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Using deep neural networks to improve the precision of fast-sampled particle timing detectors

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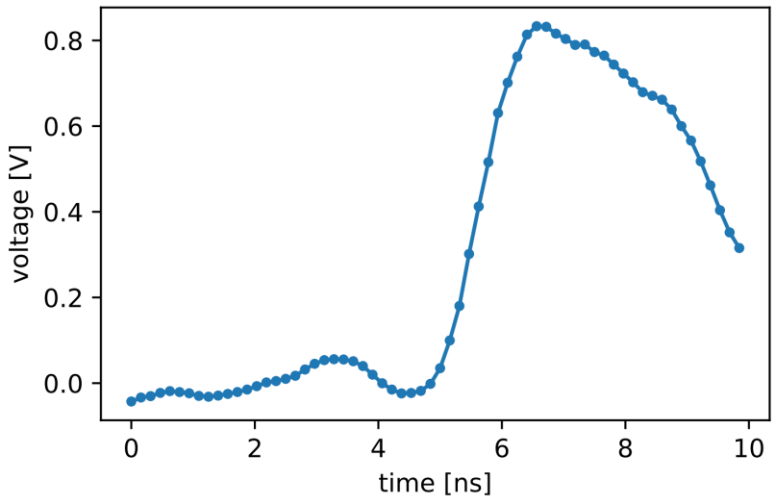
Contents

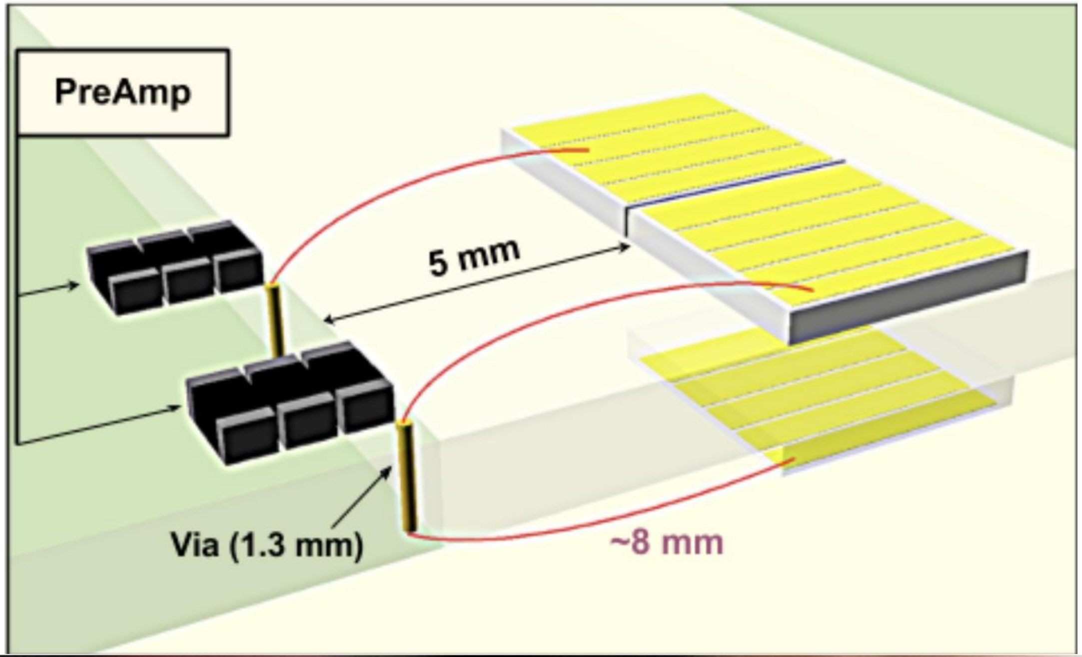
Time of arrival prediction

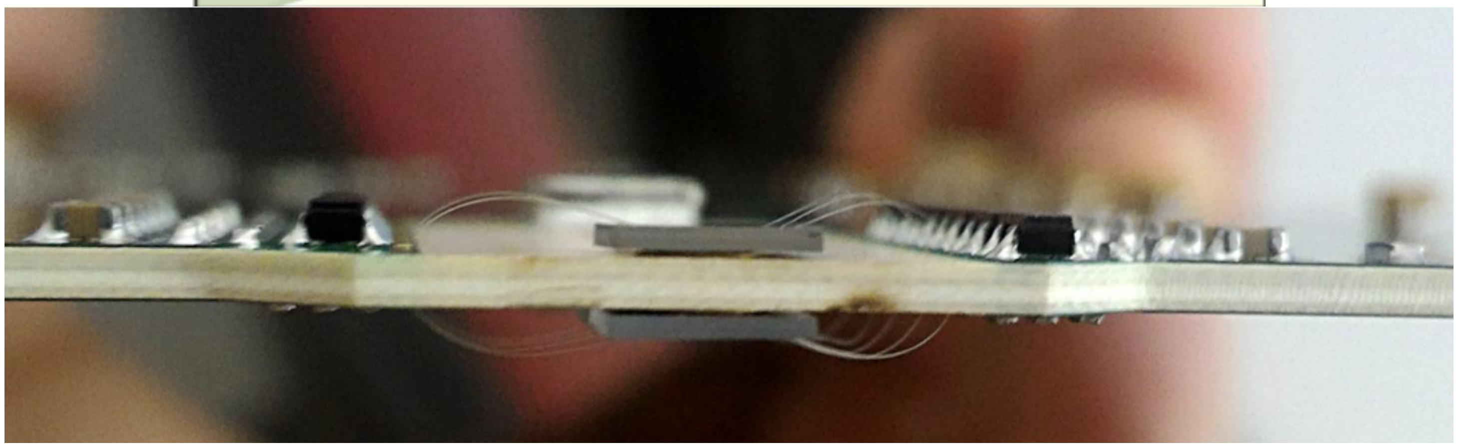
- Diamond detectors (*double diamond* architecture)
  - Devised and used in the CMS-PPS (Precision Proton Spectrometer) system, at the LHC (CERN).
- A particle flying through a detector generates a voltage signal.
- A sampling device (SAMPIC) produces a sampled **time series of voltage**.
- Measurement goal: precise timing of the passage of the particle
- **Project goal: estimate the performance of neural networks with respect to the method used currently.**



Example time series from a diamond detector

Double diamond



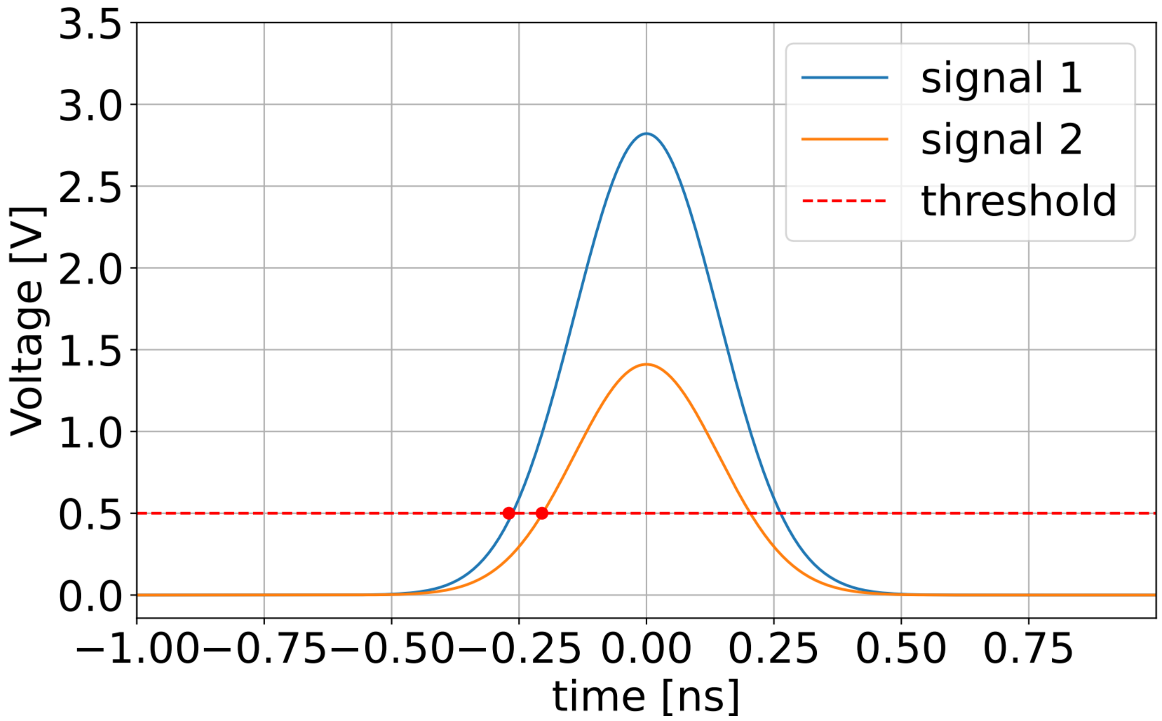


Two diamond sensors on both sides of the board are connected to the same readout channel.

Time walk effect

» Easiest algorithm to compute the time of arrival: **constant threshold**

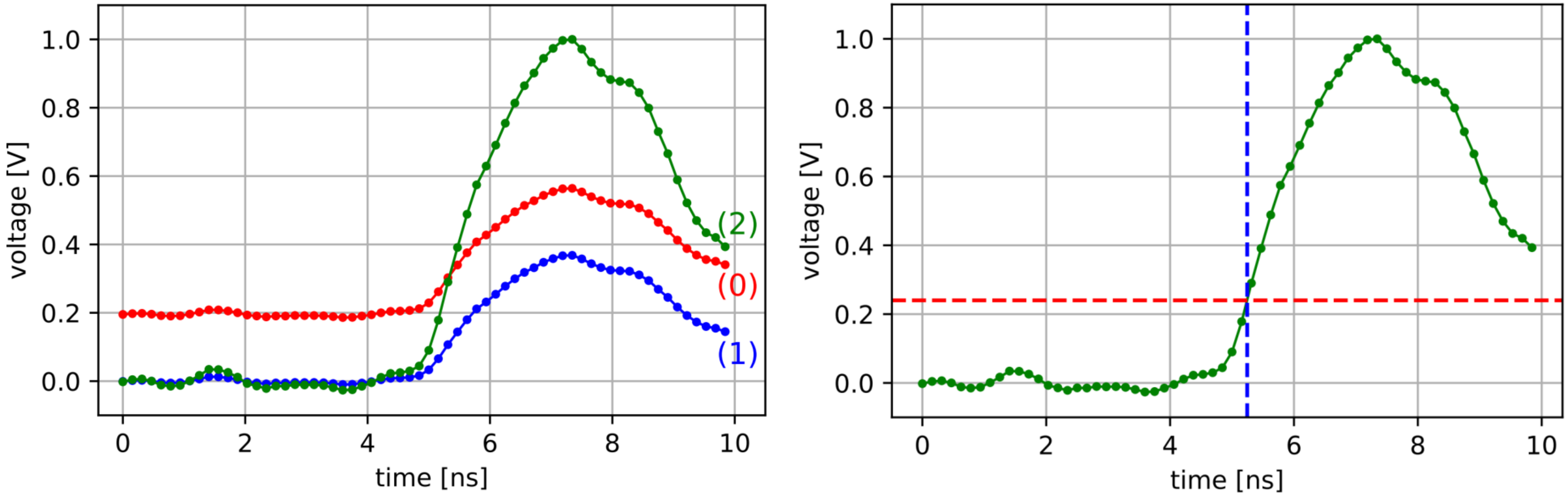
– Disadvantage: prone to the time walk effect



Example of the time walk effect. Although both signals reach their maximum at the same time, the threshold-crossing time is different.

Constant Fraction Discriminator

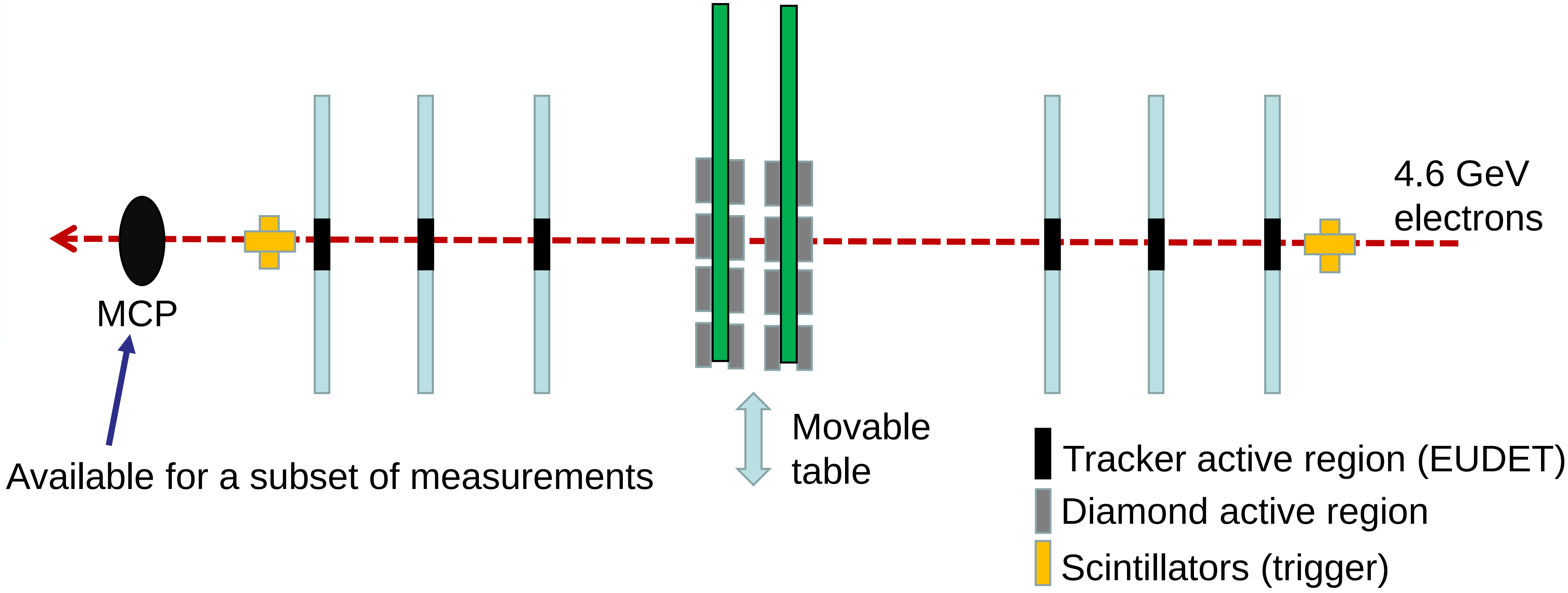
- The CFD algorithm (Constant Fraction Discriminator)
  - Method currently used in the CMS-PPS reconstruction
  - Goal: mitigation of the time walk effect
  - Implemented as the **normalised threshold algorithm** preceded by the baseline subtraction



The CFD algorithm. Left: (0) before normalisation, (1) baseline subtraction, (2) division by maximum. Right: after the normalisation the timestamp can be found using the fixed threshold algorithm

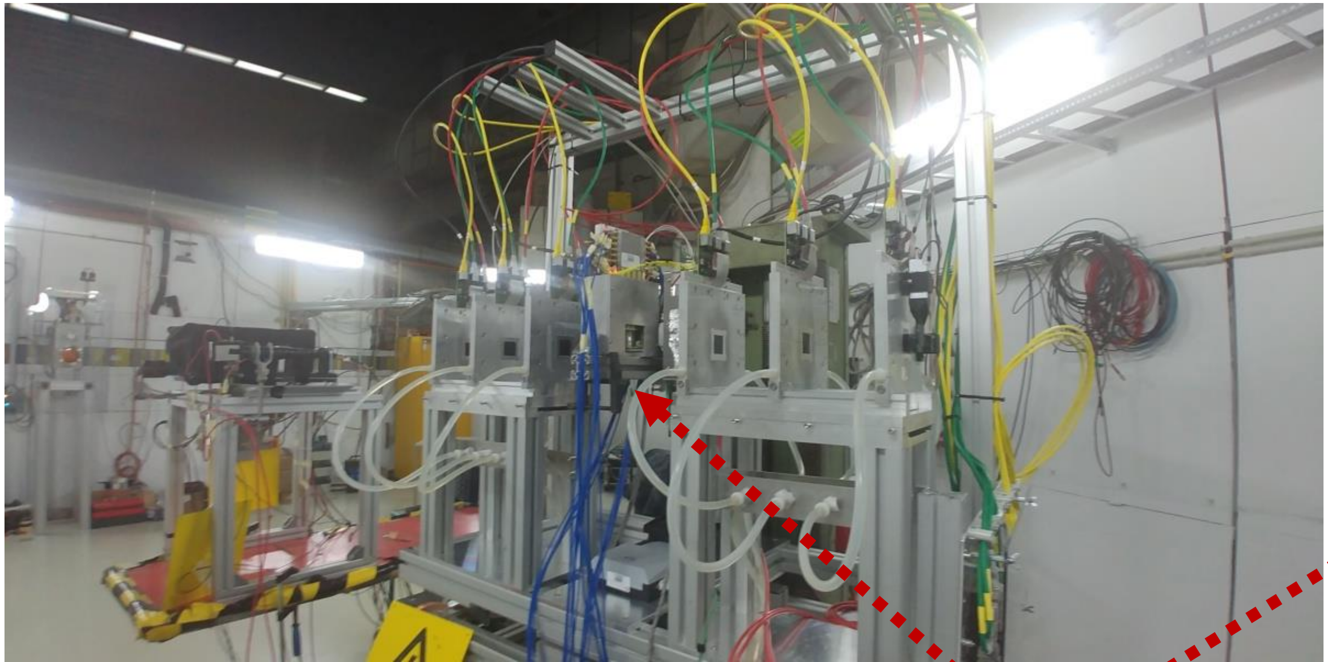
Detector setup (1)

- 2020 – test beam facility at the DESY-II synchrotron.
- Combined data taking with **diamond detectors** and a more precise **MCP-PMT** (MicroChannel Plate Photomultiplier Tube)



Test beam layout

Detector setup (2)

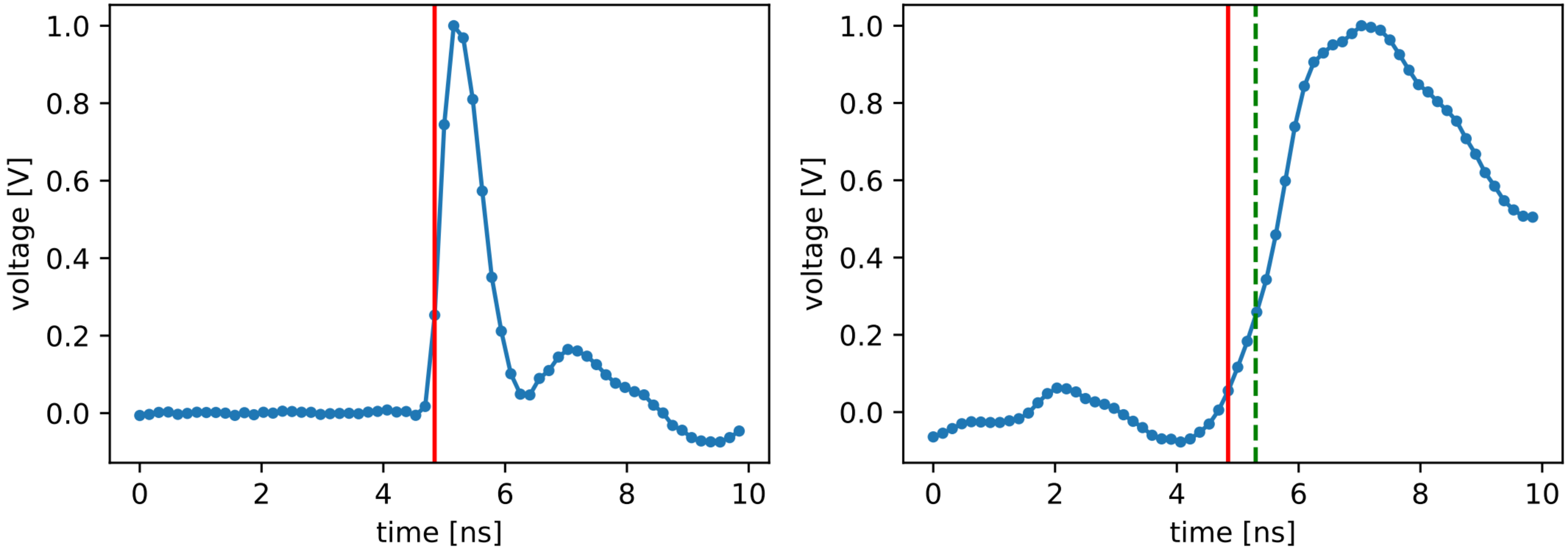


PPS timing sensors

Dataset

- The dataset needed to contain signals and the reference timestamps.
- Expected **diamond detector** precision: **50-100 ps**
- Expected **MCP-PMT** precision: **~10 ps**
- The reference timestamps (**ground-truth**) computed with the **CFD** using the **MCP-PMT** signals.
- Used only the events where a particle was detected both by a diamond detector and the MCP-PMT.
- **Goal for the neural network: minimise the difference between the predicted and ground-truth timestamps given a time series from the diamond detector.**

Dataset example



Dataset example. Left: an MCP signal with marked ground-truth timestamp. Right: a signal from a diamond detector; red: the ground-truth timestamp (includes the t_0 shift of both signals), green: the CFD timestamps computed on the diamond detector time series (used to compare the neural networks with CFD).

Neural networks

» Neural network – a machine learning algorithm modelled after the structure of the human brain.

» Made of **interconnected nodes (neurons)**, which process information.

  – Number of neurons (parameters) can reach millions or even billions.

» Used to recognise patterns in data, such as images, text or time series.

» A **neural network model** is trained on large datasets to make predictions on new data.

» **Training** – fitting the network to the data

  – Using a subset of the whole dataset – training set

» **Testing** – testing the network performance

  – Using the rest of the dataset – test set

  – Usually the training-test split is 80%-20%.

» Common testing approach: **cross-validation**

  – Divide the dataset into a few folds; test on one, train on the others.

Choosing the optimal architecture

» Tested architectures
  - Multilayer Perceptron (**MLP**)
  - Regular Convolutional Neural Network (**CNN**)
    - Devised to process images and time series.
  - **UNet**-based network
    - Devised to find keypoints or timestamps.

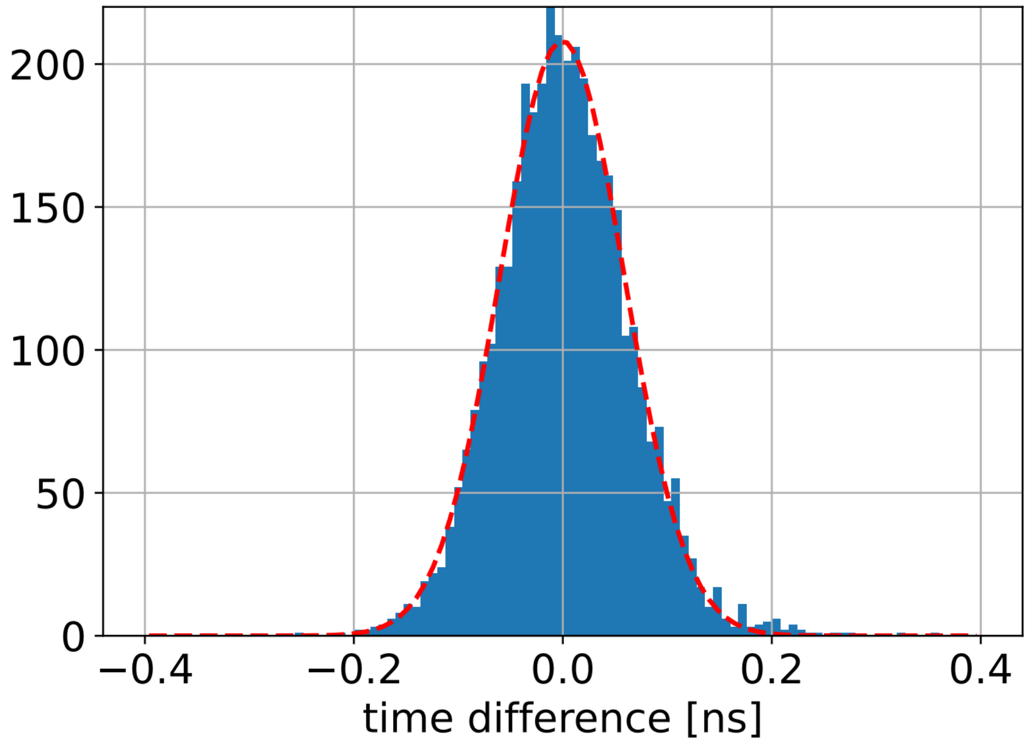
» Model selection done using **a two-step hyperparameter tuning procedure**.
  1. Find top five models using **keras-tuner** (a Python framework for TensorFlow).
  2. Use the cross-validation to find the optimal model.

» Following hyperparameters were optimised:
  - network depth,
  - number of neurons (dense layers), number of filters (convolutional layers),
  - Application of batch normalisation and/or dropout;

Precision assessment method

» Comparison with the "reference" detector – MCP
  – For each measurement: calculate the difference between the diamond det. and MCP.
  – Precision metric: std of differences

» A Gaussian can be fitted to the data to reduce the impact of outliers.
  – **Better precision metric: std of a Gaussian fitted to the difference histogram**



Example difference histogram with a fitted Gaussian

Optimal model selection

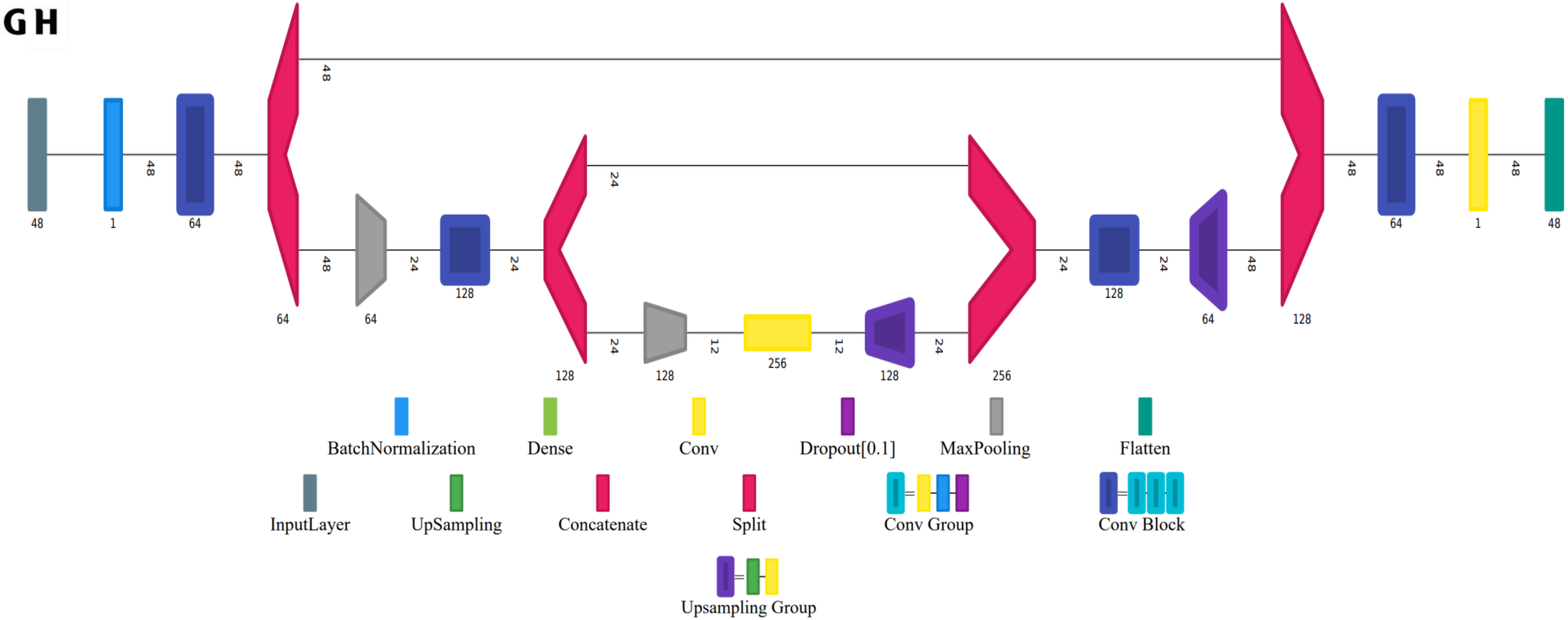
» Hyperparameter tuning used to find an optimal model for each architecture.

» Precision statistics computed through a **cross-validation** of the optimal models

architecture	mean [ps]	std [ps]	params
MLP	63.9	0.9	2,737
CNN	62.8	1.3	36,865
UNet	60.7	1.2	456,965

» **The best (smallest) precision: UNet**

Optimal UNet model

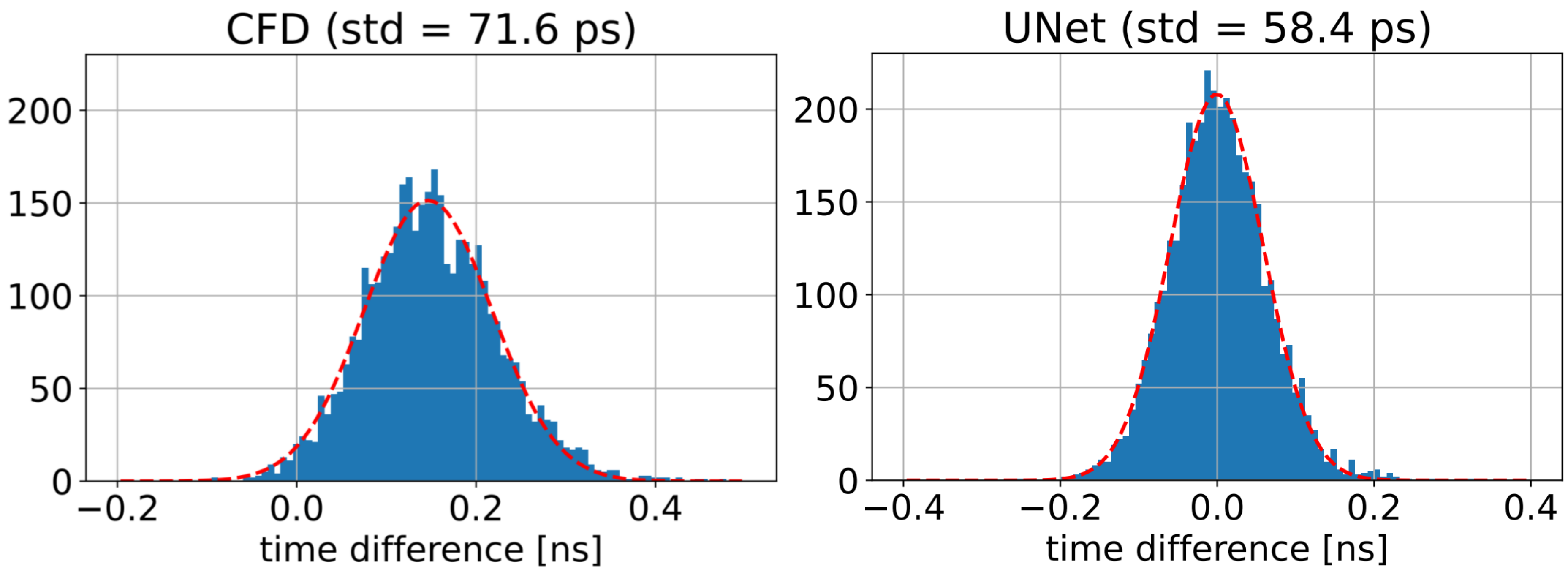


- Symmetric parts: encoder and decoder
- The encoder extracts time-independent features from a time series.
- The decoder builds a heatmap.
- The heatmap is expected to contain a Gaussian with the mean at the particle timestamp.
- The timestamp can be retrieved by applying a fit.

Results

- Final results obtained with the **test dataset** not used in the previous tests
- Precision comparison with CFD:

CFD	NN	Improvement
71.6 ps	59.4 ps	17.0%



Difference histograms with fitted Gaussians

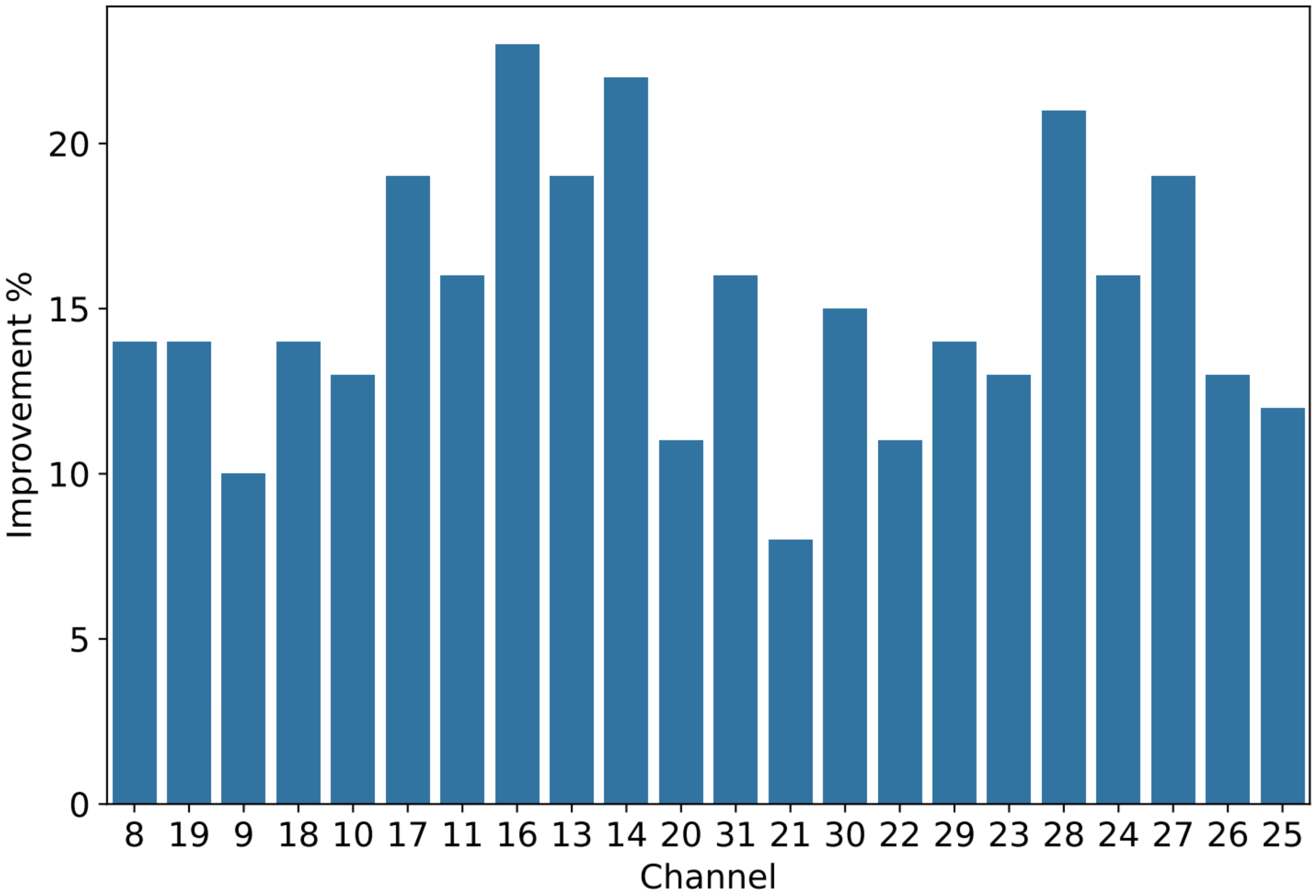
Results for many channels

» Networks trained either on single channels (representative examples) or on all the channels together (maintaining the train/test split).

» Improvements with respect to the CFD:

training channel	test channel					
	10	16	17	22	25	27
10	**13%**	10%	13%	7%	-1%	-23%
16	6%	**23%**	16%	9%	-22%	-9%
17	7%	17%	**19%**	9%	-3%	8%
22	4%	14%	-4%	11%	-84%	-51%
25	4%	4%	7%	4%	**12%**	8%
27	-13%	-10%	4%	-16%	4%	**19%**
all	8%	22%	14%	**12%**	9%	17%

Improvements for all the channels



Improvements with respect to the CFD for all the explored channels using the networks trained on particular channels. Improvements range from 8% to 23%.

Summary

» Improvements ranging 8% to 23% with respect to the CFD

» Advantages:

  – Network, once selected, has just to be trained and can work.

  – The expert knowledge is required only to find the optimal network model. Training and predicting is relatively simple.

  – In case the observed data evolves, the network can be easily retrained.

» Disadvantage: a neural network is a black-box

  – It is impossible or difficult to explain the network predictions.

» The work is continued on the LHC data.

The end

» The project was partially funded by the Polish Ministry of Education and Science, project 2022/WK/14.

» The numerical experiment was possible through computing allocation on the Ares system at ACC Cyfronet AGH under the grant plgccbmc11.