

Impact of sensor degradation on 4D CKF performance

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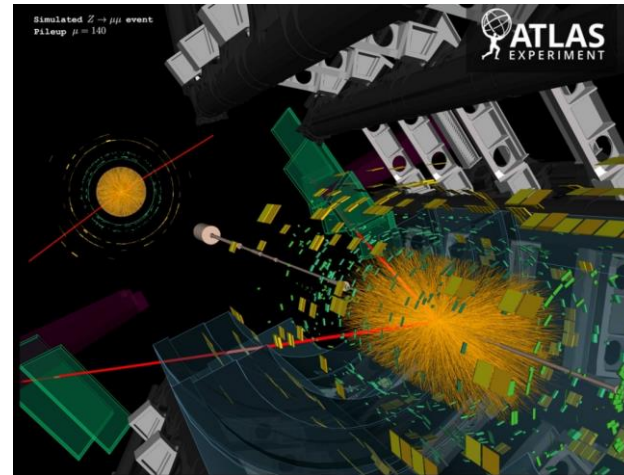
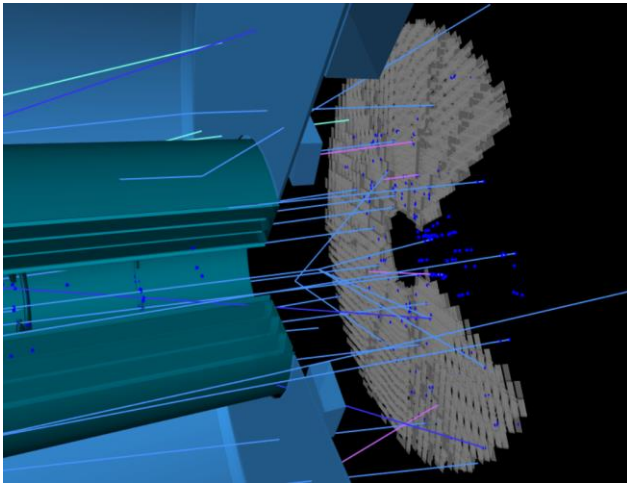
20 November, 2024

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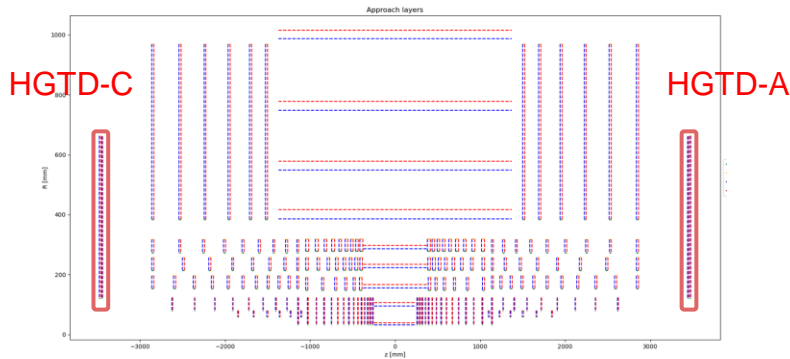
Objectives of this study

- Evaluate the performance of the **Combinatorial Kalman Filter (CKF)** reconstruction of a **timing layer detector**
 - Will be used as baseline performance for new reconstruction methods to be idealized High Luminosity (HL) environments
- Measure the impact of the **radiation damage** on the reconstruction performance
 - Important information for sensor commissioning

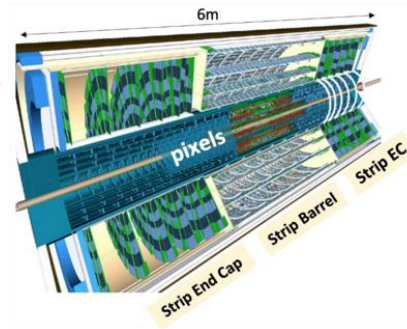


Detector geometry

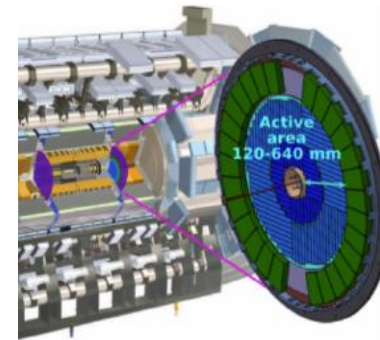
- Using ATLAS ITk and HGTD as a proxy for this study
- The **High Granularity Timing Detector (HGTD)** is the timing layer to be used on ATLAS for HL-LHC
 - Built with special silicon detectors (LGAD) with high timing resolution (around 35 ps)
- Included smearing of time measurements on HGTD layer to simulate the timing layer
 - Used the nominal 35 ps resolution as described in the HGTD TDR [1] (Table 2.1)



ITk + HGTD sensor layout in ACTS



ITk visualization

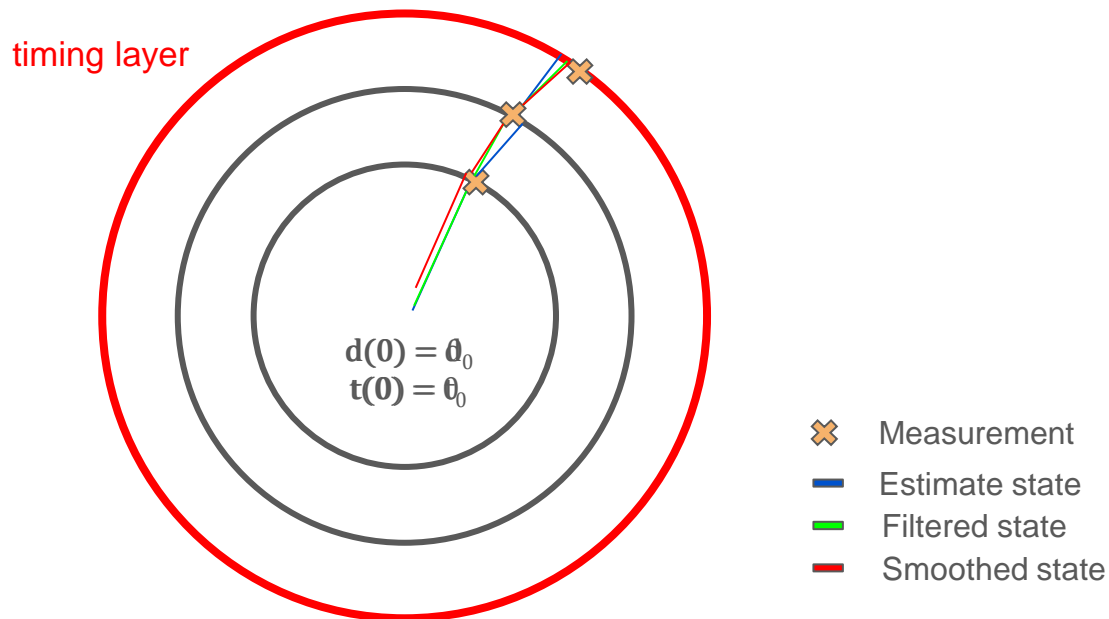


HGTD position within ATLAS

Images source: [4][5]

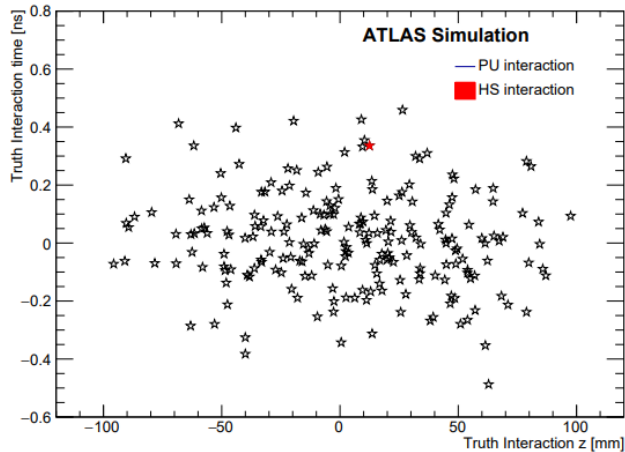
Adaptation of CKF for time reconstruction

- The present implementation of CKF already propagates correctly every parameter on the vector state
- The only adaption needed was to change the CKF's first time estimate to correspond to the travel time from origin to first hit point
 - Important for vertex reconstruction, as tracks from same vertex would be assigned different t_0



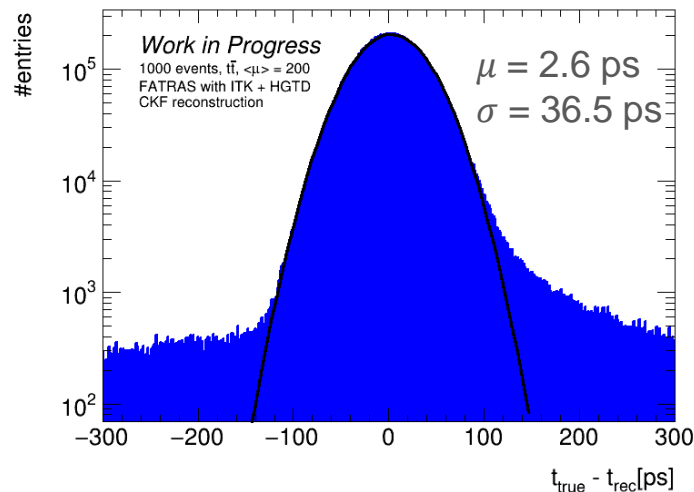
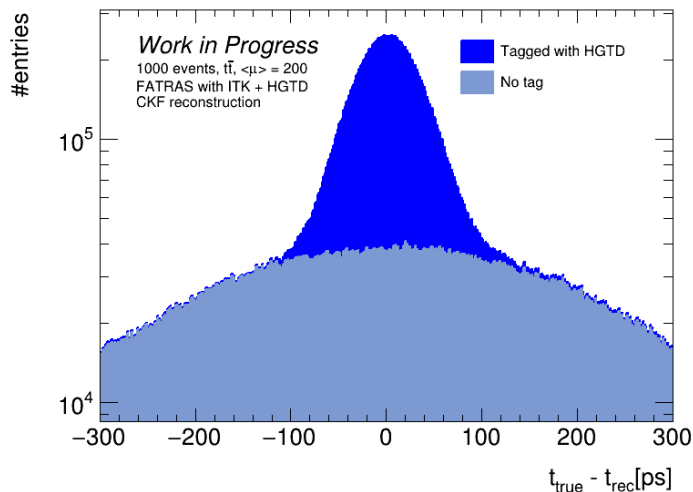
Simulating HL-LHC beam with ACTS Pythia8

- Simulated HL-LHC Bunch Crossing as described on the HGTD TDR [1](Pag.5)
 - $z_0 \sim N(0,50 \text{ mm})$, $t_0 \sim N(0,175\text{ps})$
- Simulated 1000 events of $pp \rightarrow t\bar{t}$
- Using *Fatras* for detector simulation



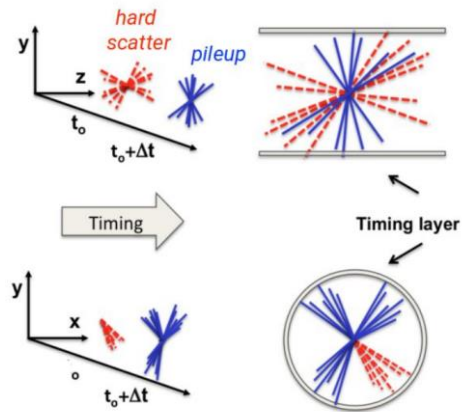
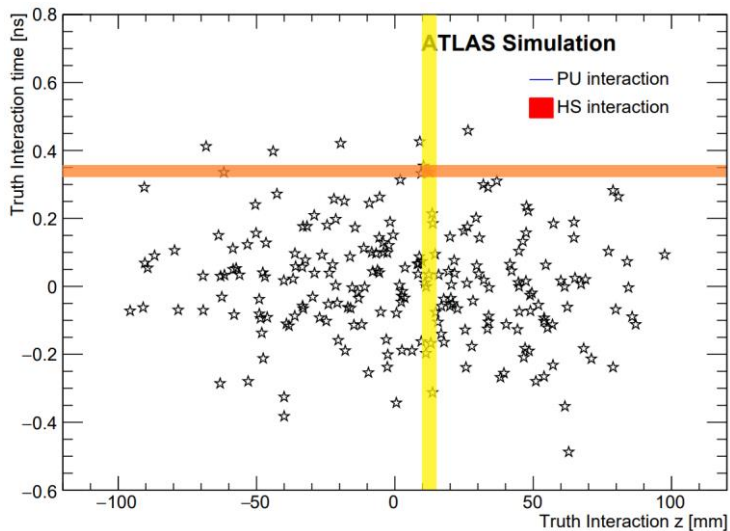
Performance evaluation: Residue plot

- Tracks without HGTD tagging rely on first estimate for time reconstruction, which has a high error associated with.
- When a track reaches HGTD, the error drops significantly because of the low error attributed to the measure
- In the plots below, the covariance threshold to separate the tracks (err_eT) was set to 1000



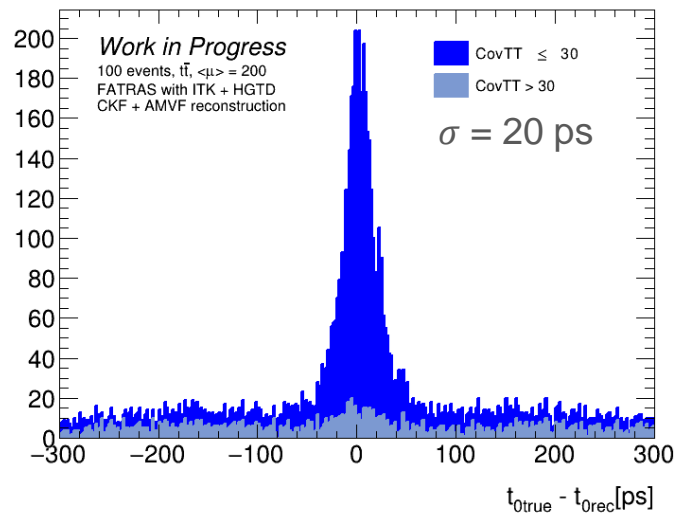
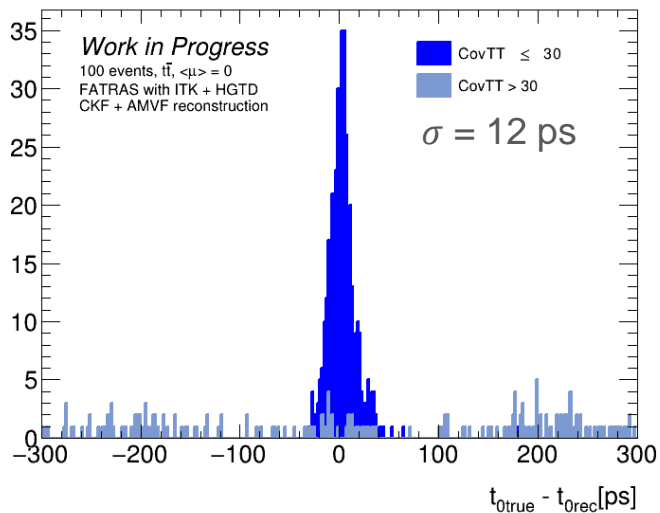
Global vertex time (t_0) reconstruction

- One of the main objectives of a timing layer detector is to provide an additional dimension for pileup rejection
- If we estimate (z_0, t_0) with enough resolution, it is possible to use this information to better isolate hard scatter from pileup
 - HGTD TDR proposes Jet reconstruction algorithms where the time information can be used



AMVF Vertex time reconstruction

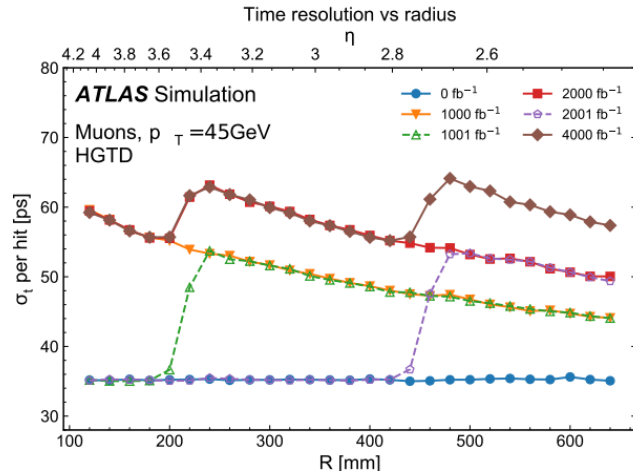
- To understand the impact of CKF on the global t_0 reconstruction we added a step to estimate primary vertex positions using AMVF
 - Need to include time information on the primary vertex seeder!
- Estimates with high residual can mostly be filtered by the time error parameter on the covariance matrix (internal parameter of AMVF)
 - Work point choice of purity x sensibility
- After filtering out high error estimates, a Gaussian fit was made to get $t_{0\text{rec}}$ resolution



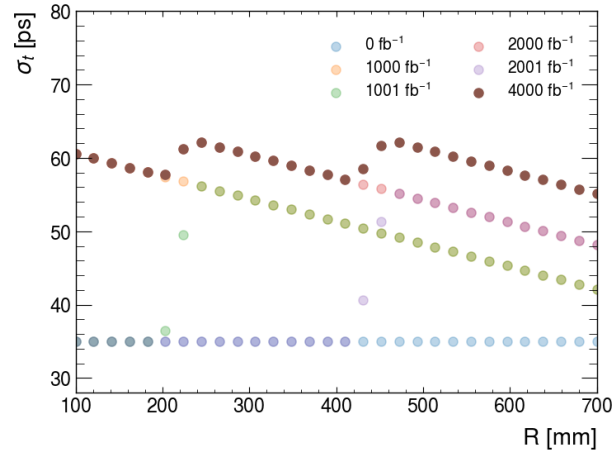
How to evaluate the impact of sensor degradation effects on ACTS?

Simulation of sensor deterioration

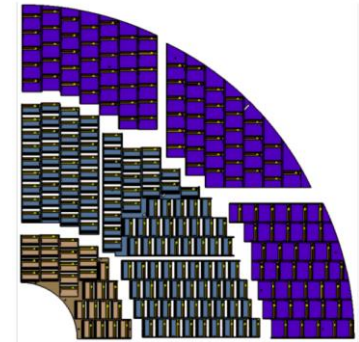
- HGTD sensors will degrade with integrated luminosity of LHC
 - The degradation is well characterized with test beams
- Asserting changes of sensor resolution is important for commissioning
- We simulated the sensor deterioration with increasing integrated luminosity
 - Using what is informed at the HGTD TDR [1] (Fig.2.13)



HGTD sensor resolution curves for various integrated luminosities



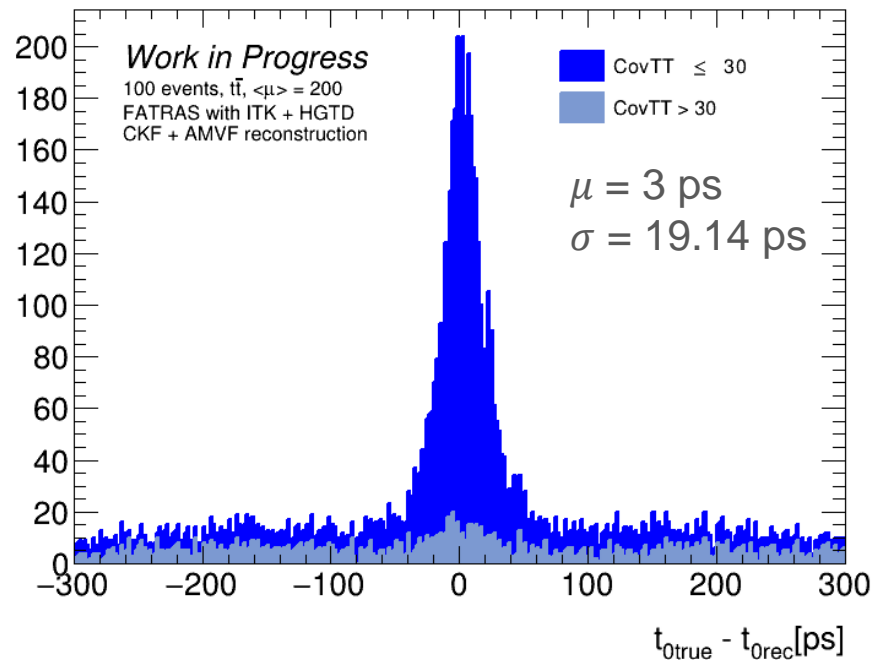
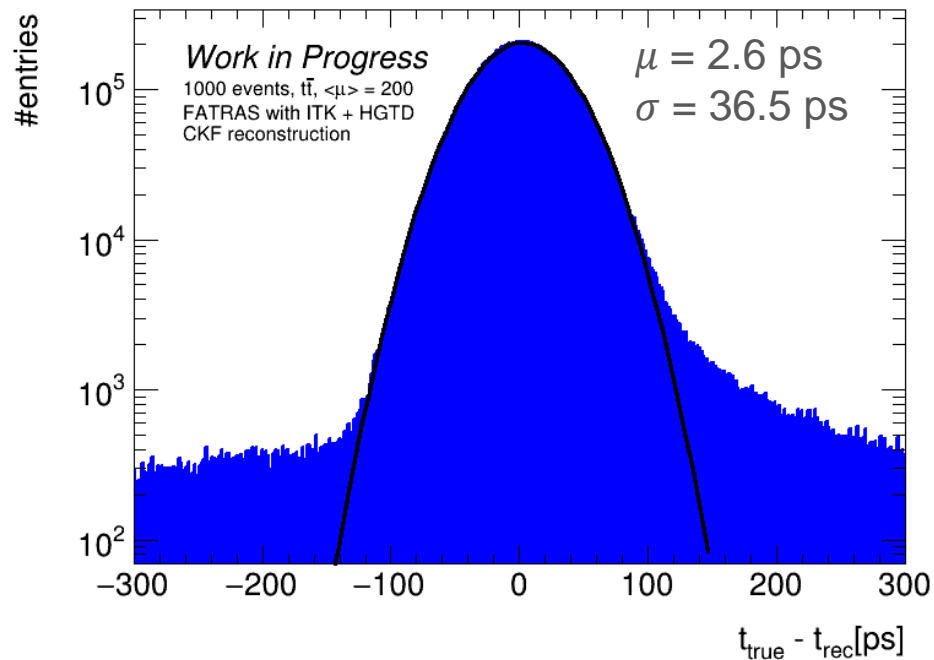
Analytical approximation of sensor resolution curves



HGTD detector unit layers (TDR Fig.7.19)

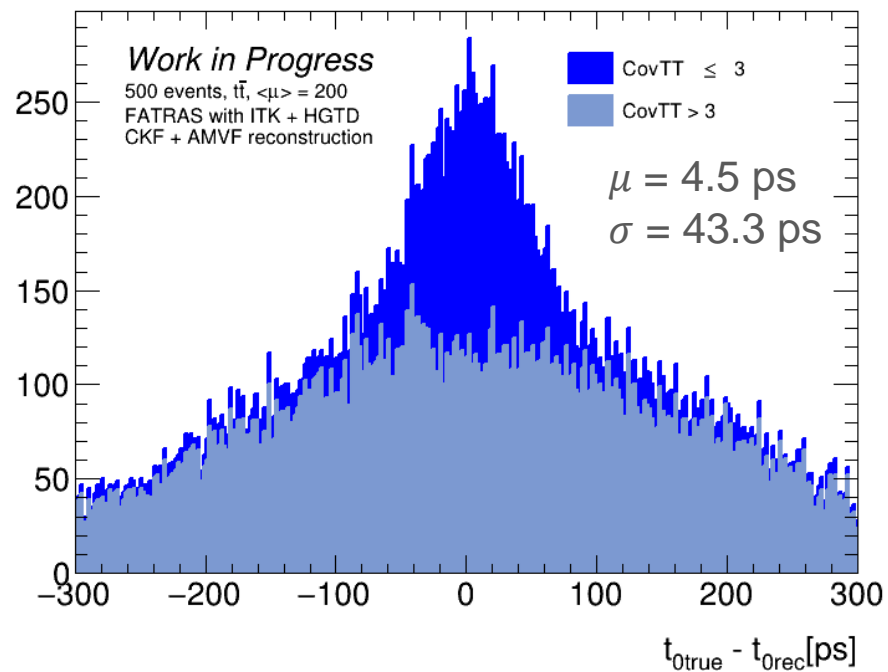
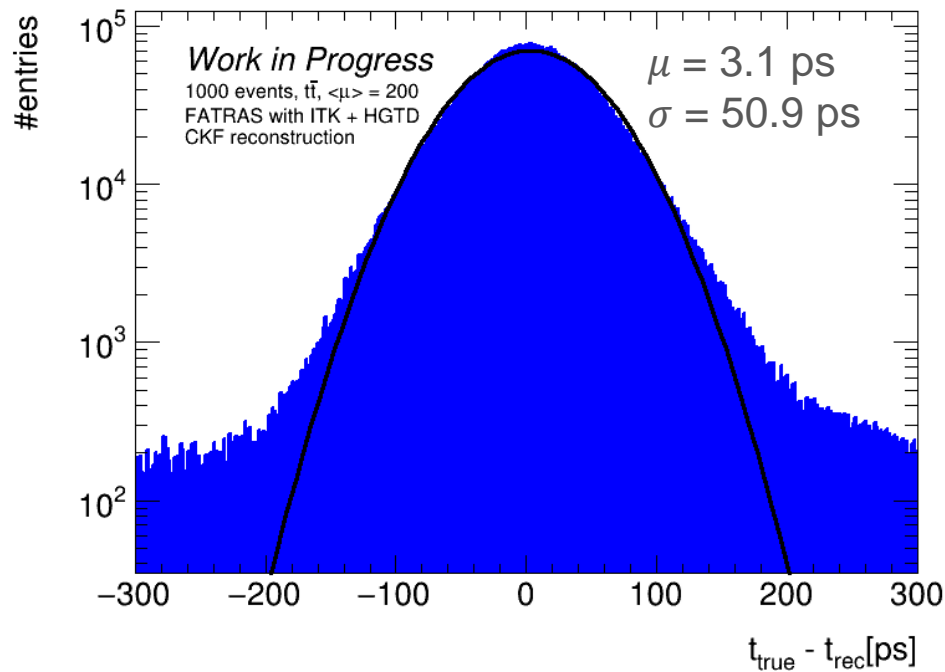
Reconstruction performance at 0 fb⁻¹

0 fb⁻¹: 36.5 ps



Reconstruction performance at 1000 fb⁻¹

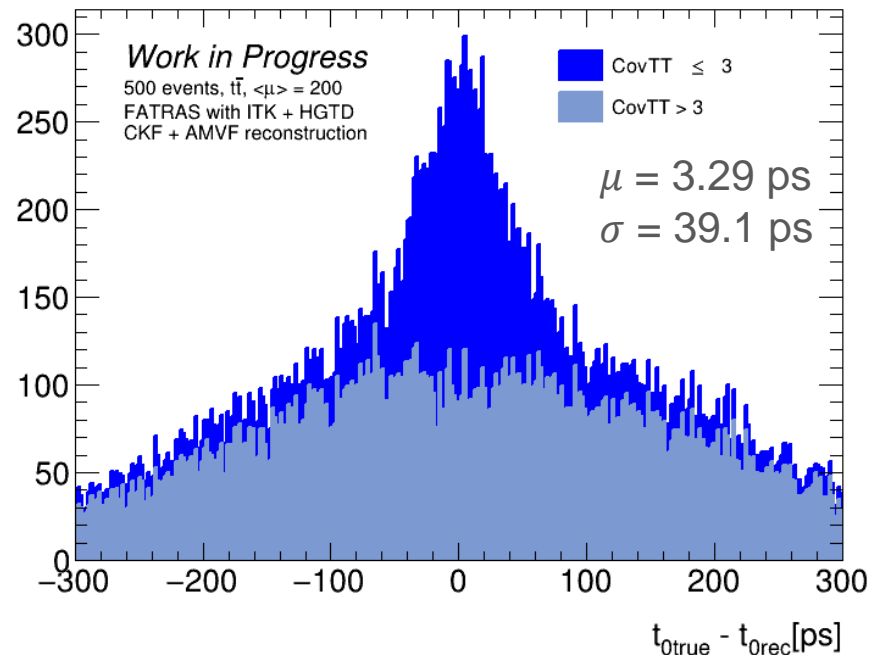
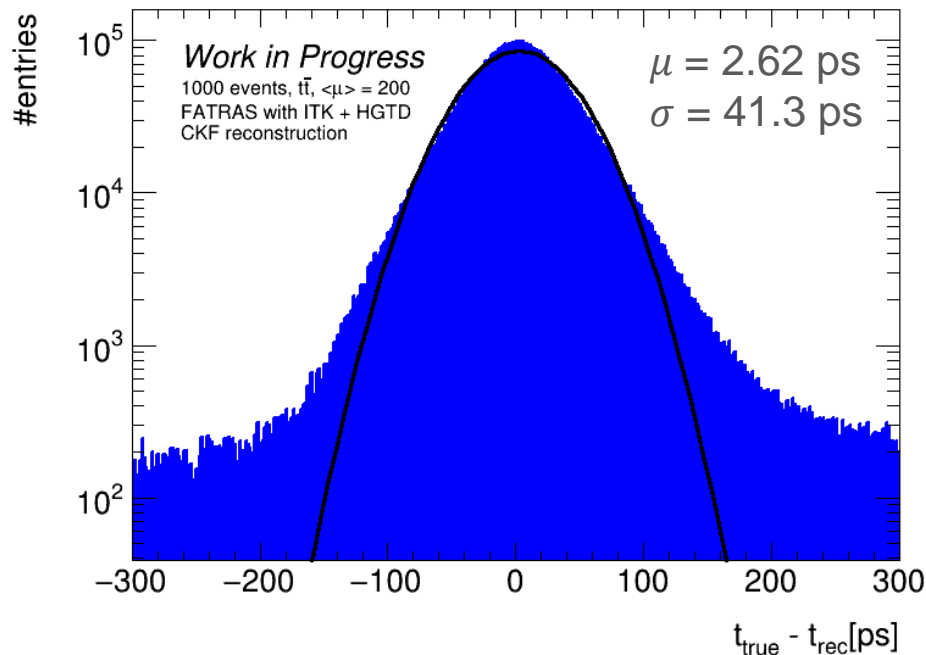
0 fb⁻¹: 36.5 ps → 1000 fb⁻¹: 50.9 ps



Reconstruction performance at 1001 fb⁻¹

0 fb⁻¹: 36.5 ps → 1000 fb⁻¹: 50.9 ps → 1001 fb⁻¹: 41.3 ps

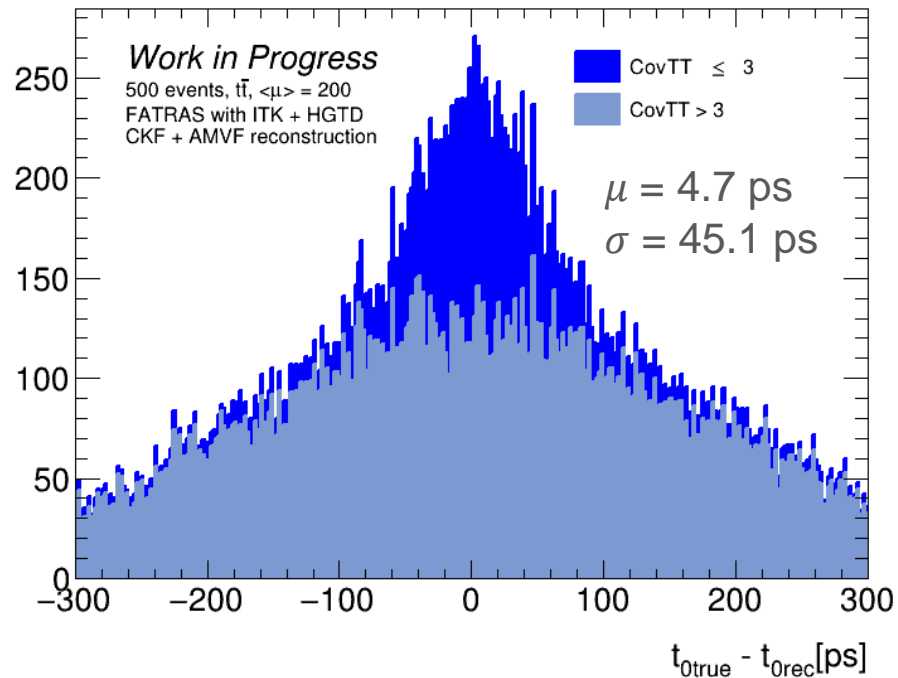
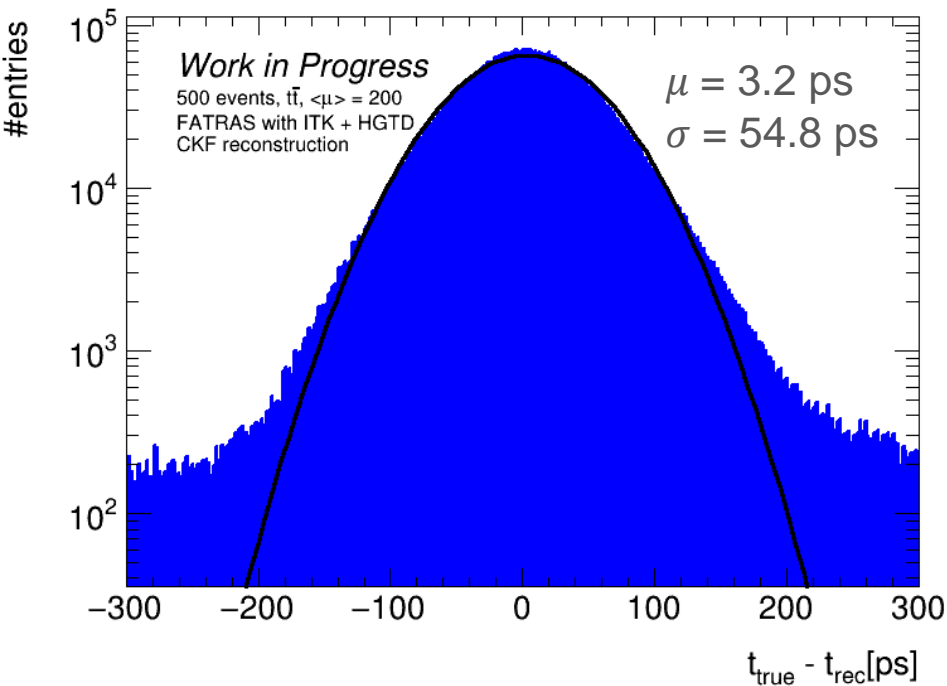
inner ring
replacement



Reconstruction performance at 2000 fb⁻¹

0 fb⁻¹: 36.5 ps → 1000 fb⁻¹: 50.9 ps → 1001 fb⁻¹: 41.3 ps → 2000 fb⁻¹: 54.8 ps

inner ring
replacement

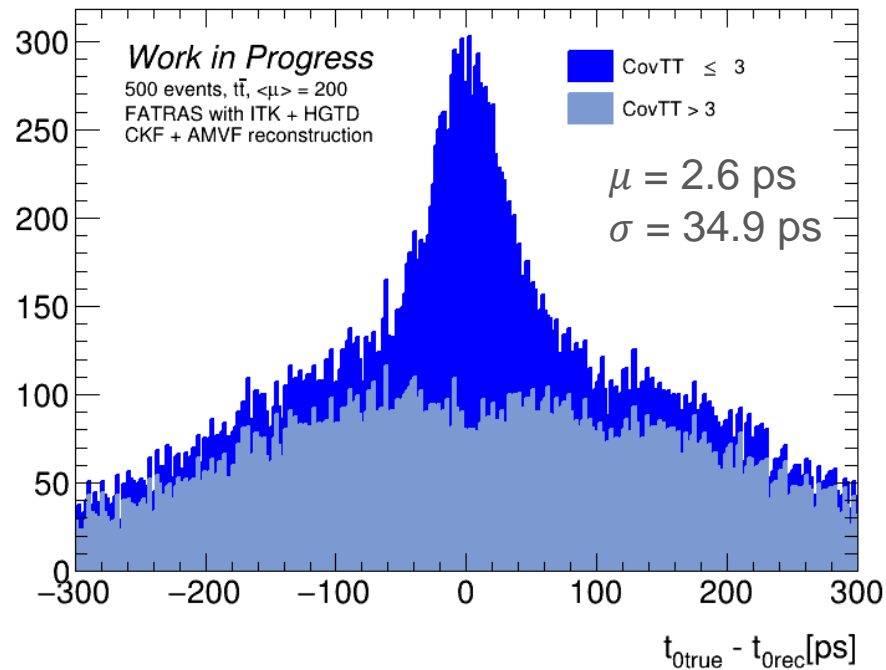
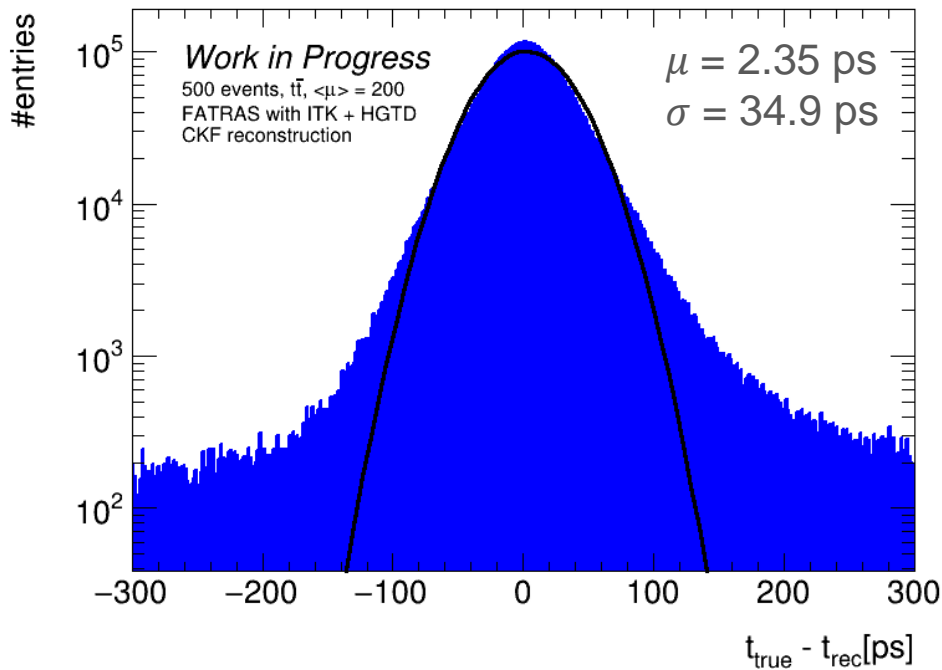


Reconstruction performance at 2001 fb⁻¹

0 fb⁻¹: 36.5 ps → 1000 fb⁻¹: 50.9 ps → 1001 fb⁻¹: 41.3 ps → 2000 fb⁻¹: 54.8 ps → 2001 fb⁻¹: 34.9 ps

inner ring
replacement

middle and inner ring
replacement

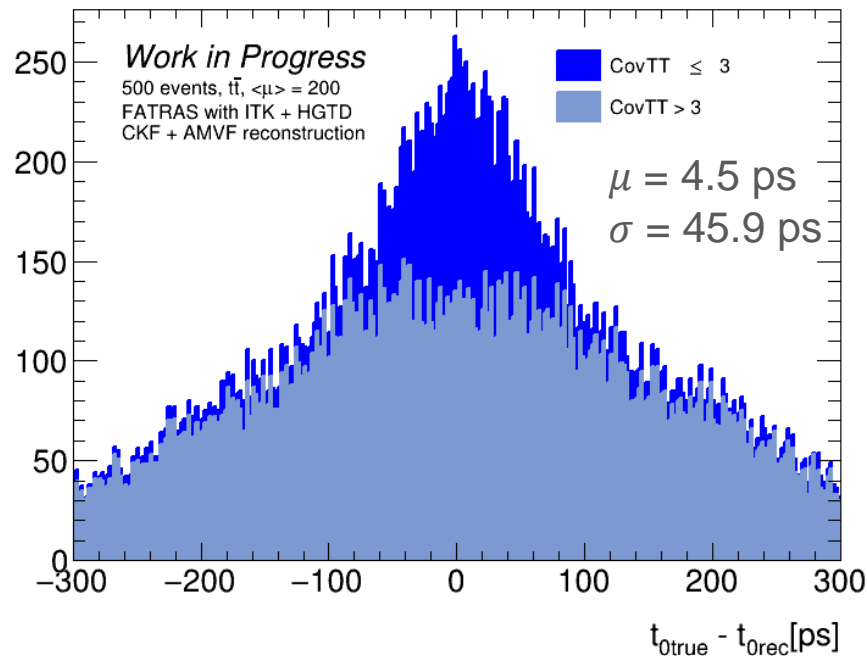
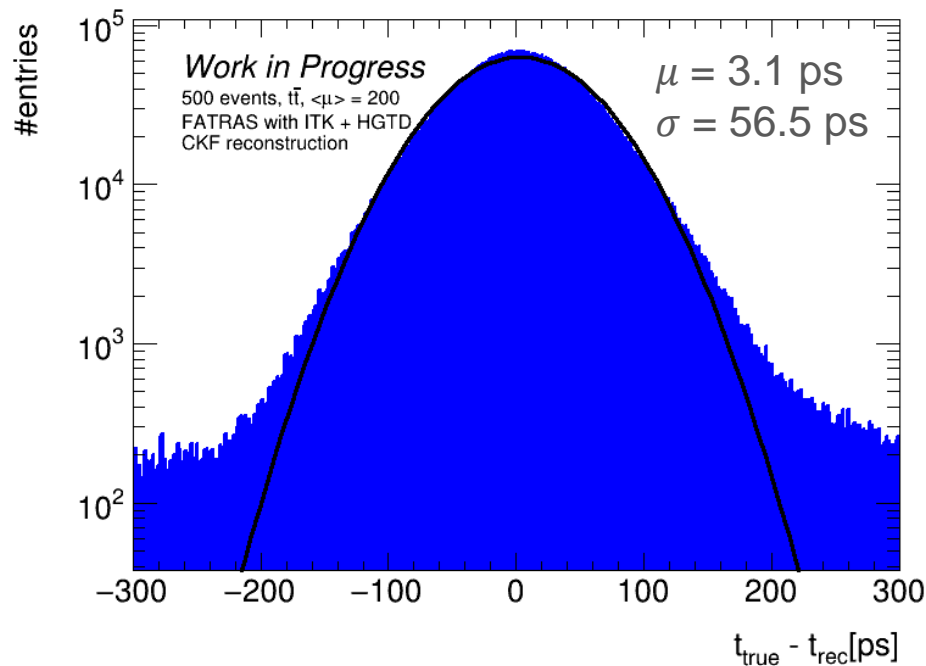


Reconstruction performance at 4000 fb⁻¹

0 fb⁻¹: 36.5 ps → 1000 fb⁻¹: 50.9 ps → 1001 fb⁻¹: 41.3 ps → 2000 fb⁻¹: 54.8 ps → 2001 fb⁻¹: 34.9 ps → 4000 fb⁻¹: 56.5 ps

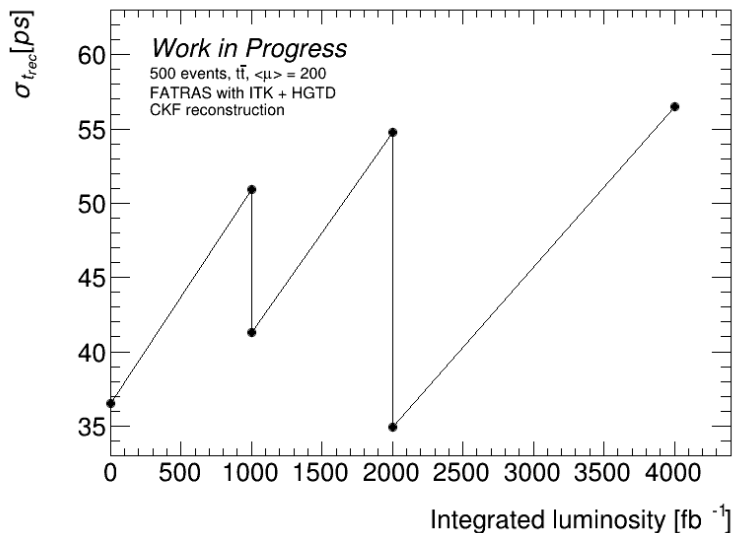
inner ring
replacement

middle and inner ring
replacement

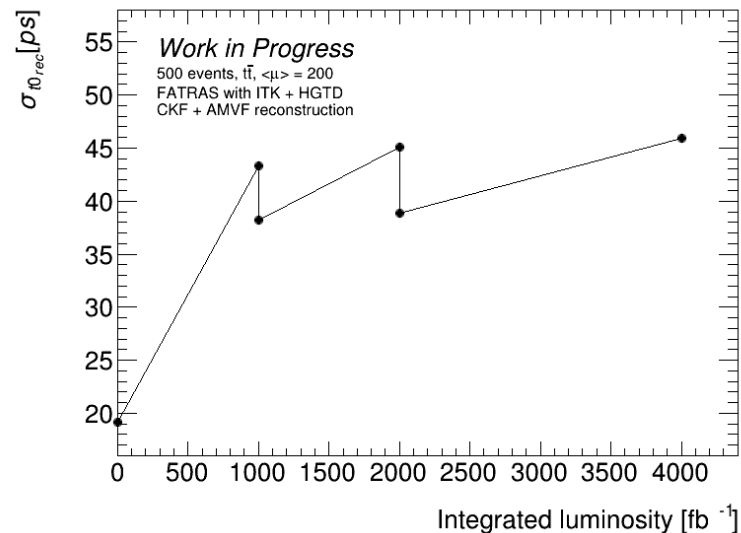


Time reconstruction x integrated luminosity

- Errors when performing the Gaussian fit to estimate the standard deviation can explain the “weird” results 2000 fb⁻¹
 - hit time residual curve is more non-Gaussian at 2000 fb⁻¹, but the fit estimates a lower std than the original one
- Replacing inner and middle layer at 2000 fb⁻¹ has low impact on the t0 resolution
 - Need to better understand



hit time resolution



t0 resolution

Outlook

- We managed to include HGTD time information in the CKF track reconstruction
 - Still need to evaluate (and improve) track efficiency
- This reconstruction chain can be used to assert sensor performance in different phases of its lifetime
 - We could include the custom smearer (resolution vs int. lumi) in the main repository
 - could use an input file with a table resolution vs sensor position vs int. luminosity
 - or an analytical function (as it is implemented today)
- The time reconstruction performance of the CKF can also be used as a baseline for new methods

**Thank you for your
attention!**

Questions?

References

- [1] ATLAS Collaboration (2020). *Technical Design Report: A High-Granularity Timing Detector for the ATLAS Phase-II Upgrade* [White paper]. CERN.
- [2] Gessinger-Befurt, Paul, 30.04.2021. *Development and improvement of track reconstruction software and search for disappearing tracks with the ATLAS experiment*. 10.25358/openscience-5901
- [3] M. Gullstrand, and S.Maraš. “Using Graph Neural Networks for Track Classification and Time Determination of Primary Vertices in the ATLAS Experiment” (Dissertation). Available at: <http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-288505>
- [4] A. Garcia. ATLAS ITk project at Nikhef. Available at: https://wiki.nikhef.nl/atlas/ITk_Endcap_Homepage
- [5] S. Malik. *Detector upgrade at Run3 and HL-LHC*. Available at: https://indico.cern.ch/event/783977/contributions/3467002/attachments/1893181/3123312/Malik_DMatLHC_DetectorUpgradeAtRun3andHL-LHC1.pdf

Backup

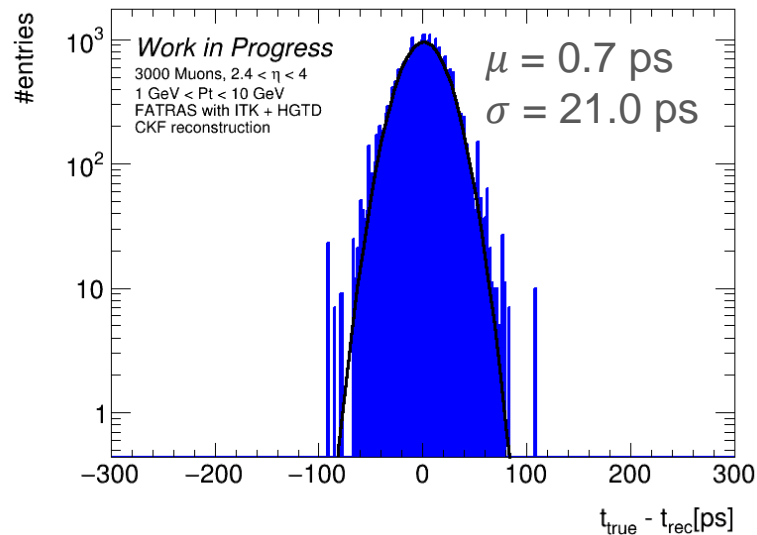
CKF Muon time reconstruction performance

Setup:

- Particle gun of single muon
- Direction $2.4 < \eta < 4.0$
- Primary vertex of following distribution:
 - $z_0 \sim N(0, 50 \text{ mm})$, $t_0 \sim N(0, 175 \text{ ps})$

Performance:

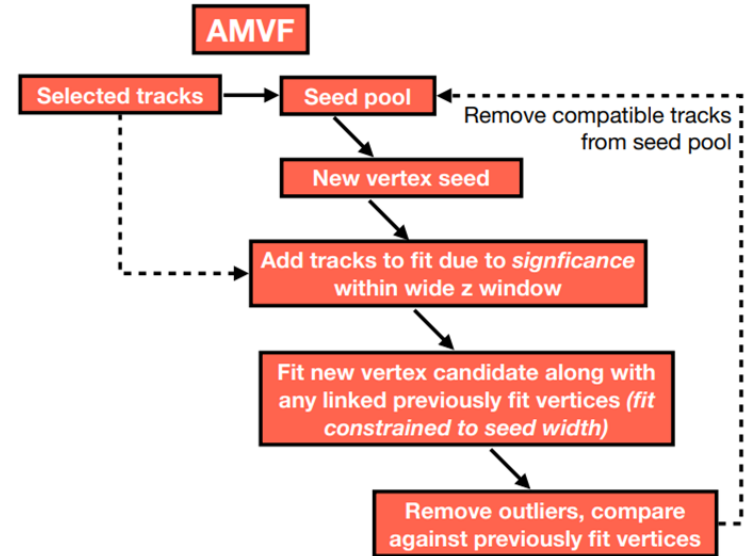
- Better resolution than ttbar events
- Distribution still shows slight deviation from zero
 - Even if smaller than ttbar events



AMVF Time reconstruction

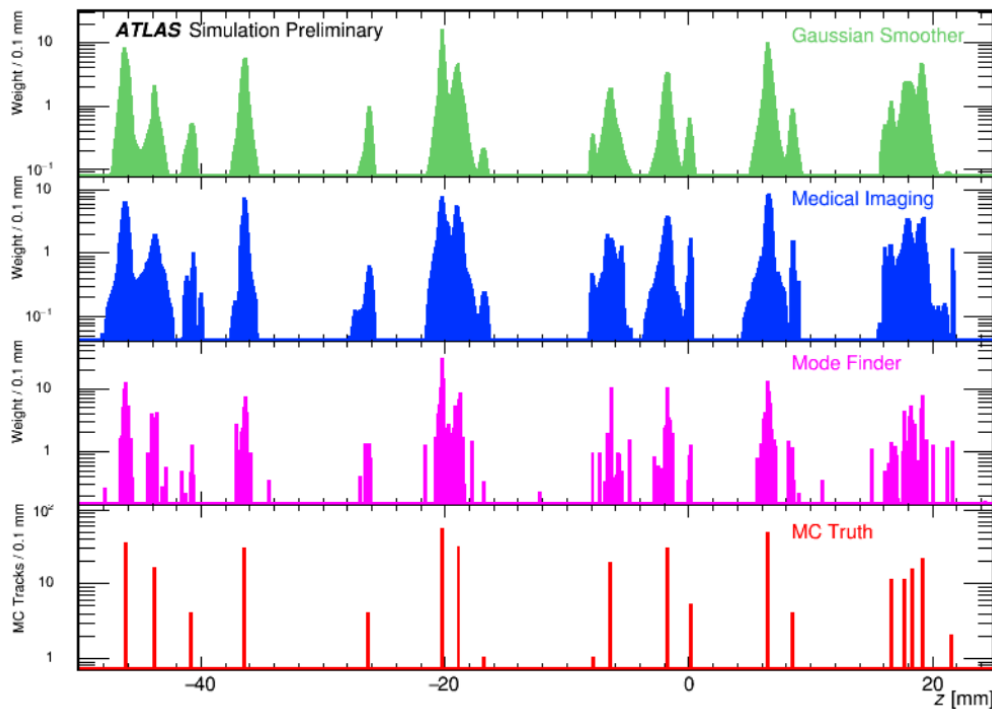
AMVF overview

- I managed to include time information in the AMVF reconstruction
- The following slides will be an overview of the method in order to understand its performance
- The process can be divided into three steps:
 - Vertex seeding: Gaussian Track Density
 - Vertex finding: AMVF
 - Vertex fitting: Kalman Filter updater
- The steps are looped until all (valid) tracks are assigned to a vertex
- Reference for this section:
 - [ATLAS Collaboration \(2019\). Development of ATLAS Primary Vertex Reconstruction for LHC Run 3 \[White paper\]. CERN.](#)



Vertex seeder

- The seeding step establishes first estimates for primary vertices positions



- Most of the vertex seeders project tracks to origin and evaluate density distribution
 - The peaks of the distribution will be the seeds for vertices

Gaussian Track Density

- The density of track origin can be represented by a multi-variate Gaussian distribution:

$$P(r, z) = \frac{1}{2\pi\sqrt{|\Sigma|}} e^{-\frac{1}{2}((r-d_0), (z-z_0))^T \Sigma^{-1} ((r-d_0), (z-z_0))}. \quad \Sigma = \begin{pmatrix} \sigma^2(d_0) & \sigma(d_0, z_0) \\ \sigma(d_0, z_0) & \sigma^2(z_0) \end{pmatrix}.$$

- If we project it to the z-axis, we have the density at that axis. Furthermore, if we consider the distribution to be locally Gaussian, it's possible to do a peak search with steps of size:

$$W(z) = \sum_{i \in \text{tracks}} P_i(0, z). \quad \Delta z = \frac{W(z)W'(z)}{W'^2(z) - W''(z)W(z)}.$$

- The output will be the position of the peak and the width of the distribution around it

$$z_{max} = \max_z W(z) \quad \sigma(z) = \sqrt{-\frac{W(z_{max})}{W''(z_{max})}}$$

Adaptive Multi Vertex Finding (AMVF)

- Given a collection of reconstructed tracks and estimates of vertexes, establishes a “compatibility” value for each track-vertex
- The algorithm is adaptive in a sense that vertexes compete for the same track (multiple vertex-tracks weights)
- Iterate over association weights until convergence
- [Short paper explaining](#)

Fitting procedure

- Fit all vertexes using the assignment probability as track weights
- Recompute the assignment probabilities using the most recent vertex positions

Weight function

- Having n tracks to be fitted to m vertexes

The weight of vertex j to track i is:

$$w_{ij} = \frac{\exp(-\chi_{ij}^2/2T)}{\exp(-\chi_{\text{cut}}^2/2T) + \sum_{k=1}^m \exp(-\chi_{ik}^2/2T)}$$

T is a temperature parameter

χ_{cut}^2 is a cut-off to suppress not assigned tracks

χ_{ij}^2 is the chi2 distance between track and vertex

Kalman Filter Updater

- From the collection of tracks assigned to a vertex originated from the previous step, a Kalman Filter is used to fit the vertex position
- The position of the first deposition (measurement) is used to evaluate the vertex position and momentum of the track (vector state)
- The measurement equation would be:

$$q_i = h_i(v, p_i), \quad i = 1 \dots, n.$$

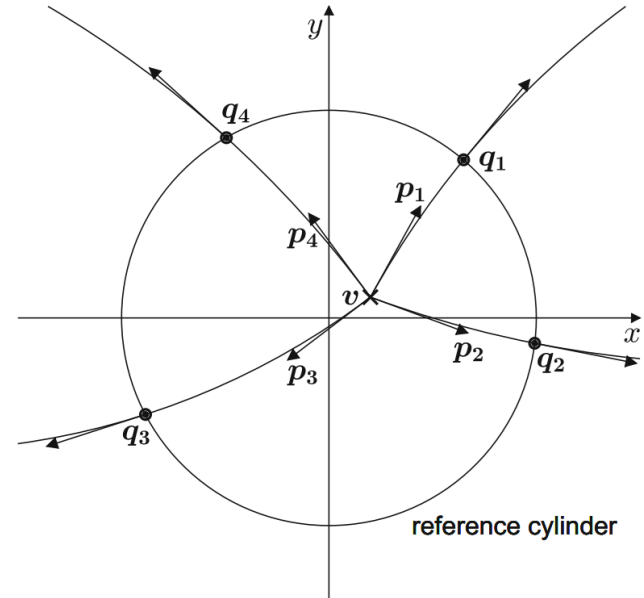


Fig. 8.1 A vertex fit with four tracks. The parameters of the fit are the vertex v and the momentum vectors p_i ; the observations are the estimated track parameters q_i

Kalman Filter updater equations

- The measurement equation is linearized so the Kalman Filter can be used
- Check on the book for detailed explanation
- The AMVF weights multiply the inverse of the covariance matrix as to imitate a “significance” of the measurement

$$\mathbf{v}_i = \mathbf{C}_i \left[\mathbf{C}_{i-1}^{-1} \mathbf{v}_{i-1} + \mathbf{A}_i^\top \mathbf{G}_i^B (\mathbf{q}_i - \mathbf{c}_i) \right],$$

$$\text{Var}[\mathbf{v}_i] = \mathbf{C}_i = \left(\mathbf{C}_{i-1}^{-1} + \mathbf{A}_i^\top \mathbf{G}_i^B \mathbf{A}_i \right)^{-1},$$

$$\text{Var}[\mathbf{p}_i] = \mathbf{W}_i + \mathbf{W}_i \mathbf{B}_i^\top \mathbf{G}_i \mathbf{A}_i \mathbf{C}_i \mathbf{A}_i^\top \mathbf{G}_i \mathbf{B}_i \mathbf{W}_i,$$

$$\mathbf{p}_i = \mathbf{W}_i \mathbf{B}_i^\top \mathbf{G}_i (\mathbf{q}_i - \mathbf{c}_i - \mathbf{A}_i \mathbf{v}_i),$$

$$\text{Cov}[\mathbf{v}_i, \mathbf{p}_i] = -\mathbf{C}_i \mathbf{A}_i^\top \mathbf{G}_i \mathbf{B}_i \mathbf{W}_i.$$

update equation for both vertex position and particle momentum

update equation for both vertex position and particle momentum

AMVF overview (again)

- The process can be divided into three steps:
 - Vertex seeding: Gaussian Track Density
 - Vertex finding: AMVF
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- The steps are looped until all (valid) tracks are assigned to a vertex

