

Studies of Tracking and Reconstruction in ATLAS: GPU-based Strip Clustering and  
Optimization of a Run3 Search for Higgs Decays to Dark Photons

by

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A dissertation accepted and approved in partial fulfillment of the  
requirements for the degree of  
Master of Science  
in Physics

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June 2026

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## DISSERTATION ABSTRACT

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Master of Science in Physics

Title: Studies of Tracking and Reconstruction in ATLAS: GPU-based Strip Clustering and Optimization of a Run3 Search for Higgs Decays to Dark Photons

The first study focuses on the development and validation of a GPU-based strip clustering algorithm implemented within the `Traccc` framework. Designed for the high-luminosity environment of ATLAS Run 4 data, the algorithm reconstructs hit clusters from silicon strip sensors and is designed for integration with the ATLAS Event Filter (EF) tracking chain in the Athena framework.

Because the same clustering implementation in `Traccc` can also be used for offline reconstruction, its interoperability is important for both trigger and offline workflows. Its GPU-oriented design aims to improve throughput for high-pileup conditions expected at the High-Luminosity LHC. By comparing the differences in local x and y coordinates between `Traccc` and Athena, the results show good consistency in strip clustering performance in `Traccc`.

The second study investigates the sensitivity of the dark photon search in the process  $ggH \rightarrow \gamma\gamma_D$ , using Monte Carlo data. The analysis aims to optimize the selection criteria on key variables to maximize the signal significance by studying their individual performance distributions, receiver operating characteristic (ROC) curves, and the impact of variable thresholds on overall significance. A Machine Learning (ML) classifier (XGBoost BDT) study was also investigated to further enhance the significance of the signal over the backgrounds.

The third component of this thesis (in Appendix), conducted as part of the Institute for Research and Innovation in Software for High Energy Physics (IRIS-HEP) Fellowship, validates a fast analytical tracking resolution calculator against full ACTS reconstruction using the Open Data Detector geometry. Analytical predictions of resolution of the track parameters  $\sigma(d_0)$ ,  $\sigma(z_0)$ ,  $\sigma(\theta)$ ,  $\sigma(\phi)$  and  $\sigma(p_T)/p_T$  were compared to ACTS simulations across a range of transverse momenta and pseudorapidities of the particle gun, revealing systematic differences attributable to multiple-scattering modeling and detector material assumptions.

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## ACKNOWLEDGEMENTS

Here is an acknowledgment

To so-and-so...

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##### A.1.3 Python Tracking Resolution Calculator.

#### A.2 Methodology

##### A.2.1 Analytical Resolution Formulation.

The analytical model computes the uncertainties of the five standard ACTS track parameters:  $(d_0, z_0, \phi, \theta, q/p)$ . The covariance matrix is obtained from closed-form expressions derived from linearized track fits in the presence of Gaussian measurement errors and small-angle multiple scattering.

##### A.2.2 Measurement and Multiple Scattering Terms.

The measurement term scales according to the intrinsic hit resolutions and the lever arm of the detector. It typically dominates at high momenta where multiple scattering is negligible.

The multiple scattering contribution follows the Highland approximation,

$$\theta_{\text{ms}} \simeq \frac{13.6 \text{ MeV}}{\beta p} \sqrt{\frac{x}{X_0}} \left[ 1 + 0.038 \ln \left( \frac{x}{X_0} \right) \right],$$

where  $x/X_0$  is the material thickness. This term becomes dominant at low  $p_T$  and is sensitive to the accuracy of the material map.

One recurring challenge observed during the project was interpreting the material distribution in the ODD geometry. Differences between the analytical material assumptions and the more detailed ACTS material description were found to contribute significantly to discrepancies in  $\sigma(d_0)$  and  $\sigma(z_0)$  at low  $p_T$ .

**A.2.3 Matrix Representation of Track Parameters.** Track resolutions are determined by inverting the normal-equation matrix associated with the linearized track model. The calculator constructs both the design matrix and the noise matrix using detector layer positions and resolutions, then derives the covariance matrix via:

$$\mathbf{C} = (\mathbf{A}^\top \mathbf{W} \mathbf{A})^{-1},$$

where  $\mathbf{W}$  contains both measurement and scattering weights. This framework allows the analytical model to remain computationally light while still capturing key geometric dependencies.

### A.3 ACTS Configuration and Simulation Setup

The ACTS validation used the full ODD geometry with a  $B = 2$  T magnetic field and default digitization and reconstruction settings. Tracks were generated at fixed  $p_T$  values ranging from 1 GeV to 200 GeV and at several representative pseudorapidity values. The resulting reconstructed track parameters and covariance matrices were extracted from `tracksummary.ckf.root` and converted into flat tables for comparison.

This workflow mirrors typical detector performance studies in ATLAS and ensures that the results incorporate realistic navigation, material interactions, and Kalman filter behavior.

### A.4 Comparison Strategy

For each  $(p_T, \eta)$  point, the analytical prediction for each parameter's resolution was compared with the RMS width (or Gaussian core width) of the ACTS simulation. The comparison was performed for:

- $\sigma(d_0)$

- $\sigma(z_0)$
- $\sigma(\phi)$
- $\sigma(\theta)$
- $\sigma(p_T)/p_T$

Residual fractional differences were computed to highlight systematic trends, and discrepancies were traced back to underlying assumptions such as: material description, hit resolution mapping, and the treatment of scattering correlations within the Kalman filter.

## A.5 Results and Discussion

**A.5.1 Resolution vs.  $p_T$  and  $\eta$ .** Across most  $p_T$  values, the analytical model and ACTS simulation show good agreement in the high-momentum regime, where measurement errors dominate. The  $p_T$  dependence follows the expected scaling  $\sigma \propto 1/p_T$  for the momentum resolution and constant behavior for angular uncertainties.

At central  $\eta \approx 0$ , the agreement in  $\sigma(d_0)$  and  $\sigma(z_0)$  is excellent above approximately 20 GeV. However, at low  $p_T$ , ACTS resolutions rise more steeply than predicted, reflecting stronger real-material multiple scattering effects.

**A.5.2 Discrepancies and Model Validation.** The largest discrepancies appear in regions with significant material interactions, particularly the endcap regions and low-momentum regimes. These differences were traced to:

- Simplified analytical treatment of the ODD material map,
- Non-uniform detector layer spacing in the endcaps,

- Additional scattering terms handled automatically by the ACTS Kalman filter but absent in the analytical model,
- Slight differences in hit resolution interpretation between ACTS and the analytical tool.

Despite these differences, the analytical model captures the overall behavior and correctly predicts the scale of the resolutions.

**A.5.3 Implications for Fast Performance Estimation.** The study confirms that analytical resolution models are highly effective for quick performance estimates in the central detector region and in the high-momentum regime. However, caution is required when applying these models in low- $p_T$  or high- $\eta$  regions where realistic material and scattering effects dominate.

This validation provides meaningful guidance for future detector optimization workflows, and it highlights the importance of maintaining consistency between analytical assumptions and full simulation frameworks such as ACTS.

## A.6 Conclusions

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