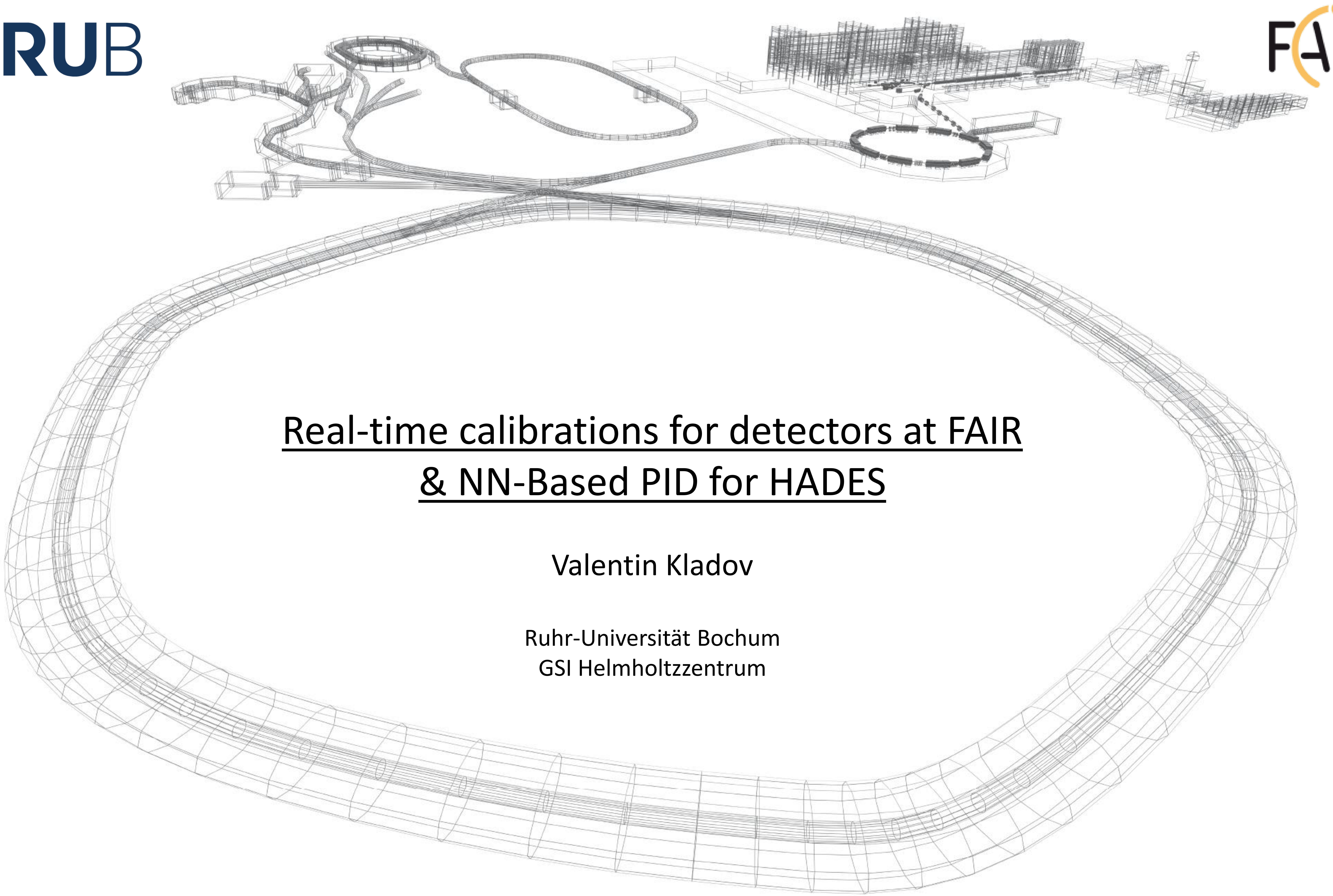


Real-time calibrations for detectors at FAIR & NN-Based PID for HADES

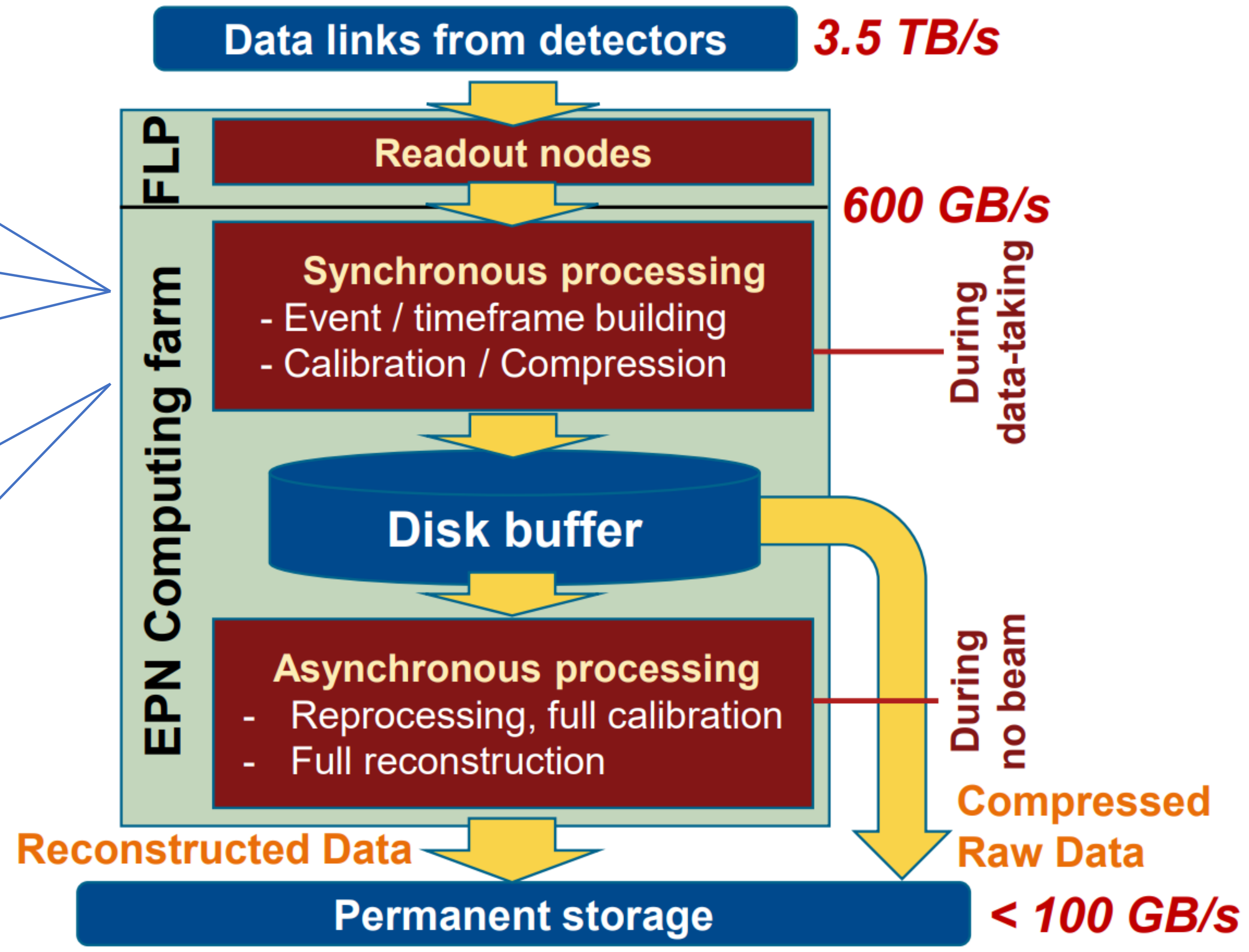
Valentin Kladov

Ruhr-Universität Bochum
GSI Helmholtzzentrum

Real-time reconstruction and calibration

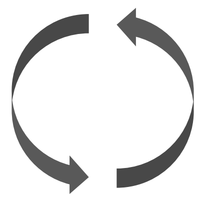
- Tracking
- Identification
- Triggering

- Calibrations
- Slow control



Synchronous reconstruction for high level online triggering

Time consuming

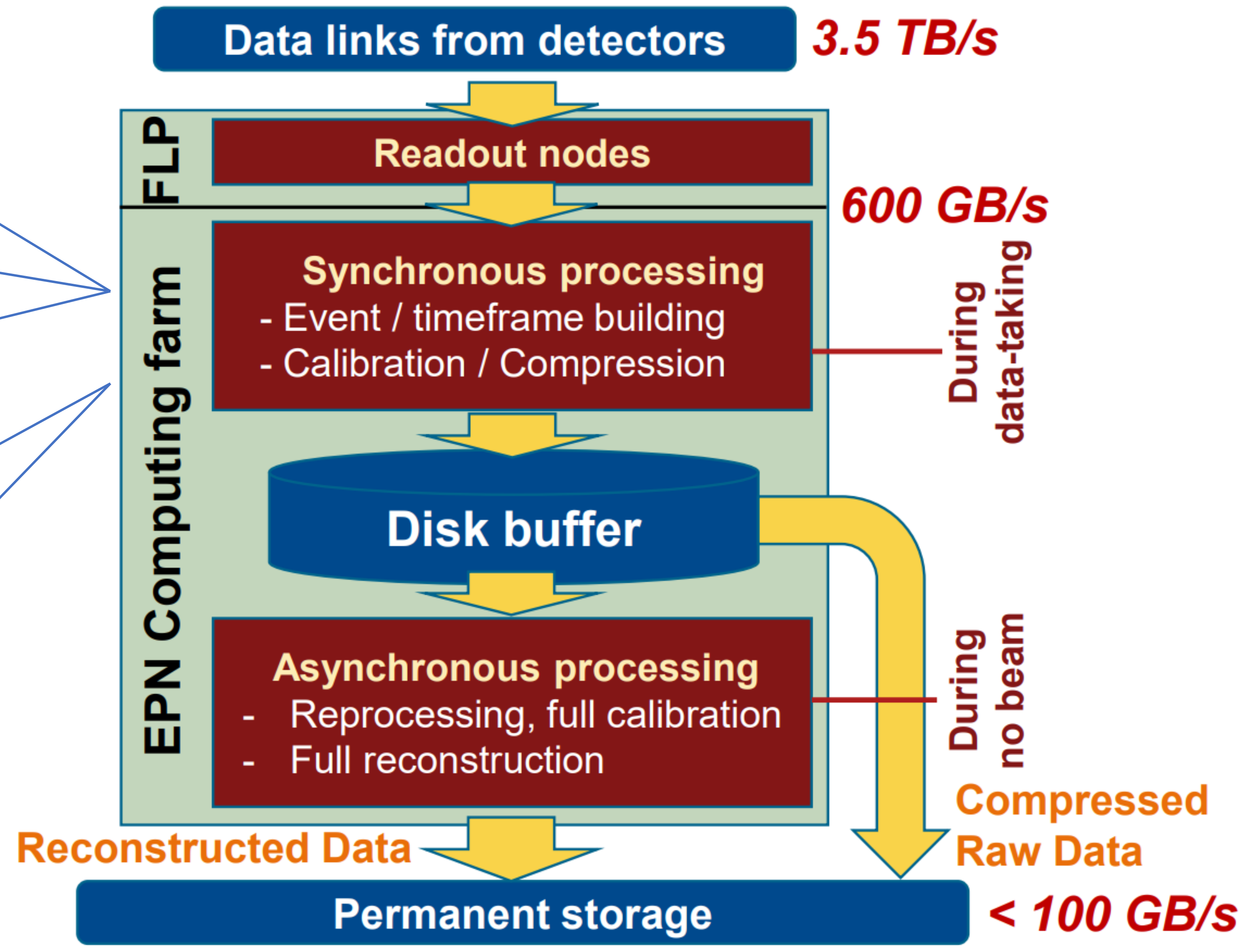


Online calibrations

Real-time reconstruction and calibration

- Tracking
- Identification
- Triggering

- Calibrations
- Slow control



Synchronous reconstruction
for high level online triggering

Time consuming

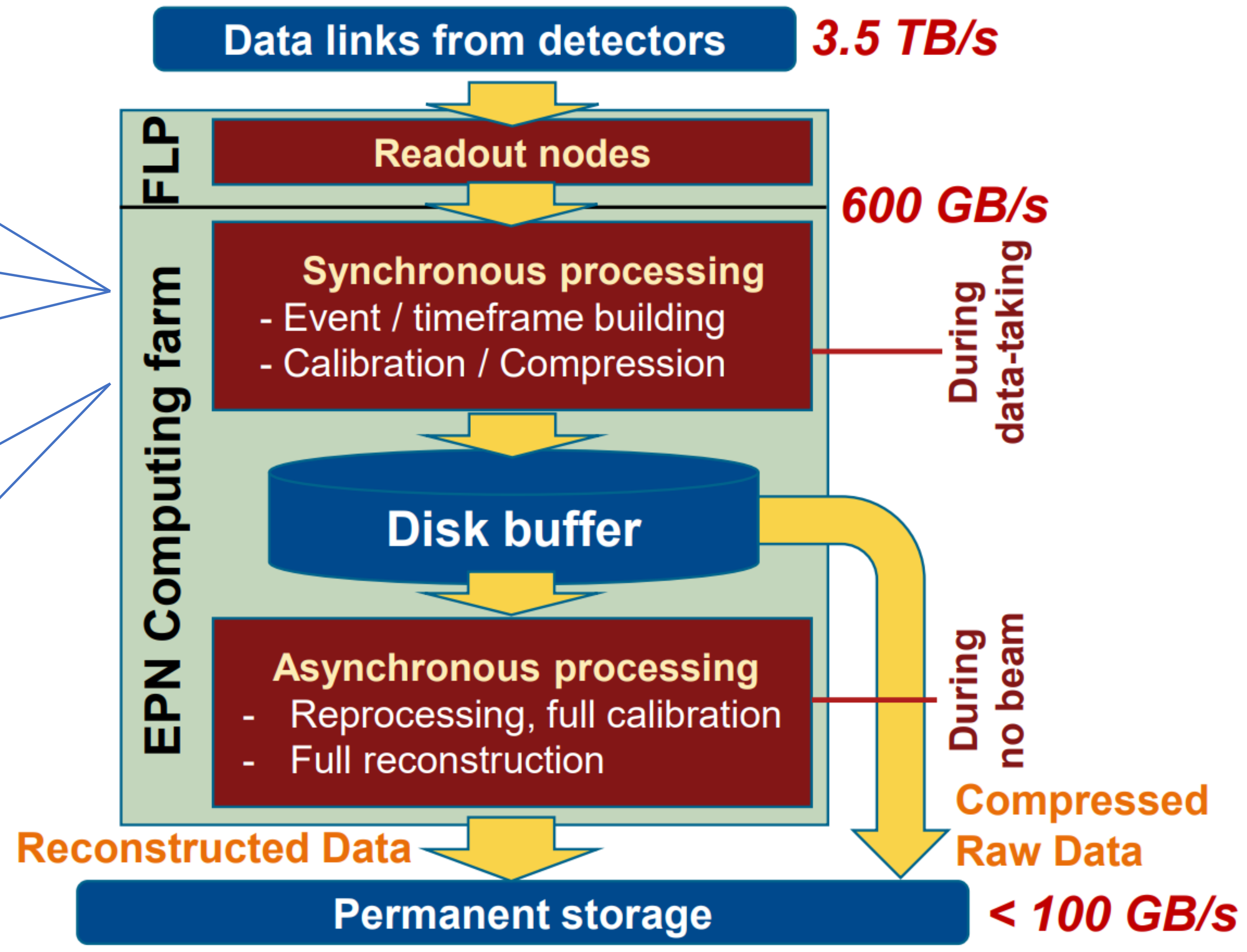
Online calibrations

Can we avoid the loop?

Real-time reconstruction and calibration

- Tracking
- Identification
- Triggering

- Calibrations
- Slow control

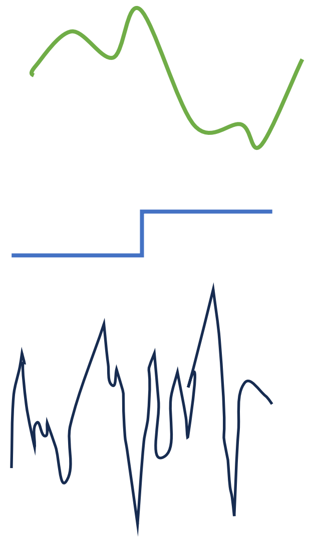


Synchronous reconstruction
for high level online triggering

Time consuming

Online calibrations

- Environment (P, T)
- Settings (V, beam)
- Trigger rates

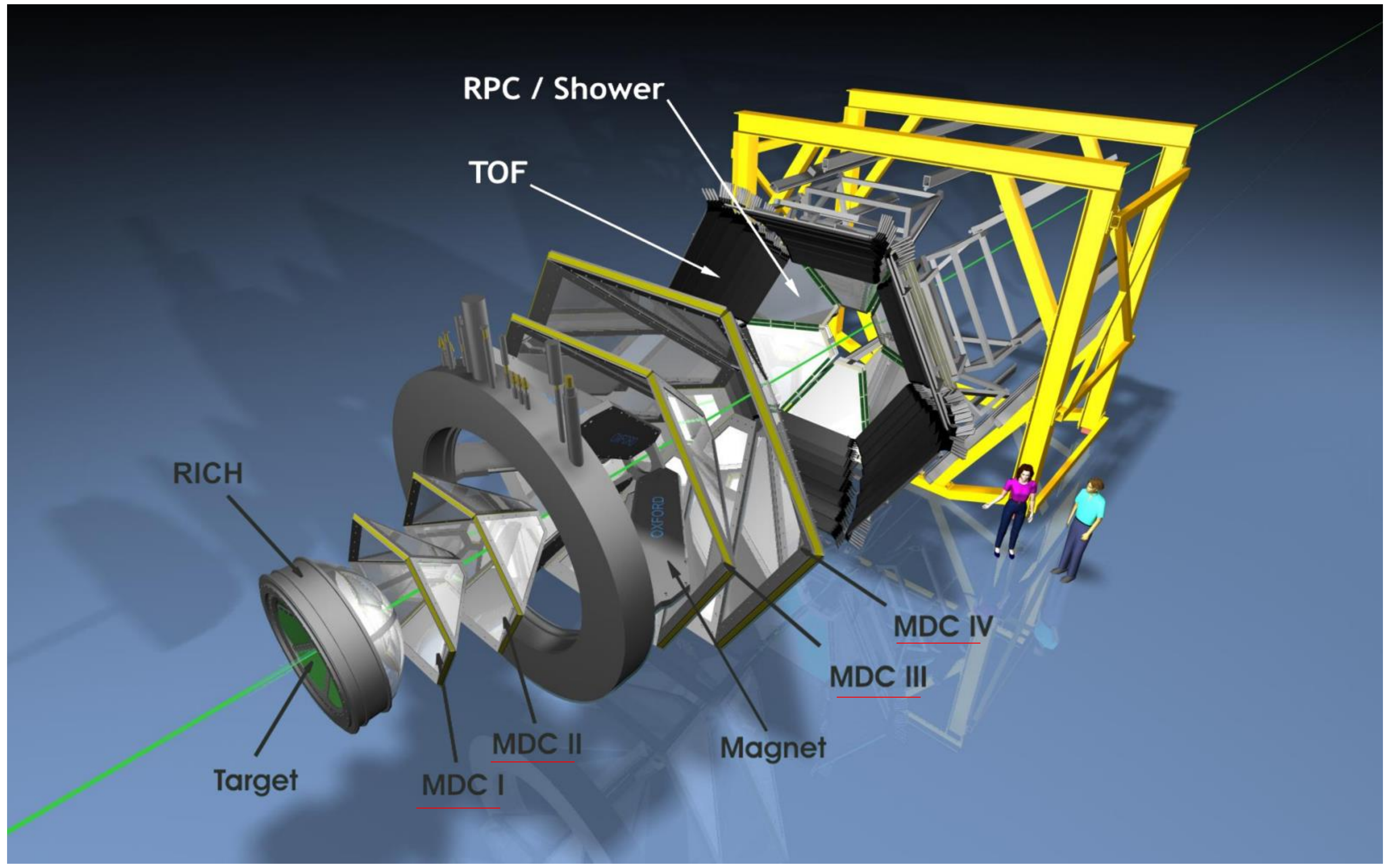


NN

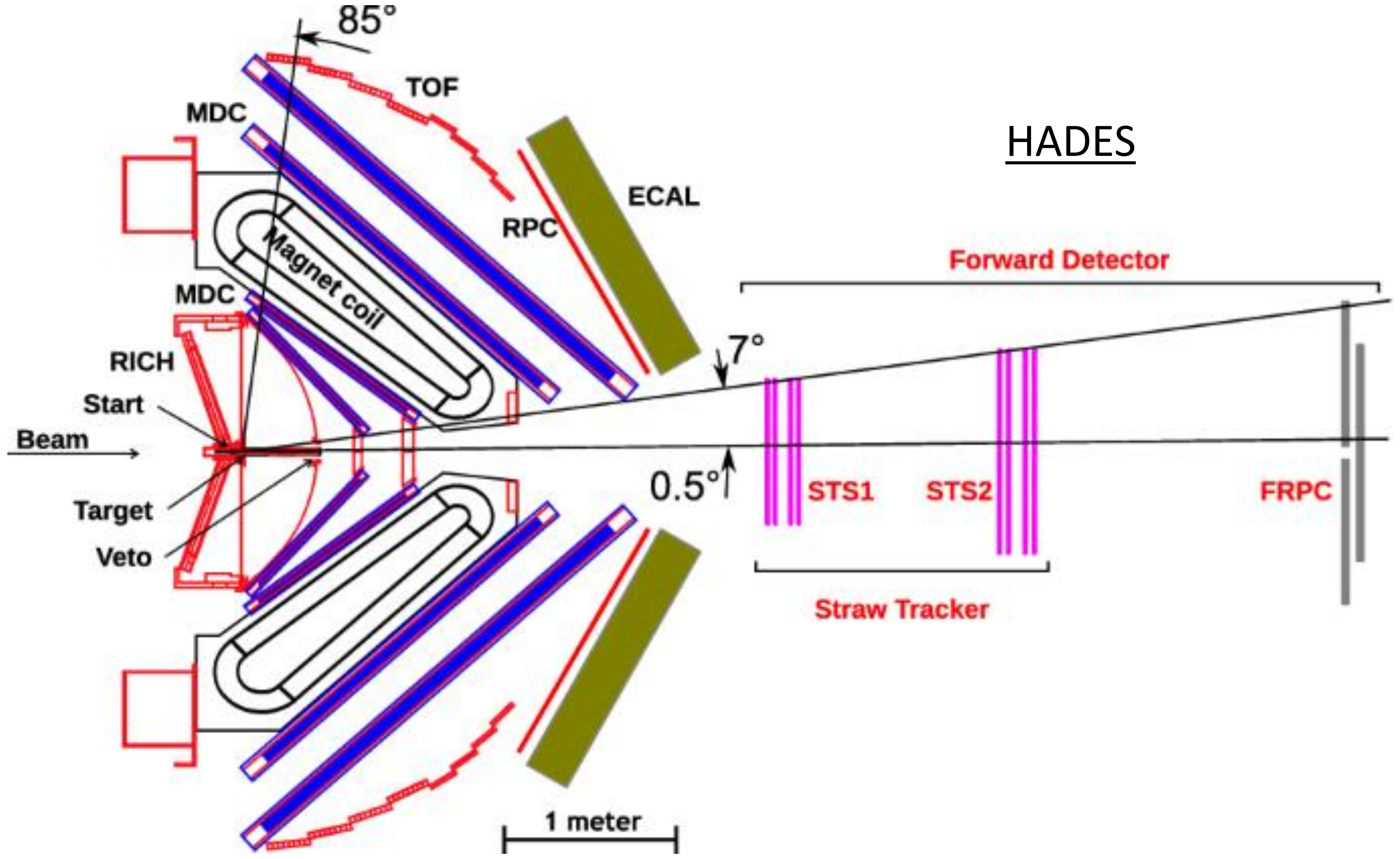
- Calibration factors
- Recommended settings (HV)
- Anomaly detection

HADES experiment

- FAIR Phase Zero experiment;
- Currently running with regular data taking (every 1-2 years);
- Developed infrastructure;



4 planes x 6 sectors of MDC = 24 chambers



MDC – mini drift chambers

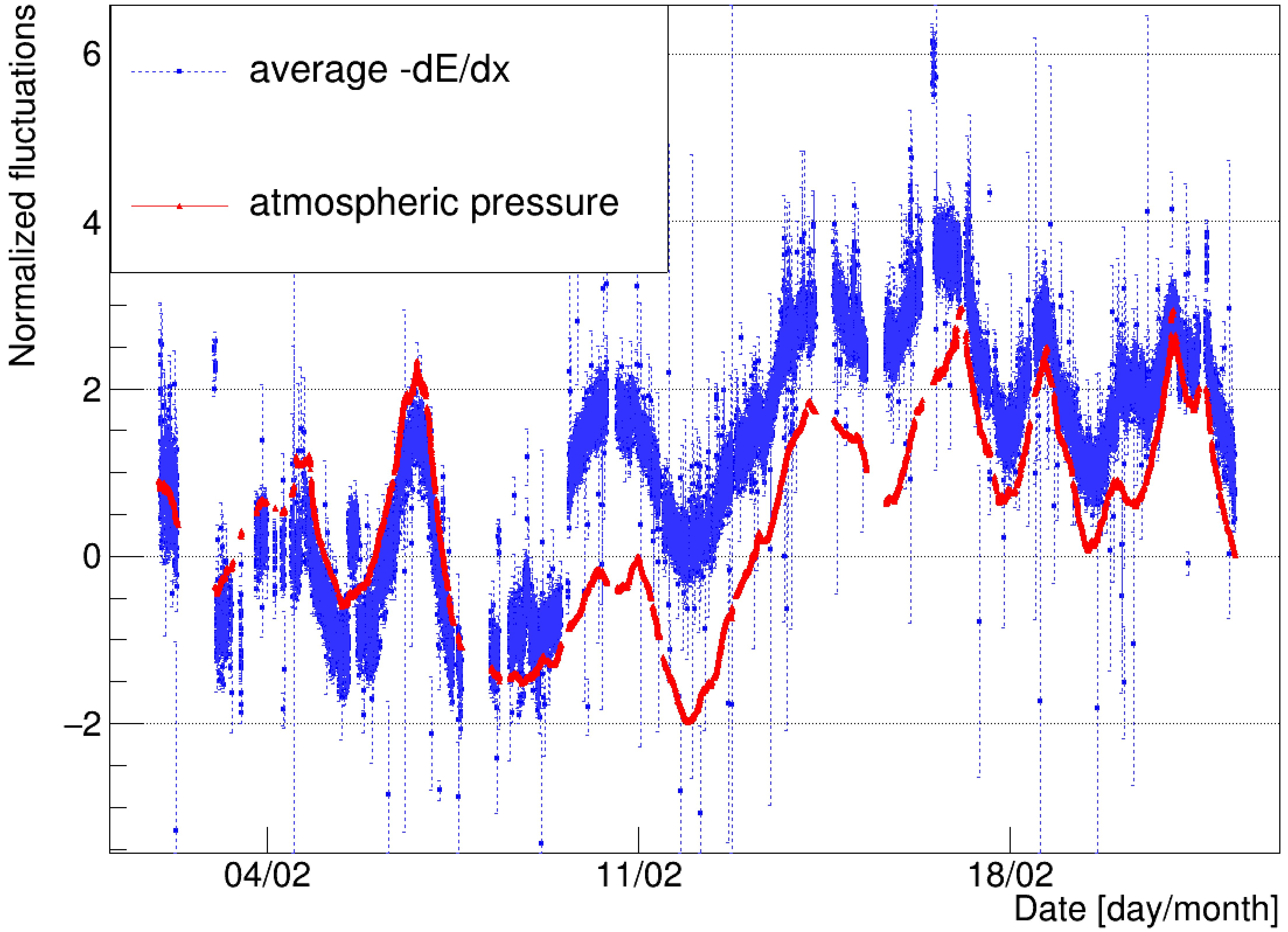
Possible values to predict:

- Drift time (~"measured" distance) – used for track reconstruction.
- Chamber gain (~"measured" dE/dx). – used for PID

Ionization losses in drift chambers

Reasons to test on MDC:

- Significant fluctuations (5-10%);
- Clear dependence on environmental parameters;
- Environmental parameters are measured and stored.



Correlations between atmospheric pressure (red) and averaged ionization losses (blue). Feb22.

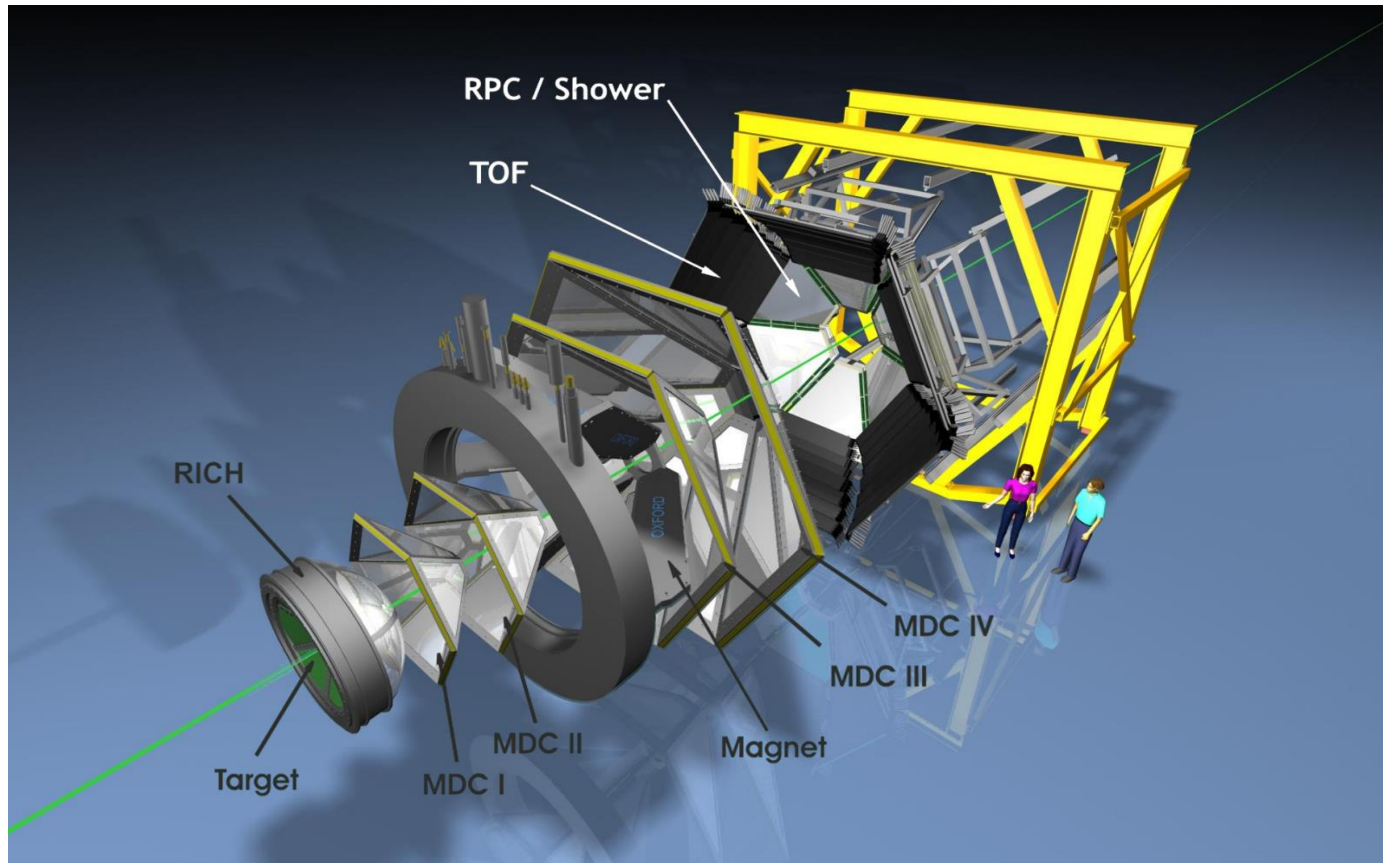
Each dot is a single run, ~100k/24 events, 1-2 min

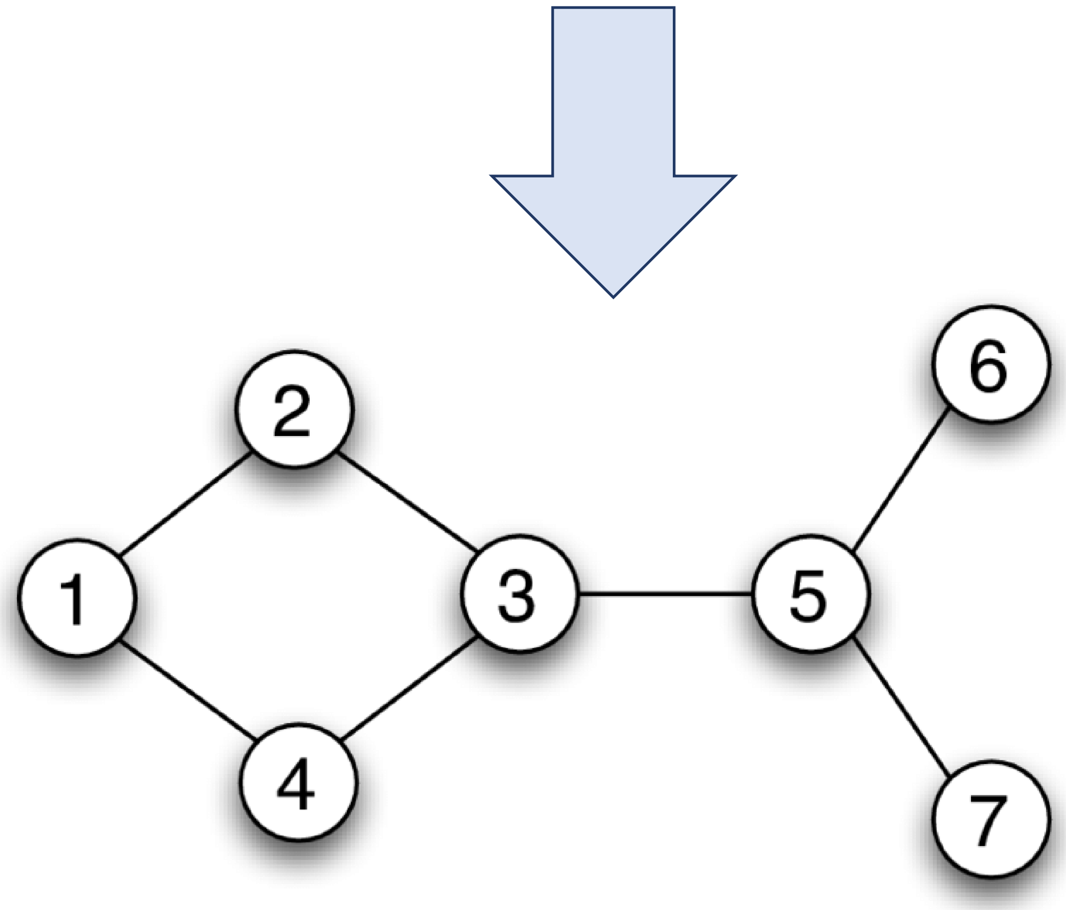
Smooth change with time (~15 min).

Input parameters:

- Atmospheric pressure;
- High voltage;
- CO_2 concentration;
- Overpressure;
- H_2O concentration;
- Dew Point;
- Electronics temperature;

Multi-channel prediction



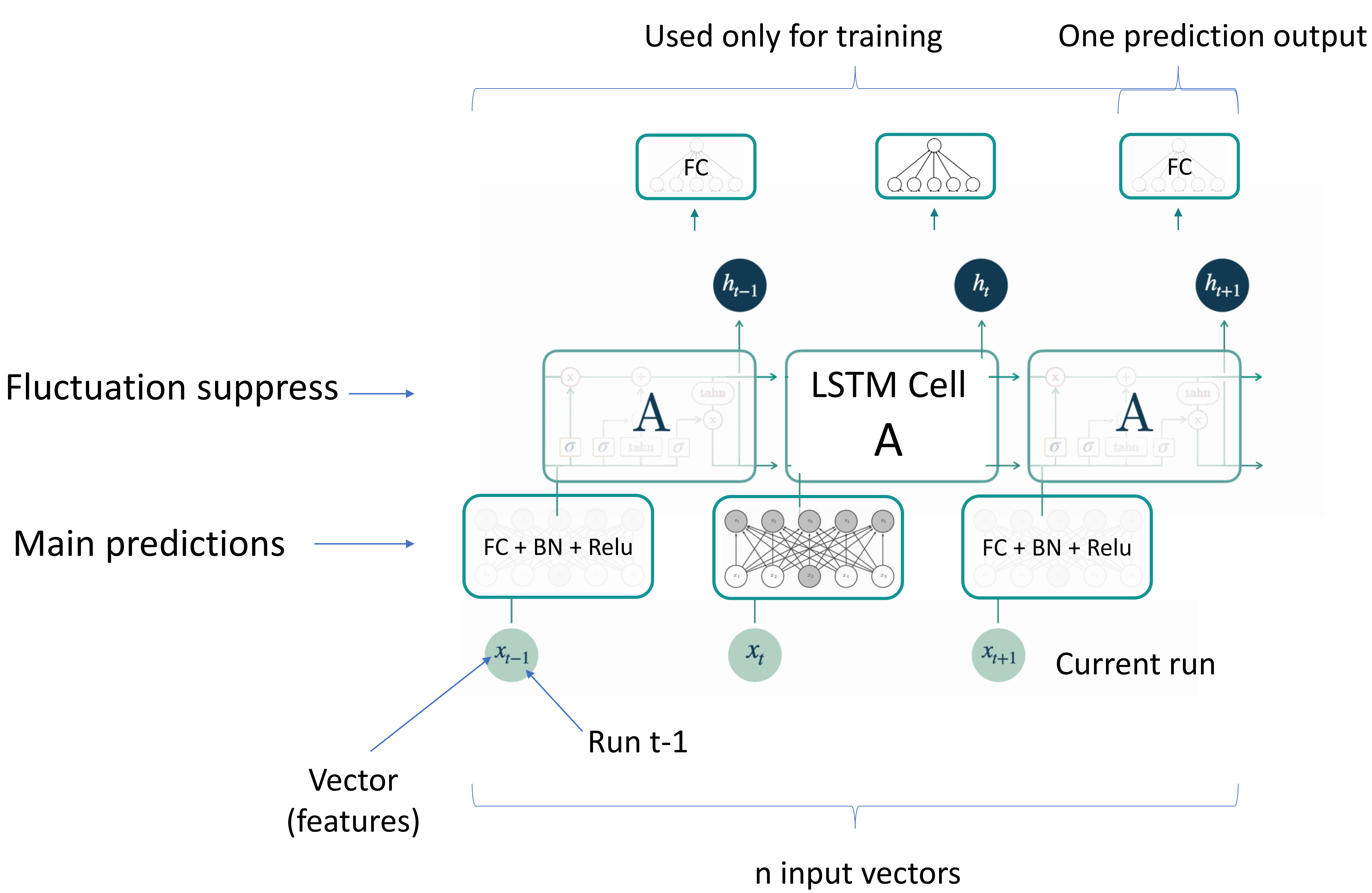


→ Represent detector as a graph
(4 planes X 6 sectors)

→ Utilize similarities by convolutions.

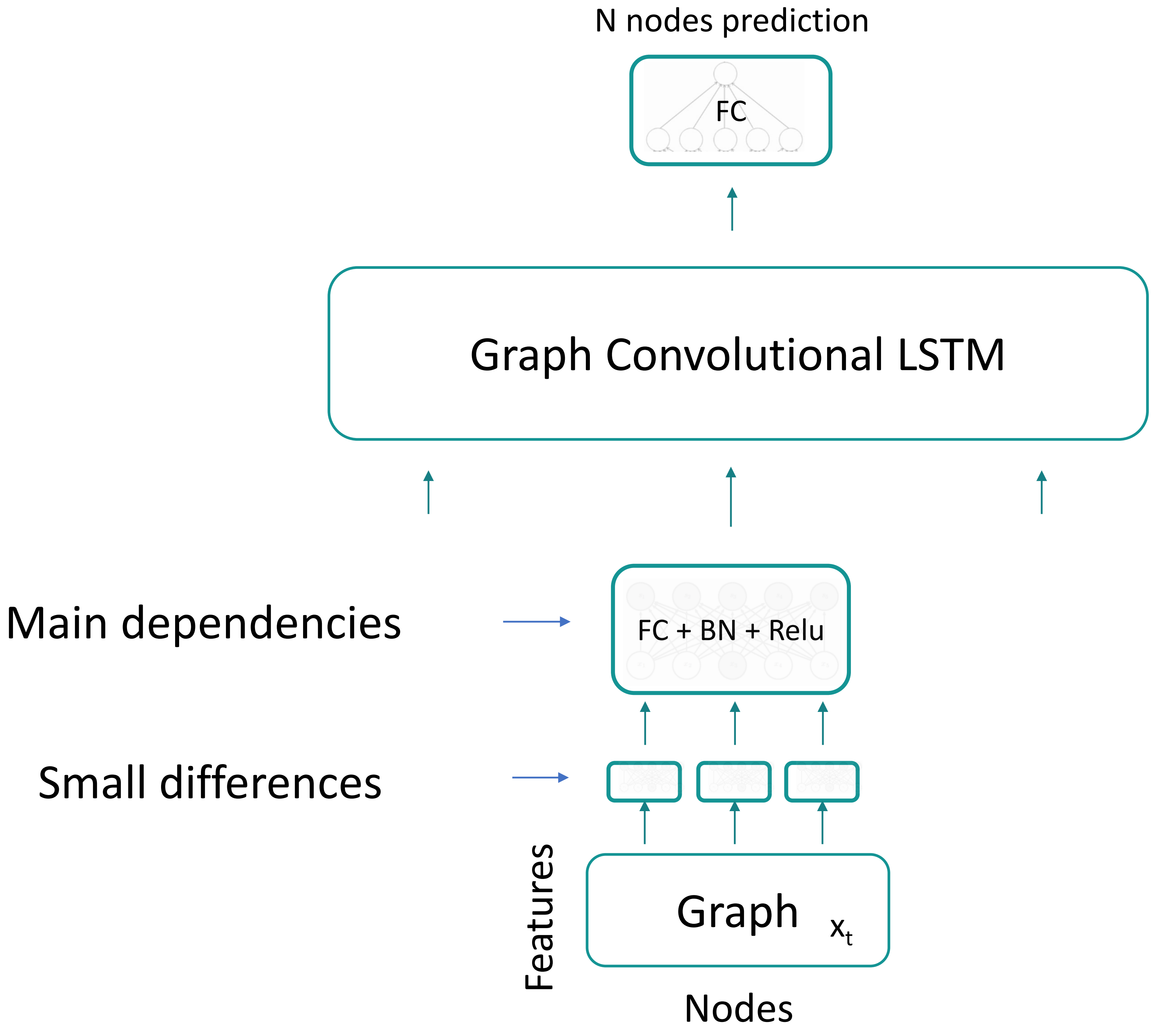
Neural network architecture

Single parameter prediction



Smoothness of the environment change

Multi-channel prediction



Similar behavior between channels

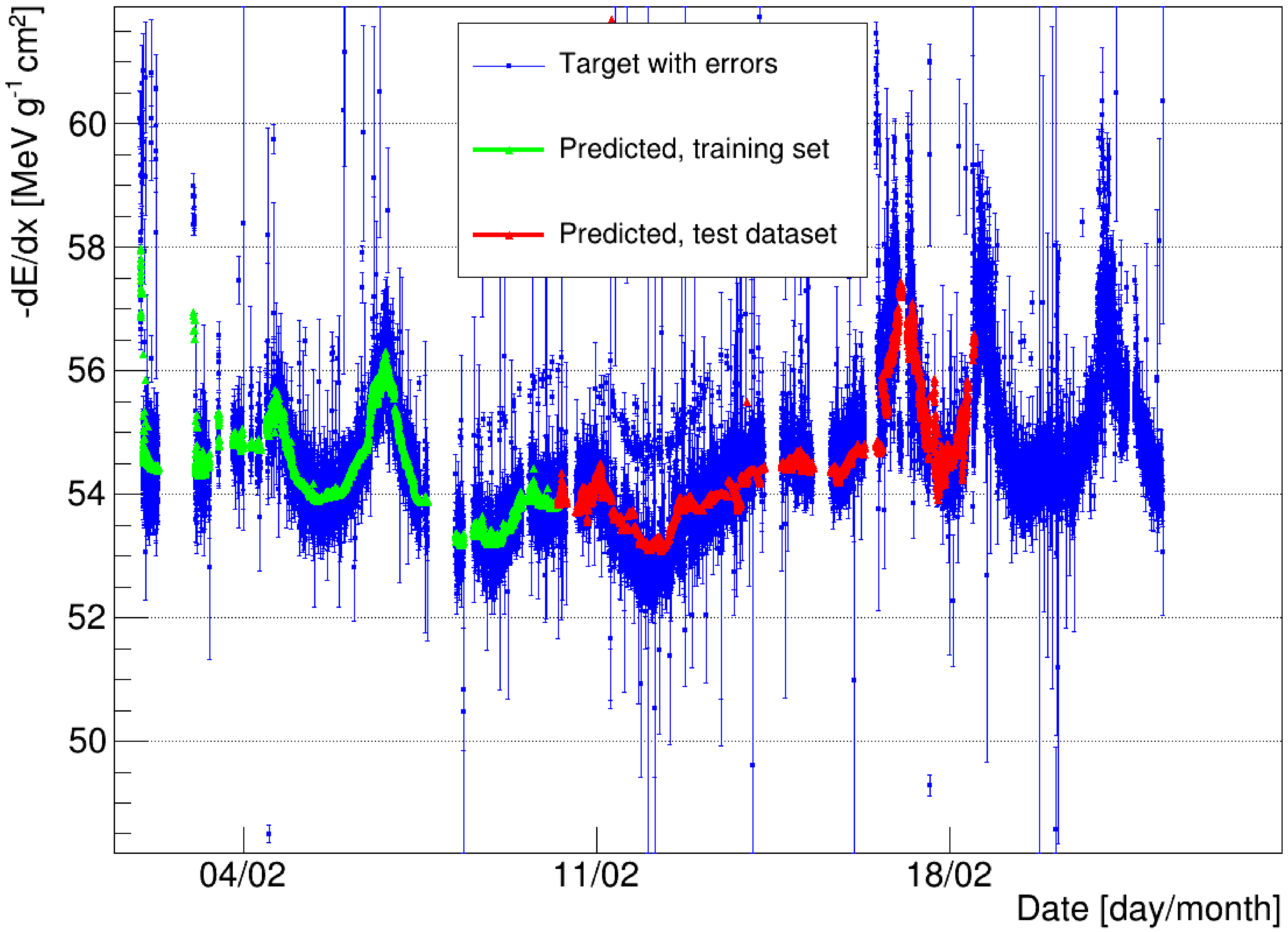
Prediction time consumption

Source	Depends on	Time
NN Computation speed	NN propagation $O(N_{nodes})$	$50 \pm 10\ ms$ (24 nodes)
Database readout from GSI network	$\sim(N_{nodes})$	$1 \pm 0.1\ s$ (24 nodes)
Standard run duration (1 data point)	-	$1 - 2\ min$
Environmental parameter stability interval	-	$\sim 15\ min$
NN initial training	$O(N_{epochs} * N_{nodes} * N_{runs})$ + Init	$\sim 30\ min$ (150 epochs, 24 nodes, 10^3 runs)
NN retraining	$O(N_{epochs} * N_{nodes} * N_{runs})$ + Init	$\sim 1\ min$ (50 epochs, 24 nodes, 10^2 runs)

Prediction quality

Simulating new beamtime:

1. Get average dE/dx from offline calibration in feb22 data;
2. Train on the part of data, fix most of the parameters after;
3. Predict with added regularization and a regular retraining.



Significant room for improvements:

1. No temperature information stored;
2. Target offline calibration is unstable.

Particle identification for HADES

We have all parameters calibrated online → reconstruction → identification → triggering

Input parameters

- $Momentum$
- $Charge$
- $Theta$
- dE/dx_{MDC}
- dE/dx_{TOF}
- ToF
- $Distmeta$
- $Beta$
- $Metamatch$
- $Mass^2$

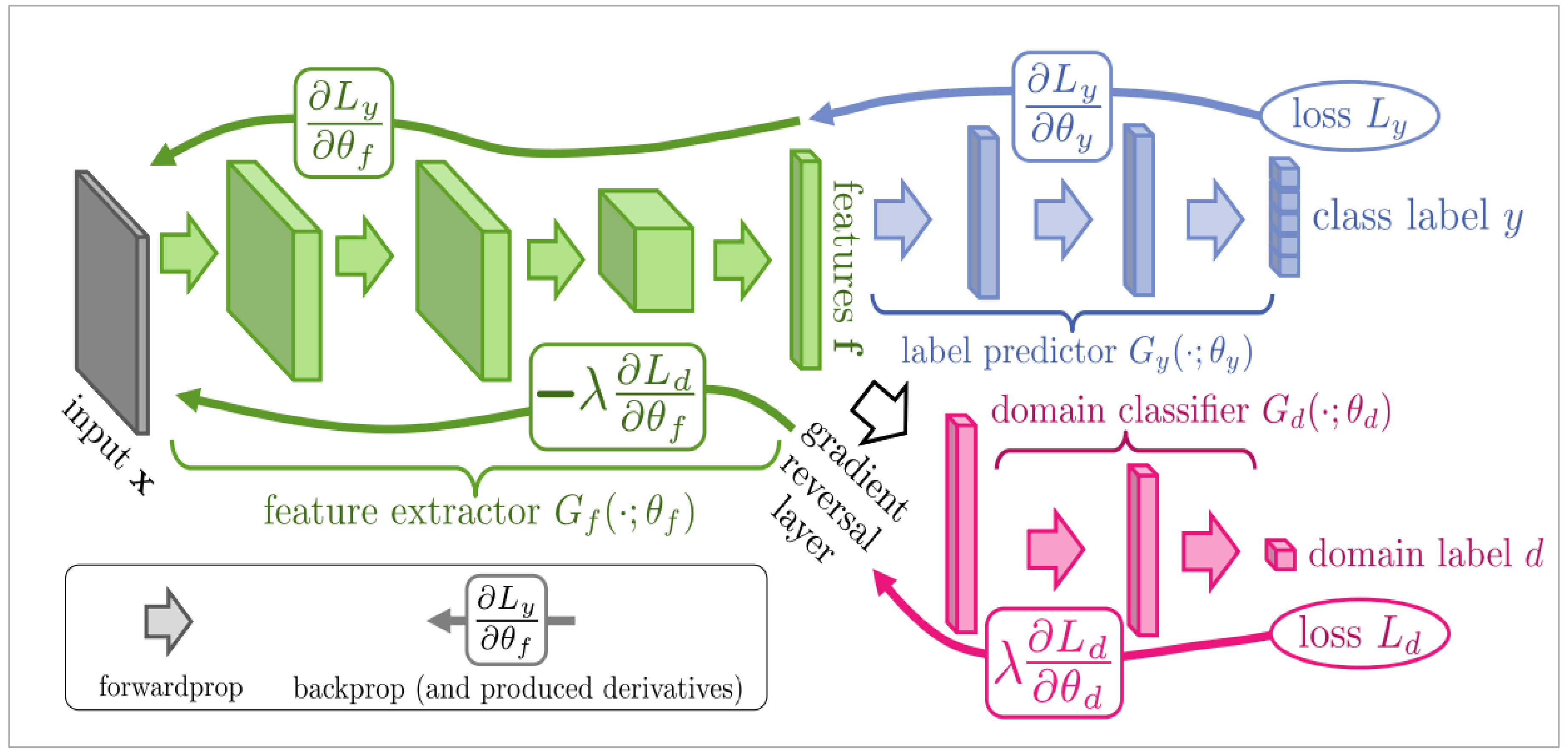


Image source: https://doi.org/10.48550/arXiv.1505.07818

Predicted probabilities

- P_p
- P_{π^+}
- P_{π^-}
- P_{K^+}
- P_{K^-}

- Uses all available information simultaneously, allowing for better <u>precision and efficiency</u> ("merge")
- Operates with probabilities, allowing for <u>flexible classification</u>
  (change only one parameter to tune)

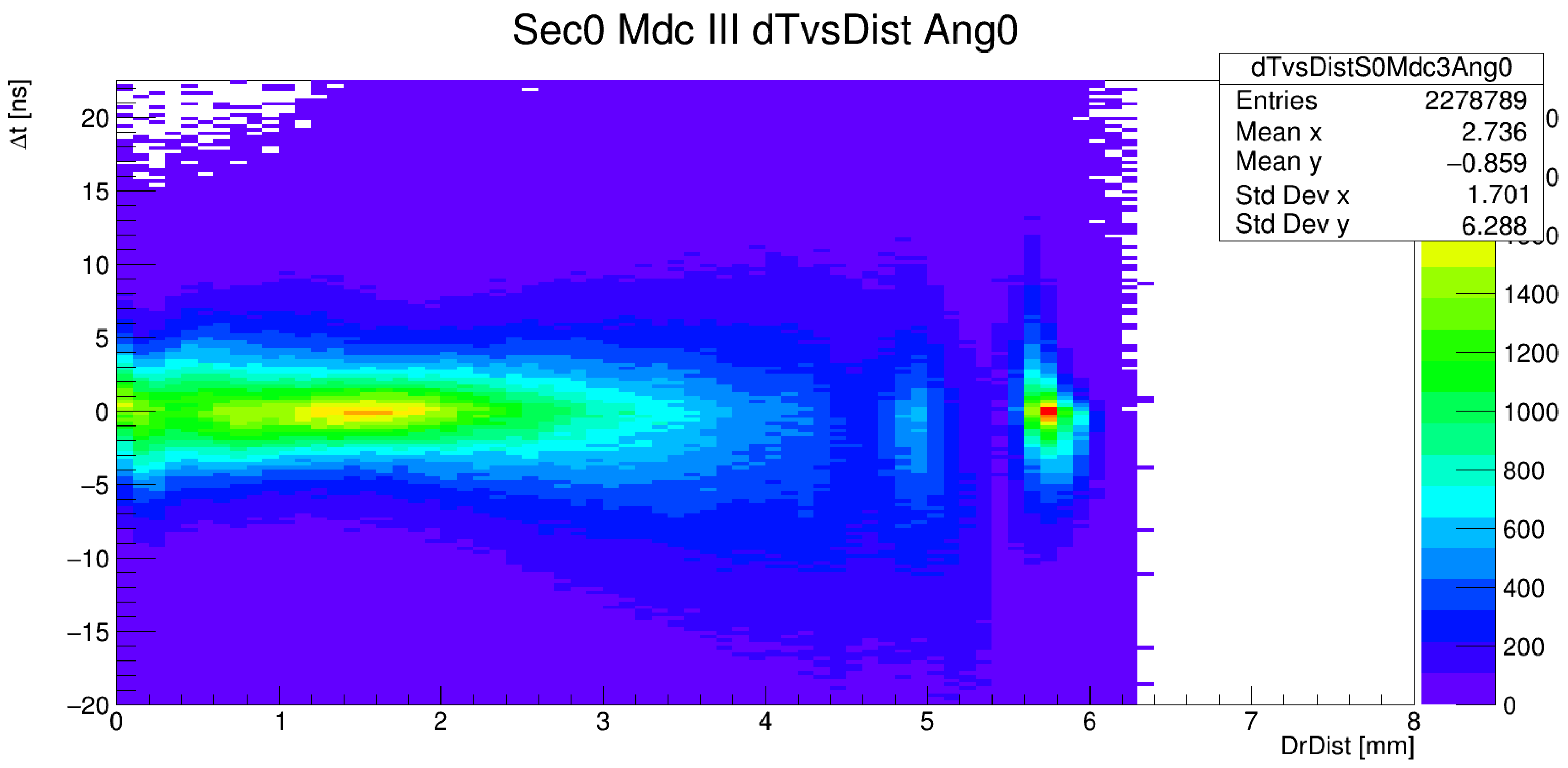
Summary & Outlook

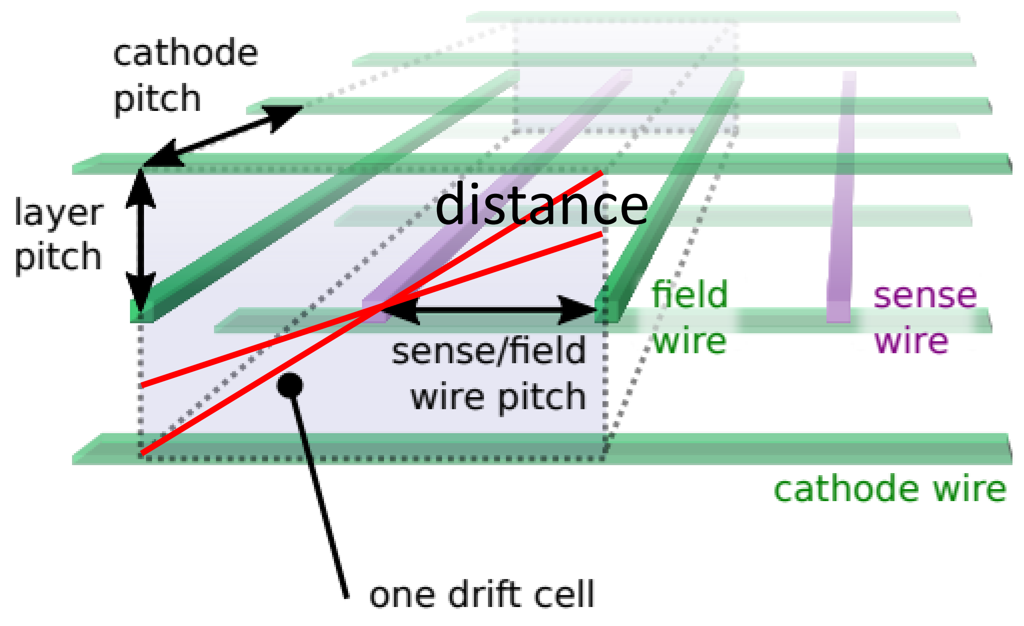
1. NNs can provide fast (<1s) calibrations with accuracy, compatible with usual methods.
2. Synchronous processing can benefit from ML techniques at almost all stages, giving faster and/or better results.

- Improvements in the offline dE/dx calibration.
- Test on the MDC time-distance calibration.
- Fine-tuning for real applications.
- Test of HV predictions (slow control).

Backup

Overview of different calibrations



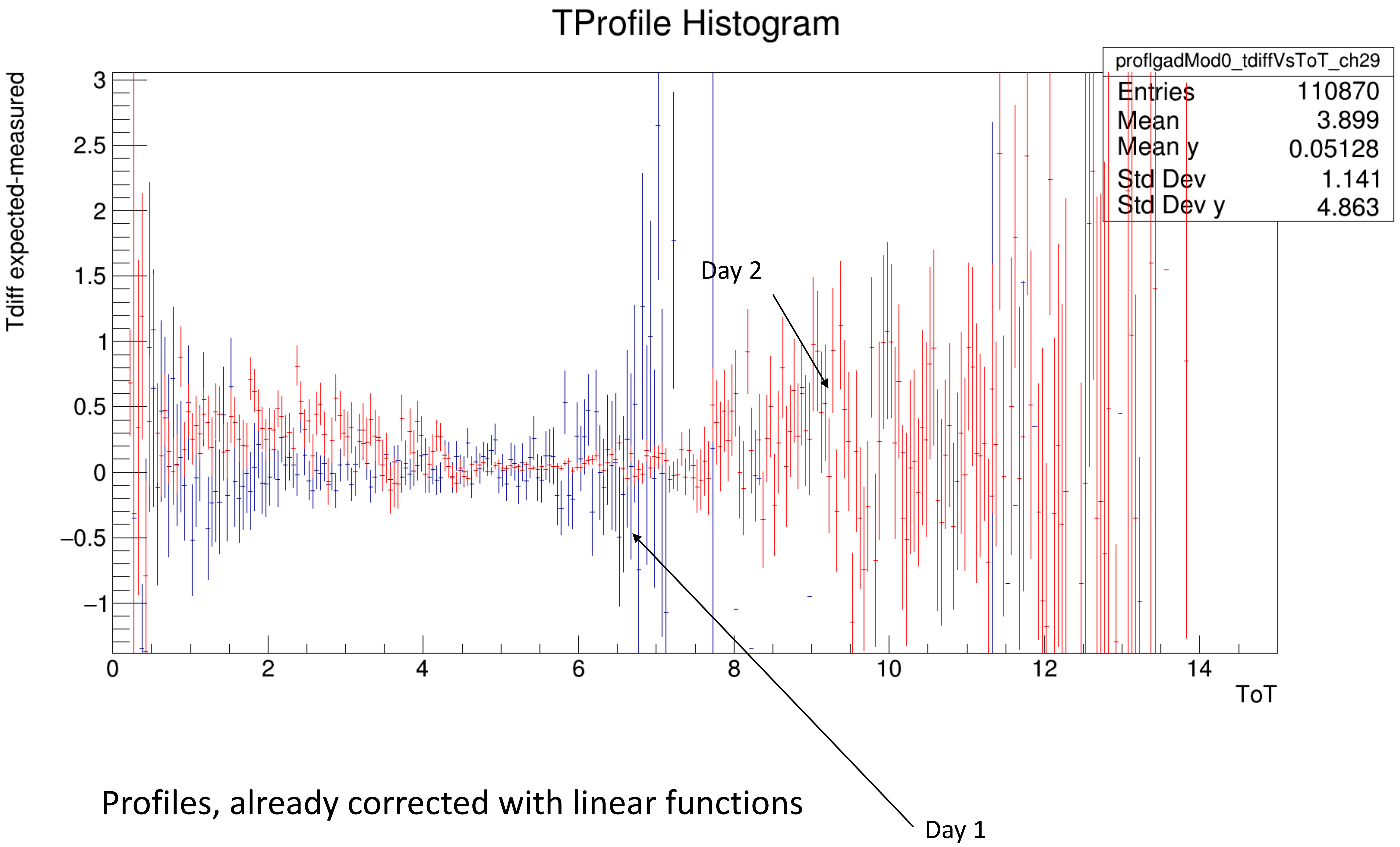


- Drift time – distance. Electronics (offset, tdc etc) and drift velocity. Calibrated initially with Garfield, after that iteratively corrected with data.

- Stored as a table sector, module, angle, distance – drift time.

  Can be possible to calibrate with NN if one reduces this to few parameters: module-sector as nodes, angles as input parameter. Target as parameters of fitting function. Or just both of angle and distance as input parameters and then fill the table with them.

Overview of different calibrations



Profiles, already corrected with linear functions

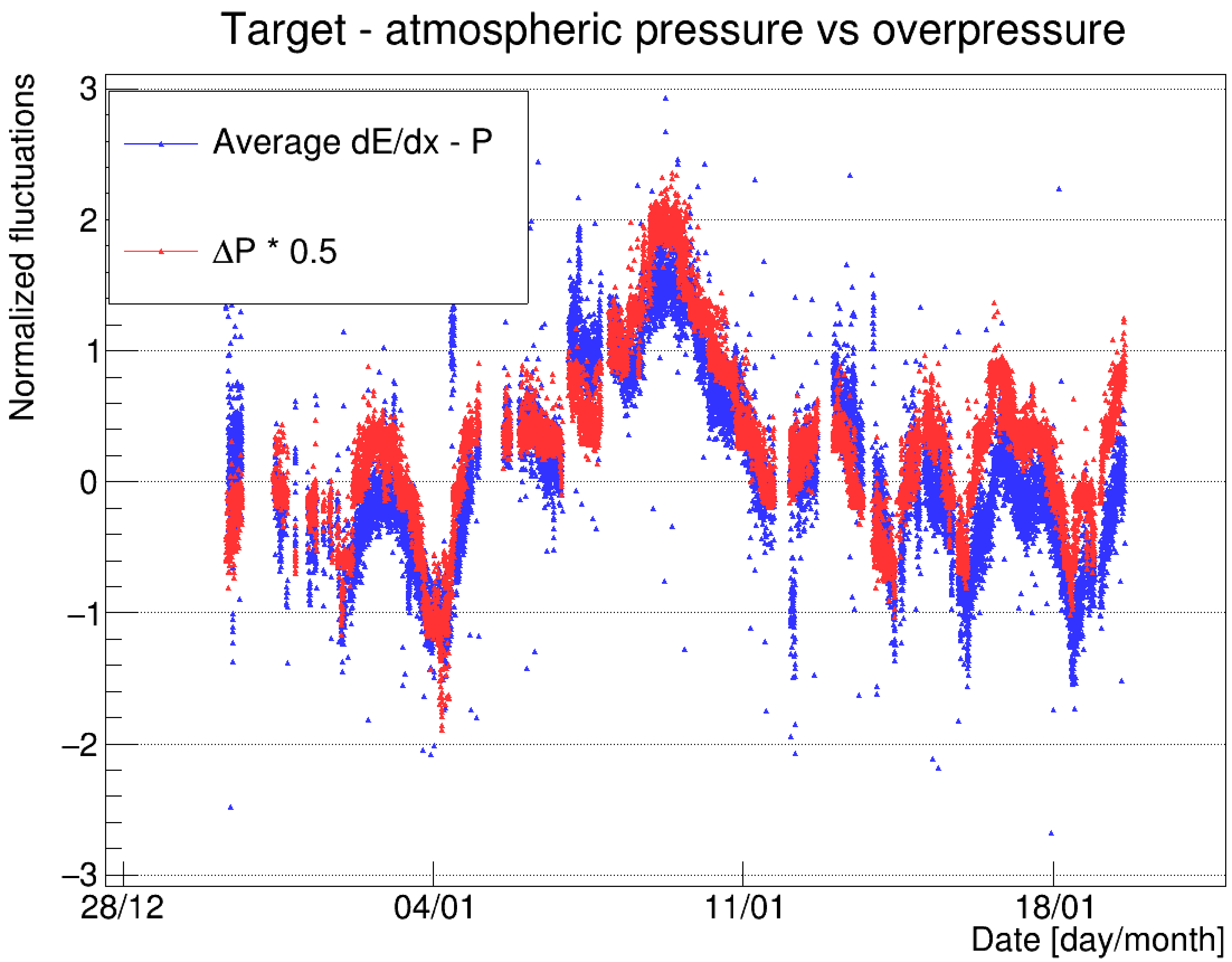
- T0 LGAD. Reconstruct events, calculate expected T0 from other ToF detectors. Correction of time-walk with a linear function of a profile, which appears from the fits in each bin.

- Problems for existing hades are at low values, where statistics is low and has nonlinearities in time-walk. Too low statistics to make it even as a target – bad application of NN

Ionization losses in drift chambers

Reasons to test on MDC:

- Significant fluctuations (5-10%);
- Clear dependence on environmental parameters;
- A lot of environmental parameters being measured.



Correlations between overpressure (red) and ionization losses, corrected on atmospheric pressure (blue). Feb22.

Each dot is a single run, ~100k/24 events, 1-2 min

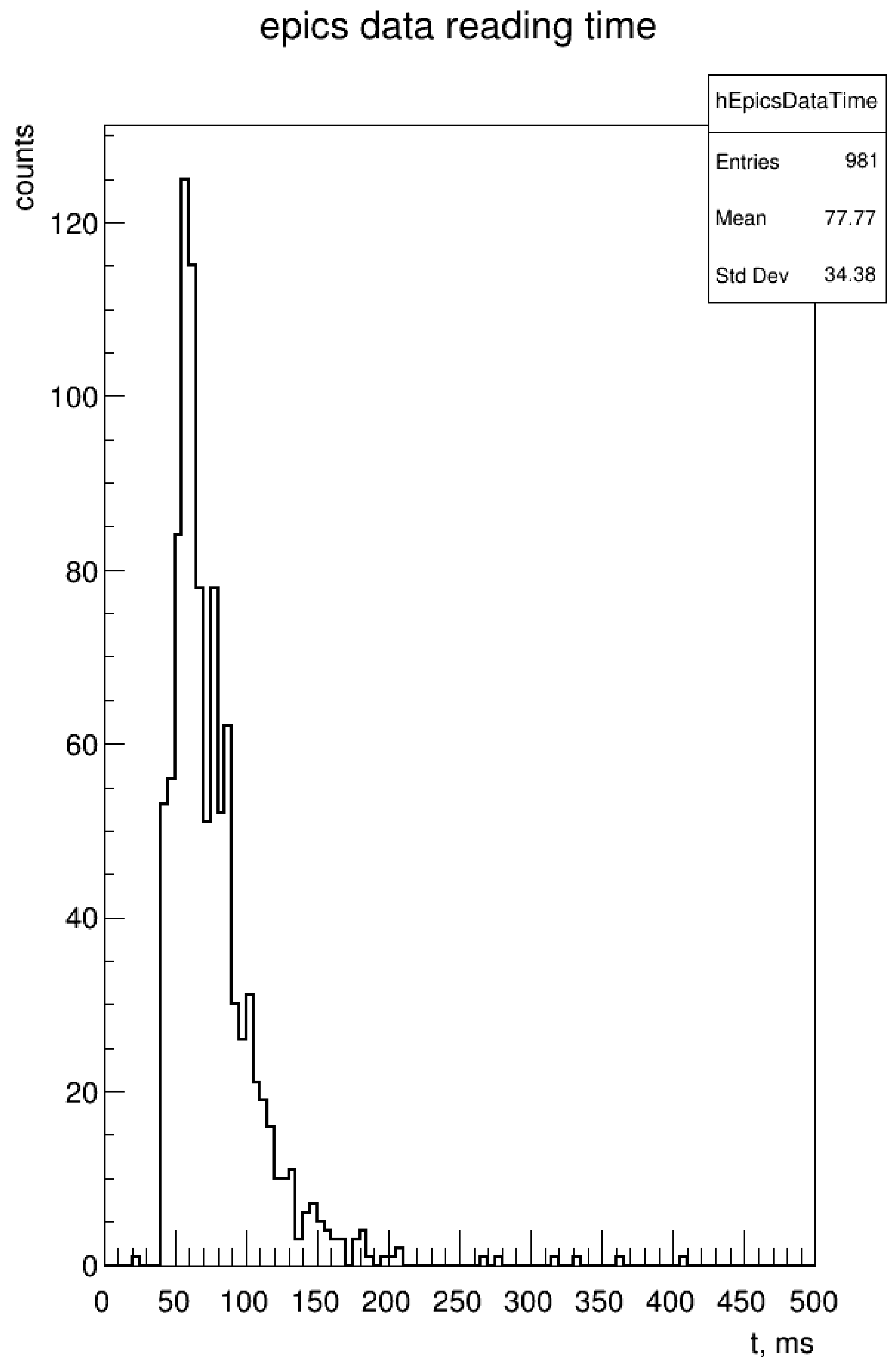
Smooth change with time (~15 min).

Input parameters:

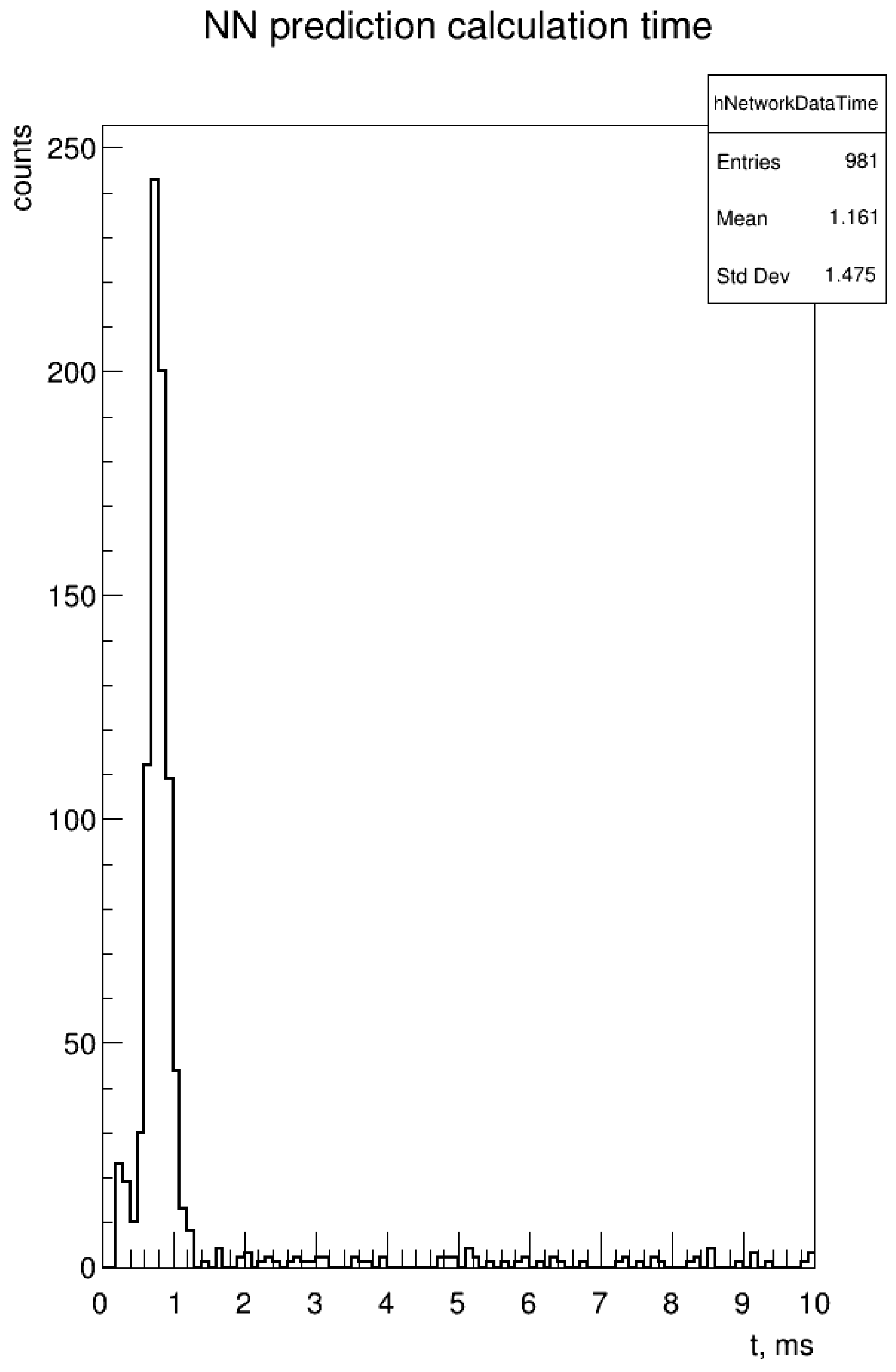
- Atmospheric pressure;
- High voltage;
- CO_2 concentration;
- Overpressure;
- H_2O concentration;
- Dew Point;
- Electronics temperature;

Prediction time consumption

Single parameter, simple network

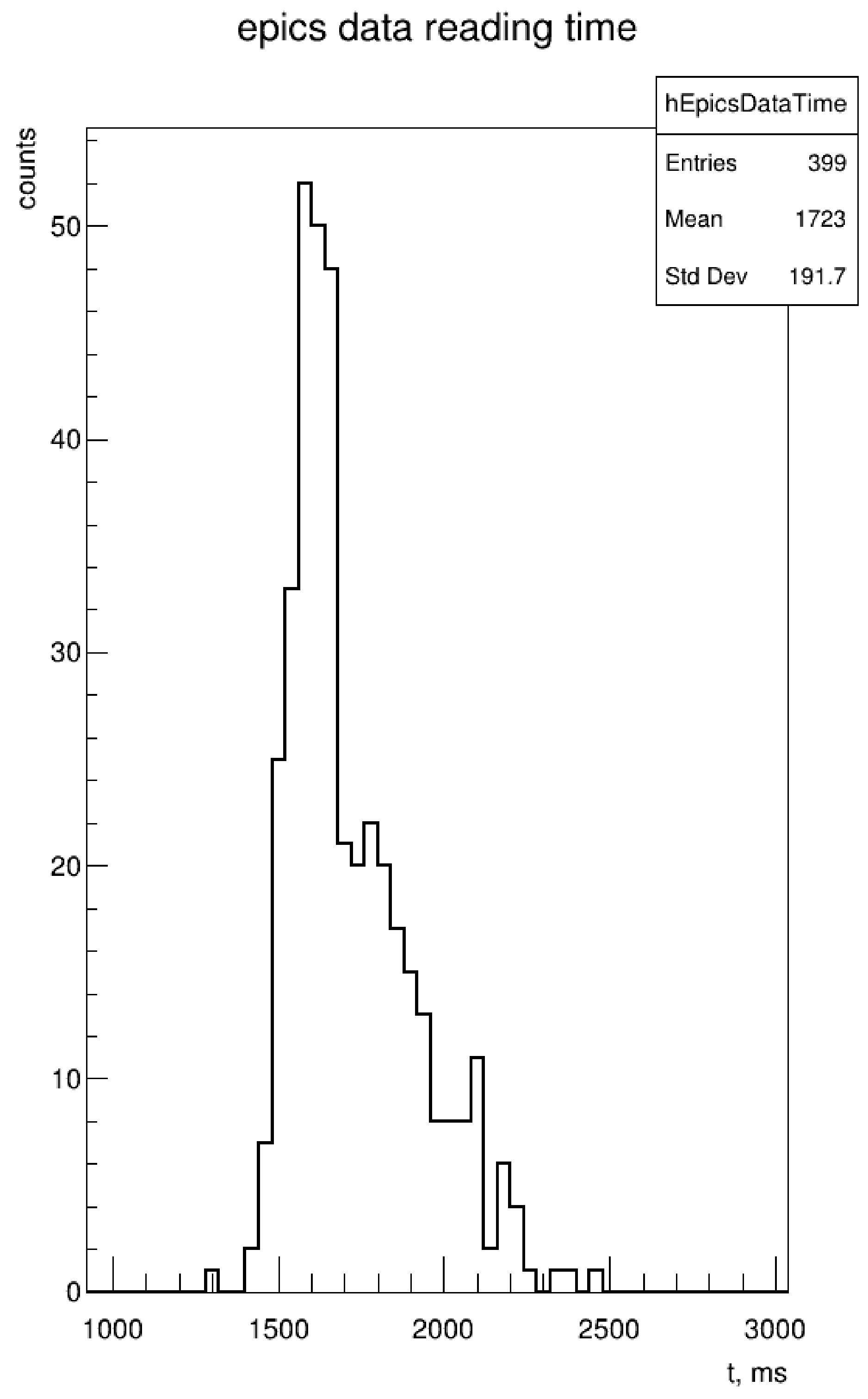


From GSI network

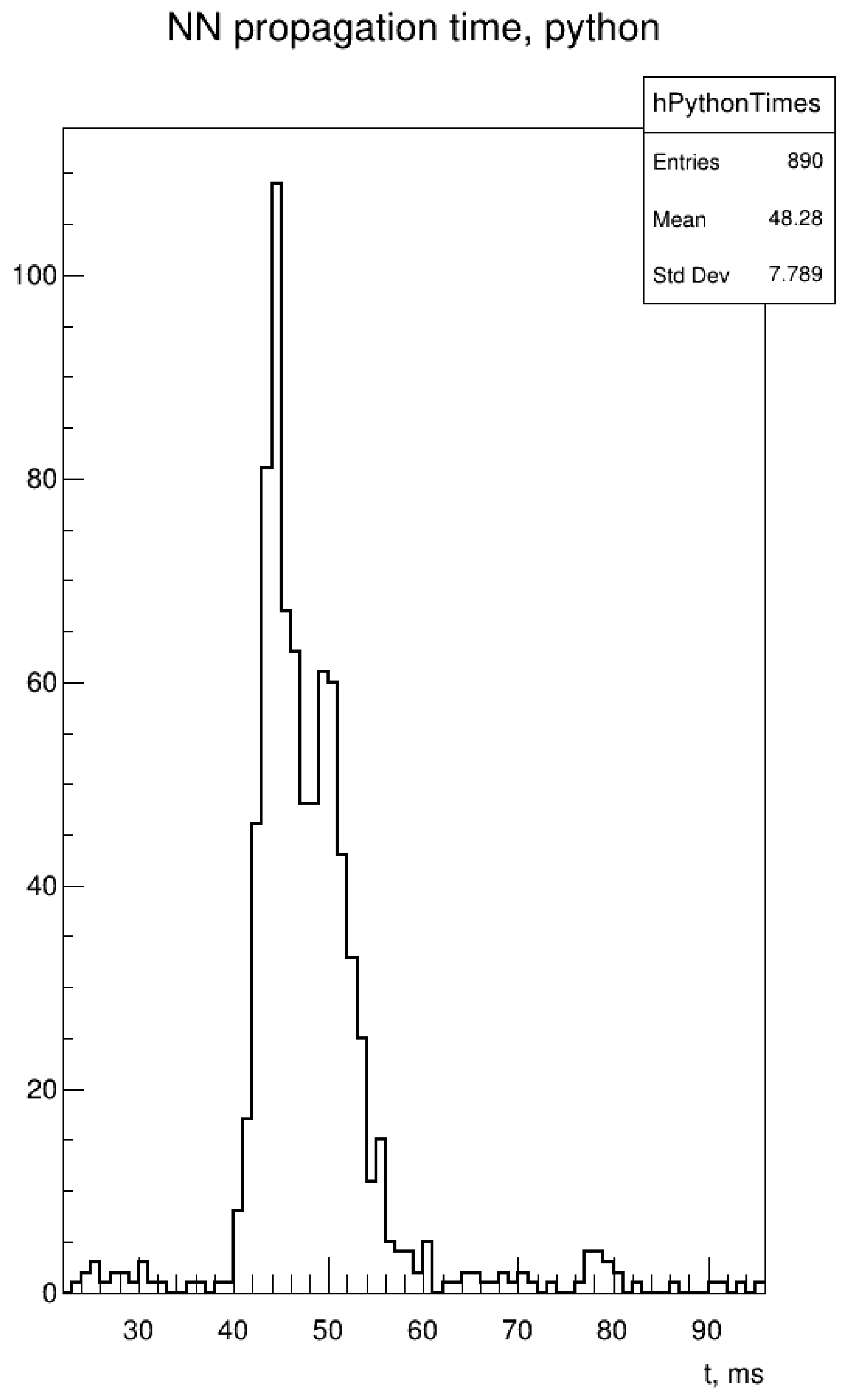


I7-1265U 10 cores 400$

24 parameters, GConv



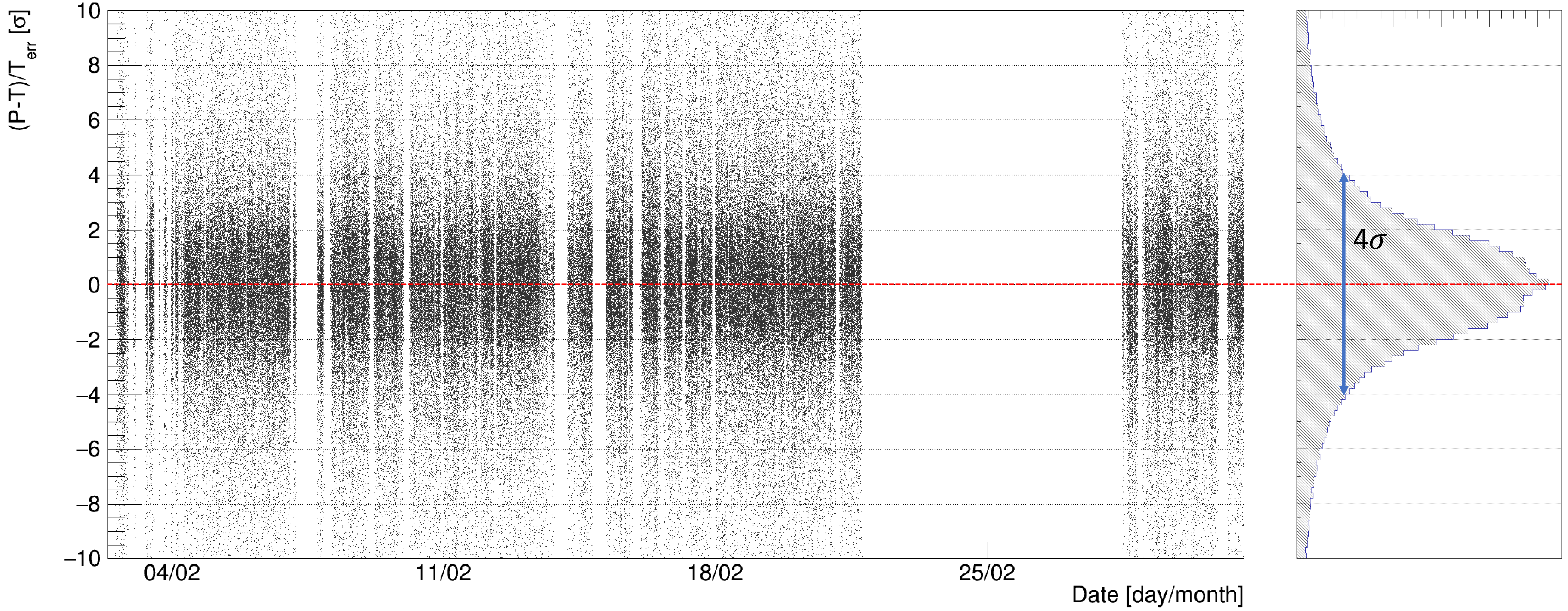
Wi-Fi, 50 MB/s



I7-1265U 10 cores 400$

Prediction Accuracy (training part)

$(\frac{dE}{dx})_{prediction} - (\frac{dE}{dx})_{target}$ in terms of calibration error σ



- Stable performance over the beam time.
- Compatible with target, the errors are underestimated.

High voltage prediction x_i

(General) Training procedure if we have data with varied HV:

1. Train the model f. Fix parameters.

2. Train model G using $|f(X_{i-1}x_i) - Y_c|$ as loss.

$$f(X) = Y$$

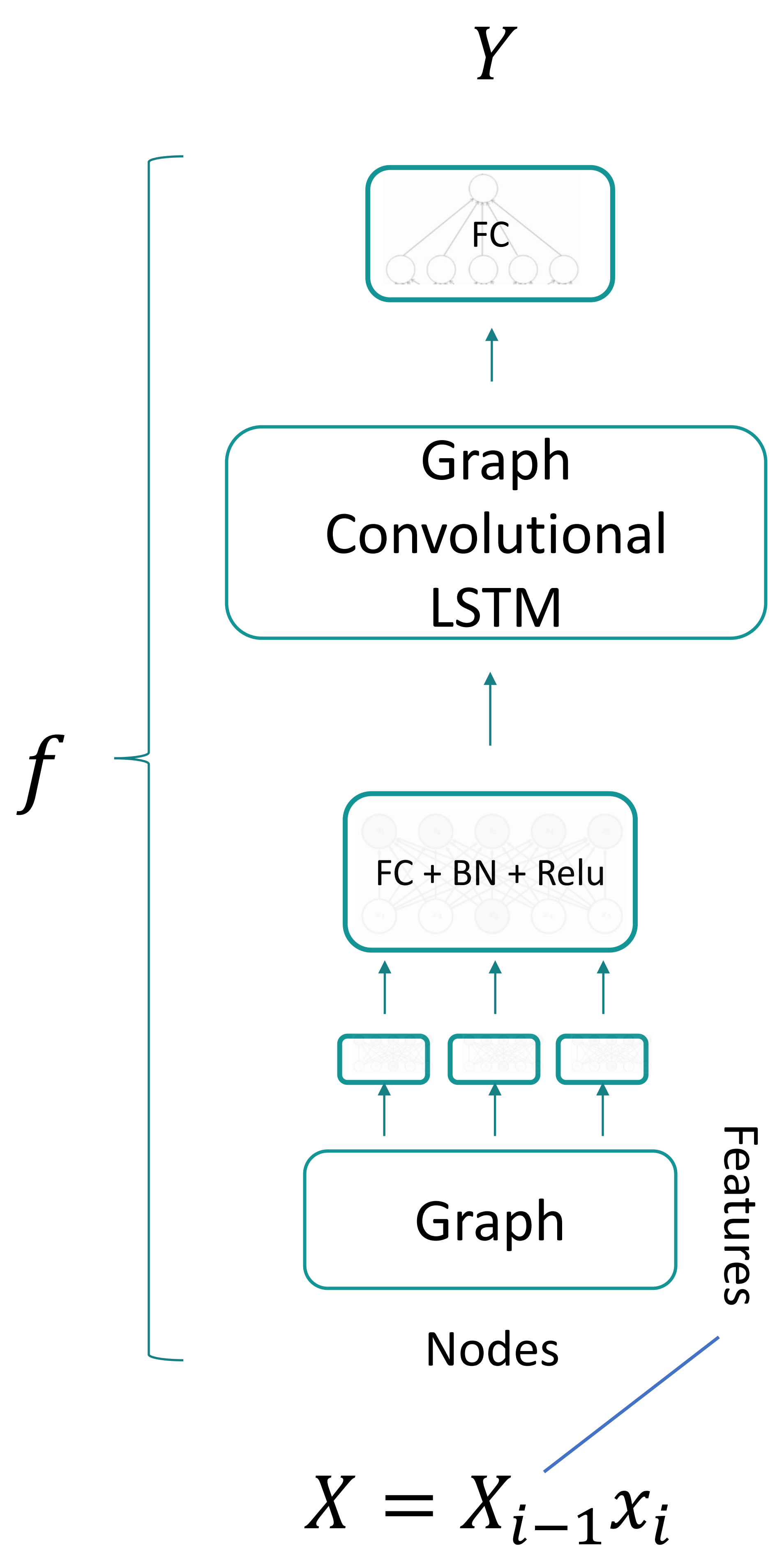
$$G(X_{i-1}|Y_c) = x_i$$

Sources of generating HV dataset:

1. Vary HV during cosmic runs.

2. Generate data with Garfield.

Multi-channel prediction



Statistics accumulation is possible this year! (~December)

Software development

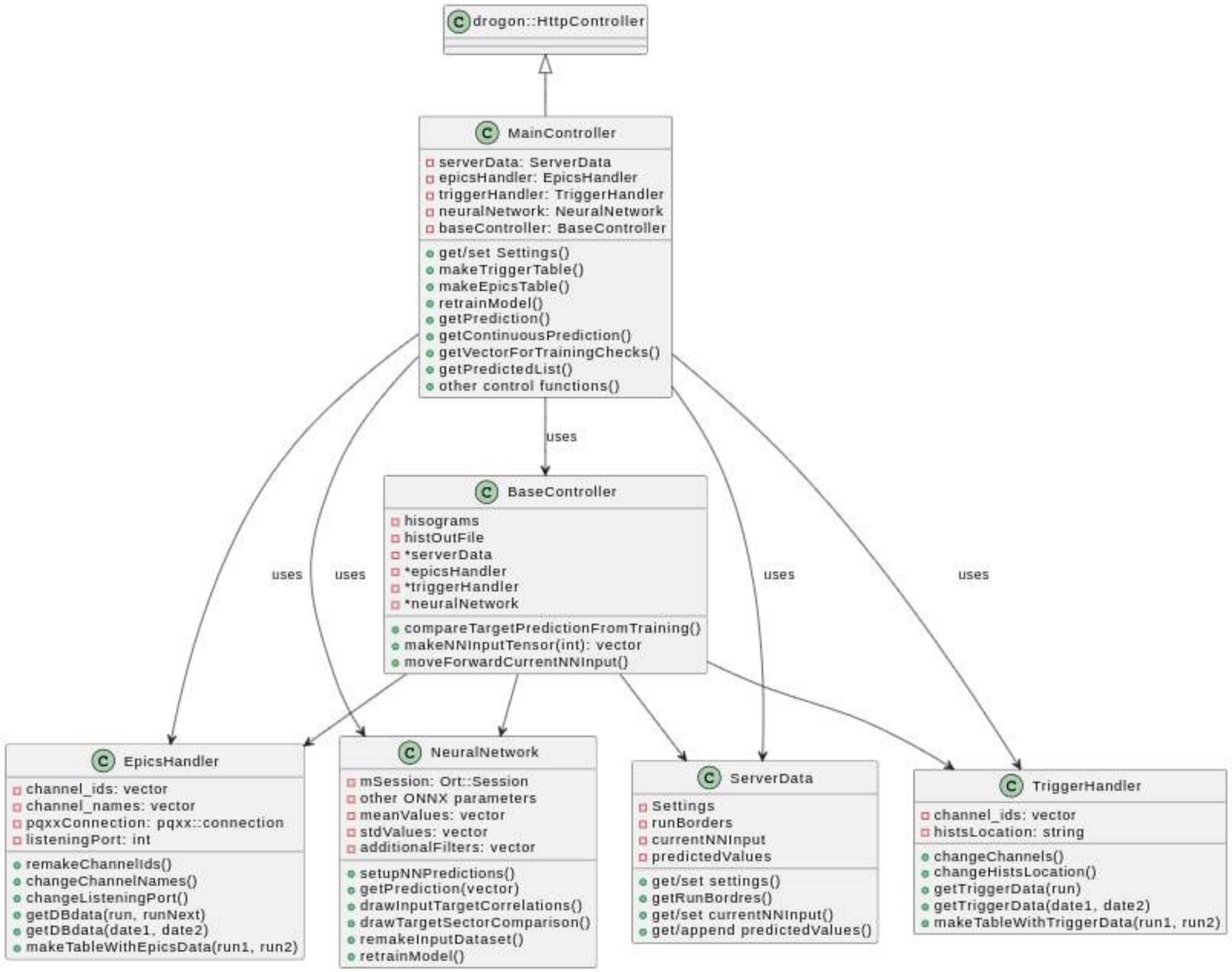
https://github.com/KladovValentin/drogonapp

Features:

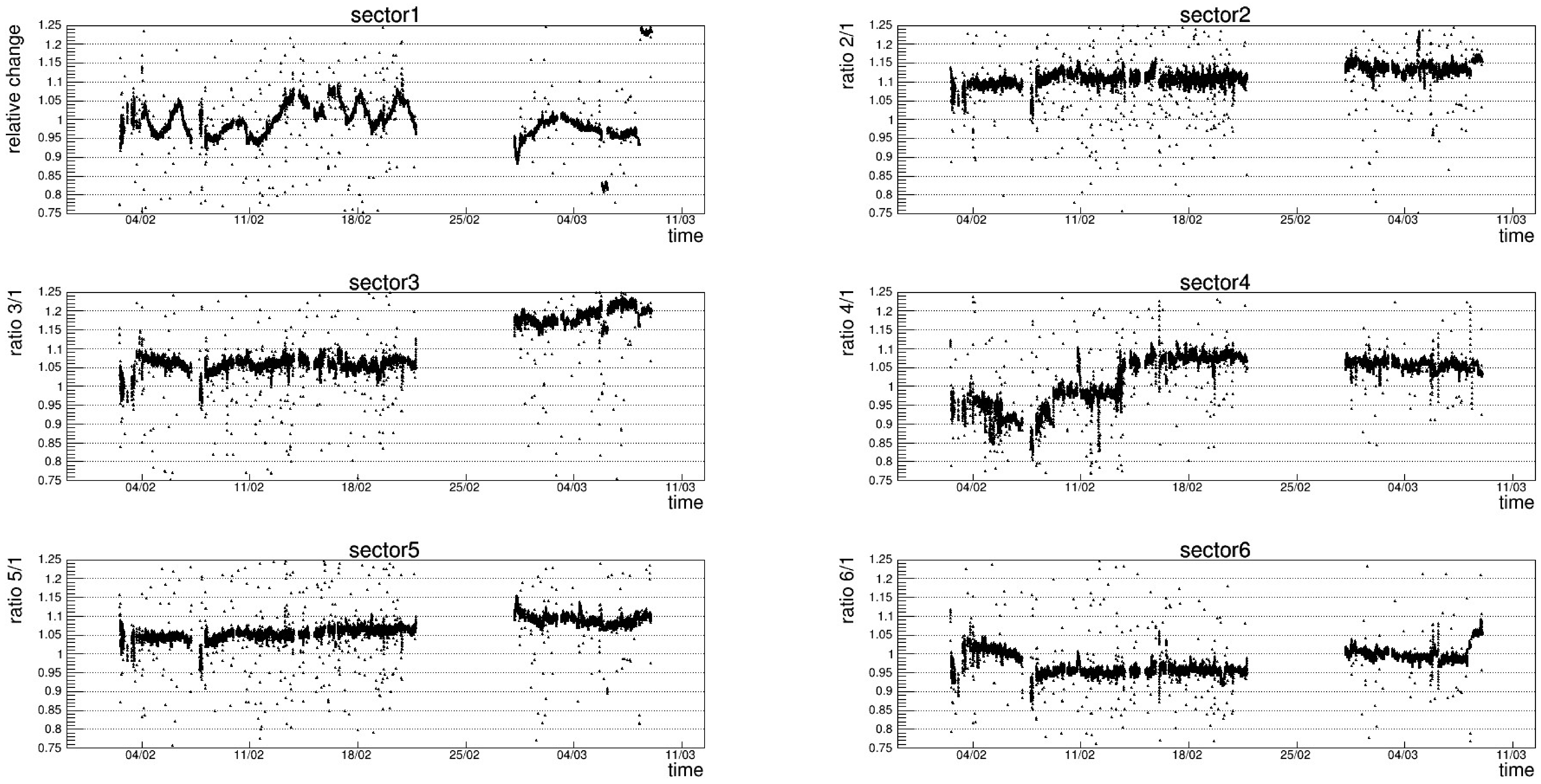
- Retraining with automated hyperparameter search.
- Automatic training set creation with given:
  - Epics channel names.
  - Trigger channel numbers and DQ files location.
  - List of runs, run borders or experimental files directory.
- Methods to save and change above settings + saves of NN data.
- Automated work with epics database:
  - connection,
  - conversation names-numbers,
  - handle missing data,
  - nn part of input on demand for run / list of runs.
- Automated work with trigger DQ files in the same way as for epics.
- Various methods to check training performance and correlations.

Methods:

- Based on C++ and object-oriented programming paradigm.
- Epics db reading with SQL commands.
- Trigger data reading and graphics with ROOT CERN.
- NN training with pytorch in python and predictions in C++ with ONNX.
- Backend written in Drogon framework for C++.
- Frontend with react.js (little for now).

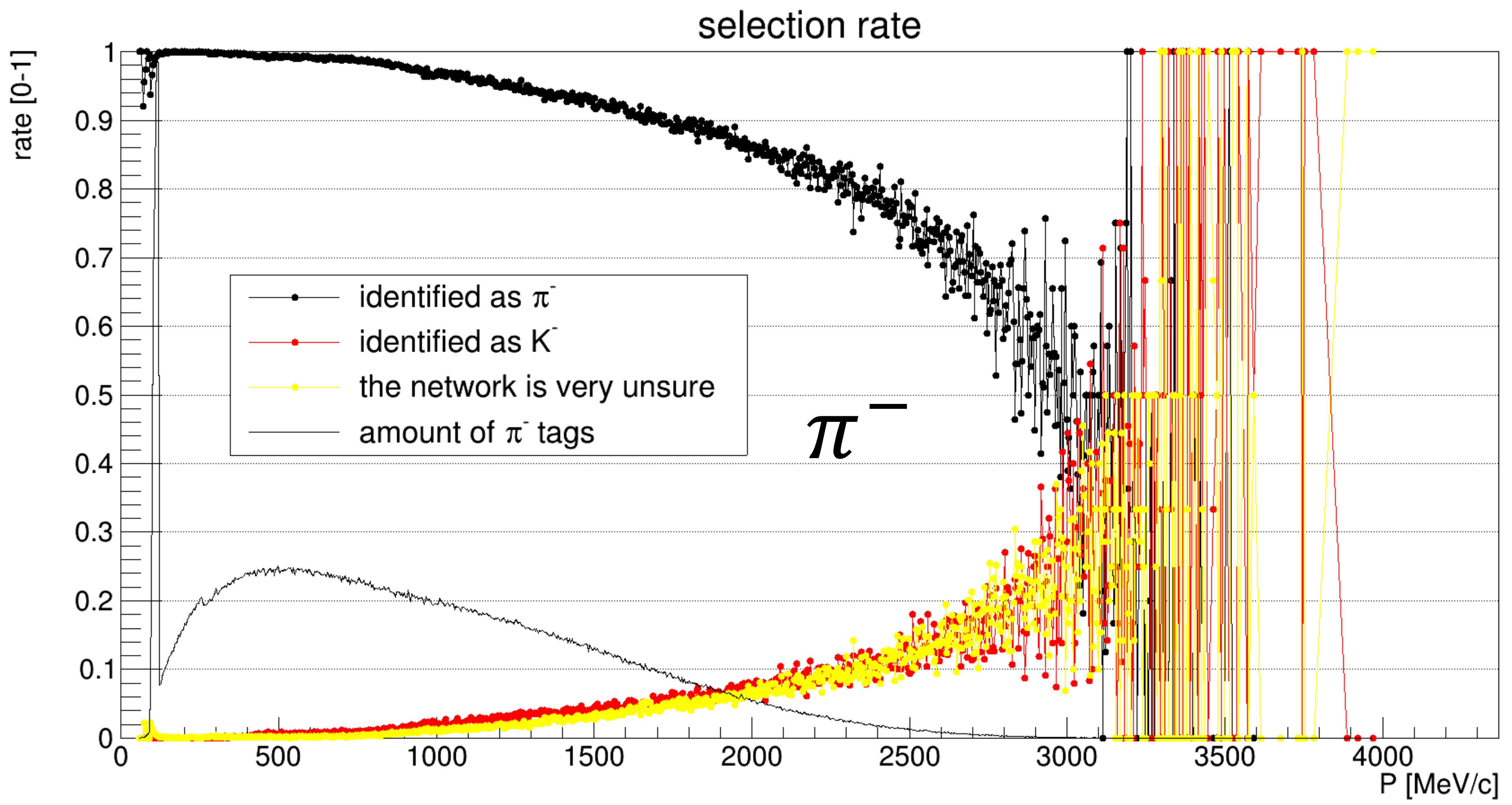


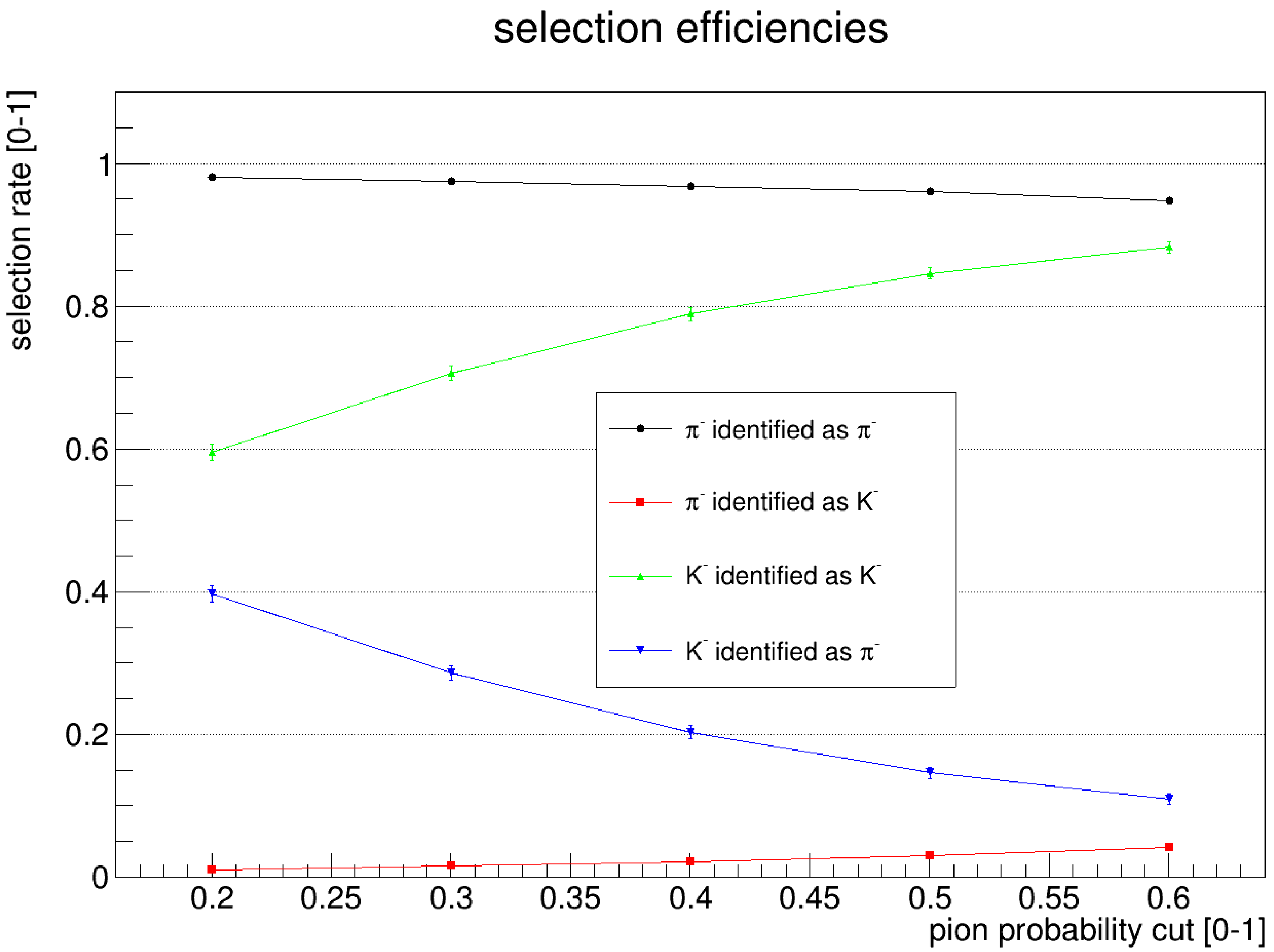
Multi-channel prediction

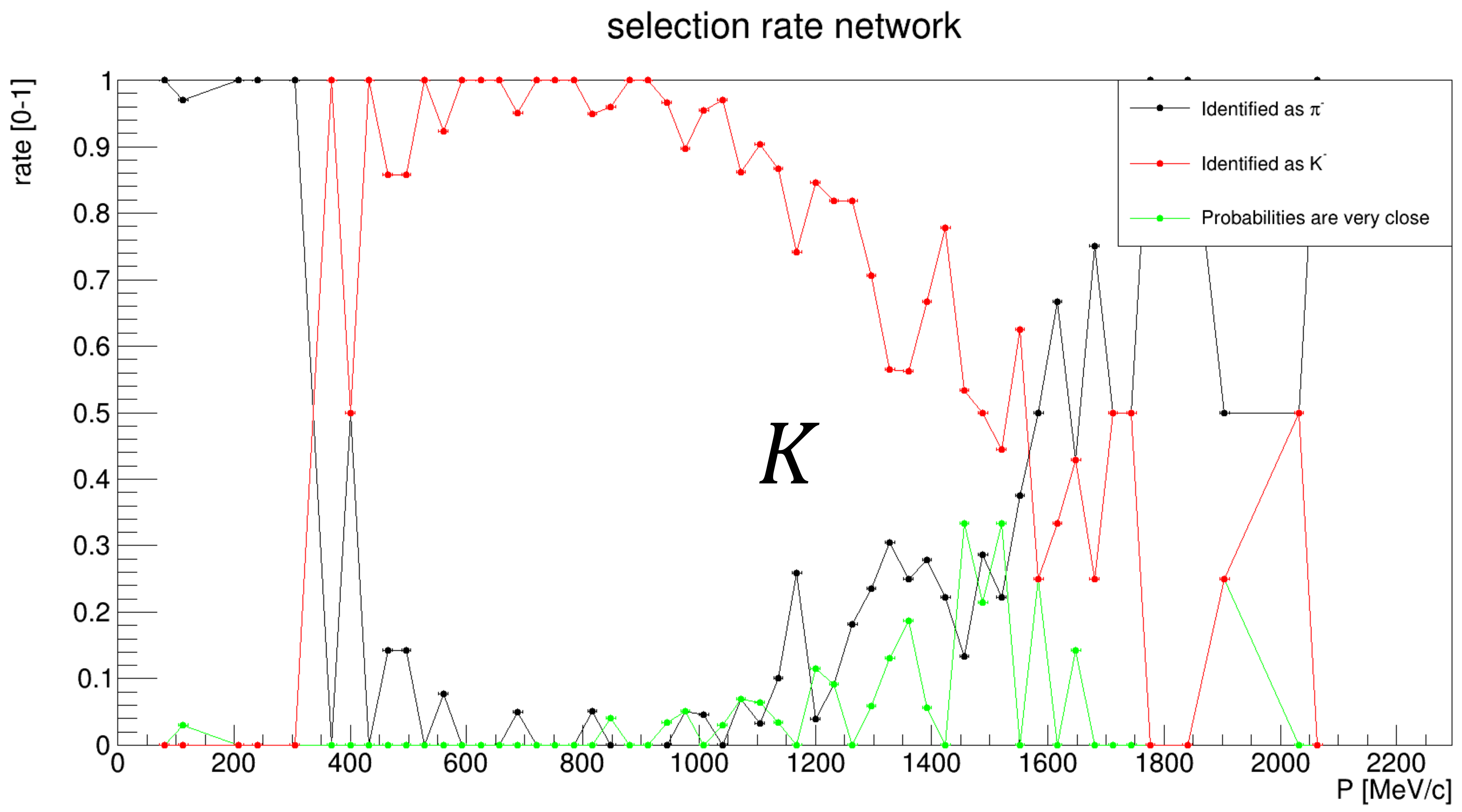


- In general, MDC sectors behave similarly.
- Need to account for differences.
- Some input parameters are shared (Atm. pressure).

Flexibility of pid







No strict cut – merge to the region of pions