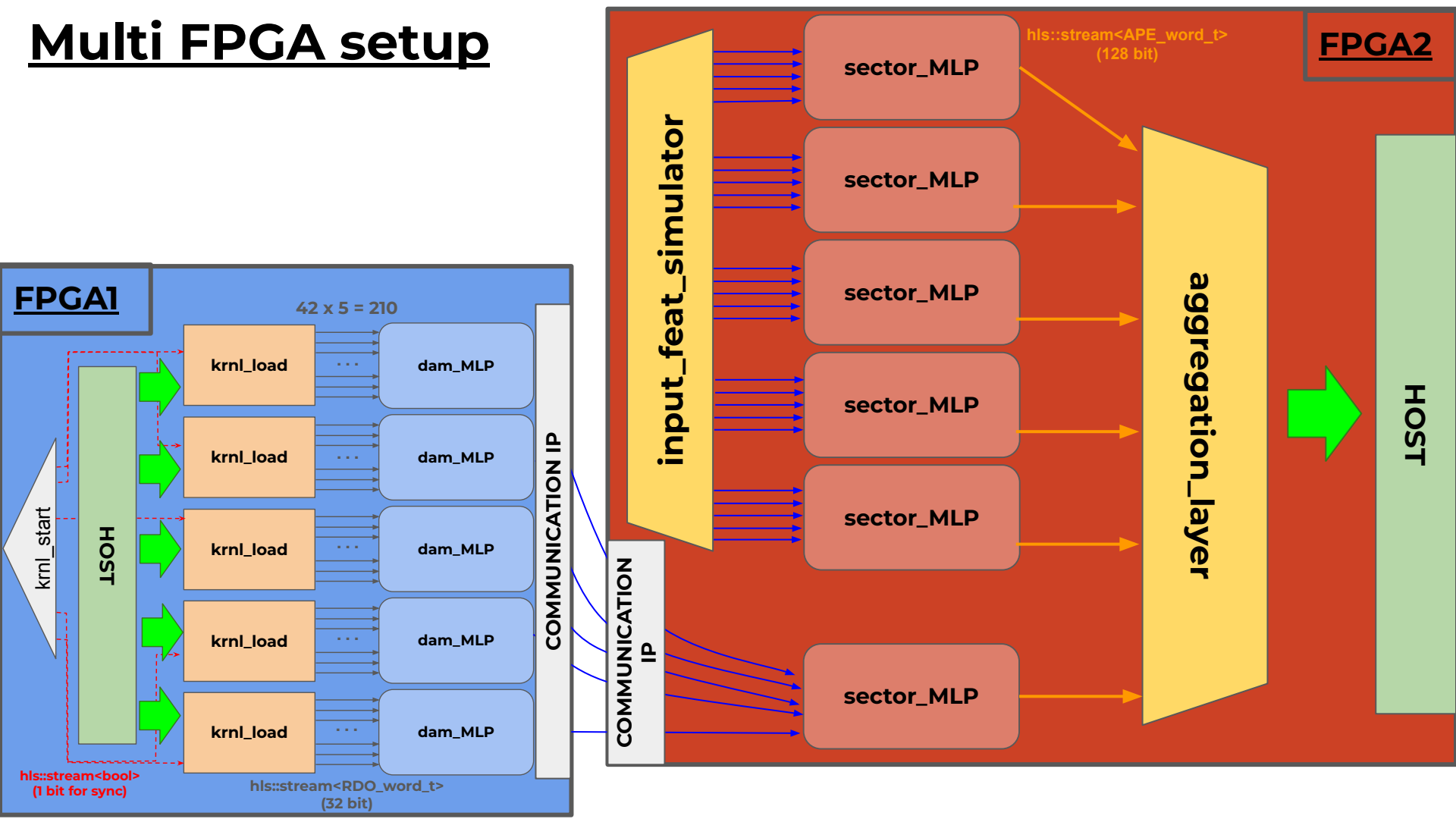
FPGA2

⇒ 5 input links coming aggregated as input of a single Sector_MLP (simulated datastream for the remaining 5 ones)
⇒ FLX-182



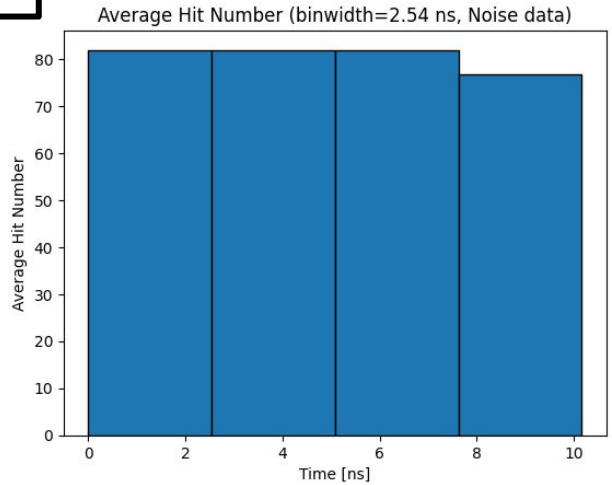


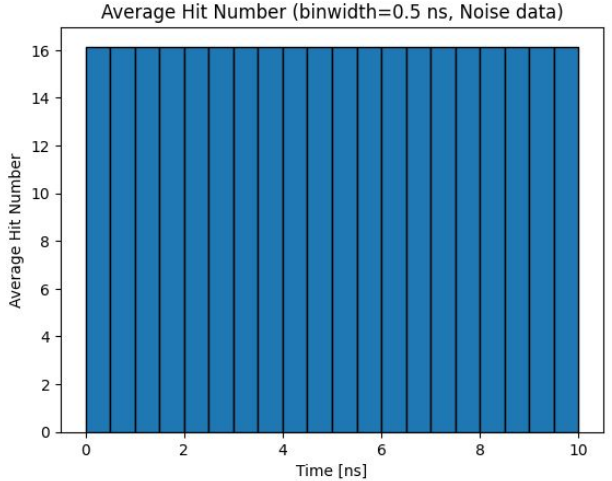
Multi FPGA setup

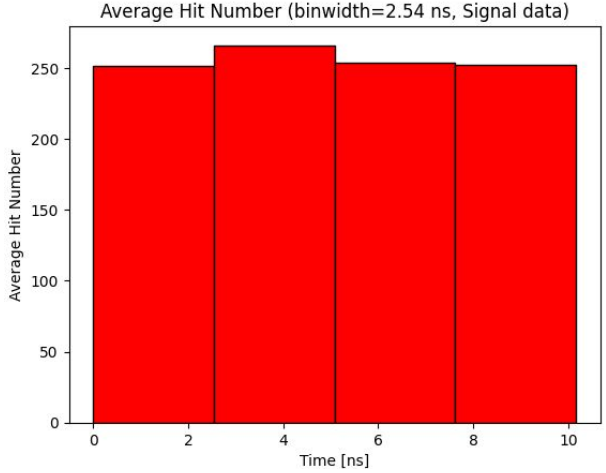


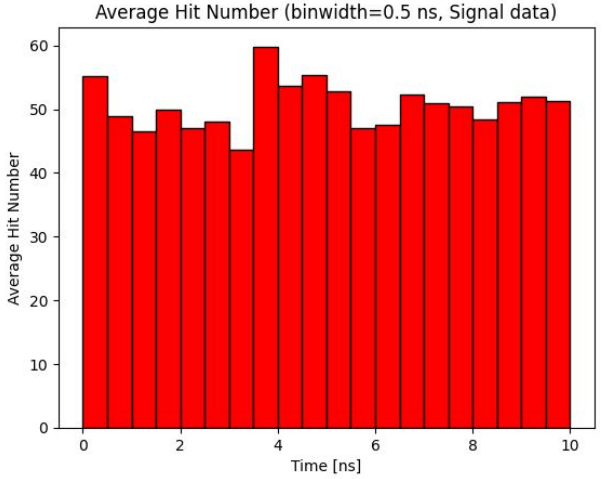
BACKUP

DCR=100kHz


Average Hit Number (binwidth=2.54 ns, Noise data)
Average Hit Number
Time [ns]


Average Hit Number (binwidth=0.5 ns, Noise data)
Average Hit Number
Time [ns]


Average Hit Number (binwidth=2.54 ns, Signal data)
Average Hit Number
Time [ns]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