

SEARCH FOR HIGGSINOS IN COMPRESSED MASS SPECTRA USING NEURAL  
NETWORKS IN THE ATLAS DETECTOR AND DESIGN VERIFICATION OF THE AMAC  
ASIC FOR THE ITK UPGRADE

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A DISSERTATION

in

Physics and Astronomy

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2024

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## ACKNOWLEDGEMENT

I have been fortunate to receive support from many individuals and groups throughout this journey, and while I cannot name everyone, I am profoundly grateful for their encouragement and contributions. I sincerely apologize for any unintentional omissions.

I am deeply grateful to the ATLAS Collaboration at CERN for the opportunity to contribute to one of the most impactful experiments in particle physics. I also acknowledge the support of participating institutes and funding agencies, particularly the U.S. Department of Energy, whose resources and infrastructure were instrumental in making my research possible.

I owe my deepest gratitude to my advisor, I. Joseph Kroll, for his unwavering guidance, insightful counsel, and steadfast encouragement throughout my Ph.D. journey. His mentorship has significantly shaped both my academic pursuits and personal growth.

I am genuinely appreciative of the faculty members of the Penn ATLAS group—Professors Hugh Williams, Elliot Lipeles, Evelyn Thomson, and Dylan Rankin—for their generous advice and supportive involvement in academic and technical matters.

I also wish to thank Dr. Haichen Wang, my undergraduate research supervisor at Lawrence Berkeley National Laboratory, who introduced me to the exciting world of SUSY searches and collider experiments. I am equally thankful to Professors Jenny Harrison and Marina Ratner at UC Berkeley, whose mathematics courses kindled my passion for mathematical theory, a source of lasting intellectual enjoyment and inspiration in my life.

I am indebted to the professors who taught insightful and enlightening courses during graduate school, including Professors Justin Khoury, Jonathan Heckman, Mirjam Cvetič, Burt Ovrut, and Gene Mele. Their teachings have profoundly influenced my understanding and approach to physics. I also want to extend my appreciation to the Physics and Astronomy Department for fostering a supportive, vibrant research environment and for hosting regular seminars and colloquia that broadened my perspective with a wide range of fascinating topics.

I want to express my gratitude to the members of the Penn ATLAS group for their camaraderie and support. In particular, I am deeply appreciative of the postdoctoral scholars—including Jeff Dandoy, Shion Chen, and Jeff Shahinian—for their exceptional expertise and insightful mentorship. As the Analysis Contact for the Displaced Track project, Jeff Shahinian kindly and consistently provided thoughtful guidance and critical advice, for which I am profoundly grateful.

Collaboration has been essential to my research endeavors. I have received invaluable support and guidance from the ATLAS collaboration and learned extensively from its shared knowledge resources. I am indebted to the many members who served as reviewers or offered thoughtful suggestions during meetings, helping to refine and strengthen my research. I am particularly grateful to my collaborators in the Electroweak SUSY subgroup for their insights and contributions. In particular, I wish to acknowledge Yuya Mino from Kyoto University, as well as Alessandro Sala, Sonia Carra, and Tommaso Lari from INFN Milano, for their indispensable work in optimizing the traditional cut-and-count approach of the displaced track analysis, providing an essential cross-check for our results. I am also deeply appreciative of Michael Holzbock from the Max Planck Institute for his critical insights and steadfast support as the other Analysis Contact.

Among my collaborators on hardware projects, I am immensely thankful to the Penn Instrumentation Group, particularly Mitch Newcomer, Paul Keener, Adrian Nikolica, and Godwin Mayers, for their invaluable guidance in ASIC design and testing. Their expertise and patience were instrumental in helping me develop the skills needed to navigate this project. I am also grateful for the longstanding collaboration of fellow graduate students: I greatly appreciate the early mentorship of Joey Reichert and Benjamin Rosser, who guided me through the initial stages of coding and technical understanding. I particularly want to acknowledge Luis Felipe Gutierrez Zagazeta, whose partnership and dedication were critical to the success of our work on AMAC testing and grading, making the long hours in the lab both productive and enjoyable. Thomas Gosart, your enthusiasm and diligence in expanding the AMAC testing framework have ensured the continued success of this project.

To my parents, your belief in my abilities and the sacrifices you made to support my education and

aspirations have been a constant source of strength. I remain profoundly grateful for your love, encouragement, and support.

Finally, to Yan Liang: your intelligence, patience, and unwavering support have been my anchor and a constant source of inspiration through every challenge and triumph. Sharing this journey with you has been a privilege, and learning about astrophysics from you has been a truly joyful experience. Advancing analyses together with exciting new techniques has been one of the most rewarding aspects of this journey.

# ABSTRACT

## SEARCH FOR HIGGSINOS IN COMPRESSED MASS SPECTRA USING NEURAL NETWORKS IN THE ATLAS DETECTOR AND DESIGN VERIFICATION OF THE AMAC ASIC FOR THE ITK UPGRADE

Sicong Lu

I. Joseph Kroll

This dissertation presents two major projects undertaken during my PhD in the Penn ATLAS group, addressing challenges in high-energy physics analysis and detector development to advance our understanding of the universe.

The first project focuses on the search for Higgsinos in compressed mass spectra, a promising scenario in Supersymmetry (SUSY) that addresses the hierarchy problem and provides a viable dark matter candidate. Nearly mass-degenerate Higgsinos with splittings of  $\mathcal{O}(1 \text{ GeV})$  have been challenging to detect due to their elusive signals and overwhelming backgrounds. Using  $140 \text{ fb}^{-1}$  of proton-proton collision data at  $\sqrt{s} = 13 \text{ TeV}$  collected by the ATLAS detector, a novel analysis targeted events with a high- $p_T$  jet, significant missing transverse momentum, and a low-momentum displaced pion track. My work utilizes fully connected neural networks and an improved semi-data-driven background estimation method, achieving exclusions of Higgsino masses up to  $190 \text{ GeV}$  with splittings between  $0.3$  to  $1.1 \text{ GeV}$ , significantly extending sensitivity beyond the LEP limit of  $95 \text{ GeV}$ . The results show excellent agreement with Standard Model predictions, demonstrating the robustness of the analysis.

The second project involves the design verification of an Application-Specific Integrated Circuit (ASIC), the Autonomous Monitoring and Control (AMAC) chip, developed for the Inner Tracker (ITk) in the ATLAS Upgrade for the High-Luminosity LHC (HL-LHC). My contributions include developing an automated analog-function testing framework, a workflow for chip characterization, identifying critical prototype design flaws, and a cocotb-based design simulation routine. Simula-

tions and prototype testing confirmed the ASICs robustness against radiation-induced single-event effects (SEE) and compliance with specifications, enabling the transition to production. These efforts ensure the reliable operation of the ITk detector under HL-LHC conditions, supporting the pursuit of new physics discoveries.

Collectively, these projects advanced experimental particle physics, providing tools for probing Beyond Standard Model theories, including SUSY, while laying the foundation for future discoveries at the HL-LHC.

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## PREFACE

This dissertation documents the main research projects and analyses I undertook as a graduate student in the Penn ATLAS Group from 2018 to 2024. This preface provides a brief overview of my personal journey through the PhD program.

### Undergraduate

As an undergraduate at UC Berkeley, I majored in both mathematics and physics. My research experiences—working on  $ttH \rightarrow \gamma\gamma$  and multijet RPV SUSY analyses under Dr. Haichen Wang at LBNL—sparked my passion for collider experiments and set me on the path to a PhD in particle physics. Before entering the PhD program at Penn, I briefly contributed to EWK SUSY searches with  $WH$  final states in Professor Wuerthwein’s CMS group at UC San Diego. This opportunity allowed me to explore event topology and signal region design, which laid some groundwork for my future analyses.

### Coursework

During the first three years of my PhD program, I completed a range of coursework, including all Relativistic Quantum Field Theory (QFT) classes. I also audited two Advanced Theoretical Physics courses that focused on Supersymmetry (SUSY) and the geometric and topological foundations related to QFT. These courses provided a systematic education in the theoretical framework underpinning modern SUSY searches conducted in the ATLAS experiment.

I am deeply grateful to the professors who guided me through these courses. Deriving the foundations of the Standard Model and exploring how SUSY addresses unresolved mysteries were particularly fulfilling. These exercises not only deepened my understanding but also reinforced my passion for the elegance and power of theoretical physics. My heartfelt thanks go to the knowledgeable and kind instructors who made this learning experience so rewarding.

One of the most engaging projects during this time was my attempt to build a symbolic calculator

for Feynman diagrams, aimed at solving tree-level QCD problems. Although my research priorities eventually shifted and the project remained limited to handling homework-level problems, it was an enjoyable and intellectually stimulating experience. This project was motivated by my vision (or aesthetics) in machine computable knowledge and the potential to create automated derivations rooted in mathematical logic.

### **ATLAS Qualification Task & the AMAC ASIC**

The Penn ATLAS Group led the design of two critical ASICs for the ITk-Strips detector in the ATLAS Upgrade: the HCC and the AMAC. I was introduced to the AMAC project at the start of my PhD program.

As part of the ATLAS collaboration, members are required to complete a “qualification task” before being added as an author on collaboration papers. I officially began my qualification task in Spring 2019, focusing on building the testing framework for the AMACv2a prototype, with a special emphasis on the analog components, result analysis, chip grading, and database integration. My fellow PhD student, Luis Felipe Gutierrez Zagazeta, worked on logic function testing and probe station operations. I completed the qualification task in 2020.

During the prototype testing phase, I evaluated physical prototypes of the AMACv2a to ensure they met design specifications. My contributions included setting up test-bench circuit boards, developing C++ testing procedures, and creating a Python-based framework for quantitative analysis. These efforts were instrumental in identifying design flaws and discrepancies, leading to refinements in the prototype. I also developed a grading system to categorize and evaluate production chips based on performance metrics, synchronizing results with the ITk Production Database for use by collaborating institutions.

Following the prototype testing, I expanded my involvement to design verification for the AMAC-Star production version, using computer simulations to validate its functionalities. This work built upon the approach pioneered by a former student, Benjamin Rosser, for the HCC ASIC design. For design validation, I utilized simulation tools to verify the chip’s performance, with a particular fo-

cus on its functionality in high-radiation environments prone to Single-Event Effects (SEE). These simulations were essential for identifying potential design issues before large-scale manufacturing. I helped establish a simulation testing routine, including nightly checks and SEE injection stress tests, to assess the chip’s radiation hardness and ensure it met performance specifications.

Despite my initial lack of experience in ASIC design and testing, I benefited greatly from the kind guidance of experts in the Instrumentation Group, including Mitch Newcomer, Paul Keener, Adrian Nikolica, and Godwin Meyers. I also received invaluable support and inherited simulation tools from senior PhD students Joseph Reichert and Benjamin Rosser. A highlight of this work was presenting the AMACStar testing and verification report at multiple Final Design Reviews, helping to lead to its production approval in Summer 2021. Later, I transitioned my responsibilities to Thomas Gosart, a junior PhD student, who built upon the framework for subsequent production versions.

### **Search for Higgsinos with Displaced Track using Neural Networks**

While wrapping up my qualification tasks, I began exploring promising SUSY scenarios that had not been excluded by existing experiments. Among these, I found a phenomenological study highlighting the potential of detecting Higgsinos through low-momentum displaced charged particles combined with Missing Transverse Momentum. This signature arises from the compressed mass spectra of the lightest chargino and neutralinos, making it a compelling target for further investigation.

The search began with a traditional cut-based analysis, which improves the signal-to-background ratio by applying sequential cuts on individual kinematic variables. A separate team from Kyoto University and INFN Milano, led by PhD student Yuya Mino and Alessandro Sala under the supervision of Dr. Shion Chen and Dr. Tommaso Lari, continued optimizing this traditional cut-based approach in parallel, utilizing the ABCD Method for background estimation. During the early stages of this work, including the generation of Monte Carlo (MC) samples, I attended the CoDaS-HEP 2019 Summer School at Princeton University. This experience was particularly rewarding,

as it helped me build a more systematic understanding of machine learning, high-performance computing, and parallelization techniques. In particular, I learned methods to optimize Python code to achieve performance comparable to C++. These techniques later prevailed in all my analysis frameworks.

To enhance sensitivity to Higgsino signatures beyond the traditional cut-based approach, I developed neural network-based classifiers for both signal-like events and signal-like tracks, trained using MC simulations. Background contributions in the Signal Regions (SR) were also modeled using MC simulation samples. Recognizing the limitations of purely simulation-based predictions, I implemented a semi-data-driven method to reduce systematic errors. This approach corrected simulation mis-modeling by adjusting event weights based on observations in Control Regions (CR), where signal contributions are negligible. I am particularly proud of this method, as it systematically improves both signal and background modeling and is especially effective in machine learning-based analyses.

To validate the neural network approach, I developed an orthogonal validation framework that leveraged two independent neural networks to cross-check results. I also introduced cross-validation techniques to mitigate overtraining and enhance the robustness of the models. Additionally, I utilized SHAP values to make the neural networks more interpretable, providing physical insights into the model's decision-making process.

Through the challenges and errors encountered while running the statistical interpretation package, I gained a deeper understanding of likelihood-based fits and model constraints. The analysis received ATLAS “unblinding” approval to examine real data in the signal region in Spring 2024, and I successfully defended my dissertation in Summer 2024.

### **Beyond High Energy Physics: Galaxy Autoencoder**

In addition to my work in high energy physics, I dabbled into astrophysics research through the Galaxy Autoencoder Project. This project was initiated during Ms. Yan Liang’s rotation in the Princeton Astrophysics Department under the supervision of Prof. Peter Melchior. Its goal was to

develop a robust autoencoder framework for characterizing galaxy types using spectral data and identifying outliers. My contributions focused on addressing the challenge of encoding degeneracy and introducing a new loss function to define a latent space metric. This work improved the interpretability of unsupervised machine learning analyses of galaxy spectra and laid the groundwork for future advancements. I particularly enjoyed applying physics intuition to a project driven by unsupervised machine learning. It was really gratifying to see the framework achieve its expected outcomes while also yielding unexpected and exciting results.

### **Concluding Remarks**

This document provides an overview of the theoretical framework, experimental setup, and analysis methods, presented in a hierarchical and big-picture manner, while focusing on the most relevant details. My aim is to convey a comprehensive roadmap of the key subjects to the best of my understanding.

Looking ahead, I am eager to continue advancing theoretical modeling, data analysis, and computational techniques in the next stage of my career.

# CHAPTER 1

## Overview

### **Introduction to High Energy Physics and Motivations (Chapter 2)**

High Energy Physics (HEP) seeks to answer some of the most profound questions about the universe: What are the fundamental building blocks of matter? What governs their interactions? And what lies beyond the Standard Model of particle physics? These questions drive the ongoing quest to uncover the deepest mysteries of the universe. The Standard Model (SM), a highly successful theoretical framework, has provided remarkable insights but leaves critical questions unanswered, such as the origin of dark matter and the hierarchy problem. Supersymmetry (SUSY) offers a compelling extension to the SM, addressing these issues by introducing a new symmetry between fermions and bosons. SUSY predicts new particles, including the lightest supersymmetric particle (LSP), which could be a dark matter candidate. These theoretical advancements motivate experimental searches at the Large Hadron Collider (LHC).

### **Experimental Apparatus (Chapter 3)**

The LHC, the most powerful particle accelerator in the world, operates at a center-of-mass energy of  $\sqrt{s} = 13$  TeV, providing a unique facility to probe fundamental questions about the universe.<sup>1</sup> Among its general-purpose detectors, the ATLAS detector is equipped with advanced instrumentation to precisely measure the trajectories and energies of particles produced in collisions. These capabilities enable the detailed study of particle properties and the search for new physics, including particles predicted by SUSY. The High-Luminosity LHC (HL-LHC) upgrade will further enhance these opportunities by increasing data volume and collision rates, offering unprecedented potential for discoveries.

### **My PhD Projects**

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<sup>1</sup>The analysis presented in this dissertation uses data collected during Run 2 of the LHC, which operated at a center-of-mass energy of 13 TeV. In Run 3, the energy was increased to 13.6 TeV.

During my PhD, I mainly worked on two projects addressing key challenges in high-energy physics: the search for Higgsinos in compressed mass spectra using neural networks and the design verification of the AMAC Application-Specific Integrated Circuit (ASIC) for the HL-LHC. Additionally, I collaborated on a machine learning project in astrophysics, aimed at integrating physics intuition into the analysis of galaxy spectra with advanced computation techniques.

## **Search for Higgsinos in Compressed Mass Spectra with Neural Networks (Chapter 4)**

One of the primary goals of the LHC and the ATLAS experiment is to search for evidence of supersymmetry. In the Higgsino-like lightest neutralino ( $\tilde{\chi}_1^0$ ) scenario, we search for the invisible  $\tilde{\chi}_1^0$  (LSP) by identifying a high  $p_T$  initial-state-radiation (ISR) jet and significant missing transverse momentum (MET). The small mass difference between the  $\tilde{\chi}_1^0$  and the next-to-lightest supersymmetric particles,  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$ , further results in a unique experimental signature: a low  $p_T$  pion track displaced from the primary vertex.

I employed a two-leveled neural-network-based approach to efficiently identify high-sensitivity signal regions for these SUSY events, leveraging modern machine learning (ML) techniques to mitigate overfitting and statistical bias. In parallel, a separate team optimized the traditional cut-based approach with the ABCD method for background estimation. This complementary effort provided an independent cross-check and explored alternative optimization strategies for the same signal models.

I adopted a semi-data-driven approach, combining Monte Carlo (MC) simulations with data-driven corrections to improve background estimation accuracy. This method applies kinematics-dependent reweighting factors to correct inconsistencies between data and the simulations extracted from Control Regions (CRs). By systematically correcting individual sources of mis-modeling based on their underlying causes, this approach eliminates the need to rely on assumptions about extrapolating mis-modeling from control regions to signal regions, as required in the ABCD method. Additionally, by improving the accuracy of the Monte Carlo simulation, this approach provides high-quality training samples for the neural networks, thereby maximizing sensitivity to the signal.

The validation strategy employed multiple orthogonal validation regions, defined using two-level independent FCNN selection criteria. These regions were designed to closely match the kinematics of the Signal Regions (SR) while minimizing signal contamination. By achieving strong MC-data agreement in the validation regions, this approach provides confidence in the accuracy of the corrected MC simulation modeling within the Signal Regions.

A combined likelihood model was constructed, incorporating all experimental and theoretical systematic uncertainties considered in ATLAS, as well as analysis-specific systematic uncertainties. In the unblinded signal regions, the data were consistent with the Standard Model background-only hypothesis, leading to the rejection of the Higgsino model signal hypothesis. Confidence levels were established, and exclusion contours were interpolated. The analysis excludes the production of chargino/neutralino with masses up to approximately 190 GeV and  $\tilde{\chi}_1^\pm$ - $\tilde{\chi}_1^0$  mass splittings between 300 MeV and 1.1 GeV. The NN-based methodology demonstrated greater sensitivity than the traditional method optimized in parallel.

## **Design Verification of the AMAC ASIC (Chapter 5)**

In addition to the Higgsino search, significant efforts were directed toward the proto-type testing and design verification of the Autonomous Monitoring And Control (AMAC) ASIC, a critical component of the ITk upgrade for the HL-LHC. The AMAC ASIC is designed to monitor and control various operational parameters of the ITk, ensuring stable and efficient operation in a high radiation environment.

The prototype testing phase involved developing a comprehensive framework for device calibration, functionality testing, and performance evaluation. Individual chip performance was assessed by analyzing metrics such as measurement accuracy, controlling mechanism response, and power consumption. The AMACv2a prototypes demonstrated strong performance in most aspects, providing a solid foundation for further refinement. During this phase, several unforeseen design issues were identified through testing, contributing to the improved robustness of the subsequent production design.



The design verification phase ensures the AMAC ASIC meets all design specifications and performance requirements. This phase includes verifying the triplication implementation to safeguard against radiation-induced logic errors called Single-Event Effects (SEE). Comprehensive simulation tests using the `cocotb` framework assess the expected functionalities and radiation hardness of the AMAC under extreme SEE conditions in its production design (AMACStar).

These efforts were instrumental in helping the AMAC to pass the ATLAS Final Design Reviews (FDR) and advance the design to the production stage. By enabling the ITk detector to perform optimally under HL-LHC conditions, this work contributes to maximizing the discovery potential for new physics in the next decades.

### **Collaboration on Astrophysics Autoencoder (Appendix A)**

In addition to my work in high-energy physics, I collaborated on a galaxy autoencoder project, applying machine learning techniques to astrophysical data analysis. Conducted with Ms. Yan Liang, a PhD candidate at the Princeton Astro Data Lab, this project focused on developing the SPENDER autoencoder model to encode the Sloan Digital Sky Survey (SDSS) spectroscopic galaxy samples in low-dimensional representations and decode them to realistic spectra. I introduced a novel similarity loss term to create a robust and interpretable latent space, effectively encoding the physical properties of galaxies. This approach enhanced redshift invariance, improved physically motivated galaxy type classification, and facilitated outlier detection by clustering similar galaxies and isolating anomalies. These results not only advance astrophysical analysis but also demonstrate the potential of techniques like autoencoders for identifying outliers in high-energy physics data, which may reveal hints of new physics. Furthermore, incorporating physics-informed priors into machine learning architectures highlights their potential to enhance the interpretability and robustness of ML-driven data analysis in physics.

## CHAPTER 2

### Theoretical Framework: From the Standard Model to Supersymmetry

This chapter provides a comprehensive overview of the theoretical foundation leading from the Standard Model and its limitations to the principles of supersymmetry, culminating in the motivation and framework for Higgsino searches, the primary focus of my research.

To keep the discussion focused, only some key ideas and results are summarized, without including all detailed derivations or intermediate equations. Readers seeking a more comprehensive treatment are encouraged to consult Srednicki's *Quantum Field Theory* [30], Schwartz's *Quantum Field Theory and the Standard Model* [31], Martin's *Supersymmetry Primer* [2], Dreiner, Haber, and Martin's work on *Two-component spinor techniques and Feynman rules for quantum field theory and supersymmetry* [1].

## 2.1 Symmetry

### 2.1.1 Symmetry in Physics

Symmetry plays a fundamental role in understanding the laws of nature. In physics, symmetries are not merely aesthetic attributes but are deeply connected to the conservation laws governing physical systems. A symmetry of a physical system is: a transformation that leaves some observable aspect of the system unchanged, indicating invariance under a set of operations.

According to Noether's theorem, each continuous symmetry corresponds to a conserved quantity. For example, the rotational symmetries correspond to the conservation of angular momentum, and Lorentz boost symmetries imply the conservation of four-momentum (including the energy). This profound connection between symmetry and conservation laws helps physicists uncover the underlying symmetries of physical laws by observing which quantities are conserved. By constructing our theory based on the representations<sup>2</sup> invariant under the relevant symmetries, we are able to

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<sup>2</sup>A "representation" refers to a mathematical structure that describes how symmetries act on objects or variables in physical systems, e.g., through linear transformations on vector spaces.

simplify our model to the minimum.

### **2.1.2 Group Theory & the Standard Model**

Modern particle physics is based on quantum field theory, built upon special relativity encapsulated by the Lorentz symmetries. The Standard Model of particle physics is a theoretical framework describing electromagnetic, weak, and strong interactions through gauge symmetries. These symmetries are fundamental to the laws of physics as they dictate the interactions and transformations of the elementary particles.

The mathematical framework for dealing with symmetries in physics is provided by group theory. Groups are sets equipped with a single operation satisfying certain axioms (closure, associativity, identity, and invertibility). In physics, these groups often represent the set of all symmetries of a system. In our current theory of Nature, the objects (fields) transform exactly as the fundamental representations (with relevant well-defined properties) under the transformations in the relevant symmetries, while the interactions (described by the Lagrangians) are invariant under these transformations.

For example, in the Standard Model, fields such as complex fields, spinors, multiplets, and Lorentz four-vectors are constructed within the fundamental representations of these groups, and we construct the interaction terms such that they remain invariant under symmetry transformations. This also ensures the conservation of relevant physical quantities.

#### **2.1.2.1 Lie Groups and Lie Algebras**

The Lie groups are groups that are also differentiable manifolds, meaning that group operations (multiplication and inversion) are smooth (differentiable). This smooth structure allows the powerful machinery of calculus to be applied to study these groups. For example, the Lorentz group governing special relativity consists of elements (transformations) that are smooth functions of parameters such as rotation angles or boost velocities. The sequential application of the transformation forms the group operations. Most of the Lie groups relevant to physics, such as the rotation

group  $SO(3)$  or the Lorentz group  $SO(3, 1)$ , are finite-dimensional and can be described locally by a set of continuous parameters (e.g., angles in rotations). For a Lie group, the group elements of the infinitesimal transformations (or we usually call them “generators”) lead to a Lie algebra. This algebra is crucial for understanding the behavior of gauge fields and their interactions. The Lie Algebra provides a linearization of the group structure near the identity element. This algebra is a vector space equipped with an additional binary operation called the Lie bracket, defined by

$$[X, Y] = XY - YX, \tag{2.1}$$

which is bilinear, anti-commutative, and satisfies the Jacobi identity:

$$[X, [Y, Z]] + [Y, [Z, X]] + [Z, [X, Y]] = 0. \tag{2.2}$$

### 2.1.3 Lorentz Symmetry and Fundamental Representations

Among the many important symmetries in the Standard Model, we take the first example with the Lorentz symmetries and discuss some of its fundamental representation, which covers the spacetime symmetries for the Standard Model.

#### 2.1.3.1 Lorentz Symmetry

The Lorentz group, commonly denoted as  $SO(3, 1)$ , is crucial for describing symmetries of spacetime under rotations and Lorentz boosts. It plays a vital role in ensuring that physical laws are invariant under spacetime transformations, a fundamental aspect of relativity. The Lorentz group has six total generators acting on the four-vectors, with three rotations  $J_i$  and three boosts  $K_i$ , with the following Lie Algebra:

$$\begin{aligned}
[J_i, J_j] &= \epsilon_{ijk} J_k, \\
[K_i, K_j] &= -\epsilon_{ijk} J_k, \\
[J_i, K_j] &= \epsilon_{ijk} K_k.
\end{aligned}
\tag{2.3}$$

### 2.1.3.2 Lorentz Four Vectors as Fundamental Representations

The Lorentz Four Vectors  $x^\mu$  can be transformed by the elements (transformation)  $\Lambda_\nu^\mu$  in the Lorentz Group using a matrix operation:

$$x^\mu \rightarrow x'^\mu = \Lambda_\nu^\mu x^\nu \tag{2.4}$$

With this form of writing the fields, it is straightforward to construct terms that are covariant or invariant under the Lorentz Group element (e.g., rotation, boosting, etc.). Bosonic fields such as gauge bosons are often represented as four-vectors under the Lorentz group.

### 2.1.3.3 Other Fundamental Representations (Spinors)

The Lorentz group  $SO(3, 1)$  can be considered as an isomorphism of  $SU(2) \times SU(2)$ , by defining the  $A = \frac{1}{2}(J + iK)$ ;  $B = \frac{1}{2}(J - iK)$ , we have

$$\begin{aligned}
[A_i, A_j] &= i\epsilon_{ijk} A_k, \\
[B_i, B_j] &= i\epsilon_{ijk} B_k, \\
[A_i, B_j] &= 0.
\end{aligned}
\tag{2.5}$$

Because of this, we can write the fields in the representation that transforms under  $SU(2) \times SU(2)$ , which are called Weyl-Spinors. For a  $(0, \frac{1}{2})$  example  $\psi_\alpha$ :

$$\psi_\alpha \rightarrow \psi'_\alpha = M_\alpha^\beta \psi_\beta \tag{2.6}$$

The Weyl spinors transform according to this representation of the Lorentz group, where  $M_\alpha^\beta$  denotes the transformation matrix associated with Lorentz group elements. This framework allows the

straightforward construction of terms that are covariant or invariant under Lorentz transformations (e.g., rotations, boosts, etc.).

Within the framework of Lorentz symmetry, spinors are fundamental because they describe the states of elementary particles well with half-integer spin, such as electrons and quarks. Another common Lorentz transformation representation is the Dirac Spinors, which combine two Weyl spinors of opposite chirality, describing particles that have both mass and spin, such as electrons.

### **2.1.4 Other Essential Symmetries in the Standard Model**

Many important symmetries were embedded in the construction of the Standard Model to ensure mathematical consistency while aligning theoretical predictions with physical observations.

#### **Non-Abelian Gauge Groups**

The strong interaction and the electroweak interaction in the Standard Model are governed by non-Abelian gauge groups like  $SU(3)$  in Quantum Chromodynamics (QCD), which will be elaborated in later sections (Section 2.3).

#### **Ward-Takahashi Identities**

These identities articulate the conservation of electrical charge in quantum electrodynamics (QED) and similar gauge theories through the properties of Green's functions, arising from local  $U(1)$  gauge invariance. They are crucial for establishing the renormalizability of QED.

#### **Becchi-Rouet-Stora-Tyutin (BRST) symmetry**

The BRST symmetry is a gauge symmetry extended to include ghost fields, which are introduced in the quantization of gauge theories (particularly non-abelian gauge theories like QCD). It is crucial for proving the renormalizability and unitarity of gauge theories.

Later in this chapter, we will discuss how the proposed “Supersymmetry” elegantly extends the current model, addressing many unresolved mysteries in physics.

## 2.2 Quantum Field Theory Basics

### 2.2.1 Overview of QFT

Quantum Field Theory (QFT) is an essential framework in modern physics, combining the principles of quantum mechanics with those of special relativity to describe the behavior of subatomic particles. This section introduces the key concepts and mathematical formalism of QFT, emphasizing its logical structure. The section will roughly follow a hierarchical approach inspired by the organization of the textbook *Quantum Field Theory* by Dr. Mark Srednicki [30] as illustrated in Figure 2.1. This structure guides our logical progression, starting with foundational concepts and advancing toward the techniques required for high-energy interactions.

### 2.2.2 Core Framework of QFT

Quantum Field Theory (QFT) begins with the principles of **special relativity** and **classical field theory**, ensuring that all physical laws respect **Lorentz Invariance**. Classical field theory provides a mathematical framework for describing physical systems with fields, such as the electromagnetic field, across spacetime. However, to describe particle interactions at quantum scales, these classical fields are **quantized**, extending quantum mechanics to fields in addition to particles.

A key formalism in QFT is the **path integral** formulation, which sums over all possible field configurations to calculate physical quantities. This approach introduces the **action**, defined as the integral of the **Lagrangian** over spacetime, and weights each configuration by the exponential of the action. The path integral is particularly powerful for describing particle interactions and computing transition probabilities, making it a cornerstone of QFT's mathematical framework.

The foundation of QFT relies on defining the **Lagrangian density**, a function that encodes the kinetic and potential energy of fields and their interactions. This Lagrangian governs the equations of motion for fields and forms the starting point for quantization. With the **canonical quantization**, classical fields are promoted to **operator fields** acting in a Hilbert space. These operators

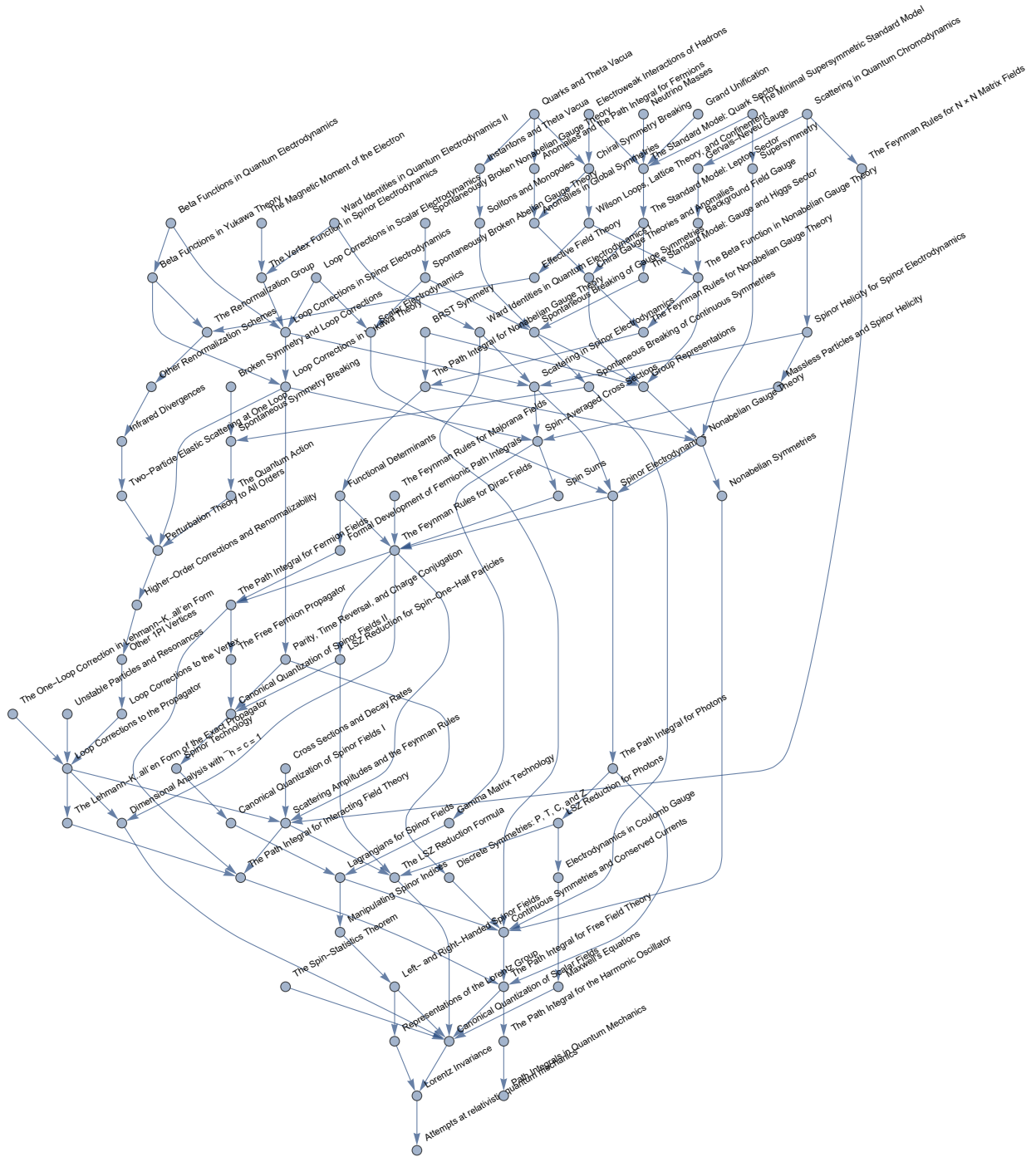


Figure 2.1: Hierarchical structure of key concepts in Quantum Field Theory, adapted from the textbook *Quantum Field Theory* by Dr. Mark Srednicki[30]. This structure guides the logical progression of QFT.



depend on spacetime coordinates and obey specific **commutation relations**, such as:

$$[\phi(x), \pi(x')] = i\hbar\delta(x - x'), \quad (2.7)$$

where  $\phi(x)$  is the field operator,  $\pi(x)$  is its conjugate momentum and  $\hbar$  is the reduced Planck's constant. These relations represent the quantum analog of Poisson brackets in classical mechanics.

One of the simplest quantum fields is the scalar field, whose dynamics are described by the **Klein-Gordon equation**. Derived from the Lagrangian, this equation governs the relativistic behavior of scalar particles, providing a fundamental example of how quantum fields predict particle dynamics.

### 2.2.3 Particle Dynamics and Interactions

The dynamics of quantum fields and their interactions are at the heart of QFT. By connecting field operators to observable phenomena, QFT provides tools to calculate particle scattering amplitudes and understand interaction processes.

The canonical commutation relations form the foundation for field quantization. These relations, introduced earlier, lead to advanced techniques like the **Lehmann-Symanzik-Zimmermann (LSZ) reduction formula**. The LSZ formula bridges the gap between abstract quantum fields and physical observables by relating field operators to the **S-matrix**, which describes **particle scattering** processes.

To study interactions systematically, QFT employs the **generating functional**, a mathematical construct that encodes all possible correlation functions of a field. **Correlation functions**, also known as **Green's functions**, describe the propagation of particles and interactions in spacetime. From the generating functional, one can derive the **Feynman propagator**, which provides the probability amplitude for a particle to propagate between two points.

Simplifying calculations involving multiple interactions requires tools like **Wick's theorem**, which reduces complicated products of field operators into combinations of propagators. These simpli-

fications are essential for applying the **Feynman rules**, a systematic approach to constructing mathematical expressions for probabilities using diagrams that represent particle interactions. In these **Feynman diagrams**, lines represent particles, and vertices represent interaction points, making the rules intuitive and practical for calculating scattering probabilities. These diagrams are not just intuitive visual aids but also correspond directly to terms in a **perturbation theory** expansion, where interactions are approximated by expanding in powers of the coupling constant. At **zeroth order**, particles propagate freely in space, while higher orders correspond to increasingly complex interactions with other fields or itself, represented by additional loops in Feynman diagrams.

While perturbation theory provides a powerful framework for most calculations, it has limitations. The **Schwinger-Dyson equations (SDEs)** offer a complementary, non-perturbative approach. These integral equations encapsulate all possible interactions and are derived from the generating functional. SDEs can account for effects beyond perturbation theory, making them invaluable for studying strongly coupled systems and capturing the full quantum behavior of fields.

By combining these tools—canonical commutation, propagators, Feynman diagrams, and advanced techniques like SDEs—QFT enables predictions of particle interactions. These methods are not only theoretical but also directly applicable to experimental contexts, such as understanding and predicting particle scattering processes observed at colliders like the LHC.

## 2.2.4 Divergences and Renormalization

As one calculates higher-order corrections in perturbation theory, **Feynman diagrams** with loops often lead to mathematical expressions that diverge, producing infinities. These **divergences** arise from specific physical processes and can be categorized as either **ultraviolet (UV) divergences**, which occur due to interactions at very short distances (high momenta), or **infrared (IR) divergences**, which arise from long-distance (low-momentum) contributions. Addressing these divergences is crucial to making Quantum Field Theory (QFT) predictive and physically meaningful.

The process of handling these divergences systematically is known as **renormalization**. This

involves several key steps:

1. **Regularization** introduces mathematical techniques, such as **cutoff regularization** or **dimensional regularization**, to temporarily make the divergences finite by introducing a scale or altering the spacetime dimensions.
2. **Renormalization of Parameters** adjusts the parameters of the theory, such as masses and coupling constants, so they absorb the divergences. These adjusted parameters are called **renormalized parameters**.
3. **Renormalized Lagrangian and Counterterms** reformulates the theory by adding specific terms, called **counterterms**, to the original Lagrangian. These terms systematically cancel the infinities encountered in perturbative calculations, ensuring finite and consistent predictions.

To identify which Feynman diagrams might lead to divergences, we often use the concept of **superficial degree of divergence**. This measure depends on the number of loops, external lines, and the types of fields involved in the diagram. This concept plays a key role in determining the interactions permitted in extended theories like Supersymmetry (SUSY), which will be explored in Section 2.5.2.4.

Renormalization also provides insights beyond handling divergences. The **renormalization group (RG)** describes how the parameters of a theory, such as coupling constants, evolve with changes in the energy scale. This is often referred to as the **running of coupling constants**.

By making QFT predictions finite and linking theory to experimental scales, renormalization ensures the consistency of QFT across different energy regimes. Moreover, it highlights the limitations of the Standard Model and motivates the search for more comprehensive frameworks, such as SUSY, as discussed in Section 2.4.

## 2.3 The Standard Model

### 2.3.1 Standard Model Contents

In this section, we review the particle content of the Standard Model, emphasizing the particles' properties, especially their representation under gauge symmetries and the origins of their masses, rather than delving into detailed interactions and Feynman diagrams.

The Standard Model is founded upon the gauge symmetry group  $SU(3)_C \times SU(2)_L \times U(1)_Y$ :

- $SU(3)_C$ : Governs the strong interaction, influencing quarks and gluons.
- $SU(2)_L$ : Governs the weak interaction, impacting left-handed fermions and the Higgs boson.
- $U(1)_Y$ : Governs hypercharge, affecting both electromagnetic and weak interactions.

The Standard Model includes three generations of particles, with each generation comprising 7 two-component Weyl fermion fields. Below is a breakdown of these particles, showing their respective properties across different gauge groups and how these properties contribute to their overall electric charge.

| Name    | Generation $i$                                                | $SU(3)$      | $SU(2)_L$ | $Y$            | $T_3$          | $Q = T_3 + Y$  |
|---------|---------------------------------------------------------------|--------------|-----------|----------------|----------------|----------------|
| Quarks  | $Q_i \equiv \begin{pmatrix} u_{L,i} \\ d_{L,i} \end{pmatrix}$ | triplet      | doublet   | $\frac{1}{6}$  | $\frac{1}{2}$  | $\frac{2}{3}$  |
|         |                                                               | triplet      |           | $\frac{1}{6}$  | $-\frac{1}{2}$ | $-\frac{1}{3}$ |
|         | $u_{R,i}^\dagger$                                             | anti-triplet | singlet   | $-\frac{2}{3}$ | 0              | $-\frac{2}{3}$ |
|         | $d_{R,i}^\dagger$                                             | anti-triplet | singlet   | $\frac{1}{3}$  | 0              | $\frac{1}{3}$  |
| Leptons | $L_i \equiv \begin{pmatrix} \nu_i \\ l_{L,i} \end{pmatrix}$   | singlet      | doublet   | $-\frac{1}{2}$ | $\frac{1}{2}$  | 0              |
|         |                                                               | singlet      |           | $-\frac{1}{2}$ | $-\frac{1}{2}$ | -1             |
|         | $l_{R,i}^\dagger$                                             | singlet      | singlet   | 1              | 0              | 1              |

Table 2.1: Table Adapted from [1].

The table above lists all fermions represented as complex two-component left-handed Weyl spinors. Note that the hermitian conjugate of a left-handed Weyl spinor transforms like a right-handed Weyl spinor and vice-versa. Within the  $SU(3)$  group, two fields transform as triplets and two as anti-triplets, with three additional fields transforming as singlets, indicating no transformation under this group. This will be further detailed in Section 2.3.2. For  $SU(2)_L$ , the table includes two sets of doublet fields and three singlet fields that do not transform under  $SU(2)_L$ . The hypercharges of individual fields under the  $U(1)_Y$  transformation are quoted under the column  $Y$ .

Additionally, beyond the fermions listed in Table 2.1, there exists a scalar particle, specifically a single complex Higgs doublet of  $SU(2)_L$  with a hypercharge  $Y = \frac{1}{2}$ . After Electroweak Symmetry Breaking (EWSB, as will be elaborated in Section 2.3.3), quark and lepton fields acquire masses via Yukawa coupling, forming four-component Dirac fermions, such as  $U_i \equiv \begin{pmatrix} u_{L,i} \\ u_R^i \end{pmatrix}$  for up-type quarks and similarly for down-type quarks and leptons. Neutrinos, however, remain massless. The resulting electric charges of the fields, as shown in the last two columns of the table.

## 2.3.2 Non-Abelian Gauge Theory

Quantum Chromodynamics (QCD), an essential component of the Standard Model, is an example of non-Abelian gauge theory framed by the  $SU(3)$  group. In QCD, the gauge bosons are gluons. These gluons are the mediators of the strong force, acting between quarks.

### 2.3.2.1 Gauge Boson and Gauge Group

The gauge group  $SU(3)$  is a non-Abelian group with eight generators, corresponding to the eight gluons. Each gluon can be represented mathematically as follows:

The  $SU(3)$  group has eight independent generators  $T^a$  (with  $a = 1, 2, \dots, 8$ ), which correspond to the Lie algebra of  $SU(3)$ . These generators are traceless Hermitian matrices that satisfy the commutation relation:

$$[T^a, T^b] = if^{abc}T^c \quad (2.8)$$

Here,  $f^{abc}$  are the structure constants of the  $SU(3)$  algebra. The gluons are associated with these generators. In the language of gauge theory, the gluon fields  $A_\mu^a$  (where  $\mu$  is the Lorentz spacetime index and  $a$  is the color index) couple to quarks and to each other through these generators.

### 2.3.2.2 Quark Representation

Quarks, the fundamental fermions in QCD, transform under the fundamental representation of  $SU(3)$ . There are two relevant representations for quarks: Each quark is a triplet ( $\mathbf{3}$ ), meaning it carries one of the three color charges. The transformation of a quark field  $q$  under an  $SU(3)$  gauge transformation  $U(x)$  ( $3 \times 3$  unitary matrix with determinant one) is given by:

$$q \rightarrow U(x)q. \quad (2.9)$$

The anti-quarks transform under the conjugate representation ( $\bar{\mathbf{3}}$ ). Let  $\bar{q}$  denote an antiquark field, its transformation is:

$$\bar{q} \rightarrow \bar{q}U^\dagger(x), \quad (2.10)$$

where  $U^\dagger(x)$  is the Hermitian conjugate of  $U(x)$ .

### 2.3.2.3 Gauge Boson-Fermion Interaction

The interaction between gluons and quarks in the Lagrangian of QCD is given by the term involving the covariant derivative  $D_\mu$ , which encapsulates the interaction with the gluon field:

$$D_\mu q = (\partial_\mu + ig_s A_\mu^a T^a) q \quad (2.11)$$

Here,  $g_s$  is the strong coupling constant, and  $A_\mu^a T^a$  represents the gluon field, with  $A_\mu^a$  being the gluon fields and  $T^a$  the  $SU(3)$  generators in the fundamental representation. This setup ensures that the theory of quantum chromodynamics, in particular, its Lagrangian is invariant under local  $SU(3)$  transformations, which is a cornerstone for gauge theories, reflecting the principle that: Physical laws should not depend on arbitrary local field transformations.

### 2.3.3 Higgs Mechanism & EWSB

The Higgs mechanism, through Electroweak Symmetry Breaking (EWSB), is a fundamental process in the Standard Model that explains how particles acquire mass. This section outlines the transformation from the symmetric state to the broken symmetry state near the Higgs potential minima. It also highlights the emergence of mass for the gauge bosons and fermions.

#### 2.3.3.1 Higgs Field and Potential

The Lagrangian for the electroweak interaction includes the kinetic and potential terms for the Higgs field, coupled to the gauge fields through covariant derivatives. The symmetry breaking of  $SU(2)_L \times U(1)_Y$  to  $U(1)_{EM}$  occurs when the Higgs field acquires its vacuum expectation value (vev).

The Higgs boson field,  $\Phi$ , is a complex doublet of the  $SU(2)_L$  gauge group with a hypercharge  $Y = \frac{1}{2}$ . The Higgs potential is given by:

$$V(\Phi) = -m^2|\Phi|^2 + \lambda|\Phi|^4 \quad (2.12)$$

where  $m^2$  and  $\lambda$  are positive constants, ensuring a stable potential with a non-trivial minimum. The minimum of the potential, vev, is not the origin, and occurs at  $\langle\phi\rangle = \frac{v}{\sqrt{2}}$ , where  $v = \sqrt{\frac{m^2}{\lambda}}$  is the vev of the Higgs field.

This can be written for the Higgs doublet as:

$$\Phi = \begin{pmatrix} \phi^+ \\ \phi^0 \end{pmatrix} = \begin{pmatrix} G^+ \\ \frac{v}{\sqrt{2}} + \frac{1}{\sqrt{2}} (h_{SM} + iG^0) \end{pmatrix} \quad (2.13)$$

, where:  $v$  is vev;  $h_{SM}$  is the physical Higgs scalar;  $G^+, G^0$  are the Goldstone bosons. The corresponding charges are  $Y = \frac{1}{2}$ ;  $T_3 = \pm\frac{1}{2}$ ;  $Q = 1, 0$ . That is, after Electroweak Symmetry breaking, expanding around the vacuum, the Higgs field becomes the real Higgs scalar, the neutral real Goldstone scalar boson, and a complex, positively-charged Goldstone boson.

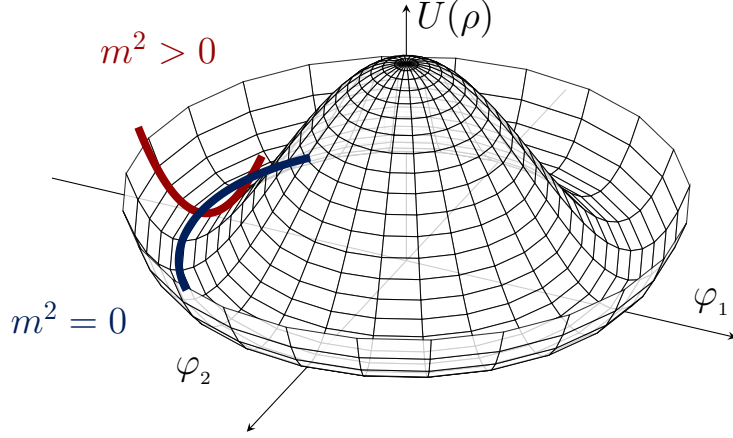


Figure 2.2: The “Mexican hat” potential for the Higgs field.

The Higgs potential, illustrated in Figure 2.2, demonstrates the mechanism of symmetry breaking. The circular valley at the minimum of the potential represents the degenerate vacuum states. Key features of this potential are as follows:

- **Residual Symmetry:** After the spontaneous symmetry breaking of  $SU(2)_L \times U(1)_Y$ , the  $U(1)_{EM}$  symmetry remains intact.
- **Vacuum Expectation Value (vev):** The potential is minimized at the vev of the Higgs field:

$$v = \sqrt{\frac{m^2}{\lambda}}$$

where  $m^2$  and  $\lambda$  are parameters of the Higgs potential.

- **Physical Higgs Boson ( $h_{SM}$ ):** Fluctuations along the radial direction in the field space correspond to the physical massive Higgs boson. The quadratic curvature of the potential along this direction indicates that the Higgs boson has a non-zero mass.
- **Massless Goldstone Bosons ( $G^+$  and  $G^0$ ):** Fluctuations along the angular directions correspond to the massless Goldstone bosons,  $G^+$  and  $G^0$ .



### 2.3.3.2 Gauge Boson Masses

Following EWSB, the gauge bosons acquire mass through interaction terms with the non-zero vev of the Higgs field. This interaction redefines the terms for the gauge bosons in the Lagrangian, leading to mass terms for the  $W$  and  $Z$  bosons, but not for the photon, maintaining its masslessness as required by electromagnetism.

Disregarding the real Higgs field interaction term, and rotating away the massless Goldstone bosons, the relevant Higgs-Gauge Boson interaction Lagrangian terms in the covariant derivative look like the following:

$$|D_\mu \Phi|^2 = g^2 \frac{v^2}{8} \left[ (W_\mu^1)^2 + (W_\mu^2)^2 + \left( \frac{g'}{g} B_\mu - W_\mu^3 \right)^2 \right]. \quad (2.14)$$

The  $W^1$ ,  $W^2$ , and  $W^3$  fields are the gauge bosons associated with the  $SU(2)_L$  symmetry, while  $B$  is the gauge boson associated with the  $U(1)_Y$  symmetry in the Standard Model.  $g$  and  $g'$  denote the gauge coupling constants of the  $SU(2)_L$  and  $U(1)_Y$  gauge groups, respectively. These coupling constants determine the interaction strength of the Higgs field with the corresponding gauge bosons.

The mass eigenstates for the gauge bosons in the Lagrangian, derived from diagonalizing the Higgs kinetic term, are:

$$W^\pm = \frac{1}{\sqrt{2}}(W^1 \mp iW^2) \quad (2.15)$$

$$\begin{pmatrix} Z_\mu \\ A_\mu \end{pmatrix} = \begin{pmatrix} \cos \theta_w & -\sin \theta_w \\ \sin \theta_w & \cos \theta_w \end{pmatrix} \begin{pmatrix} W_\mu^3 \\ B_\mu \end{pmatrix} \quad (2.16)$$

, where we define:

$$\tan \theta_w = \frac{g'}{g}. \quad (2.17)$$

Here,  $\theta_w$  is the Weinberg angle (or weak mixing angle), quantifying the mixing of  $W_\mu^3$  and  $B_\mu$  to form the  $Z_\mu$  (massive  $Z$ -boson) and  $A_\mu$  (massless photon) fields.

The mass terms of the gauge bosons thus arose from re-written Lagrangian:

$$\mathcal{L}_{\text{masses}} = \frac{1}{2}m_Z Z^\mu Z_\mu + m_W^2 W_\mu^+ W_\mu^-, \quad (2.18)$$

where:

$$m_W = \frac{v}{2}g; \quad m_Z = \frac{1}{2\cos\theta_w}gv = \frac{m_W}{\cos\theta_w}. \quad (2.19)$$

The photon field  $A_\mu$  remains massless ( $m_\gamma = 0$ ), as required by the unbroken  $U(1)_{EM}$  symmetry.

### 2.3.3.3 Fermion Mass via Yukawa Coupling

The electroweak symmetry breaking also affects the fermion sector, where fermions acquire mass via their coupling to the Higgs field in the Lagrangian, with the leptons (shown in Table 2.1) as an example:

$$\mathcal{L}_{\text{Yukawa}} = -y_f(\bar{L}\Phi l_R + \text{h.c.}). \quad (2.20)$$

Note that this Yukawa term is also  $SU(3)_C \times SU(2)_L \times U(1)_Y$  invariant. After the EWSB, we re-write the Higgs field around its vev, and the mass term will pop up:

$$-m_f(\bar{\psi}_L\psi_R + \bar{\psi}_R\psi_L), \quad (2.21)$$

with  $m_f = \frac{y_f}{\sqrt{2}}v$ . Note that it also comes along with the Yukawa interaction with the physical massive higgs field  $h$  with the proportional coupling strength:

$$-\frac{y_f}{\sqrt{2}}h(\bar{\psi}_L\psi_R + \bar{\psi}_R\psi_L) \quad (2.22)$$

.

## 2.4 Unsolved Mysteries of the Standard Model

### 2.4.1 Quadratic Divergence & Fine Tuning

The previous section outlined the Higgs mechanism and its implications for Yukawa interactions; in this section, we focus on a critical issue in the renormalization of the Higgs mass: the emergence of quadratic divergences due to loop corrections from fermions and bosons. This section details the formulation of these divergences and discusses their physical implications, which raise questions about the Standard Model.

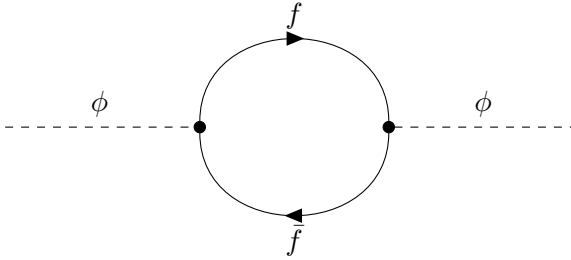


Figure 2.3: Dirac Fermion Contribution

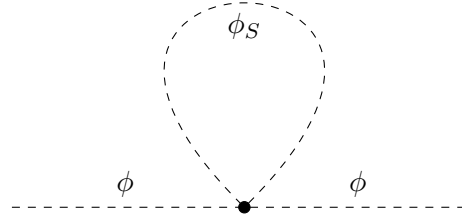


Figure 2.4: Scalar Boson Contribution

#### 2.4.1.1 Higgs Mass Loop (Fermion and Bosons)

**Fermion Contribution:** To understand the quadratic divergence from fermions, we consider the generic coupling of a fermion with a complex scalar using the Dirac spinor Lagrangian:

$$\mathcal{L}_{Dirac} = \partial_\mu \phi^\dagger \partial^\mu \phi + \bar{\psi} (i \not{\partial} - M_\psi) \psi \quad (2.23)$$

$$\mathcal{L}_{int} = \lambda_F \phi \bar{\psi} \psi + \lambda_F^* \phi^\dagger \bar{\psi} \psi \quad (2.24)$$

Starting from the Feynman Diagram in Figure 2.3, applying Feynman rules and integrating with Feynman parameters and Wick's rotation up to a UV cutoff scale  $\Lambda$ , we derive the following leading-

order quadratic divergence:

$$\begin{aligned}
& (-1) |i\lambda_F|^2 \int \frac{d^4 k}{(2\pi)^4} \frac{i \text{Tr} [((\not{p} + \not{k}) + M)(\not{k} + M)]}{(p-k)^2 - m^2 + i\epsilon} \frac{i}{k^2 - m^2 + i\epsilon} \\
&= 4 |\lambda_F|^2 \int \frac{d^4 k}{(2\pi)^4} \int_0^1 dx \left[ \frac{1}{k^2 - \Delta} + \frac{2\Delta}{[k^2 - \Delta]^2} \right] \\
&= 4 |\lambda_F|^2 \int_0^1 dx \left[ -\frac{1}{16\pi^2} \left\{ \Lambda^2 - \Delta \ln \frac{\Delta + \Lambda^2}{\Delta} \right\} + \frac{\Delta}{8\pi^2} \left\{ \frac{\Delta}{\Delta + \Lambda^2} - 1 + \ln \frac{\Delta + \Lambda^2}{\Delta} \right\} \right] \\
&= -\frac{|\lambda_F|^2}{4\pi^2} \Lambda^2 + \text{some logarithmic divergence}
\end{aligned} \tag{2.25}$$

, where:

$$\Delta = M^2 - p^2 x (1 - x). \tag{2.26}$$

Note that as described in Section 2.3.3, we have the Higgs-fermion interaction from Yukawa coupling, with the coupling strength being  $\lambda_F = y/\sqrt{2}$ . That is, we have:

$$\delta m_{\text{Higgs, Fermion}} = -\frac{|y|^2}{8\pi^2} \Lambda^2 + \dots \tag{2.27}$$

**Scalar Contribution:** For scalar contributions, we write down the general bosonic part of the Lagrangian, and let us assume it to be a generic four-point vertex interaction term in the Lagrangian, where  $\phi$  denotes a complex Higgs field, and  $\phi_S$  is some other generic complex scalar field.

$$\mathcal{L}_{\text{scalar boson}} = \partial_\mu \phi_S^\dagger \partial^\mu \phi_S - m_S \phi_S^\dagger \phi_S - \lambda_S (\phi^\dagger \phi) (\phi_S^\dagger \phi_S) \tag{2.28}$$

We draw the Feynman diagrams as shown in Figure 2.4, following the Feynman Rules to construct the expression in Equation 2.29. Similar analytical steps lead to a quadratic divergence of the

opposite sign.

$$\begin{aligned}
& (i\lambda_S) \int \frac{d^4k}{(2\pi)^4} \frac{i}{k^2 - m_S^2 + i\epsilon} \\
&= i\lambda_S \frac{1}{8\pi^2} \int_0^\infty k_E^3 dk_E \frac{i}{-k_E^2 - m_S^2} \\
&= \frac{\lambda_S}{16\pi^2} \left[ \Lambda^2 - m_s^2 \ln \left( \frac{\Lambda^2 + m^2}{m_S^2} \right) \right] \\
&= \frac{\lambda_S}{16\pi^2} \Lambda^2 + \text{logarithmic divergence.}
\end{aligned} \tag{2.29}$$

#### 2.4.1.2 Interpretation of Quadratic Divergence

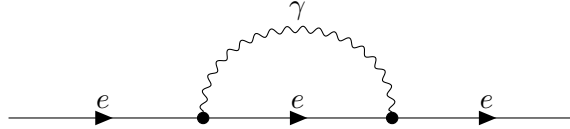


Figure 2.5: Feynman Diagram for electron self-energy at one-loop.

In exploring the implications of quantum corrections on particle masses, a comparison between the electron and the Higgs boson is particularly illustrative. As a comparison with the case of electron mass renormalization in the context of Quantum electrodynamics (QED), the one-loop contribution from Figure 2.5 is:

$$2 \frac{\alpha}{\pi} m_e \ln \frac{\Lambda}{m_e} \approx 0.239 m_e \tag{2.30}$$

, where  $\Lambda$  represents the UV cut-off scale, and  $\alpha$  is the fine-structure constant. Taking the Planck scale as an example for  $\Lambda$ , the correction to the electron mass is only about a quarter of the electron's mass.

For the top quark ( $y_t \sim 1$ ),  $\delta m_{\text{Higgs, Fermion}}^2$  becomes proportional to  $-\Lambda^2$ . Taking  $\Lambda$  to the Planck scale, the correction to the Higgs mass squared would be on the order of  $-10^{38} \text{ GeV}^2$ . This is extraordinarily larger than the observed Higgs mass squared,  $(125.22 \text{ GeV})^2 \sim 10^4 \text{ GeV}^2$  [32], by approximately 34 orders of magnitude. This sensitivity to the UV cut-off scale is a peculiarity not observed in fermions or Goldstone bosons.

The fact that the Higgs mass is sensitive to any scale of new physics, and thus the need for such

precise adjustments in the Higgs mass parameters, is described as “**fine-tuning**”. This fine-tuning problem is unique to elementary scalars like the Higgs boson, and it highlights a fundamental issue in particle physics known as the “**hierarchy problem**”, where the Higgs mass is several orders of magnitude smaller than the Planck scale. The concept of “**naturalness**” suggests that all fundamental theory parameters should be of order 1. However, this is not the case with the Higgs mass due to its sensitivity to new physics scales.

### 2.4.1.3 Motivation for SUSY: Cancelling Divergences

While alternative theories offer potential solutions to the fine-tuning problem, Supersymmetry (SUSY) is particularly notable for its ability to address this issue by stabilizing the Higgs mass against large quantum corrections in an intuitive way. SUSY suggests that each fermion and boson has a supersymmetric partner, which can lead to the cancellation of quadratic divergences due to opposite signs in their loop contributions.

Moreover, in the SUSY framework, the difference between fermion and scalar contributions calculated above, specifically a factor of 2, is reconciled by recognizing that a Dirac spinor consists of two chiral Weyl spinors. Hence, each chiral Weyl spinor corresponds to one complex scalar field. This relationship is encapsulated by the equation:

$$\lambda_S = |y_{\text{Yukawa}}|^2, \quad (2.31)$$

where  $\lambda_S$  represents the scalar coupling, directly linked to the Yukawa coupling strength,  $y_{\text{Yukawa}}$ , squared. The details of how the equation is automatically enforced by the Supersymmetry will be discussed in Section 2.5.

### 2.4.2 Astrophysical Observations of Dark Matter

Another important motivation of beyond Standard Model (BSM) theories is the astrophysical observations of “Dark Matter”. In this subsection, I will discuss experimental evidence supporting the existence of dark matter.

### 2.4.2.1 Galactic Rotation Curves

The rotation curves of galaxies provide compelling evidence for the existence of dark matter. These curves plot the rotational velocities of stars against their distance from the galactic center. Contrary to expectations based on the visible mass distribution, where velocities should decrease with distance due to less gravitational pull, observations reveal that the speeds remain constant or even increase slightly at the outer edges of galaxies. This phenomenon suggests that an additional, unseen mass must be present to provide the necessary gravitational force to sustain these velocities. It was first noted by Vera Rubin and her colleagues, who systematically studied several galaxies, establishing the universality of flat rotation curves across a wide range of galaxy types [33]. These findings are fundamental to current astrophysical models and underscore the necessity of including dark matter in simulations and theories regarding the structure and dynamics of galaxies.

A classic example of this observation is seen in the rotation curve of the spiral galaxy Messier 33 (M33), illustrated in Figure 2.6. The flatness of M33's rotation curve at large radii, where visible matter is scarce, implies the presence of dark matter extending well beyond the luminous regions of the galaxy.

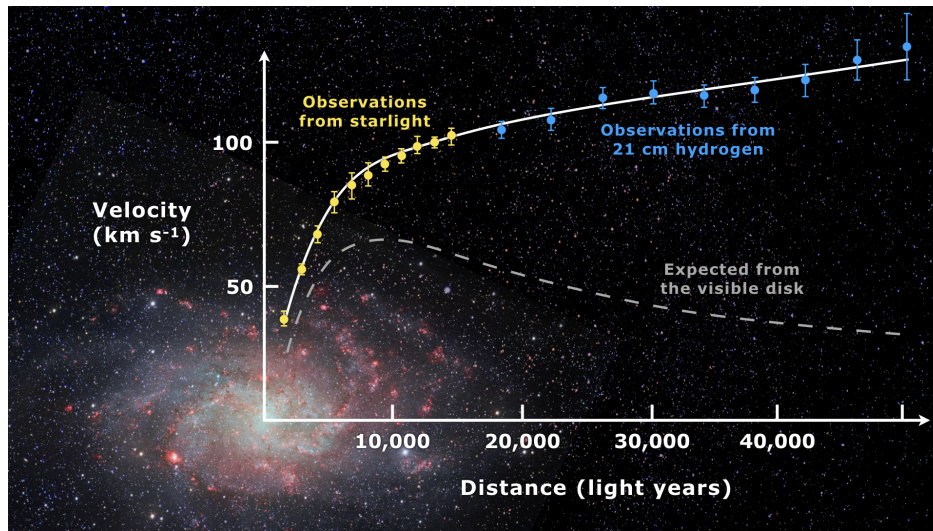


Figure 2.6: Rotation curve of the spiral galaxy Messier 33, showing constant rotational speeds in the galaxy's outer regions, indicative of the presence of dark matter. Figure adapted from [3].

### 2.4.2.2 Strong Gravitational Lensing & Total Mass Measurement

Strong gravitational lensing is a powerful astrophysical phenomenon that occurs when the gravitational field of a massive foreground object, such as a galaxy cluster, bends the light from a more distant galaxy. This bending causes the appearance of multiple distorted and magnified images of the background galaxy. It serves as a natural telescope, enhancing our ability to observe distant astronomical objects and providing a method to infer the total mass of the lensing object—critical for studying dark matter.



Figure 2.7: First near-infrared (NIR) image from the James Webb Space Telescope (JWST) reveals galaxy cluster SMACS 0723, showcasing strong gravitational lensing effects. This image offers insight into dark matter distribution and provides detailed views of distant galaxies. [4]

An exemplary case is the galaxy cluster SMACS 0723, recently imaged by the James Webb Space Telescope (JWST). Analysis of the strong lensing effects within this cluster indicates a total enclosed mass of approximately  $3.5 \times 10^{14}$  solar masses within a radius of 400 kpc. Despite such a significant mass, X-ray observations of the cluster show that the gas mass fraction—the primary portion for the baryonic (normal) matter—is only about 11% of this total enclosed mass [34]. This discrepancy

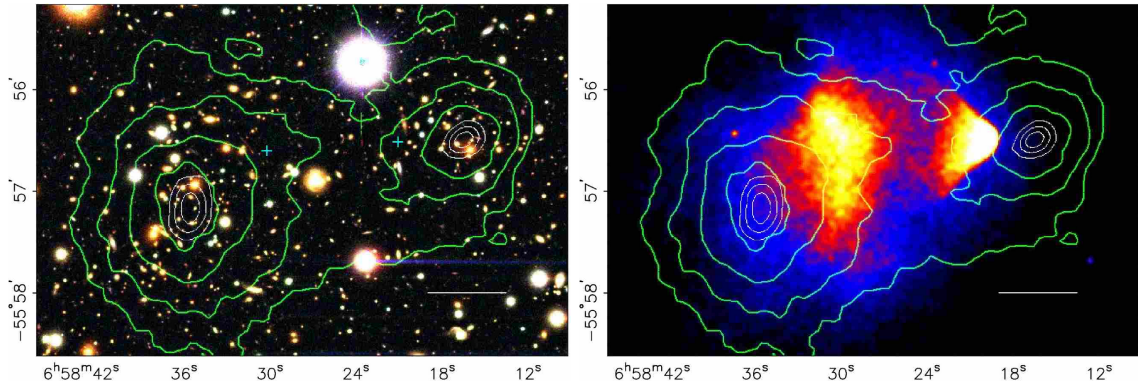


suggests that a substantial portion of the mass within this cluster is non-luminous, providing compelling evidence for the presence of dark matter.

### 2.4.2.3 Weak Lensing & Bullet Clusters

Weak gravitational lensing is a subtle effect where the images of distant galaxies are slightly distorted by the gravitational fields of intervening mass, typically not associated with visible matter. This phenomenon has been crucial in studying the distribution and properties of dark matter. One of the most compelling pieces of evidence for the existence and collisionless nature of dark matter comes from observations of the Bullet Cluster (1E 0657-56).

The Bullet Cluster consists of two colliding galaxy clusters and is a spectacular example of how dark matter behaves differently from ordinary baryonic matter. During the collision, while the baryonic matter (detected via X-ray emissions from hot gas) interacted and slowed down, the dark matter components passed through each other without any interaction. This separation was distinctly captured through weak lensing analyses, which mapped the mass distribution independently of the visible matter.



(a) Mass contour plots overlaid on the X-ray image of the Bullet Cluster. The contours represent the Bullet Cluster overlaid with the weak lensing reconstruction, indicating the separation between the hot mass distribution of dark matter separate from gas (visible) and the dark matter (inferred from the hot gas seen in X-rays [35].

(b) High-resolution Chandra X-ray imagery of the Bullet Cluster overlaid with the weak lensing reconstruction, highlighting the separation between the hot mass distribution of dark matter separate from gas (visible) and the dark matter (inferred from the hot gas seen in X-rays [35].

Figure 2.8: Combined imaging and lensing analysis of the Bullet Cluster (1E 0657-56) revealing the spatial segregation of dark matter and normal baryonic matter during a cluster collision. The left image shows optical data with lensing mass contours, and the right image shows X-ray data with corresponding error contours on mass peak positions.

This separation and the inability to attribute the gravitational effects to modifications of gravity alone, as shown by an 8-sigma significance spatial offset between the total mass center and the baryonic mass peaks[35], robustly demonstrates that the majority of matter within the Bullet Cluster is non-luminous dark matter. Such observations provide direct empirical proof of dark matter, confirming its existence and non-interacting nature in a compelling visual and analytical manner.

#### 2.4.2.4 Dark Matter and Baryon Densities from Planck 2018 Observations

The Planck satellite’s full-mission data [36] provides essential insights into the cosmological parameters that help us understand the composition and expansion of the universe. These observations, particularly of the Cosmic Microwave Background (CMB) anisotropies, offer a precise measurement of density parameters within the framework of the Lambda Cold Dark Matter ( $\Lambda$ CDM) cosmology[37].

CMB anisotropies are small temperature fluctuations in the cosmic microwave background radiation, which provide a snapshot of the universe approximately 380,000 years after the Big Bang. These anisotropies are crucial because they encode information about the early universe’s density fluctuations, which eventually evolves into the large-scale structures observed today. By studying the pattern and scale of these anisotropies, cosmologists can infer the composition of the universe, including the proportions and properties of dark matter, baryonic matter, and dark energy.

The  $\Lambda$ CDM model[37], which is supported by Planck’s findings, assumes a universe that is flat and expanding, influenced primarily by dark energy ( $\Lambda$ ) and cold dark matter. It is described by six key parameters:

- $\Omega_b h^2$ : Baryon density parameter.
- $\Omega_c h^2$ : Cold dark matter density parameter.
- $\Omega_\Lambda$ : Dark energy density parameter.

- $n_s$ : Scalar spectral index of primordial fluctuations.
- $\tau$ : Optical depth due to reionization.
- $H_0$ : Hubble constant today.

The model is usually named as the “Spatially-Flat 6-Parameter  $\Lambda$ CDM Cosmology”. These parameters are constrained by solving the Friedmann equation [38] for a flat universe:

$$H^2 = H_0^2 [\Omega_r a^{-4} + \Omega_m a^{-3} + \Omega_k a^{-2} + \Omega_\Lambda]$$

Here,  $\Omega_m$  and  $\Omega_r$  represent the density parameters for matter (including dark matter and baryonic matter) and radiation, respectively, while  $\Omega_k$  (which is zero in a flat universe) and  $\Omega_\Lambda$  account for curvature and dark energy. The scale factor  $a$  describes the relative expansion of the universe.

The critical density  $\rho_c$ , which is the density at which the universe is flat, is defined by the equation:

$$\rho_c = \frac{3H^2}{8\pi G}$$

Each component’s density parameter,  $\Omega_x$ , is then the ratio of that component’s actual density  $\rho_x$  to the critical density:

$$\Omega_x = \frac{\rho_x}{\rho_c} = \frac{8\pi G \rho_x}{3H^2}$$

Based on the Planck 2018 results [36], the key estimates are:

- **Dark Matter Density** ( $\Omega_c h^2$ ): The cold dark matter density is:  $\Omega_c h^2 = 0.120 \pm 0.001$
- **Baryon Density** ( $\Omega_b h^2$ ): The baryonic matter density is:  $\Omega_b h^2 = 0.0224 \pm 0.0001$

These measurements suggest a universe composition with approximately **26.8% dark matter** and **4.9% baryonic matter**, supporting the spatially flat  $\Lambda$ CDM cosmological model.

### 2.4.3 Other Key Motivations for BSM Physics

#### 2.4.3.1 Muon g-2 Anomaly

The muon g-2 anomaly, a notable deviation between experimental measurements and Standard Model predictions of the muon's anomalous magnetic dipole moment,  $a_\mu$ , has been a compelling hint at possible new physics beyond the Standard Model. The measurement of  $a_\mu$  is now known to be  $116592057(25) \times 10^{-11}$  with a precision of 0.21 parts per million (ppm) [5], enhancing the statistical significance of the deviation to 5.0 sigma (w.r.t. theory prediction in [39]). This discrepancy suggests contributions from new physics, potentially including supersymmetric particles, which could reconcile these measurements with theoretical expectations.<sup>3</sup>

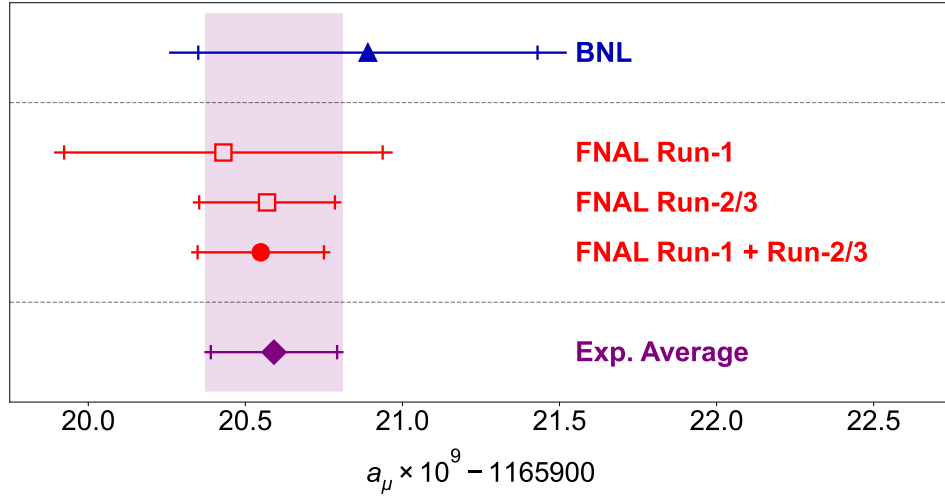


Figure 2.9: Experimental values of  $a_\mu$  from Brookhaven National Lab (BNL) E821, Fermilab's Run-1 result, and the new experimental average[5].

#### 2.4.3.2 Unification of Forces

In addition to the muon g-2 anomaly, the unification of the three gauge couplings at a high energy scale in supersymmetric models like MSSM remains a fundamental motivation for considering BSM physics. This unification suggests a single unified force at the time of the Big Bang, which later diverged into the strong, weak, and electromagnetic forces as the universe cooled.

<sup>3</sup>Recent findings from the BMW Collaboration and CMD-3 experiment reveal theoretical and some experimental discrepancies in muon g-2 data analysis, suggesting that further studies might alter the extent of the observed anomaly

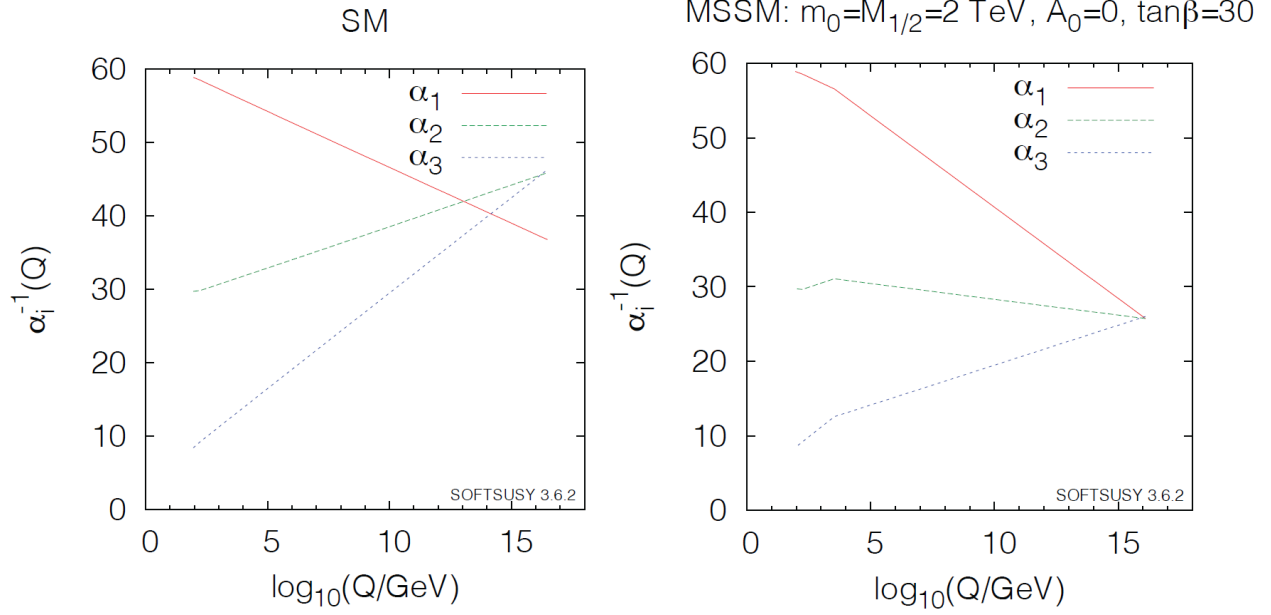


Figure 2.10: Running couplings in the Standard Model (SM) and Minimal Supersymmetric Standard Model (MSSM) using two-loop Renormalization Group (RG) evolution. This plot highlights how the gauge couplings in the MSSM converge at a high energy scale, suggesting unification, whereas the couplings in the SM do not. (Adapted from [6], licensed under CC-BY-NC-4.0.)

This result is supported by the gauge coupling unification plots (Figure 2.10) provided by the Particle Data Group, which demonstrate the convergence of couplings in SUSY models and the lack of convergence in the Standard Model.

### 2.4.3.3 Neutrino Masses

Furthermore, the observation of neutrino oscillations [42], which indicate that neutrinos have mass, poses a challenge to the Standard Model, which predicts massless neutrinos. The seesaw mechanism is a popular solution, which introduces heavy right-handed neutrinos. These neutrinos do not interact with the Standard Model gauge fields other than through their Yukawa couplings to the left-handed neutrinos and the Higgs field. In SUSY theories, particularly those extending into GUTs like  $SO(10)$ , the seesaw mechanism is a natural fit because these theories often include right-handed neutrinos, which are crucial for the seesaw mechanism [43].

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[40, 41].

These diverse and significant observations together strongly motivate the pursuit of theories beyond the Standard Model, such as Supersymmetry, to resolve these anomalies and provide a more comprehensive understanding of fundamental physics.

## 2.5 Supersymmetry

**Supersymmetry (SUSY)** is a theoretical framework that extends the Standard Model (SM) by introducing a fundamental symmetry between fermionic and bosonic fields. SUSY provides a natural resolution to the hierarchy problem by stabilizing the Higgs mass against quadratically diverging corrections. This section introduces the core principles of SUSY, starting with the chiral super-multiplet as its simplest representation, followed by a discussion of renormalizable SUSY interactions and their implications. The section concludes with gauge supermultiplets, a central focus of my PhD research, as further elaborated in Section 2.6.7.

### 2.5.1 Basic Chiral Super-Multiplet

#### 2.5.1.1 Lagrangian and SUSY variataion

Let us start with the most basic form of Lagrangian, a free fermionic particle embodied in the form of a 2-component Weyl spinor  $\psi$  and a bosonic complex scalar field  $\phi$ , added with a term for complex scalar auxiliary field  $F$ . The lagrangian for a chiral super-multiplet, includes  $\phi_i, \psi_i, F_i$ :

$$\mathcal{L}_{\text{free},i} = \partial^\mu \phi^{*i} \partial_\mu \phi_i + i \psi^{\dagger i} \bar{\sigma}^\mu \partial_\mu \psi_i + F^{*i} F_i. \quad (2.32)$$

Note that, for each complex scalar field  $\phi$ , there are two free parameters, and for each complex Weyl spinor field  $\psi$ , there are four free parameters (two if the spinor field is on the mass shell). The purpose of introducing the auxiliary field is to make the SUSY algebra close even at the off-mass-shell condition, thus we need to match the degree of freedom for bosonic field and fermionic field. Therefore, we need to introduce the auxiliary complex scalar field  $F$ .

#### 2.5.1.2 Infinitesimal SUSY Transformation

The simplest way to go between the spinor and a scalar is to provide another infinitesimal anti-commuting two-component Weyl spinor  $\epsilon$ . Let  $\epsilon$  be an infinitesimal Weyl Spinor, under this infinitesimal SUSY variation as described in Equations 2.33, we have the free field Langrangian

invariant.

$$\begin{aligned}
\delta\phi_i &= \epsilon\psi_i \\
\delta(\psi_i)_\alpha &= -i\left(\sigma^\mu\epsilon^\dagger\partial_\mu\phi_i\right)_\alpha + \epsilon_\alpha F_i \\
\delta F_i &= -i\epsilon^\dagger\bar{\sigma}^\mu\partial_\mu\psi_i
\end{aligned} \tag{2.33}$$

## 2.5.2 Renormalizable SUSY Interaction

In order to build a proper quantum field theory that we can compute useful physics quantities, it must be renormalizable. In this section, we will discuss that a renormalizable SUSY Interaction resolves the fine-tuning problem, as the renormalization condition automatically enforces the cancellation of quadratic divergence that appeared in the Higgs mass renormalization.

### 2.5.2.1 Superficial Degree of divergence

Considering the UV cut-off scheme, we can calculate the superficial degree of divergence  $\Lambda^D$  for matrix element calculation, like Equation 2.34.

$$\mathcal{M} \sim \int dk^4 \frac{1}{k^n} \sim \Lambda^D \Rightarrow D = 4 - n; \tag{2.34}$$

We should note that logarithmic divergence is relatively harmless in terms of potential fine-tuning problems:

$$D = 0 \Rightarrow \mathcal{M} \sim \ln \Lambda^2 \tag{2.35}$$

Notice that we can assign the mass dimension to the Lagrangian and the relevant field components:

$$\mathcal{L} \propto [\text{mass}]^4; \phi \propto [\text{mass}]; \psi \propto [\text{mass}]^{\frac{3}{2}}; F \propto [\text{mass}]^2. \tag{2.36}$$



Therefore, when we have some interaction term of the scalar, Weyl spinor and auxiliary field in the Lagrangian  $g_i \phi^a \psi^b F^c$ , where  $g_i \sim [\text{mass}]^{\Delta_i}$ , we would have:

$$\Delta_i = 4 - a - \frac{3}{2}b - 2c \quad (2.37)$$

Thus, by adding  $n_i$  such vertex into some of the matrix calculations of a diagram, we have:

$$\mathcal{M}_{\text{old}} \propto \int k^{D_{\text{old}}} \rightarrow \mathcal{M}_{\text{new}} \propto (g_i)^{n_i} \int k^{D_{\text{new}}} \quad (2.38)$$

, where the new superficial degree of divergence would be:

$$D_{\text{new}} = D_{\text{old}} - n_i \Delta_i. \quad (2.39)$$

If we have coupling constant mass degree  $\Delta_i < 0$ , then we can easily add a new vertex to get a new graph, and we will arrive at a divergent diagram with other  $f$ ,  $b$ , then we need a new counter term to cancel the divergence at  $D_{\text{new}} = D_{\text{old}} - n_i \Delta_i$ . If we add these vertices infinitely, we need an infinite number of new counter terms in the UV renormalization scheme, which means the Lagrangian would be non-renormalizable by definition.

### 2.5.2.2 Renormalizability from Potentially SUSY-Invariant Lagrangian

To keep a coupling constant mass degree non-negative while maintaining the Lagrangian invariant under super-symmetric variation of  $\epsilon$ , the only possible interaction terms with  $\Delta_i \geq 0$  become:

$$\mathcal{L}_{\text{int}} = -\frac{1}{2}W^{ij}\psi_i\psi_j + W^i F_i + c.c. \quad (2.40)$$

, where the polynomial degree satisfies:

$$W^{ij}(\phi) \text{ degree} \leq 1; W^i(\phi) \text{ degree} \leq 2. \quad (2.41)$$

By requiring that the variation of each term be canceled by the other under SUSY variation, we have:

$$W^{ij} = \frac{\delta^2}{\delta\phi_i\delta\phi_j}W \quad (2.42)$$

and

$$W^i = \frac{\delta W}{\delta\phi_i} = M^{ij}\phi_j + \frac{1}{2}y^{ijk}\phi_j\phi_k \quad (2.43)$$

, where:

$$W = \frac{1}{2}M^{ij}\phi_i\phi_j + \frac{1}{6}y^{ijk}\phi_i\phi_j\phi_k. \quad (2.44)$$

Note that:  $M^{ij}$  is the fermion mass matrix (or mixing matrix), which describes the mass terms and possible mixing between the fermionic fields  $\psi_i$  and  $\psi_j$ ;  $y^{ijk}$  represents the Yukawa coupling constants, which determine the strength of interactions between the fermionic fields  $\psi_i$ ,  $\psi_j$ , and the scalar field  $\phi_k$ .

### 2.5.2.3 Integrating out the Auxiliary Field

To simplify the Lagrangian and eliminate the auxiliary field  $F$ , we first focus on the terms in the Lagrangian involving  $F$ :

$$\mathcal{L}_F = F^{*i}F_i + W^iF_i + c.c. \quad (2.45)$$

The equation of motion for  $F$  can be derived as:

$$\frac{\partial\mathcal{L}}{\partial F} = \frac{d}{dt}\left(\frac{\partial\mathcal{L}}{\partial\dot{F}}\right) \Rightarrow F^{*i} + W^i = 0, \text{ and } c.c. \Rightarrow F^{*i} = -W^i; F_i = -W_i. \quad (2.46)$$

### 2.5.2.4 Most General Form of SUSY Lagrangian

By integrating out the auxiliary field  $F$ , the most general form of SUSY-invariant interaction Lagrangian constraint by the Superficial Degree of Divergence to keep the theory renormalizable

look like:

$$\mathcal{L} = \partial^\mu \phi^{*i} \partial_\mu \phi_i - V(\phi, \phi^*) + i\psi^{\dagger i} \bar{\sigma}^\mu \partial_\mu \psi_i - \frac{1}{2} M^{ij} \psi_i \psi_j - \frac{1}{2} M_{ij}^* \psi^{\dagger i} \psi^{\dagger j} - \frac{1}{2} y^{ijk} \phi_i \psi_j \psi_k - \frac{1}{2} y_{ijk}^* \phi^{*i} \psi^{\dagger j} \psi^{\dagger k} \quad (2.47)$$

, where the scalar potential looks like:

$$V(\phi, \phi^*) = W^k W_k^* = M_{ik}^* M^{kj} \phi^{*i} \phi_j + \frac{1}{2} M^{in} y_{jkn}^* \phi_i \phi^{*j} \phi^{*k} + \frac{1}{2} M_{in}^* y^{jkn} \phi^{*i} \phi_j \phi_k + \frac{1}{4} y^{ijn} y_{klm}^* \phi_i \phi_j \phi^{*k} \phi^{*l} \quad (2.48)$$

### 2.5.2.5 Yukawa Coupling & Cancellation

To take the above result in a bit more context, the Yukawa Coupling between the scalar Higgs boson  $\phi_H$  and a Weyl Fermion, take the top quark, for example,  $\psi_t$ , would be

$$\mathcal{L}_{Htt} = -\frac{1}{2} y^{Htt} \phi_H \psi_t \psi_t - \frac{1}{2} y_{Htt}^* \phi^{*H} \psi_t^{\dagger} \psi_t^{\dagger} - \frac{1}{4} y^{Htt} y_{Htt}^* \phi_H \phi_t \phi^{*H} \phi^{*t} \quad (2.49)$$

, where  $\phi_t$  would be the complex scalar fields that appeared in the Chiral Super-multiplet that includes the top quark; we call it the super-partner of the top quark (or “stop”).

$$|y_u|^2 = \left| \frac{1}{2} y^{Htt} \right|^2 = \frac{1}{4} y^{Htt} y_{Htt}^* = \lambda_S \quad (2.50)$$

In this case, the top super-partner 1-loop contribution to the Higgs boson mass will exactly cancel the top quark 1-loop contribution.

To summarize, the basic requirement of re-normalization and SUSY-invariance will ensure the cancellation of quadratic divergence that appeared in the Higgs self-energy diagram renormalization in Section 2.4.1.

### 2.5.3 Gauge Supermultiplets

Apart from the Chiral Super-multiplet for fermions, we also need the gauge boson and the relevant gauge covariant derivative term invariant under the SUSY transformation. Thus, we need gauge

multiplets. For a gauge super multiplet, it includes the usual gauge field  $A_\mu^a$ , its corresponding fermionic field (commonly referred to as the “gaugino”)  $\lambda^a$ , and the real auxiliary field  $D^a$  for the Lagrangian to be still invariant off the mass shell. Note that the off-shell gauge bosons have a degree of freedom of 3, and the complex 2-component Weyl spinor fermion has a degree of freedom of 4. Thus, for the bosonic and fermionic components to have the same degree of freedom, we must introduce an auxiliary real bosonic field that vanishes on the mass shell.

The free field Lagrangian of the gauge super-multiplet is:

$$\mathcal{L}_{\text{gauge}} = -\frac{1}{4}F_{\mu\nu}^a F^{\mu\nu a} + i\lambda^{\dagger a}\bar{\sigma}^\mu\nabla_\mu\lambda^a + \frac{1}{2}D^a D^a \quad (2.51)$$

, where we have the usual field strength tensor for  $A_\nu^a$ :

$$F_{\mu\nu}^a = \partial_\mu A_\nu^a - \partial_\nu A_\mu^a + gf^{abc}A_\mu^b A_\nu^c \quad (2.52)$$

and the covariant derivative for the gaugino  $\lambda^a$  :

$$\nabla_\mu\lambda^a = \partial_\mu\lambda^a + gf^{abc}A_\mu^b\lambda^c \quad (2.53)$$

Under infinitesimal gauge transformation of  $\Lambda^a$ , we have:

$$\begin{aligned} \delta A_\mu^a &= \partial_\mu\Lambda^a + gf^{abc}A_\mu^b\Lambda^c \\ \delta\lambda^a &= gf^{abc}\lambda^b\Lambda^c \end{aligned} \quad (2.54)$$

Under the infinitesimal SUSY transformation of Weyl Spinor  $\epsilon$ , we have:

$$\begin{aligned} \delta A_\mu^a &= -\frac{1}{\sqrt{2}}\left(\epsilon^\dagger\bar{\sigma}_\mu\lambda^a + \lambda^{\dagger a}\bar{\sigma}_\mu\epsilon\right) \\ \delta\lambda_\alpha^a &= \frac{i}{2\sqrt{2}}(\sigma^\mu\bar{\sigma}^\nu\epsilon)_\alpha F_{\mu\nu}^a + \frac{1}{\sqrt{2}}\epsilon_\alpha D^a \\ \delta D^a &= \frac{i}{\sqrt{2}}(-\epsilon^\dagger\bar{\sigma}^\mu\nabla_\mu\lambda^a + \nabla_\mu\lambda^{\dagger a}\bar{\sigma}^\mu\epsilon) \end{aligned} \quad (2.55)$$

## 2.6 Minimal Super-symmetric Standard Model (MSSM)

The following section is primarily reorganized and reviewed based on *A Supersymmetry Primer* by Stephen P. Martin [2]. This foundational text provides the detailed derivations and explanations that form the core of our discussion and analysis.

In this section, I will describe the Super Symmetric Model that extends the standard model minimally by going over its basic assumptions, including Minimal Gauge Group (Section 2.6.1), Minimal Particle Content (Section 2.6.2), R-parity Conservation (Section 2.6.3) and Soft SUSY Breaking (Section 2.6.5). Then, I will discuss the masses of some of particles after the EWSB (Section 2.6.6), in particular, the Neutralino and Charginos (Section 2.6.7), which will be the subject of my main PhD research analysis in Chapter 4.

### 2.6.1 Symmetry: Minimal Gauge Group

In the MSSM, we have the first assumption: Minimal Gauge group. That is, only necessary gauge groups in the Standard Model will be used. The standard model has three gauge symmetry Lie groups: SU(3) of color for strong interaction, SU(2)<sub>L</sub> for weak interaction, and U(1) hypercharge.

For each of them we construct the gauge multiplets, which includes  $A_\mu^a$  as the gauge bosons;  $\lambda^a$  as the corresponding gaugino (two-component left-handed Weyl fermion spinor). In particular, we have:

- 8 gluon fields  $A_\mu^a$  and 8 gluino fermion fields  $\tilde{g}^a$
- 3  $W$ -boson fields  $W_\mu^a$  and 3 Wino fermion fields  $\tilde{W}^a$
- 1  $B$ -boson fields  $B_\mu$  and 1 Bino fermion field  $\tilde{B}$

To summarize the gauge supermultiplet in the MSSM, we quote Table 2.2.

Table 2.2: Gauge supermultiplets in the Minimal Supersymmetric Standard Model. Adapted from [2].

| Names           | spin 1/2                          | spin 1            | $SU(3)_C, SU(2)_L, U(1)_Y$ |
|-----------------|-----------------------------------|-------------------|----------------------------|
| gluino, gluon   | $\tilde{g}$                       | $g$               | $(8, 1, 0)$                |
| winos, W bosons | $\tilde{W}^\pm \quad \tilde{W}^0$ | $W^\pm \quad W^0$ | $(1, 3, 0)$                |
| bino, B boson   | $\tilde{B}^0$                     | $B^0$             | $(1, 1, 0)$                |

## 2.6.2 Minimal Particle Content: Chiral Multiplet

Now, we introduce the second assumption: Minimal Particle Content. That is, the MSSM only contains the necessary chiral supermultiplet to include the Standard Model particles.

Recall we have listed the particle content in the Standard Model in Table 2.1. Now we extend it to the Chiral Supermultiplet in Table 2.3 by adding the squarks, sleptons, and higgsinos as the super-partners of the quarks, leptons, and the Higgs boson.

In summary, each Standard Model quark and lepton is paired with a corresponding squark or slepton, across the three generations: up and down, charm and strange, top and bottom for quarks; and electron, muon, tau, along with their respective neutrinos, for leptons.

### 2.6.2.1 Two Higgs Doublet Model (2HDM)

Notice that we have two complex Higgs  $SU(2)_L$  doublet boson fields here, written as  $H_u$  and  $H_d$ . I will briefly explain why we need the Two Higgs Doublet Model (commonly referred to as the 2HDM).

Recall that obtaining masses for the  $W$  and  $Z$  bosons requires electroweak symmetry breaking, which requires one complex  $SU(2)$  doublet Higgs field to ensure proper transformation under the  $U(1)$  hypercharge symmetry. To keep the Yukawa Lagrangian gauge invariant, take the hypercharge, for example:

$$Y_{u\bar{u}H_u} = 0; Y_{u\bar{u}} = \frac{1}{6} + \left(-\frac{2}{3}\right) = -\frac{1}{2} \Rightarrow Y_{H_u} = \frac{1}{2}. \quad (2.56)$$

| Name                     |             | spin 0                                                             | spin 1/2                                                       | SU(3)        | SU(2) <sub>L</sub> | Y              | T <sub>3</sub> | Q = T <sub>3</sub> + Y      |
|--------------------------|-------------|--------------------------------------------------------------------|----------------------------------------------------------------|--------------|--------------------|----------------|----------------|-----------------------------|
| Squarks<br>&<br>Quarks   | $Q_i$       | $\begin{pmatrix} \tilde{u}_{L,i} \\ \tilde{d}_{L,i} \end{pmatrix}$ | $\begin{pmatrix} u_{L,i} \\ d_{L,i} \end{pmatrix}$             | triplet      | doublet            | $\frac{1}{6}$  | $\frac{1}{2}$  | $\frac{2}{3} - \frac{1}{3}$ |
|                          |             |                                                                    |                                                                | triplet      |                    | $\frac{1}{6}$  | $-\frac{1}{2}$ | $-\frac{1}{3}$              |
|                          | $\bar{u}_i$ | $\tilde{u}_{R,i}^*$                                                | $u_{R,i}^\dagger$                                              | anti-triplet | singlet            | $-\frac{2}{3}$ | 0              | $-\frac{2}{3}$              |
|                          | $\bar{d}_i$ | $\tilde{d}_{R,i}^*$                                                | $d_{R,i}^\dagger$                                              | anti-triplet | singlet            | $\frac{1}{3}$  | 0              | $\frac{1}{3}$               |
| Sleptons<br>&<br>Leptons | $L_i$       | $\begin{pmatrix} \tilde{\nu}_i \\ \tilde{l}_{L,i} \end{pmatrix}$   | $\begin{pmatrix} \nu_i \\ l_{L,i} \end{pmatrix}$               | singlet      | doublet            | $-\frac{1}{2}$ | $\frac{1}{2}$  | 0                           |
|                          |             |                                                                    |                                                                | singlet      |                    | $-\frac{1}{2}$ | $-\frac{1}{2}$ | -1                          |
|                          | $\bar{l}_i$ | $\tilde{l}_{R,i}^*$                                                | $l_{R,i}^\dagger$                                              | singlet      | singlet            | 1              | 0              | 1                           |
| Higgs<br>&<br>Higgsinos  | $H_u$       | $\begin{pmatrix} H_u^+ \\ H_u^0 \end{pmatrix}$                     | $\begin{pmatrix} \tilde{H}_u^+ \\ \tilde{H}_u^0 \end{pmatrix}$ | singlet      | doublet            | $\frac{1}{2}$  | $\frac{1}{2}$  | 1                           |
|                          |             |                                                                    |                                                                | singlet      |                    | $\frac{1}{2}$  | $-\frac{1}{2}$ | 0                           |
|                          | $H_d$       | $\begin{pmatrix} H_d^0 \\ H_d^- \end{pmatrix}$                     | $\begin{pmatrix} \tilde{H}_d^0 \\ \tilde{H}_d^- \end{pmatrix}$ | singlet      | doublet            | $-\frac{1}{2}$ | $\frac{1}{2}$  | 0                           |
|                          |             |                                                                    |                                                                | singlet      |                    | $-\frac{1}{2}$ | $-\frac{1}{2}$ | -1                          |

Table 2.3: Minimal extension of the Standard Model particle content to include the three generations of supersymmetric partners (superpartners) of Standard Model fermions ( $i \in \{1, 2, 3\}$ ), along with the Higgs bosons and their corresponding Higgsinos. The table specifies the spin, representations under SU(3)<sub>C</sub> and SU(2)<sub>L</sub> gauge groups, hypercharge (Y), and electric charge ( $Q = T_3 + Y$ ) for each particle. Adapted from [2].

By the same reasoning, we have Higgs down-type quark coupling. We need the hypercharge for the  $H$  field for down-type quarks (and leptons) to be minus one-half:

$$Y_{d\bar{d}H_u} = 0; Y_{d\bar{d}} = \frac{1}{6} + \frac{1}{3} = +\frac{1}{2} \Rightarrow Y_{H_d} = -\frac{1}{2}. \quad (2.57)$$

In the Standard model, we simply use:

$$H_d = H_u^\dagger \quad (2.58)$$

, and thus have:

$$Y_{H_u} = Y_H = \frac{1}{2}; Y_{H_d} = Y_{\bar{H}} = -\frac{1}{2}. \quad (2.59)$$

However, with SUSY added, we need Higgs to be part of the chiral supermultiplets. To keep the Lagrangian SUSY invariant as mentioned in Section 2.5, in the most general SUSY-invariant potential form, there is no complex conjugate of the field in the Yukawa Lagrangian, but only:

$$W_{ij}\psi_i\psi_j = \frac{1}{6}y^{ijk}\phi_k\psi_i\psi_j. \quad (2.60)$$

Thus, we must have two complex Higgs  $SU(2)_L$  Doublet in the MSSM separately for  $H_u$ ,  $H_d$  with hypercharge  $+\frac{1}{2}$  and  $-\frac{1}{2}$ . Correspondingly, there will be two higgsinos, which will be the main subject of our discussion later.

### 2.6.3 R-Parity Conservation

The last assumption of the MSSM would be R-Parity conservation, which is a discrete multiplicative symmetry that plays a crucial role in the theoretical and experimental landscape of supersymmetry.

It is defined as

$$R = (-1)^{2s+3B+L} \quad (2.61)$$

, where  $B$  is the baryon number,  $L$  is the lepton number, and  $s$  is the spin of the particle. The primary motivation for introducing R-parity is to prevent rapid proton decay, which would otherwise occur due to dimension-4 and dimension-5 operators that violate baryon and lepton numbers.



R-parity conservation has significant experimental consequences. Firstly, it ensures that the lightest supersymmetric particle (LSP) is stable, making it a compelling dark matter candidate. Since the LSP does not decay, it contributes to the missing transverse energy ( $E_T^{\text{miss}}$ ) signature in collider experiments, providing a distinctive signal for supersymmetry searches. Additionally, R-parity conservation implies that supersymmetric particles must be produced in pairs in high-energy collisions. This pair-production requirement further aids in distinguishing supersymmetric events from Standard Model backgrounds. Therefore, the conservation of R-parity not only addresses theoretical issues such as proton stability but also provides clear and testable predictions for experimental searches for supersymmetry.

The most general globally supersymmetric potential compatible with gauge invariance, renormalizability and R-parity conserving is:

$$W = \sum_{i,j} -Y_{ij}^u \bar{u}^i \epsilon_{ab} (H_u)^a (Q^j)^b + Y_{ij}^d \bar{d}^i \epsilon_{ab} (H_d)^a (Q^j)^b \pm Y_{ij}^l \bar{e}^i \epsilon_{ab} (H_u)^a (L^j)^b + \mu \epsilon_{ab} (H_u)^a (H_d)^b \quad (2.62)$$

Notice the explicit gauge invariance and renormalizability mass degree count here. Again we have the indices  $i, j, k$ , to represent our particle generations from 1 to 3.

#### 2.6.4 SUSY Conserving Lagrangian

Now we have all the components, the full SUSY-conserving Lagrangian of MSSM would be:

$$\mathcal{L} = \mathcal{L}_{\text{kin}} - V_F - V_D + \mathcal{L}_{\text{chiral,int}} + \mathcal{L}_{\text{mix}} \quad (2.63)$$

, where:

$$\mathcal{L}_{\text{chiral,int}} = -\frac{1}{2} \sum_{i,j} W^{ij} \psi_i \psi_j, \text{ where: } W^{ij} = \frac{\partial^2 W_{\text{MSSM}}}{\partial \phi_i \partial \phi_j} \quad (2.64)$$

$$\mathcal{L}_{\text{mix}} = -i\sqrt{2} \sum_{A,i} \frac{\partial D_A}{\partial \phi_i} \psi_i \lambda_A + h.c. \quad (2.65)$$

$$V_D = \frac{1}{2} \left[ \left( D_{U(1)_Y} \right)^2 + \left( D_{SU(2)_L} \right)^2 + \left( D_{SU(3)_C} \right)^2 \right], \text{ where : } D^a = -g (\phi^* T^a \phi) \quad (2.66)$$

, more specifically:

$$D_{U(1)_Y} = g' \left[ \sum_{i=\text{generation}} \left( \frac{1}{6} \tilde{Q}_i^\dagger \tilde{Q}_i - \frac{1}{2} \tilde{L}_i^\dagger \tilde{L}_i - \frac{2}{3} \tilde{u}_{R,i}^\dagger \tilde{u}_{R,i} + \frac{1}{3} \tilde{d}_{R,i}^\dagger \tilde{d}_{R,i} + \tilde{e}_{R,i}^\dagger \tilde{e}_{R,i} \right) + \frac{1}{2} H_u^\dagger H_u - \frac{1}{2} H_d^\dagger H_d \right] \quad (2.67)$$

$$D_{SU(2)_L} = g \left[ H_u^\dagger \frac{\vec{\sigma}}{2} H_u + H_d^\dagger \frac{\vec{\sigma}}{2} H_d + \sum_{i=\text{generation}} \tilde{Q}_i^\dagger \frac{\vec{\sigma}}{2} \tilde{Q}_i + \tilde{L}_i^\dagger \frac{\vec{\sigma}}{2} \tilde{L}_i \right] \quad (2.68)$$

$$D_{SU(3)_C} = g_s \left[ \sum_{i=\text{generation}} \tilde{Q}_i^\dagger \frac{\vec{\lambda}}{2} \tilde{Q}_i - \tilde{u}_{R,i}^\dagger \frac{\vec{\lambda}^*}{2} \tilde{u}_{R,i} - \tilde{d}_{R,i}^\dagger \frac{\vec{\lambda}^*}{2} \tilde{d}_{R,i} \right] \quad (2.69)$$

### 2.6.5 Soft SUSY Breaking

Here, we discuss the last assumption of the MSSM, which is called the Soft SUSY Breaking. Below are the terms to break the SUSY-invariance of the Lagrangian while preventing the reappearance of the quadratic divergence during the calculation of Higgs 1-loop renormalization. Note that these terms are used to explain partly why we have not been seeing these SUSY particles.

First, we could have the mass term for gauginos, including the gluinos, winos and bino.

$$-\mathcal{L}_{\text{gaugino}} = \frac{1}{2} \left[ M_1 \tilde{B} \tilde{B} + M_2 \sum_{a=1}^3 \tilde{W}^a \tilde{W}_a + M_3 \sum_{a=1}^8 \tilde{G}^a \tilde{G}_a \right] + h.c. \quad (2.70)$$

Then, we could add mass terms for the scalar super-partners of Standard Model fermions for each generation  $i$ , including the  $SU(2)_L$  doublets, the left-handed quarks and leptons, and individual

terms for all the right-handed particles:

$$-\mathcal{L}_{\text{sfermions}} = \sum_{i=\text{generation}} m_{\tilde{Q},i}^2 \tilde{Q}_i^\dagger \tilde{Q}_i + m_{\tilde{L},i}^2 \tilde{L}_i^\dagger \tilde{L}_i + m_{\tilde{u}_R,i}^2 |\tilde{u}_{R,i}|^2 + m_{\tilde{d}_R,i}^2 |\tilde{d}_{R,i}|^2 + m_{\tilde{e}_R,i}^2 |\tilde{e}_{R,i}|^2 \quad (2.71)$$

Then we have the Mass and bilinear terms of the Higgs boson:

$$-\mathcal{L}_{\text{Higgs}} = m_{H_u}^2 H_u^\dagger H_u + m_{H_d}^2 H_d^\dagger H_d + b \left( \epsilon_{ab} (H_u)^a (H_d)^b + h.c. \right) \quad (2.72)$$

And Trilinear couplings between sFermions and Higgs boson,

$$-\mathcal{L}_{\text{trilinear}} = \sum_{i,j=\text{generations}} \left[ A_{ij}^u Y_{ij}^u \tilde{u}_i H_u \epsilon_{ab} (H_u)^a (\tilde{Q}^j)^b + A_{ij}^d Y_{ij}^d \tilde{d}_i H_d \epsilon_{ab} (H_d)^a (\tilde{Q}^j)^b - A_{ij}^l Y_{ij}^l \tilde{e}_i \epsilon_{ab} (H_u)^a (\tilde{L}^j)^b \right] + h.c. \quad (2.73)$$

All of these Lagrangian terms keep the gauge invariance and renormalizability while breaking the explicit SUSY invariance in the Lagrangian, thus allowing for SUSY particles not to have the same mass as the Standard Model partners (or else we would have seen it already).

### 2.6.6 SUSY EWSB

With the SUSY EWSB, the W and B bosons can be re-written with the same convention as the Standard Model EWSB, while we would expect two Higgs Doublet to be re-written around its vev:

$$\vec{H}_d = \begin{pmatrix} H_d^0 \\ H_d^- \end{pmatrix}; \langle \vec{H}_d \rangle = \begin{pmatrix} v_d \\ 0 \end{pmatrix} \quad (2.74)$$

$$\vec{H}_u = \begin{pmatrix} H_u^+ \\ H_u^0 \end{pmatrix}; \langle \vec{H}_u \rangle = \begin{pmatrix} 0 \\ v_u \end{pmatrix} \quad (2.75)$$

### 2.6.7 Chargino and Neutralinos

The focus of the main analysis in the dissertation (Chapter 4) is on the charginos and neutralinos from the mixing of Higgsinos, Winos, and Binors, and we want to discuss their masses here briefly.

Consider the charginos first, we could first find the relevant mass term, including: the mixing term of Higgs scalar, Higgsino fermion and the gauginos; the Soft SUSY breaking term  $M_2$ , and then the Higgsino mass term in the super-potential  $W_{\text{MSSM}}$ .

$$\mathcal{L}_{\text{chargino, mass}} = \frac{ig}{\sqrt{2}} \left[ v_u \widetilde{W}^+ \widetilde{H}_d^- + v_d \widetilde{W}^- \widetilde{H}_u^+ \right] + \frac{1}{2} M_2 \left( 2 \widetilde{W}^+ \widetilde{W}^- \right) - \mu \widetilde{H}_u^+ \widetilde{H}_d^-. \quad (2.76)$$

We could then define the charged fermion as  $\psi^+$  and  $\psi^-$  for the electric charge

$$\psi^+ = \left( -i \widetilde{W}^+, \widetilde{H}_u^+ \right); \psi^- = \left( -i \widetilde{W}^-, \widetilde{H}_d^- \right), \quad (2.77)$$

and we could find the mass diagonalization as below:

$$\mathcal{L}_{\text{chargino, mass}} = -\frac{1}{2} (\psi^+, \psi^-) \begin{pmatrix} 0 & X^T \\ X & 0 \end{pmatrix} \begin{pmatrix} \psi^+ \\ \psi^- \end{pmatrix}, \quad (2.78)$$

where:

$$X = \begin{pmatrix} M & m_w \sqrt{2} \cos \theta_v \\ m_w \sqrt{2} \sin \theta_v & \mu \end{pmatrix}. \quad (2.79)$$

Note that we need two unitary matrices  $V$  and  $U$  to rotate the charged fermion to the mass eigenstates (called charginos):

$$\widetilde{\chi}_i^+ = V_{ij} \psi_j^+; \widetilde{\chi}_i^- = U_{ij} \psi_j^-; U^* X V^{-1} = M_{\text{Diagonal}}. \quad (2.80)$$

Thus we have the Lagrangian (Dirac Mass):

$$\mathcal{L}_{\text{chargino, mass}} = - \left( \widetilde{\chi}_i^- (M_{\text{Diagonal}})_{ij} \widetilde{\chi}_j^+ + h.c. \right) = - \left( \widetilde{M}_+ \widetilde{\chi}_1 \widetilde{\chi}_1 + \widetilde{M}_- \widetilde{\chi}_2 \widetilde{\chi}_2 \right) \quad (2.81)$$

Similarly, we can derive the neutralino mass diagonalization by a unitary matrix  $N$ : it has all the relevant terms just like in the chargino case, except now we have four neutral fermions, which are: The neutral Wino and Bino, and the two neutral Higgsinos. We would have the four neutral fermions mass eigenstates  $\chi_{i=1,2,3,4}^0$  (called neutralinos), with masses from small to large. In the notation of Martin:

$$\mathcal{L}_{\text{chargino,mass}} = \frac{1}{2}ig\widetilde{W}^3 \left( v_u\widetilde{H}_u^0 - v_d\widetilde{H}_d^0 \right) - ig'\widetilde{B} \left( v_u\widetilde{H}_u^0 - v_d\widetilde{H}_d^0 \right) + \frac{1}{2}M_2\widetilde{W}^3\widetilde{W}^3 + \frac{1}{2}M_1\widetilde{B}\widetilde{B} + \mu\widetilde{H}_u^0\widetilde{H}_d^0 + h.c. \quad (2.82)$$

We put together the neutral fermions in its gauge eigenstates:

$$\psi_j^0 = \left( -i\widetilde{B}, -i\widetilde{W}^3, \widetilde{H}_u^0, \widetilde{H}_d^0 \right), \quad (2.83)$$

and then we apply the mass diagonalization:

$$\mathcal{L}_{\text{neutralino,mass}} = -\frac{1}{2}(\psi^0)^T Y \psi^0 + h.c., \quad (2.84)$$

where:

$$Y = \begin{pmatrix} M_1 & 0 & -m_z \sin \theta_v \sin \theta_w & m_z \cos \theta_v \sin \theta_w \\ 0 & M_2 & m_z \sin \theta_v \cos \theta_w & -m_z \cos \theta_v \cos \theta_w \\ -m_z \sin \theta_v \sin \theta_w & m_z \sin \theta_v \cos \theta_w & 0 & -\mu \\ m_z \cos \theta_v \sin \theta_w & -m_z \cos \theta_v \cos \theta_w & -\mu & 0 \end{pmatrix}. \quad (2.85)$$

The resulting mass eigenstates are the neutralinos:

$$\widetilde{\chi}_i^0 = N_{ij}\psi_j^0, \quad (2.86)$$

where unitary matrix satisfying:  $N^* Y N^{-1} = N_D$ .

### 2.6.8 Low- $\mu$ Split SUSY Scenario

In this dissertation, we focus on the case where  $\mu \ll M_1 < M_2$ , commonly known as the low- $\mu$  split SUSY scenario. Here, the Higgsino mass parameter ( $\mu$ ) is relatively low compared to the masses of other superpartners. This model splits the SUSY particles into two distinct groups:

**Light Higgsinos:** These fermionic superpartners of the Higgs boson have masses close to the weak scale, typically around 100 GeV to a few TeV. They are well-motivated by the naturalness argument, serve as good dark matter candidates, and provide distinct collider phenomenology. Further details are elaborated in Chapter 4.

**Heavy Scalars and Gauginos:** The scalar superpartners (squarks and sleptons) and gauginos (gluinos and other gauge boson superpartners) are assumed to be much heavier, often at the multi-TeV scale. Consequently, they are less accessible to current collider experiments.

As shown by [44], we can expand the tree-level neutralino and chargino masses in terms of  $\delta = \mu/M_1$ :

$$m'_{\tilde{\chi}_1^0} = \mu \left[ 1 - \frac{1}{2}(1 - \sin 2\beta)(\cos \theta_w^2 + r_2 \sin \theta_w^2) \frac{r_z^2}{r_2} \delta + \mathcal{O}(\delta^2) \right], \quad (2.87)$$

$$m'_{\tilde{\chi}_2^0} = -\mu \left[ 1 + \frac{1}{2}(1 + \sin 2\beta)(\cos \theta_w^2 + r_2 \sin \theta_w^2) \frac{r_z^2}{r_2} \delta + \mathcal{O}(\delta^2) \right], \quad (2.88)$$

$$m'_{\tilde{\chi}_3^0} = M_1 [1 + \mathcal{O}(\delta^2)], \quad (2.89)$$

$$m'_{\tilde{\chi}_4^0} = M_2 [1 + \mathcal{O}(\delta^2)], \quad (2.90)$$

$$m_{\tilde{\chi}_1^\pm} = \left| \mu \left( 1 + \sin 2\beta \frac{m_W^2}{M_2 \mu} \right) \right|, \quad (2.91)$$

$$m_{\tilde{\chi}_2^\pm} = M_2 \left( 1 + \sin 2\beta \frac{m_W^2}{M_2^2} \right), \quad (2.92)$$

, where  $r_2 = M_2/M_1$ , and  $r_z = m_Z/\mu$ .

In the main analysis of this dissertation, this scenario is referred to as a compressed mass spectrum for the lightest chargino and neutralinos, because the mass differences result in significant collider event signatures, discussed in more detail in Chapter 4.

As shown in Equations 2.93, if  $\tan \beta \gg 1$ , we will have  $\Delta M_{12}^{\text{tree}} \simeq 2 \Delta M_+^{\text{tree}}$ . This will be an assumption used in the sample generation and statistical interpretation of the displaced-track analysis described in Chapter 4.

$$\Delta M_{12}^{\text{tree}} \equiv m_{\tilde{\chi}_2^0} - m_{\tilde{\chi}_1^0} = \left[ 1 + \tan^2 \theta_W \frac{M_2}{M_1} \right] \frac{m_W^2}{M_2}, \quad (2.93)$$

$$\Delta M_+^{\text{tree}} \equiv m_{\tilde{\chi}_1^+} - m_{\tilde{\chi}_1^0} = \frac{1}{2} \left[ 1 + (1 - \sin 2\beta) \tan^2 \theta_W \frac{M_2}{M_1} \right] \frac{m_W^2}{M_2}. \quad (2.94)$$

## 2.7 Search for MSSM

### 2.7.1 Phenomenological-MSSM (pMSSM)

The unconstrained MSSM (uMSSM) features an overwhelmingly large parameter space, with 105 free parameters beyond the 19 parameters of the Standard Model, posing significant challenges for phenomenological analysis and predictive modeling<sup>4</sup>. To render the MSSM more practical for experimental and theoretical studies, several phenomenological constraints are applied to reduce the number of free parameters significantly.

1. **CP Violation:** Experimental constraints on electric dipole moments in systems such as electrons and neutrons severely limit new sources of CP violation. By setting all phases in the soft SUSY-breaking potential to zero, the model effectively eliminates any new sources of CP violation, drastically reducing the number of parameters.
2. **Flavor Changing Neutral Currents (FCNCs):** To avoid large FCNCs, which are tightly constrained by experimental data (e.g., from  $K^0 - \bar{K}^0$  mixing), the non-diagonal terms in the sfermion mass matrices and the trilinear coupling matrices are set to be zero, further simplifying the parameter space.
3. **First and Second Generation Universality:** Given the stringent experimental limits on the mass differences between the first and second-generation squarks, these masses are

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<sup>4</sup>This section briefly summarizes the discussion made in [45].

assumed to be equal unless they exceed 1 TeV. This uniformity extends to the trilinear couplings  $A_u$ ,  $A_d$ , and  $A_l$  for the first two generations, which are set to zero due to their proportionality to the small fermion masses of these generations.

These assumptions lead to a more manageable model known as the phenomenological MSSM (pMSSM), which comprises only 19 input parameters:

- $\tan \beta$ : The ratio of the vacuum expectation values (vev) of the two Higgs doublets.
- $M_A$ : The mass of the pseudo-scalar Higgs boson.
- $\mu$ : The Higgsino mass parameter.
- $M_1, M_2, M_3$ : The mass parameters for the bino, wino, and gluino, respectively.
- $m_{\tilde{q}}, m_{\tilde{u}_R}, m_{\tilde{d}_R}, m_{\tilde{l}}, m_{\tilde{e}_R}$ : Masses for the first/second generation sfermions.
- $m_{\tilde{Q}}, m_{\tilde{t}_R}, m_{\tilde{b}_R}, m_{\tilde{L}}, m_{\tilde{\tau}_R}$ : Masses for the third generation sfermions.
- $A_t, A_b, A_\tau$ : Third-generation trilinear couplings.

### 2.7.2 Likelihood-Driven Parameter Scan in the EWKH Model

In a study documented by the ATLAS collaboration [7], a focused scan of a five-dimensional effective model—labeled as EWKH—was conducted, emphasizing the gaugino-higgsino and Higgs sectors of the pMSSM. This model is driven by parameters relevant to dark matter characteristics and constraints from precision physics, making it highly pertinent for studies targeting dark matter within the MSSM framework.

The primary motivation for this scan is to identify models within the pMSSM parameter space that correspond to realistic dark matter scenarios, particularly focusing on the properties of the lightest neutralino ( $\tilde{\chi}_1^0$ ) as a dark matter candidate.

The EWKH model contains a set of parameters ( $M_1, M_2, \mu, \tan \beta$ , and  $m_A$ ) that define the gaugino-



higgsino interactions and the Higgs sector at tree level. The constraints applied in the scan include:

- Direct dark matter detection limits.
- Relic density of dark matter as measured by the Planck observatory.
- Flavor physics results and electroweak precision data.
- ATLAS measurements of the Higgs boson mass and chargino mass limits from LEP.

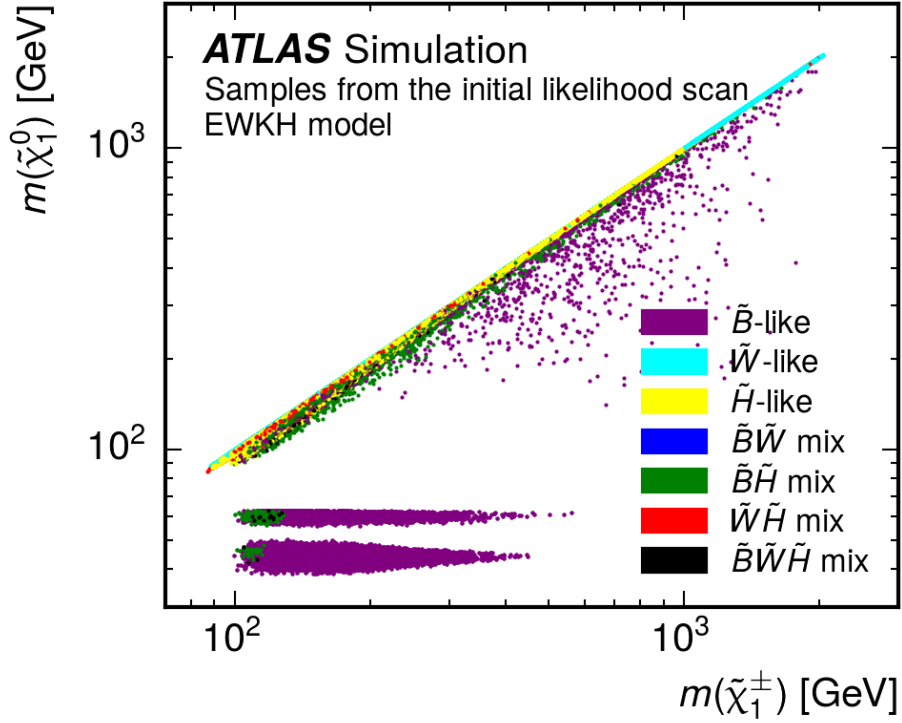


Figure 2.11: From Paper [7]: Scatter plot of models in the  $m(\tilde{\chi}_1^0)$  vs.  $m(\tilde{\chi}_1^\pm)$  plane with the colour encoding which category of  $\tilde{\chi}_1^0$  composition the model belongs to. The  $\tilde{\chi}_1^0$  is defined as bino-like ( $\tilde{B}$ -like), wino-like ( $\tilde{W}$ -like) or higgsino-like ( $\tilde{H}$ -like) if the corresponding fraction of contribution is at least 80%. A mixed  $\tilde{\chi}_1^0$  has at least 20% of each denoted component and  $< 20\%$  of any other component. The models considered are all within the 95% confidence region found using the initial likelihood scan.

The results 2.11 from the initial likelihood scan identified regions with distinct neutralino compositions:

- **Z-funnel and h-funnel regions:** These areas are characterized by enhanced annihilation cross-sections due to proximity to the Z-boson or the lightest Higgs boson mass, making them significant for studies involving bino-like or mixed neutralino compositions.
- **Compressed Spectrum Region:** This region is particularly intriguing as it suggests scenarios where the LSP is nearly degenerate in mass with the next-to-lightest supersymmetric particle (NLSP), typically leading to distinct long-lived or semi-long-lived chargino experimental signatures. Such regions are promising for higgsino-like LSPs, aligning with the focus of higgsino-centric dark matter analyses.

The EWKH model, with its emphasis on a manageable number of defining parameters and a robust set of physical constraints, serves as a good framework for exploring the implications of SUSY in the context of dark matter. It suggests promising starting points in the mass plane for detecting SUSY particles in collider experiments. In Chapter 4, we present a compressed spectra Higgsino search with the ATLAS Run-2 dataset.

## CHAPTER 3

### The Large Hadron Collider and the ATLAS Experiment

## 3.1 The Large Hadron Collider

### 3.1.1 Basic Principles of Large Hadron Collider

The Large Hadron Collider (LHC) at the European Organization for Nuclear Research (CERN) is the world's most powerful particle accelerator, designed to investigate the fundamental structure of matter.

- The **de Broglie wavelength principle** states that a particle's wavelength is inversely proportional to its momentum,  $\lambda = h/p$ . Operating at center-of-mass energies up to 13 teraelectronvolts (TeV), the LHC enables studies at scales as small as  $1.91 \times 10^{-7}$  picometers. This capability enables studies of matter interactions at unprecedented scales.
- According to **Einstein's mass-energy equivalence**,  $E = mc^2$ , the LHCs high energies can convert kinetic energy into mass, allowing for the creation of previously unobserved particles. This capability led to the 2012 discovery of the Higgs boson, a particle with a mass of about 125 gigaelectronvolts (GeV), highlighting the colliders unique role in probing new physics.
- By **Boltzmann's relation**,  $E = k_B T$ , the LHCs energies correspond to extreme temperatures similar to those just after the Big Bang. This allows physicists to study matter and fundamental forces under such extreme conditions, providing experimental insights into the universe's early moments.

Through these principles, the LHC opens pathways to understanding both elementary particles and the conditions of the early universe.

### 3.1.2 Why Proton-Proton Collisions

Proton-proton (pp) collisions were chosen for the LHC, replacing the Large Electron-Positron (LEP) Collider, because protons, being approximately 2,000 times heavier than electrons, lose far less energy to synchrotron radiation when accelerated in circular paths. Synchrotron radiation scales inversely with the fourth power of the particle's mass, making electron-based circular colliders impractical at such high energies, as the required energy input would be unfeasible. Additionally, the energy of pp collisions is limited by the radius of the inherited LHC tunnel (from LEP) and the practical operational limits of its superconducting magnet technology, which define the maximum magnetic field and, consequently, the maximum energy of the protons.

Asymptotic Freedom dictates that quarks and gluons interact more weakly at high energies. This principle makes it possible for the LHC to use perturbative QCD calculations for accurate experimental predictions, which are essential for exploring new particles. It also enables the study of short-distance phenomena, such as quark-gluon plasma formation.

Proton accelerators are currently more practical and cost-effective than electron-positron or muon colliders, although the latter is advancing. Recently, the U.S. established a Muon Collider Collaboration to pursue the development of a muon collider as a compact, energy-efficient alternative capable of reaching energies beyond 10 TeV. However, this technology remains in the R&D stage, with a projected timeline of 20 years for readiness of the machine [46].

Proton collisions also bring specific challenges. They produce complex events with high background noise, complicating data analysis (see Section 3.2.2). Collisions also create multiple interactions and thus jets per bunch crossing, as quarks recombine into hadrons, which can obscure detector readings (see Section 4.7.3). Additionally, only a fraction of a proton's momentum participates in each collision, leading to unknown momentum along the beamline. In electron-positron collisions, by contrast, incoming momenta are known and will make event reconstruction better.

## The CERN accelerator complex *Complexe des accélérateurs du CERN*

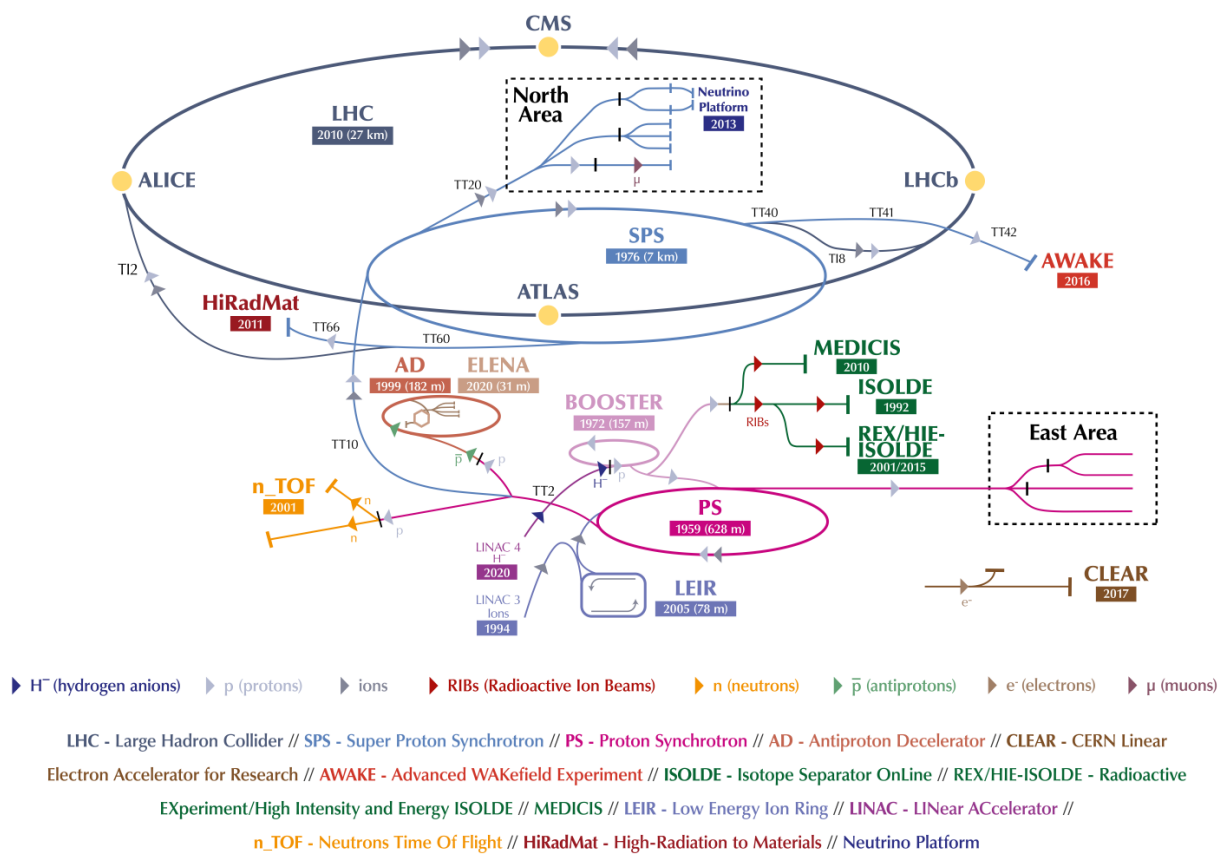


Figure 3.1: The CERN accelerator complex, layout in 2022. [8]

### 3.1.3 Basic Information of LHC

The LHC is the final stage in CERNs Accelerator Complex (Figure 3.1). Protons begin in a linear accelerator (LINAC), which injects low-energy protons into the Proton Synchrotron Booster (PSB). From there, they are transferred to the Proton Synchrotron (PS), reaching 25 GeV, and then to the Super Proton Synchrotron (SPS), where they are accelerated to 450 GeV. Finally, protons enter the LHC, where they reach a collision energy of 13 TeV in detectors like ATLAS.

The LHC consists of a 27-kilometer ring of superconducting magnets and accelerating structures. Inside, two particle beams travel in opposite directions at nearly the speed of light within ultra-high vacuum beam pipes. The beams are guided by strong magnetic fields generated by superconducting magnets operating at cryogenic temperatures, allowing efficient, resistance-free current flow.

In the LHC, protons are organized into bunches, with each bunch containing approximately  $1.1 \times 10^{11}$  protons. These bunches cross every 25 nanoseconds, producing frequent proton-proton collisions. This high rate of collisions is essential for data collection but also causes multiple simultaneous collisions, or “pile-up”, which complicate data interpretation (see Section 4.7.3).

Since its commissioning in 2008, the LHC has evolved through distinct Runs. **Run 1** (2010-2013) operated at 7-8 TeV and led to the discovery of the Higgs boson. **Run 2** (2015-2018) achieved 13 TeV and unprecedented luminosity, enabling precise Higgs measurements and new physics searches. **Run 3** (2022-2025) pushes on with higher energy (13.6 TeV) and higher luminosity, paving the way for the **High Luminosity LHC (HL-LHC)**, which aims for a tenfold increase in integrated luminosity.

Luminosity, a key performance measure, represents the number of potential collisions per area per second. The integrated luminosity of the full ATLAS Run-2 dataset is measured at  $L = 140.1 \pm 1.2 \text{ fb}^{-1}$ , with a precision of 0.83%, and reached a peak of  $1.9 \times 10^{34} \text{ cm}^{-2} \text{ s}^{-1}$  [47]. This increased luminosity has been essential for probing rare processes with low cross-sections, such as chargino and neutralino production in supersymmetry theories—which is central to this dissertation—and has significantly expanded the experimental reach of ATLAS for new physics discoveries.

## 3.2 Observable Objects from Proton Collisions

This section aims to discuss what might come out of the proton-proton collisions in the Large Hadron Colliders and get detected by the ATLAS detector.

### 3.2.1 Elementary Particles & Long-lived Particles

In high-energy proton-proton collisions at the Large Hadron Collider, a diverse array of particles is produced, primarily through interactions described by the Standard Model Lagrangian. These interactions give rise to a variety of elementary particles including quarks, gluons, W and Z bosons, photons, and the Higgs boson. Although these particles often decay almost instantaneously, the collisions eventually yield more stable particles that are detectable by instruments such as the ATLAS detector.

Among these detectable particles are elementary particles such as electrons and muons, which are noted for their relatively long lifetimes and stability. Photons, which are massless, are also readily observed due to their distinct interactions with the detector material. Additionally, long-lived hadrons—including neutrons and protons, as well as mesons like pions and kaons—can be identified. These hadrons are relatively long-lived compared to other members of their family, making them detectable after traversing measurable distances within the detector. Figure 4.9 illustrates some of these particles, noting their lifetimes and masses.

The detection and analysis of these observable particles are instrumental to experimental research at the LHC. Specific detection techniques and methodologies are discussed in Section 3.3.

### 3.2.2 Jet Formation in High-Energy Collisions

In high-energy collisions at the LHC, protons are accelerated to near-light speeds and collide. Despite the high energy sufficient to unbind quarks (due to asymptotic freedom), these quarks do not exist freely after the initial collision (due to color confinement); instead, they rapidly form “jets” of particles through a process known as hadronization.

**Jets** are essentially narrow cones of particles produced in high-energy processes involving quarks and gluons. The formation of jets occurs in several distinct stages:

- **Scattering:** Inside the protons, quarks, and gluons are scattered outwards by the immense energy of the collision.
- **Parton Shower:** The scattered high-energy quarks and gluons emit additional gluons, all carrying their individual color charges. These gluons can decay into quark-antiquark pairs, initiating a cascade of particles known as a parton shower. This process occurs rapidly and involves multiple generations of particle production.
- **Hadronization:** As partons (quarks and gluons) move away from the collision point, the energy of the gluon field between them increases. When it becomes energetically favorable, strong force fields generate new quark-antiquark pairs. These pairs, along with the original quarks and anti-quarks, combine to form hadrons—typically mesons (quark-antiquark pairs) and baryons (triplets of quarks), so that they are color-neutral. An illustration of parton showering and hadronization can be found in Figure 3.2.
- **Jet Detection:** The resulting group of hadrons moves in almost the same direction as the original high-energy quark or gluon, forming a “jet”. These jets are detected in the ATLAS detector as clusters of energy deposits across various detector components. An example of a mono-jet event in the ATLAS detector can be found in Figure 3.3, where one could observe a cluster of particle tracks and energy deposit in the calorimeters. Jets are crucial for experiments because they provide insight into the high-energy quarks and gluons initially involved in the collision. Further details on jet detection and reconstruction techniques will be discussed in Section 3.5.

### 3.2.3 Detection of Invisible Particles

During proton-proton collisions at the LHC, certain particles such as neutrinos ( $\nu$ ) and hypothesized dark matter candidates (e.g., the lightest neutralino  $\tilde{\chi}_1^0$  in the Minimal Supersymmetric Standard



### Generation of an $e^+e^- \rightarrow t\bar{t} \rightarrow b\bar{b}W^+W^-$ event

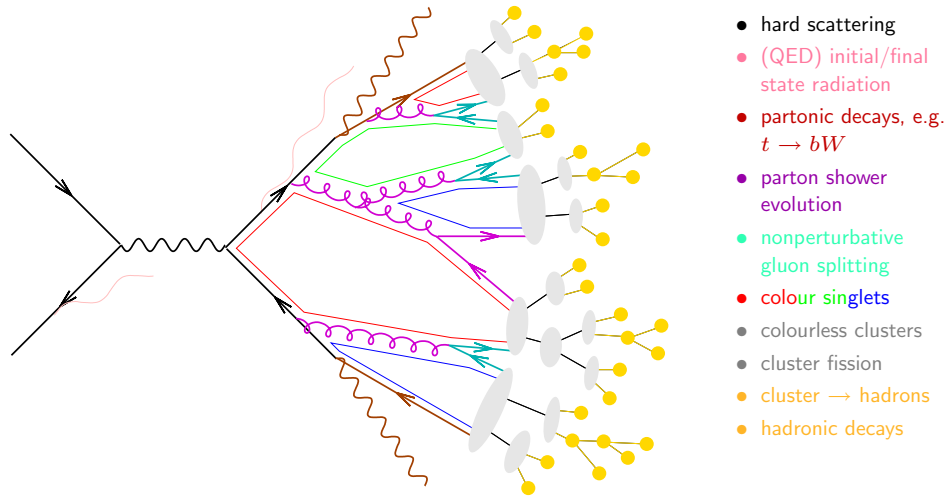


Figure 3.2: Generation of an  $e^+e^- \rightarrow t\bar{t} \rightarrow b\bar{b}W^+W^-$  event. The figure illustrates various stages of the process, including hard scattering, partonic decays, parton shower evolution, non-perturbative gluon splitting, formation of color singlets, and hadronic decays. Slide by Dr. Dieter Zeppenfeld (University of Karlsruhe) during the Prospects in Theoretical Physics (PiTP) 2005 Lecture Series at IAS, Princeton ([9]). Although this example originates from  $e^+e^-$  collision, the focus is on the resulting jets, so the collision type is not important.

Model (MSSM)) are not detectable directly, due to their weak or non-existent interactions with matter in the detector. These particles are referred to as “invisible particles”.

The presence of invisible particles can be inferred from the conservation of momentum, a principle governed by Lorentz symmetry in the framework of special relativity. When invisible particles carry away significant momentum, they create an imbalance detectable in the orthogonal plane to the collision axis. This is described as the missing transverse momentum, denoted as  $\vec{E}_{\text{miss}}^T$ .

Due to the protons being composed of quarks and gluons, which are the actual collision participants, precise momentum of the colliding quarks and gluons along the beamline ( $Z$  direction) remains unknown. This uncertainty restricts the momentum measurement to a two-dimensional plane perpendicular to the beam direction. A typical event at the ATLAS detector illustrating such a momentum imbalance is shown in Figure 3.3, where the missing transverse momentum is a key indicator suggesting the presence of invisible particles.

The measurement of  $\vec{E}_{\text{miss}}^T$  is crucial for searches aiming to discover new physics phenomena, such as those predicted by supersymmetry or theories involving dark matter, such as the search for charginos and neutralinos in the Compressed Mass Spectra presented in Chapter 4.

## 3.3 The ATLAS Detector

### 3.3.1 Overview of Particle Detection in the ATLAS Detector

A Toroidal LHC ApparatuS (ATLAS) is a multi-purpose detector designed to observe and measure the myriad of particles produced by the proton-proton collisions at the Large Hadron Collider. It incorporates various components designed to detect different types of particles and interactions. The ATLAS detector includes four major components, :

- **The Inner Detector (Section 3.3.2)** for tracking charged particles,
- **The Calorimeter (Section 3.3.3)** for measuring particle energy,

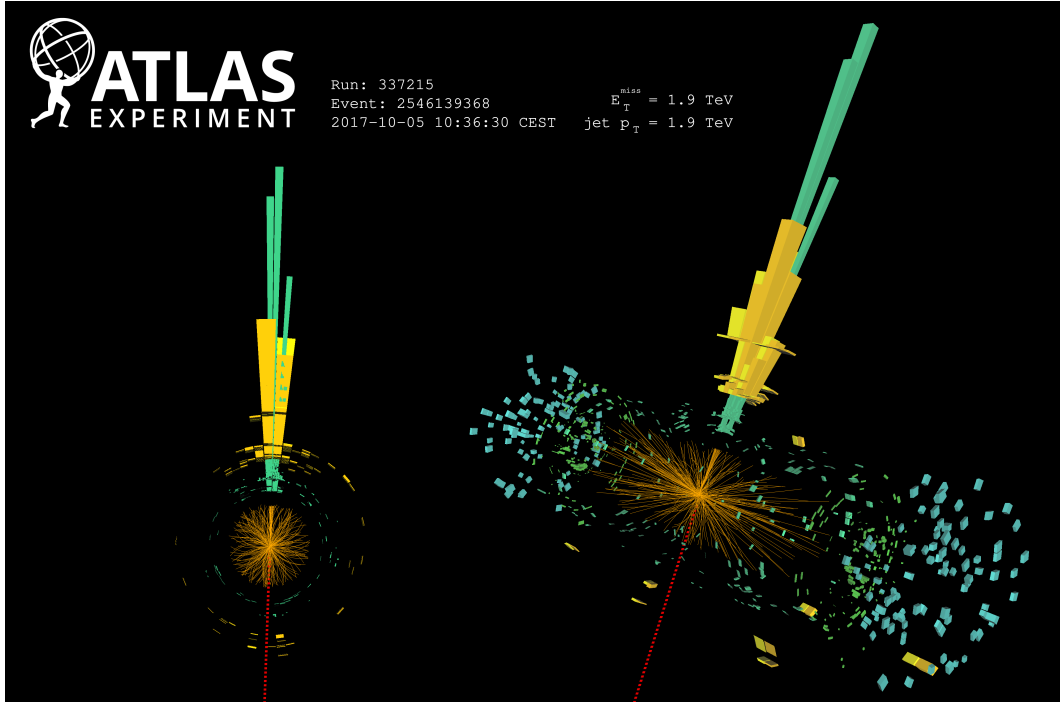


Figure 3.3: An ATLAS monojet event [10] with a 1.9 TeV jet recoiling against an invisible particle carrying the “missing transverse momentum” (MET). Green and yellow bars indicate energy deposits in the electromagnetic and hadronic calorimeters, respectively, while the red dashed line represents MET on the opposite side.

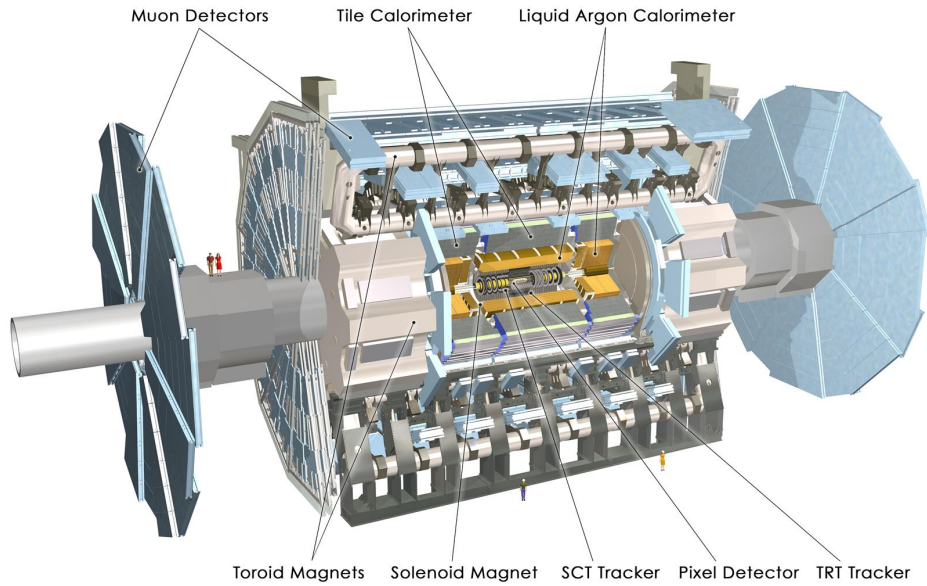


Figure 3.4: A computer-generated image [11] of the ATLAS detector including the Inner Detector trackers, the Calorimeters, the Muon Spectrometer and the Magnet System.

- **The Muon Spectrometer (Section 3.3.4)** for detecting muons,
- **The Magnet System (Section 3.3.5)** which consists of a solenoid around the inner detector and toroids around the muon spectrometer, facilitating precise measurement of particle momentum.

Figure 3.5 shows how the analysis objects discussed in Section 3.2 can be identified and measured by individual parts of the detector.

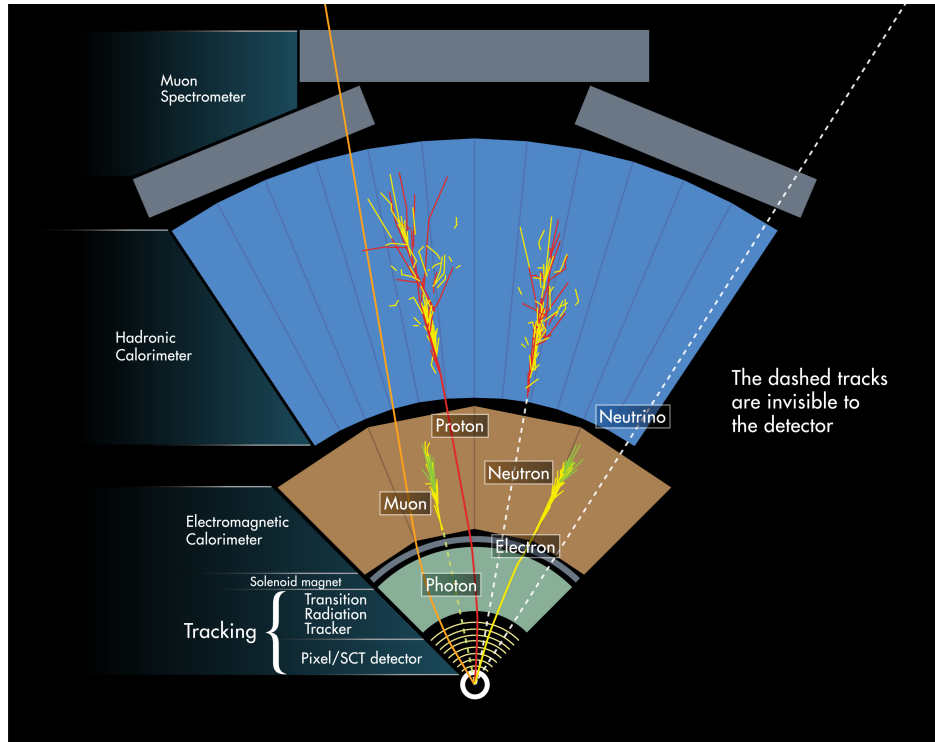


Figure 3.5: How ATLAS detects particles [12]: diagram of particle paths in the detector. The charged particles trajectories will be bent by the magnets and detectable in the tracking layers. Photons and Electron will create distinct shower shape in the Electromagnetic Calorimeter, and all baryonic particles will deposit their energy in the hadronic calorimeter. The muon will penetrate the whole system, and be measured by the dedicated Muon Spectrometer. The weakly-interacting particles like the neutrinos will leave no trace in the detector.

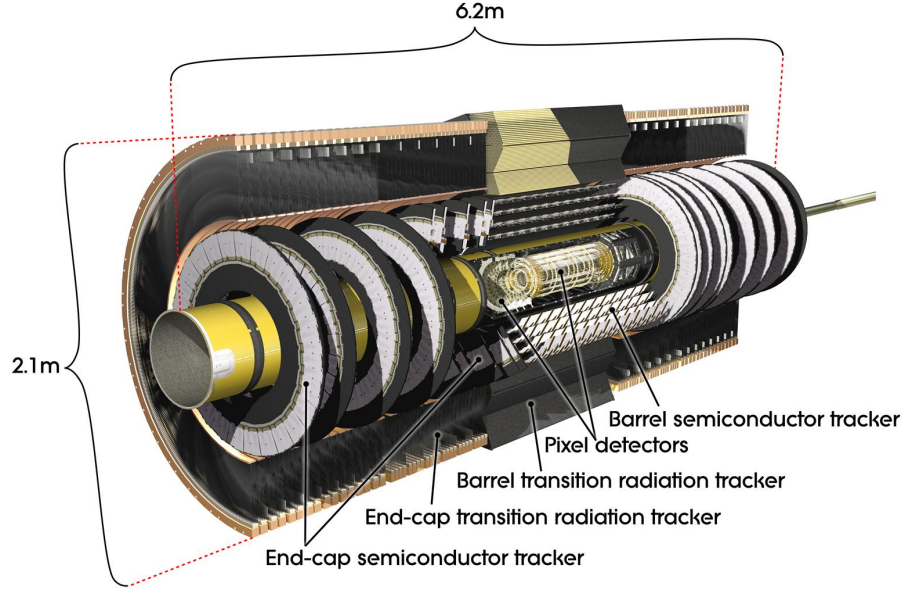


Figure 3.6: A computer-generated image of the ATLAS inner detector [13] including: pixel detectors, semiconductor tracker (SCT) and transition radiation tracker (TRT).

### 3.3.2 Particle Tracking: Inner Detector

The Inner Detector is crucial for observing the trajectories and capturing the properties of charged particles emerging from collisions. It is composed of three main components, each specialized in various aspects of particle tracking and identification:

#### Pixel Detector

- With the innermost layer positioned 3.3 cm from the LHC beam line, the Pixel Detector is the closest to the collision point.
- Comprised of four layers of silicon pixels, it has a total of 92 million pixels covering an area of approximately  $1.9 \text{ m}^2$ .
- Each pixel measures  $50 \times 400 \mu\text{m}^2$  in the outer layers and  $50 \times 250 \mu\text{m}^2$  in the innermost layer, providing high-resolution tracking capabilities.

**Semiconductor Tracker (SCT)** - Surrounding the Pixel Detector, the SCT extends the tracking

capabilities by using over 6 million micro-strip silicon sensors arranged in 4,088 two-sided modules.

- These micro-strips are spaced every  $80\text{ }\mu\text{m}$  and span a total silicon area of  $60\text{ m}^2$  across the cylindrical barrels and planar endcaps.
- The layout ensures that each charged particle crosses at least four layers of sensors, allowing for precise track reconstruction.

**Transition Radiation Tracker (TRT)** - The outermost component of the Inner Detector, the TRT, consists of 300,000 thin-walled drift tubes, each 4 mm in diameter.

- A central  $30\text{ }\mu\text{m}$  gold-plated tungsten wire runs through each straw tube, which is filled with a gas mixture, initially xenon-based, now primarily argon due to excessive leakage, as xenon is significantly more expensive.
- As charged particles pass through these straws, they ionize the gas, and the liberated electrons drift toward the wire, creating a detectable electric signal.
- The TRT not only tracks particles but also helps identify them. Electrons, being much lighter than pions, achieve relativistic speeds at lower energies and emit significantly more transition radiation, making them distinguishable from pions in the TRT.

The Inner Detector plays a crucial role in the initial detection and precise measurement of charged particle trajectories, enabling accurate momentum determination and providing essential data for subsequent detector layers. Pixel detectors, positioned near the interaction point, offer high-resolution tracking in dense particle regions, while strip detectors, located further out, provide cost-effective tracking over larger areas with slightly lower spatial resolution. A layered visualization of the three different components can be found in Figure 3.7.

### 3.3.3 Energy Measurement: Calorimetry

The calorimeters in the ATLAS detector measure the energy of the particles. They are designed to ensure that most particles interact and deposit all of their energy in the detector and measure

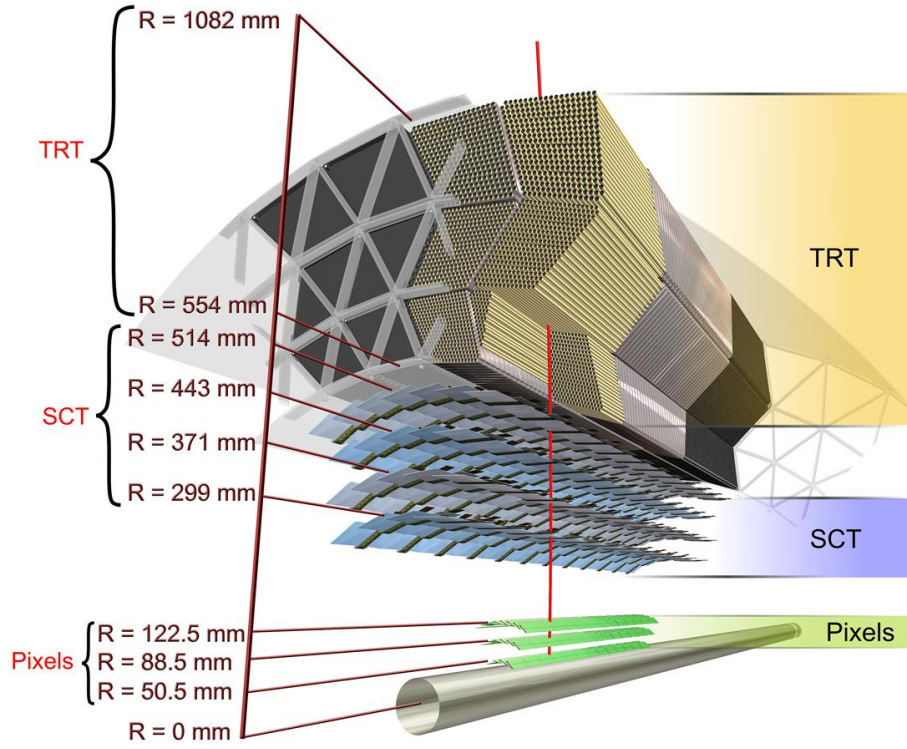


Figure 3.7: Cross-sectional view of the three major components of the ATLAS Inner Detector. [13]

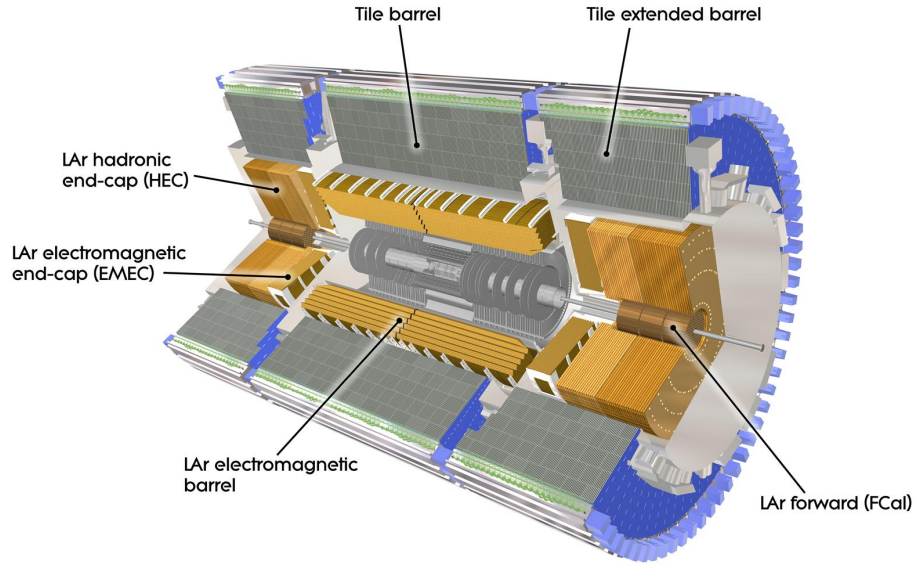


Figure 3.8: A computer-generated image of the ATLAS Calorimeters including the liquid argon Electromagnetic calorimeter, and steel and scintillator tile calorimeters. [14]

the deposited energy; the exceptions are muons and neutrinos. The calorimeters are layered, with the inner layers optimized for electromagnetic (EM) interactions and the outer layers designed for hadronic interactions. To achieve this, two technologies are employed: liquid argon (LAr) is used for both EM and hadronic calorimetry, while tile calorimetry serves as a key component of the hadronic calorimeter in the central region.

### Liquid Argon (LAr) Calorimeter

The LAr Calorimeter, surrounding the ATLAS Inner Detector, is essential for measuring the energy of electrons, photons, and hadrons. It consists of alternating layers of metal absorbers (tungsten, copper, or lead) and liquid argon—the active medium. As particles penetrate the metal layers, they initiate a cascade of lower energy particles that ionize the liquid argon, generating an electric current proportionate to their energy.

The LAr Calorimeter combines the liquid argon (LAr) sampling technique with an accordion geometry and a fast readout, achieved by utilizing the fast rise of the signal pulse in the LAr and



efficiently transmitting it directly through the accordion electrodes to the preamplifiers[48]. This design, pioneered by the RD3 Collaboration, ensures high granularity, low noise, and uniform coverage, meeting the LHCs stringent 25 ns timing requirements[49]. This system is maintained at -184°C to keep the argon in a liquid state, with vacuum-sealed cables transmitting signals to the external readout electronics.

- EM Barrel: 6.4m long, 53cm thick, with 110,000 readout channels. It consists of two wheels, each containing 1024 steel-clad lead absorbers. These absorbers are interleaved with an equal number of electrodes, separated by a 2.1 mm honeycomb structure that defines the gap size.[50]
- EM Endcaps: Each with a thickness of 0.632m and radius of 2.077m and follows the same alternating structure of absorbers and liquid argon layers..
- Hadronic Endcap Calorimeter (HEC): Consist of two wheels, each with thicknesses of 0.8m and 1.0m, and a radius of 2.09m. Each is divided into 32 modules. These modules alternate between copper absorbers, 25 mm thick in the first wheel and 50 mm thick in the second, and liquid argon layers for energy sampling.
- Forward Calorimeter (FCal): Includes three modules, each with a radius of 0.455m and thickness of 0.45m, using alternating tungsten absorbers and liquid argon layers.

## **Tile Calorimeter**

Surrounding the LAr Calorimeter, the Tile Calorimeter is measures the energy of the heavier hadronic particles that traverse the LAr layers. Constructed from steel and scintillating plastic tiles, this calorimeter captures the energy of particle showers initiated by interactions in the steel. The scintillating tiles absorb the particle energy and emit photons, which are then converted into electrical signals. The Tile Calorimeter is the heaviest component of the ATLAS detector, weighing approximately 2900 tonnes. It is composed of:

- A central barrel with 64 wedges, each 5.6m long, and two extended barrels, each with 64

wedges, 2.6m long.

- 420,000 scintillating tiles, utilizing 9,500 photomultiplier tubes to detect emitted photons.

### 3.3.4 Muon Detection: Muon Spectrometer

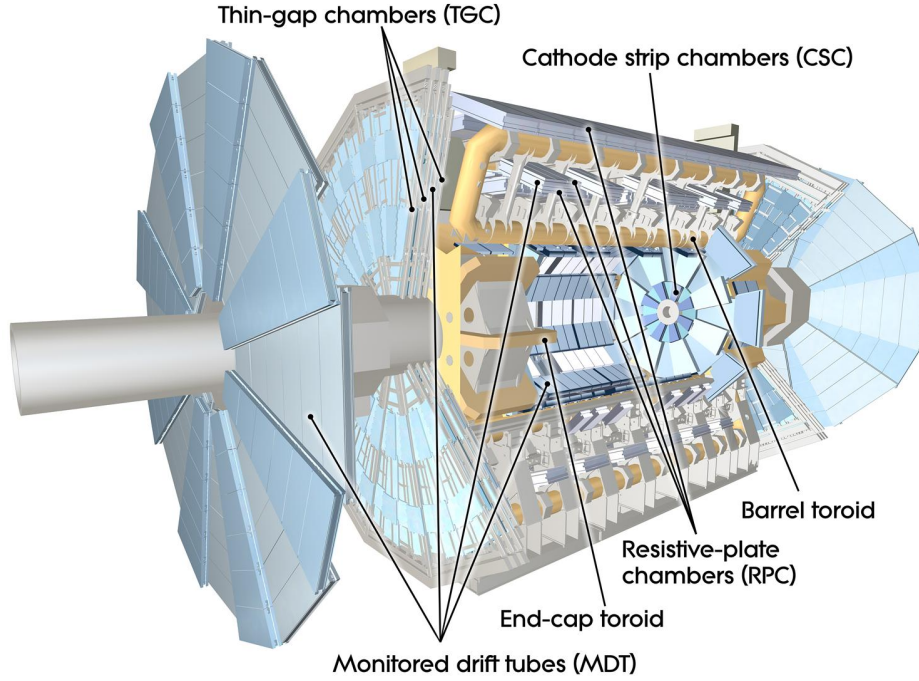


Figure 3.9: Computer generated image of the ATLAS Muon System and its components: Monitored Drift Tubes (MDTs), Cathode Strip Chambers (CSC), Resistive Plate Chambers (RPC) and Thin Gap Chambers (TGC). [15]

The Muon Spectrometer (MS) is the outermost layer of the ATLAS experiment and is critical for identifying muons and measuring their momenta. Due to the muons' mass—about 200 times greater than that of electrons—muons can penetrate the dense material of the calorimeters. This Muon Spectrometer operates independently from the Inner Detector, focusing exclusively on muon measurement due to its significance in physics analysis. The Muon Spectrometer utilizes three large air-core superconducting toroidal magnets, comprising two endcaps and one barrel, each equipped with eight coils (Section 3.3.5). These magnets generate a field integral ranging from 2.0 Tm to 6.0 Tm across most detector acceptance, which is crucial for bending the muon trajectories and allowing for precise momentum measurements.

In the central barrel region, the detectors form three concentric cylindrical shells around the beam axis, whereas in the endcap regions, the detectors are organized into large wheels perpendicular to the Z-axis. This configuration ensures comprehensive coverage around the collision point.

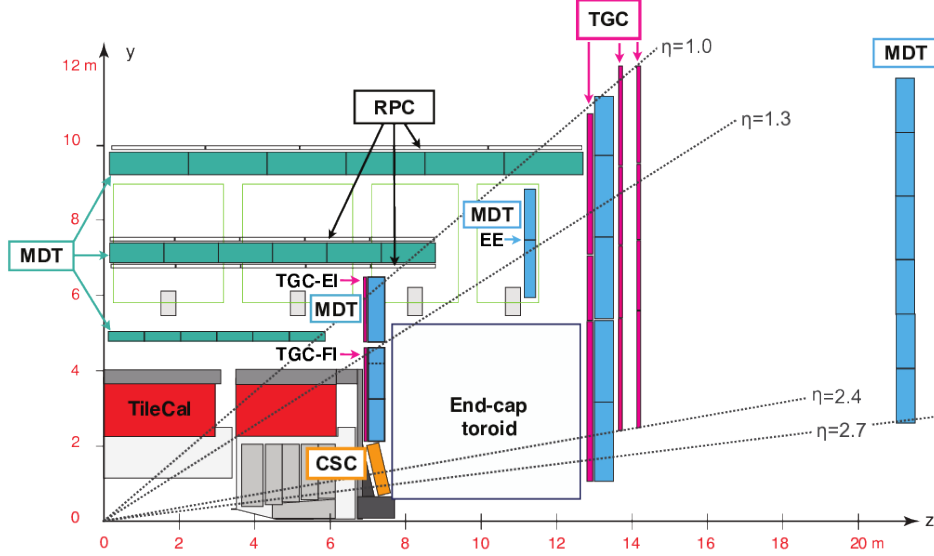


Figure 3.10: Schematic showing a quarter-section of the Muon System. [16]

The Muon System incorporates the following components for precision tracking and effective triggering (layout shown in Figure 3.10):

- **Monitored Drift Tubes (MDTs):** Used for precision tracking, MDT chambers consist of three layers for  $|\eta| < 2.0$ .
- **Cathode Strip Chambers (CSC)** Positioned in the forward regions, CSCs enhances the measurement capability in the range of  $2.0 < |\eta| < 2.7$ . The CSCs ensure robustness and high-resolution measurement in the forward region with intense particle flux.
- **Resistive Plate Chambers (RPC) and Thin Gap Chambers (TGC):** These technologies provide fast response times necessary for Level 1 (L1) muon triggering. RPCs are deployed in the barrel region for  $|\eta| < 1.05$ , while TGCs are utilized in the endcap regions between  $1.05 < |\eta| < 2.4$ . The arrangement makes rapid read-out of coordinates, which is critical for timely event selection and data acquisition.

### 3.3.5 Magnet System

The ATLAS magnet system is crucial for bending the trajectories of charged particles, allowing for precise measurements of their momentum and charge. This system uses two types of superconducting magnets, solenoidal and toroidal, are cooled to about 4.5 K (268°C).

#### Central Solenoid Magnet

The Central Solenoid Magnet is positioned to surround the Inner Detector at the core of the ATLAS experiment. This magnet bends the paths of charged particles passing through the inner detector, facilitating accurate momentum measurement. Its compact design minimizes interaction with particles. It consists of over 9 km of niobium-titanium superconductor wires embedded in strengthened aluminum strips: **Length:** 5.8 meters, **Outer Diameter:** 2.56 meters, **Thickness:** 4.5 cm, **Magnetic Field:** 2 Tesla

#### Toroid Magnet System

The ATLAS Toroid Magnet System consists of a central barrel toroid and two end-cap toroids, utilizing eight coils to generate a magnetic field of up to 3.5 Tesla, specifically designed for muon momentum measurement. The central barrel toroid is the largest toroidal magnet ever constructed, with a length of 25.3 meters, a distinctive feature of the ATLAS detector that is underscored by the detector's name. These end-cap toroids extend the magnetic field effectively to particles exiting near the beam pipe, enhancing the detector's coverage and measurement accuracy.

Together, these magnet systems enable ATLAS to measure the properties of particles with high precision, supporting the detector's broad physics objectives.

## 3.4 Geometric Coordinate System in ATLAS

### 3.4.1 Cylindrically Symmetric Coordinate System

The ATLAS detector employs a cylindrical coordinate system, which is particularly suited to the cylindrical geometry of the detector, which exhibits rotational symmetry about the beam axis

( $Z$ -direction).

**Spatial Coordinates:** Position within the detector is described using  $(z, r, \phi)$ :

- $z$ : Along the beam axis.
- $r$ : Radial distance from the beam axis.
- $\phi$ : Azimuthal angle around the beam axis.

**Momentum Coordinates:** Momentum is typically expressed in terms of  $(p_T, \eta, \phi)$ :

- $p_T$ : Transverse momentum, crucial due to the unknown momentum along the  $Z$ -axis of colliding partons.
- $\eta$  (pseudo-rapidity): Describes the angle of particle emission relative to the beam axis.

### 3.4.2 Rapidity and Lorentz Boost

In hadron colliders like the ATLAS, coordinates of  $(\eta, \phi)$  replace the spherical  $(\theta, \phi)$ , with  $\eta$  being the pseudo-rapidity, essential for describing particle interactions in the detector. It is essential because of the unknown Lorentz boost in the interaction frame of the two interacting partons in the colliding protons.

Rapidity  $y$ , derived from the Lorentz boost parameter  $w$ , simplifies the description of particle velocities in collider physics. Defined as:

$$\Lambda_\nu^\mu = \begin{pmatrix} \cosh(w) & 0 & 0 & -\sinh w \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -\sinh(w) & 0 & 0 & \cosh w \end{pmatrix} \quad (3.1)$$

Unlike velocities, rapidity adds directly across consecutive boosts:

$$\Lambda_\nu^\mu(\vec{w}_1) \Lambda_\rho^\nu(\vec{w}_2) = \Lambda_\rho^\mu(\vec{w}_1 + \vec{w}_2) \quad (3.2)$$

For collider physics, longitudinal rapidity  $y = w_z$  is typically used, representing boosts along the  $Z$ -axis. In the ATLAS detector, pseudo-rapidity  $\eta$  is preferred over rapidity  $y$  for two main reasons:

**Measurement Simplicity:**  $\eta$  can be determined from the geometric angle  $\theta$ :

$$\eta = -\ln \left[ \tan \left( \frac{\theta}{2} \right) \right] = \tanh^{-1} \left( \frac{p_L}{|p|} \right) \quad (3.3)$$

, where we need to measure both  $E$  and  $p_L$  to get rapidity  $y$ , with neither easy to measure accurately:

$$y = \frac{1}{2} \ln \left( \frac{E + p_z}{E - p_z} \right) \quad (3.4)$$

**High Energy Approximation:** At high energies,  $\eta$  closely approximates  $y$ , especially when  $p_T$  significantly exceeds particle mass:

$$y \approx \eta - \frac{1}{2} \cos \theta \left( \frac{m}{p_T} \right)^2 + \mathcal{O} \left[ \left( \frac{m}{p_T} \right)^3 \right] \quad (3.5)$$

Because the relative angular separation of particles is physically important, angular variables must have consistent definitions in all frames. Note that  $\Delta\phi$  is orthogonal to the boosting direction and thus is invariant under the  $Z$ -boost. However,  $\Delta\theta$  is not invariant under  $Z$ -boost, while  $\Delta\eta$  is invariant as shown in Equation 3.2). Therefore,  $\eta$  is vital for describing the angular spread of jets and other objects:

$$\Delta R = \sqrt{(\Delta\phi)^2 + (\Delta\eta)^2} \quad (3.6)$$

### 3.4.3 Trajectory of Charged Particle

In the uniform magnetic field provided by the solenoid in the ATLAS detector along the  $Z$  direction, charged particles such as  $\pi^\pm$  are expected to follow a helical trajectory. This characteristic path is crucial for determining the origin and properties of the particle within the detector.

Although the innermost layer of the detector is positioned close to the beamline, it cannot capture the exact origin of the particle's generation. Therefore, the “origin” of a track is defined by the “Perigee” – the point on the helical trajectory closest to the fitted origin of the collision and its direction at this closest approach. Figure 3.11 illustrates a charged particle, which is a decay

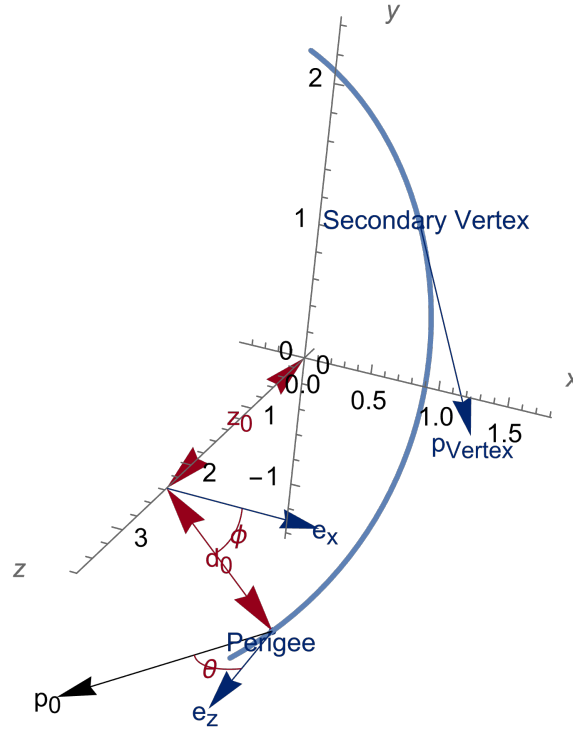


Figure 3.11: Schematic showing the track origin coordinate system in the ATLAS using the perigee of the helical trajectory.

product from a secondary vertex displaced from the beamline, following this helical path. By

fitting the hits in the tracking layers of the Inner Detector along this trajectory, we can determine the perigee of the track.

For each particle track, the following spatial coordinates at the perigee are measured:

**Longitudinal Impact Parameter ( $z_0$ ):** The  $Z$ -coordinate at the perigee relative to the origin. Because there are usually multiple pile-up collision points, this impact parameter helps identify if the track originates from the primary collision vertex, which is associated with the most energetic jets or missing transverse energy (MET).

**Transverse Impact Parameter ( $d_0$ ):** The shortest distance between the perigee and the  $Z$ -axis (beam line). A significant  $d_0$  value beyond its measurement uncertainty  $\sigma(d_0)$  can indicate that the track originates from a decay of a long-lived particle, occurring at a secondary vertex away from the primary vertex.

**Azimuthal Angle ( $\phi$ ):** The angle of the track's perigee relative to the  $x$ -direction, providing directional information about the particle's origin, which could be useful to compare its alignment with other particles if they are generated together.

These impact parameters are critical in analyses (such as in Chapter 4) that rely on distinguishing tracks coming from different types of interaction vertices.

## 3.5 Trigger, Data Acquisition and Reconstruction

The ATLAS detector observes up to 1.7 billion proton-proton collisions per second, producing over 60 terabytes of data per second. The **Trigger and Data Acquisition (TDAQ)** system selectively captures only the most promising events for new physics discoveries, reducing data to a manageable level.

The TDAQ system (Figure 3.12) uses two main stages: the **Level-1 Trigger (L1)**, a fast hardware-based filter, makes a decision within 2.5 ms, matching the LHC's collision rate; and the **High-Level Trigger (HLT)**, a software-based filter making a decision with 200 ms using 40,000 core CPU farm.



Together, they reduce the data flow from billions of events to about a thousand events per second, focusing on events indicative of significant physics phenomena.

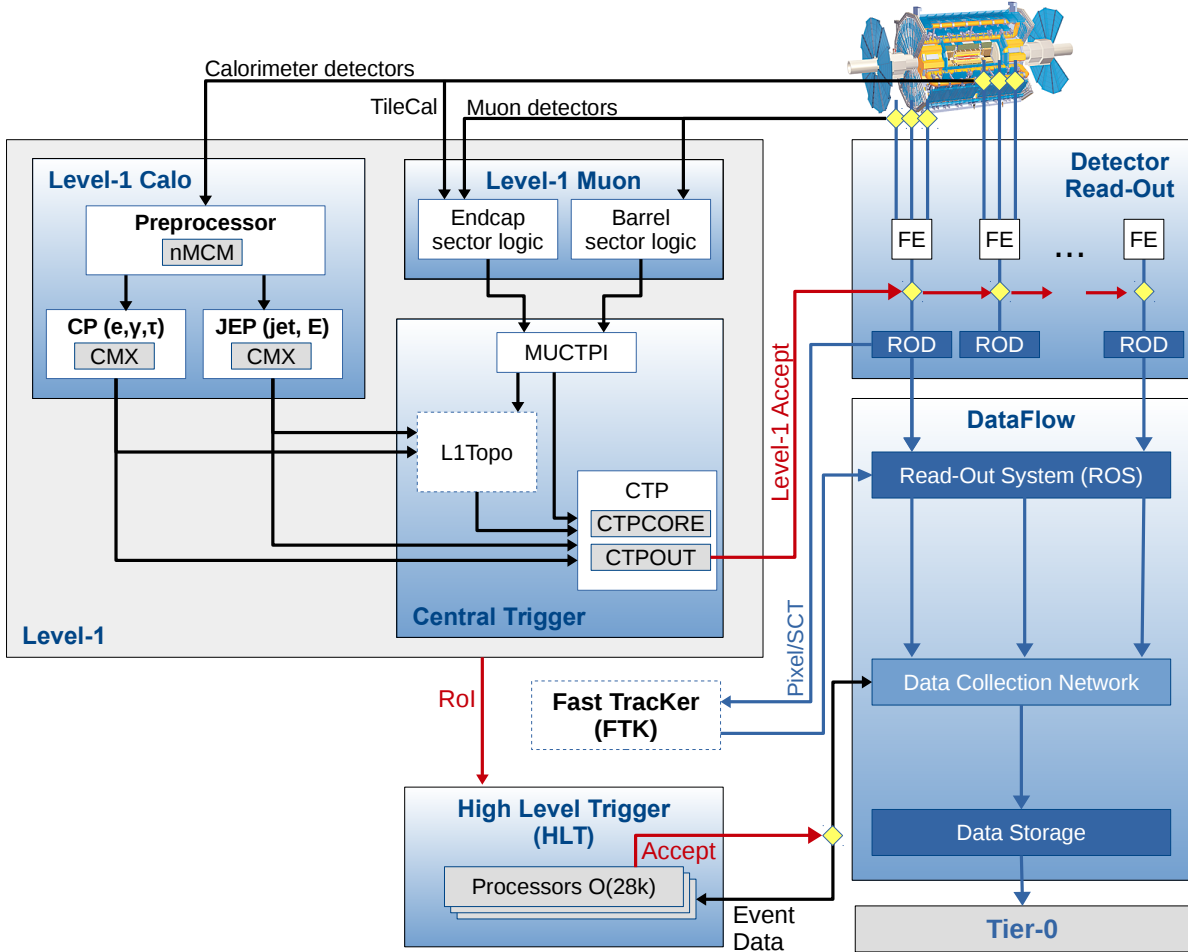


Figure 3.12: Schematic showing the dataflow of ATLAS TDAQ for LHC Run 2. [17]

### 3.5.1 Level-1 Trigger

The Level-1 Trigger, a hardware-based system, uses calorimeter and muon detectors (RPCs and TGCs) to identify potential high-energy events based on initial energy deposits and muon tracks. The system is positioned close to the detector cavern to minimize transmission times, L1 processes data within 2.5 microseconds—less than the maximum buffer depth of about 3 microseconds on the detector, ensuring that no data is lost during transfer. It consists of three types of triggers:

- The **L1 Calorimeter Trigger** analyzes energy patterns in the calorimeters to detect high-

energy jets, electron/photon candidates, and missing transverse energy.

- The **L1 Muon Trigger** identifies high-momentum muons using muon detector signals.
- The **L1 Topological Trigger** performs real-time calculations, such as evaluating kinematic and geometric relationships and global quantities like missing transverse momentum ( $E_{\text{miss}}^T$ ) using Field-Programmable Gate Array (FPGA)-based processor modules.

Events accepted by L1 Trigger is transferred from the detector-specific front-end buffers via the common ReadOut System (ROS), facilitating access to the event data through an Ethernet-based network for the second level of triggering and the Event Builder.

### 3.5.2 High-Level Trigger (HLT) and Object Reconstruction

After L1 selection of event generated at 1kHz, the HLT refines event selection to 1 kHz for offline analysis. This stage accesses detailed calorimeter, muon spectrometer, and inner detector data to reconstruct particle tracks in Regions of Interest (RoIs) identified at L1.

- **Track Reconstruction:** Fast tracking algorithms quickly identify potential tracks, followed by precision tracking algorithms for accurate particle trajectories.
- **Electron, Photon, Tau Reconstruction:** Algorithms process calorimeter data to identify objects like electrons, photons, and tau leptons, focusing on shower shapes and isolation properties.
- **Muon Reconstruction:** Muon candidates from L1 are refined using precision data from MDT and CSC chambers, improving momentum estimates.
- **Jet Reconstruction:** Jets are reconstructed using the anti- $k_t$  algorithm, ([51]) with radius parameters of either  $R = 0.4$  or  $R = 1.0$ , based on calorimeter topo-clusters. It also come With pile-up correction and calibration steps using simulation-derived factors.
- **B-Jet Trigger:** The b-jet trigger identifies jets from bottom quarks, which is crucial for

studying the Higgs boson and heavy-flavor physics.

- **Missing Transverse Energy (MET) Trigger:** The MET trigger captures events with significant missing energy, crucial for Beyond-Standard-Model (BSM) searches.

The trigger menu defines all operational triggers in ATLAS, including primary physics triggers, performance support triggers, experimental triggers, and calibration triggers. These triggers are continually optimized to balance physics output with the ATLAS detectors and TDAQ systems capabilities, enabling the High-Level Trigger to reduce the event rate to hundreds per second for efficient analysis of significant physics events.

## 3.6 Monte Carlo Simulation & Computation

### 3.6.1 Monte Carlo Simulation Workflow

Accurate Monte Carlo (MC) simulations are essential for analyzing ATLAS data and validating theoretical models. This section outlines the ATLAS MC workflow (Figure 3.13) as implemented within the Athena software framework [18].

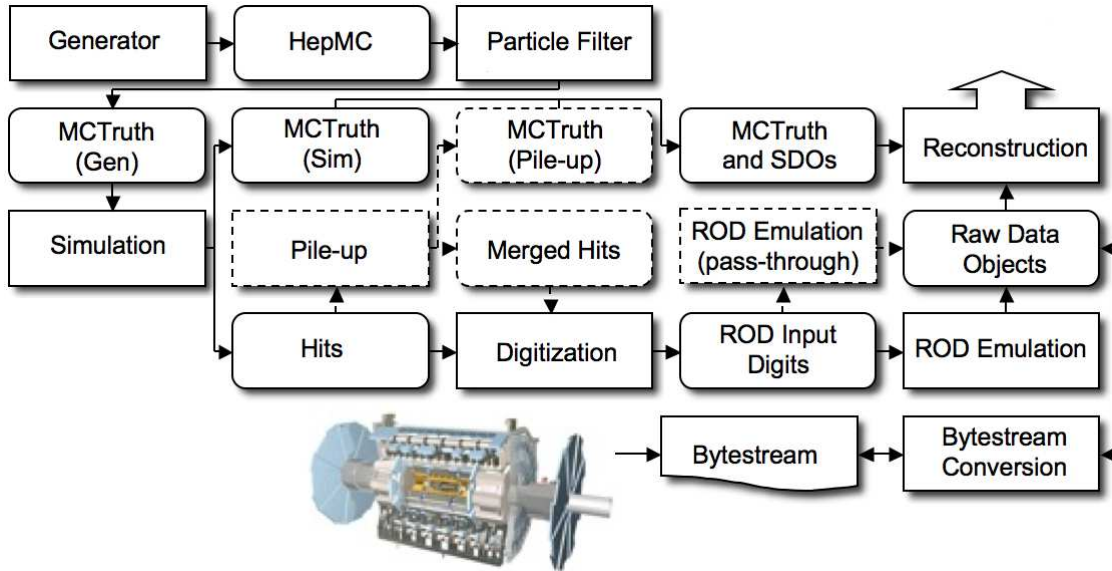


Figure 3.13: Overview of the ATLAS simulation workflow.[18]

- **Event Generation:** Event generation produces primary collision events in the standard HepMC

format[52], with filters selecting only relevant events, such as those with specific decay channels or missing energy, to streamline analysis. Generated events are assigned unique run and event numbers, which mimic those used during actual data collection, facilitating comparison between simulated and real data.

- **Detector Simulation:** **Geant4** ([53]) simulates each particle’s trajectory within different materials in the ATLAS detector geometry, recording energy deposits (“hits”) essential for reconstructing paths and interaction points.
- **Digitization:** Digitization converts Geant4 hits to electronic signals (“digits”), replicating detector conditions and incorporating effects like noise, cross-talk and variation in detector responses for realistic simulation. Additionally, multiple proton-proton interactions (“pile-up”) and non-collision backgrounds (e.g., cosmic rays) are overlaid on the primary event to enhance the realism of the simulation.
- **Output and Reconstruction:** The final output includes Raw Data Objects (RDOs), which mimic real data, and Simulated Data Objects (SDOs), with detailed truth record of particle-level information. This allows full reconstruction and analysis of simulated events, employing the same software that is used for the analysis of real data.

To optimize resources, some of the ATLAS samples employ fast simulation (AFII) options, reducing detail in calorimeter simulation. High-Level Trigger (HLT) simulation also applies real-time selection criteria, allowing consistency with live data processing.

### 3.6.2 Distributed Computing for LHC

The Worldwide LHC Computing Grid (WLCG) distributes data storage and processing through a hierarchical Tier structure (Figure 3.14). CERNs Tier-0 handles initial data processing, with Tier-1 centers storing and reprocessing data and Tier-2 centers providing additional analysis and simulation. Tier-3 includes local resources for grid access, supporting data processing needs across institutions [19]. Rucio manages data across WLCG tiers, supporting dynamic data placement to optimize

resource use and handle LHC data volumes efficiently [54]. The Production and Distributed Analysis system (PanDA) manages workload distribution across the grid, optimizing resource use and ensuring efficient data processing for ATLAS analysis [55].

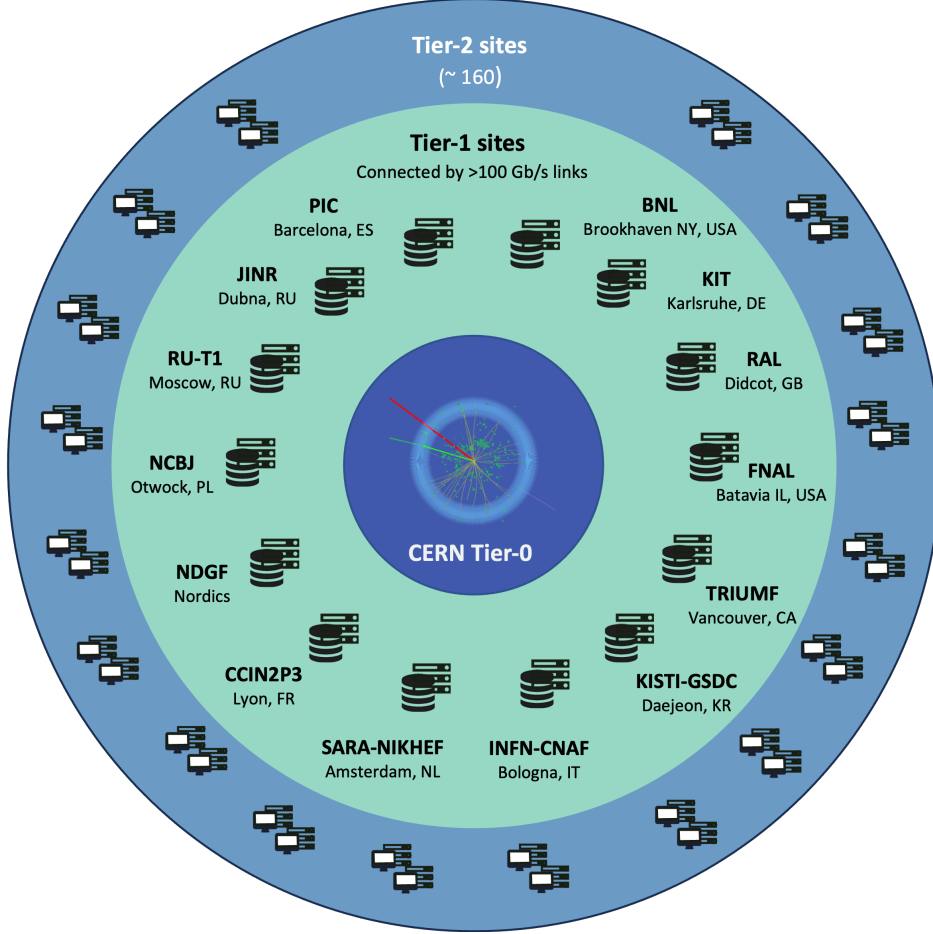


Figure 3.14: The WLCG Tier Structure illustrates the hierarchical organization of computing resources for LHC experiments, from Tier-0 at CERN for initial data processing to Tier-1, Tier-2, and Tier-3 centers globally, supporting data storage and analysis. This visual underscores the collaborative and distributed nature of WLCG infrastructure vital for high-energy physics research.[19]

For my analysis, key computational tasks—including Monte Carlo simulation generation, Analysis Object Data (DAOD) production, and n-tuple formatting—were performed using PanDA on the Worldwide LHC Computing Grid. Large datasets were distributed via the Grid and stored locally on the Rucio node at the Scientific Data and Computing Center (SDCC) at Brookhaven National Laboratory, enabling efficient access for analysis. Most of the computational work was

executed on SDCCs specialized resources, including SPAR nodes, Jupyter nodes, and Condor High-Throughput Computing (HTC) clusters, with earlier work utilizing the Institution Cluster (IC) High-Performance Computing (HPC) system prior to its upgrade.

## CHAPTER 4

### Search for Higgsinos in Compressed Mass Spectra using Neural Networks

## 4.1 Introduction

### 4.1.1 Supersymmetry and Higgsino Searches

Supersymmetry (SUSY) offers elegant solutions to key challenges in high-energy physics, such as resolving the hierarchy problem and providing candidates for dark matter particles (Chapter 2). Extensive searches by the ATLAS and CMS detectors at the Large Hadron Collider, have placed strong experimental constraints on SUSY models [56]. One remaining viable pathway for natural SUSY lies in a compressed-mass scenario of the lightest chargino ( $\tilde{\chi}_1^\pm$ ) and neutralinos ( $\tilde{\chi}_2^0, \tilde{\chi}_1^0$ ). This chapter describes my work on the search for these higgsinos-like charginos and neutralinos, using the ATLAS Run-2 dataset of 13 TeV proton-proton collisions. The search targets  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$  that are 0.3-1.5 GeV heavier than the lightest neutralino ( $\tilde{\chi}_1^0$ ), which is assumed to be the lightest supersymmetric particle (LSP) and stable. The lightest neutralino  $\tilde{\chi}_1^0$  also serves as a good dark matter candidate[23].

The search targets a gap in current ATLAS sensitivity (Figure 4.1), and extends the 95 GeV LSP mass limit, established by searches at the Large Electron Positron (LEP) collider, to masses as high as 190 GeV.

### 4.1.2 Signature of Compressed Mass Spectra

The compressed mass spectra have two key consequences:

1. The decays of  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$  to  $\tilde{\chi}_1^0$  produce only one or two low-momentum charged particles.
2. The  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$  have macroscopic lifetimes, resulting in charged decay products with detectable displacement from the primary interaction point.

In this search, we target final-state signatures [23] with a high- $p_T$  jet from initial-state-radiation

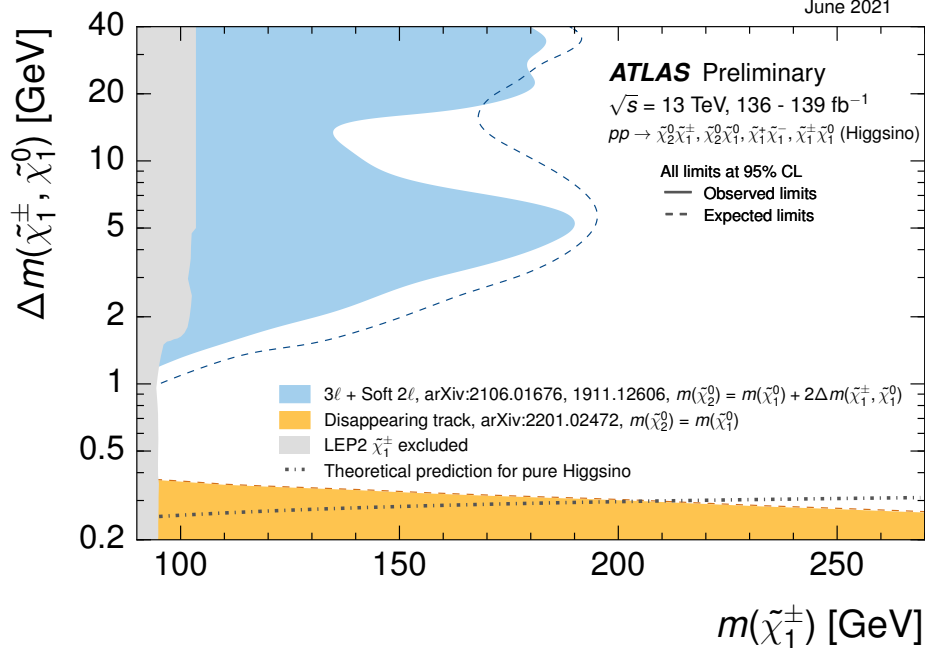
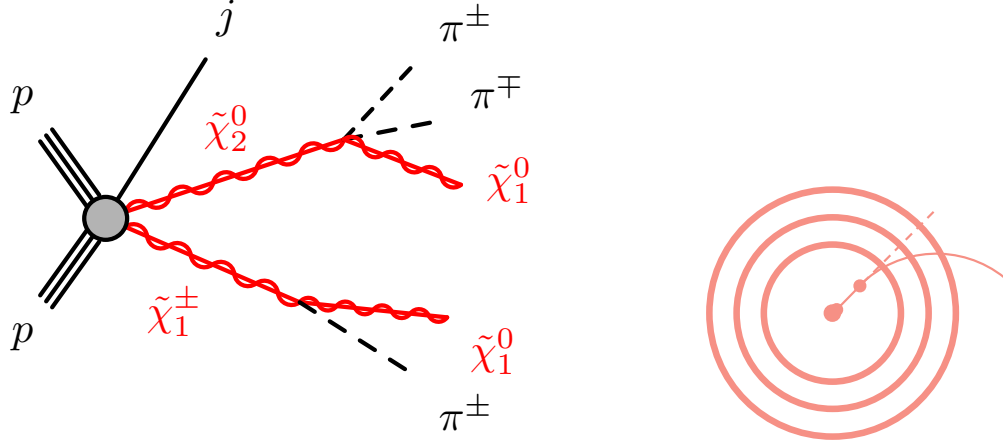


Figure 4.1: The ATLAS collaboration has published exclusions based on the disappearing track analysis [20] (yellow region) and the multi-lepton analysis [21] (blue region). A gap remains between these analyses for mass splittings ( $\Delta m$ ) of approximately 0.3 to 1.5 GeV. This search targets this intermediate region, aiming to fill the gap and extend the LEP exclusion limits of 95 GeV for the  $\tilde{\chi}_1^0$  mass [22] (grey region).

and significant missing transverse energy from the  $\tilde{\chi}_1^0$ 's recoiling this jet. As will be described in Section 4.2, our search focuses on final states with a low- $p_T$  track, helping suppress Standard Model backgrounds with true missing transverse energy from neutrinos recoiling against an ISR jet, such as  $Z \rightarrow \nu\nu + \text{jet}$  and  $W \rightarrow l\nu + \text{jet}$ , particularly  $W \rightarrow \tau\nu + \text{jet}$ . This approach is challenging and had not previously been explored in ATLAS and CMS analyses. Figure 4.2a shows a typical Feynman diagram for the compressed mass spectra targeted by this search, and Figure 4.2b visualizes the signature of the displaced low- $p_T$  charged particle produced by a semi-long-lived chargino decay inside the tracking layers.





(a) Typical Feynman diagram for  $\Delta m \in [0.3, 1.5]$  GeV. The  $j$  denotes an ISR jet.

(b) Displaced  $\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_1^0 \pi^\pm$  decay inside the pixel tracking layers.

Figure 4.2: Search target and decay visualization for compressed mass spectra. The decay products of  $\tilde{\chi}_2^0$  are not easily visible because: (1) the  $\tilde{\chi}_2^0 \rightarrow \tilde{\chi}_1^0 \pi^0$  decay dominates at lower mass splittings; (2)  $\tilde{\chi}_2^0$  has a much shorter lifetime at higher mass splittings. Consequently, the more representative visualization on the right focuses on the pion from  $\tilde{\chi}_1^\pm$  decay, which is typically observable within the tracking layers.

#### 4.1.3 Neural Network-Based Higgsino Search Strategy

The search initially began as a traditional cut-based analysis<sup>5</sup>, which improves the signal-to-background ratio by applying sequential cuts on individual kinematic variables. To better identify Higgsino signatures, I developed neural network-based classifiers for both signal-like events and signal-like tracks, trained on Monte Carlo (MC) simulations. Background contributions in the Signal Regions (SR) were also predicted using MC simulation samples. To reduce systematic errors in background predictions, I implemented a semi-data-driven method. This involved correcting simulation mis-modeling by adjusting MC event weights based on observations in control regions (CR), where signal contributions are negligible.

This chapter covers the following topics: phenomenological signatures (4.2), the corresponding search strategy (4.3), simulation & data samples (4.4), detector object definitions (4.5). The data

<sup>5</sup>A separate team from Kyoto University and INFN Milano, led by PhD student Yuya Mino and Alessandro Sala under the supervision of Dr. Shion Chen and Dr. Tommaso Lari, continued optimizing this traditional cut-based approach in parallel, with background estimation using the ABCD Method. I contributed to this analysis by providing the signal Monte Carlo configuration, assisting with data processing jobs, and cross-checking the results. The findings of this work were published in Physical Review Letters [25].

analysis includes: optimizing the sensitivity to SUSY in the signal regions (SR) using neural networks (4.6), the data-driven corrections to the MC simulation using control regions (CR) (4.7) and a four-fold validation strategy using validation regions (VR) (4.8). Finally, we use the PyHF package for statistical interpretation to test and determine limits on our signal hypothesis (4.9).

## 4.2 Phenomenology of Compressed Mass Spectra

This analysis targets the mass splitting range of approximately 300 MeV to 2 GeV between the two lightest neutralinos ( $\tilde{\chi}_{1,2}^0$ ) and the lightest chargino ( $\tilde{\chi}_1^\pm$ ). In such compressed spectra, the small mass difference is mainly due to the mixing of the dominant Higgsino components with much heavier winos and binos, as discussed in Section 2.6.7. The mass differences are defined as:

$$\begin{aligned}\Delta m_0 &\equiv m(\tilde{\chi}_2^0) - m(\tilde{\chi}_1^0); \\ \Delta m_\pm &\equiv m(\tilde{\chi}_1^\pm) - m(\tilde{\chi}_1^0).\end{aligned}\tag{4.1}$$

These can be approximated by [23]:

$$\Delta m_0^{\text{tree}} \simeq M_Z^2 \left| \frac{\cos^2(\theta_W)}{M_2} + \frac{\sin^2(\theta_W)}{M_1} \right|,\tag{4.2}$$

and

$$\Delta m_\pm = \Delta m_\pm^{\text{tree}} + \Delta m_\pm^{\text{rad}},\tag{4.3}$$

where<sup>6</sup>:

$$\begin{aligned}\Delta m_\pm^{\text{tree}} &\simeq \frac{\Delta m_0^{\text{tree}}}{2} + \sin(2\beta) M_Z^2 \left( \frac{\cos^2(\theta_W)}{M_2} - \frac{\sin^2(\theta_W)}{M_1} \right); \\ \Delta m_\pm^{\text{rad}} &\simeq \frac{\alpha_{SU(2)_L} M_Z}{2} \sin^2(\theta_W) \simeq 354 \text{ MeV}.\end{aligned}\tag{4.4}$$

The small mass splitting reduces the available momentum phase space for decays, leading to macro-

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<sup>6</sup>Recall that  $M_1$  and  $M_2$  refer to the bino and wino mass parameters, which are assumed to be much greater than  $M_Z$  in this Higgsino-dominant scenario. Additionally,  $\alpha_{SU(2)_L}$  is the fine structure constant for the  $SU(2)_L$  gauge interaction,  $\tan(\beta) = \langle H_u \rangle / \langle H_d \rangle$  represents the ratio of the vacuum expectation values of the two Higgs doublets, and  $\theta_w$  is the Weinberg angle.

scopically observable lifetimes for  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$ . The partial decay length for  $\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_1^0 \pi^\pm$  is approximated by:

$$\Gamma_{\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_1^0 \pi^\pm}^{-1} \simeq \frac{14\text{mm}}{\hbar c} \times \left[ \left( \frac{\Delta m_\pm}{340\text{MeV}} \right)^3 \sqrt{1 - \frac{m_{\pi^\pm}^2}{\Delta m_\pm^2}} \right]^{-1} \quad (4.5)$$

As shown in Figure 4.3, smaller  $\Delta m$  leads to longer lifetimes, allowing  $\tilde{\chi}_1^\pm$  to travel measurable distances before decaying inside the first tracking layers.

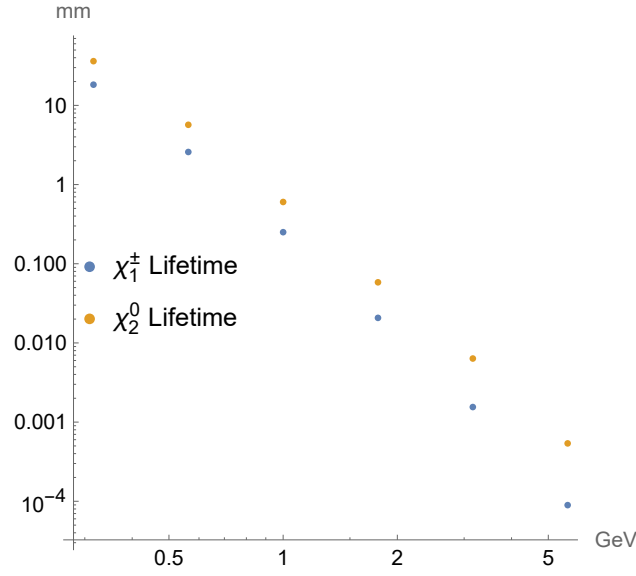


Figure 4.3: The  $\tilde{\chi}_2^0$  and  $\tilde{\chi}_1^\pm$  lifetime ( $c\tau$ ) as a function of the mass splitting  $\Delta m$ , where  $\Delta m = m(\tilde{\chi}_2^0) - m(\tilde{\chi}_1^0) = m(\tilde{\chi}_1^\pm) - m(\tilde{\chi}_1^0)$ . The x-axis represents  $\Delta m$  in GeV, while the y-axis shows the expected flight distance, calculated as the product of the speed of light and the nominal lifetime ( $c\tau$ ). As  $\Delta m$  decreases, the expected lifetime of  $\tilde{\chi}_2^0$  and  $\tilde{\chi}_1^\pm$  increases, leading to decays occurring at a vertex displaced from the primary vertex where they were produced in the proton-proton collision.

Figure 4.4 shows that as  $\Delta m$  decreases, decays shift from leptonic to hadronic channels, with pions dominating in the target mass splitting range of 0.3-2 GeV. Since the detector response for low-momentum pions, electrons, and muons is similar due to their insufficient energy to create distinctive calorimeter signatures, we use  $\pi^\pm$  to represent all visible decay products (including  $\pi^\pm, e^\pm$  and  $\mu^\pm$  in this analysis).

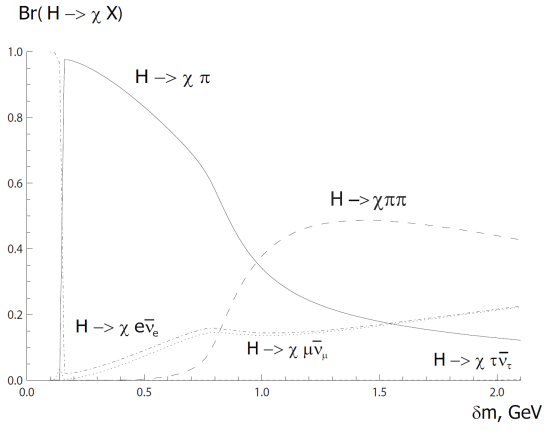


Fig. 2. Branching ratios for chargino decays as functions of mass splitting.

(a) Branching ratios of  $\tilde{\chi}_1^\pm$

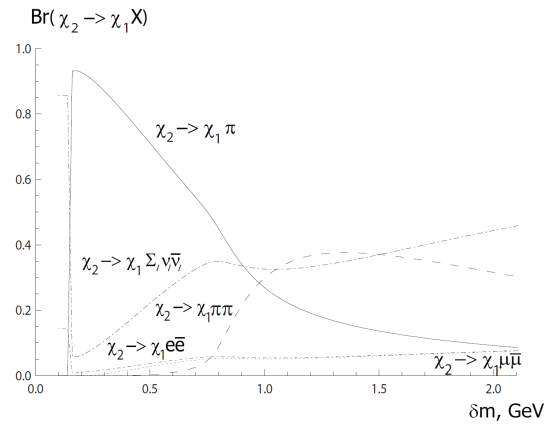


Fig. 3. Branching ratios for neutralino decays as functions of mass splitting.

(b) Branching ratios of  $\tilde{\chi}_2^0$ .

Figure 4.4: Branching ratio of Higgsino-like (H)  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$ , with varying mass splitting  $\Delta m$ .

## 4.3 Search Strategy & Standard Model Backgrounds

### 4.3.1 Event-Level Signal Signature

In the decays of  $\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_1^0 \pi^\pm$  and  $\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_1^0 \pi^0 / \pi^\pm \pi^\mp$ ,  $\tilde{\chi}_1^0$  carries most of the momentum due to the small mass difference. The typical production of Higgsino pair results in a topology with two  $\tilde{\chi}_1^0$  moving back-to-back in azimuth, accompanied by a few low-momentum charged particles. However, this final state is impractical for detection purposes: since  $\tilde{\chi}_1^0$  interacts only weakly, its presence must be inferred through missing transverse energy ( $E_T^{\text{miss}}$ ).

To trigger event recording, the two stable  $\tilde{\chi}_1^0$  particles need to be aligned, which can be achieved by requiring initial state radiation of a high- $p_T$  quark or gluon. This recoils against the neutralino pair, producing large  $E_T^{\text{miss}}$ . The charged particle decay products are thus also boosted along the  $\vec{E}_T^{\text{miss}}$  direction with measurable displacement from the primary vertex associated with the ISR jet.

In summary, the event-level signature is a high- $p_T$  jet recoiling against large  $E_T^{\text{miss}}$ , which is aligned in azimuth with a low- $p_T$  charged particle displaced from the primary vertex, as shown in Figure 4.5.

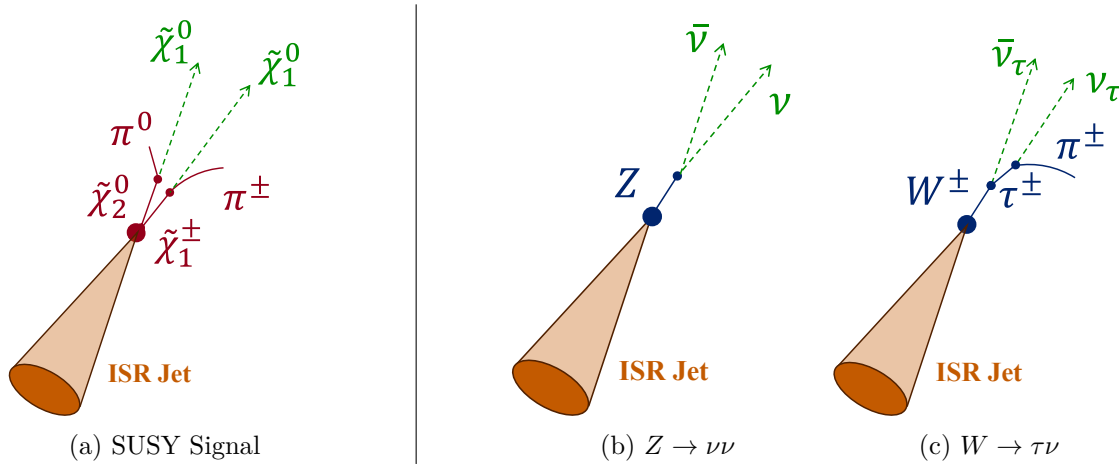


Figure 4.5: Visualization of event-level signatures for the SUSY signal and the main Standard Model backgrounds. Here, only the tree-level decay products are shown.

With the large value of  $E_T^{\text{miss}}$  required in this analysis, the dominant Standard Model backgrounds are processes that produce true missing transverse momentum via neutrino decays, primarily  $Z \rightarrow \nu\nu + \text{jets}$  and  $W \rightarrow \tau\nu + \text{jets}$  (also illustrated in Figure 4.5).

Figure 4.6 shows the expected signal event kinematics from a Monte Carlo simulation of  $pp \rightarrow \tilde{\chi}_2^0 \tilde{\chi}_1^\pm$ , where the displaced  $\pi^\pm$  trajectory from the SUSY particle decay is highlighted in dotted red.

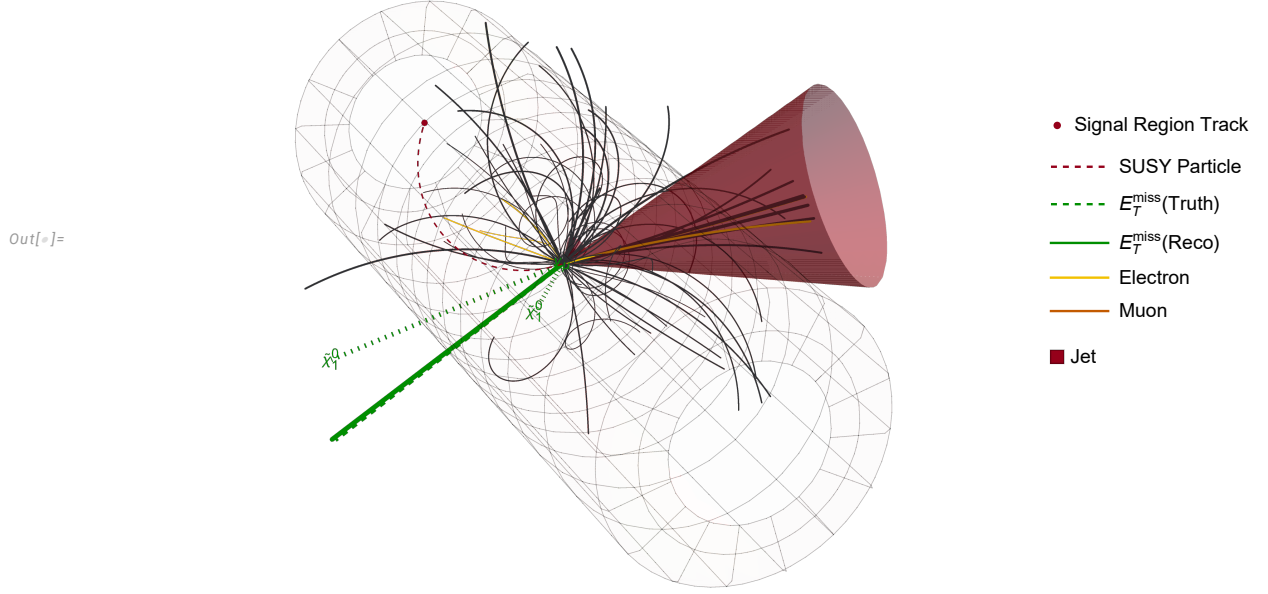


Figure 4.6: Visualization of a  $pp \rightarrow \tilde{\chi}_2^0 \tilde{\chi}_1^\pm$  signal event in the ATLAS detector, corresponding to the Feynman diagram in Figure 4.2a. Created with Mathematica based on Analysis Object Data (AOD) from the Monte Carlo simulation.

### 4.3.2 Track-Level Signal Signature

To suppress backgrounds from  $W$  and  $Z$  boson decays, we look for the charged pion ( $\pi^\pm$ ) produced in the decays of chargino ( $\tilde{\chi}_1^\pm$ ) and neutralino ( $\tilde{\chi}_2^0$ ). Due to the small mass splitting,  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$  have moderate lifetimes, allowing them to travel measurable distances before decaying into  $\tilde{\chi}_1^0$  and pions. The  $\pi^\pm$  can be identified through the following features in its trajectory ("track"):

### Momentum Vector Signatures:

- **Low  $p_T$ :** The charged pion has low transverse momentum ( $p_T \sim \mathcal{O}(1 \text{ GeV})$ ) due to the small mass difference  $\Delta m$ .
- **Small  $\Delta\phi(\vec{E}_T^{\text{miss}}, \text{Trk})$ :** The  $\pi^\pm$  track align closely with the  $\tilde{\chi}_1^0$  direction, resulting in a small angular difference  $\Delta\phi(\vec{E}_T^{\text{miss}}, \text{Trk})$ .
- **Isolation:** The pion is produced alone, without nearby charged particles. We measure the track isolation by Trk.  $\text{ISO} \equiv \sum p_{T, \text{IsoCone}}$ .

### Spatial Vector Signatures:

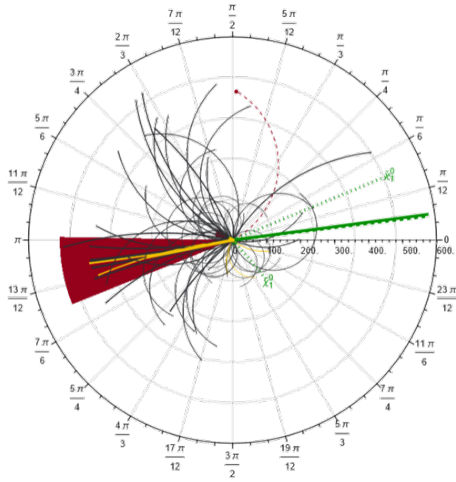
- **Displaced Origin:**  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$  are semi-long-lived, leading to a large transverse impact parameter ( $d_0$ ) with high significance  $S(d_0) \equiv \frac{d_0}{\sigma(d_0)}$ , indicating a displaced interaction vertex.
- **Near Primary Vertex:** The longitudinal impact parameter  $z_0 \sin \theta$  is used to suppress charged particle tracks from pile-up collisions in the same bunch crossing.

Figure 4.7 illustrates these signatures in the transverse plane. The left panel shows an event overview with the jet,  $E_T^{\text{miss}}$ , and various tracks—the signal track is highlighted in red. The right panel zooms in on the transverse displacement of the signal track and its alignment with  $\vec{E}_T^{\text{miss}}$ .

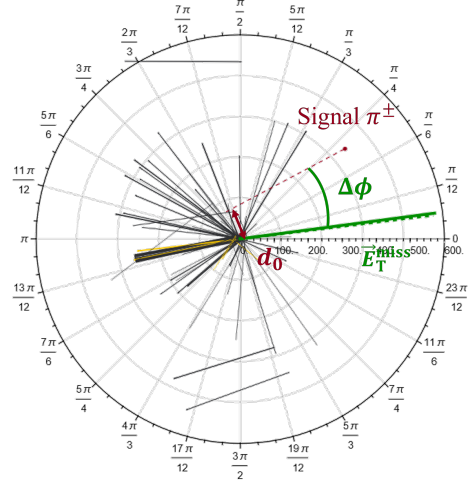
### 4.3.3 Semi-Long-Lived SM Particles

Although no Standard Model process perfectly mimics the SUSY decay, some backgrounds produce similar signatures. A notable example is  $W \rightarrow \tau \nu$ , where the  $\tau$  decays into neutrinos and slightly displaced  $\pi^\pm$ ,  $e^\pm$  or  $\mu^\pm$  with a much shorter displacement.

In the case of  $Z \rightarrow \nu \nu$ , the low- $p_T$  displaced track comes from a random charged particle from either the primary interaction or pile-up. These possible backgrounds arise from semi-long-lived Standard Model particles produced in  $pp$  collisions, such as  $K_S^0$  and  $\Lambda^0/\bar{\Lambda}^0$ . They have lifetimes comparable to the SUSY signal, and can mimic the displaced track signature if they align with



(a) 2D cross-section Event Overview



(b) Zoom-In on Track Displacement

Figure 4.7: Visualization of a Monte Carlo simulated signal event, displaying the correctly tagged SUSY track within the track signal region. This is the same event as in Figure 4.6, sharing the same legend.

$\vec{E}_T^{\text{miss}}$  by chance.

In Figure 4.8, we compare the track-level signatures of the SUSY signal with these Standard Model backgrounds.

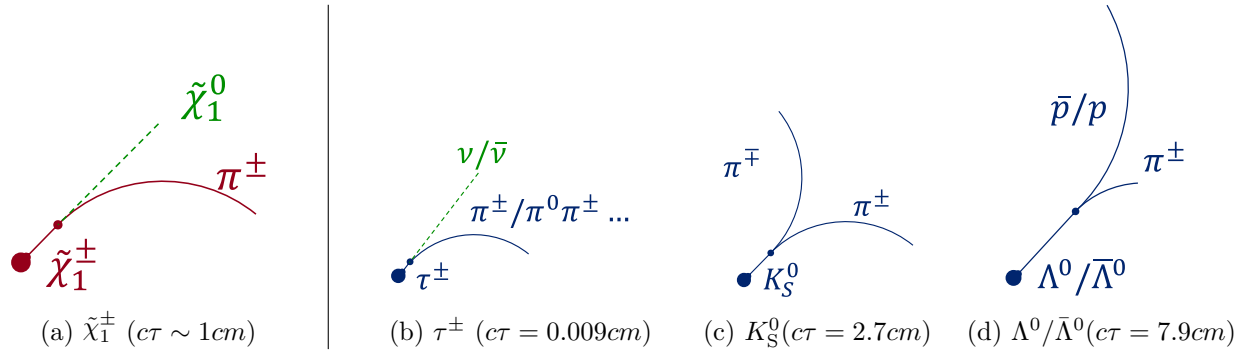


Figure 4.8: Visualization of track-level signatures for the SUSY signal and the leading Standard Model backgrounds.

We consider all Standard model mesons and baryons with macroscopic lifetimes that can be produced in the LHC. Figure 4.9 plots these particles exhaustively with their mass and lifetime ( $c\tau$ ), along with a table listing those comparable to the SUSY signal. Note that semi-long-lived particles like  $\Omega^-$  decay into  $K_S^0$  and  $\Lambda^0$ .



$K_S^0$  and  $\Lambda^0$  are typically produced from hadronization of the primary or pile-up collisions, and are not kinematically correlated with  $W$  and  $Z$  boson production. Their decay products align with  $E_T^{\text{miss}}$  only by chance, whereas the boosted decay products of  $\tilde{\chi}_1^\pm$ ,  $\tilde{\chi}_2^0$ , and  $\tau^\pm$  are more likely to align due to the ISR jet. Therefore, the angular difference  $\Delta\phi$  between the track and  $E_T^{\text{miss}}$  is a key discriminator for suppressing the abundant  $K_S^0$  and  $\Lambda^0$  backgrounds.

Furthermore,  $K_S^0$  and  $\Lambda^0$  decay into two charged particles, unlike the single  $\pi^\pm$  from  $\tilde{\chi}_1^\pm$  decay. This allows us to suppress these backgrounds by reconstructing secondary vertices with multiple tracks. We reject charged particle candidates that is matched to a secondary vertex whose reconstructed invariant mass is consistent with  $K_S^0$  and  $\Lambda^0$ .

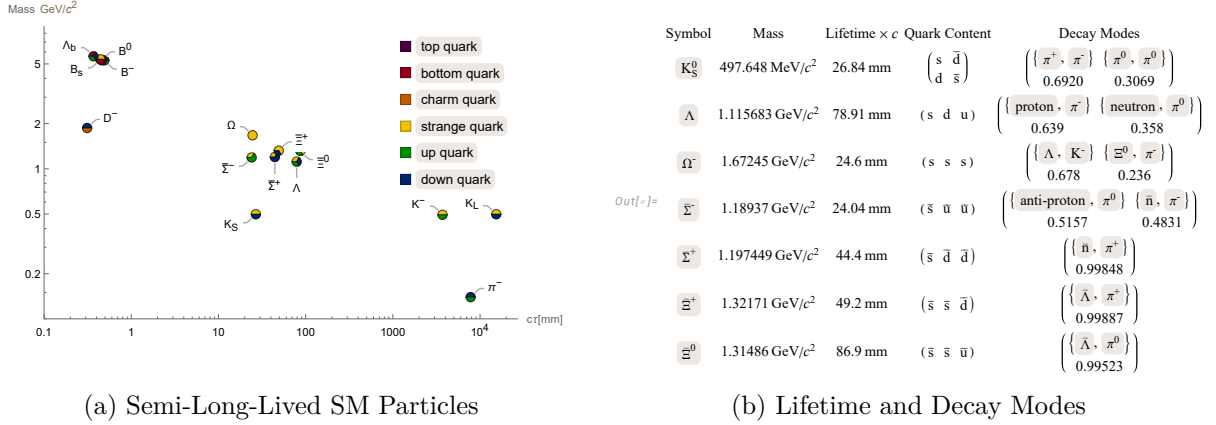


Figure 4.9: Semi-long-lived hadrons in the Standard Model. Produced with Wolfram Mathematica.

## 4.4 Monte Carlo Simulation & Data

The Monte Carlo simulation data and actual experimental data collected by the ATLAS detector form the backbone of this analysis. The Monte Carlo (MC) simulations embed our current physics knowledge and consist of two main components: signal samples (hereafter referred to as "Signal"), representing the hypothetical SUSY models with compressed mass spectra that we aim to discover (4.4.1), and background samples (hereafter "Background"), which model Standard Model processes. These background samples help us estimate the Standard Model contributions that could mimic the signal (4.4.2). Details on the preparation of the experimental data (hereafter "Data") and

trigger selections can be found in 4.4.3. The workflow for efficient data formatting and processing, applicable to both Monte Carlo and Data, is described in 4.4.4.

#### 4.4.1 Signal MC Samples on the Mass Grid

The signal sample simulations target electroweakinos with a mass hierarchy of  $m(\tilde{\chi}_2^0) > m(\tilde{\chi}_1^\pm) > m(\tilde{\chi}_1^0)$ , with equidistant mass splittings:  $\Delta m(\tilde{\chi}_2^0, \tilde{\chi}_1^\pm) = \Delta m(\tilde{\chi}_1^\pm, \tilde{\chi}_1^0)$ . The mass splittings considered are 1.50, 1.00, 0.75, 0.50, 0.35, and 0.25 GeV, with  $\tilde{\chi}_1^0$  mass ranging from 85 to 225 GeV.

Figure 4.10 illustrates the signal grid, and a comprehensive list of MC samples is provided in Appendix B.2. For each mass point, six samples are generated corresponding to the SUSY processes  $(\tilde{\chi}_2^0 \tilde{\chi}_1^0, \tilde{\chi}_2^0 \tilde{\chi}_1^\pm, \tilde{\chi}_1^0 \tilde{\chi}_1^\pm, \tilde{\chi}_1^\pm \tilde{\chi}_1^\mp)$ .

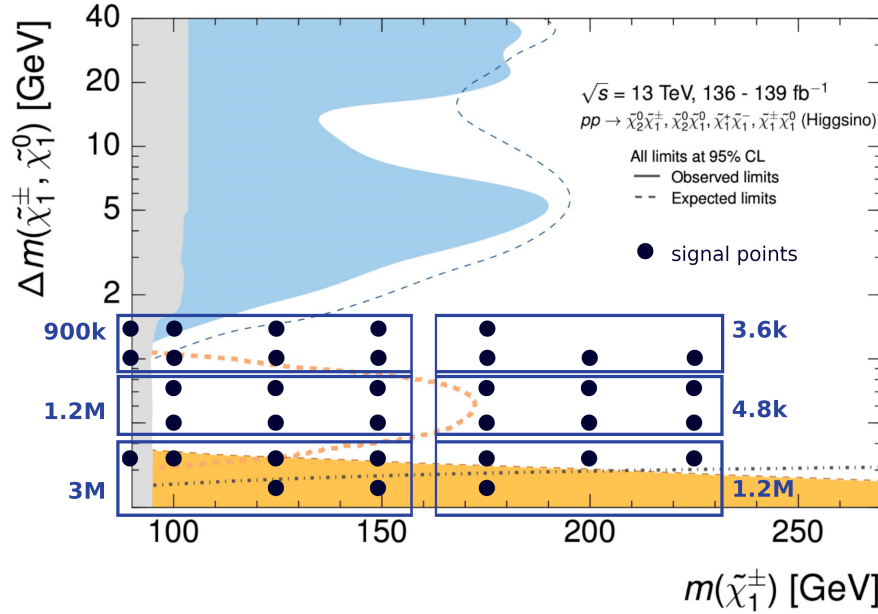


Figure 4.10: Schematic view of the signal point used in the analysis, overlaid on existing constraint as described in Figure 4.1. For each point, the mass hierarchy is assumed to be  $m(\tilde{\chi}_1^\pm) = \frac{1}{2}[m(\tilde{\chi}_2^0) + m(\tilde{\chi}_1^0)]$  and a separate MC sample for each of the SUSY process considered is generated.

The signal samples are produced using `AthGeneration` release 21.6.90 [57] with `MADGRAPH` 2.9.5 [58] for collisions and `PYTHIA` 8.306 [59] for parton showering. The electroweakino states are modeled as pure higgsino-like. Cross-sections are calculated to NLO+NLL accuracy using RE-

SUMMINO [60]. Branching ratios and decay widths for  $\tilde{\chi}_2^0$  and  $\tilde{\chi}_1^\pm$  are computed using **Wolfram Mathematica** 13.1 [61], based on the theoretical approximated formula [62], where the branching ratios are dependent on mass splittings  $\Delta m$  but not absolute masses.

The samples include at least one jet with  $p_T > 50$  GeV for the signal ISR topology (as discussed in Section 4.2), and a weight correction factor  $\sigma(1, 2 \text{ jets})/\sigma(0, 1, 2 \text{ jets})$  is applied. This correction ensures that the event weights properly account for the nominal cross section, which includes contributions from all possible jet multiplicities, thereby maintaining consistency with the theoretical cross-section calculations. A  $E_T^{\text{miss}} > 125$  GeV filter is applied at the generator level to remove events that have no chance of passing the ATLAS trigger, significantly improving simulation efficiency by focusing computational resources on relevant events.

The merging scheme CKKW-L [63] is employed with a merging scale of 15 GeV. This scheme combines matrix-element calculations for hard processes with parton-shower simulations for softer emissions, ensuring a smooth transition between these two regimes (see Section 3.2.2). The merging scale of 15 GeV is chosen to balance accuracy and computational efficiency, avoiding double-counting while retaining the correct jet multiplicity and kinematic distributions in the final state.

#### 4.4.2 Background MC Samples

We use the centrally generated Standard Model process samples, focusing on the processes that could mimic the signals, and those that helps us to calibrate the background contributions:

- The  $V$  + jets processes, including  $Z$ ,  $W$ , and  $\gamma$  production with multiple jets, are modeled using the **SHERPA** generator [64] with the NNPDF30NNLO PDF set [65]. Specifically,  $Z$  + jets and  $W$  + jets samples are generated using **SHERPA version 2.2.11**, categorized by hadronic transverse momentum (**maxHTPTV**) and quark flavor content to enhance modeling accuracy and efficiency. The  $\gamma$  + jets samples, generated with **SHERPA version 2.2.2**, are sliced based on photon transverse momentum ( $p_{T,\gamma}$ ) to ensure detailed phase space coverage.
- Diboson processes (denoted as  $VV = WW, ZZ, WZ$ ) are also modeled using **SHERPA** with the

NNPDF30NNLO PDF set. These processes are utilized for estimating electroweak backgrounds in SUSY searches.

- Top quark production, including single top ( $t$ - and  $s$ -channel), associated production ( $tW$ ), and  $t\bar{t}$  processes, is modeled using **POWHEG** [66], interfaced with **PYTHIA 8** for parton showering.

For a comprehensive list of background samples used across various MC campaigns, please refer to Appendix B.2.

### 4.4.3 Detector Data Samples

This analysis utilizes the LHC Run 2 proton-proton ( $pp$ ) collision data at  $\sqrt{s} = 13$  TeV, collected by the ATLAS detector, which corresponds to an integrated luminosity of  $139 \text{ fb}^{-1}$ . All data samples included in the analysis are required to meet stringent quality criteria, encapsulated in the recommended Good Run Lists (GRLs). These lists identify data-taking periods where the ATLAS detector and its subsystems were fully operational, ensuring that only the data used for analysis are free from detector issues that could compromise the sensitivity.

The signal region event selection is based on the lowest unrescaled inclusive  $E_{\text{T}}^{\text{miss}}$  triggers (see Appendix B.2), designed to capture events with high  $E_{\text{T}}^{\text{miss}}$ , which is the key feature of the SUSY signal. Although trigger thresholds were periodically adjusted to handle increasing trigger rates from higher pileup levels, the trigger maintains full efficiency above 200 GeV. To mitigate potential efficiency fluctuations, a conservative  $E_{\text{T}}^{\text{miss}}$  threshold of 275 GeV is applied.

### 4.4.4 Sample Preparation Workflow

The common ATLAS data preparation and processing steps are applied sequentially, starting from the raw Analysis Data Objects (AOD) of MC simulations and experimental data, and concluding with the final .root files of n-tuples (Figure 4.11).

The ‘SUSY20’ derivation configuration is used for both MC and Data samples, with p-tags ‘p5241’ and ‘p5242’, respectively. To optimize data collection, specific event selections are applied: events



Figure 4.11: Workflow from AOD files of MC and Data samples to .root file of n-tuples, highlighting key stages in the process.

must include at least one jet with  $p_T > 200$  GeV,  $|\eta| < 2.8$ , and pass MET, single lepton, or single photon triggers.

NTuples are generated using the common `SusySkimAna` package, configured for this analysis via the `SusySkimHiggsino` framework. The process is optimized within the `MonojetSelector` class, utilizing `AnalysisBase` version 21.2.222 for NTuple production.

For this analysis, I developed a `Python`-based framework designed to efficiently handle large datasets by leveraging the highly optimized array-like computations. Figure 4.12 illustrates this approach compared to traditional event-by-event analysis in `C++`, commonly used in the Cut-and-Count method. This framework easily incorporates modern tools such as `PyTorch` for machine learning and `PyHF` for statistical interpretation.

## 4.5 Analysis Object Definition & Pre-Selection

This section outlines the reconstruction of physics objects (electrons, muons, jets, photons) and the associated pre-selection criteria used in this analysis, based on standard guidelines from the Combined Performance groups and implemented using `SUSYTools`. A detailed summary of baseline and signal object definitions is provided in Table 4.1.

The analysis objects are classified into two categories:

- **Baseline objects:** A loose selection of objects, typically used for veto purposes to ensure no contamination from these objects in specific regions. For example, baseline electrons and muons are vetoed in the signal region to suppress contamination from  $W \rightarrow \mu\nu/e\nu$  decays.
- **Signal objects:** A refined subset of objects that meet stricter quality and isolation criteria

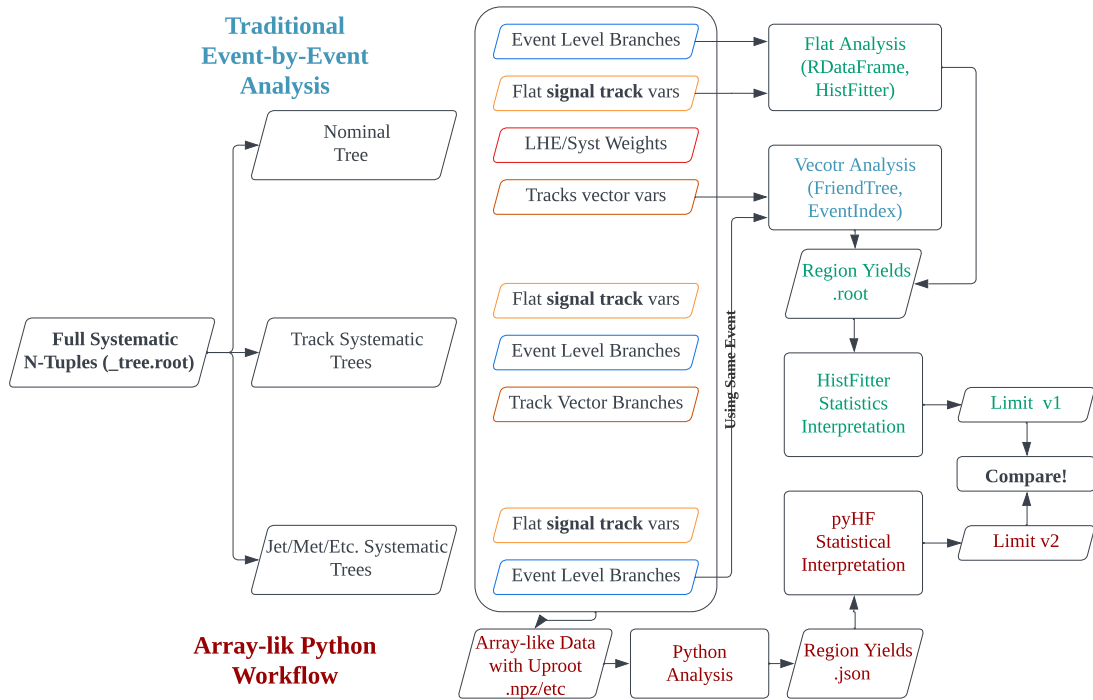


Figure 4.12: Comparison of the N-Tuple structure: traditional event-by-event analysis in C++ versus the array-like analysis with Python. This analysis employs the latter approach, utilizing Python for array-based operations which are efficient for this type of data handling.

to ensure higher purity in the analysis. These are typically required in control regions to check processes like  $W \rightarrow \mu\nu/e\nu$ .

### 4.5.1 Event Objects

**Electrons and Muons** are reconstructed using inner detector tracks (matched to electromagnetic calorimeter deposits for electrons, or combined with the Muon Spectrometer for muons). Both must satisfy  $p_T$ ,  $|\eta|$ , and impact parameter requirements. Signal versions are selected using tighter isolation and identification criteria (see Table 4.1).

**Jets** are reconstructed using the anti- $k_t$  algorithm with a radius parameter of  $R = 0.4$  from particle-flow objects, including tracks from the hard-scatter event and residual calorimeter clusters. Pileup mitigation is applied using the Jet Vertex Tagger (JVT) with the *Tight* working point for jets with  $p_T < 60$  GeV. Baseline jets must satisfy basic  $p_T$  and  $|\eta|$  requirements. Signal jets have tighter  $|\eta| < 2.8$  requirement. Jets from b-hadrons are tagged using the DL1r algorithm at the 85% efficiency working point.

**Photons** are identified and calibrated from electromagnetic clusters in the calorimeter. Baseline photons must meet basic  $p_T$  and  $|\eta|$  criteria and *Tight* identification requirement, while signal photons are subject to stricter isolation and higher  $p_T$  thresholds to enhance the purity of selected events (see Table 4.1).

**Missing Transverse Momentum** ( $E_T^{\text{miss}}$ ) is calculated as the negative vector sum of the transverse momenta of all identified objects (electrons, muons, jets, and photons) along with the soft term derived from tracks associated with the primary vertex but not linked to any object. This ensures optimal calibration of jets and other physics objects while maintaining pileup independence in the soft term. The *Tight* working point is used for the best precision.

In addition to standard  $E_T^{\text{miss}}$ , a 'lepton-invisible'  $E_T^{\text{miss}}$  is calculated by excluding leptons, treating electrons and muons as invisible like neutrinos. This adjustment allows for the creation of control and validation regions to test Standard Model background modeling and neural network perfor-

| Property                                | Signal                                                | Baseline                              |
|-----------------------------------------|-------------------------------------------------------|---------------------------------------|
| Electrons                               |                                                       |                                       |
| Kinematic                               | $p_T > 4.5 \text{ GeV},  \eta  < 2.47$                |                                       |
| Identification                          | MediumLLH                                             | LooseAndBLayerLLH                     |
| Isolation                               | Loose_VarRad                                          | –                                     |
| Impact parameter                        | $ d_0/\sigma(d_0)  < 5,  z_0  < 0.5 \text{ mm}$       | $ z_0  < 0.5 \text{ mm}$              |
| Muons                                   |                                                       |                                       |
| Kinematic                               | $p_T > 3 \text{ GeV},  \eta  < 2.5$                   | $p_T > 3 \text{ GeV},  \eta  < 2.7$   |
| Identification                          | Medium                                                | Medium                                |
| Isolation                               | PflowLoose_VarRad                                     | –                                     |
| Impact parameter                        | $ d_0/\sigma(d_0)  < 3 \ \& \  z_0  < 0.5 \text{ mm}$ | $ z_0  < 0.5 \text{ mm}$              |
| Photons                                 |                                                       |                                       |
| Kinematic                               | $p_T > 130 \text{ GeV},  \eta  < 2.37$                | $p_T > 25 \text{ GeV},  \eta  < 2.37$ |
| Identification                          | Tight                                                 | Tight                                 |
| Isolation                               | FixedCutTight                                         | –                                     |
| Jets (Anti- $k_t$ $R = 0.4$ PFlow)      |                                                       |                                       |
| Kinematic                               | $p_T > 20 \text{ GeV},  \eta  < 2.8$                  | $p_T > 20 \text{ GeV},  \eta  < 4.5$  |
| Pileup mitigation                       | JVT Tight for $p_T < 60 \text{ GeV},  \eta  < 2.4$    |                                       |
| $b$ -Jets (Anti- $k_t$ $R = 0.4$ PFlow) |                                                       |                                       |
| Kinematic                               | $p_T > 20 \text{ GeV},  \eta  < 2.5$                  |                                       |
| Pileup mitigation                       | JVT Tight for $p_T < 60 \text{ GeV},  \eta  < 2.4$    |                                       |
| $b$ -tagging                            | DL1r FixedCutBeff 85%                                 |                                       |
| Missing transverse momentum             |                                                       |                                       |
| Working point                           | Tight                                                 |                                       |
| Soft term                               | Track-based (TST)                                     |                                       |

Table 4.1: Summary of event-level analysis object definitions.



mance in events with leptons before applying to the signal regions. The signal regions includes a veto of event with identified electrons and muons.

### 4.5.2 Overlap Removal

Overlap removal (OR) is a systematic procedure used to ensure that no physics object is counted more than once across multiple object collections, such as electrons, muons, jets, and photons. This process is applied to baseline objects, excluding fat jets and taus.

OR is primarily based on  $\Delta R$  matching between potentially double-counted objects or shared inner detector tracks to uniquely assign each object to only one category. Special functionalities include: **Boosted leptons**, where a sliding cone  $\Delta R$  (which decreases with increasing jet  $p_T$ ) is used in lepton-jet overlaps; and **Heavy-flavor prioritization**, where b-tagged jets are prioritized in jet-lepton overlaps.

The sequence of overlap removal is as follows:

**Muon-electron OR:** reject muon ID track is shared with electron

**Photon-electron/muon OR** rejection photon if  $\Delta R < 0.4$

**Jet-electron OR:** reject jet if not a b-jet and  $\Delta R < 0.2$

**Electron-jet OR:** reject electron if  $\Delta R < 0.4 < \min(0.4, 0.04 + 10\text{GeV}/p_T(e))$

**Jet-muons OR:** reject jet if not a b-jet and  $\Delta R < 0.2$

**Muon-jet OR:** reject muon if  $\Delta R < 0.4 < \min(0.4, 0.04 + 10\text{GeV}/p_T(\mu))$

**Photon-jet OR:** reject photon if  $\Delta R < 0.4$

### 4.5.3 Track Object Definition

The tracks are required to pass *Tight Primary* working point criteria to reduce fake tracks and ensure precise measurement, which includes:

- $p_T > 500 \text{ MeV} \ \& \ |\eta| < 2.5$
- $N_{\text{mod}}^{\text{sh}} \leq 1$ : Less than or equal to 1 Pixel/SCT hits assigned to multiple tracks
- $N_{\text{si}}^{\text{hole}} \leq 2$ : Less than or equal to 2 Pixel/SCT hits missing
- $N_{\text{Si}} \geq 9$  (if  $|\eta| < 1.65$ ): At least 9 hits in the silicon detectors (if  $|\eta| < 1.65$ )
- $N_{\text{Si}} \geq 11$  (if  $|\eta| > 1.65$ ): At least 11 hits in the silicon detectors (if  $|\eta| > 1.65$ )
- $N_{\text{IBL}} + N_{\text{B-Layer}} > 0$ : At least 1 hit in either one of the two innermost layers (the IBL or the B-Layer)
- $N_{\text{pix}}^{\text{hole}} = 0$ : No Pixel hits missing

## 4.6 Neural-Network-based Signal Region Design

### 4.6.1 Introduction & Motivation

Traditional signal region (SR) construction in high-energy physics often relies on cut-based methods, where kinematic variables are sequentially constrained to separate signal from background. These methods use binary decisions and can miss more complex correlations between variables. A typical example of the cut flow is illustrated in Figure 4.13, which includes the event and track kinematics-based cuts applied sequentially.

In this analysis, I implement a neural network (NN)-based approach, replacing the cut-based criteria with a more flexible model that do not depend on a single cut value on individual kinematic variables. As demonstrated by [67] and [68], fully connected neural networks (FCNNs) can effectively simulate generic functions, making them well-suited for this task. Instead of limited to a rectangular box selection in the high-dimensional parameter space, we can draw a signal-background classification boundary with a generic parameterized function. In this case, the FCNN takes multiple input features and produces a single score that optimally distinguishes the signal from background, capturing complex relationships in high-dimensional spaces.

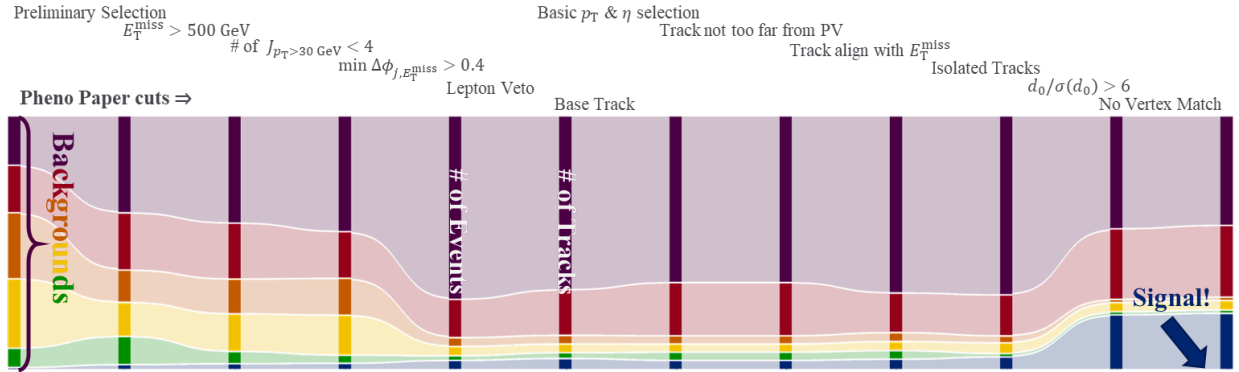


Figure 4.13: Sankey diagram illustrating the relative contributions of different backgrounds (from top to bottom:  $Z \rightarrow \nu\nu$ ,  $W \rightarrow \tau\nu$  (Hadronicdecay),  $W \rightarrow \tau\nu$  (Leptonicdecay),  $W \rightarrow \mu\nu$ ,  $W \rightarrow e\nu$ , and  $t\bar{t}$ ) and a signal sample using the cuts originally suggested in [23]. The diagram showcases the impact of each kinematic cut, progressing from the event level on the left to the track level on the right. Note that, in the middle, the counting switches from the number of events to the number of tracks in these events.

A two-level NN design is employed:

- At the event level, the NN processes variables unique to each event (e.g., MET, number of jets) and outputs an event-level score.
- At the track level, the NN processes variables specific to each track (e.g.  $d_0$ ,  $p_T$ ) and outputs a track-level score.

This two-level approach is integrated throughout the analysis, from histogramming and counting to MC corrections.

In the following sections, I will cover the NN model setup (4.6.2) and the construction of signal regions (4.6.3). To ensure robustness and avoid overfitting, techniques such as k-fold cross-validation and early stopping are implemented, helping to ensure the model generalizes well to unseen data, i.e., test data that the model has not encountered during training. Additional discussions on input feature importance using SHAP values (4.6.4) and machine learning-related uncertainties (4.6.5) will also be provided. While not directly part of the signal region selection, these techniques were valuable lessons learned during this project. They helped optimize the analysis setup and provided deeper insights into the NN model.

## 4.6.2 FCNN Model Description

### 4.6.2.1 Basic Architecture Setup

In this analysis, a two-level neural network architecture is employed to optimize signal region selection. The implementation is based on the PyTorch library [69], which provides flexibility and efficiency for building and training neural networks. Each level consists of a fully connected neural network (FCNN), where the output from each node in one layer is fed into the next layer through linear multiplication with a matrix of weights. Each FCNN comprises three hidden layers with 50, 30, and 15 nodes, respectively, as visualized in Figure 4.14. Each layer uses a Rectified Linear Unit (ReLU) activation function to introduce non-linearity, enabling the model to capture complex correlations between input features. The final output is computed using a sigmoid activation

function, which produces a score between 0 and 1, indicating whether an event or track should be classified as Standard Model (SM) background (close to 0) or SUSY signal (close to 1).

Various combinations of layers and nodes were tested, and I found that the current setup of 3 hidden layers (50, 30, and 15 nodes) worked well without signs of overfitting. Adding more nodes or layers didn't improve performance. The exact layer construction is not essential, as long as the network captures the signal features and avoids overfitting. The model's flexibility to learn from the data ensures that it can effectively distinguish between signal and background within a wide range of architectures.

At the event level, the FCNN processes global event kinematic variables, such as missing transverse energy (MET) and jet kinematics, to output an Event Score that differentiates SUSY-like events from SM-like events. The track-level FCNN focuses on track-level variables to identify soft, mildly displaced tracks from  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$  decays, and distinguish them from tracks originating from SM processes.

#### 4.6.2.2 Input Features for Event- and Track-Level FCNNs

The input features for both the event- and track-level FCNNs are selected based on kinematic variables relevant to identifying SUSY signals, as described in Section 4.3. The goal is for the FCNN to utilize these features to produce the best score for distinguishing SUSY signals from Standard Model backgrounds. For the **Event-Level FCNN**, we summarize the key input features below:

- $E_T^{\text{miss}}$ : The missing transverse energy is the most salient signature of Higgsino events, as it can indicate the presence of two neutralinos ( $\tilde{\chi}_1^0$ ) escaping detection.
- $\text{jet}_{\text{lead}} p_T$  and  $\text{jet}_{\text{lead}} \eta$ : These variables describe the leading jet<sup>7</sup> transverse momentum and its pseudo-rapidity, helping to determine whether this jet is likely from initial-state radiation.

---

<sup>7</sup>Jets are ordered by their transverse momentum ( $p_T$ ) from highest to lowest, with the "leading jet" referring to the one with the highest  $p_T$ .

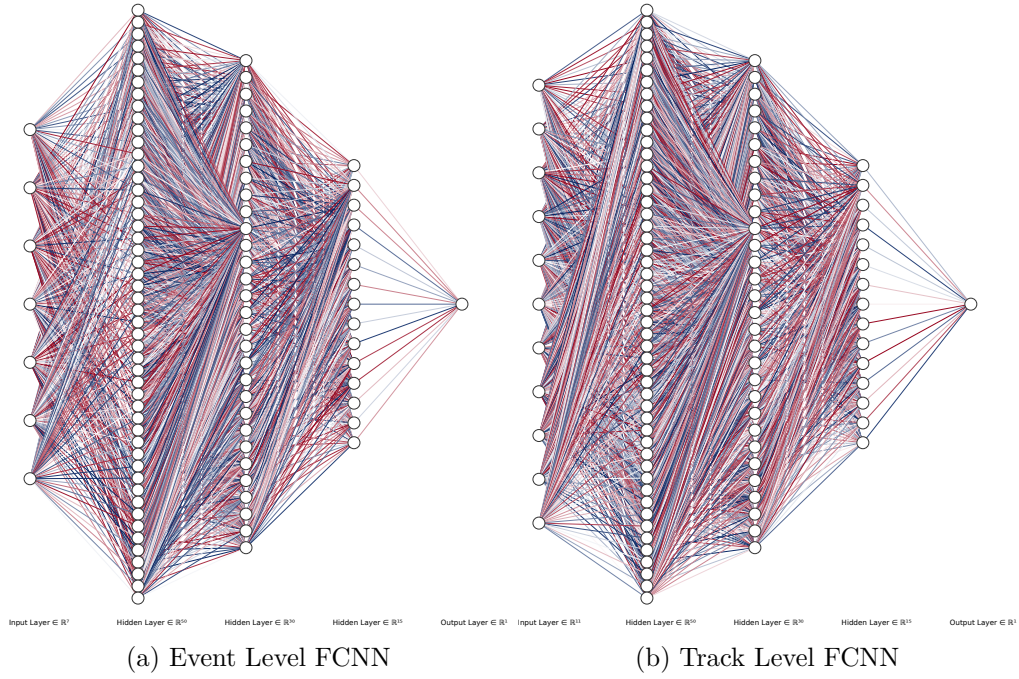


Figure 4.14: Visualization of the two-level neural network structure. Each network processes event- or track-level kinematic variables and outputs a probability score determining whether an event or track is signal-like. On the left, each node corresponds to the input features, and are passed through three hidden layers in the middle. On the right, the network outputs a single score.

- $N_{\text{jet}>30\text{GeV}}$ : Counting the number of jets above 30 GeV helps reject high  $E_T^{\text{miss}}$  events caused by jet mis-measurements or those SM backgrounds with large jet multiplicity, such as  $t\bar{t}$ .
- $\min \Delta\phi_{E_T^{\text{miss}}, \text{jet}>30\text{GeV}, 1-4}$ : This variable measures the azimuthal separation between the four leading jets and  $E_T^{\text{miss}}$ , ensuring that high  $E_T^{\text{miss}}$  events are not due to miscalculations/mis-measurement of momentum imbalance or QCD processes.
- $H_{T, \text{jet}>30\text{GeV}}$ : The total hadronic transverse energy provides a measure of the overall jet activity in the event, calculated as the scalar sum of transverse momentum of jets with  $p_T > 30\text{GeV}$ :

$$H_{T, \text{jet}>30\text{GeV}} = \sum_j p_{T,j}$$

- $m_{\text{eff}, \text{jet}>30\text{GeV}}$ : The effective mass  $m_{\text{eff}}$  represents the total energy of the event, combining contributions from jets, leptons, and  $E_T^{\text{miss}}$ :

$$m_{\text{eff}, \text{jet}>30\text{GeV}} = \sum_{j, p_T > 30\text{GeV}} p_{T,j} + \sum_{\mu} p_{T,\mu} + \sum_e p_{T,e} + E_T^{\text{miss}}$$

This captures the overall energy scale of the event, helping to differentiate between SUSY-like events and SM backgrounds.

The key **Track-Level FCNN** input features have been discussed in detail in Section 4.3.2. In this subsection, we highlight additional variables that are introduced to enhance signal discrimination.

- **Track Isolation (Trk ISO)**: The track isolation is calculated in two ways: within a larger cone ( $\Delta R \leq 1$ ) and a smaller cone ( $\Delta R \leq 0.4$ ), represented as:  $\text{Trk ISO, cone} = 1.0$  and  $\text{Trk ISO, cone} = 0.4$ . These variables help to quantify the isolation of the pion track, with low isolation values expected for SUSY signal events.
- **Secondary Vertex Matching**: The track-level FCNN uses variables from the secondary vertex matching algorithm (`VrtSecInclusive`, abbreviated as **VSI**) to suppress Standard Model backgrounds, such as  $K_S^0 \rightarrow \pi^+ \pi^-$  decays. The `matched-to-VSI` variable indicates

whether a successful match to a secondary vertex was made by the **VSI** algorithm. The reconstructed invariant mass of the tracks associated with the secondary vertex, **matched-VSI-mass**, is calculated from the sum of four-momenta.

The input features are summarized in Table 4.2. Each input roughly scaled to a floating-point number near the range of 0 to 1 before feeding it to the neural network. This scaling helps the latent parameters in the NN layers stay on the order of 1. The feature importance ranking in the networks' decision-making will be discussed in Section 4.6.4.

Table 4.2: Input variables used in the Neural Networks

| Event Level                                                            | Track Level                                  |
|------------------------------------------------------------------------|----------------------------------------------|
| $E_T^{\text{miss}}$                                                    | Trk $p_T$                                    |
| $\text{jet}_{\text{lead}} p_T$                                         | Trk $\eta$                                   |
| $\text{jet}_{\text{lead}} \eta$                                        | Trk $D_0$                                    |
| $\min \Delta\phi_{E_T^{\text{miss}}, \text{jet}_{>30\text{GeV}, 1-4}}$ | Trk $S(D_0)$                                 |
| $m_{\text{eff}, \text{jet}_{>30\text{GeV}}}$                           | Trk $Z_0 \sin(\theta)$                       |
| $H_{T, \text{jet}_{>30\text{GeV}}}$                                    | $\Delta\phi_{E_T^{\text{miss}}, \text{Trk}}$ |
| $N_{\text{jet}_{>30\text{GeV}}}$                                       | Trk ISO, cone = 1.0                          |
|                                                                        | Trk ISO, cone = 0.4                          |
|                                                                        | Trk matched to VSI                           |
|                                                                        | Trk matchedVSI mass                          |
|                                                                        | Trk TightPrimary                             |

#### 4.6.2.3 The Loss Function & the Training Process

For binary classification tasks like distinguishing SUSY signals from Standard Model backgrounds, we use the **Binary Cross-Entropy (BCE) loss function**<sup>8</sup>. This loss function is particularly well suited for two-class classifiers, where the goal is to output a probability score between 0 and 1 for each event.

The Binary Cross-Entropy loss is defined as:

$$\mathcal{L}_{\text{BCE}} = - \sum w_i [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)]$$

<sup>8</sup>An earlier version of the model utilized the estimated sensitivity  $Z$  as the loss function, combined with regularizing terms. This approach was particularly suited for small Monte Carlo sample sizes and a single signal region. However, as we targeted multiple signal points with multiple signal regions and generated larger datasets, this method was replaced by the more conventional BCE loss.



where  $y_i$  is the true label (0 for background, 1 for signal),  $p_i$  is the predicted probability score and  $w_i$  is the object weight. By back-propagating the BCE loss gradient to the FCNN’s hidden parameters, the model learns to minimize the difference between predicted and true labels, i.e., improving its ability to distinguish between signal and background events according to the simulated events. To address the dataset imbalance—where there are fewer signal events compared to background events—the signal and background samples are reweighted. This is mainly an issue for track-level. By ensuring that the sum of weights for both classes is equal, the Binary Cross-Entropy loss function treats both signal and background equitably, preventing bias toward the majority class (background). This improves the model’s performance in detecting the minority (signal) class.

The training process for our FCNN models spans around 80 epochs, where each epoch represents one complete pass through the training dataset. The model is trained using the Adaptive Moment Estimation (ADAM) optimizer [70], which boasts several notable advantages that have contributed to its wide usage.

Firstly, it combines the benefits of two other extensions to stochastic gradient descent: **AdaGrad** [71], which works well with sparse gradients, and **RMSProp** [72], which works well in online and non-stationary settings. This makes ADAM particularly effective in **handling noisy or sparse gradient**. In this case, because our Monte Carlo sample is limited by the number of simulated events, the resulting gradient of the loss would be noisy because of the statistical uncertainty and thus would benefit from using the ADAM optimizer.

Secondly, ADAM utilizes **adaptive learning rates**, meaning it adjusts the rate at which it updates the model weights based on the first and second moments of the gradients. This feature leads to faster convergence and less sensitivity to the initial learning rate. This is beneficial for a newcomer in machine learning (like a physicist) who is not familiar with hyperparameter tuning.

These advantages make ADAM an appropriate choice for the efficient and effective training of our FCNN models, aiming to optimize their performance in identifying SUSY-like events and tracks.

#### 4.6.2.4 k-fold Cross Validation & Early Stopping

To make sure the trained FCNN is robust and generalizable to testing dataset, we employ a  $k$ -fold cross-validation approach with early stopping. Specifically, we evenly divide our dataset into three distinct parts (corresponding to  $k = 3$ ): a training set, a validation set, and a testing set.

The **training set** is used to determine the model weights, allowing the FCNN to learn how to distinguish between signal and background. During this process, the performance of the model is monitored on the **validation set**, which is not used for weight updates. This allows for hyperparameter tuning and provides a mechanism for **early stopping**, preventing overfitting of the NN weights to statistical fluctuations. Training is stopped when the model's performance on the validation set stops improving, ensuring it generalizes well to unseen data, and we save the highest-performing version as observed by the validation set in terms of the loss function. After training and validation, the model is applied to the **testing set**, which it has not seen during training. This provides an unbiased evaluation of the performance of the model. To increase the statistics, thereby reducing the statistical uncertainty of the simulated samples, we train three copies of the Neural Networks using the alternating training dataset and apply them to the respective testing datasets.

The diagram in Figure 4.15 shows an example of  $k = 5$  cross-validation scheme, which we had used at the beginning of the search, we were more limited by signal statistics (later more events were generated).

## k-fold Cross Validation

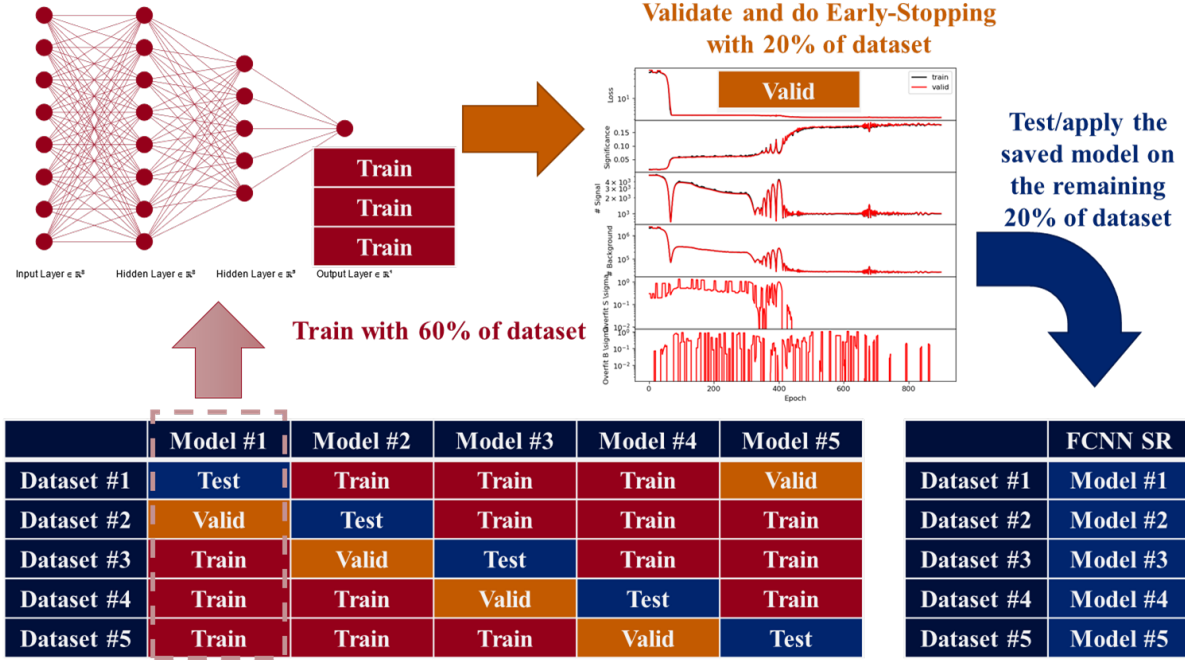


Figure 4.15: By training multiple copies of neural networks and using the dataset alternatively, we keep as many events in both training and testing as possible to reduce the statistical uncertainties of the prediction.

### 4.6.2.5 Dataset from MC Simulation & Preselection

The FCNN models, at both event and track levels, are trained using Monte Carlo simulated datasets (see Section 4.4). As discussed, these datasets are divided into training, validation, and testing sets, and further subdivided into five batches to accommodate GPU memory constraints. Each batch contains approximately  $2 \times 10^4$  background events and  $4 \times 10^4$  signal events, with all events passing basic preselection criteria (Table 4.3).

Additionally, each batch includes the pre-selected charged particle tracks from the selected events. These tracks meet the following criteria: they pass tight identification requirements, are not matched to reconstructed electrons or muons, and have a displacement of  $D_0 > 0.1\text{mm}$ . This results in approximately  $7.2 \times 10^6$  background tracks and  $10^5$  signal tracks originating from SUSY particle decays per batch.

| Variable                                                                     | Requirement                          |
|------------------------------------------------------------------------------|--------------------------------------|
| Trigger                                                                      | $E_{\text{T}}^{\text{miss}}$ trigger |
| Leading jet $p_{\text{T}}$ [GeV]                                             | $> 250$                              |
| Leading jet working point                                                    | <i>Tight</i>                         |
| Leading jet $ \eta $                                                         | $< 2.4$                              |
| Leading jet cleaning working point                                           | <i>Tight</i>                         |
| $E_{\text{T}}^{\text{miss}}$ [GeV]                                           | $> 275$                              |
| Number of base leptons                                                       | $= 0$                                |
| Number of $>30$ GeV jets                                                     | $\leq 4$                             |
| $\min \Delta\phi_{E_{\text{T}}^{\text{miss}}, \text{jet}>30\text{GeV}, 1-4}$ | $> 0.4$                              |

Table 4.3: Event kinematics preselection applied to all events for Signal Regions.

These preselection criteria help the analysis focus on SUSY-like events and reduce irrelevant backgrounds. Before training, we apply semi-data-driven corrections to the MC data, reweighting objects based on control regions (details in Section 4.7). This correction ensures that the MC simulation aligns more closely with real data at both the event and track levels.

### 4.6.3 Constructing the Signal Regions using NN Models

To achieve the highest possible sensitivity and extend exclusion limits in our search for Higgsino signals, we define four signal regions (SRs) using the output scores of the two FCNNs.

In SUSY searches, different mass points correspond to distinct physical signatures. Traditionally, this would require separate models for each mass point, which would overly complicate the analysis. Instead, we optimize the score cut on our model’s output using an averaged sensitivity,  $Z_{\text{average}}$ , calculated across selected mass points where we expect sensitivity. Each  $Z_i$  is estimated by a simplified PyHF model accounting for systematic uncertainties ( $\sigma_{\text{MC,Syst}}$ ), statistical uncertainties from the Monte Carlo (MC) samples, and Poisson uncertainties in the SR yield. For this analysis, we assume 10% systematic uncertainty for backgrounds and 35% for signals, with a flat uncertainty on the SR yield. Background systematic uncertainty is relatively lower, as theory uncertainties are constrained in the Control Region during the fit. These systematic uncertainties are consistent with the full nuisance parameter background-only fits, and is validated through MC-Data agreement in the Validation Regions (VRs).

$$Z_{\text{average}} = \sum_{i \in \text{select mass points}} Z_i \quad (4.6)$$

Here the selected mass points include signal grid points at  $(\tilde{\chi}_2^0, \tilde{\chi}_1^\pm, \tilde{\chi}_1^0)$  in GeV: (85.7, 85.35, 85), (87, 86, 85), (100.7, 100.35, 100), (102, 101, 100), (125.7, 125.35, 125), (126, 125.5, 125), (126.5, 125.75, 125), (127, 126, 125), (150.7, 150.35, 150), (151, 150.5, 150), (151.5, 150.75, 150), (176, 175.5, 175), and (176.5, 175.75, 175).

We assign both Event-Level and Track-Level FCNN scores to each event and associated track. Since most signal events typically contain only one signal-like track, we assign the highest track score in the event to represent the Track-Level score. This simplifies the counting and decision-making process, avoiding complex track combinatorics (see Section B.7.2). Score cuts are placed on the Event Score vs. Track Score plane, as shown in Figure 4.16.

We define four signal regions to optimize sensitivity across various SUSY models with different kinematic features:

- High  $\Delta m$  and Low  $m_{\tilde{\chi}_1^0}$ : These scenarios feature relatively higher Higgsino cross-sections but fewer displaced tracks, making them more sensitive to signal regions with larger statistics but lower Signal-to-Background (S/B) ratios.
- Low  $\Delta m$  and High  $m_{\tilde{\chi}_1^0}$ : These scenarios involve lower Higgsino cross-sections but more displaced tracks, favoring signal regions with higher S/B ratios but lower statistics.

Through testing, we found that the 4-SR configuration offered better sensitivity than the 3-SR setup, while moving to 5 SRs showed only marginal improvements, reflecting a point of diminishing returns. The four SRs progressively loosen the score cuts from high S/B, low-statistics regions to lower S/B, higher-statistics regions, ensuring we capture as many SUSY signals as possible without compromising sensitivity in different regions of the parameter space.

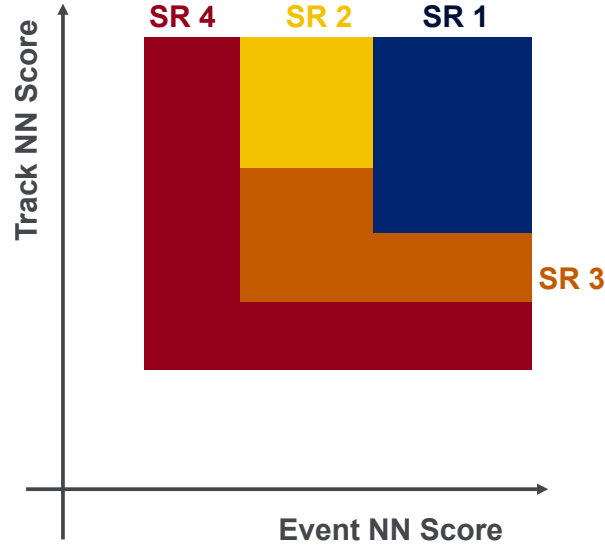


Figure 4.16: Score cut demonstration for the four Signal Regions defined based on Event and Track FCNN scores.

The SRs are mutually exclusive to simplify the statistical interpretation. Tighter selection (higher S/B) regions are excluded from looser selections. See Table 4.4 for the specific score requirement.

Figure 4.17 shows an estimated exclusion region based on this model.

Table 4.4: FCNN Model and Signal Region Definitions by Score Cuts. The score cut values are optimized for the four signal region configuration. (Neural Network trained by BCE loss.)

| Signal Region | Event Score Cut | Track Score Cut | Additional Cut                          |
|---------------|-----------------|-----------------|-----------------------------------------|
| SR 1          | $> 0.7122$      | $> 0.7875$      | -                                       |
| SR 2          | $> 0.6453$      | $> 0.7993$      | $\notin$ SR 1                           |
| SR 3          | $> 0.6452$      | $> 0.7160$      | $\notin$ (SR 1 $\cup$ SR 2)             |
| SR 4          | $> 0.5817$      | $> 0.7051$      | $\notin$ (SR 1 $\cup$ SR 2 $\cup$ SR 3) |

There are 8 score cuts that need to be optimized for four signal region configuration. To optimize  $Z_{\text{average}}$ , we use `scipy.optimize.minimize` [73] to find the cut values that maximizes the averaged sensitivity rather than scanning through the 8-dimensional grid of cut scores.

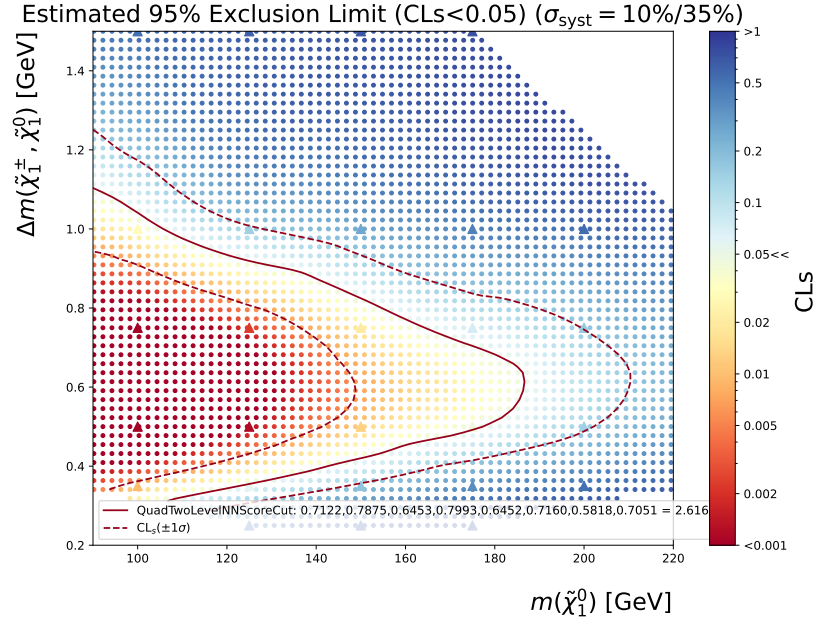


Figure 4.17: Estimated exclusion region at 95% Confidence Level using the  $CL_s$  test, calculated from the two orthogonal FCNN Signal Regions (SR) with PyHF. The exclusion contour has a substantial improvement over the Cut & Count analysis. Assumed 10% systematic uncertainty for backgrounds and 35% for signals.

## 4.6.4 Discussion: SHAP Value & Input Feature Importance

### 4.6.4.1 SHAP: Impact of a feature value

In particle physics, machine learning techniques are essential for analyzing the vast data from experiments. SHAP (SHapley Additive exPlanations) values (Ref [74]) provide a powerful method for interpreting predictions from models like neural networks. In this analysis, we applied SHAP values to two neural networks (event-level and track-level) to define signal regions.

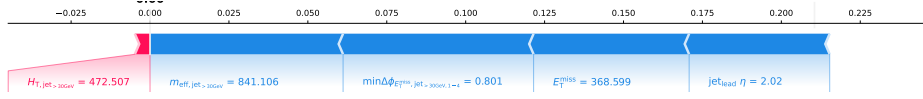
SHAP values, based on game theory, distribute a model’s prediction (signal or background) across its features (e.g., missing transverse energy or impact parameter). By evaluating all possible combinations of features and their joint effects on the prediction, SHAP ensures fair attribution, clarifying each feature’s contribution. This model-agnostic approach applies to various machine learning models, from the simple fully connected networks in our analysis to the more complex architectures used in ATLAS.

To illustrate the use of SHAP values, we provide two examples based on the SHAP value decomposition plots. In these plots, red bars extending to the right represent features that contribute positively to a signal-like classification, while blue bars extending to the left indicate features that contribute negatively, suggesting a background-like classification. The length of each bar reflects the magnitude of the feature’s impact on the model’s prediction. The central marker shows the overall prediction score, combining contributions from all features.

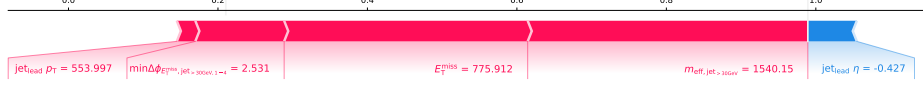
**Event-Level Analysis:** A key feature of the Higgsino signal event is high Missing Transverse Energy (MET), i.e. higher MET has higher probability being signal. SHAP values quantify MET’s importance in the FCNN model when distinguishing signals from background events. We can see a large positive SHAP value for higher MET. This supports the intuition that significant MET correlates with the likelihood of classifying it as a signal event (see Figure 4.18b).

Conversely, we find a negative SHAP value for low MET and small  $\Delta\phi$  between MET and jet indicates that: these two variables being low suggests the event is more background-like. This also align with our physics intuition(see Figure 4.18a).





(a) **Background Example:** The neural network classifies this event as background-like (score near 0), mainly due to the relatively low  $E_T^{\text{miss}}$  of 369 GeV and a minimum  $\Delta\phi$  of 0.8 between the leading jet and  $E_T^{\text{miss}}$ , indicating they are not back-to-back, as expected for background events.



(b) **Signal Example:** This event is classified as signal-like (score near 1), driven by the high  $E_T^{\text{miss}}$  of 775 GeV, which strongly indicates the presence of invisible particles, and a minimum  $\Delta\phi$  of 2.53 between the leading jet and  $E_T^{\text{miss}}$ , suggesting a back-to-back configuration typical for signal events.

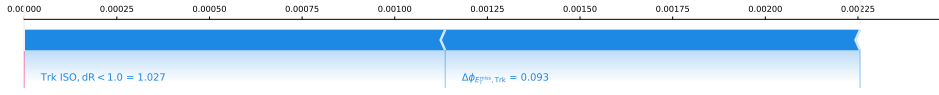
Figure 4.18: Event-Level SHAP Value Decomposition Analysis

**Track-Level Analysis:** A critical feature at the track level is the significance of the impact parameter,  $S(D_0)$ . High  $S(D_0)$  values suggest the charged particle originates from the decay of semi-long-lived particles, such as  $\tilde{\chi}_1^\pm$ . SHAP values quantify the impact of  $S(D_0)$ , and a large positive SHAP value for high  $S(D_0)$  means that the neural network associates a strong positive correlation between  $S(D_0)$  and the likelihood of being signal, aligning with our physics intuition (see Figure 4.19b).

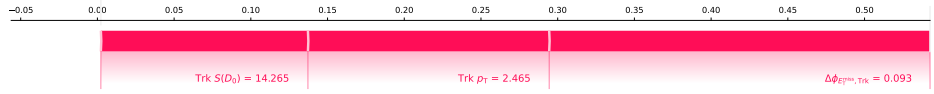
Conversely, a negative SHAP value for a large sum of track isolation cone  $p_T$  ( $\Delta R < 1.0$ ) indicates that the FCNN finds a strong negative correlation between  $\text{Trk ISO}_{\text{cone} = 1.0}$  and the signal likelihood of the track. This matches the expectation that signal-like tracks typically lack nearby secondary tracks (see Figure 4.19a).

#### 4.6.4.2 Importance Ranking: Trends in Parameter Contributions

While SHAP values help interpret how individual features influence neural network predictions, correlations between kinematic variables can make interpretation for single instances obscure. Aggregating SHAP values across many events or tracks (e.g., 1,000) reveals general trends in how different parameters influence the model's classification decisions.



(a) **Background Example:** The neural network classifies this track as background-like (score near 0). This classification is mainly due to a high track isolation sum (Trk ISO, cone = 1.0) of 1.03, indicating the presence of nearby tracks, which is more characteristic of background events.



(b) **Signal Example:** The neural network classifies this track as signal-like (score around 0.54). This is primarily due to a high  $S(D_0)$  value of 14.27, indicating a significant displacement from the expected path, which is characteristic of tracks originating from the decay of semi-long-lived particles.

Figure 4.19: Track-Level SHAP Value Decomposition Analysis.

Figure 4.20a illustrates these trends. For example, events with higher MET typically show positive SHAP values, indicating its contribution to a higher likelihood of being signal-like, consistent with expectations for new physics involving invisible particles. In contrast, events with more jets often have negative SHAP values, reflecting a contribution to a "Standard Model-like" classification by the FCNN model.

Figure 4.20b ranks features based on averaged absolute SHAP values, highlighting kinematic parameters that influence model predictions the most. The effective energy scale of the event ( $m_{\text{eff}}$ ) and the transverse momentum of the leading jet ( $p_T^{\text{jet}}$ ) emerge as the most influential features, while the number of jets and the leading jet's  $\eta$  have less impact. This ranking aligns well with our physical expectations for the SUSY model and the SM backgrounds.

Similar patterns emerge in the track-level analysis shown in Figure 4.21.

Figure 4.21a shows that tracks with a higher significance of the impact parameter,  $S(D_0)$ , generally have positive SHAP values, suggesting a contribution to higher likelihood of being signal-like. This aligns with the expectation that semi-long-lived charginos. In contrast, tracks with a larger angular separation ( $\Delta\phi$ ) between the track and MET direction exhibit negative SHAP values, indicating

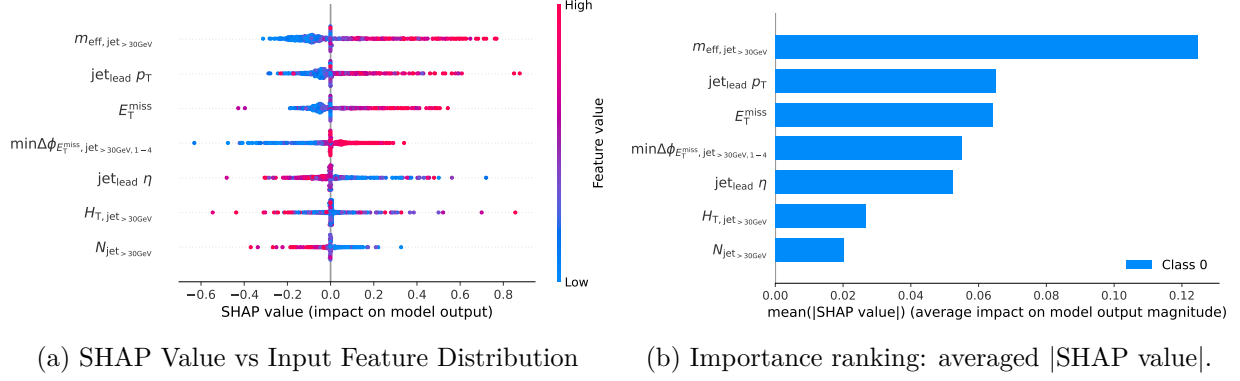


Figure 4.20: Feature Importance Ranking by SHAP Values for the Event-Level FCNN:

- (a) displays a scatter plot where each dot represents an input feature's SHAP value, with the color indicating the feature's value (red for high, blue for low). The horizontal position of each dot shows its impact on the model's prediction, with dots positioned towards the right indicating a push towards a signal-like classification and those to the left indicating a push towards a background-like classification.
- (b) presents a bar plot ranking the kinematic parameters by their average absolute SHAP value over 1000 events. The length of each bar indicates the impact a parameter has on the model's prediction, highlighting which features are most influential.

its push towards background-like classification. This supports the understanding that signal tracks should align more closely with the direction of the neutralino  $\tilde{\chi}_1^0$  and MET.

Figure 4.21b ranks features based on averaged absolute SHAP values, with  $S(D_0)$  and  $\Delta\phi_{E_T^{\text{miss}}, \text{Trk}}$  being the most influential. This ranking confirms that features closely related to the SUSY model have the most significant impact, rather than the longitudinal impact parameter  $\text{Trk } Z_0 \sin(\theta)$ . This aligns with our physical intuition.

#### 4.6.4.3 Summary on SHAP value interpretations

SHAP values provide a practical framework for interpreting neural network predictions, with several key features enhancing their utility. Their additive nature ensures that the contributions of all features sum to the difference between the model's prediction and the average output, allowing for clear attribution of each feature's impact.

SHAP values also capture feature interactions and correlations by considering contributions in all possible combinations, reflecting the complex relationships used by neural networks. This approach

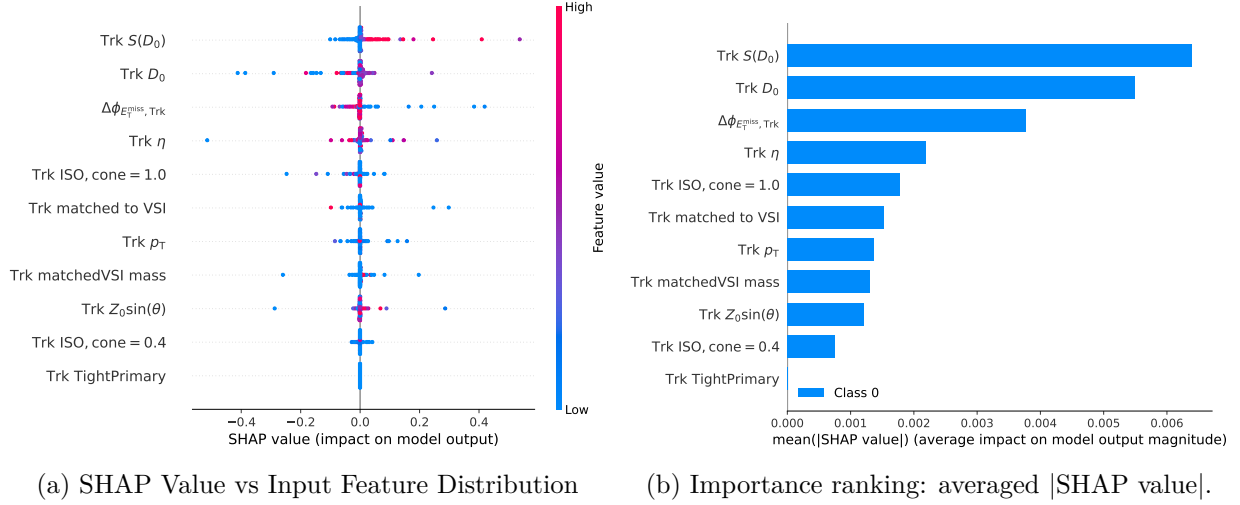


Figure 4.21: Feature Importance Ranking by SHAP Values for Track-Level FCNN model, following the same convention as Figure 4.20.

can reveal the importance of features that may not be significant individually but contribute to distinguishing signal from background when combined with others.

Additionally, SHAP values are consistent across different models that maintain the same input-output relationships and are unaffected by the order in which features are presented. This ensures fair and reliable interpretations.

These attributes make SHAP values valuable for high-energy physics (HEP) experiments, offering insights into how features influence model predictions, validating alignment with physical expectations, and identifying areas for improvement.

#### 4.6.5 Discussion: Breakdown of Machine Learning-Related Uncertainties

This section reviews the uncertainties associated with machine learning and discusses how they are addressed in the analysis, following the categories in Figure 4.22.

**Limited Training and Prediction Statistics:** Uncertainties arise from limited statistics in the selected signal region, similar to traditional analyses with human-placed cuts. Poisson counting uncertainty ( $\sigma_{(\text{yield,stat})}$ ) reflects this limitation if the SR is too small, while evaluating the FCNN

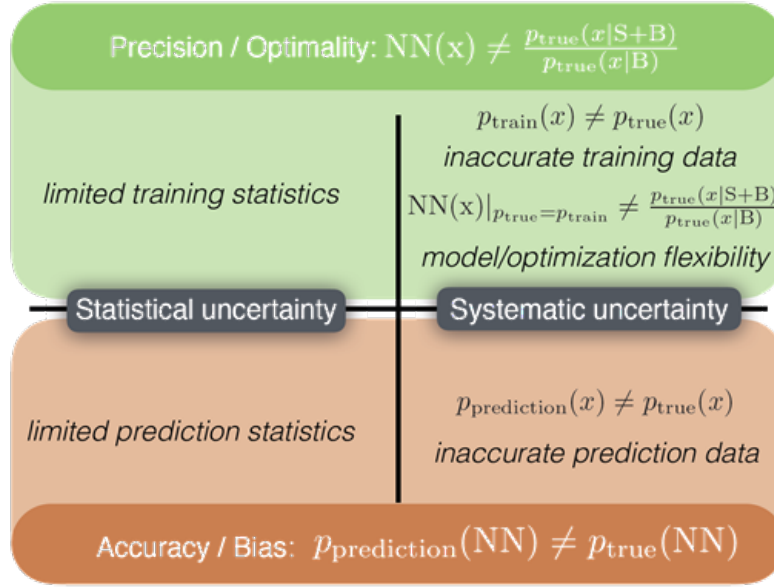


Figure 4.22: Diagram excerpt from Ben Nachman, *SciPost Phys.* 8, 090 (2020) [24], categorizing different sources of uncertainties in neural network-based analyses. The x-axis distinguishes uncertainties by their origin, separating those of statistical nature from systematic sources. The y-axis further classifies uncertainties based on their impact, differentiating between issues of accuracy (bias or mis-modeling) and precision (random fluctuations or noise). This framework provides a clear structure for analyzing and addressing the diverse uncertainties inherent in machine learning applications.

model on a low-statistics simulation sample can also affect model precision, denoted by  $\sigma_{(\text{MC},\text{stat})}$ .

**Inaccurate Training Data:** Uncertainty due to potential inaccuracies in the Monte Carlo simulation used for training (denoted by  $\sigma_{(\text{MC},\text{syst})}$ ) is addressed by our semi-data-driven MC corrections (Section 4.7). The MC-Data agreement in kinematics distributions are checked extensively in the four-fold Validation Regions (Section 4.8). The two-level architecture’s cross-validation, in particular, helps to check consistency in signal-like regions.

**Inaccurate Prediction Data:** The model’s flexibility in parameter optimization introduces uncertainty related to overfitting, especially with limited training data. Strategies like  $k$ -fold cross-validation, early stopping, and orthogonal datasets are used to mitigate these risks, as detailed in Section 4.6.2.4.

#### 4.6.5.1 Further Discussion on Method Choice of Two-Level FCNN

The choice of a two-level fully connected neural network was driven by the need for an efficient, fast-to-train model that offers flexibility in validation. While more advanced methods, such as Recurrent Neural Networks (RNNs) and Graph Neural Networks (GNNs), could capture additional inter-object correlations, the two-level FCNN was particularly well-suited for this analysis due to its simplicity and specific advantages:

- **Orthogonal Validation Regions:** A key feature of the two-level structure is its ability to validate one of the FCNN model’s predictions in orthogonal, background-dominant regions by requiring a low score in the other FCNN model (see details in Section 4.8). This cross-validation boosts confidence in the models’ robustness when applied to real data. It also helps validate the modeling of kinematic variables in signal-like events and tracks, a feature that would be difficult to implement with a single-level model.
- **Independent Features & No Sensitivity Improvement with Single-Level Approach:** For this analysis, the event-level signatures like  $E_{\text{T}}^{\text{miss}}$  and track signatures are quite independent. We tested a single-level FCNN approach, and it did not improve sensitivity. Further-

more, it lacked the cross-validation advantage provided by the two-level architecture, making it harder to extrapolate our confidence in consistent predictions from Control Regions to Signal Regions.

- **Simplicity and Speed:** The FCNN architecture is easy to train and implement, allowing for rapid iterations and efficient testing.

The two-level design strikes an optimal balance for this analysis, offering simplicity and cross-validation features without sacrificing performance. Future work with more complex signatures may benefit from methods with greater representational power, such as GNNs.

## 4.7 Semi-Data-Driven Monte Carlo Simulation Correction

In this section, we present the semi-data-driven approach used for background estimation, which addresses mismodeling—discrepancies between data and Monte Carlo simulations—through a multi-step correction process. The workflow consists of reweighting factors derived from Control Regions (CRs), validated in independent Validation Regions (VRs), and applied to Signal Regions (SRs) for final background estimation (see CR/VR/SR construction in Section 4.7.1).

Discrepancies arise because simulation setups won't exactly match physics cross-sections or the real detector conditions. To ensure reliable background predictions in SRs, corrections must be made when significant data-MC discrepancies are observed in CRs. The semi-data-driven strategy reweights event probabilities based on control regions to bring the simulation closer to real data.

The main sources of misestimate are addressed by my corrections include: cross-section uncertainties in the specific phase space of a high- $p_T$  ISR jet and large MET, inadequate modeling of the contribution from additional inelastic collisions occurring in the same bunch crossing (Pile-up), and mismodeling of hadronic  $\tau$  decays. As demonstrated in Figure 4.23, our approach involves sequentially correcting different sources of mismodeling:

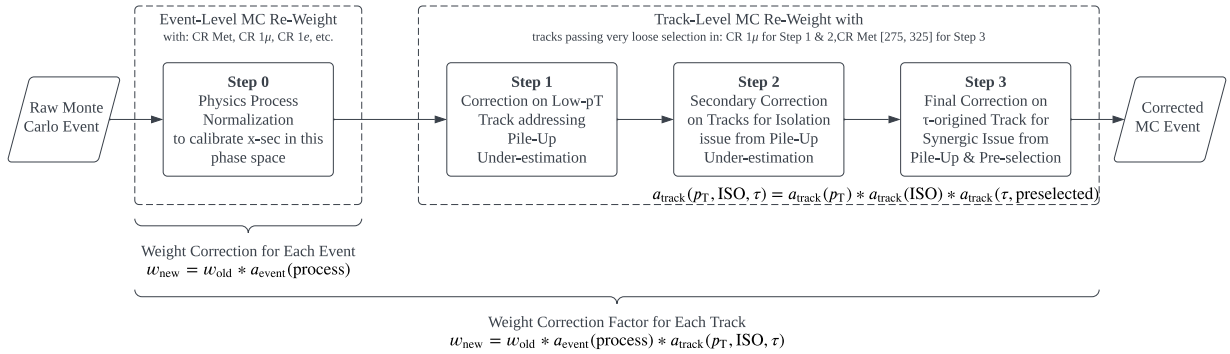


Figure 4.23: We employ an object-oriented two-level Monte Carlo correction workflow to address various mismodelings on different analysis objects, utilizing kinematics-dependent re-weighting factors for accurate adjustments. Note that the "Raw" MC event has already included all weight corrections recommended from the ATLAS Combined Performance (CP) group.

- Step 0 (4.7.2) — Event-Level Normalization: Adjusts the overall normalization of MC weights



to match data in the relevant phase space.

- Step 1 (4.7.3) – Pile-Up Track Reweighting (Leading Order): Corrects for an excess of low- $p_T$  pile-up tracks in the simulation near the primary collision.
- Step 2 (4.7.4) – Isolation Reweighting (Second Order): Addresses the impact of excess tracks on track isolation variables.
- Step 3 (4.7.5) – Tau-Originated Track Reweighting: Corrects higher-order effects on  $\tau$ -originated tracks from  $W \rightarrow \tau\nu$  processes.

Each step focuses on the most significant mismodeling at that stage, with the corrections applied in sequence. This allows for isolating individual effects and refining predictions based on remaining data-MC differences observed in the Control Regions.

### **Validation and Justification**

The effectiveness of the corrections is verified using VRs that target various mismodeling sources and their correlations (see details in Section 4.8). Agreement in these regions supports the validity of these correction factors beyond CRs, justifying their extrapolation to SRs. Additionally, cross-checks are performed using an independent, fully data-driven background estimation method in the Cut & Count SRs to confirm the consistency of the corrected MC predictions.

### **Simultaneous vs. Sequential Fitting**

While our main analysis uses sequential reweighting, a simultaneous fit of all correction factors is performed during statistical interpretation, accounting for systematic uncertainties across the entire model (see Section 4.9). This approach combines observations in both CR and SR into a unified statistical framework.

### **Avoiding Ad Hoc Corrections**

Corrections are applied only when a clear source of mismodeling is identified and supported by

physical motivations observed across multiple CRs. This ensures that adjustments are data-driven and not arbitrary. Additionally, the corrections are derived from much looser selection criteria, minimizing biases associated with SR-specific effects.

#### 4.7.1 Control Regions and Validation Regions

The definitions of Control Regions (CRs) and Validation Regions (VRs), including the event-level and track-level criteria, are summarized in Tables 4.5 and 4.6.

The "Pheno-Paper" Signal Region cuts for both event-level and track-level, derived from Ref [23], serve as guides for identifying signal-like criteria and for loosened selection criteria.

CRs are designed to have minimal signal contamination, as confirmed by the post-fit yield tables in Appendix B.7.4. This ensures that any observed discrepancies between data and MC in the CRs can be attributed to mismodeling rather than the presence of signal events.

| Variable                                        | Pheno SR        | CR $E_{\text{miss}}^T$ | VR $E_{\text{miss}}^T$ | CR $1\mu/e$     | CR $2\mu/e$     | CR $1\mu 1e$    |
|-------------------------------------------------|-----------------|------------------------|------------------------|-----------------|-----------------|-----------------|
| Trigger                                         |                 | $E_{\text{miss}}^T$    | Trigger                |                 | Single Lepton   | Trigger         |
| $E_{\text{miss}}^T$ [GeV]                       | $[500, \infty]$ | $[275, 325]$           | $[325, 500]$           | $[200, \infty]$ | $[200, \infty]$ | $[200, \infty]$ |
| $n_{\text{lepton,base}}$                        | 0               | 0                      | 0                      | —               | —               | —               |
| $n_{\text{lepton,signal}}$                      | —               | —                      | —                      | 1 $\mu/e$       | 2 $\mu/e$       | 1 $\mu$ & 1 $e$ |
| $n_{b\text{-jet}}$                              | —               | —                      | —                      | 0               | 0               | 0               |
| $n_{\text{jet}}$                                |                 |                        |                        | (0, 4)          |                 |                 |
| jet <sub>lead</sub> $p_T$                       |                 |                        |                        | > 250 GeV       |                 |                 |
| jet <sub>lead</sub> $\eta$                      |                 |                        |                        | (-2.4, +2.4)    |                 |                 |
| min $\Delta\phi(\text{jet}, E_{\text{miss}}^T)$ |                 |                        |                        | (0.4, $\pi$ ]   |                 |                 |

Table 4.5: Definitions of event-level Pheno Signal Region and Control Regions Designed. Notice that in leptonic control regions, the  $\vec{E}_{\text{miss}}^T$  is calculated with leptons ( $\mu, e$ ) treated as invisible, denoted as  $\vec{E}_{\text{miss,lep}}^T$ . Note that the jet selection is  $p_T > 30\text{GeV}$ , and  $b$ -jet selection is  $p_T > 20\text{GeV}$ . Here the  $b$ -jet veto is applied to reduce contributions from  $t\bar{t}$  background which could have some contribution to the leptonic control regions.

#### Notes on Neural Network Signal Regions

The NN-based Signal Regions are preselected with a MET trigger,  $\text{MET} > 275\text{ GeV}$ , and leading jet  $p_T > 250\text{ GeV}$ . Neural networks are trained on events with  $\text{MET} > 350\text{ GeV}$ , as events below

Table 4.6: Track-Level selection used in the Semi-Data-Driven background estimation approach. Note that these are applied after the preselection applied during n-tuple creation. Note that ( $\text{ISO} = \sum_{\text{Trk in ISO cone}} p_T$ )

| Track Variables                                          | Pheno-Paper  | Preselect | $\tau$ -Enrich | $\tau$ -Enrich (Iso) | $\tau$ -Only |
|----------------------------------------------------------|--------------|-----------|----------------|----------------------|--------------|
| $p_T$                                                    | [1.2, 5] GeV | -         | >2.5 GeV       | >2.5 GeV             | >8 GeV       |
| $ \eta $                                                 | <1.5         | -         | <1.5           | <1.5                 | <1.5         |
| $D_0$                                                    | <10 mm       | -         | <10 mm         | <10 mm               | <10 mm       |
| $S(D_0)$                                                 | >=6          | -         | -              | -                    | -            |
| $ Z_0 \sin(\theta) $                                     | <=1.5mm      | -         | <=1.5mm        | <=1.5mm              | <=1.5mm      |
| $\Delta\phi(E_{T,\text{lep}}^{\text{miss}}, \text{Trk})$ | <=1          | <=1       | <=1            | <=1                  | <=1          |
| ISO                                                      | <1 GeV       | -         | -              | <1 GeV               | <1 GeV       |
| Tight Primary ID                                         | True         | True      | True           | True                 | True         |
| Lepton-Veto                                              | True         | True      | True           | True                 | True         |

this threshold have a low signal-to-background ratio. The final NN-SR optimization selects events predominantly above  $\text{MET} > 400$  GeV.

**Signal Contamination in CR/VR** CRs are defined with MET between 275 and 325 GeV, where signal contamination is negligible, making an explicit neural network score veto unnecessary.

To maintain orthogonality with the SRs, VRs include "high-NN-score vetoes", particularly in the 0-lepton VRs. These regions are defined with  $\text{MET} < 500$  GeV to further reduce any potential signal contamination, ensuring they are suitable for verifying the corrections.

#### 4.7.2 Semi-Data-Driven Correction Step 0: Event-Level Normalization

The first correction step addresses discrepancies between Data and Monte Carlo simulations by applying normalization factors (NF) to event weights across different processes. This correction targets potential errors in the calculation of cross-sections, especially in the subset of phase-space characterized by a high  $p_T$  jet and high MET.

##### Approach to Normalization

Normalization factors are applied across several processes, with a single factor used for all Z decays ( $Z \rightarrow ee$ ,  $Z \rightarrow \mu\mu$ ,  $Z \rightarrow \nu\nu$ ,  $Z \rightarrow \tau\tau$ ), as only  $Z \rightarrow \nu\nu$  is a significant background in the Signal

Region. For  $W$  decays ( $W \rightarrow e\nu$ ,  $W \rightarrow \mu\nu$ ,  $W \rightarrow \tau\nu$ ), separate scale factors are derived, with  $W \rightarrow \tau\nu$  further split into hadronic and leptonic decays. This separation is important because hadronic decays consist primarily of lower-momentum pions and lack leptons, making them more susceptible to mismodeling in the prior preselection (likely related to excess track that will be discussed in 4.7.3). For di-boson processes ( $WW$ ,  $WZ$ ,  $ZZ$ ), a single normalization factor is applied. These corrections are crucial because  $Z \rightarrow \nu\nu$  and  $W \rightarrow \tau\nu$  (both hadronic and leptonic) are the main contributors to the Signal Region background. Other processes, having minimal contributions in the analysis, are assumed to be accurately simulated by MC, because any mismodeling would have a minimal impact on background estimation.

In Appendix B.5.1, we present plots of basic event kinematics, such as  $\text{jet}_{\text{lead}} p_T$  and  $E_T^{\text{miss}}$ , demonstrating that the flat normalization factors achieve good Data-MC agreement in core event kinematic distributions.

#### 4.7.2.1 Control Regions for Normalization Factor Determination

Control Regions are used to derive normalization factors by comparing data and Monte Carlo simulation distributions. Figure 4.24 presents key kinematic variables for the primary processes in these regions.

##### Single-Lepton Control Regions (CR $1\mu/e$ )

In the single-lepton CRs, the transverse mass ( $m_T$ ) distribution of a single lepton (electron or muon) is used to distinguish between  $W \rightarrow l\nu$  (where  $l$  represents an electron or muon) and  $W \rightarrow \tau\nu$ . The  $m_T$  distribution for  $W \rightarrow l\nu$  peaks at the  $W$  boson mass, while  $W \rightarrow \tau\nu$ , with a tau decaying leptonically, exhibits a smooth decline in  $m_T$ . This difference allows the CRs to be divided into two bins to simultaneously constrain the normalization factors for  $W \rightarrow l\nu$  and  $W \rightarrow \tau\nu$ , albeit with larger uncertainties for  $W \rightarrow \tau\nu$  due to lower purity.

##### Di-Lepton Control Regions (CR $2\mu/e$ )

For the di-lepton CRs, the invariant mass of the two leading leptons ( $m_{ll}$ ) serves as a key variable.

The  $m_{ll}$  distribution peaks at the Z boson mass, reflecting the dominant  $Z \rightarrow ee$  and  $Z \rightarrow \mu\mu$  contributions in these regions.

### **Low MET Control Region (CR $E_{\text{miss}}^T$ )**

The low MET CR is defined with MET between 275 and 325 GeV, providing a relatively signal-like 0-lepton phase space with a negligible signal contribution. This CR helps constrain background processes like  $Z \rightarrow \nu\nu$  and  $W \rightarrow \tau\nu(\text{H})$ , which can resemble the signal.

In  $W \rightarrow \tau\nu$  events with hadronic tau decay, a jet often aligns with MET due to the boost from a high- $p_T$  initial-state radiation jet. We use the minimum azimuthal separation between MET and any jet ( $\Delta\Phi(\text{MET}, \text{jet})$ ) to partition this CR. Smaller  $\Delta\Phi$  values indicate a higher likelihood of hadronic  $W \rightarrow \tau\nu$  contribution as shown in Figure 4.24. The different distribution of  $Z \rightarrow \nu\nu$  and  $W \rightarrow \tau\nu(\text{H})$  in  $\Delta\Phi(\text{MET}, \text{jet})$  help us constrain both of their normalization factors.

#### **4.7.2.2 Event-Level Normalization Results**

Overall, data and MC simulations show good agreement in the shapes of key kinematic distributions across the CRs, with the differences primarily addressed by applying normalization factors. The relevant kinematic plots are shown in Figure 4.24, and the binning summary for the fits is provided in Figure 4.25.

The normalization factors, summarized in Table 4.7, are estimated using a fit that accounts for both statistical and a subset of systematic uncertainties. While these factors are derived as initial corrections, more precise uncertainties are detailed in Section 4.9.2.4 after simultaneous fit with full systematic uncertainties and correction factors.

### **4.7.3 Semi-Data-Driven Correction Step 1: Leading-order pile-up track mis-modeling**

Following the normalization of cross-sectional mismodeling in control regions, the next significant discrepancy is the pile-up vertex distribution. In data, pile-up vertices are more concentrated

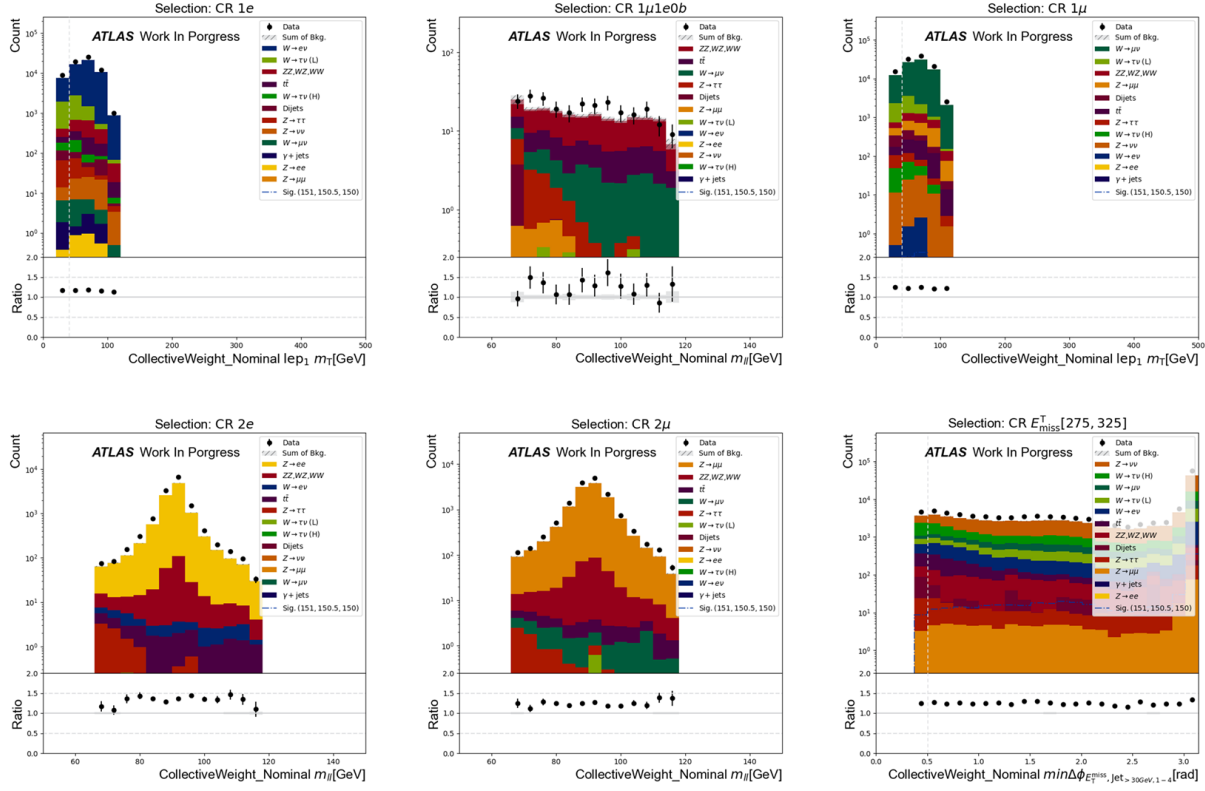


Figure 4.24: The figures are the most useful kinematics variables for the dominant process in the control regions mentioned in Section 4.7.1 . The light gray dashed lines separate the histograms into two bins so that we can constrain the two most dominant processes in a single control region, utilizing their difference in the distribution of the kinematic parameters ( $\text{lep}_1 m_T$ ,  $\min \Delta\phi(E_T^{\text{miss}}, \text{Jet}_{>30\text{GeV}, 1-4})$ ) in the event.

in the longitudinal direction compared to the MC simulation, leading to an underestimation of low-momentum tracks near the primary collision.

This step addresses the impact of this mismodeling, which causes more low-momentum pile-up tracks in data than expected in simulation. We begin by categorizing tracks by origin—primary vertex versus pile-up vertex (4.7.3.1)—and then analyze the origin of the discrepancy, focusing on longitudinal vertex distributions and  $p_T$  distributions of low-momentum tracks (4.7.3.2). To correct for these mismodelings, track-by-track reweighting factors are applied, with separate correction factors extracted for primary and pile-up vertex tracks, based on their  $p_T$  (4.7.3.3). Finally, the correction method is validated in orthogonal control regions to ensure robustness and improved

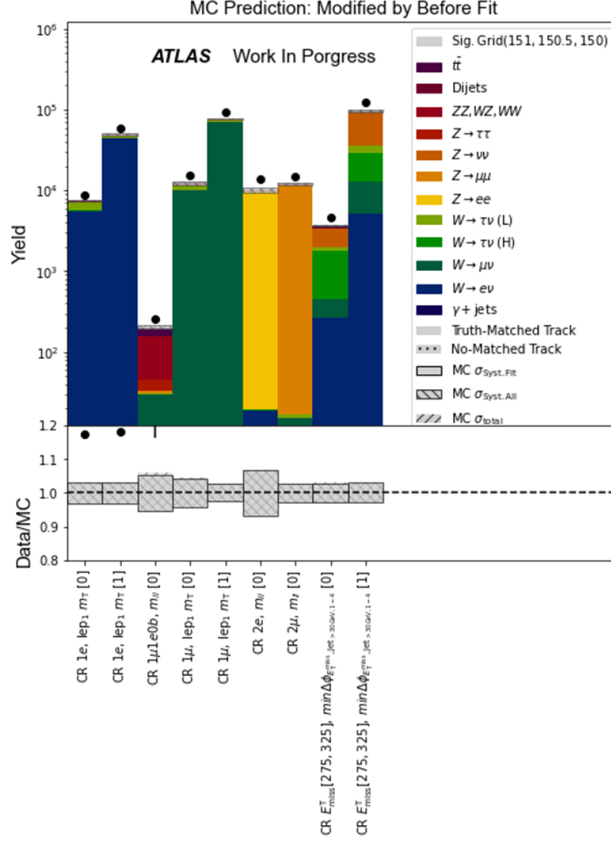


Figure 4.25: The figure summarizes bins used in the event-level normalization factor fit, based on histograms from Figure 4.24. Stacked MC contributions, including systematic and statistical uncertainties, are shown in the shaded area, while data points with Poisson error bars are displayed as black dots. Multiple bins may correspond to a single control region, distinguished by kinematic variables.

data-MC agreement.

#### 4.7.3.1 Tracks from Primary Vertex and Pile-up Vertex

In the ATLAS MC simulation, charged particles from the primary collision are matched to Inner Detector tracks using simulation truth information (**Truth-Matched** tracks). In contrast, tracks from soft pile-up collisions—protons interacting in the same bunch crossing—lack such truth matching and are labeled **No-Truth-Matched**.

To distinguish and quantify these contributions, we categorize tracks using the longitudinal impact parameter ( $Z_0 \sin(\theta)$ ):

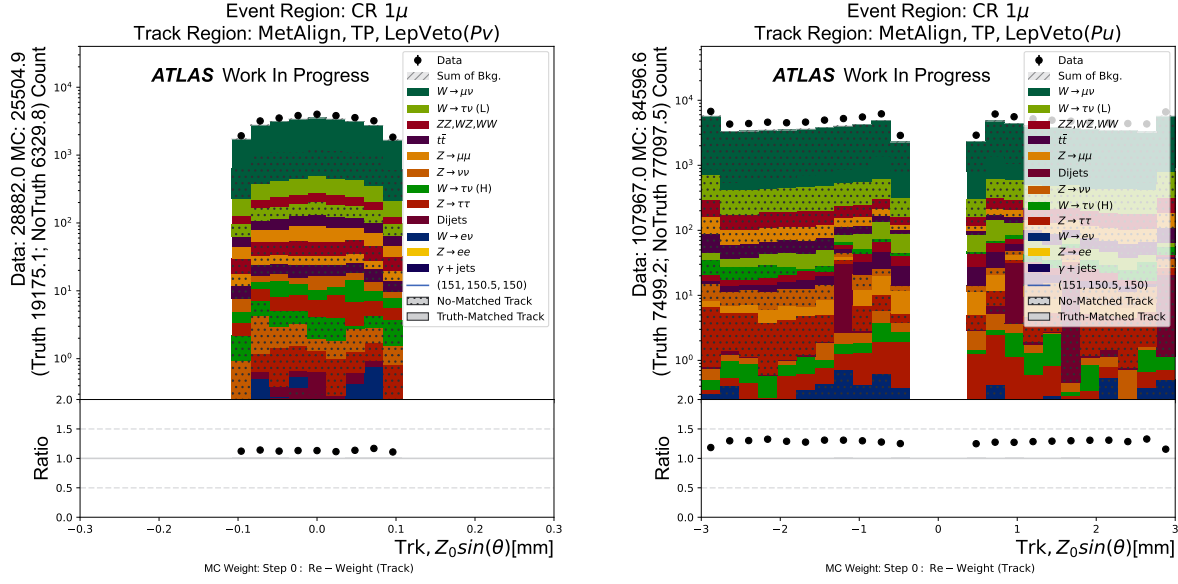
Table 4.7: Fitted Factors for Background Processes. Fit errors are not included here, as they are not used in any histograms. Full systematic uncertainties are provided in Section 4.9.2.4.

| Background Process                        | Fitted Factor |
|-------------------------------------------|---------------|
| $W \rightarrow (e/\mu)\nu$                | 1.20          |
| $W \rightarrow \tau\nu$ (L)               | 1.19          |
| $W \rightarrow \tau\nu$ (H)               | 1.37          |
| $Z \rightarrow ee/\mu\mu/\tau\tau/\nu\nu$ | 1.29          |
| WZ, WW, and ZZ                            | 1.40          |

- **Primary Vertex (Pv) Dominant Region:** Tracks close to the primary vertex along the beam ( $z$ ) direction, defined by  $|Z_0 \sin(\theta)| < 0.1$  mm.
- **Pile-up Vertex (Pu) Dominant Region:** Tracks farther from the primary vertex in the  $z$  direction, with  $|Z_0 \sin(\theta)| > 0.5$  mm.

We check the purity of this selection in single-muon control region CR  $1\mu$  events. We select tracks that meet the the basic pre-selection: Tight-Primary track ID, no lepton matching, aligned with MET ( $\Delta\phi(\text{MET}, \text{track}) < 1.0$ ), and slightly displaced from the beam line ( $D_0 > 0.1$ , mm). As shown in Figure 4.26, the **Pu** region is predominantly composed of No-Truth-Matched tracks, while the **Pv** region mainly contains Truth-Matched tracks.





(a) Primary Vertex (Pv) Dominant Region

(b) Pile-up Vertex (Pu) Dominant Region

Figure 4.26: The stacked bins distinguish between "No-Truth-Matched" tracks (shaded), originating from pile-up collisions, and "Truth-Matched" tracks (solid filled), matched to particles from the primary collision. The **Pu** region (right), with larger  $|Z_0 \sin(\theta)|$  values, consists mainly of No-Truth-Matched tracks, while the Pv region (left), with smaller  $|Z_0 \sin(\theta)|$  values, is dominated by Truth-Matched tracks. In the Pu-dominant region, 91% of tracks are No-Truth-Matched, while only 25% are No-Truth-Matched in the Pv-dominant region, consistent with expectations.

#### 4.7.3.2 Origin of the Mismodeling

Our analysis identified two primary sources of mismodeling that affect both the yield and kinematic distributions of tracks: mismodeling of the pile-up vertex distribution and the  $p_T$  distribution of low- $p_T$  tracks ( $p_T < 3$  GeV). **Pile-Up Vertex Distribution Mismodeling:** As shown in Figure 4.26, track counts are underestimated in both the Primary Vertex (Pv) and Pu regions, with a stronger effect in the Pu region, which consists primarily of "No-Truth-Matched" tracks. This suggests that pile-up tracks are systematically underestimated in the simulated background.

This discrepancy likely stems from differences in the longitudinal distribution of pile-up vertices between data and simulation. The real distribution of collisions in ATLAS is more concentrated than the MC simulation predicts, as illustrated in Figure 4.27. This effect is evident in Figure

4.28, where data shows tighter vertex distributions with smaller pile-up vertex standard deviations compared to the simulation.

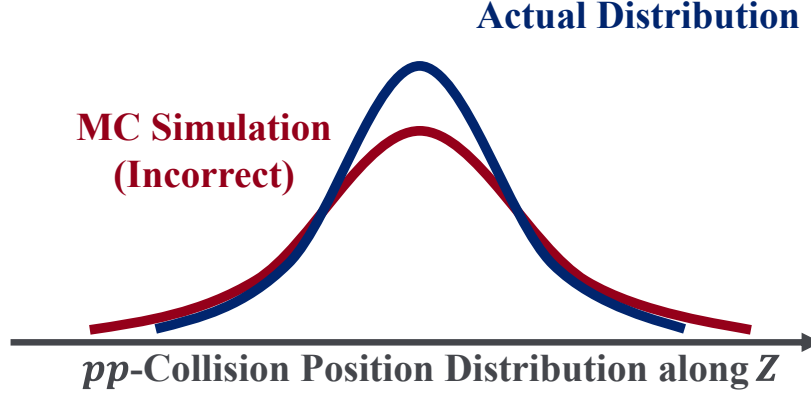
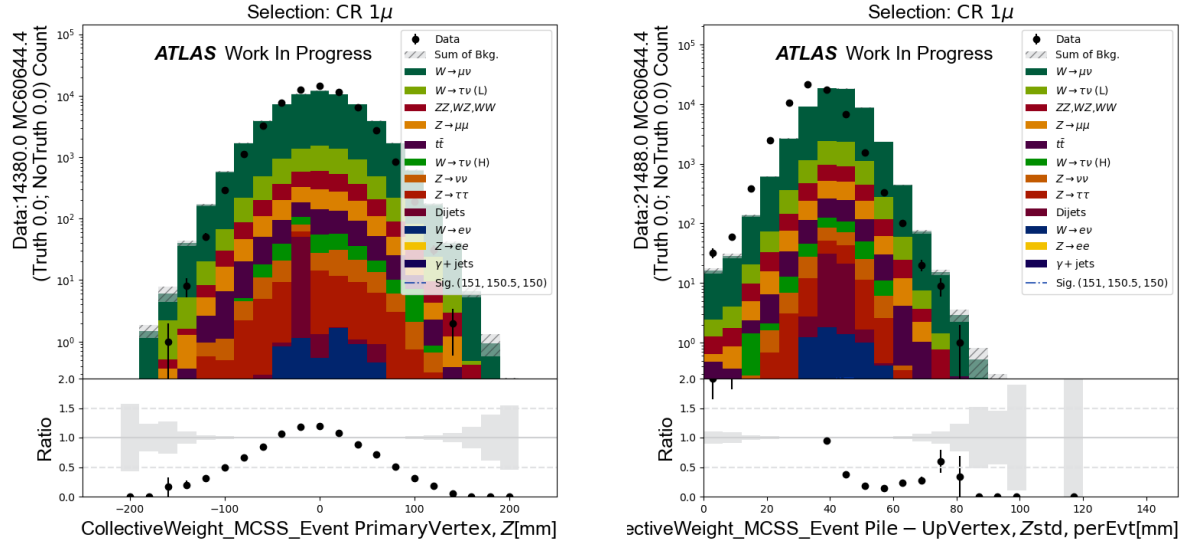


Figure 4.27: Intuitive illustration on that real distribution of collisions in ATLAS appearing more concentrated than the simulated collisions.

The standard CP-recommended pile-up reweighting algorithm (PRW) adjusts event weights based on pile-up jet activity but does not account for mismatches in the  $z$ -distribution of pile-up vertices. Although PRW corrections are applied to the MC events, they do not fully address the excess pile-up tracks near the primary vertex observed in our track-level analysis. Therefore, we apply track-based reweighting, using distinct factors for primary and pile-up tracks based on their truth-matching information.

**Mismodeling of Low- $p_T$  Tracks** In addition to vertex distribution mismodeling, we identified discrepancies between data and MC in the  $p_T$  distribution of low-momentum tracks. Other kinematic variables, such as  $Z_0 \sin(\theta)$ , show only constant offsets between data and MC (Figure 4.26). This suggests that the mismodeling may occur during parton showering or track reconstruction.

Since low- $p_T$  tracks are often overlooked in most ATLAS analyses, these discrepancies were not corrected by standard CP recommendations. Therefore, we apply specific corrections in this analysis to ensure consistency between data and MC.



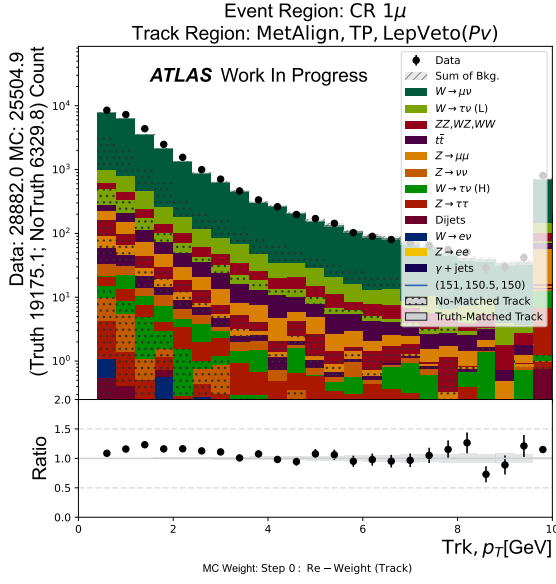
(a) Primary vertex distribution in longitudinal direction ( $Z$ ) (b) Standard Deviation of Pile-up Vertex distribution in  $Z$  (w.r.t. the primary vertex in the same event)

Figure 4.28: Vertex distribution of single-muon Control Region CR  $1\mu$ .

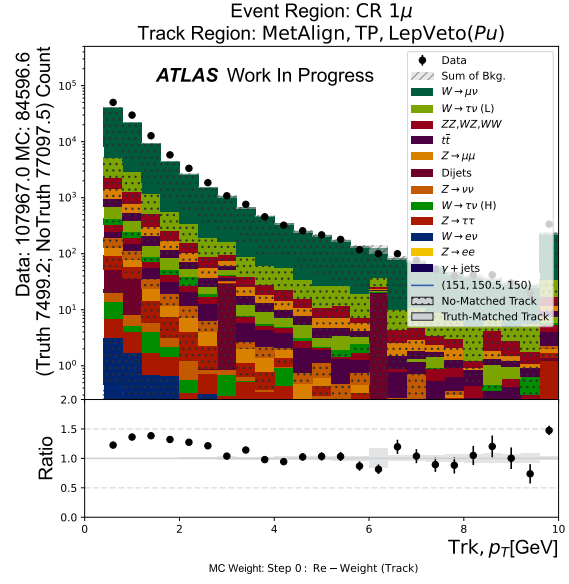
#### 4.7.3.3 Correction of mis-modeling through $p_T$ -binned re-weighting

Since identifying the exact origin of mismodeling is complex and re-simulation is resource-intensive, we adopt a data-driven approach to correct it. Tracks are re-weighted based on their  $p_T$ , using events from the single-muon control region (CR  $1\mu$ ) with the same preselection as Figure 4.26 above. The choice of CR  $1\mu$  for deriving the reweighting factors is based on the following considerations:

- **Process Isolation:** This region is dominated by a single process, minimizing process-specific effects in the MC simulation. We verify that the reweighting factors derived from  $W \rightarrow \mu\nu$  can also be applied to other processes such as  $W \rightarrow \tau\nu$  and  $Z \rightarrow \nu\nu$ .
- **Statistical Robustness:** CR  $1\mu$  offers higher statistical yields than other regions (e.g., CR  $2e$ , CR  $1\mu 1e$ ), making it more reliable for extracting factors. We validate the extracted factors using CR  $1e$  and CR MET[275, 325] to ensure their applicability across regions with different background processes. This validation is detailed in Figures B.17 through B.19 in Appendix B.5.3.



(a) Primary Vertex (Pv) Dominant Region



(b) Pile-up Vertex (Pu) Dominant Region

Figure 4.29: The set-up is the same as Figure 4.26. This figure highlights the different MC-data discrepancies between tracks from pile-up (**No-Truth-Matched**) and primary collisions (**Truth-Matched**) across  $p_T$  bins. The discrepancies are more pronounced for pile-up tracks and exhibit  $p_T$  dependence, suggesting the need for  $p_T$ -binned reweighting.

Our track  $p_T$  correction method operates under three key assumptions:

1. **Dependence on  $p_T$ :** The correction factor for each track depends solely on its  $p_T$ , justified by the consistent kinematic shape agreement shown in Figure B.12 (Appendix B.5.2).
2. **Focus on Low- $p_T$  Tracks:** The largest discrepancies between data and MC are observed for tracks with  $p_T < 3.2$  GeV, so corrections are applied only in these bins.
3. **Separate Corrections for Primary and Pile-up Tracks:** Since tracks from primary and pile-up collisions are simulated separately and exhibit different MC-data mismatches, we apply distinct correction factors for "Truth-Matched" and "No-Truth-Matched" tracks within the same  $p_T$  bin.

To solve for the appropriate correction factors, we construct two equations for each  $p_T$  bin using the data and MC-predicted yields  $y$ :

$$\begin{aligned}\text{Data}_{\text{Pu}} &= a_{\text{Truth}} \cdot y_{\text{Truth,Pu}} + a_{\text{No-Truth}} \cdot y_{\text{No-Truth,Pu}} \\ \text{Data}_{\text{Pv}} &= a_{\text{Truth}} \cdot y_{\text{Truth,Pv}} + a_{\text{No-Truth}} \cdot y_{\text{No-Truth,Pv}}\end{aligned}\tag{4.7}$$

The correction factors, shown in Table 4.8, are validated across orthogonal control regions to ensure their robustness and applicability beyond the CR  $1\mu$ . These factors address the underestimation of tracks from pile-up collisions, caused by an overestimated spread of the longitudinal vertex distribution. This discrepancy primarily affects low- $p_{\text{T}}$  tracks, necessitating  $p_{\text{T}}$ -binned corrections with separate factors for "Truth-Matched" and "No-Truth-Matched" tracks.

| Track $p_{\text{T}}$ Bin [GeV] | Truth-Track Re-weight Factor | No-Truth-Track Re-weight Factor |
|--------------------------------|------------------------------|---------------------------------|
| 0.4-0.8                        | $0.998 \pm 0.016$            | $1.248 \pm 0.004$               |
| 0.8-1.2                        | $1.077 \pm 0.016$            | $1.389 \pm 0.007$               |
| 1.2-1.6                        | $1.187 \pm 0.021$            | $1.404 \pm 0.011$               |
| 1.6-2.0                        | $1.120 \pm 0.025$            | $1.343 \pm 0.017$               |
| 2.0-2.4                        | $1.138 \pm 0.031$            | $1.288 \pm 0.021$               |
| 2.4-2.8                        | $1.110 \pm 0.037$            | $1.226 \pm 0.027$               |
| 2.8-3.2                        | $1.124 \pm 0.044$            | $1.030 \pm 0.030$               |

Table 4.8: Step-1 correction reweighting factors for **Truth-Matched** and **No-Truth-Matched** tracks, binned by  $p_{\text{T}}$ . Quoted uncertainties are statistical, based on bin counts.

Validation is performed in CR  $1e$  and CR MET [275, 325] GeV, which feature distinct dominant background processes. Other kinematic variables such as  $D_0$ ,  $\eta$ , and  $\Delta\phi(\text{MET}, \text{Trk})$  are relatively unaffected by low- $p_{\text{T}}$  mismodeling and require only flat pile-up corrections. As shown in Appendix B.5.2, the uncorrected distributions highlight the MC-Data discrepancies, while the corrected distributions (Appendix B.5.3) achieve good agreement.

The consistency of MC-data agreement across multiple orthogonal control regions ( $1e$ ,  $2\mu$ , and MET) is demonstrated in Figures B.17, B.18, and B.19. This consistency confirms that the reweighting method effectively aligns the simulation with real data for tracks in the track-level Signal Region.

#### 4.7.4 Semi-Data-Driven Correction Step 2: Second-Order Pile-Up Impact on Track Isolation

Although the leading pile-up effects on track yield and  $p_T$  shape were corrected in Section 4.7.3, we address here a secondary effect: pile-up impact on track isolation. Since pile-up collisions produce more tracks near the primary vertex than simulated, these additional tracks are more likely to fall within the isolation cone of any target track, resulting in fewer isolated tracks (defined by  $\text{ISO} = \sum_{\text{Trk in ISO cone}} p_T$ ) and more non-isolated tracks than expected.

We correct this effect using the same binned reweighting method as in Step 1, with the following key assumptions:

- **Dependence on Track Isolation:** The correction factor for each track depends solely on the isolation cone momentum sum  $\text{Trk, ISO}$ , validated by the kinematic shape agreement in Figure B.16 (Appendix B.5.3).
- **Separate Correction for Pile-Up and Primary Tracks:** Due to the distinct MC-data discrepancies between pile-up and primary collision tracks (Figure 4.30), separate correction factors are applied to **Truth-Matched** (primary collision) and **No-Truth-Matched** (pile-up) tracks within each ISO bin.

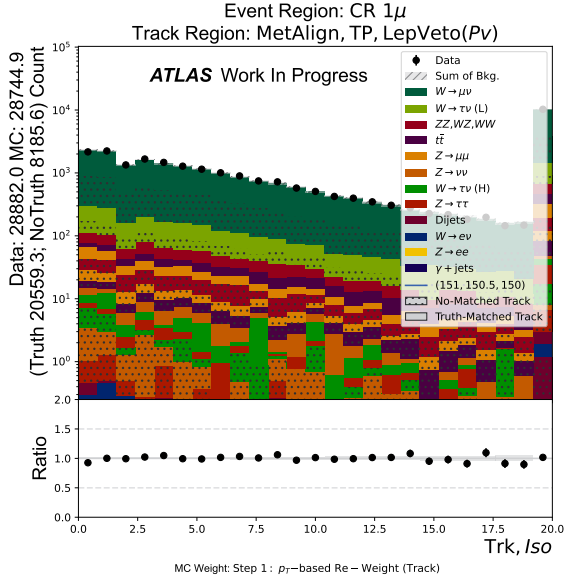
The resulting correction factors (Table 4.9), derived from Figure 4.30, are validated across multiple control regions: CR  $1e$ , CR  $2\mu$ , and CR MET  $[275, 325]$  GeV. As shown in Figures B.21, B.22, and B.23 (Appendix B.5.4), these factors align the simulation with data, confirming their reliability across different processes.

#### 4.7.5 Semi-Data-Driven Correction Step 3: Higher-Order Pre-Selection Issue for Tau-Originated Tracks

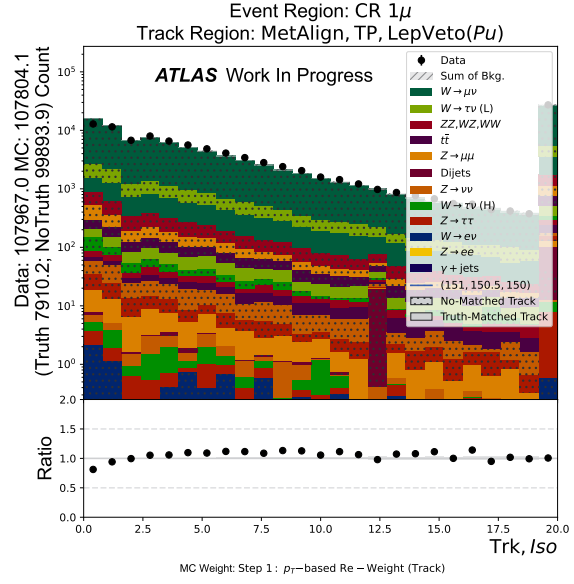
This final correction addresses potential mis-modeling of  $\tau$  decay products and the impact of displaced track pre-selection. As detailed in Section 4.3.2, the majority of background tracks in the signal region originate from two sources:

| Track ISO Bin [GeV] | Truth-Track Re-weight Factor | No-Truth-Track Re-weight Factor |
|---------------------|------------------------------|---------------------------------|
| 0.0-0.8             | $0.980 \pm 0.026$            | $0.803 \pm 0.006$               |
| 0.8-1.6             | $1.030 \pm 0.027$            | $0.935 \pm 0.008$               |
| 1.6-2.4             | $0.994 \pm 0.034$            | $0.996 \pm 0.011$               |
| 2.4-3.2             | $1.008 \pm 0.031$            | $1.057 \pm 0.010$               |
| 3.2-4.0             | $1.043 \pm 0.034$            | $1.060 \pm 0.011$               |
| 4.0-4.8             | $0.947 \pm 0.034$            | $1.109 \pm 0.013$               |
| 4.8-5.6             | $0.942 \pm 0.036$            | $1.103 \pm 0.014$               |
| 5.6-6.4             | $0.969 \pm 0.039$            | $1.131 \pm 0.016$               |
| 6.4-7.2             | $0.993 \pm 0.042$            | $1.126 \pm 0.017$               |
| 7.2-8.0             | $0.974 \pm 0.044$            | $1.098 \pm 0.018$               |
| 8.0-8.8             | $1.029 \pm 0.047$            | $1.143 \pm 0.021$               |
| 8.8-9.6             | $0.905 \pm 0.047$            | $1.147 \pm 0.023$               |
| 9.6-10.4            | $0.993 \pm 0.054$            | $1.062 \pm 0.024$               |
| 10.4-11.2           | $0.932 \pm 0.056$            | $1.133 \pm 0.027$               |
| 11.2-12.0           | $0.966 \pm 0.058$            | $1.074 \pm 0.028$               |
| 12.0-12.8           | $1.029 \pm 0.064$            | $0.974 \pm 0.028$               |
| 12.8-13.6           | $0.991 \pm 0.068$            | $1.083 \pm 0.033$               |
| 13.6-14.4           | $1.084 \pm 0.075$            | $1.079 \pm 0.036$               |
| 14.4-15.2           | $0.881 \pm 0.072$            | $1.139 \pm 0.040$               |
| 15.2-16.0           | $0.970 \pm 0.078$            | $1.004 \pm 0.038$               |
| 16.0-16.8           | $0.805 \pm 0.076$            | $1.183 \pm 0.046$               |
| 16.8-17.6           | $1.165 \pm 0.094$            | $0.925 \pm 0.040$               |
| 17.6-18.4           | $0.865 \pm 0.088$            | $1.033 \pm 0.046$               |
| 18.4-19.2           | $0.860 \pm 0.083$            | $1.010 \pm 0.047$               |
| 19.2-20.0           | $1.022 \pm 0.012$            | $1.005 \pm 0.006$               |

Table 4.9: Step-2 correction re-weighting factors for Truth-Matched tracks (from primary collisions) and No-Truth-Matched tracks (from pile-up collisions), binned by the Track ISO variable. The quoted error reflects uncertainty from limited bin statistics. For the final fit, we combined the reweighting bins as shown in Table 4.16. The histograms plotted in this chapter are still using the 25bin correction, however, the difference is negligible.



(a) Primary Vertex (Pv) Dominant Region



(b) Pile-up Vertex (Pu) Dominant Region

Figure 4.30: The stacked bins show Data-MC discrepancies between “No-Truth-Matched” (shaded) pile-up tracks and “Truth-Matched” (solid) primary collision tracks, requiring separate correction factors. The event and track selection are the same as in Figure 4.26.

1. **Semi-long-lived hadrons** (e.g.,  $\Lambda$  and  $K_S$ ) with lifetimes on the centimeter scale, occasionally aligning with the MET direction.

2.  **$\tau$  decay products:** These include low- $p_T$  leptons, too weak to be identified as  $e/\mu$ , and charged pions from hadronic  $\tau$  decays (e.g., 1-prong and 2-prong decays), aligned with MET due to ISR jet boosting.

While previous corrections (Sections 4.7.3 and 4.7.4) effectively addressed soft displaced tracks from semi-long-lived particles,  $\tau$ -associated tracks require additional corrections. Specifically, in the 0-lepton control region and  $\tau$ -enriched regions, we identified significant Data-MC discrepancies in the track isolation bin ( $\text{Trk-iso} = 0$ ). This indicated the need for further correction for  $\tau$ -originated tracks.

The mis-modeling arises from a combination of pile-up issues and event pre-selection. During the skimming pre-selection, events lacking at least one isolated displaced track were removed—



an unintended filtering step discovered too late to fix efficiently. To correct for this, we apply a post-simulation correction factor, which ensures Data-MC consistency across control and validation regions.

We select a **0-lepton, lower-MET control region** ( $E_{\text{miss}}^{\text{T}}[275, 325] \text{ GeV}$ ) to isolate  $\tau$ -track contributions. This selection ensures events contain substantial MET from processes such as  $W \rightarrow \tau\nu$  or  $Z \rightarrow \nu\nu$ . To minimize contamination from semi-long-lived particles (e.g.,  $\Lambda$ ,  $K_S$ ) coinciding with  $Z \rightarrow \nu\nu$  decays, we apply a higher track  $p_T$  cut ( $\text{Trk}, p_T > 2.5 \text{ GeV}$ ) and use a Pheno-SR-like selection, as defined in Section 4.7.1.

In this control region, Data-MC discrepancies were most evident for the **Leading Isolated Displaced Track** (referred to as the **ST** track), which was selected by the highest  $S(D_0)$  and used for event pre-selection. The key kinematic distributions for these tracks are shown in Figure 4.31. As the Data-MC mismatch appeared as a constant offset, we derive the single correction factor as the Data-to-MC yield ratio, focusing on  $W \rightarrow \tau\nu$ -associated contributions. This correction factor is applied to all isolated **ST** tracks in the simulated samples to align with observed data.

As detailed in the Validation Region Section 4.8 (specifically Subsection 4.8.4), we design a dedicated  $\tau$  validation region using event-level NN Signal Regions and a Pheno-SR-like track selection with  $p_T > 8 \text{ GeV}$  to isolate  $\tau$  contributions. (They will be orthogonal to track-level NN SRs, as high- $p_T$  tracks yield low NN scores.) The correction method demonstrates robustness, as shown in the figures and tables in Section 4.8.4 and Appendix B.6.5.

#### 4.7.6 Consistency Check in Cut & Count Signal Region

While the semi-data-driven corrections have been validated in their respective validation regions, we perform an additional crosscheck with the independent background estimates from the Cut & Count (CC) strategy (ABCD for QCD + semi-data-driven for  $W \rightarrow \tau\nu$ ).

The same CC Signal Region cuts are applied within the NN-based framework, and yields are estimated using the re-weighted Monte Carlo simulation based on the corrections described in this

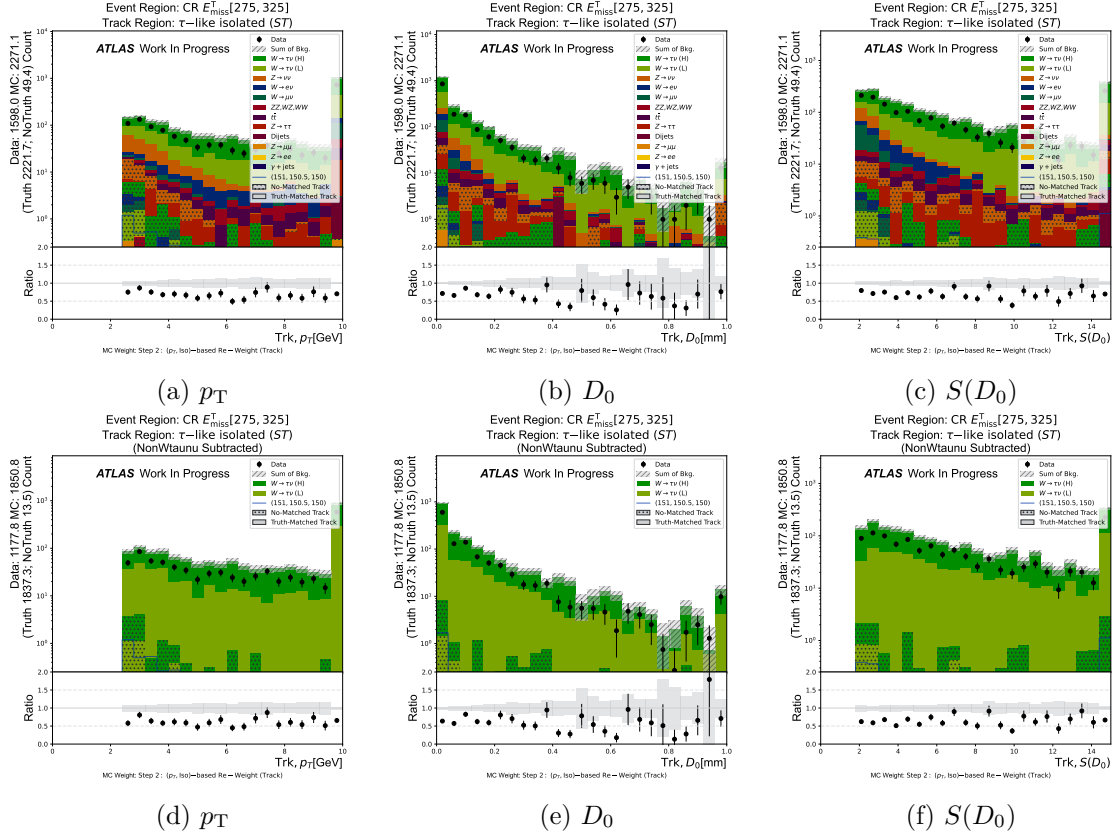


Figure 4.31: The stacked bins compare contributions from "No-Truth-Matched" (shaded) pile-up tracks and "Truth-Matched" (solid) primary collision tracks, selected using the  $\tau$ -**Enrich (Iso)** criteria matching an ST track. All kinematic variables are derived from tracks within the event-level control region  $CR E_{miss}^T [275, 325]$ . The first row shows MC contributions with corrections (Steps 02) alongside detector data. In the second row, other processes are subtracted from both MC and Data, and the overall Data/MC yield ratio is applied as a correction factor to  $W \rightarrow \tau\nu$ -associated ST tracks in the MC samples. The Data/MC panel shows a constant yield factor difference.

section.

Table 4.10 shows that the semi-data-driven reweighting in this analysis are consistent with the CC-based estimates, within statistical and systematic uncertainties. This agreement indicates that both methods are robust against independent checks.

A comparison of the two background estimation strategies:

1. **Common Focus:** Both methods rely on estimating the dominant backgrounds: semi-long-lived hadrons/mesons coinciding with  $Z \rightarrow \nu\nu + \text{jets}$  and single-prong  $\tau$  decays from  $W \rightarrow \tau\nu + \text{jets}$ .

2. **CC Strategy:** The CC method extrapolates to the Signal Region from a kinematically similar region (in terms of tracks), attempting to capture all mismodeling effects at once.

3. **NN-Based Strategy:** We further analyzes mismodeling sources to minimize MC-data discrepancies, reducing biases in the Neural Network predictions from correlated mismodelings between variables.

| Event Region                   | C&C SR              | C&C SR             |
|--------------------------------|---------------------|--------------------|
| Track Region                   | C&C A – High        | C&C A – Low        |
| Others                         | $0.4 \pm 0.2$       | $1.1 \pm 0.4$      |
| $W \rightarrow e\nu$           | $0.1 \pm 0.2$       | $0.4 \pm 0.1$      |
| $W \rightarrow \mu\nu$         | $0.5 \pm 0.3$       | $0.3 \pm 0.1$      |
| $W \rightarrow \tau\nu$ (H)    | $3.0 \pm 1.2$       | $13.0 \pm 4.5$     |
| $W \rightarrow \tau\nu$ (L)    | $1.8 \pm 0.6$       | $8.8 \pm 1.6$      |
| $Z \rightarrow ll$             | $6.9 \pm 1.7$       | $9.5 \pm 1.5$      |
| $ZZ, WZ, WW$                   | $0.3 \pm 0.3$       | $1.5 \pm 0.2$      |
| Sum Bkg. $\pm \sigma_{MC}$     | $12.9 \pm 2.4$      | $34.3 \pm 4.1$     |
| <b>C&amp;C SR Yields</b>       | SR-0 $\ell$ -A-High | SR-0 $\ell$ -A-Low |
| Prediction with C&C Estimation | $14.69 \pm 2.02$    | $37.19 \pm 3.75$   |

Table 4.10: Here we make the prediction of background yields of Cut & Count Signal Regions using semi-data-driven MC correction methods prescribed in this section. (After simultaneous fit with all control regions with background-only processes and all uncertainties.) In the bottom row, we quote the background yield prediction from ABCD + Semi-data-driven background estimation used in the Cut & Count strategy.

#### 4.7.7 Discussion on Semi-Data-Driven Correction Strategy

After outlining the semi-data-driven correction process, we provide a discussion of key considerations in the approach, including the rationale for multi-step reweighting, handling of probabilistic Monte Carlo corrections, and the comparison between sequential and simultaneous fitting strategies. These points offer further insights into the choices made and practical implications for background estimation.

#### Identifying and Correcting Mismodeling

Mismodeling refers to any discrepancy between data and simulation, originating from factors such

as physics calculations or detector reconstruction. These discrepancies are corrected to improve the accuracy of predictions in the Signal Region. In cases where the sources of mismodeling are identifiable, specific corrections are applied. However, even when the exact causes are unclear, our strategy addresses the observable effects to better align the MC simulation with real data.

### **Probabilistic Nature of Monte Carlo Simulations**

The probabilistic nature of MC simulations means that each event’s weight represents the likelihood of that event appearing in the collected data. Correcting for mismodeling involves adjusting these weights to ensure that the simulated distributions match the observed data distributions. This approach is effective when the parameter space is sufficiently populated by MC events. However, it is less reliable in sparsely populated regions, where reweighting may not fully capture the discrepancies.

### **Multi-Step Reweighting Rationale**

Multi-step reweighting is adopted to sequentially isolate the primary sources of mismodeling. Starting with the most significant discrepancies, corrections are applied one step at a time, with each stage refining the results by addressing the remaining data-MC differences. This recursive strategy allows for targeted corrections, such as addressing pile-up effects first, followed by higher-order impacts like track isolation mismodeling. The stepwise approach helps manage complexity and provides a clear path for iterative improvements.

### **Sequential vs. Simultaneous Fitting**

In our analysis, corrections are applied sequentially for simplicity, producing histograms for Control, Validation, and Signal Regions. While this step-by-step approach is efficient, a simultaneous fitting method is also used later to account for all nuisance parameters, including systematic uncertainties. The simultaneous fit combines corrections into a unified statistical model, refining the results by incorporating detector and theory systematic variations. This dual approach balances simplicity and thoroughness.

## **Flexibility of the Reweighting Approach**

While ideally, mismodelings would be corrected at the simulation level, the flexibility of the reweighting method allows for corrections to be applied during the analysis. This is computationally less expensive and enables us to address the majority of data-MC discrepancies in the regions of interest. Although reweighting may appear ad hoc, corrections are implemented only when supported by physically motivated evidence across multiple Control Regions and verified in independent Validation Regions.

## 4.8 3-Way FCNN Validation Regions and Tau Validation Region

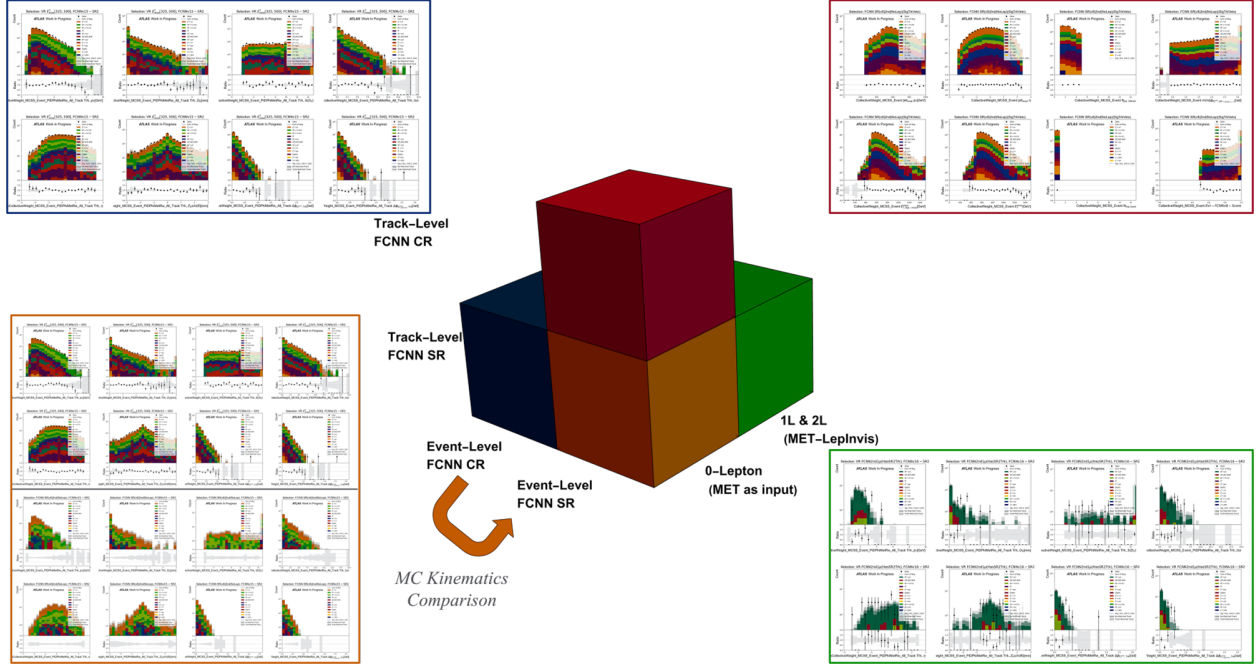


Figure 4.32: Construction of the FCNN Validation Region using independent two-level FCNN criteria. By examining tracks in event-level control regions and excluding those resembling signal-region tracks, a validation region with minimal signal contamination is achieved. See Table 4.11 for detailed definitions.

This section validates the event-level and track-level FCNN Signal Regions by constructing corresponding validation regions. Thanks to the independent design of our two-level FCNN selection, we can isolate validation regions as follows:

- **Track-Level Validation Region (VR Track):** Examines high-score tracks within low-score events to validate track kinematics and track NN model. See Section 4.8.1.
- **Event-Level Validation Region (VR Event):** Focuses on high-score events containing only low-score tracks to ensure event-level kinematics modeling accuracy and robustness of event-level NN. See Section 4.8.2.

To assess potential synergies or mis-modeling from simultaneous event and track selection, we create a **Two-Level Validation Region (VR Lepton)**. This replaces the 0-lepton requirement

with events from the single-muon control region (CR  $1\mu$ ) and substitutes MET with lepton-invisible MET. See Section 4.8.3.

Since additional corrections are applied for  $\tau$  decay modeling (see Section 4.7.5), we introduce a **Tau Validation Region** (VR Tau). This region focuses on  $\tau$ -enriched track selection with  $p_T > 8$  GeV to isolate  $\tau$ -originated tracks in  $W \rightarrow \tau\nu$  events. See Section 4.8.4.

We also examine the NN score distributions within control regions to confirm that the MC simulation is consistent with data and that the Neural Network is not biased by statistical feature of Monte Carlo or mis-modeling of the Monte Carlo (i.e. overtrained) (Section 4.8.5).

Figure 4.32 illustrates the three-way FCNN validation regions. Their approximate locations in the (Event Score, Track Score) plane are shown in Figure 4.33. Since we have four Signal Regions, each validation region is sliced accordingly. Detailed definitions are in Table 4.11.

By checking Data-MC agreement across all 16 validation region slices, we ensure reliable MC simulation and an unbiased Neural Network model. In addition to validation region yields, the kinematics distributions and NN score distribution confirm accurate modeling and unbiased NN setup.

Table 4.11: The 3-Way FCNN Validation Region and Tau Validation Region Definition. Note that in VR Track, we also require events to have lower scores than all SR to ensure orthogonality.

| <b>Selection</b> | VR Event (4.8.1) | VR Track (4.8.2)                  | VR Lepton(4.8.3) | VR Tau (4.8.4) |
|------------------|------------------|-----------------------------------|------------------|----------------|
| <b>Lepton</b>    | No Lepton        | No Lepton                         | $1\mu$           | No Lepton      |
| <b>Event</b>     | High-Score       | VR $E_{\text{miss}}^T [325, 500]$ | High-Score       | High-Score     |
| <b>Track</b>     | No High-Score    | High-Score                        | High-Score       | $\tau$ -only   |

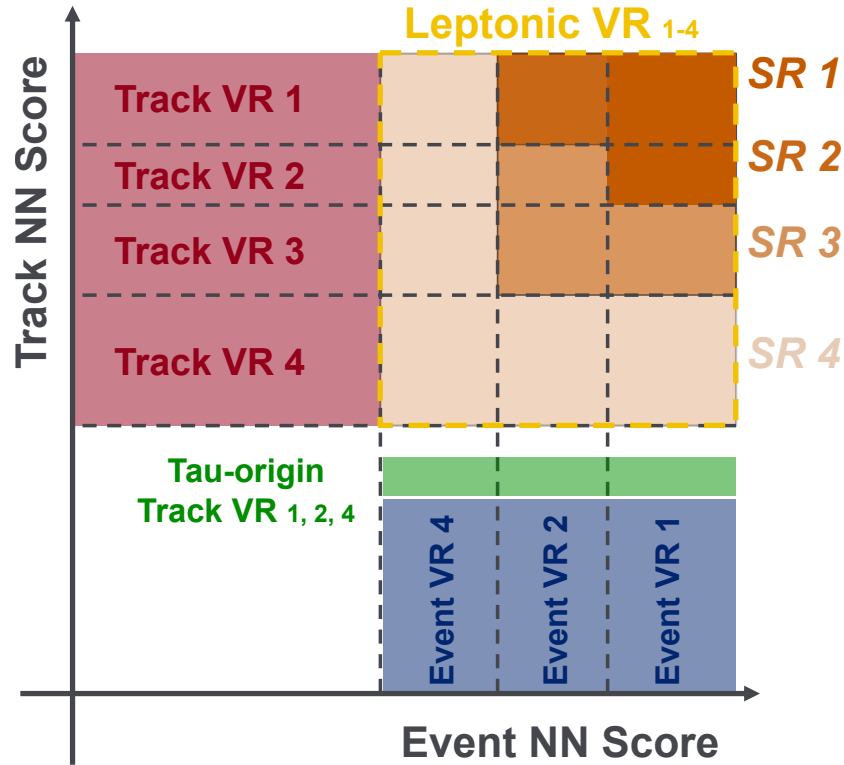


Figure 4.33: Score cut demonstration for four different Validation Regions (each has 4 slices corresponding to each of the SR) defined based on Event and Track NN Scores and other kinematics selections (See Table 4.11). Note that in the latest configuration the event NN score cut difference between SR 2 and SR 3 is small as shown in 4.4, and thus VR-Event-3 and VR-Tau-3 will be omitted. Note that the Signal Regions are denoted with 1 through 4).



### 4.8.1 Event-Level FCNN SR Validation

The Event-Level FCNN Validation Region (VR Event) is constructed by excluding events with Signal Region-like tracks (high-score tracks) to minimize signal contamination. This allows us to validate the kinematic distributions without bias from potential signal events.

Figure 4.34 shows distributions of eight key kinematic variables, comparing data with MC predictions for one of the four Event-Level FCNN Validation Regions. Additional histograms are available in Appendix B.6.1 (Figures B.28 to B.30). Table 4.12 summarizes the agreement between measured data and MC predictions across all four regions.

The results confirm the following:

1. **Robust MC Modeling:** The corrected MC simulation accurately reproduces event yields and kinematic shapes, demonstrating that the correction factors are reliably extrapolated to the validation region.
2. **Non-Biased Neural Network:** The neural network model shows no signs of overfitting or bias, proving the effectiveness of k-fold validation and early stopping during training.

Additionally, the similarity between kinematic distributions in the validation and signal regions reinforces confidence in our MC modeling and neural network performance. Relevant Signal Region histograms can be found in Appendix B.6.2.

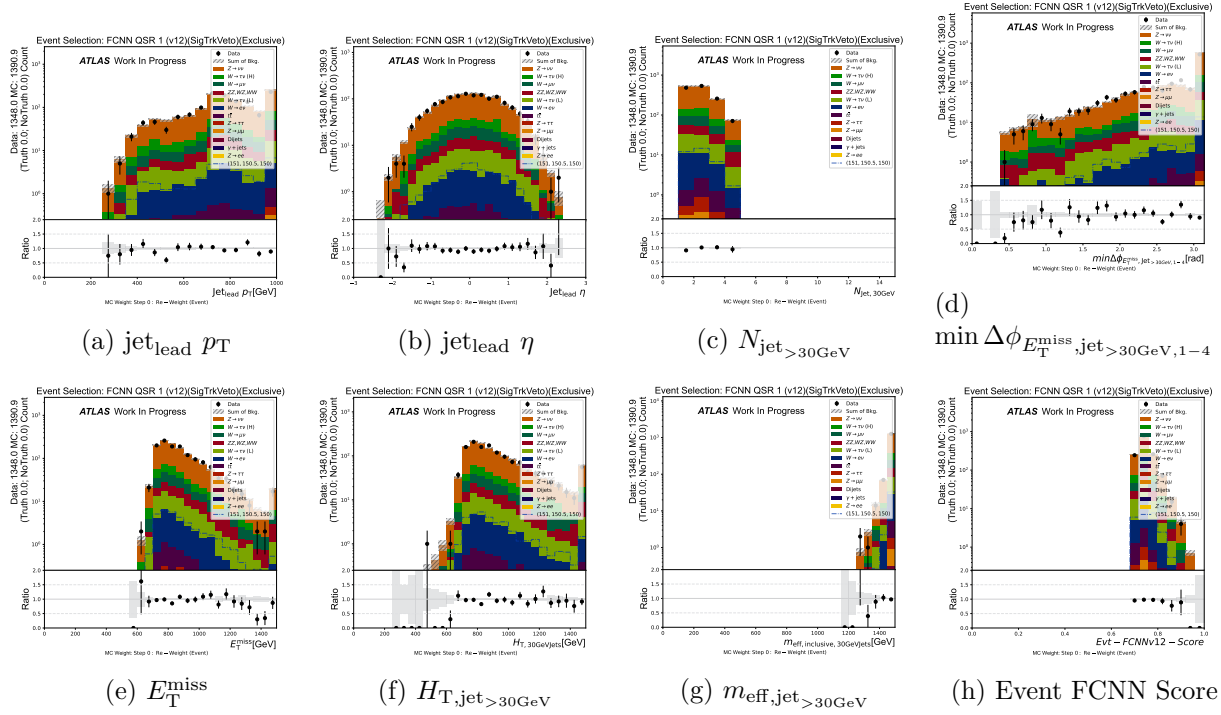


Figure 4.34: Distributions of eight key kinematic variables in the 1st Event-Level FCNN Validation Region (trained with BCE loss), defined by excluding events with SR-like tracks (e.g., tracks with FCNN scores  $> 0.00001$ ). The strong agreement between Data and MC demonstrates the robustness of our k-fold validation and early stopping techniques.

Table 4.12: Validation regions for Event-Level FCNN SR. These results correspond to figures such as Figure 4.34 (First Column). Due to minimal differences in event-level cut values, SR 3 contains no events and is excluded. The corrected MC simulation shows excellent agreement with Data across all validation regions. Additionally, using a benchmark signal model, we confirm that signal contamination is very low, smaller than the statistical uncertainty.

| Event Region<br>Track Region | FCNN QSR 1 (v12) | FCNN QSR 2 (v12) | FCNN QSR 4 (v12) |
|------------------------------|------------------|------------------|------------------|
| Others                       | $3.7 \pm 5.8$    | $18 \pm 35$      | $58 \pm 27$      |
| $W \rightarrow e\nu$         | $24.2 \pm 5.1$   | $113 \pm 26$     | $262 \pm 55$     |
| $W \rightarrow \mu\nu$       | $106.6 \pm 4.7$  | $289 \pm 11$     | $581 \pm 22$     |
| $W \rightarrow \tau\nu$ (H)  | $135 \pm 32$     | $495 \pm 83$     | $1138 \pm 219$   |
| $W \rightarrow \tau\nu$ (L)  | $60 \pm 14$      | $196 \pm 40$     | $429 \pm 76$     |
| $Z \rightarrow ll$           | $980 \pm 80$     | $2974 \pm 235$   | $6123 \pm 482$   |
| $ZZ, WZ, WW$                 | $66 \pm 10$      | $157 \pm 48$     | $297 \pm 42$     |
| Sum Bkg. $\pm \sigma_{MC}$   | $1390 \pm 96$    | $4285 \pm 244$   | $8967 \pm 467$   |
| Data $\pm \sigma_{Pois}$     | $1343 \pm 36.6$  | $4230 \pm 65.0$  | $9017 \pm 95.0$  |
| (151, 150.5, 150)            | $35 \pm 11$      | $83 \pm 24$      | $132 \pm 37$     |

### 4.8.2 Track-Level FCNN SR Validation

Similar to event-level, to ensure the accuracy of our track-level Monte Carlo modeling, we validate the consistency between MC simulations and real data, focusing on the kinematic distributions of track-level signal region tracks. This validation involves comparing simulations in the event-level validation region (**VR MET**) with those in the event-level signal regions.

Out of the four signal regions (and their corresponding track-level validation regions), we focus here on the first signal region. Results for the remaining regions can be found in Appendix B.6.3 and B.6.4, which show similar conclusions.

Figures 4.36 and 4.35 display the kinematic distributions for the 1st FCNN Signal Region (with highest S/B) and the corresponding track-level validation region, respectively. The similarity between these distributions supports us to extrapolate the confidence from the validation region to the signal region. In the validation region (Figure 4.36), we observe strong agreement between the MC and data for the track-level signal region.

This consistent agreement validates that the event-level and track-level selections are largely independent, and confirms that the kinematics observed in the track-level validation region can be reliably extrapolated to the signal region. Given the demonstrated agreement between MC and data in the event-level validation and track-level signal regions, we anticipate similar consistency in the actual signal regions.

#### Summary

1. **Track-level kinematics consistency:** The agreement between MC track-level distributions in the event-level validation region and the event-level signal region demonstrates that both regions share similar physics in tracks with similar score range.
2. **Validation of MC corrections:** The agreement between MC and data in the event-level validation region in both the yields (Table 4.13) and kinematics variable distributions (Figure 4.35). It supports the effectiveness of the applied corrections, justifying our confidence in MC modeling

in the signal regions.

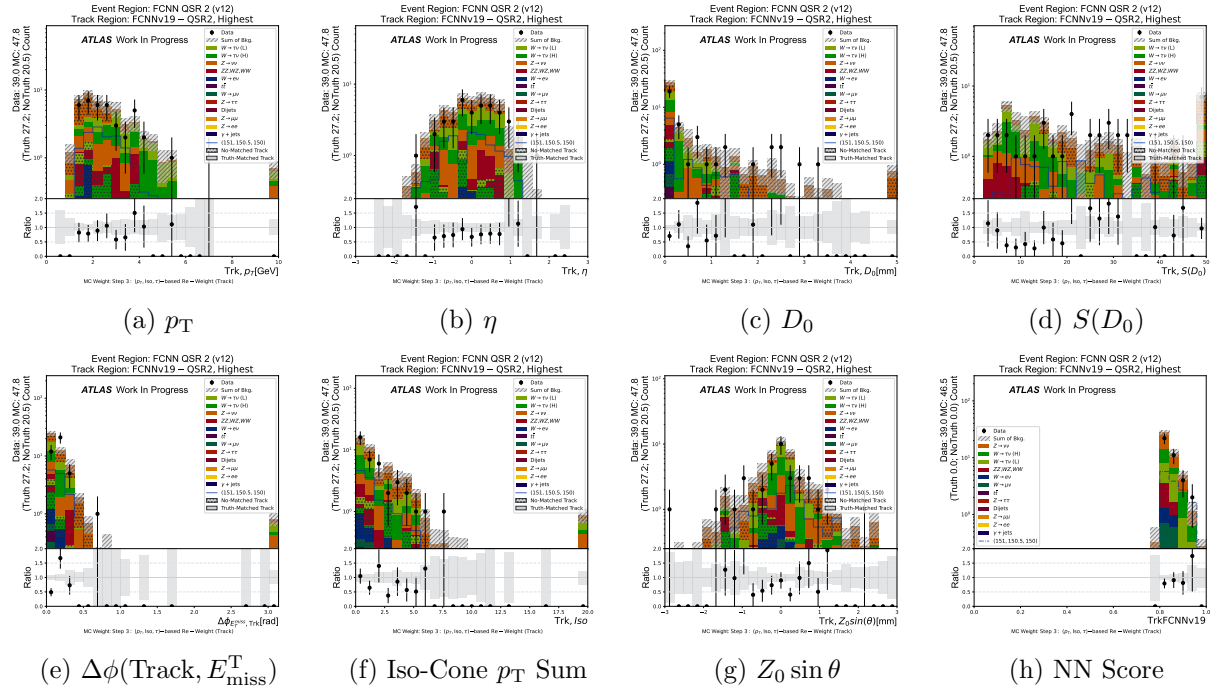


Figure 4.35: Track-level kinematic histograms for events passing both event-level SR 2 and track-level SR 2 selections. The similarity in kinematics across the SR and VR selections supports the validity of our extrapolation from the validation region to the Signal Regions.

Table 4.13: Yields for the track-level FCNN signal regions in the validation regions, showing excellent agreement between MC predictions and measured data. Note that the signal contamination is minimal, comparable to or below the level of statistical uncertainties.

| Event Region                      | VR $E_{\text{miss}}^T [325, 500]$ |                |                 |                |
|-----------------------------------|-----------------------------------|----------------|-----------------|----------------|
| Track Region                      | SR1                               | SR2            | SR3             | SR4            |
| Others                            | $32 \pm 12$                       | $5.2 \pm 2.7$  | $49 \pm 20$     | $9.8 \pm 2.7$  |
| $W \rightarrow e\nu$              | $39.2 \pm 8.5$                    | $8.3 \pm 2.8$  | $110 \pm 31$    | $19.8 \pm 5.5$ |
| $W \rightarrow \mu\nu$            | $34.2 \pm 2.5$                    | $9.3 \pm 1.0$  | $92.1 \pm 4.8$  | $21.5 \pm 1.8$ |
| $W \rightarrow \tau\nu$ (H)       | $303 \pm 76$                      | $86 \pm 24$    | $572 \pm 94$    | $113 \pm 30$   |
| $W \rightarrow \tau\nu$ (L)       | $187 \pm 33$                      | $41.1 \pm 8.6$ | $317 \pm 63$    | $58 \pm 12$    |
| $Z \rightarrow ll$                | $553 \pm 82$                      | $130 \pm 18$   | $1367 \pm 189$  | $304 \pm 44$   |
| $ZZ, WZ, WW$                      | $32.2 \pm 5.2$                    | $7.0 \pm 1.1$  | $66.0 \pm 7.1$  | $13.0 \pm 1.4$ |
| Sum Bkg. $\pm \sigma_{\text{MC}}$ | $1177 \pm 76$                     | $285 \pm 21$   | $2576 \pm 154$  | $540 \pm 43$   |
| Data $\pm \sigma_{\text{Pois}}$   | $1084 \pm 32.9$                   | $264 \pm 16.2$ | $2619 \pm 51.2$ | $562 \pm 23.7$ |
| (151, 150.5, 150)                 | $53 \pm 15$                       | $8.9 \pm 2.5$  | $71 \pm 19$     | $11.9 \pm 3.3$ |

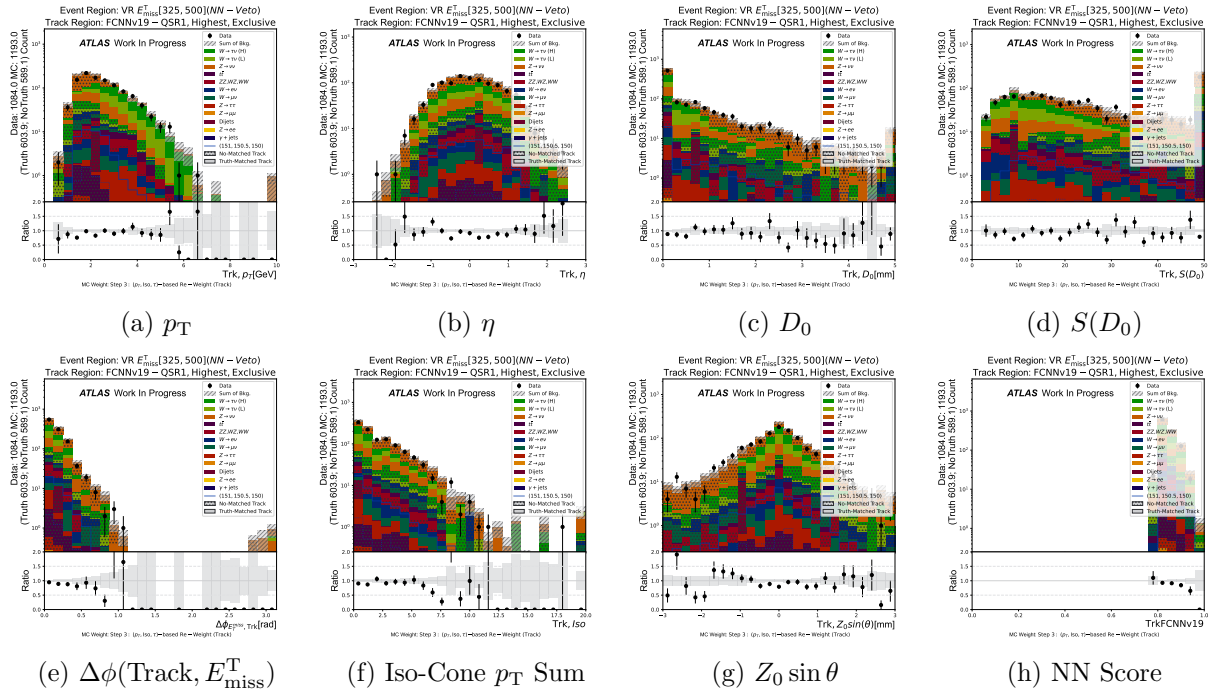


Figure 4.36: Track-level kinematic histograms for events selected from the medium MET validation region ( $[325, 500]$  GeV) at the event level and SR 1 at the track level. We have excellent Data-MC agreement in the kinematics distribution in the Track-Level validation regions.

### 4.8.3 Two-Level FCNN SR Validation via Leptonic Channel

This validation ensures that combining event-level and track-level signal regions does not introduce unintended effects, such as distortions in track kinematics due to higher MET values. In the Leptonic FCNN Validation Region, we replace the 0-lepton requirement with a 1-muon selection and substitute the MET vector with the lepton-invisible MET vector to compute all input parameters for the FCNN model. Figure 4.37 compares track-level kinematics across both track-level and event-level signal regions, demonstrating consistency between the Data and Monte Carlo. Table 4.14 shows that the observed yields, despite being statistically limited, align closely with MC predictions—well within statistical uncertainties. These observations provide evidence that:

**MC modeling is accurate**, and the neural network (NN) introduces no apparent bias.

**Event SR + Track SR behaves as expected:** Higher MET does not negatively affect track-level kinematics modeling. The FCNN score output extrapolates reliably into high-MET SRs.

Table 4.14: Yields from the Leptonic Validation Region, where event-level and track-level signal region selections are applied, replacing MET with lepton-invisible MET. The excellent agreement between corrected MC and Data, both in overall yield and statistical uncertainties, supports the robustness of our corrections and validates the reliability of the FCNN model.

| Event Region                | VR – Lep 1( $1\mu$ ) | VR – Lep 2( $1\mu$ ) | VR – Lep 3( $1\mu$ ) | VR – Lep 4( $1\mu$ ) |
|-----------------------------|----------------------|----------------------|----------------------|----------------------|
| Track Region                | Lep – SR1            | Lep – SR2            | Lep – SR3            | Lep – SR4            |
| Others                      | $0.011 \pm 0.006$    | $0.06 \pm 0.09$      | $0.12 \pm 0.07$      | $0.6 \pm 0.3$        |
| $W \rightarrow e\nu$        | $0.0 \pm 0.0$        | $0.0 \pm 0.0$        | $0.0 \pm 0.0$        | $0.0 \pm 0.0$        |
| $W \rightarrow \mu\nu$      | $1.7 \pm 0.3$        | $4.7 \pm 0.8$        | $14.9 \pm 1.5$       | $41.6 \pm 3.9$       |
| $W \rightarrow \tau\nu$ (H) | $0.0 \pm 0.0$        | $0.0 \pm 0.0$        | $0.0 \pm 0.0$        | $0.0 \pm 0.0$        |
| $W \rightarrow \tau\nu$ (L) | $0.01 \pm 0.08$      | $0.03 \pm 0.06$      | $0.5 \pm 0.4$        | $1.4 \pm 0.5$        |
| $Z \rightarrow ll$          | $0.00 \pm 0.01$      | $0.00 \pm 0.06$      | $0.16 \pm 0.08$      | $0.19 \pm 0.08$      |
| $ZZ, WZ, WW$                | $0.009 \pm 0.005$    | $0.4 \pm 0.2$        | $0.6 \pm 8.9$        | $2.4 \pm 0.5$        |
| Sum Bkg. $\pm \sigma_{MC}$  | $1.7 \pm 0.3$        | $5.2 \pm 0.9$        | $16.5 \pm 9.2$       | $46.9 \pm 3.4$       |
| Data $\pm \sigma_{Pois}$    | $3 \pm 1.7$          | $3 \pm 1.7$          | $15 \pm 3.9$         | $50 \pm 7.1$         |
| (151, 150.5, 150)           | $0.0 \pm 0.0$        | $0.0 \pm 0.0$        | $0.0 \pm 0.0$        | $0.0 \pm 0.0$        |

### 4.8.4 FCNN Tau Contribution Validation

Figure 4.38 shows strong Data-MC agreement, validating the  $W \rightarrow \tau\nu$  track modeling in the Event FCNN Signal Regions. This analysis uses a Pheno-Paper SR-like track selection, with a higher



$p_T$  threshold applied (as detailed in Table 4.6). The figure includes track-level kinematics for the following selection: **Event Level:** SR 1 (the highest S/B region); **Track Level:**  $\tau$ -enriched high  $p_T$  selection (similar to Pheno SR).

Complete kinematic distributions for all four Tau Validation Regions can be found in Figures B.35 through B.38 in Appendix B.6.5.

The event yields listed in Table 4.15 closely match our MC predictions, confirming accurate modeling of the  $W \rightarrow \tau \nu$  (L/H) contributions. This agreement provides strong confidence that the  $\tau$ -specific Step-3 correction (Section 4.7.5) is reliable and can be effectively applied to signal-like regions.

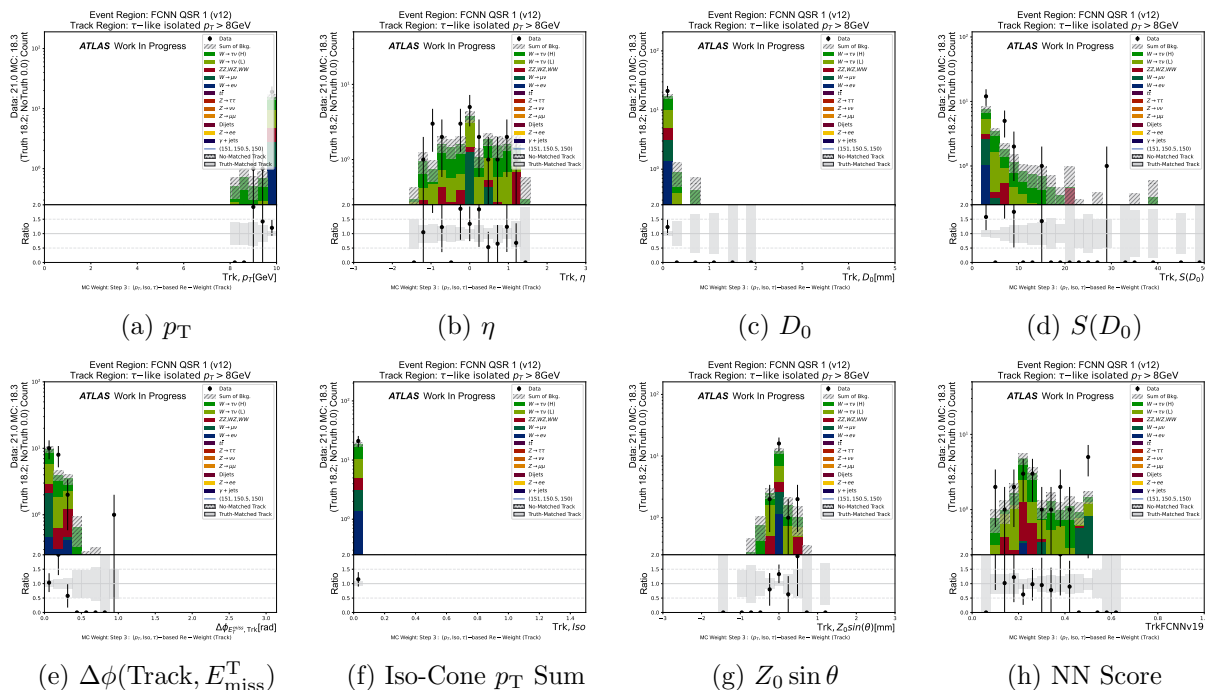


Figure 4.38: **Track-level kinematics histograms** validating the  $W \rightarrow \tau\nu$  track modeling within the Event FCNN Signal Region. This analysis uses a Pheno-Paper SR-like track selection with a higher  $p_T$  threshold. Selection criteria: **Event Level:** SR 1; **Track Level:**  $\tau$ -enriched high  $p_T$ . The excellent agreement between Data and corrected MC supports the robustness of our corrections and the accuracy of the modeling.



Table 4.15: FCNN Tau Validation Region Yields: No signal contamination detected. The agreement between Data and MC simulation confirms reliable  $W \rightarrow \tau\nu$  modeling and supports the applicability of the corrections in signal-like regions.

| Event Region                      | SR 1                                      | SR 2            | SR 4            |
|-----------------------------------|-------------------------------------------|-----------------|-----------------|
| Track Region                      | $\tau$ -like isolated $p_T > 8\text{GeV}$ |                 |                 |
| Others                            | $0.10 \pm 0.05$                           | $0.6 \pm 0.2$   | $1.6 \pm 1.0$   |
| $W \rightarrow e\nu$              | $1.2 \pm 0.5$                             | $4.3 \pm 1.3$   | $5.2 \pm 1.3$   |
| $W \rightarrow \mu\nu$            | $1.6 \pm 0.3$                             | $5.7 \pm 1.0$   | $11.0 \pm 1.3$  |
| $W \rightarrow \tau\nu$ (H)       | $8.0 \pm 2.0$                             | $27.6 \pm 6.0$  | $66 \pm 16$     |
| $W \rightarrow \tau\nu$ (L)       | $5.5 \pm 1.8$                             | $17.2 \pm 4.8$  | $29.4 \pm 7.5$  |
| $Z \rightarrow ll$                | $0.10 \pm 0.06$                           | $0.63 \pm 0.10$ | $0.7 \pm 0.3$   |
| $ZZ, WZ, WW$                      | $2.0 \pm 0.6$                             | $2.7 \pm 0.8$   | $4.8 \pm 1.1$   |
| Sum Bkg. $\pm \sigma_{\text{MC}}$ | $18.3 \pm 2.4$                            | $57.7 \pm 4.8$  | $115.8 \pm 8.3$ |
| Data $\pm \sigma_{\text{Pois}}$   | $21 \pm 4.6$                              | $53 \pm 7.3$    | $110 \pm 10.5$  |
| (151, 150.5, 150)                 | $0.05 \pm 0.02$                           | $0.0 \pm 0.0$   | $0.0 \pm 0.0$   |

#### 4.8.5 FCNN Score Distribution in Event Control Regions

The **Track-Level FCNN Validation Region** consists of tracks selected by the Track-Level FCNN Signal Region within the lower MET control region. Given the negligible signal contamination, we observe strong agreement between MC and data in both the yield and the shape of key kinematic distributions. This agreement is illustrated in Figures B.6 through B.11 in Appendix B.5.1. These plots confirm that the model avoids overfitting or bias from statistical noise, validating the success of our k-fold cross-validation and early stopping strategies.

A complementary way to confirm the unbiased nature of the FCNN model is by examining its **Score Distribution in Control Regions**. As shown in Figure 4.39, the Event-Level FCNN Score distribution aligns closely between MC simulation and Data across the various Control and Validation Regions. This alignment further supports the absence of overfitting or unexpected behaviors in the model.

Special attention is given to **leptonic control regions**, which provide a crucial test since the FCNN model does not incorporate lepton-specific information. These regions are also orthogonal to the datasets used during training and validation. Notably, we manually enforce a zero-lepton

condition in the actual signal region, meaning that the model scores events in these control regions under the assumption of zero leptons, regardless of their actual lepton content (including CR  $1e$ , CR  $1\mu$ , and CR  $2\mu$ ).

The excellent agreement across the entire score range in these leptonic control regions further reinforces our confidence in the robustness of the FCNN model.

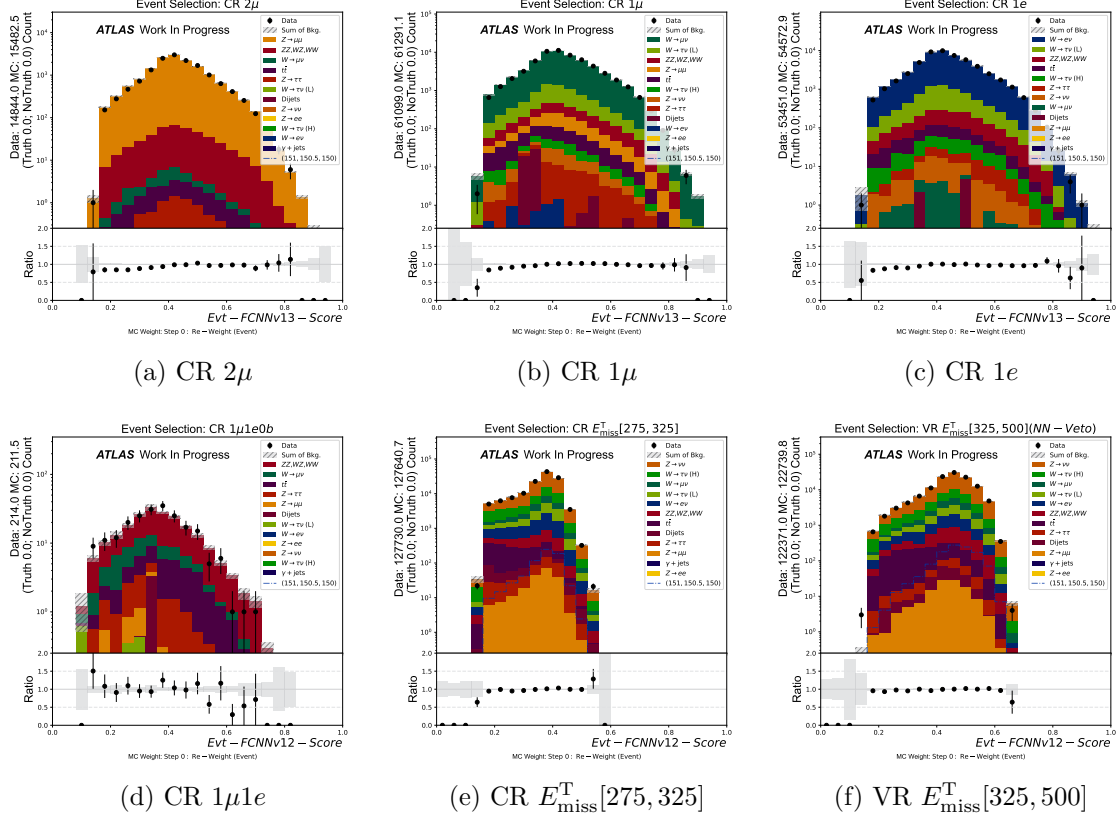


Figure 4.39: Event-Level FCNN Score distribution in Control and Validation Regions, showing excellent agreement between MC simulation and Data. (High scores are vetoed for the 0L VR  $E_{\text{miss}}^T[325, 500]$  region.) Note: Minor discrepancies appear in the low-score regions of the leptonic Control Regions. However, this has minimal impact on the analysis, as we focus on high-score events.

## 4.9 Statistical Interpretation with PyHF

The goal of the statistical interpretation is to quantify the agreement between the observed data and the Standard Model background prediction, and to test the presence of a potential Higgsino signal.

In this section, we present the statistical interpretation of the analysis, using the `PyHF` package to perform background-only fits and signal hypothesis tests. The key elements of the model setup, systematic uncertainties, and final results are discussed. The results are presented in terms of MC-Data yield agreement, kinematic distributions in the signal regions, and the exclusion limits. Additionally, we compare the performance of neural network-based signal regions with traditional cut-based analysis.

### 4.9.1 Statistical Model Setup

The statistical model includes background processes, signal regions, control regions, and nuisance parameters (NP). The nuisance parameters handle uncertainties in this analysis from both experimental and theoretical sources. These parameters are floated simultaneously during the fit. Experimental uncertainties, including detector efficiency, energy resolution, and luminosity, are considered, along with theoretical uncertainties on parton distribution functions, physical constant and higher-order corrections. To ensure a robust background estimation, control regions are used to constrain background processes, focusing on regions with minimal signal contamination. Event and track-level validation regions, while not included in the fit, are used to check the accuracy of the fitted background model. These regions help ensure the reliability of the background estimates, and their results were presented in the previous section.

The `PyHF` model uses a likelihood function constructed from the signal, background, and nuisance parameters. We perform both background-only fits and simultaneous signal + background fits. Systematic uncertainties are incorporated as nuisance parameters and are constrained by the control regions used in the fits.

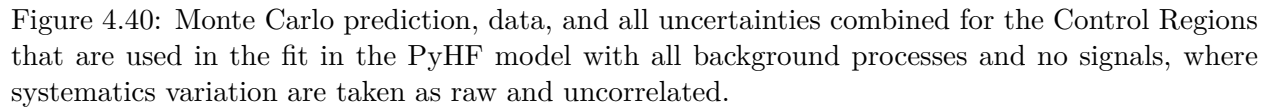
The background-only fit is performed using the control region data to estimate the expected background yield in the signal regions. This fit incorporates all background processes but excludes any signal contribution, allowing us to estimate both the yields and the uncertainties in the signal regions under the background-only hypothesis. The uncertainties derived from this fit are decomposed into contributions from various nuisance parameters. This background-only fit serves as a

baseline for comparing the unblinded data in the signal regions with our model.

To illustrate the performance of the fit, Figure 4.40 shows the Monte Carlo prediction, data, and all uncertainties combined for the control regions before the fit, where the systematics variations are uncorrelated. Figure 4.41 shows the same data after the background-only fit has been performed, where the systematics are constrained by the control-region-only fit. These figures demonstrate excellent agreement between the background model and the data in the orthogonal validation regions, providing confidence in the background estimation that is later applied to the signal regions.

For the signal hypothesis tests, we add the four neural network-based signal regions with high sensitivity to Higgsino-like signatures. To quantify any deviation from the background-only hypothesis, we use the profile likelihood ratio as a test statistic. This allows us to measure the compatibility of the observed data with the signal hypothesis, compared to the background-only model. The test statistic is used to calculate the significance of any excess events observed in the data, and to derive exclusion limits on the Higgsino signal[75].

As a side note, based on feedback to simplify the fit, we combined reweighting bins that share similar correction factors in the PyHF model. The updated correction factors for **Track Isolation (Step 2)** are shown in Table 4.16. This simplification had negligible impact on the yield.



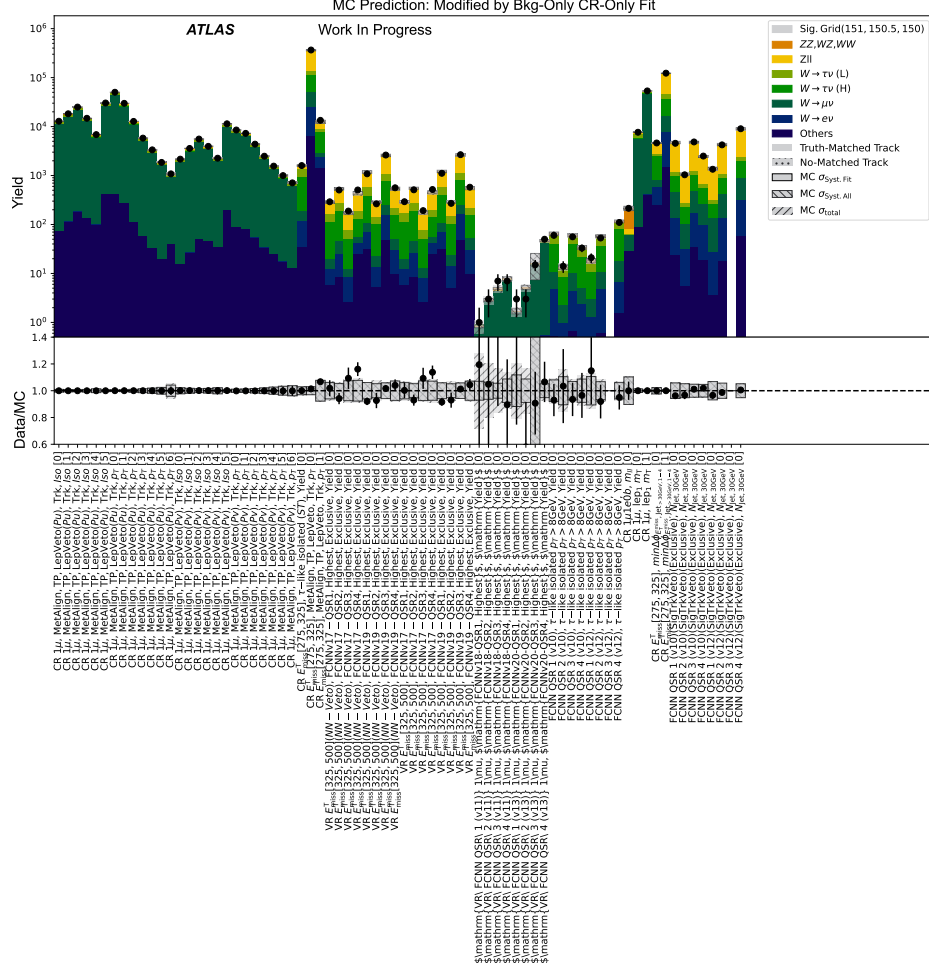


Figure 4.41: Monte Carlo prediction, data, and all uncertainties combined for all of the channels (except signal regions) in the PyHF model with all background processes and no signals, where systematics variation are constrained by the Control-Region-Only, Background-Process-Only fit. The observed data in these orthogonal validation regions agree well with the model prediction.

| Track ISO Bin [GeV] | Truth-Track Re-weight Factor | No-Truth-Track Re-weight Factor |
|---------------------|------------------------------|---------------------------------|
| 0.0-0.8             | $0.980 \pm 0.026$            | $0.803 \pm 0.006$               |
| 0.8-2.4             | $1.016 \pm 0.021$            | $0.957 \pm 0.006$               |
| 2.4-5.6             | $0.989 \pm 0.017$            | $1.078 \pm 0.006$               |
| 5.6-9.6             | $0.976 \pm 0.019$            | $1.127 \pm 0.008$               |
| 9.6-14.4            | $0.992 \pm 0.025$            | $1.069 \pm 0.012$               |
| 14.4-20.0           | $1.012 \pm 0.011$            | $1.010 \pm 0.005$               |

Table 4.16: Simplified Step 2 correction re-weighting factors binned by Track ISO variable. This is the simplified version of Table 4.9, and will be used for all the post-fit results.

## 4.9.2 Background-Only Fit and Nuisance Parameters

### 4.9.2.1 Systematic Uncertainties

This analysis incorporates a range of systematic uncertainties that affect experimental measurements and theoretical predictions. These uncertainties are treated as nuisance parameters in the fit and are constrained by the control region data. A complete list of the uncertainties used in this analysis is provided in Table 4.17 and 4.18, and detailed descriptions are included in Appendix B.3. Key sources of uncertainties include detector efficiency, energy resolution, luminosity, and theoretical modeling of cross sections, as well as corrections related to background processes.

The uncertainties are implemented using the following types of nuisance parameters:

- The luminosity uncertainty is applied as a global scale factor across all samples in a channel, affecting rates derived from theory calculations.
- The analysis event correction factors for the signals and the leading background processes ( $\mu_{\text{process}}$ ) are treated using normalization factor nuisance parameters (*normfactor*), which allows the normalization of individual background processes to float during the fit.
- All other systematic uncertainties are implemented using the *histosys* type, which allows for shape variations in the distribution of key observables, represented by up/down variations in the histograms.

The analysis-specific uncertainties are those related to the semi-data-driven background estimation methods, as described in Sections 4.7. These uncertainties are included in the fit as nuisance parameters and are constrained using the control region data. For simplicity, the nominal values of the semi-data-driven correction factors are taken from the initial best-fit values obtained during the background estimation. The  $1\sigma$  up/down variations for the *histosys* type uncertainties are calculated as the larger of 10% or twice the statistical uncertainty of the correction factors, allowing it to float with reasonable amount of freedom.

The track resolution uncertainty is handled by taking the nominal yield as the central value, and

utilizing an alternative version, randomly "smearing" the measured impact parameter within its resolution. The  $1\sigma$  up/down variations are implemented by varying the yield by  $\pm|\Delta\text{Yield}| = \pm|\text{NominalYield} - \text{SmearedYield}|$  for each bin in the distribution.

Theoretical uncertainties are evaluated using variations in QCD renormalization and factorization scales, parton density functions (PDF), and the strong coupling constant ( $\alpha_S$ ). The background processes, particularly  $V$ +jets and  $t\bar{t}$ , also include uncertainties from electroweak corrections. A few more systematic uncertainties will be included in the published paper, and they are expected to have a minimal impact on the exclusion limits. These include Multi-Parton Interaction (MPI) and parton shower (PS) uncertainties for the signal, as well as CKKW and QSF merging scale uncertainties for the backgrounds. The CKKW matching scale is used to match jets between matrix element calculations and the parton shower, while the QSF (quark-soft factor) scale accounts for the resummation of soft gluon emissions.

| Category (Abbrev.)                    | Type                                    | DAOD Tree/Weight Label                                                                                                              |
|---------------------------------------|-----------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|
| Weight Variations                     |                                         |                                                                                                                                     |
| Lepton Triggers (Trigger Weight)      | Electron Efficiency                     | EG_Trig_Eff                                                                                                                         |
|                                       | Electron Scale factor                   | EG_Trig_Total                                                                                                                       |
|                                       | Muon Efficiency (statistical )          | MUON_Trig_Stat                                                                                                                      |
|                                       | Muon Efficiency (systematic )           | MUON_Trig_Syst                                                                                                                      |
| Electron Efficiencies (Lepton Weight) | Identification                          | EL_EFF_ID                                                                                                                           |
|                                       | Isolation                               | EL_EFF_Iso                                                                                                                          |
|                                       | Reconstruction                          | EL_EFF_Reco                                                                                                                         |
| Muon Efficiencies (Lepton Weight)     | Identification (statistical )           | MUON_EFF_RECO_STAT                                                                                                                  |
|                                       | Identification (systematic )            | MUON_EFF_RECO_SYS                                                                                                                   |
|                                       | low $p_T$ identification (statistical ) | MUON_EFF_RECO_STAT_LOWPT                                                                                                            |
|                                       | low $p_T$ identification (systematic )  | MUON_EFF_RECO_SYS_LOWPT                                                                                                             |
|                                       | Isolation (statistical )                | MUON_EFF_ISO_STAT                                                                                                                   |
|                                       | Isolation (systematic )                 | MUON_EFF_ISO_SYS                                                                                                                    |
|                                       | TTVA (statistical )                     | MUON_EFF_TTVA_STAT                                                                                                                  |
|                                       | TTVA (systematic )                      | MUON_EFF_TTVA_SYS                                                                                                                   |
| Jet Efficiencies (JVT Weight)         | JVT                                     | JvtEfficiency<br>fJvtEfficiency                                                                                                     |
| $b$ -Tagging ( $b$ -Tag)              | $b$ -Tagging                            | FT_EFF_B_systematics<br>FT_EFF_C_systematics<br>FT_EFF_Light_systematics<br>FT_EFF_extrapolation<br>FT_EFF_extrapolation_from_charm |
| Luminosity                            |                                         | lumi                                                                                                                                |

Table 4.17: Summarized list of all used systematic uncertainties. (Part 1).



| Category (Abbrev.)                                          | Type                                                                                                        | DAOD Tree/Weight Label                                                                                                                                    |
|-------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Event Kinematics Tree Variations</b>                     |                                                                                                             |                                                                                                                                                           |
| $e/\gamma$ Calibration (EG Resolution)                      | Resolution                                                                                                  | EG_RESOLUTION_ALL                                                                                                                                         |
| Muon Calibration (Muon Syst.)                               | Variation in the momentum scale                                                                             | MUON_SCALE                                                                                                                                                |
|                                                             | Variation in the ID track resolution                                                                        | MUON_ID                                                                                                                                                   |
|                                                             | Variation in the MS track resolution                                                                        | MUON_MS                                                                                                                                                   |
|                                                             | Statistical error on the charge-dependent corrections                                                       | MUON_SAGITTA_DATASTAT                                                                                                                                     |
|                                                             | Variation in the momentum scale, data/MC nonClosure                                                         | MUON_SAGITTA_RESBIAS                                                                                                                                      |
| Jet Calibration (Jet Syst.)                                 | Jet energy scale                                                                                            | JET_EffectiveNP_*<br>JET_EtaIntercalibration_*<br>JET_Pileup_*<br>JET_Flavor_*<br>JET_SingleParticle_HighPt<br>JET_BJES_Response<br>JET_JER_EffectiveNP_* |
|                                                             | Jet energy resolution                                                                                       |                                                                                                                                                           |
| $E_T^{\text{miss}}$ soft track ( $E_T^{\text{miss}}$ Scale) | Offset along the $p_T^{\text{Hard}}$ axis                                                                   | MET_SoftTrk_Scale                                                                                                                                         |
| <b>Track Kinematics Tree Variations</b>                     |                                                                                                             |                                                                                                                                                           |
| Track Resolution (Track Resolution)                         | Impact parameter resolution                                                                                 | TRK_RES_DO_MEAS<br>TRK_RES_ZO_MEAS                                                                                                                        |
| <b>Theory Event Weight Variations</b>                       |                                                                                                             |                                                                                                                                                           |
| Theory uncertainties ( $\sigma_{\text{Theory}}$ (process))  | Theory uncertainty for all MC processes<br>CKKW & QSF uncertainty for $W \rightarrow \tau\nu + \text{jets}$ | *_TheoryUnc<br>CKKW_QSF                                                                                                                                   |
| <b>Analysis Track Correction Factors</b>                    |                                                                                                             |                                                                                                                                                           |
| Step-1 ( $\sigma_{\text{Step 1 } p_T \text{ RW Factor}}$ )  | $p_T$ -based Track Re-weight Factors                                                                        | Track $p_T$ Bin [1-7] [Truth/NoTruth]                                                                                                                     |
| Step-2 ( $\sigma_{\text{Step 2 ISO RW Factor}}$ )           | ISO-based Track Re-weight Factors                                                                           | Track ISO Bin [0-24] [Truth/NoTruth]                                                                                                                      |
| Step-3 ( $\sigma_{\text{Step 3 } \tau \text{ RW Factor}}$ ) | $W \rightarrow \tau\nu + \text{jets}$ Track Re-weight Factor                                                | Single Scale Factor                                                                                                                                       |
| <b>Analysis Event Correction Factors</b>                    |                                                                                                             |                                                                                                                                                           |
| Step-0 Normalization ( $\mu_{\text{process}}$ )             | Step-0 Event Normalization Factors                                                                          | For Signal & Leading Bkg Processes                                                                                                                        |

Table 4.18: Summarized list of all used systematic uncertainties. (Part 2).

#### 4.9.2.2 Expected Yield of Signal Regions

The fitted yields for the signal regions are presented in Table 4.19. As an example, we predict 46 background events and 43 signal events for the mass point model (101, 100.5, 100) in one of the signal region, indicating a highly sensitive signal region with excellent signal purity and a good amount of statistics. The total systematic uncertainties are on the order of 10%, and are less for higher statistics signal regions. This neural network-based configuration provides high sensitivity to potential new physics, offering significant statistical power to detect any excess events beyond the Standard Model background prediction. However, the data agrees well with the background-only hypothesis, showing no significant excess, with all results within  $1\sigma$  of the total uncertainty ( $\sigma_{\text{total}} = \sqrt{\sigma_{\text{MC}}^2 + \sigma_{\text{Pois}}^2}$ ). This agreement suggests no evidence for SUSY, and we can set stringent exclusion limits on the mass points tested. These exclusion limits will be presented in the following section (4.9.4).

#### 4.9.2.3 Uncertainty Decomposition

We quantify the contributions from various sources of uncertainty, including both experimental and theoretical uncertainties, and assess their impact on the fit results. As an example, the uncertainty composition for Signal Region 1 is shown in Table 4.20, with other signal regions provided in Appendix B.7.3. This breakdown help us evaluate the contribution of each uncertainty source and understand how they affect the overall sensitivity of the analysis.

The decomposition reveals that experimental uncertainties are relatively small compared to theoretical and model uncertainties. The leading sources of uncertainty are the jet energy scale and the track impact parameter resolution. These uncertainties align with expectations, as they are known to significantly affect the reconstruction of key observables like missing transverse momentum and jet kinematics. Another prominent source of uncertainty comes from the correction factor uncertainties. These are derived from the statistical uncertainties in the control region bins used to extract the correction factors.

The systematic uncertainties on the yields were estimated by varying the nuisance parameters by

Table 4.19: Estimated Signal Region track yields after full event & track reweighting corrections applied (after full systematics, simultaneous fit). Note that the 4 FCNN selection of tracks are orthogonal to each other.

| Signal Region                                           | FCNN SR 1       | FCNN SR 2       | FCNN SR 3      | FCNN SR 4      |
|---------------------------------------------------------|-----------------|-----------------|----------------|----------------|
| Others                                                  | $0.1 \pm 0.1$   | $0.4 \pm 0.2$   | $1.3 \pm 0.4$  | $4.2 \pm 1.5$  |
| $W \rightarrow e\nu$                                    | $0.5 \pm 0.2$   | $1.1 \pm 0.5$   | $3.2 \pm 1.5$  | $9.7 \pm 3.4$  |
| $W \rightarrow \mu\nu$                                  | $0.20 \pm 0.05$ | $0.84 \pm 0.07$ | $3.1 \pm 0.3$  | $10.5 \pm 0.9$ |
| $W \rightarrow \tau\nu$ (H)                             | $3.0 \pm 0.7$   | $9.6 \pm 3.1$   | $31.3 \pm 5.5$ | $99 \pm 22$    |
| $W \rightarrow \tau\nu$ (L)                             | $3.5 \pm 1.1$   | $9.4 \pm 1.7$   | $21.2 \pm 5.2$ | $59.8 \pm 9.6$ |
| $Z \rightarrow ll$                                      | $10.4 \pm 1.6$  | $21.8 \pm 3.3$  | $87 \pm 11$    | $226 \pm 31$   |
| $ZZ, WZ, WW$                                            | $1.1 \pm 0.4$   | $2.9 \pm 0.5$   | $4.8 \pm 0.9$  | $13.3 \pm 2.4$ |
| Sum Bkg. $\pm \sigma_{MC}$                              | $18.9 \pm 2.2$  | $46.1 \pm 4.6$  | $152 \pm 11$   | $422 \pm 29$   |
| DataUnblind                                             | 17              | 39              | 160            | 386            |
| $\sigma_{total} = \sqrt{\sigma_{MC}^2 + \sigma_{Pois}}$ | 4.9             | 8.2             | 16.5           | 35             |
| (Data – MC)/ $\sigma_{total}$                           | –0.4            | –0.9            | 0.5            | –1.0           |
| (100.7, 100.35, 100)                                    | $13.4 \pm 4.3$  | $21.9 \pm 6.9$  | $20.4 \pm 6.1$ | $51 \pm 14$    |
| (101, 100.5, 100)                                       | $16.4 \pm 5.4$  | $43 \pm 13$     | $38 \pm 11$    | $114 \pm 33$   |
| (101.5, 100.75, 100)                                    | $14.6 \pm 4.8$  | $27.0 \pm 8.0$  | $44 \pm 13$    | $90 \pm 26$    |
| (102, 101, 100)                                         | $6.4 \pm 1.9$   | $10.9 \pm 3.2$  | $28.4 \pm 8.7$ | $54 \pm 16$    |
| (103, 101.5, 100)                                       | $1.2 \pm 0.4$   | $1.4 \pm 0.6$   | $7.5 \pm 2.4$  | $19.6 \pm 5.6$ |
| (125.5, 125.25, 125)                                    | $1.7 \pm 0.5$   | $3.0 \pm 1.0$   | $6.3 \pm 1.9$  | $12.9 \pm 3.8$ |
| (125.7, 125.35, 125)                                    | $8.2 \pm 2.5$   | $12.8 \pm 3.8$  | $13.4 \pm 3.9$ | $32.6 \pm 9.2$ |
| (126, 125.5, 125)                                       | $13.6 \pm 4.2$  | $24.2 \pm 7.0$  | $35 \pm 11$    | $68 \pm 20$    |
| (126.5, 125.75, 125)                                    | $11.6 \pm 4.6$  | $16.2 \pm 4.7$  | $29.2 \pm 8.6$ | $66 \pm 20$    |
| (127, 126, 125)                                         | $3.7 \pm 1.2$   | $3.5 \pm 1.1$   | $19.0 \pm 5.7$ | $33 \pm 10$    |
| (128, 126.5, 125)                                       | $1.3 \pm 0.5$   | $0.7 \pm 0.2$   | $7.5 \pm 2.2$  | $12.4 \pm 3.5$ |
| (150.5, 150.25, 150)                                    | $1.5 \pm 0.5$   | $2.2 \pm 0.6$   | $4.3 \pm 1.3$  | $8.4 \pm 2.5$  |
| (150.7, 150.35, 150)                                    | $5.7 \pm 1.6$   | $6.7 \pm 1.9$   | $8.6 \pm 2.5$  | $21.4 \pm 6.3$ |
| (151, 150.5, 150)                                       | $11.5 \pm 4.1$  | $15.5 \pm 4.5$  | $20.9 \pm 6.2$ | $43 \pm 13$    |
| (151.5, 150.75, 150)                                    | $9.0 \pm 2.8$   | $10.6 \pm 3.2$  | $23.8 \pm 7.2$ | $44 \pm 13$    |
| (152, 151, 150)                                         | $2.5 \pm 0.8$   | $4.8 \pm 1.4$   | $13.3 \pm 4.0$ | $26.1 \pm 7.4$ |
| (153, 151.5, 150)                                       | $0.5 \pm 0.1$   | $1.0 \pm 0.4$   | $6.0 \pm 1.8$  | $8.7 \pm 2.5$  |
| (175.5, 175.25, 175)                                    | $1.5 \pm 0.5$   | $0.6 \pm 0.2$   | $3.3 \pm 1.0$  | $5.2 \pm 1.5$  |
| (175.7, 175.35, 175)                                    | $3.2 \pm 1.0$   | $3.3 \pm 1.0$   | $7.9 \pm 2.4$  | $13.0 \pm 3.9$ |
| (176, 175.5, 175)                                       | $8.7 \pm 2.7$   | $9.9 \pm 2.9$   | $15.8 \pm 4.7$ | $29.0 \pm 8.4$ |
| (176.5, 175.75, 175)                                    | $6.4 \pm 2.0$   | $7.6 \pm 2.3$   | $16.1 \pm 4.9$ | $30.8 \pm 8.9$ |
| (177, 176, 175)                                         | $2.0 \pm 0.6$   | $3.1 \pm 1.0$   | $12.0 \pm 3.7$ | $18.0 \pm 5.3$ |
| (178, 176.5, 175)                                       | $0.8 \pm 0.3$   | $0.4 \pm 0.1$   | $4.4 \pm 1.4$  | $7.1 \pm 2.1$  |
| (200.7, 200.35, 200)                                    | $2.7 \pm 0.8$   | $2.3 \pm 0.7$   | $5.4 \pm 1.6$  | $10.0 \pm 2.9$ |
| (201, 200.5, 200)                                       | $7.1 \pm 2.3$   | $6.4 \pm 1.9$   | $12.4 \pm 3.8$ | $17.5 \pm 5.2$ |
| (201.5, 200.75, 200)                                    | $4.4 \pm 1.3$   | $6.6 \pm 2.0$   | $14.3 \pm 4.3$ | $19.9 \pm 5.9$ |
| (202, 201, 200)                                         | $1.5 \pm 0.4$   | $2.1 \pm 0.7$   | $7.1 \pm 2.2$  | $11.6 \pm 3.4$ |
| (225.7, 225.35, 225)                                    | $1.7 \pm 0.5$   | $1.5 \pm 0.5$   | $4.0 \pm 1.2$  | $5.5 \pm 1.6$  |
| (226, 225.5, 225)                                       | $4.5 \pm 1.4$   | $4.7 \pm 1.5$   | $8.8 \pm 2.6$  | $12.6 \pm 3.7$ |
| (226.5, 225.75, 225)                                    | $3.7 \pm 1.1$   | $3.8 \pm 1.2$   | $9.2 \pm 2.8$  | $14.1 \pm 4.1$ |
| (227, 226, 225)                                         | $1.1 \pm 0.3$   | $1.4 \pm 0.4$   | $6.0 \pm 1.9$  | $7.6 \pm 2.2$  |
| (85.7, 85.35, 85)                                       | $16.2 \pm 6.3$  | $23.5 \pm 7.0$  | $18.0 \pm 6.7$ | $79 \pm 23$    |
| (87, 86, 85)                                            | $6.0 \pm 1.7$   | $11.8 \pm 3.5$  | $29.3 \pm 8.5$ | $67 \pm 19$    |
| (88, 86.5, 85)                                          | $1.5 \pm 0.4$   | $1.4 \pm 0.4$   | $11.3 \pm 3.7$ | $26.1 \pm 7.5$ |

$\pm 1\sigma_{\text{Hesse}}$ , with the uncertainty for each nuisance parameter calculated using the **Hesse** algorithm in **iminuit**. The systematic uncertainties are relatively small and well-controlled, contributing similarly to the statistical uncertainties due to limited Monte Carlo simulation samples.

Table 4.20: Fitted systematic uncertainty contributions and their relative percentages for Signal Region 1 (the signal region with the highest signal-to-background ratio). Note that individual sources of uncertainty may be correlated. The naming convention for nuisance parameter groups is defined in Tables 4.17 and 4.18.

|              |                                                                            |
|--------------|----------------------------------------------------------------------------|
| Event Region | SR 1                                                                       |
| Track Region | SR 1                                                                       |
|              | 18.9 (MC Pred. Yield)                                                      |
|              | $\pm 1.4$ (7.4%) ( $\sigma_{\text{MC Stat.}}$ )                            |
|              | $\pm 1.7$ (9.0%) ( $\sigma_{\text{MC Syst.}}$ )                            |
| Order        | MC Syst. Sources                                                           |
| 1            | 1.36 (7.2%) ( $\sigma_{\text{Theory}} (Z \rightarrow ll)$ )                |
| 2            | 1.00 (5.3%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau\nu (\text{L})))$ |
| 3            | 0.82 (4.3%) ( $\mu_{W \rightarrow \tau\nu (\text{H})}$ )                   |
| 4            | 0.78 (4.1%) (Jet Syst.)                                                    |
| 5            | 0.69 (3.6%) ( $\mu_{W \rightarrow \tau\nu (\text{L})}$ )                   |
| 6            | 0.66 (3.5%) ( $\mu_{Z \rightarrow ll}$ )                                   |
| 7            | 0.54 (2.8%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau\nu (\text{H})))$ |
| 8            | 0.48 (2.5%) ( $\mu_{ZZ, WZ, WW}$ )                                         |
| 9            | 0.38 (2.0%) ( $\sigma_{\text{Step 2 ISO RW Factor}}$ )                     |
| 10           | 0.31 (1.6%) ( $\sigma_{\text{Step 3 } \tau \text{ RW Factor}}$ )           |
| 11           | 0.27 (1.4%) (Track Resolution)                                             |
| 12           | 0.26 (1.3%) ( $\sigma_{\text{Step 1 } p_{\text{T}} \text{ RW Factor}}$ )   |
| 13           | 0.25 (1.3%) ( $\sigma_{\text{Theory}} (ZZ, WZ, WW))$                       |
| 14           | 0.18 (0.9%) ( $\sigma_{\text{Theory}} (W \rightarrow e\nu)$ )              |
| 15           | 0.11 (0.6%) ( $\sigma_{\text{Theory}} (\text{Others})$ )                   |
| 16           | 0.09 (0.5%) ( $b$ -Tag)                                                    |
| 17           | 0.07 (0.4%) ( $E_{\text{T}}^{\text{miss}}$ Scale)                          |
| 18           | 0.04 (0.2%) ( $\sigma_{\text{Theory}} (W \rightarrow \mu\nu)$ )            |
| 19           | 0.03 (0.2%) ( $\mu_{W \rightarrow \mu\nu}$ )                               |
| 20           | 0.02 (0.1%) (EG Resolution)                                                |
| 21           | 0.01 (0.0%) (JVT Weight)                                                   |
| 22           | 0.00 (0.0%) (Muon Syst.)                                                   |
| 23           | 0.00 (0.0%) (Lepton Weight)                                                |
| 24           | 0.00 (0.0%) (Trigger Weight)                                               |

#### 4.9.2.4 Post-fit Pull and Impact Plot

This section presents the pulls of the nuisance parameters (from the control-region-only background-only fit) are shown along the lower horizontal axis, indicating deviations in units of standard deviation. It also overlays with the NP-impact plots, which visualize the influence of various nuisance parameters on the signal strength parameter,  $\mu$ . The nuisance parameters are ranked by their impact on  $\mu$ , measured as  $\Delta\mu$ , with mass point (151, 150.5, 150) as a representative model. The pre-fit impacts are shown as empty rectangles, while post-fit impacts are shown as filled rectangles. The  $\Delta\mu$  values, calculated by shifting each nuisance parameter in both directions, are displayed along the upper horizontal axis in different colors.

These plots highlight the most influential nuisance parameters affecting the precision of  $\mu$ , offering insights into which systematic uncertainties dominate and how the fit has constrained them. Figures 4.43, 4.42, and 4.44 provide a ranking of impact and pulls across experimental and theoretical uncertainties, normalization factors, and track-level correction factors.

The post-fit values of most nuisance parameters remain close to their pre-fit values, indicating minimal significant pulls, which means the fit does not strongly deviate from initial expectations. For the experimental and theoretical systematic uncertainties, the post-fit uncertainties are nearly identical to the pre-fit uncertainties. This consistency suggests that the systematic uncertainties are not overly constrained by our analysis model, meaning the model allows them to vary freely within the reasonable bounds suggested by the ATLAS combined performance group.

Two notable exceptions are:

**1. Impact Parameter Resolution Uncertainty:** Since this analysis depends heavily on selecting tracks with high transverse impact parameter ( $D_0$ ), it is expected that the impact parameter resolution will be more tightly constrained compared to other analyses.

**2.  $W \rightarrow \mu\nu$  Theoretical Uncertainty:** This uncertainty is more difficult to constrain due to the heavy reliance on control regions dominated by the  $W \rightarrow \mu\nu$  process. While it complicates the

fit by introducing challenges in finding a best-fit value for all other nuisance parameters, it has minimal impact on the final results since the contribution from  $W \rightarrow \mu\nu$  to the signal region is negligible.

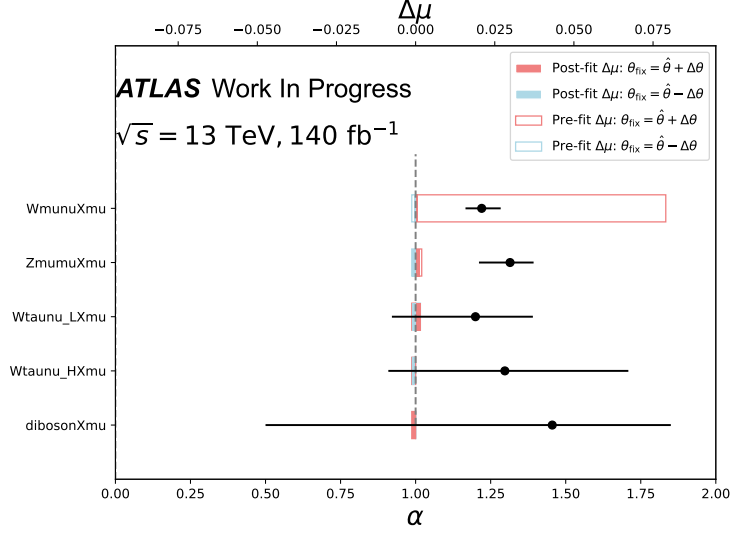


Figure 4.42: Ranked Impact of Nuisance Parameters on Signal Strength  $\mu_{\text{signal}}$  (Event-Level Normalization Factors): Nuisance parameters are ranked by their impact on  $\Delta\mu$  (upper axis), with pre-fit (empty rectangles) and post-fit (filled rectangles) impacts shown. Pulls (lower axis) illustrates the constraints placed by background-only fit in Control Regions.



Figure 4.43: Ranked Impact of Nuisance Parameters on Signal Strength  $\mu_{\text{signal}}$  (Experimental & Theory Systematic Uncertainty), with legend and format as in Figure 4.42. Here, the pulls (lower axis) reflect parameter deviations in units of standard deviation.

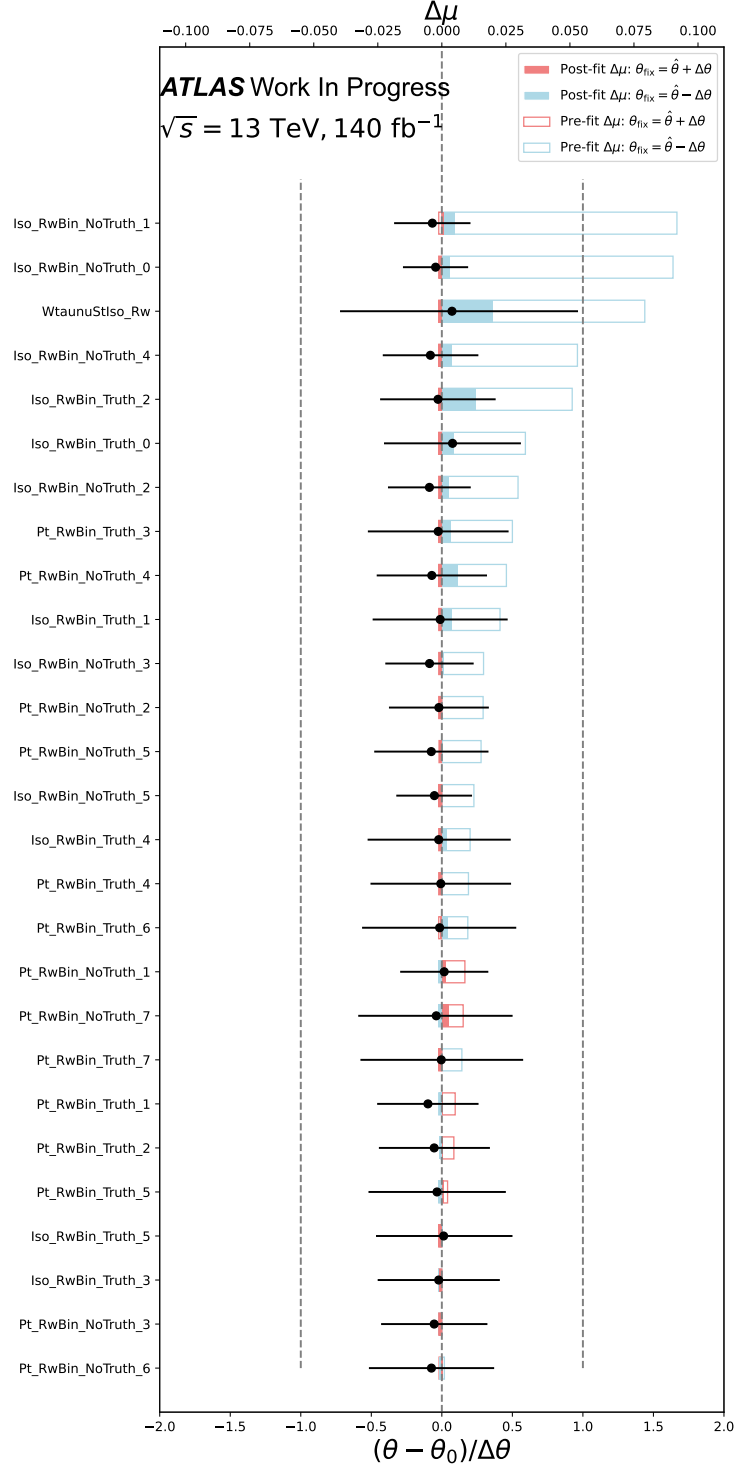


Figure 4.44: Ranked Impact of Nuisance Parameters on Signal Strength  $\mu_{\text{signal}}$  (Track-Level Correction Re-Weighting Factors), with legend and format as in Figure 4.43. For the analysis-specific correction factors (this figure), the pre-fit uncertainty are intentionally set to be larger.



### 4.9.3 Data vs. MC in Key Kinematic Distributions

As can be shown above in Figure 4.45, the Data agrees well with the pre-simultaneous fit corrected Monte Carlo prediction, in the shape of key kinematics distributions and the NN scores. They suggest that our corrected MC simulation models the Standard Model background kinematics well, and that the Neural Network is not biased. More histograms can be found in Appendix B.6.4.

### 4.9.4 Results: Exclusion Limits

In this analysis, exclusion limits are derived using the  $CL_s$  method, a widely-used technique in high-energy physics to test signal hypotheses. The  $CL_s$  value is calculated as the ratio of confidence levels for the signal + background hypothesis ( $CL_{s+b}$ ) and the background-only hypothesis ( $CL_b$ ). By using the profile likelihood ratio as the test statistic and applying asymptotic approximations [75], we efficiently calculate these confidence levels to set stringent limits on the Higgsino signal hypothesis. A model is excluded if  $CL_s < 0.05$ , corresponding to a 95% confidence level exclusion. This indicates that the likelihood of the signal+background hypothesis is significantly lower than the background-only hypothesis, meaning the data do not support the presence of the hypothesized signal at the tested mass points.

Figure 4.46 presents the exclusion contour with the four NN-based Signal Regions, where full-systematic hypothesis testing was performed across all signal mass points. Intermediate points were interpolated using a cubic function. For comparison, the expected and observed exclusion contours from the traditional Cut & Count (C&C) analysis are overlaid in green and grey.

Key findings from the unblinded data in Table 4.19 include:

- No significant excess is observed.
- The data in the signal regions align well with Standard Model predictions, staying within the  $1\sigma$  uncertainty range of the corrected MC estimates.
- A slight deficit in SR 1, SR 2, and SR 4 results in a larger exclusion contour than nominally

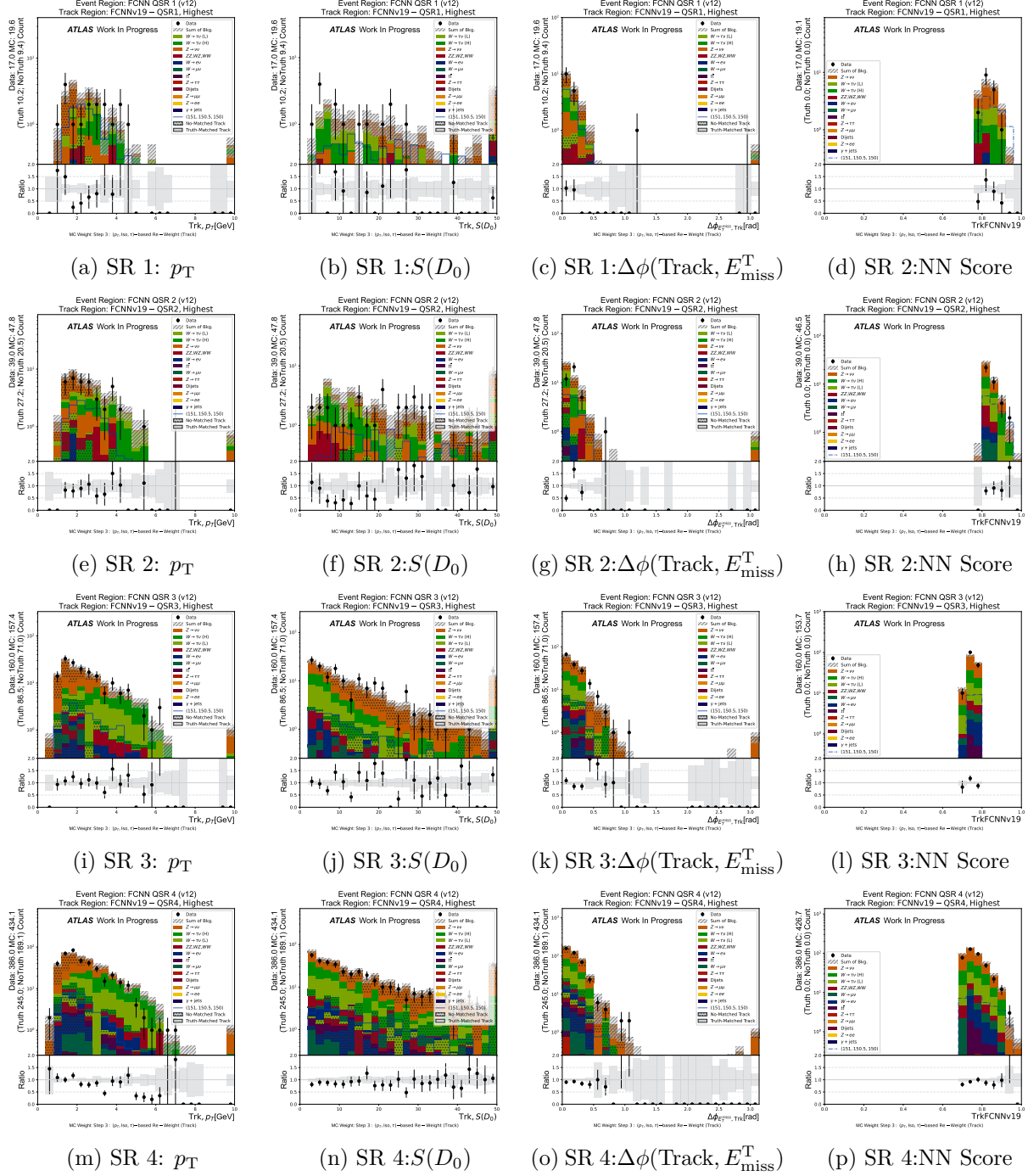


Figure 4.45: Track-level kinematics histograms in the four signal regions (SR 1 through 4, top to bottom). For each region, four key kinematic variables are displayed (from left to right), illustrating the comparison between data and pre-simultaneous fit corrected Monte Carlo predictions. The plots show excellent agreement in both the overall yield and the shape of the distributions, indicating that the corrected MC simulation accurately models the Standard Model background kinematics and that the Neural Network predictions are unbiased.

expected.

As shown in Figure 4.46, the FCNN approach yields stronger exclusion contours than the traditional Cut & Count approach, over all chargino-neutralino mass splittings. This improvement is evident in both the expected and observed exclusion limits.

The FCNN-based exclusion contour excludes chargino masses up to **190 GeV**, with mass splittings  $\Delta m(\tilde{\chi}_1^\pm, \tilde{\chi}_1^0)$  ranging from **300 MeV to 1.1 GeV**. In contrast, the C&C method excludes chargino masses up to 170-175 GeV, with a slightly narrower range of mass splittings ( $\sim 300 \text{ MeV} - 0.9 \text{ GeV}$ ).

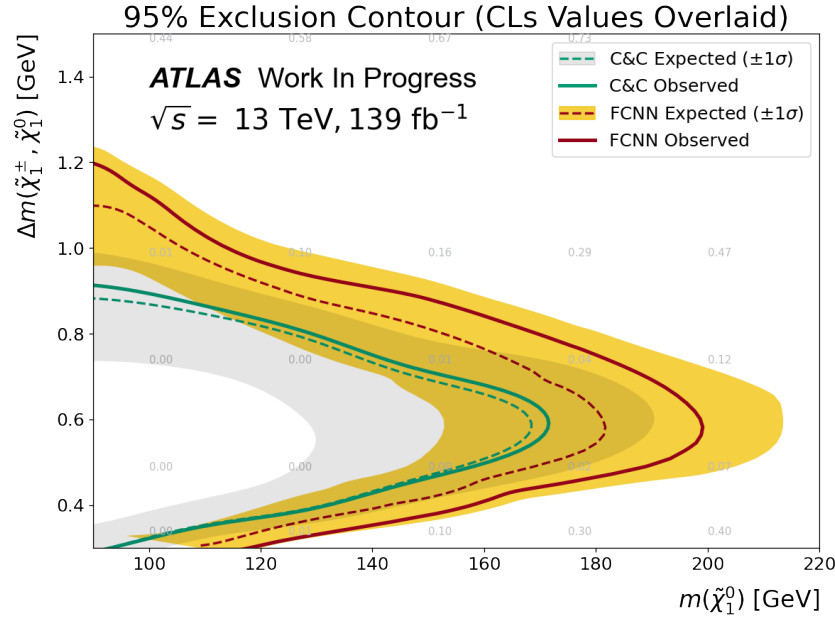


Figure 4.46: **95% Confidence Level ( $CL_s$ ) Exclusion Contour for FCNN-based analysis and Cut & Count (C&C) method:** The figure shows the exclusion limits based on the full systematic hypothesis testing of the neural network signal regions, overlaid with the Cut & Count results from HepData (<https://www.hepdata.net/record/146944>) [25]. The solid red line represents the observed exclusion for the NN-based approach, and the dashed red line is the expected exclusion, with the yellow band showing the  $\pm 1\sigma$  uncertainty range. The solid green line indicates the observed exclusion for C&C, and the dashed green line is the expected exclusion, with the grey band showing  $\pm 1\sigma$  uncertainty for C&C. The FCNN-based analysis demonstrates improved sensitivity and tighter exclusion limits, excluding a wider parameter space for chargino-neutralino mass splittings.

This demonstrates that the FCNN-based analysis achieves approximately 15 GeV improvement in

the exclusion of chargino masses compared to the C&C method, especially in regions of large mass splittings. Additionally, the FCNN analysis shows a tighter exclusion limit in areas where the C&C method becomes less sensitive, particularly for splittings near 1 GeV, where the C&C exclusion rapidly degrades. The FCNN method provides more consistent and reliable exclusion power across the parameter space, owing to its better handling of complex signal shapes and improved sensitivity to subtle variations in the event distributions.

By leveraging the neural network’s ability to optimize signal regions, the FCNN-based analysis delivers better exclusion of the Higgsino hypothesis, surpassing the traditional C&C approach in terms of both coverage and sensitivity. In this analysis, we also introduce the concept of **CLs-equivalent luminosity increase** to quantitatively compare the sensitivity of the two approaches. This metric allows us to determine how much additional data (in terms of integrated luminosity) would be needed for the C&C analysis to achieve the same level of sensitivity as the NN-based method. Our results show that, for the most relevant mass points, the NN-based approach is equivalent to an increase in integrated luminosity ranging from 80% to over 320%. Notably, the NN-based analysis allows us to exclude several mass points that were previously not excluded by the C&C method, demonstrating the superior sensitivity and flexibility of the NN approach. Full details of this comparison, along with the specific excluded mass points, can be found in Appendix B.4.

## CHAPTER 5

### The Proto-Type Testing and Design Verification of the AMAC ASIC in the ATLAS Inner Tracker (ITk) Upgrade

#### 5.1 Introduction

Sometime in the next decade, the High-Luminosity Large Hadron Collider (HL-LHC) will begin operation for more than a decade, increasing the peak luminosity fivefold compared to the LHC ([76, 77]). This upgrade will result in three times the inelastic collisions per bunch crossing (Pile-Up) and a total tenfold increase in integrated luminosity, reaching  $4000 \text{ fb}^{-1}$ . These improvements will allow the ATLAS and CMS experiments to collect substantially more data, producing over 15 million Higgs bosons annually, crucial for precise Higgs boson measurements and probing for new physics beyond the Standard Model.

The increased luminosity demands an upgrade to the ATLAS detector, requiring finer granularity, higher read-out rates, and components capable of withstanding high-radiation environments over several years. The ATLAS Collaboration is constructing an essentially new detector. The entire current Inner Detector, which includes silicon pixel detector, silicon strip Semiconductor Tracker (SCT), and Transition Radiation Tracker (TRT) components, will be replaced by the full-silicon Inner Tracker (ITk). This upgrade will eliminate the limitations of the TRT's occupancy, allowing the ITk's silicon pixel and silicon-strip detectors to offer the precision and data-handling capacity required for the HL-LHC's increased luminosity.

The ATLAS group at the University of Pennsylvania is making leading contributions to the ITk-Strip detector. Three application-specific integrated circuits (ASICs) or “chips” were custom-designed for this detector:

- **ATLAS Binary Chip (ABCStar):** Reads out the signals from the silicon strips, forms clusters of these data, and stores them in the pipeline.

- **Hybrid Chip Controller (HCCStar):** Manages data readout from about a dozen ABCStars in a star-shaped layout, where each HCCStar directly reads data from all individual ABCStars on the same board.
- **Autonomous Monitor And Control chip (AMACStar):** Regulates the silicon sensor's biasing voltage and low-voltage power for the ABCStar, HCCStar and itself while monitoring currents, voltages, and temperatures, triggering interlocks if values exceed safe thresholds.

The HCCStar and AMACStar were designed by instrumentation specialists in the Penn experimental particle physics group. These specialists also made major contributions to the design of the ABCStar.

Increased luminosity means higher levels of radiation, which can damage detector components and disrupt data collection. The ASICs and detector modules are inaccessible once installed. If a component becomes damaged, it can cause issues such as current leakage, leading to local heating or even the loss of power to parts of the detector. AMAC plays a critical role in addressing these challenges by autonomously detecting and isolating defective components, preventing issues from spreading, and reducing the need for disruptive detector repair. The detailed design of the AMAC can be found in Section 5.2.2. The AMAC chip protects itself against Single-Event Effects (SEE) that can flip logic signals when high-energy particles pass through. Redundant data pathways and rigorous SEE resistance tests ensure the detector's reliable operation in the HL-LHC's high-radiation environment.

Given the critical role of AMAC in controlling ITk-Strip modules, its reliability is essential. After the Penn ASIC experts completed the AMAC prototype design and manufacturing, I participated in the validation of AMAC's real-time monitoring capabilities and testing the robustness of its radiation-hard design. This validation process was two-pronged: physical prototype testing focused on the analog components of the AMAC, and digital simulation focused on its logic components.

For the prototype testing, I tested the physical prototypes (AMACv2a) to ensure they met design specifications. I contributed to the setting-up of test-bench circuit boards, developing C++ testing

procedures, and creating a Python framework for quantitative analysis. These efforts were crucial in identifying discrepancies from the specification and design flaws in the prototype. I also developed a grading system to categorize and evaluate production chips based on performance metrics, with results synchronized to the ITk Production Database for use by other institutions collaborating on the ITk-Strip project (see Section 5.3).

For the design validation, I used simulation tools to verify the chip’s functional integrity, focusing on its performance in high-radiation environments subject to Single-Event Effects. Before large-scale manufacturing, simulation verification was essential to identifying design issues in the production version (AMACStar). I helped develop a simulation test routine to ensure the latest logic circuit designs met specifications, including nightly checks and SEE injection stress tests to evaluate the chip’s radiation hardness (see Section 5.4).

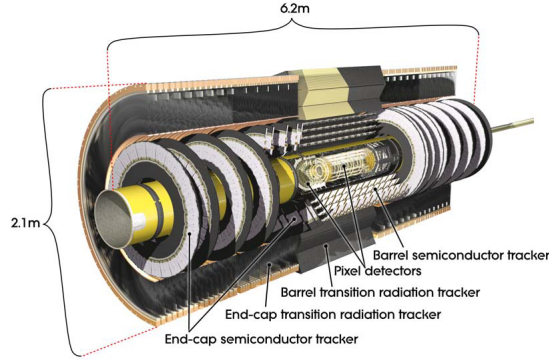
## 5.2 Overview of AMAC in ITk-Strip Detector

### 5.2.1 Detector Modules in the ITk-Strip

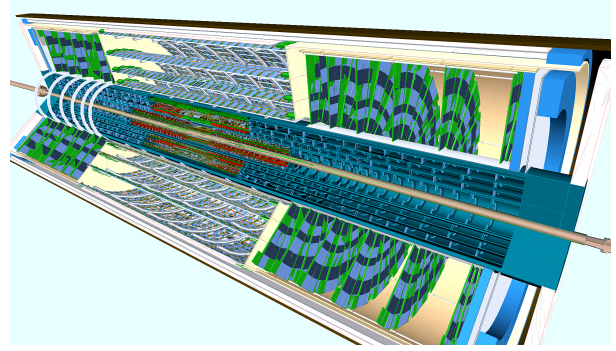
The **Inner Tracker (ITk)** is structured into two primary components: pixel detectors (ITk-Pixel) and strip detectors (ITk-Strip). The cross-sectional layout and comparison with the current Inner Detector can be seen in Figure 5.1.

The **ITk-Pixel**, situated closest to the beam line, offers fine granularity and low occupancy for precise vertex and track reconstruction, which is critical for identifying impact parameters of short-lived particles. Positioned further out from the beam line, the **ITk-Strip** extends tracking coverage and enhances particle identification, crucial for accurate momentum determination over a wide area.

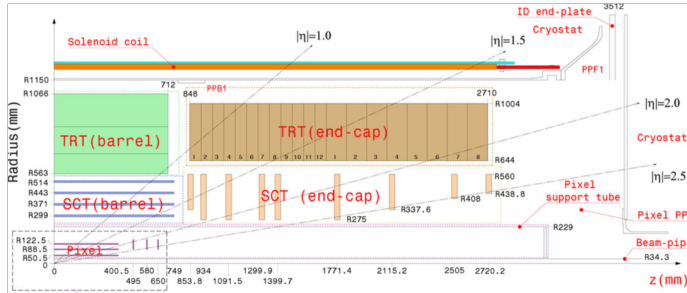
As shown in Figure 5.2, the ITk-Strip Detector is constructed from **staves** in the barrel region and **petals** in the endcap regions. Staves are linear assemblies that host a series of strip modules along the barrel, while petals are radially arranged in the endcaps, adapting to the cylindrical geometry of the ATLAS detector.



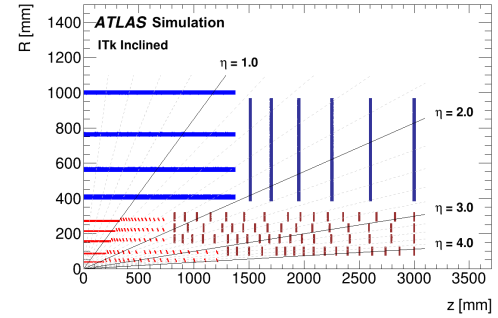
(a) Current ATLAS Inner Detector



(b) ITk for ATLAS Upgrade



(c) Current ATLAS Inner Detector (TRT, SCT, Pixel) Layout (Upper-Right Portion Cross-Section)



(d) ITk Strip Detector (Blue) and Pixel Detector (Red) (Upper-Right Cross-Section)

Figure 5.1: Detector layout comparison: The new ITk, which extends to pseudo-rapidity  $|\eta| \leq 4$  [26] greatly extends coverage beyond the current Inner Detector, which extends to  $|\eta| \leq 2.5$  [27]. Notice that there are two only main parts of ITk, as shown in blue and red in the cross-sectional view.

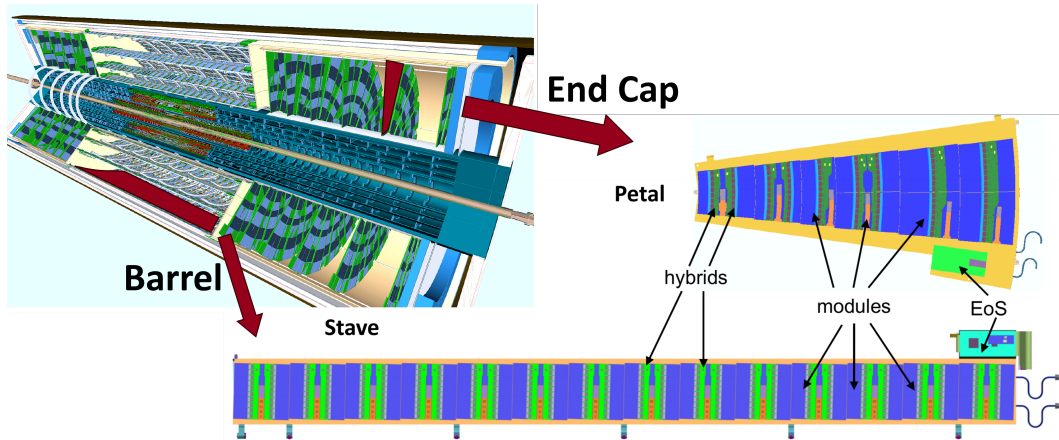


Figure 5.2: Construction of ITk-Strip detector from stave in the barrel region and petals in the endcap regions.



Each module, whether on a stave or petal, is a self-contained unit comprising silicon-strip sensors, readout electronics, and support structures as shown in Figure 5.3. The **Silicon-Strip Sensors** detect passing charged particles via ionization, providing the spatial resolution necessary for precise track reconstruction. A **High Voltage Bias** is applied across the silicon sensors to create an electric field that directs charge carriers toward the readout electronics. Three hybrid printed circuit boards (**Hybrid**) are bound onto the strip sensor:

**Hybrids X and Y:** Each hosts one **HCCStar** and twelve **ABCStar** chips on either side, responsible for data readout and processing.

**Powerboard:** Positioned in the center, this board hosts the **DC-DC converters**, which supply power to the module by providing low-voltage inputs for the ASICs. The **AMAC**, centrally located on the powerboard, regulates the module’s operation by monitoring and adjusting critical parameters. While the DC-DC converters handle power delivery, the 500V high voltage required for sensor biasing originates from the End-of-Stave device and is controlled by the AMAC. A photo of the Powerboard within the module, along with a close-up of the AMAC in its center, is shown in Figure 5.3.

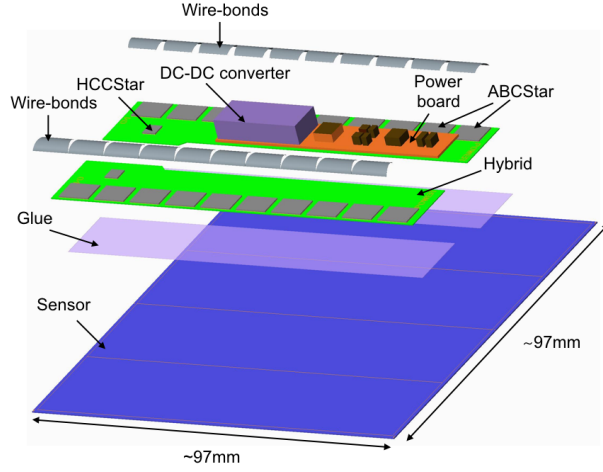
### 5.2.2 Autonomous Monitoring And Control

The Autonomous Monitoring And Control (AMAC) ASIC is a key component of the ITk-Strip Detector Module. Its functionality can be broken down into the three areas in its name: monitoring of physical parameters (5.2.2.1), control of module components (5.2.2.2), and autonomous actions in response to anomalies (5.2.2.3). The latest production version, AMACStar<sup>9</sup>, incorporates a Triple Module Redundancy (TMR) design to enhance fault tolerance[81], as detailed in Section 5.2.4. An overview of the main components of AMAC’s design and verification processes discussed in this chapter is shown in Figure 5.4.

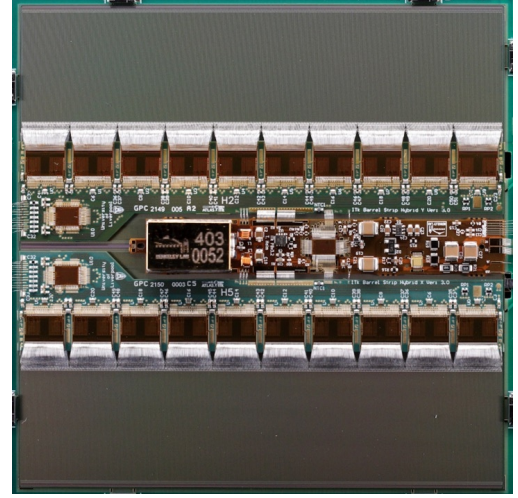
The AMACStar die measures 3.5 mm x 5.2 mm and is fabricated using Global Foundries’ CMOS8RF

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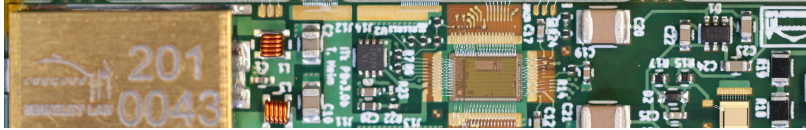
<sup>9</sup>Star = Simplified, Triplicated, And Respun. Refers to the production AMAC version after the AMACv2a prototype design.



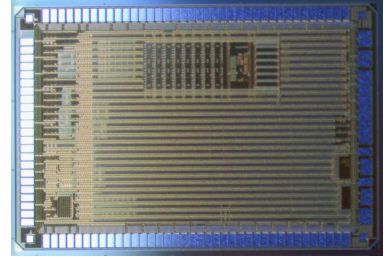
(a) ITk-Strip Module Exploded View [26]



(b) Photo of an ITk Strip module [78].



(c) Powerboard photo [79].



(d) AMAC under microscope [80].

Figure 5.3: Exploded view and photographs of the ITk Strip Detector module and AMAC. The exploded view illustrates the layered structure of the module, including the strip sensor, Hybrid PCBs, DC-DC converters, read-out ASICs, and wire bonds connecting these components. On the right is a prototype of the module with all components assembled. The Powerboard, with the AMAC chip centrally located, provides power to the module and regulates its operation by monitoring and controlling critical voltages and switches. Additionally, a microscope image shows an AMAC chip with a ring of input/output pads, which will be wire-bonded to the Powerboard.

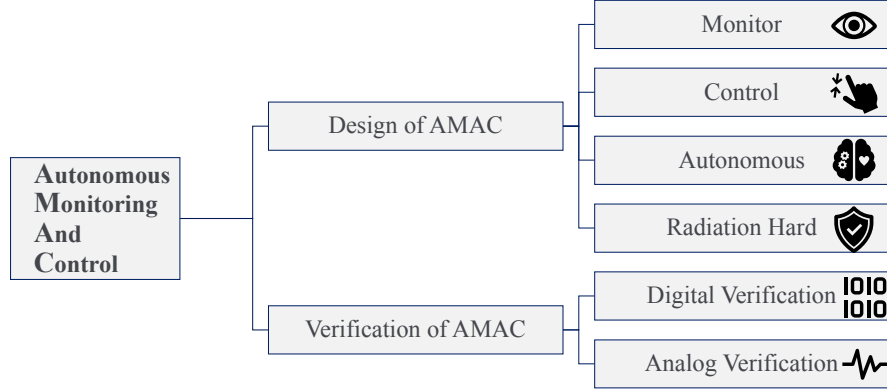


Figure 5.4: Overview diagram of AMAC ASIC’s design and verification process, highlighting autonomous monitoring, control functions, radiation hardness, and digital and analog verification.

130-nm technology on 200-mm-diameter wafers. The ITk Strips Upgrade Project will require approximately 18,000 AMACStar chips, with yield considerations pushing the total to 24,000.

#### 5.2.2.1 What AMAC is monitoring

AMAC continuously monitors the ITk Module’s status by executing analog checks every 0.5 milliseconds across various channels of measurements (Figure 5.5). At its core is the Analog Monitor (AM), which operates as an Analog-to-Digital Converter (ADC). The ADC steps through a voltage ramp every half millisecond with fixed capacitance charging, acting as a benchmark for comparators across input channels. When a signal exceeds a comparator’s threshold, the step number is stored in register memory, allowing AMAC to detect potential issues.

AMAC is designed to monitor and detect anomalies such as:

1. **Abnormal Temperature:** Elevated temperatures can deform sensors, reducing positional accuracy.
2. **Abnormal Current:** Short circuits or component failures can lead to excessive power consumption and overheating.
3. **Abnormal Voltages:** ASICs and sensors rely on stable voltages (e.g., 1.5V for ASICs, 500V for silicon sensors) for proper operation.

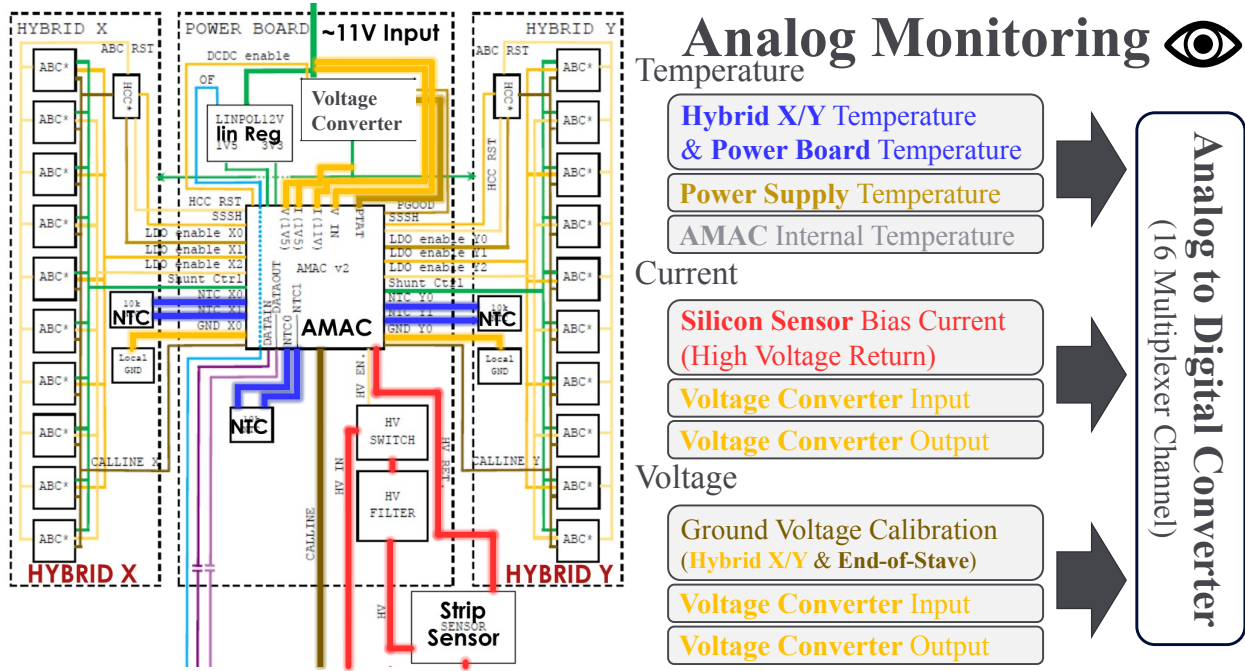


Figure 5.5: AMAC Analog Monitoring, with measurement connections highlighted by thick lines. This system includes 16-channel (with multiplexer) of Analog-to-Digital Converters to monitor temperature, current, and voltage across multiple components. The AMAC continuously assesses temperatures at key points (e.g., Hybrid X/Y, Powerboard, and AMAC internal temperature), monitors current through the silicon sensor bias, and evaluates the input and output current/voltages of the Voltage Converter.

The AMAC's analog monitoring capabilities ensure stable performance by monitoring these key parameters. A list of all monitored channels is provided in Table 5.1.

| Channel | Mux | Pad(s)    | Description                                                           |
|---------|-----|-----------|-----------------------------------------------------------------------|
| 0       |     | VDCDC     | DC/DC converter output (scaled internally by 1/2)                     |
| 1       |     | DCDCin    | Input Voltage to DC/DC converter with a 1/15 external divider         |
| 2       |     | NTCxp,n   | Hybrid $x$ NTC temperature                                            |
| 3       |     | NTCyp,n   | Hybrid $y$ NTC temperature                                            |
| 4       |     | NTCpbp,n  | Powerboard NTC temperature                                            |
| 5       |     | N/A       | Die temperature from CTAT sensor                                      |
| 6       |     | Cur1Vp,n  | DC/DC converter output current                                        |
| 7       |     | HVret     | Sensor HV bias return current                                         |
| 8       |     | PTAT      | DC/DC Proportional To Absolute Temperature                            |
| 9       |     | Hrefx     | Hybrid $x$ local ground                                               |
| 10      |     | Hrefy     | Hybrid $y$ local ground                                               |
| 11      |     | CAL       | Calibration line from the End Of Stave (EOS) card                     |
| 12      | a   | VDDLr     | Linear Regulator Voltage for AMAC Input                               |
| 12      | b   | AM900BG   | Diag: output of AM Bandgap scaled to 900 mV                           |
| 12      | c   | AM600BG   | Diag: output of AM Bandgap buffered                                   |
| 13      | a   | Cur10Vp,n | DC/DC converter input current                                         |
| 13      | b   | N/A       | Diag: output of internal voltage regulator (scaled internally by 2/3) |
| 13      | c   | N/A       | Diag: AM integrator reference                                         |
| 13      | d   | N/A       | Diag: Internal chip ground                                            |
| 13      | e   | HGND      | Powerboard ground                                                     |
| 14      | a   | VDDHI     | linPOL 12V (Power for the 3.3 V voltage) (scaled by 1/4)              |
| 14      | b   | N/A       | DC/DC input current measurement calibration test point low            |
| 14      | c   | N/A       | DC/DC input current measurement calibration test point high           |
| 14      | d   | N/A       | DC/DC output current measurement calibration test point low           |
| 14      | e   | N/A       | DC/DC output current measurement calibration test point high          |
| 15      | a   | N/A       | Diag: VDD Bandgap 600 mV reference                                    |
| 15      | b   | CALx      | Output of Hybrid $x$ Calibration DAC                                  |
| 15      | c   | CALy      | Output of Hybrid $y$ Calibration DAC                                  |
| 15      | d   | Shuntx    | Output of Hybrid $x$ Shunt DAC                                        |
| 15      | e   | Shenty    | Output of Hybrid $y$ Shunt DAC                                        |

Table 5.1: AMAC's measured values. The "MUX" (multiplexer) settings (ae) in the AMAC registers allow configurable channel input selection, enabling a single channel to read out different inputs as needed. The "Pad(s)" column indicates the connection pads on the AMAC where individual external inputs are connected; "N/A" denotes measurements internal to the AMAC. The measurements labeled "Diag" are diagnostic measurements intended to examine the functioning of AMAC. Table modified from an AMAC Paper to be published: *The AMAC ASIC for the HL-LHC ATLAS ITk Strip Detector: Design, Verification, and Probing*.

### 5.2.2.2 What AMAC is Controlling

AMAC is essential for managing various components of the ITk-Strip module, providing reliable operational control of the detector without requiring physical human intervention.

#### Control Mechanisms and Outputs

AMAC directly manages the module’s DC/DC converter (bPOL12V), which powers the entire module. It can also activate a low-power mode for the HCCStar and ABCStar chips if one of them malfunctions, preventing a power drain that could affect the whole module.

In the ITk-Strip upgrade, Patch Panels (PP1–PP4) distribute signals and power between the front-end electronics and the data acquisition systems. AMAC can also be deployed to the off-detector Patch Panel 2 (PP2) and controls up to four high-voltage (HV) switches, which could shut down power distribution in different channels during abnormal situations like overheating.

In total, the AMAC provides 13 controlled outputs, segmented into five groups corresponding to hybrid low power controls (1 to HCC Star, 2 to ABC Star (5 each) on each Hybrid), HV controls, and DC/DC converter control, as shown in Figure 5.6.

#### Calibration and Current Adjustment

AMAC is equipped with two “bandgap”<sup>10</sup> voltage references to maintain stable power and ensure consistent analog-to-digital measurements, even in the HL-LHC’s high-radiation environment. Once the detector is operational, individual components will be physically inaccessible. With AMAC, calibration values can be adjusted post-deployment to optimize regulated voltages, compensating for potential performance deterioration after prolonged radiation exposure. Additionally, AMAC controls the calibration of the ATLAS Binary Chip (ABCStar) using four 8-bit Digital-to-Analog Converters (DACs). Two DACs calibrate the ABCStar ADC, while the other two adjust the

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<sup>10</sup>The term “bandgap” is a legacy name in AMAC for this MOSFET-based voltage reference, which is not a true bandgap. Unlike bandgap references, MOSFET-based references are adjustable, allowing recalibration to compensate for performance degradation caused by radiation. This adjustability makes them more suitable for the high-radiation environment of the HL-LHC. The naming convention of “bandgap” has been retained over time.



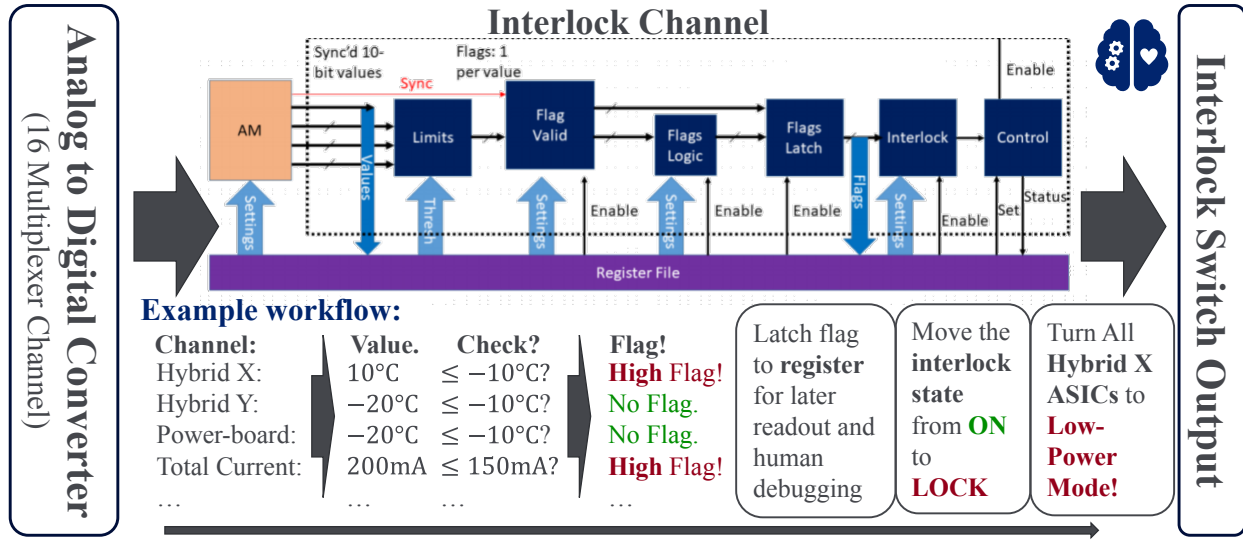


Figure 5.7: Logic workflow of the Interlock Channel.

AMAC features five dedicated interlock-controlled output sets that manage hybrid low-power modes (described in 5.2.2.2). Each interlock channel has programmable threshold and look-up table, allowing for independent responses to detected anomalies. An additional warning channel provides early indications of potential issues without directly controlling outputs, enabling preemptive measures before escalation.

### 5.2.3 Timing & Communication

In addition to monitoring, control, and autonomous correction, the AMAC ASIC has sophisticated communication and timing mechanisms, which are also critical for its operation and integration with higher and lower-level components.

**Internal Clock:** AMAC’s internal ring oscillator provides a system clock at approximately 20MHz. This frequency is adjustable within a range of -10% to +20% through register settings, offering flexibility in aligning AMAC’s operations with external systems (Communication & HV Control).

**Communication:** AMAC uses a 5-bit addressable serial protocol called “endeavour” for digital communication, tolerating up to 50% frequency variation from the nominal value. Two LVDS buses



manage communication: a unidirectional bus sends requests from the End-of-Stave (EOS) card to the CMDin pads on all AMACs, while a tri-state bus carries responses from the CMDout pads back to the EOS card. This protocol enables noise-resistant, reliable communication between AMAC and external command interfaces.

**AM & HV Oscillation Control:** The 20MHz internal clock also controls AMAC’s timing for the Analog Monitor (AM) block, dictating the voltage ramp operations. The clock is divided into 100KHz, 50KHz, and 25KHz clocks, which are used for different HV operational tasks.

### 5.2.4 Radiation Hardness and Triple Module Redundancy

In high-radiation environments like particle detectors, fault tolerance is essential for maintaining stability and data integrity. AMACStar incorporates Triple Module Redundancy (TMR), where each critical logic circuit is replicated three times, with a majority voting system (also triplicated) to decide the output. This design ensures that even if one path is affected by radiation, the system can continue functioning correctly.

Almost all of AMAC’s digital logic, including clocks and resets, is triplicated using the TMRG[81] tool, ensuring that any single event upset (SEU) in one logic path is corrected by the other two. TMR is also applied to the digital portions of the Analog Monitor, where all digital signals at the block’s border are triplicated. However, due to space and routing constraints, the 16 10-bit measured values in this block are not triplicated. Instead, they are safeguarded by a multiple-cycle flag validation mechanism, which requires the measured value to remain consistent over 2, 3, or 4 consecutive cycles before setting a flag. This approach mitigates accidental high/low readouts caused by SEU or SET.

## 5.3 AMAC Proto-Type Testing and Probing (Qualification Task)

The AMAC prototype required quantifiable testing to ensure it met its objectives. Our work with the AMACv2a version provided critical feedback for subsequent design iterations.

### 5.3.1 Single Chip-Board Testing & Wafer Probing

#### 5.3.1.1 Overview of Test Devices

Figure 5.8 shows the main components used in the physical AMAC testing. There are two types of testing: the first is called **Single-Chip-Board (SCB)** testing, which focuses on a single AMAC chip (separated from the wafer) on the lab desk. Second, is the **Probe Station testing**, which focuses on running the test procedures through all of the AMAC die on a wafer. These two tests share the same Active card and FPGA cards, and are connected via the ribbon connectors. Photos of the components and the two types of test set-ups can be found in Figure 5.9.

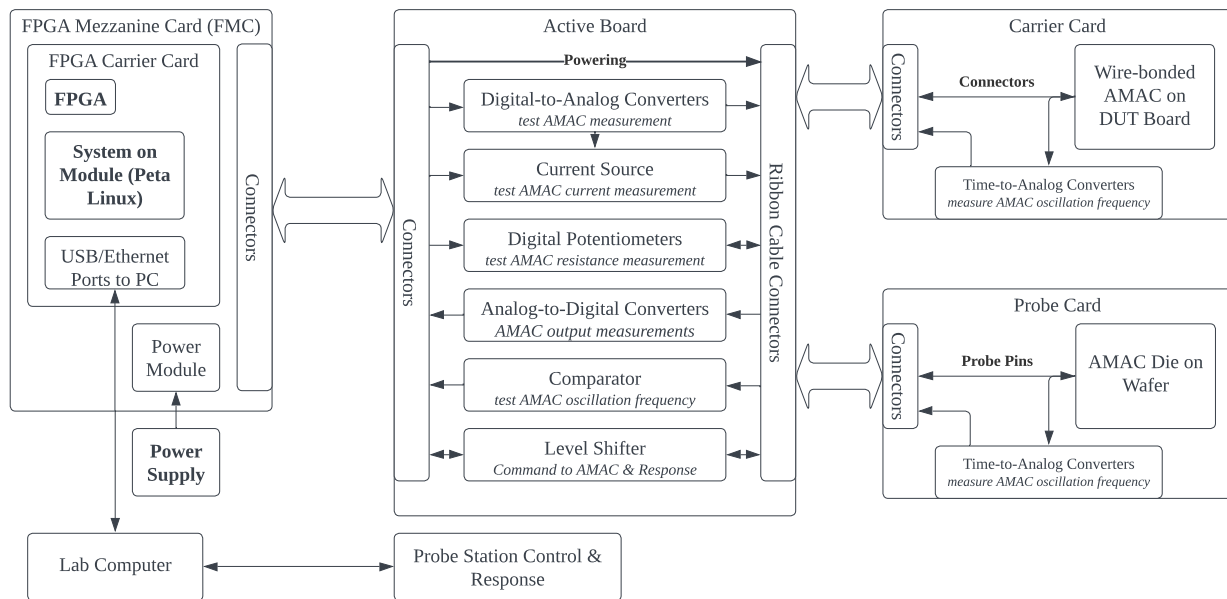
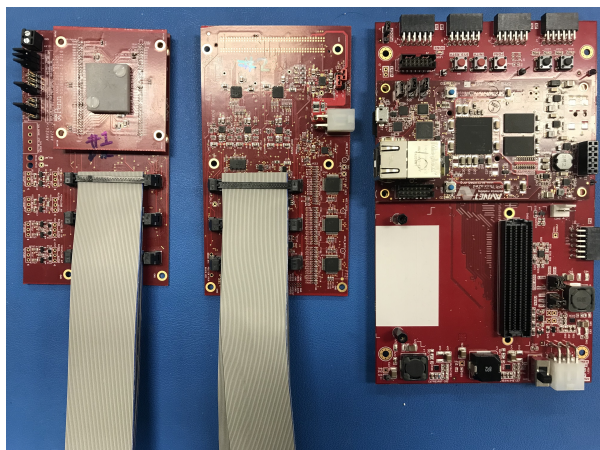
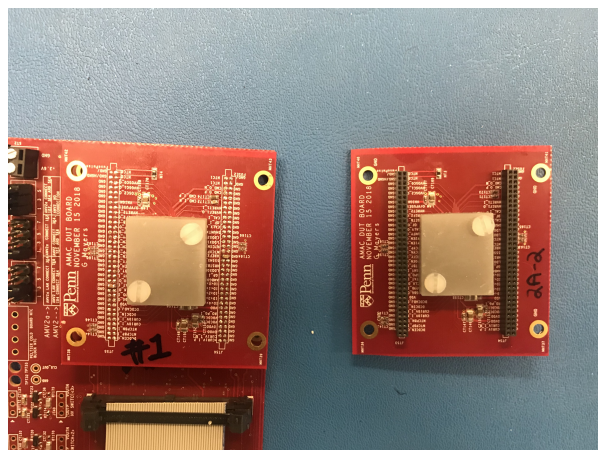


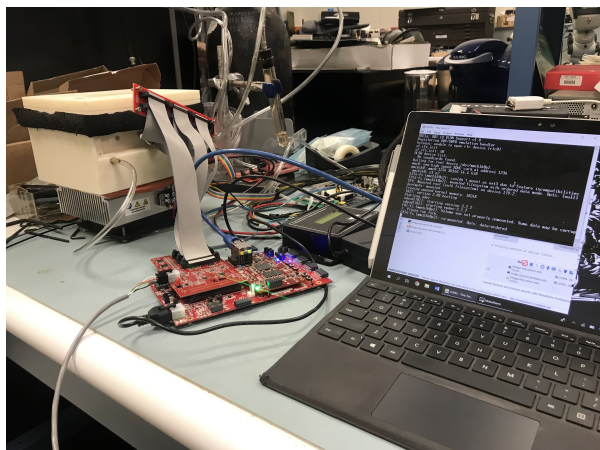
Figure 5.8: AMAC testing devices, including a MicroZed, an active board with ADC/DAC, potentiometer, and other components. Note that there are two types of AMAC connection board: a carrier board for a single chip and a probe card for the wafer.



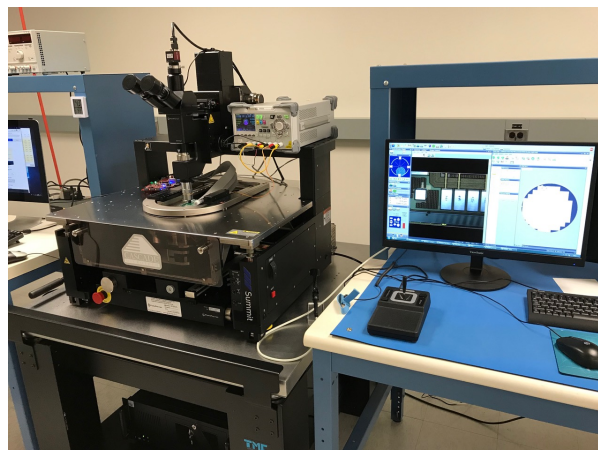
(a) From left to right: Carrier Card, Active Card and FPGA Mezzanine Card.



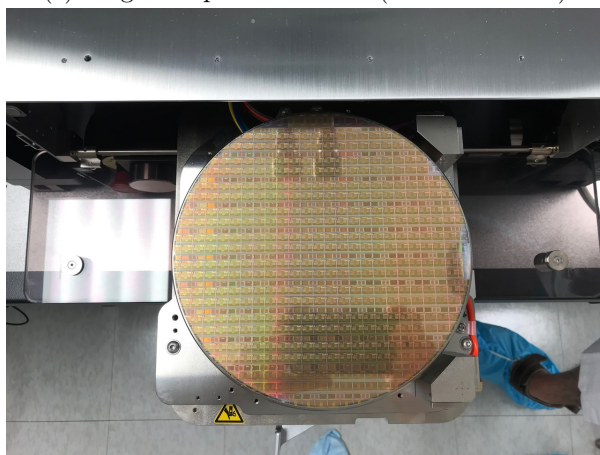
(b) Zoom-in of DUT board with AMACv2a on Carrier Card



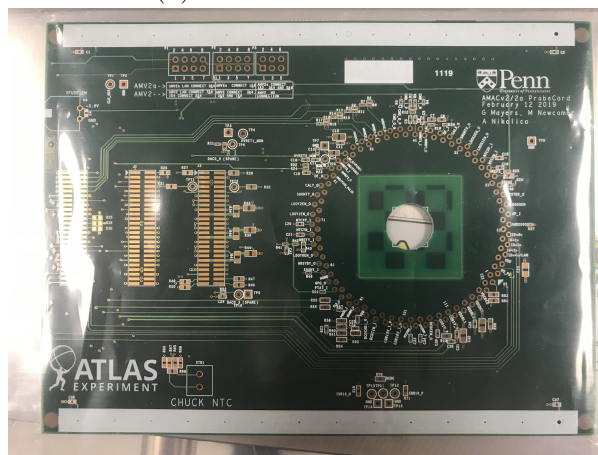
(c) Single Chip Test Station (with Cold Box)



(d) Probe Station at Penn



(e) Wafer on Probe Station



(f) Probe Card

Figure 5.9: Test devices corresponding to Figure 5.8.

### 5.3.1.2 Single Chip Testing

Since the test setup is custom-designed by the Penn team, we first need to verify that the test device and coded test routines function correctly before proceeding with probing. This verification requires multiple debugging iterations, including adjustments to the test hardware, C++ code, and occasionally replacing mis-positioned components on the Active Board. I was one of the main contributors to the setup process and the development of the testing routine, particularly for the analog component of the AMAC. This work involved close collaboration with the engineering team and fellow graduate students.

An AMAC chip is diced from the wafer and wire-bonded to a Device-Under-Test (DUT) board, connecting the ASIC pads to PCB connectors. The DUT board can then be plugged into the carrier board. Multiple AMAC DUT boards are typically prepared, each with a separate AMAC chip, in case of faulty chips or damage during testing. In this setup, the entire configuration can be placed on the lab desk, allowing connection to various diagnostic devices. For example, the communication channel pads can be directly probed with an oscilloscope to verify that the command and response signals function as designed (Figure 5.10). The analog and digital signal pads can also be monitored using a multimeter. The single-chip board can also be easily placed in a temperature-controlled cold box to evaluate the chip’s performance across various temperatures (see Section 5.3.6.3).

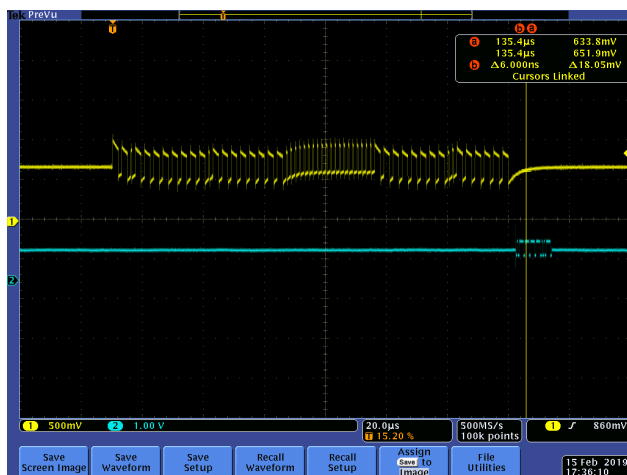


Figure 5.10: AMAC command (yellow) and response (blue) using the “endeavour” protocol read by oscilloscope, captured directly from the AMAC input and output pads.

The Single-Chip Board setup provided an in-depth understanding of both the AMAC and the primary testing device. Through comprehensive testing and iterative adjustments on this setup, we identified and resolved design flaws in the AMACv2a prototype, leading to the production-ready design, AMACStar, capable of reliable performance within the detector. Specific examples of these improvements are detailed in individual sections throughout the chapter.

### **5.3.1.3 Probe Station Testing**

After consolidating the test procedure and understanding single AMAC performance under the SCB set-up, we can then replicate the tests for all AMACs on the wafer.

This involves running the SCB test routine on chips positioned on a FormFactor Summit Probe Station, where the carrier card is replaced with a probe card fitted with pins. The probe station uses a microscope to align the pins precisely with the AMAC chip input/output pads on the wafer. The probe card remains fixed on the test station while a vacuum-secured chuck aligns each AMAC individually to the probe-card, .

The probe station is housed in a clean room established by the Penn ATLAS group. Communication channels between the lab computer Velox software (which controls the probe station) and the Peta Linux system (which controls the test routine on the on the Zynq FPGA board) run the following sequence: first the wafer is positioned to an individual die, the probe station needle contacts the pins on each AMAC die, the test routine is executed, and the probe station moves to the next AMAC die position. Test data is sent to the local server for automatic characterization and database synchronization.

### **5.3.1.4 FPGA Test System**

The FPGA test setup, based on our custom-made Active Board and controlled via a MicroZed Zynq development board, is essential for executing test routines on the AMAC chips. The setup includes an FPGA mezzanine card connected to a power module and is linked to the Active Board. The Peta Linux system on the Zynq FPGA compiles and runs C++ test scripts, which are accessible via

serial or Ethernet from a lab computer. This setup enables critical functions, including digital I/O mapping, clock frequency testing, and Serial Peripheral Interface (SPI) control for key components (ADCs, DACs, and potentiometers) on the Active Board, providing precise control and diagnostics for testing AMAC performance.

The Active Board (Figure 5.8), includes essential testing components such as Analog-to-Digital Converters (ADC), Digital-to-Analog Converters (DAC), and potentiometers. ADCs on the Active Board verify the AMAC's digital-to-analog outputs according to user-defined register settings, while DACs supply controlled analog inputs to test the Analog Monitor (AM) across various channels. Digital potentiometers simulate the resistance of Negative-to-Temperature (NTC) resistors on the powerboard, enabling temperature response tests.

#### 5.3.1.5 Method of Testing

The systematic examination of AMAC's performance involves injecting controlled voltage, current, or resistance levels into AMAC channels via the Active Board and recording the responses (Figure 5.11)—or, conversely, setting parameters on the AMAC and verifying if the output voltage or frequency matches expectations (Figure 5.12). This approach forms the basis of our quantitative assessment of AMAC's analog-to-digital conversion capabilities, using data fitting techniques to measure key parameters.

During testing, we fit mathematical functions (primarily linear relations) used in AMAC functionalities to determine constants like slope and intercept, along with residual deviations, across both the full input range and a specific target range expected in the detector setup. The common parameters include:

- **Slope ( $m$ ):** The slope of the fitted linear function.
- **Intercept ( $b$ ):** The intercept of the fitted linear function.
- **Slope Error ( $\Delta m$ ):** The error associated with the slope estimate.



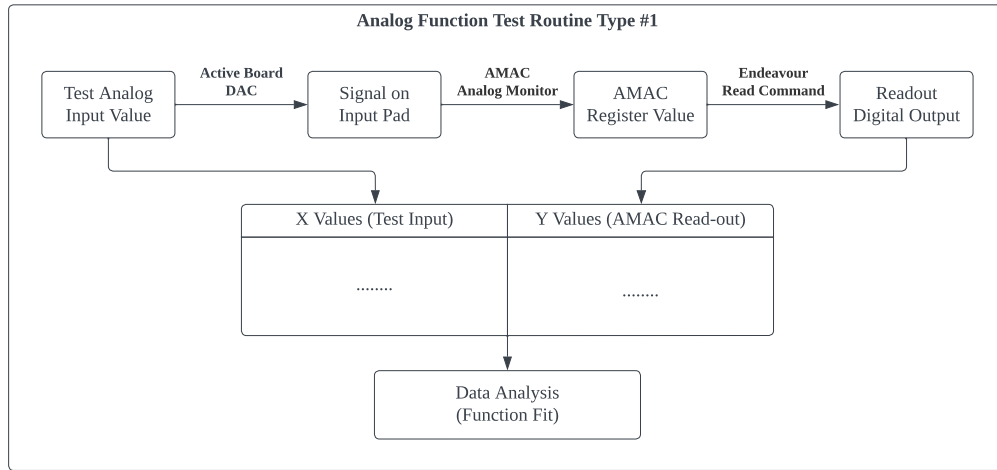


Figure 5.11: Analog Function Test Routine Type #1: Testing process for AMACs ADC-based analog monitoring, involving injecting an analog input (e.g. Voltage, Current, Resistance) on input pads, and recording the subsequent readout data from AMAC registers. The input and readout are taken as test data for subsequent data analysis, including function fitting and examination of fitted coefficients and residuals.

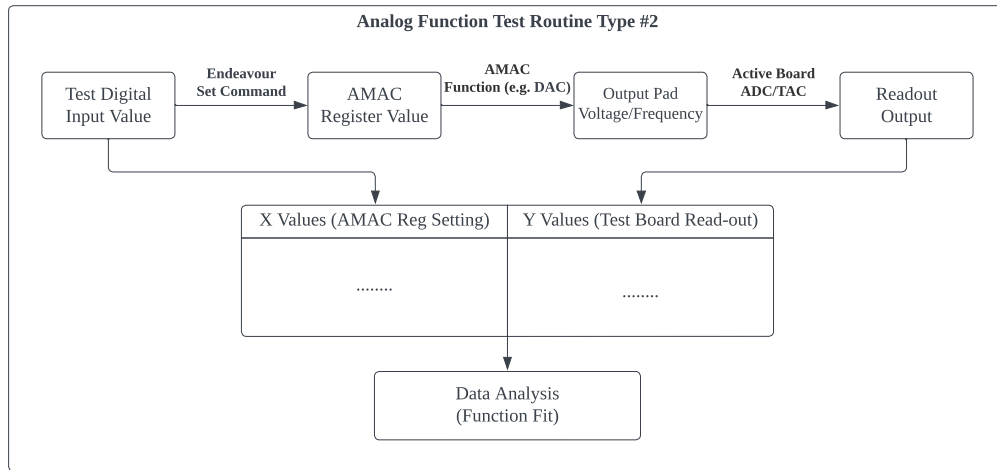


Figure 5.12: Analog Function Test Routine Type #2: DAC-like testing process, where digital input values are set in AMAC registers, and output voltages or frequencies are subsequently measured by the active boards. The input and readout are taken as test data for subsequent data analysis, including function fitting and examination of fitted coefficients and residuals.

- **Intercept Error ( $\Delta b$ ):** The error associated with the intercept estimate.
- **Target Range Min ( $x_{\min}^{\text{target}}$ ):** The minimum value of the input setting in the target range.
- **Target Range Max ( $x_{\max}^{\text{target}}$ ):** The maximum value of the input setting in the target range.
- **Output Min ( $y_{\min}^{\text{target}}$ ):** The minimum value of the measured output in the target range.
- **Output Max ( $y_{\max}^{\text{target}}$ ):** The maximum value of the measured output in the target range.
- **Max Residual (Target) ( $\Delta y_{\max}^{\text{target}}$ ):** The maximum deviation of the residue within the target range.
- **Std Dev Residual (Target) ( $\sigma_y^{\text{target}}$ ):** The standard deviation of the residue within the target range.
- **Max Residual (Full) ( $\Delta y_{\max}^{\text{full}}$ ):** The maximum deviation of the residue within the full range of input settings.
- **Std Dev Residual (Full) ( $\sigma_y^{\text{full}}$ ):** The standard deviation of the residue within the full range of input settings.

These parameters enable us to evaluate measurement precision by analyzing the standard deviation and maximum deviation of residuals. Measurement accuracy is verified by confirming that key constants (e.g., slope and intercept) fall within the target range. Insights from these evaluations help us numerically characterize the performance of the AMAC. The results guide our wafer dicing categorization, which makes sure that each AMAC chip deployed meets our performance standards. An overview of functions examined in the test routine is shown in Table 5.2.



Table 5.2: AMAC Functions to be Tested

| Category                     | Function                | Sub-function                                                                                                                                  |
|------------------------------|-------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| Calibration<br>(5.3.2)       | “Bandgap” Voltage       | VDD/AM bandgap<br>Ramp Gain                                                                                                                   |
| Analog-to-Digital<br>(5.3.3) | Voltage Measurement     | Zero Calibration of All Channels<br>EOS Calibration Voltage<br>Hybrid Local Ground (x/y)<br>DC/DC Proportional To Absolute Temperature (PTAT) |
|                              | Current Measurements    | DC/DC Input<br>DC/DC Output<br>HV return                                                                                                      |
|                              | Resistance Measurements | NTC on Power Board and Hybrid x/y                                                                                                             |
| Digital-to-Analog<br>(5.3.4) | ABC Shunt control       | Shunt (x/y)                                                                                                                                   |
|                              | ABC Calibration voltage | Cal (x/y)                                                                                                                                     |
| Clock<br>(5.3.5)             | Frequency               | Ring Oscillator Clock Frequency<br>HV Oscillation Frequency                                                                                   |
| Logic Control<br>(5.3.7)     | ID                      | eFUSE Programming<br>Comm ID Setting                                                                                                          |
|                              | Diagnostic Values       | Power Good                                                                                                                                    |
|                              | Reset of AMAC           | Communication Block<br>OF Module Resets<br>Hard AMAC Resets<br>SEU/Logic/AM/Full Resets                                                       |
|                              | Reset of Others         | HCCStar/ABCStar/Hybrid                                                                                                                        |
|                              | Interlock Functions     | Flag Validation, Logic, Latching                                                                                                              |
| Power Status<br>5.3.7)       | Voltage & Current       | Linear Regulator<br>DCDC Converter<br>3.3V Oscillation Output<br>Common Return Current                                                        |

## 5.3.2 Calibration Settings of AMAC

### 5.3.2.1 “Bandgap” Function and Calibration

The “bandgap” voltage reference in the AMAC ASIC is essential for maintaining stable, reliable voltage. This reference, implemented with a MOSFET voltage source, undergoes calibration after fabrication to ensure consistent analog-to-digital measurement accuracy over time.

There are two instances of “bandgap” voltage: VDD-BG for the internal Low Drop Out (LDO) regulator and AMBG for the Analog Monitor and various sense blocks. Together, these references stabilize both power supply and analog monitoring functions.

Calibrating the “bandgap” function is a crucial step during AMAC setup, allowing identification of optimal settings that maximize chip performance and measurement precision, which vary across individual chips. These settings are stored and applied each time an AMAC is powered on. Additionally, real-time monitoring of the “bandgap” voltage enables ongoing performance maintenance, which is critical as radiation damage accumulates and alters AMAC functionality and current consumption. This real-time adjustment capability reduces the need for physical access to replace or repair degraded chips, significantly enhancing ITk maintenance efficiency and extending operational lifespan.

### 5.3.2.2 Optimization of VDD “Bandgap” Voltage

This subsection presents an example test of an AMACv2a prototype chip to evaluate the relationship between the “bandgap” setting and the resulting VDD “bandgap” voltage. The goal was to confirm whether adjusted settings could achieve target parameters for slope, intercept, and standard deviation, verifying the reliability of MOSFET precision calibration capability of around 25mV per bit.

As shown in Figure 5.13b, the regulated voltage measured from an external ADC was plotted against the internal calibration setting in AMAC. The data was fitted to a linear function (Equation 5.1) within the available voltage range, using `scipy.optimize.curve_fit`. Note that the test device

supplied voltage only up to 1.5V, so only data points on the slope were included in the fit.

$$f = \text{slope} * x + \text{intercept} \quad (5.1)$$

Results indicated that the tested chip met the desired specifications, with the optimal VDD “bandgap” voltage setting providing a voltage closest to the target of 1.25V. This setting will be subsequently used after the chip is installed in the detector.

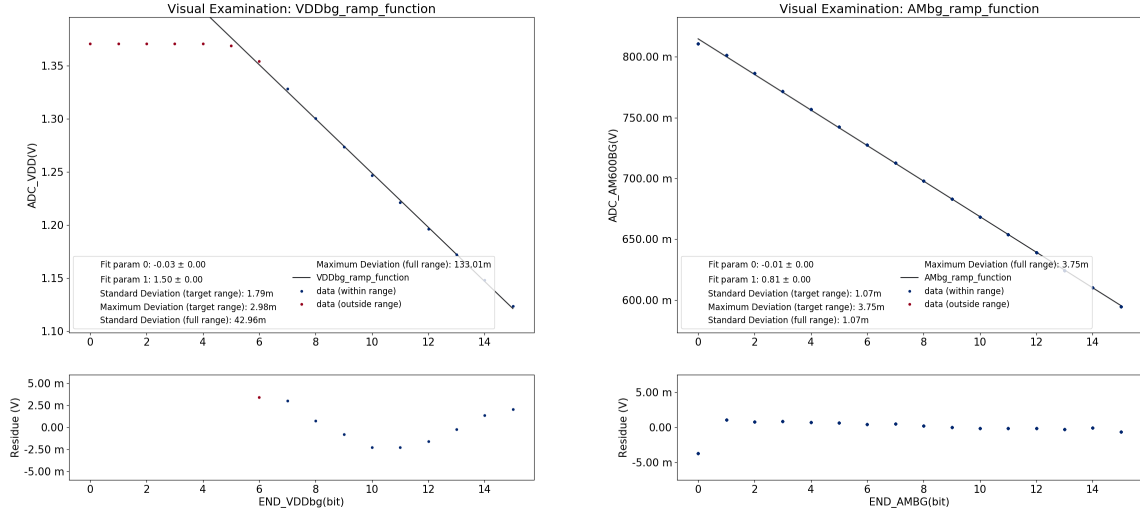
This test routine not only validates the “bandgap” function’s role in maintaining the AMAC’s operational stability but also demonstrates the precision with which the AMAC can be calibrated to ensure optimal performance within the ITk. For similar test routines, key parameters such as slope, intercept, range, standard deviations, and maximum deviations will be used as grading standards.

### 5.3.2.3 Optimization of Analog Monitor “Bandgap” (AMBG) Voltage

Extensive testing of the AMACv2a prototype revealed a limited adjustment range for the Analog Monitor “Bandgap” (AMBG) voltage. As shown in Figure 5.13b, the AMBG settings placed the designed value near the edge of the adjustable range. It suggests risks of limited operational flexibility, particularly in the face of potential manufacturing variations and radiation-induced degradation that could affect the voltage.

To resolve these constraints, the production chip, AMACStar, introduced an additional switch that doubles the AMBG adjustment range (Figure 5.14). Disabling the switch lowers the range by 100 mV, while enabling it maintains the original design range. This modification increase the adjustment range, improving resilience to manufacturing inconsistencies. These AMBG adjustment range increase from AMACv2a to AMACStar is an example of the iterative design improvement process, which is essential to high-energy physics instrumentation development.

Through optimizing the AM600BG output, we are able to identify the best settings for the AMBG



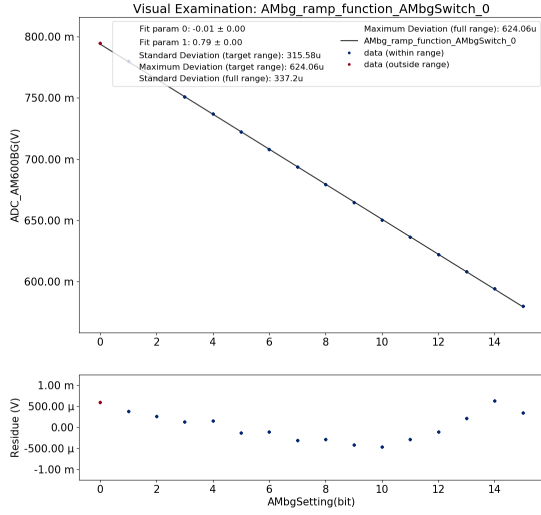
(a) VDD “Bandgap” voltage read by test device vs the “Bandgap” setting bit. (b) AM “Bandgap” voltage read by test device vs the “Bandgap” setting bit.

Figure 5.13: “Bandgap” ramp of VDDBG and AMBG in an AMACv2a prototype chip. The highest voltage on the left of the VDDBG ramp is limited by the voltage supply and probe needle contact depth. Shallower contact depth increases resistive losses, which can lower the maximum measurable voltage. This provides a useful indication of contact quality—particularly visible in parameter distribution plots (see Figure 5.35). The AM “Bandgap” voltage is designed to fall within 600mV to 640mV, though in this plot, the design voltage is at the edge of the adjustable range, an issue later addressed in the AMACStar production design.

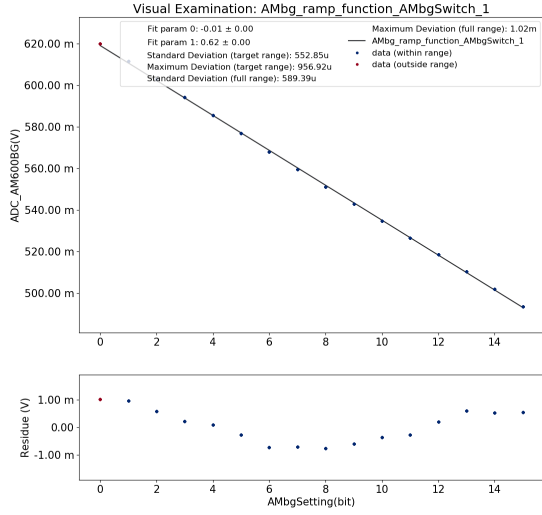
adjustment ramp to ensure that AM600BG provides a voltage between 600mV and 640mV in the AMACStar as designed.

### 5.3.2.4 Optimizing AM Comparator Ramp Gain

The Analog Monitor Comparator ramp in the AMAC ASIC is driven by a 10-bit Wilkinson ADC, which relies on the comparison of a voltage ramp with the measured value. This ramp has a resolution of approximately 1 mV/count over a range of -25 mV to 1 V. It forms the basis for all measurements, enabling direct voltage comparison or scaled measurements by adjusting the input voltage through attenuation (scaling down) or amplification (scaling up). The ramp voltage is generated by a switched capacitor integrator, which uses a programmable unit charge size, termed **Ramp Gain**, to inject charge onto an integration capacitor at a clock-dictated rate. Fine-tuning



(a) AMBG Ramp Switch 0



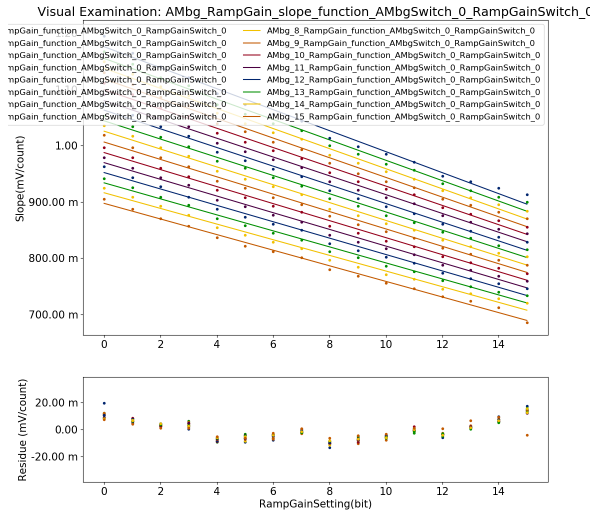
(b) AMBG Ramp Switch 1

Figure 5.14: Here are the AMBG ramp in an AMACStar chip. Note that with the updated design, we can use an additional AMbg range switch to easily find the best set-up near 600mV to 640mV, leaving ample setting options on both ends, in case of manufacturing variation or radiation damage.

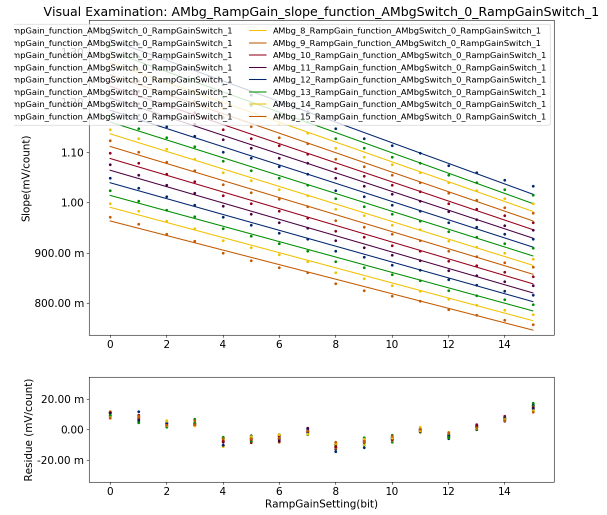
this ramp gain, along with the AMBG settings, is critical for AMAC's precision measurements.

Expanding on the 16-setting configuration in the AMACv2a prototype, the AMACStar version introduced a ramp gain switch. This switch provides finer control over unit charge size, ensuring that each step in the Analog Monitor ADC ramp approximates 1mV as much as possible.

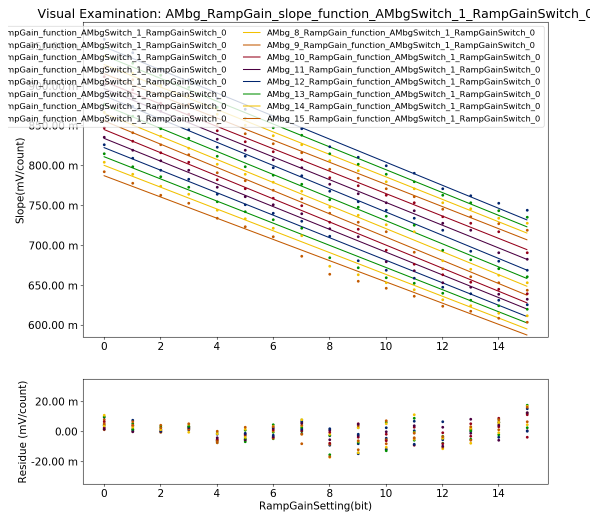
Optimal configurations for AMBG and Ramp Gain settings are carefully calibrated to maintain the AM600BG output voltage between 600mV and 640mV while achieving a ramp slope as close as possible to 1 mV/step. Each combination of AMBG and Ramp Gain settings is measured along the CAL channel to determine the AM ramp slope in mV/count (Figure 5.15).



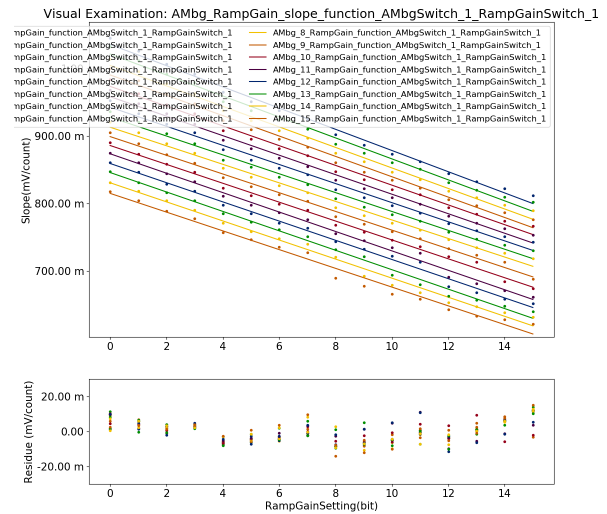
(a) AMBG Ramp Switch 0, Ramp Gain Switch 0



(b) AMBG Ramp Switch 0, Ramp Gain Switch 1



(c) AMBG Ramp Switch 1, Ramp Gain Switch 0



(d) AMBG Ramp Switch 1, Ramp Gain Switch 1

Figure 5.15: Here are the AM comparator ramp step size (in mV/step) vs the ramp gain setting scan for different AMBG switch and Ramp Gain switch settings. Each line (colored ramp) represents an AMBG setting, and each point on the downwards ramp (as indicated in the x-axis) represents a (AMBG, ramp gain) combination setting.

### 5.3.3 Quantitative AMAC Analog to Digital Measurement Testing

The following sections discuss various measurement tasks of AMAC and how its capabilities are tested through three core Analog-to-Digital Measurements: **Voltage** (Section 5.3.3.1), **Current** (Section 5.3.3.2), and **Resistance** (Section 5.3.3.3).

#### 5.3.3.1 Voltage Measurement Capability Testing

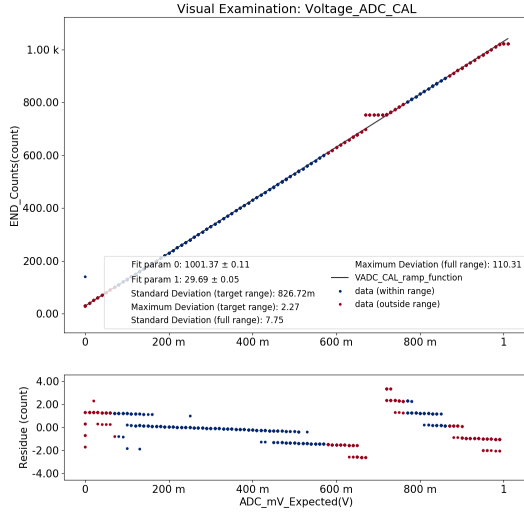
| Channel | Pad(s) | Description                                                                                                                                           |
|---------|--------|-------------------------------------------------------------------------------------------------------------------------------------------------------|
| 8       | PTAT   | DC/DC Proportional To Absolute Temperature voltage<br>PP2: Power return for 12 V supply to the front-end electronics                                  |
| 9       | Href-x | Hybrid X local ground voltage<br>PP2: 12 V voltage sense from PP1                                                                                     |
| 10      | Href-y | Hybrid Y local ground voltage<br>PP2: 12 V power return sense from PP1                                                                                |
| 11      | CAL    | Calibration line voltage from End-Of-Stave device (EOS)<br>PP2: Local measurement of 12 V power to the front-end electronics through external divider |

Table 5.3: AMAC measurement of external voltage inputs. From the AMACStar Specification.

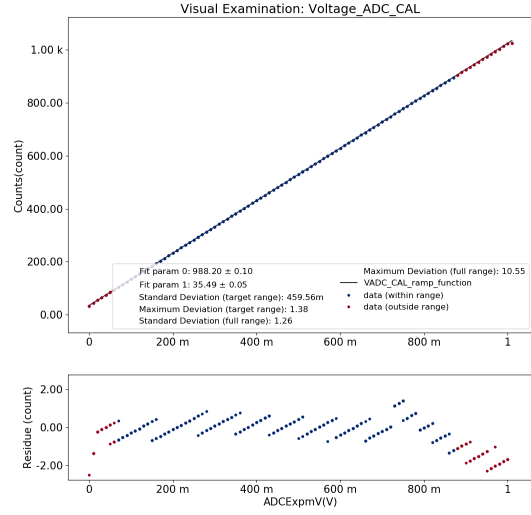
Accurate analog-to-digital conversion (ADC) of voltage inputs is essential to AMAC’s performance. The four voltage measurement channels—**CAL**, **PTAT**, **Href-x**, and **Href-y**—are summarized in Table 5.3.

During testing, a glitch was observed in the AMACv2a prototype around the 750mV threshold, as illustrated with the CAL line of a prototype AMACv2a in Figure 5.16a. This issue, occurring near the ramp count comparator switch at 750 count, was resolved in the AMACStar production design and is further detailed in Section 5.3.6.2. Figure 5.16b demonstrates that AMACStar achieved a voltage measurement precision of around 0.5 mV (standard deviation) within the target range of 100 mV to 900 mV, showing that it has successfully removed the glitch.

In both AMACv2a and AMACStar chips, a linear function (Equation 5.1) was fitted to the CAL data (reference vs readout) to evaluate ADC comparator ramp performance, including slope and intercept parameters. We assessed the performance over both the full measurement range and a target range (shown in blue) where we expect stable performance without issues like the 750 mV



(a) AMACv2a ADC (CAL)



(b) AMACStar ADC (CAL)

Figure 5.16: Here are the ADC ramps for the voltage calibration readout (CAL) in an AMACv2a and AMACStar chip. Note that we have found a bug in the Analog Monitor comparator ramp (see Section 5.3.6.2) in the AMACv2a proto-type design (see left). This is subsequently fixed in the AMACStar production version (see right).

glitch. By establishing quantitative grading standards based on precision and accuracy across these parameters, we created benchmarks for categorizing chips by performance quality. These grading standards, outlined in Section 5.3.8, are used to validate and categorize AMAC chips before deployment in modules.

To illustrate AMACStar's enhanced voltage measurement capabilities, Figure 5.17 overlays ADC ramps for all four voltage inputs (CAL, PTAT, Href-x, and Href-y). This comparison highlights the consistent and precise voltage measurements across channels, confirming AMACStar's robustness and reliability in voltage measurement.



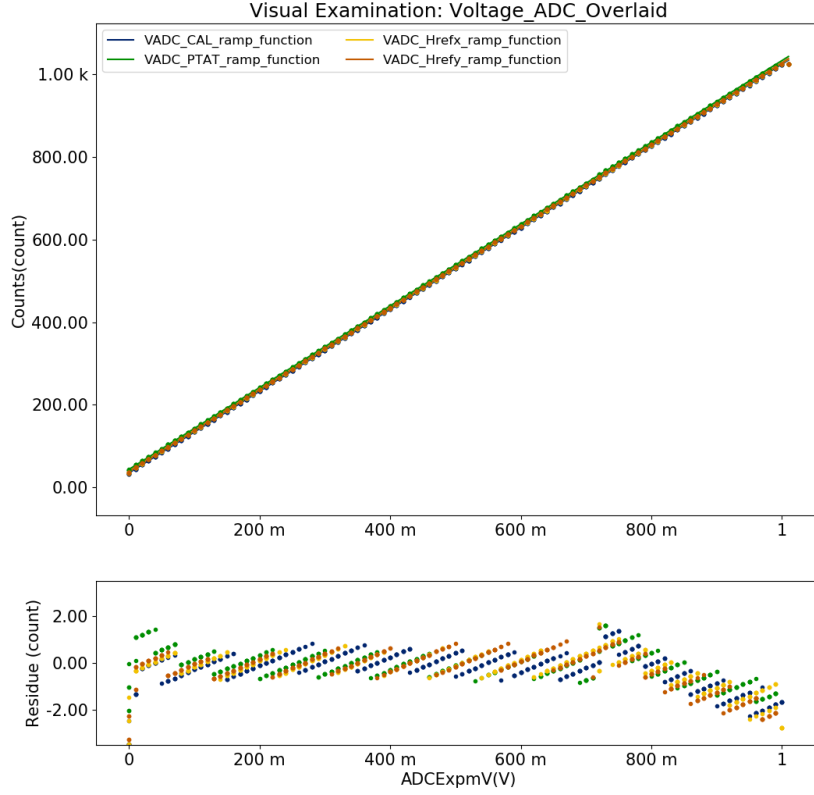


Figure 5.17: Here are the ADC voltage measurement ramps for the four voltage inputs (CAL, Hrefx, Hrefy, PTAT) in an AMACStar chip. The measurements are overlaid, showing consistent good performance in the voltage measurement capability of the AMACStar tested.

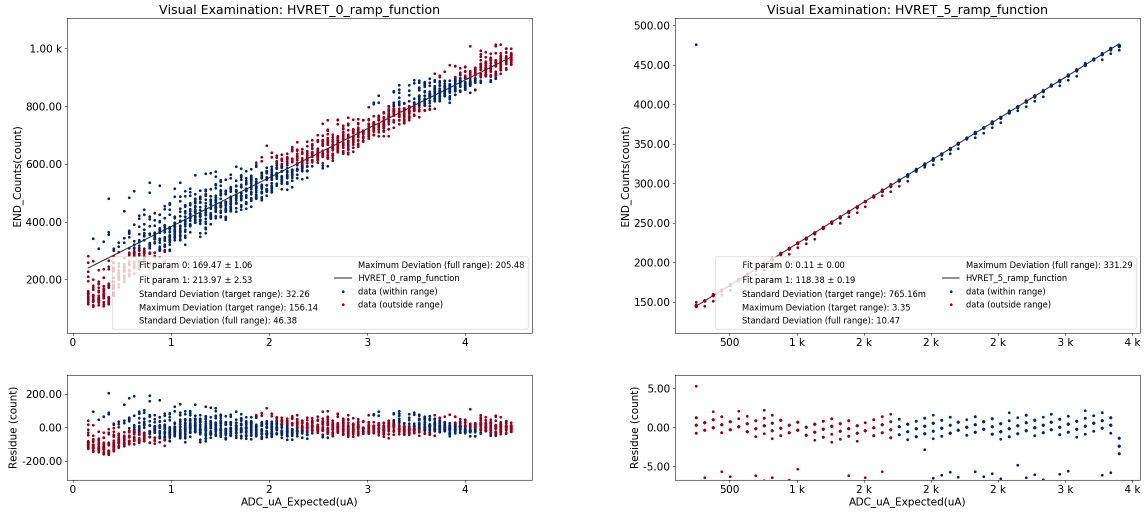
### 5.3.3.2 Current Measurement Capability Testing

The current measurement capability of the AMAC ASIC is essential for precise monitoring of the Sensor High Voltage (HV) bias return current and DC/DC converter input/output currents (Table 5.4).

The AMAC accurately measures the return current on the HV sensor bias line. Figure 5.18 illustrates the current reference vs. readout data for two settings, demonstrating AMAC's accurate measurement range from a few microamps to several milliamps – covering a sensitivity span of over three orders of magnitude. Table 5.5 details the six suggested current measurement ranges.

| Channel | Mux | Pad(s)    | Description                                                  |
|---------|-----|-----------|--------------------------------------------------------------|
| 6       |     | Cur1Vp,n  | DC/DC converter output current                               |
| 7       |     | HVret     | Sensor HV bias return current                                |
| 13      | a   | Cur10Vp,n | DC/DC converter input current<br>PP2 use: Input 48 V current |

Table 5.4: AMAC Measured Values of Currents. From the AMACStar Specification.



(a) AMACV2a lowest current range

(b) AMACV2a highest current range

Figure 5.18: Here are the current measurement ramps with different ranges for the Sensor HV bias return current measurement readout (HVret) in an AMACV2a chip. Notice that we can make precision measurements from a few micro amps to a few milliamps. (Precision measurement ranging over 3 orders of magnitude.)

Table 5.5: Suggested Current Measurement Range of AMAC.

| Setting No. | Current Range            |
|-------------|--------------------------|
| 1           | 200 nA - 4.5 $\mu$ A     |
| 2           | 270 nA - 50 $\mu$ A      |
| 3           | 40 $\mu$ A - 470 $\mu$ A |
| 4           | 100 $\mu$ A - 2.4 mA     |
| 5           | 250 $\mu$ A - 5.7 mA     |
| 6           | 250 $\mu$ A - 8 mA       |

Figure 5.19 compares current measurement ramps between the AMACv2a and AMACStar chips. A bug identified in the AMACv2a's setting-#3 comparator ramp was corrected in the AMACStar production version. This correction once again highlights the valuable role of prototype testing in identifying and addressing design refinements prior to production.

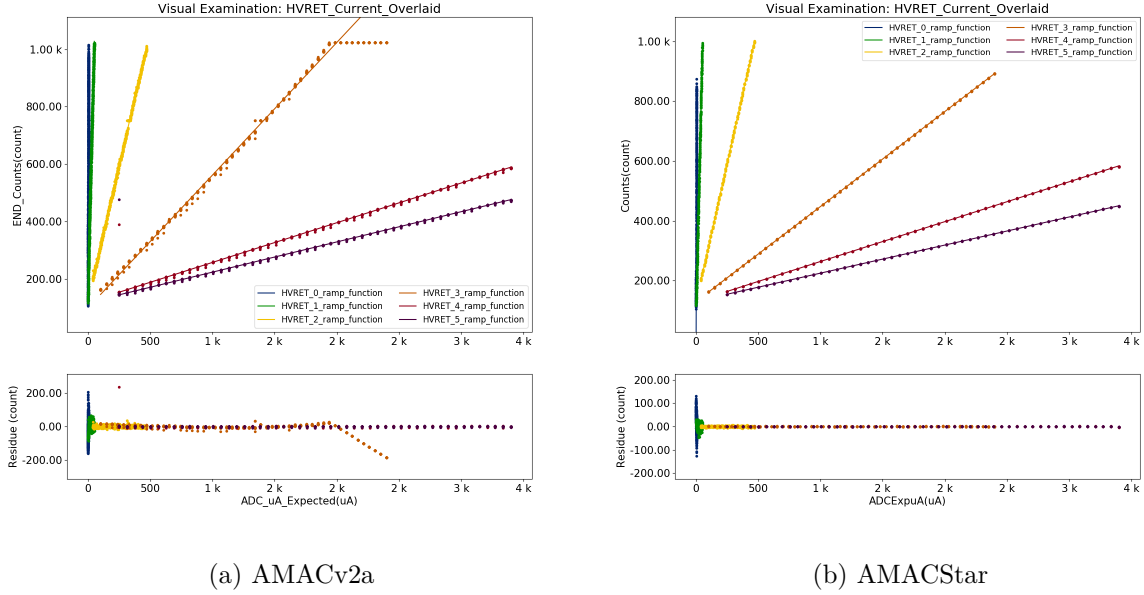


Figure 5.19: Here are the current measurement ramps with different ranges for the Sensor HV bias return current measurement readout (HVret) in an AMACv2a and AMACStar chip. Note that we have found a bug in the Current measurement comparator ramp setting #3 in the AMACv2a proto-type design (see left). This is subsequently fixed in the AMACStar production version (see right).

Following the method used in voltage measurement testing, current measurement data is analyzed through linear fitting within the operational range to assess its accuracy and precision.

### 5.3.3.3 Temperature Measurement Capability Testing

The AMAC ASIC's temperature measurement capability is essential for maintaining electronics stability and detector alignment, as abnormal temperatures can disrupt electronics performance or bend the sensor out of its position. This section reviews AMAC's ability to measure temperature, in particular, using Negative Temperature Coefficient (NTC) thermistors across a range of measurement settings.

| Channel | Mux | Pad(s)               | Description                                                                                                      |
|---------|-----|----------------------|------------------------------------------------------------------------------------------------------------------|
| 2       |     | NTC <sub>xp,n</sub>  | Hybrid X NTC temperature<br>PP2: NTC                                                                             |
| 3       |     | NTC <sub>yp,n</sub>  | Hybrid Y NTC temperature<br>PP2: NTC                                                                             |
| 4       |     | NTC <sub>pbp,n</sub> | Powerboard NTC temperature                                                                                       |
| 5       |     | N/A                  | Die temperature from CTAT sensor                                                                                 |
| 8       |     | PTAT                 | DC/DC Proportional To Absolute Temperature<br>PP2 use: Power return for 12 V supply to the front-end electronics |

Table 5.6: AMAC Temperature Measurement Channels. From the AMACStar Specification.

AMAC measures temperature through five channels (Table 5.6). Three channels use NTC thermistors on the Hybrid X, Hybrid Y, and Power Board for indirect temperature readings, while the CTAT (Complementary to Absolute Temperature) and PTAT (Proportional to Absolute Temperature) channels monitor AMAC’s own temperature and that of the DC/DC converter. Because it is time-consuming to do temperature variation during wafer probing, CTAT validation is conducted on a single-chip board in a Cold Box (Section 5.3.6.3).

To convert NTC resistance into temperature readings, AMAC applies a stable voltage across each thermistor, deriving resistance-based current through Ohm’s law. This current is then converted to a voltage signal via an Operational Amplifier and fixed internal resistances, which enables digital readout through the Analog Monitor. Figure 5.20 illustrates this conversion process.

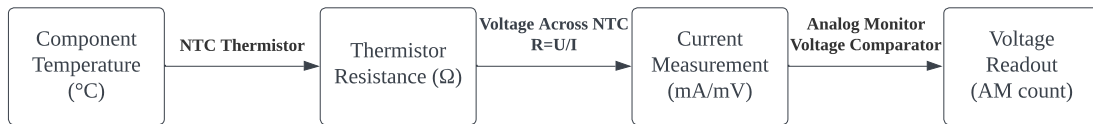


Figure 5.20: Temperature measurement workflow using the AMAC Analog Monitor via Negative Temperature Coefficient Thermistor.

Using the circuit model in Figure 5.21 and Equation 5.2, we analyze NTC resistance by fitting voltage readouts (calibrated through Voltage Measurement coefficients) that vary inversely with NTC resistance. Again the fitted coefficients and standard deviations will be used for AMAC

grading.

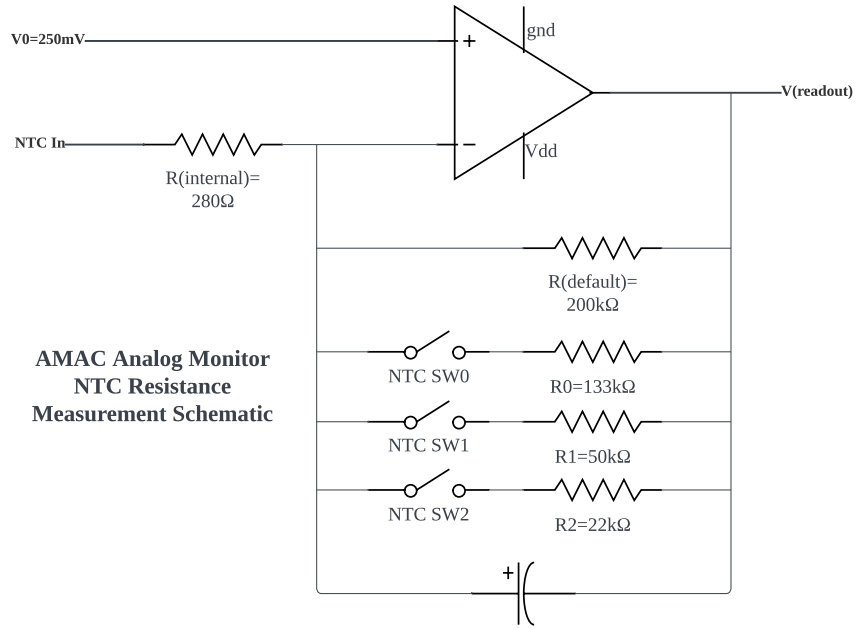


Figure 5.21: NTC resistance measurement circuit schematic inside AMAC, connecting towards the Analog Monitor voltage measurement using an Op Amp.

$$V_{\text{readout}} = (250\text{mV}) \cdot \frac{R_{\text{sw}}}{R_{\text{NTC}} + R_{\text{internal}}} + V_0 \quad (5.2)$$

Figure 5.22 demonstrates this fitting approach across five settings that help the resistance measurements cover optimal sensitivity ranges for accurate temperature sensing. Table 5.7 outlines the maximum NTC resistance measurement range, and the recommended temperature ranges for each setting.

Figure 5.23 illustrates the corresponding temperature measurement precision from the resistance measurement precision. The AMAC achieves a measurement precision of within 1°C across the operational ranges from -25°C to +50°C.

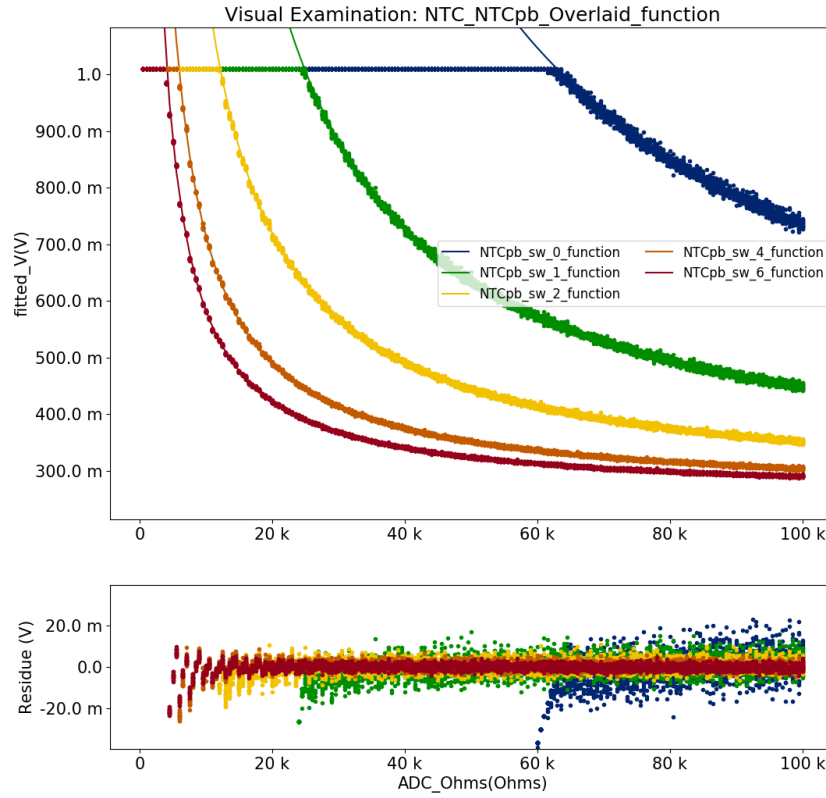
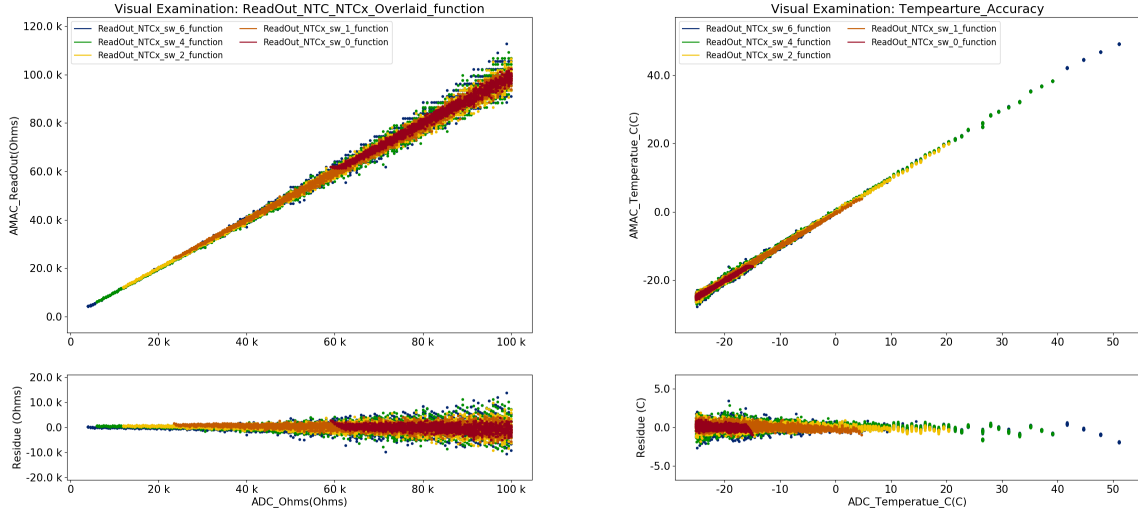


Figure 5.22: This plot shows voltage versus resistance (set by a digital potentiometer with a maximum of 100k $\Omega$ ), along with a fit using Equation 5.2. The five settings enables optimal temperature sensitivity using the different resistance measurement ranges.

Table 5.7: NTC Temperature/Resistance Measurement Circuit Settings

| Setting | ON (others off) | NTC Resistance Range   | Suggested Temperature |
|---------|-----------------|------------------------|-----------------------|
| 0       | -               | 67k to 700k $\Omega$   | -35 °C to -15 °C      |
| 1       | SW<0>           | 27k to 400k $\Omega$   | -18 °C to +4 °C       |
| 2       | SW<1>           | 13.5k to 226k $\Omega$ | -4 °C to +21 °C       |
| 4       | SW<2>           | 7.5k to 115k $\Omega$  | +12 °C to +41 °C      |
| 6       | SW<2>, <1>      | 3.6k to 80k $\Omega$   | +20 °C to +51 °C      |



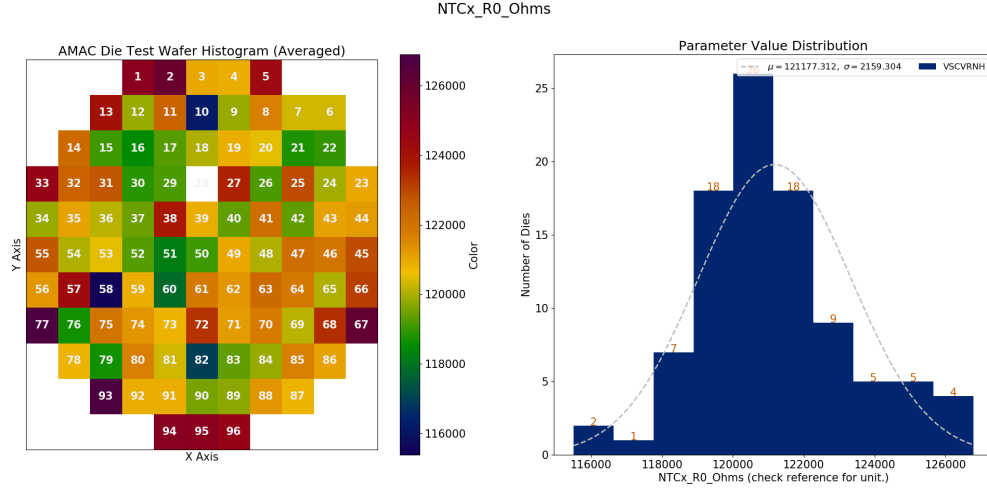
(a) AMAC resistance measurement precision

(b) AMAC temperature measurement precision

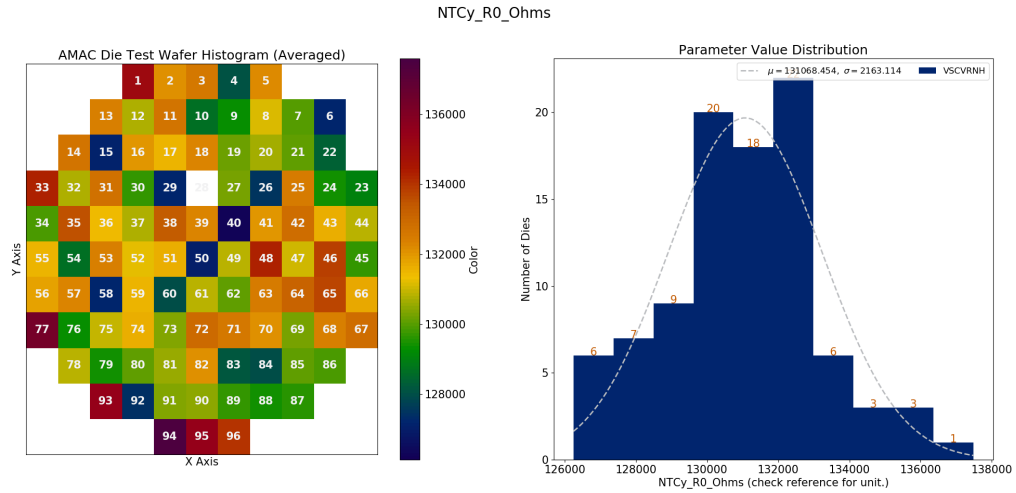
Figure 5.23: This figure demonstrates how multiple settings improve temperature precision across the ranges. In the left plot, resistance measurements are derived from voltage readings and compared to the reference resistance set by the digital potentiometer on the active board, showing improved precision within smaller measurement ranges. The right plot translates the left to temperature measurement precision, based on the nominal 10k $\Omega$ NTC thermistor response.

### Additional Discussion: Manufacturing Insights

Fitting Formula 5.2 also enables extraction of internal resistance values ( $R_{sw}$  and  $R_{internal}$ ), which could provide us insight into the manufacturing quality of the AMAC ASIC. By solving for  $R_{sw}$  across different switch settings, we can infer individual resistances ( $R_0$ ,  $R_1$ ,  $R_2$ ,  $R_{default}$ ) within the circuit. The distribution of  $R_0$  resistance values across the wafer, shown in Figure 5.24, demonstrates both the tight clustering of measured values and slight manufacturing deviations across the channels (all within the manufacturer's quoted tolerance limits). This analysis provides an additional tool that can support quality assurance and potentially aid in manufacturing optimization.



(a) NTC Channel for Hybrid X



(b) NTC Channel for Hybrid Y

Figure 5.24: Distribution of fitted  $R_0$  resistance nominally at 133k $\Omega$  over an AMACv2a prototype wafer. Note that the manufacture limit allows deviation up to 25%.

### 5.3.4 Quantitative Digital-to-Analog Capability Testing

The AMAC ASIC contains four Digital-to-Analog Converter (DAC) channels: two calibration outputs (Cal-x and Cal-y) for ABCStar calibration on each hybrid and two shunt reference voltages (Shunt-x and Shunt-y) to control current draw in ABCStar shunt devices. AMAC also monitors these DAC outputs internally (Table 5.8). The calibration DACs (CALx and CALy) use a PMOS



current mirror to deliver a 01V output range, achieved with an 8 k $\Omega$  resistor connected to ground. In contrast, the shunt reference DACs, which control current in the ABCStar shunt devices, use an NMOS current mirror with an 11 k $\Omega$  resistor connected to a regulated 1.2V supply. This 1.2V supply provides the necessary voltage headroom to handle a wider range of currents smoothly and reliably, avoiding the need for additional amplification from op-amp drivers.

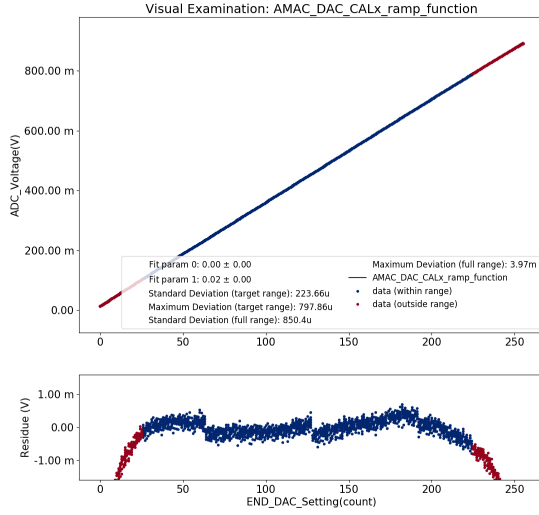
| Channel | Mux | Pad(s)  | Description                        |
|---------|-----|---------|------------------------------------|
| 15      | b   | CAL-x   | Output of Hybrid X Calibration DAC |
| 15      | c   | CAL-y   | Output of Hybrid Y Calibration DAC |
| 15      | d   | Shunt-x | Output of Hybrid X Shunt DAC       |
| 15      | e   | Shunt-y | Output of Hybrid Y Shunt DAC       |

Table 5.8: AMAC Measured Values for the AMAC DAC outputs. From the AMACStar Specification.

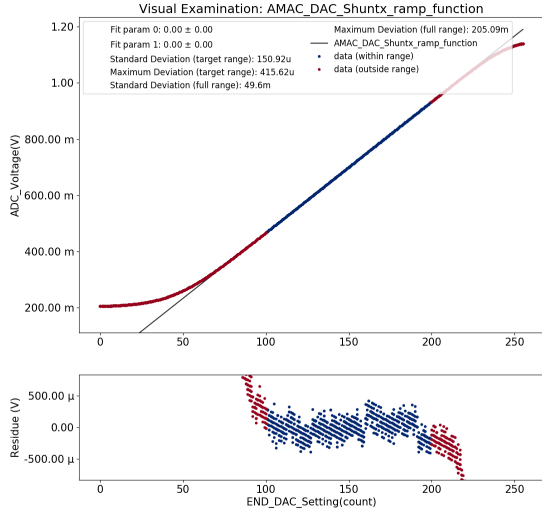
Each DAC output is tested by setting values via DAC registers and analyzing the voltage output through a linear fit within the target range. Fit parameters, standard deviation, and maximum deviation are used to assess whether the AMAC meets accuracy, precision, and output range requirements. Figure 5.25 illustrates examples of **CALx** and **Shuntx** outputs.

Linearity across the 8-bit range is essential for the calibration DACs to provide accurate voltage output to each hybrid, while monotonicity is the key criterion for the shunt reference outputs (**Shunt-x** and **Shunt-y**) to ensure smooth current control. The Spearman rank correlation coefficient (Spearman-R) is used to confirm monotonicity, with high values close to 1 indicating a consistently increasing output. In this AMAC, Spearman-R values exceed 0.99999.

The AMAC can also measure its DAC outputs internally via channel 15 of the Analog Monitor ADC, as shown in Figure 5.26. This internal feedback verifies DAC accuracy, though the Shunt-x output reaches the ADC's upper range limit at 1V.

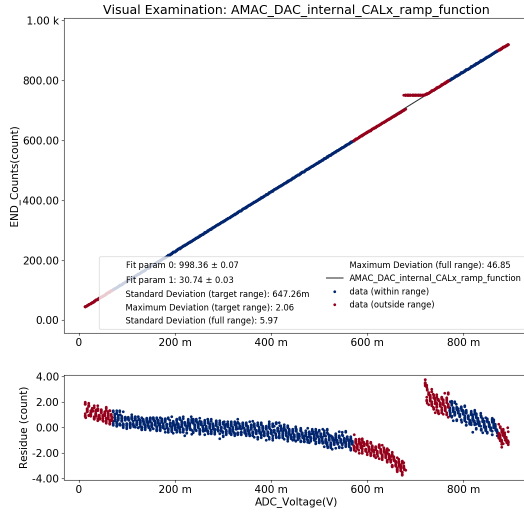


(a) DAC Channel: Calx

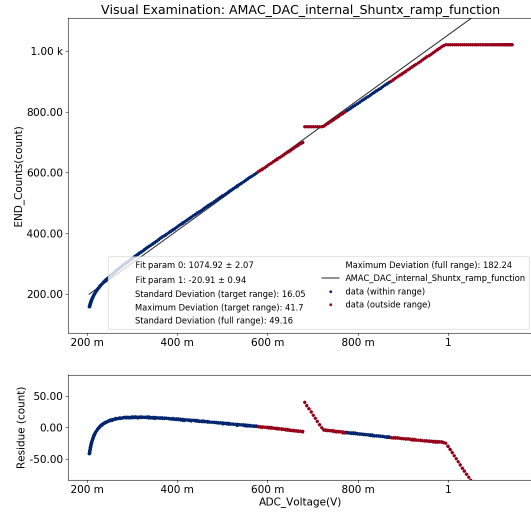


(b) DAC Channel: Shuntx

Figure 5.25: AMAC Digital to Analog (DAC) channel examples on **CAL-x** and **Shunt-x**. Notice that the **CAL-x/y** ramps are expected to be linear between 0V and 1V, while the **Shunt-x/y** ramps are pulled up to a maximum of 1.2V. The linearity is not important here, but monotonicity is.



(a) DAC Channel: Calx (Read from AMAC)



(b) DAC Channel: Shuntx (Read from AMAC)

Figure 5.26: AMAC readout of its own DAC outputs in channel 15 of the internal Analog Monitor ADC: **CAL-x** (left) and **Shunt-x** (right). Notice that we have good internal voltage measurement in these two channels, although the function maxed out of the ADC measurement range of 1V for the **Shunt-x** channel. The glitch near the 750mV is caused by the same issue in the AMACv2a proto-type design discussed in Section 5.3.6.2.

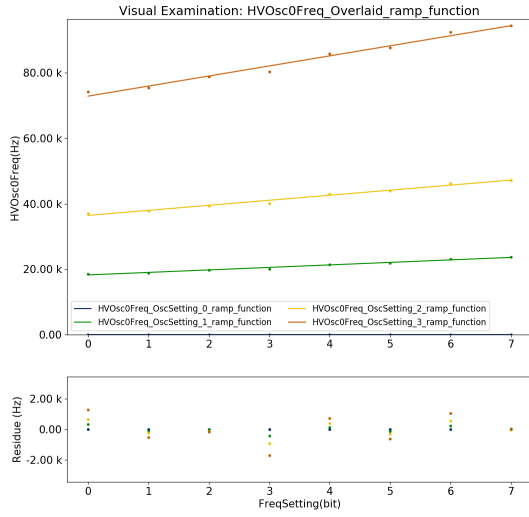
### 5.3.5 Timing and High-Voltage Oscillation Output Testing

The clocking mechanism of the AMAC ASIC is essential for reliable communication and control of High Voltage (HV) Oscillation Output. The AMAC's internal ring oscillator drives the system clock at approximately 20MHz within a  $\pm 10\%$  range, supporting all logic blocks and managing the Analog Monitor voltage ADC ramp through cycle counts. Additionally, the system clock supports the HV control circuit by generating three divided frequencies—100kHz, 50kHz, and 25kHz—used in Patch Panel 2. Each HV Oscillation output (HVOSC0, HVOSC1, HVOSC2, HVOSC3) is powered by a 3.3V input (VDDHI) and includes an inverter with dual-gate 3.3V drivers. The clock rate can be further fine-tuned via register settings from -10% to +20% to ensure precise frequency supply for these various functions.

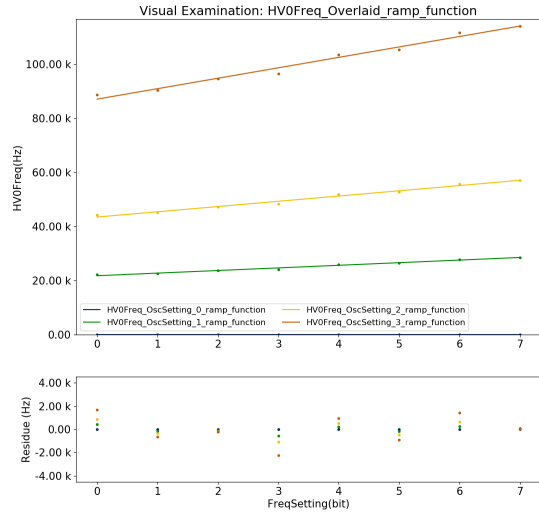
Table 5.9: High Voltage Oscillation Settings and Target Oscillation Frequencies.

| HV Osc Setting | Clock Frequency        |
|----------------|------------------------|
| 2'b00          | 0 (CMOS constant HIGH) |
| 2'b01          | $\sim 25$ KHz          |
| 2'b10          | $\sim 50$ KHz          |
| 2'b11          | $\sim 100$ KHz         |

Table 5.9 outlines the target frequencies for HV Oscillation output, while Figure 5.27 compares the clock tuning capability in various HV Oscillation frequency settings between AMACv2a and AMACStar chips. Note that a design limitation in AMACv2a reduced the frequency range and adjustment scope, leading to the revision in the AMACStar design. As shown in the comparison, AMACStar centers the frequency within the adjustment range around target outputs of 100kHz, 50kHz, 25kHz, and 0kHz (constant HIGH), allowing ample tuning room for frequencies adjustment that is potentially needed after prolonged radiation exposure.



(a) AMACv2a



(b) AMACStar

Figure 5.27: HV Oscillation Frequency setting ramps for the HV Control Oscillator outputs (HVOsc) in AMACv2a and AMACStar chips, with the x-axis representing the ring-oscillator tuning bit setting. In AMACv2a (left), a design limitation restricted the clock frequency adjustment range, placing the target frequency outside the adjustable scope—though this did not significantly impact performance. In the AMACStar production version (right), the design centers the target frequency within the adjustment range. The intended frequency outputs are 100kHz, 50kHz, 25kHz, and 0kHz (constant HIGH).

## 5.3.6 Bugs found in AMACv2a Prototype Chips

### 5.3.6.1 Overview of Bugs Found in AMACv2a

The transition from the AMACv2a prototype to the production-ready AMACStar involved thorough testing of all functionalities and corresponding design adjustments. Although AMACv2a achieved a high functionality rate, with over 92% of chips meeting Grade A standards (see Section 5.3.8.3), we found several areas for improvement, detailed in Table 5.10. The identified bugs ranged from minor glitches to design issues that required reworking specific functions.

Table 5.10: AMAC design issues identified in the AMACv2a prototype testing and corrected in the AMACStar production design.

| Issue                      | Description                                                                    |
|----------------------------|--------------------------------------------------------------------------------|
| Bandgap Linearity          | Non-linear behavior in the bandgap reference circuit                           |
| AM Bandgap and Ramp Gain   | Suboptimal slope in AM bandgap and ramp gain settings                          |
| AM Ramp Glitch             | Glitch observed at the 750 count switch point in AM ramp                       |
| Comparator Latching        | Latching inconsistencies in the AM comparator                                  |
| Oscillator Frequency Range | Limited frequency range in ring oscillator                                     |
| Sensor Bias Range Glitch   | Glitch in ramp for sensor bias current range #3                                |
| EFUSE-ID Loading           | Error in eFuse ID loading command via broadcast                                |
| SEE Mitigation             | Additional triplication required to protect against Single Event Effects (SEE) |

The issues identified included challenges with bandgap linearity, a limited calibration range in the AM Bandgap/Ramp-Gain, and glitches at specific count switch points in the AM ramp. Additional problems with the ring oscillator frequency range and the sensor bias current ramp set-out another round of design refinements in the analog circuitry of the AMAC. Beyond the analog block, issues were also found in the logic block: the EFUSE-ID<sup>11</sup> loading logic needed re-organization and the AM comparator required more robust latching logic to protect against Single Event Effects (SEE).

The resolution of these issues, as described above in Sections 5.3.3.1 through 5.3.5, re-affirms the importance of comprehensive physical prototype testing beyond simulations. This essential process has enabled the Penn ASIC team to pinpoint and correct each issue effectively, resulting in the

<sup>11</sup>The EFUSE-ID is a unique, read-only identifier programmed into the AMAC by passing high current through burnable resistors. This identifier is set upon initial contact during wafer probing or SCB testing.

refined AMACStar production version, which will contribute to a more robust ATLAS Upgrade.

### 5.3.6.2 Detailed Analysis of the AM Comparator Ramp Glitch

To improve comparator precision, the Analog Monitor analog-to-digital converter (ADC) ramp was split into two ranges with a switch point at around 750 mV. During comprehensive testing of the voltage ADC in the AMACv2a prototype, a recurring glitch was observed near this switch point, causing a flat line in reported values. This severity of this issue varied across different AMAC chips. The glitch appeared prominently in a number of units under identical test setups, suggesting a design-related issue. A similar issue was later detected in the HCCStar, which shares part of the AMAC's Analog-to-Digital Converter design. In Figure 5.28, for a given AM bandgap setting (#4), the input vs. read-out ramp across 16 different gain settings shows the glitch becoming more pronounced as the ramp gain (slope) increased.

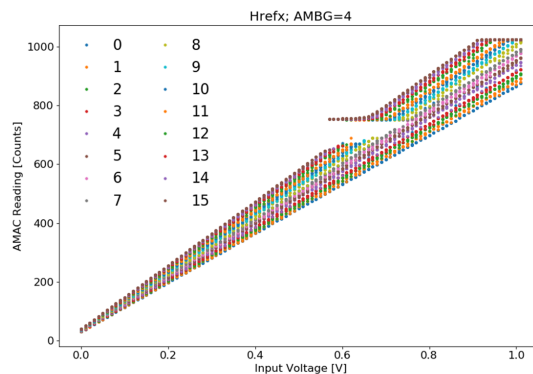


Figure 5.28: The plot corresponds to AM band gap setting number 4, and the 16 different colors corresponds to 16 different gain settings. The best combination of them will be chosen to produce the best ramp with 1 count per mili volt. Here we can find that at higher gain, we have a bigger issue at the switch point.

Further investigation revealed two main contributors to the issue:

- **Analog Component:** Voltage disturbances during range switching in the comparator caused unintended output changes, which caused the digital system to incorrectly record a flag. Simulation studies indicated that lower temperatures will increase transistor sensitivity, amplifying the glitch. Cold-box tests (5.3.6.3) confirmed this temperature dependency, with higher tem-

peratures significantly reducing the glitch. At the lowest temperature, deviations of up to 50mV were observed near the 750mV switch point.

- **Digital Recording Mechanism:** The digital part of the glitch involved the comparator’s latching logic, which recorded every instance of comparator firing. As a result, only the last comparator-flagging instance was recorded, locking the output at the start of the high range (750mV), compounding the anomaly.

The design team implemented targeted design adjustments to address both issues. On the analog side, the ramp comparison was delayed after the range switching to allow voltage disturbances to dissipate. On the digital side, latching logic was modified to only record the initial comparator flag. Figure 5.29 shows the simulation results demonstrating the improvement after delaying the comparator response, which allows the comparator to stabilize before continuing with the ramp.

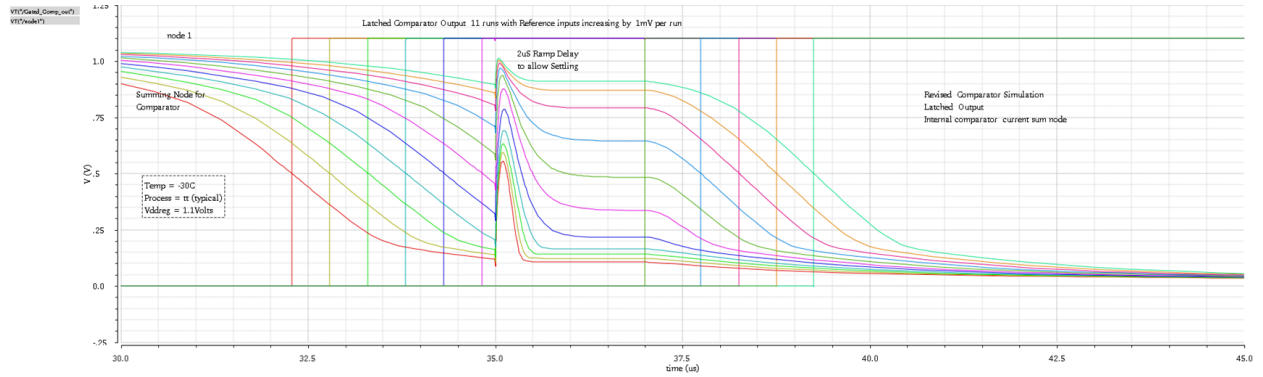


Figure 5.29: This plot shows eleven simulations, each with a 1mV increment in input voltage near the switch point. The high-range “switch” occurs as the ramp reaches 750mV. A 2-microsecond delay is injected here to prevent latching in the comparator output, holding the ramp voltage steady and allowing the comparator to settle. This simulation demonstrated that the 2-microsecond delay effectively resolved the disturbance and helped the AMAC latch the correct value. This led to an updated design accordingly. Simulations and plots were produced by Mitch Newcomer at Penn Physics Instrumentation Group.

Testing in the AMACStar production design confirmed that these adjustments successfully eliminated the glitch. Figure 5.30 shows that maximum deviations were reduced to under 4mV, with most below 2mV, proving a reliable ADC performance across the entire range.

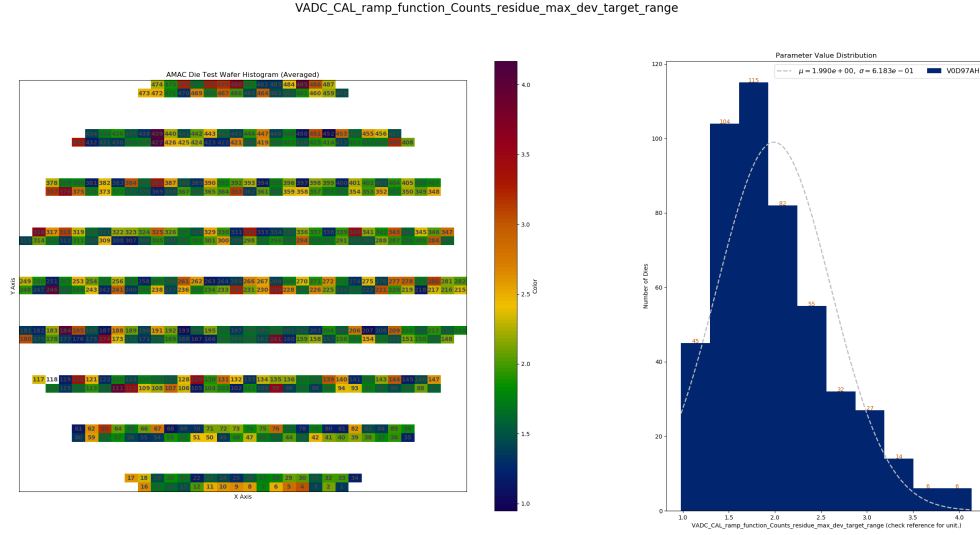


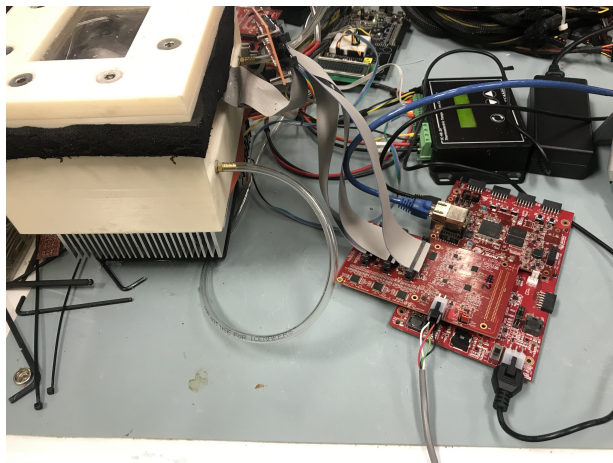
Figure 5.30: In the pre-production wafer of AMACStar, the maximum residual deviation in the target range (including the previous glitching range) was checked. Results show that most deviations are under 2mV, with all staying below 4mV. This confirms that, after resolving the glitch, the AMACStar design provides consistently high-precision and accurate voltage ADC measurements across the entire designated measurement range.

### 5.3.6.3 Cold-Box Test

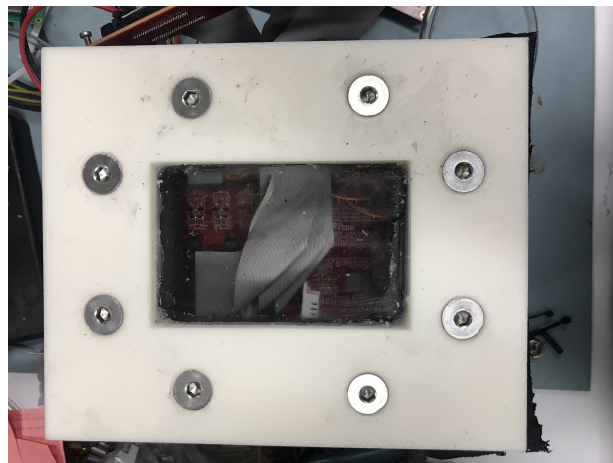
The AMAC is expected to operate below 0°C in the ITk. The cold-box setup provided critical validation of the AMACv2a’s performance at controlled low temperatures. As shown in Figure 5.31, the cold-box includes a 3D-printed enclosure with a temperature-adjustable cooler, maintaining stability within  $\pm 1^\circ\text{C}$ . The cold-box setup allowed for an assessment of the CTAT channel’s temperature-sensing accuracy within the AMAC itself. Figure 5.32 shows a stable, linear decrease in CTAT output as the temperature increased, matching the expected “complementary to absolute temperature” response.

The cold-box also enables us to examine temperature-dependent behaviors predicted in simulations. As illustrated in Figure 5.33, the comparator ramp glitch worsened as temperature dropped from  $+15^\circ\text{C}$  to  $-10^\circ\text{C}$ , aligning with expert’s predictions using simulation. Additionally, the ramp slope remained constant across these temperatures, suggesting that there is no need for recalibration for low temperature, confirming the robustness of the ADC ramp gain apart from the glitch.





(a) Cold Box Set-Up



(b) Cold Box Top View

Figure 5.31: Cold Box set-up to test AMACv2a under temperature variations.

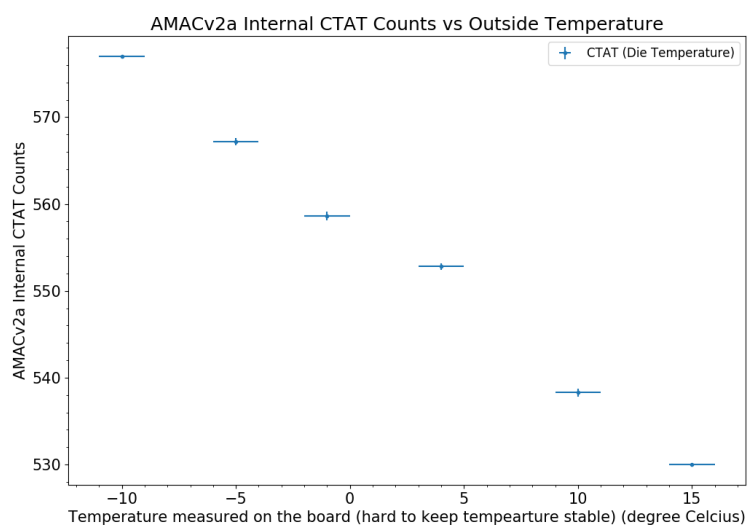
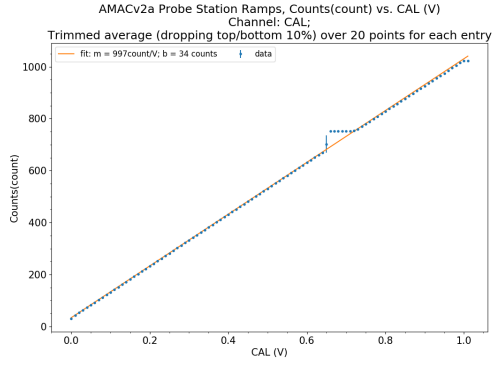
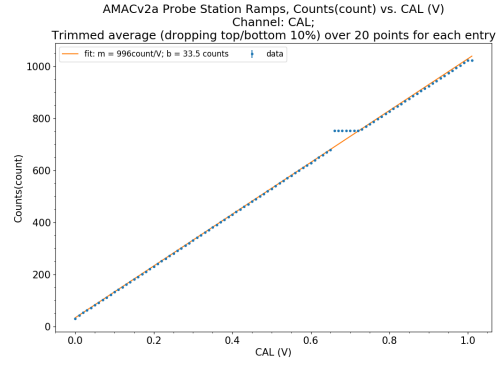


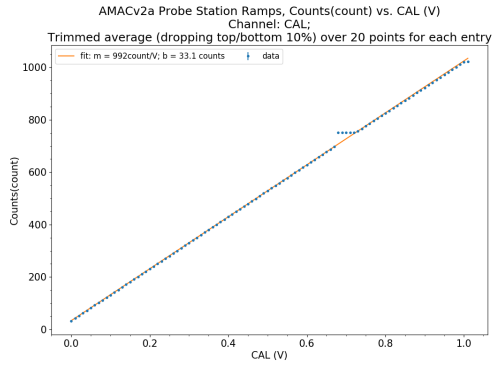
Figure 5.32: CTAT verification: The CTAT output demonstrates a steady decreasing readout with increasing temperature, despite a slight 1°C variation in cold-box temperature stability.



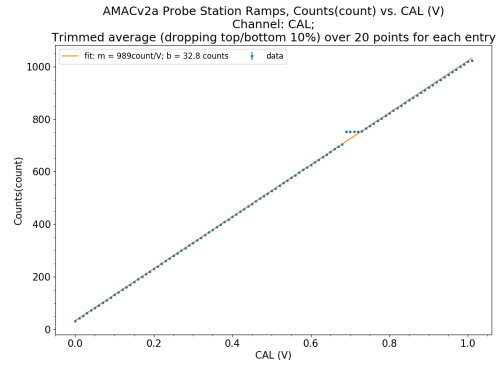
(a) -10 °C



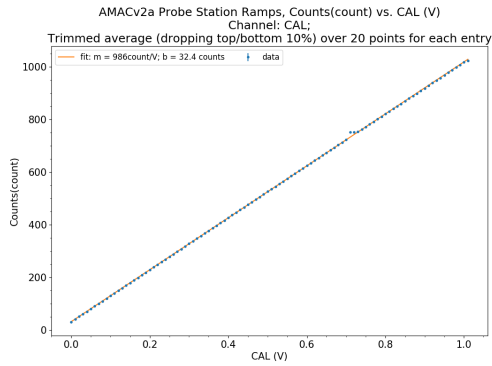
(b) -5 °C



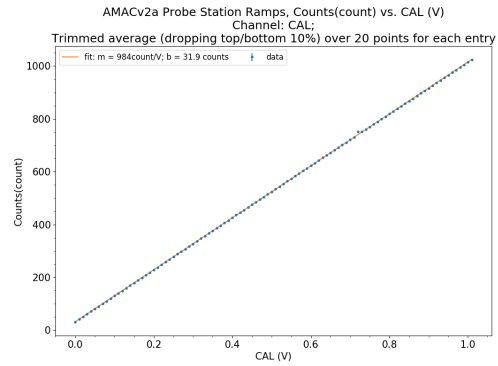
(c) -1 °C



(d) +4 °C



(e) +10 °C



(f) +15 °C

Figure 5.33: Simulation results indicated that the glitch worsens at lower temperatures due to increased transistor sensitivity. This temperature dependence was experimentally confirmed using the Cold-Box. The ramp slope remained stable, with only about a 1% variation across tested temperatures.

### 5.3.7 Logic Function Tests & Powering Status

The Logic Function Tests of the AMAC ASIC assess the AMAC's critical role as a supervisory controller within the ITk-Strip detector module. It was primarily conducted by fellow graduate student Luis Felipe Gutierrez Zagazeta, with contributions and assistance from myself. Given the AMAC's responsibility in managing operational status across various components, robust logic performance is essential. Each logic test yields a straightforward Pass/Fail outcome. Failures in these tests classify an AMAC unit as Grade F (Failure) due to potential reliability risks for the module.

The tests cover key logic functions, including:

- **Communication protocol verification:** Ensuring proper initialization, register read/write functionality, and successful EFUSE-ID loading.
- **Digital ON/OFF signaling:** Testing the AMAC's ability to send digital ON/OFF signals to other components and verifying output pads' responses.
- **Autonomous operations:** Configuring trigger lookup tables and simulating conditions to test the AMAC's autonomous control over components as intended.

The AMAC includes several reset mechanisms, divided into internal and external resets, each with specific purposes and are tested individually:

- **Internal Resets:** These include power-on resets, command-based resets (by setting Write-Only register) to reset specific interlock flags, soft resets (logic block only), and hard resets (full re-initialization).
- **External Resets:** Two key signals from HCCStar (SSSHx,y) to the AMAC manage communication block resets without restarting the module. Additionally, the OF signal can be sent through the bus tape and power board to reset the next module in sequence (using the next AMAC).

- **Resets for Other Components:** The AMAC outputs two hard reset signals (`HrstBx`, `HrstBy`) specifically for the HCCStar ASICs on Hybrid X and Y to ensure they can be reset individually as needed.

These logic tests validates the AMAC's capacity and robustness for supervisory control of other components, and the resetting capability of itself. The AMACv2a prototype batch exhibited excellent performance, with less than 1% of units experiencing logic failures. The comprehensive logic test sequence also revealed a few minor design issues, which were addressed in the AMACStar production version.

In addition to logic function tests, we assess the basic powering status of each AMAC unit in the test routine. This includes verifying that each unit draws an appropriate current (approximately 40 mA) and confirming its ability to accurately measure the input and output current and voltage connected to the Active Card. Unlike other analog tests, these measurements are not scanned; instead, a single value is taken to determine if each die meets the basic powering criteria. This powering test provides an initial check on the AMACs fundamental electrical performance, ensuring it operates within expected parameters.

### 5.3.8 Wafer Probing Results of AMACv2a Prototype Chips

#### 5.3.8.1 Overview of Data Processing Workflow

The testing and evaluation of the AMAC chips are essential for verifying their readiness for deployment in ITk. Figure 5.34 outlines the data flow from probe station testing to the creation of wafer dicing maps and the synchronization of the quantitative characteristics to the ITk Production Database. The workflow involves the following steps:

- **Raw Data Collection and Fitting:** Raw data collected from each probe station test is fitted to designed functions to assess each AMAC chip's performance in detail. Chips are graded based on these performance metrics.
- **Data Routing and Usage:** Based on the processed data, results are further processed and



parameter is a key indicator of die contact quality, as lower maximum values can suggest contact issues between the die pad and the probe needles.

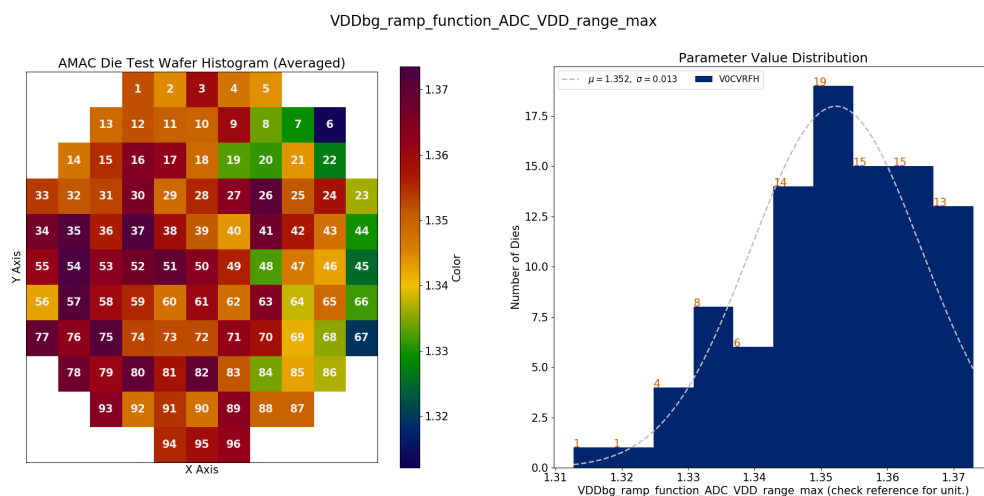


Figure 5.35: Maximum VDD bandgap voltage across the wafer, used as an indicator of die contact quality. Lower maximum VDD values suggest insufficient contact between the die and probe station. In this distribution, a slight banking angle on the wafer or probe station chuck table can be observed, trending toward the upper right corner. When maximum VDD values fall below an acceptable threshold, the testing is paused to adjust the chuck height by a few dozen microns, improving contact quality before resuming.

The observed distribution shows a slight banking angle towards the upper right corner of the wafer, indicating a potential uniformity issue in the probe station chuck table or the wafer thickness. When the Maximum VDD bandgap voltage falls below acceptable levels, signaling inadequate contact, testing is paused. The chuck height is then adjusted by a few dozen microns before re-probing, ensuring optimal contact between the probe station and each die.

This analysis highlights the usefulness of wafer-level parameter distribution in understanding manufacturing characteristics and identifying patterns across the wafer (e.g. things that may affect contact quality). Monitoring variables such as the Maximum VDD bandgap voltage helps us pinpoint potential issues and refine testing procedures, which supports a consistent and effective validation of each AMAC chip.

### 5.3.8.3 AMAC Dice Grading Standards

AMAC chips are graded through a two-part testing routine that examines both logic and analog functionalities. The logic tests yield a Pass/Fail outcome, and any failure places the chip in Grade F (Failure). The analog testing, on the other hand, is based on numerical characteristics including parameters related to accuracy (e.g., fit parameters), precision (maximum and standard deviation), and diagnostic metrics like the Spearman-R for the Shunt-X/Y DAC output test.

Table 5.11: Excerpt of AMACStar Vital Grading Standards

| Parameter Name                                                  | Upper Limit | Lower Limit | Description                                                                                                               |
|-----------------------------------------------------------------|-------------|-------------|---------------------------------------------------------------------------------------------------------------------------|
| Best_AM600BG                                                    | 0.64        | 0.60        | AM600BG Voltage under the best calibration setting (V)                                                                    |
| Best_Ext_ADC_VDD                                                | 1.25        | 1.20        | VDDBG Voltage (Measured by external ADC device) (V)                                                                       |
| Best_slope                                                      | 1.10        | 0.90        | Best Analog Monitor ramp slope (mV/count)                                                                                 |
| ExtADC_VDDLRL_Curr                                              | 0.05        | 0.025       | AMAC Input Current Consumption through VDDLRL (A)                                                                         |
| NTCpb_sw_0_Ohms                                                 | 210         | 165         | Powerboard NTC measurement channel resistance on Switch 0 (Fitted) (kOhms)                                                |
| NTCpb_sw_1_Ohms                                                 | 84          | 68          | Powerboard NTC measurement channel resistance on Switch 1 (Fitted) (kOhms)                                                |
| CAL_ramp_function_intercept                                     | 60          | 10          | EOS Calibration Voltage measurement ramp intercept (count)                                                                |
| CAL_ramp_function_slope                                         | 1100        | 950         | EOS Calibration Voltage measurement ramp slope (count/V)                                                                  |
| CAL_ramp_function_AM<br>Counts_residue_max_dev<br>_target_range | 8           | 0           | Maximum deviation of CAL voltage measurement in the target range (i.e., Precision of Measurement) (count of AM ramp step) |

Each performance parameter is represented by a unique identifier string with specific meaning. For instance, `VDDbg_ramp_function_ADC_VDD_range_max` represents the maximum target range of regulated voltage (VDD bandgap) as measured by the ADC. Since this parameter affects multiple aspects, it must be above a defined threshold, e.g., 1.3V, to ensure sufficient voltage selection range.

The analog grading standards for AMAC chips set upper and lower limits for each measured parameter. An example of these criteria is shown in Table 5.11. If any measured value exceeds these set limits, the chip does not meet the standard. Based on these standards, each AMACStar

is assigned one of three grades:

- **Category A:** Meets all critical parameters and is suitable for detector use.
- **Category B:** Fails some non-critical diagnostic parameters and is typically reserved for testing purposes, and deployable into non-critical areas in case of urgent need.
- **Category F:** Fails to meet essential criteria and will not be deployed after probing.

For AMACStar production, over 1,000 parameters are collected for each AMACStar, including:

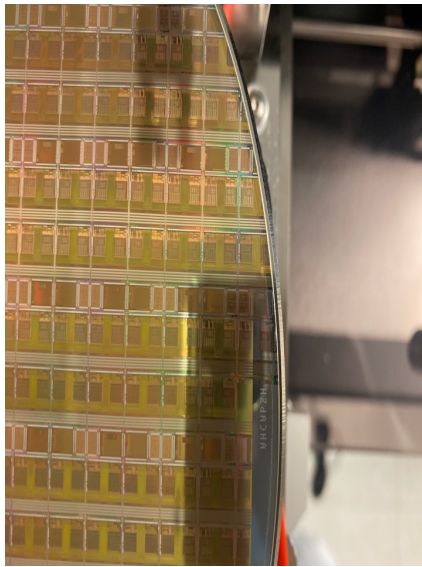
- Over 60 essential digital pass/fail standards: failure of any one results in a fail grade.
- Over 200 essential analog pass/fail parameters: failure of any one results in a fail grade.
- Over 200 analog diagnostic parameters: Outliers in these parameters trigger alerts for human examination of potential correlations. These are also visually analyzed on a wafer distribution plot, such as Figure 5.35, to detect any spatial patterns that may suggest manufacturing issues.

#### 5.3.8.4 Initial Batch of Wafer Probing Results

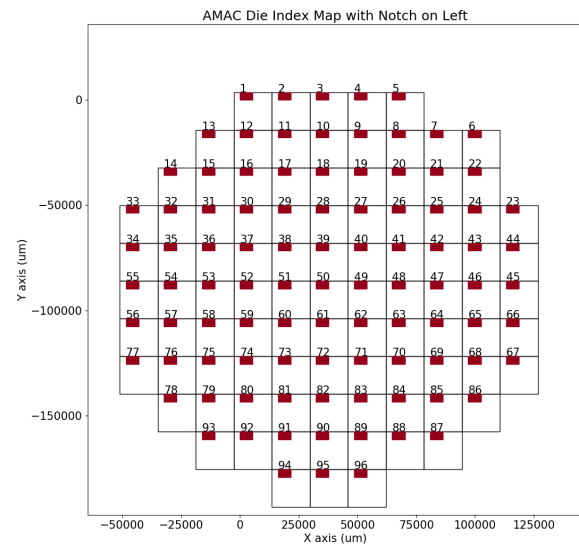
The first batch of 12 prototype wafers was manufactured by Global Foundries, each containing 96 AMACv2a, 98 HCCStar, and 371 ABCStar chips arranged on a circular wafer, as illustrated in Figure 5.36. AMAC positions are highlighted in the red rectangle on the right. For AMAC probing, the probe station chuck moves sequentially to each AMAC position, where the probe needles are placed in contact with the AMAC die's pads.

The dicing maps (Figure 5.37) reflect the grading outcomes based on a comprehensive analysis of performance data. The AMACv2a prototypes demonstrated a high passing rate of 9299% across individual wafers, averaging 96% across all 1,152 chips, which highlights the prototype's robustness.





(a) Zoom-in on AMACv2a Wafer



(b) Die Index Map with AMAC Location highlighted.

Figure 5.36: Left: Prototype wafer photo showing AMACv2a, HCCStar, and ABCStar chips[28]. Right: AMAC positions highlighted within the red rectangle in the reticle that also contains HCCStar and ABCStar.

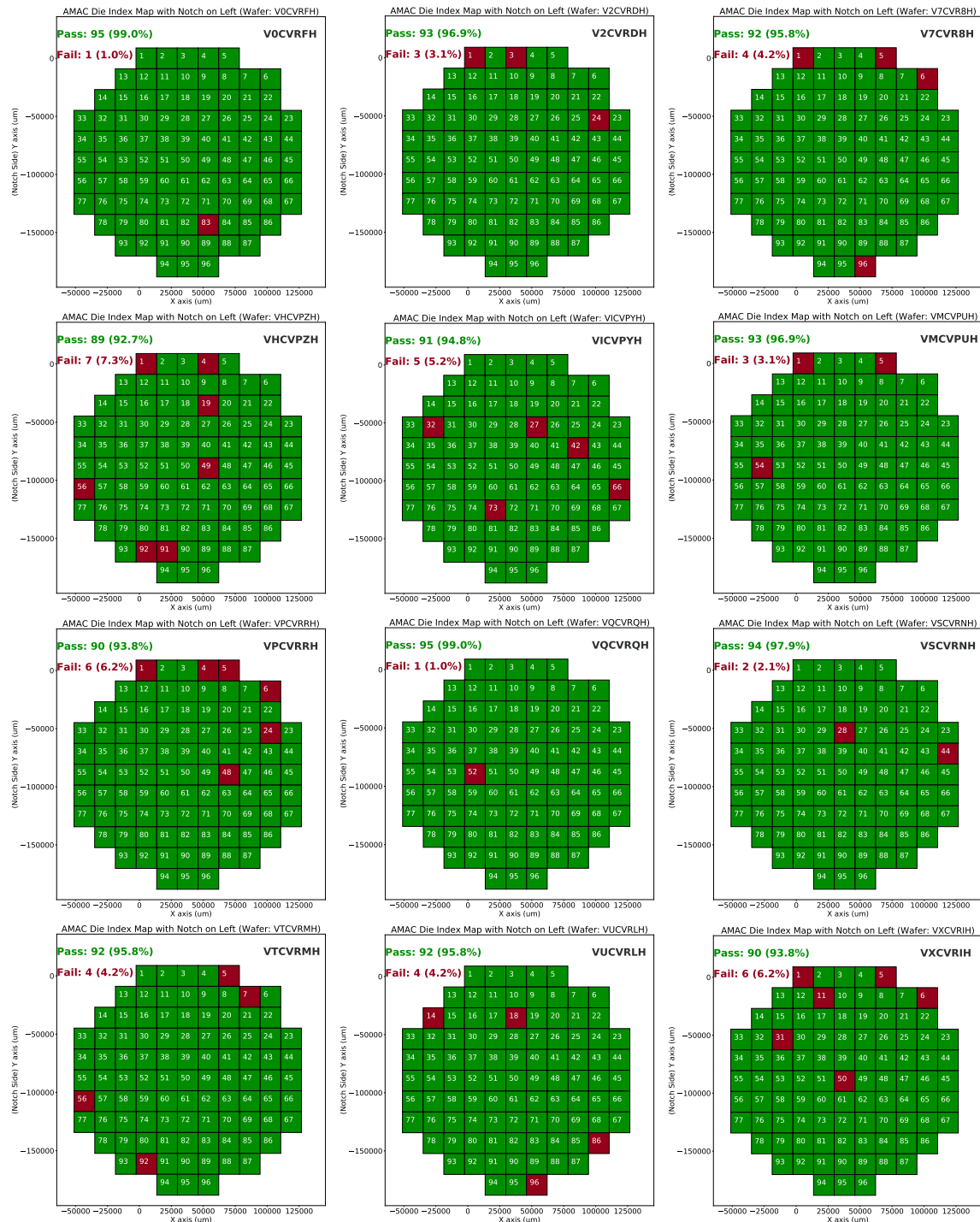


Figure 5.37: Dicing map of the first 12 wafers of AMACv2a prototype probed at Penn. The grading is generated from the quantitative characterization analysis from collected data and the set grading standard.

### 5.3.9 ITk Production Database Synchronization

The ITk Production Database (ITkPD), built on MongoDB, centrally stores and manages ITk component information and test results (including the AMAC). Figure 5.38 shows how users interact with ITkPD through a web interface (at `itkpd-test.unicorncollege.cz`). The ITkPD also has an Application Programming Interface (API), enabling efficient data entry and retrieval. This database is essential for tracking and accessing test results by all participating institutes throughout the ITk detector’s assembly and operational phases.

During the synchronization of AMAC test results with the ITkPD, I uploaded all prototype probing data for the AMACv2a, provided feedback on the user interface, and developed an automated workflow. These steps set up an initial framework to support efficient data integration as AMAC progress further in the production.

| Component                       | Serial Number  | Current stage                        | Current location           | Registered        |
|---------------------------------|----------------|--------------------------------------|----------------------------|-------------------|
| AMAC Chip - AMACv2a (v00007860) | 20USG000502033 | Probed at University of Pennsylvania | University of Pennsylvania | 6/5/2020 01:25 上午 |
| AMAC Chip - AMACv2a (v00007859) | 20USG000502032 | Probed at University of Pennsylvania | University of Pennsylvania | 6/5/2020 01:24 上午 |
| AMAC Chip - AMACv2a (v00007858) | 20USG000502031 | Probed at University of Pennsylvania | University of Pennsylvania | 6/5/2020 01:23 上午 |
| AMAC Chip - AMACv2a (v00007854) | 20USG000502030 | Probed at University of Pennsylvania | University of Pennsylvania | 6/5/2020 01:22 上午 |
| AMAC Chip - AMACv2a (v00007853) | 20USG000502029 | Probed at University of Pennsylvania | University of Pennsylvania | 6/5/2020 01:20 上午 |
| AMAC Chip - AMACv2a (v00007850) | 20USG000502028 | Probed at University of Pennsylvania | University of Pennsylvania | 6/5/2020 01:18 上午 |
| AMAC Chip - AMACv2a (v00007854) | 20USG000502027 | Probed at University of Pennsylvania | University of Pennsylvania | 6/5/2020 01:16 上午 |
| AMAC Chip - AMACv2a (v00007859) | 20USG000502026 | Probed at University of Pennsylvania | University of Pennsylvania | 6/5/2020 01:15 上午 |

Figure 5.38: Screenshot of ITk Production Database Web UI.

#### 5.3.9.1 Test Result Saving Structure in ITkPD

The AMAC test results are systematically organized within the ITkPD storage framework. Figure 5.39 illustrates the hierarchical organization of **Test Data**, with the AMAC components at the center, branching out to over 60 **Component Properties** and 72 **Test Types**. This hierarchical structure, further detailed in Figures 5.40, enables comprehensive characterization of each AMAC.

The inner ring represents the component properties for each AMAC (Figure 5.41a), with around 60 characterization properties shown in Figure 5.41b. The outer ring consists of clusters of arrows, each center representing a test type (Figure 5.42a). For example, the largest cluster represents all pass/fail logic tests, while the others clusters represents all the analog function tests.

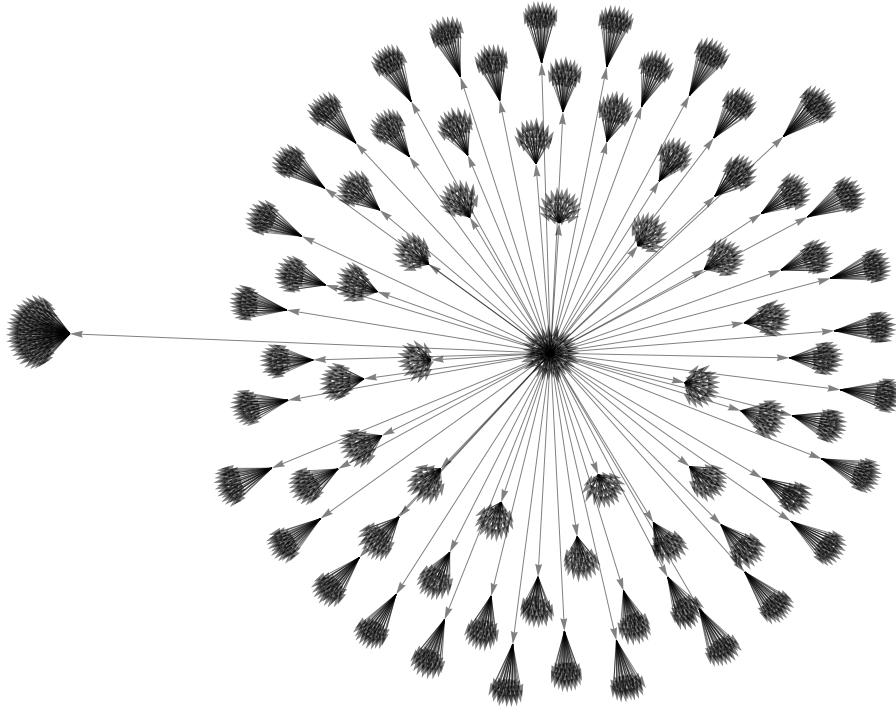


Figure 5.39: The center represents AMAC Component, and each arrow represents an object in the database (Parameters, properties, tests, etc.). This diagram provides an intuitive visualization of how information (parameters, properties, tests, etc.) is hierarchically associated with the AMAC component at the center.

Figure 5.40 provides a closer look at one such test type, showing 8 **Test Parameters** (arrays of data) in lime green and 18 **Test Properties** (single values) in red. In the Web UI, these are displayed as seen in Figure 5.42b.

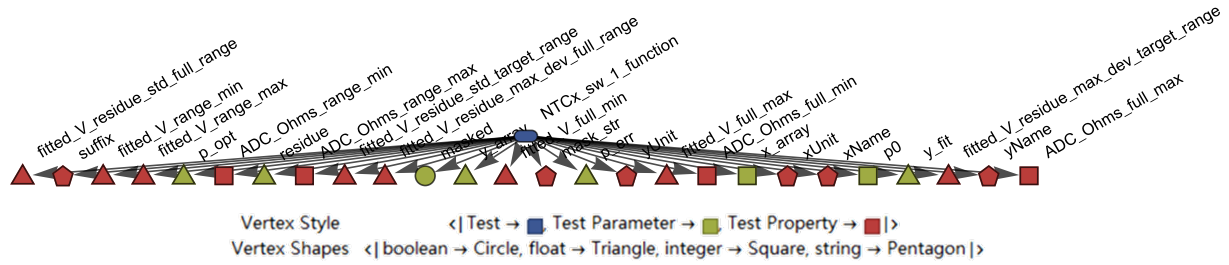


Figure 5.40: Example “Test Type” Structure which includes the characterization parameters collected by the NTC measurement (Hybrid X, range setting #1). This is one of the 72 tests in a “Test Run”.

Component Details

Show details of selected Component of the Inner Tracker.

20USG000501034

AMAC Chip - AMACv2a

Basic Properties

ATLAS SERIAL NUMBER

20USG000501034

PROJECT

Strips

COMPONENT TYPE

AMAC Chip AMAC

SUBPROJECT

Strip general

TYPE

AMACv2a

REGISTRATION

03.06.2020 11:44

CURRENT STAGE

Probed at University of Pennsylvania

OWNER INSTITUTE

University of Pennsylvania UPENN

CURRENT LOCATION

University of Pennsylvania UPENN

SHIPMENT DESTINATION

No current shipment destination

(a) AMAC Component

| Properties      |                                                                               |                     |                    |
|-----------------|-------------------------------------------------------------------------------|---------------------|--------------------|
| source_dir      | /home/u2/luisfgz/probe_station_data/AMACv2a/VTCVRMH/AMACFullTestResults/AMACv | try_num             | 2                  |
|                 | 2a_0x00001038_try2                                                            | CH13_Zero_Calib     | 23                 |
| NTCpb_sw_1_Ohms | 78574.66146782904                                                             | NTCx_sw_1_Ohms      | 71927.50487286132  |
| CH3_Zero_Calib  | 33                                                                            | CH4_Zero_Calib      | 31                 |
| NTCx_sw_0_Ohms  | 179298.33376159015                                                            | CH12_Zero_Calib     | 33                 |
| wafer_name      | VTCVRMH                                                                       | CH10_Zero_Calib     | 26                 |
| WaferNumber     | 2                                                                             | CH11_Zero_Calib     | 25                 |
| Grade           | F                                                                             | CH14_Zero_Calib     | 113                |
| NTCy_sw_4_Ohms  | 20139.10881799628                                                             | Die Index           | 56                 |
| CH5_Zero_Calib  | 25                                                                            | NTCy_sw_6_Ohms      | 14342.769095425598 |
| NTCx_R_Internal | 265.65719327860364                                                            | CH0_Zero_Calib      | 27                 |
| output_dir      | /home/u2/siconglu/html/AMACv2a_Probe_Station_Test_Reports/VTCVRMH/AMACv2a_0   | Chip Design Version | 2a                 |
|                 | x00001038_try2/                                                               | AM_Slope            | 986.6964784502597  |

(b) Component Properties

Figure 5.41: Example screenshot of an AMAC Component from the Web UI of ITk Production Database.

(a) Test Types and Test Runs(b) Example Test Run

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### 5.3.9.2 Automatic Database Synchronization

The data analysis and synchronization workflow, illustrated in Figure 5.43, employs the ITk Database API for automated data transfer, converting local database entries into a JSON format compatible with ITkPD. Each AMAC chip is uniquely identified by two identifiers: the EFUSE-ID, a hardware ID burnt onto the ASICs, and the ATLAS Serial Number (ATLAS-SN), used universally across the detector's components, including ASICs, wafers, and modules. At Penn, the local database consistently uses EFUSE-ID for all probing data associated with each AMAC, while ITkPD uses the ATLAS-SN. A mapping saved both locally and in ITkPD between these two identifiers facilitates smooth synchronization.

Integrating AMACv2a prototype test results with ITkPD organizes component testing data in a consistent and accessible format for collaborating institutions. By implementing structured data hierarchies, unique identifiers, and automated synchronization, I helped create a system for efficiently recording and accessing performance records, supporting quality control as AMAC chip production progresses for the ITk detector.

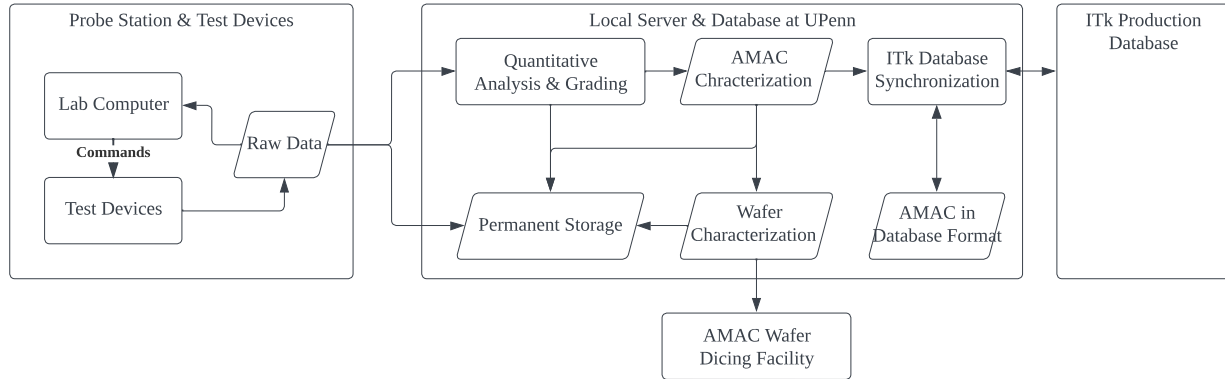


Figure 5.43: AMAC Testing/Probing Data Analysis and Synchronization Workflow to ITk Database. Synchronization was done with ITk Database API. The data-flow format is demonstrated in Figure 5.34.

## 5.4 AMAC Circuit Design Verification with Simulation

### 5.4.1 Radiation Challenges in the HL-LHC Environment and Mitigation Strategies for SEE

The increased luminosity in the HL-LHC brings a proportional rise in radiation levels, which poses significant challenges to the ATLAS detector's electronics, particularly due to Single-Event Effects (SEE) that can disrupt the logic functions of the ASICs. Through simulation-based testing, we verified AMAC's operational functionality and validated its resilience to SEE.

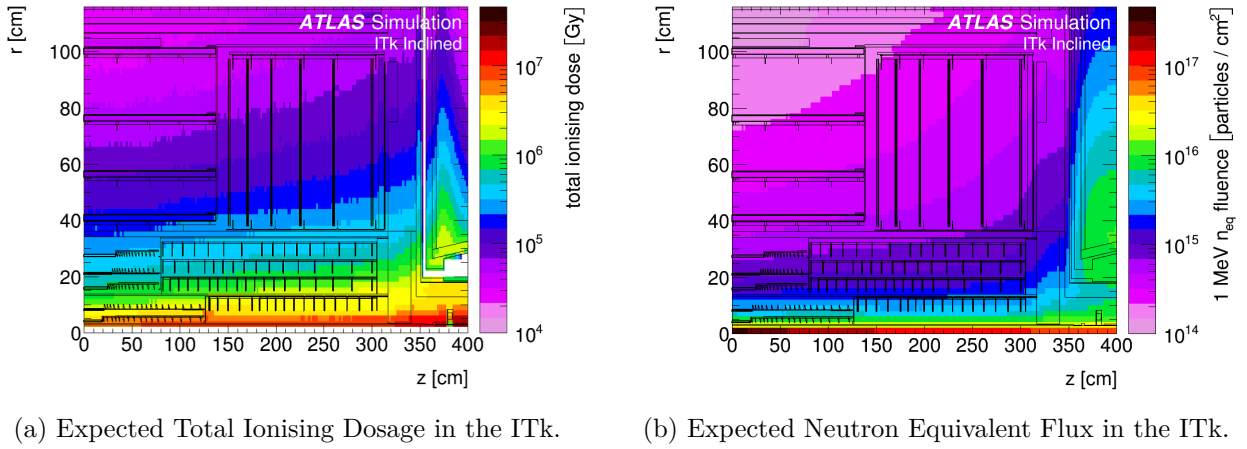


Figure 5.44: Radiation environment in the ITk that the electronics are expected to withstand.[26]

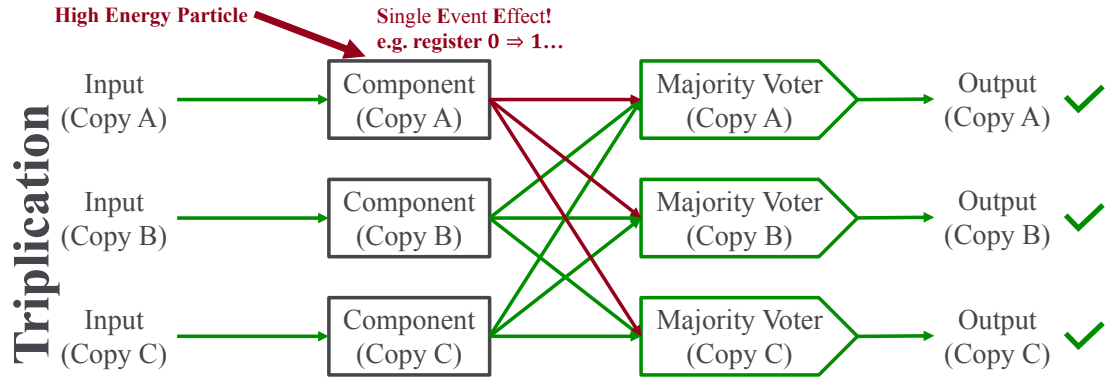
The ITk radiation environment is illustrated in Figure 5.44, indicating expected Total Ionizing Dose (TID) levels and neutron flux. Within this environment, SEE events occur when high-energy particles ionize the device material, generating electron-hole pairs that may shift voltage levels and alter AMAC's logical states. SEE events include **Single-Event Transients (SET)**, which cause temporary voltage disruptions in the wires, and **Single-Event Upsets (SEU)**, which persist and can alter memory cells or logic states. For instance, a high-energy particle strike might flip a register bit from 0 to 1, potentially leading to errors in subsequent logic operations (Figure 5.45a). Without mitigation, SEE could lead to unintended AMAC responses or even power down critical components in the module.

To address SEE, AMAC incorporates **Triple-Module Redundancy (TMR)**, replicating each





(a) Circuit component without triplication is susceptible to SEE from high energy particle.



(b) Circuit component with triplication is protected against SEE from high energy particle.

Figure 5.45: Comparison of triplicated circuit component vs non-triplicated component, demonstrating radiation hardness introduced by triplication at the cost of redundancy.

component threefold with a majority-voting system. This configuration ensures that if one component is affected by an SEE, the two unaffected components will maintain correct output through majority voting, as illustrated in Figure 5.45b. Penn instrumentation experts implemented TMR in AMAC using CERN’s TMRG tool, which automated the triplication and voting logic across AMAC’s components.

For completeness, TID effects, though not the main subject of discussion here, are mitigated using techniques like high-energy gamma pre-irradiation to stabilize ASICs against leakage currents and power consumption spikes from electron trapping in silicon oxide.

My primary contribution is in the simulation-based testing. Using the CoCoTB framework, I simulated SEE impact to confirm the effectiveness of TMR in preventing operational disruptions and validated AMAC’s performance reliability under stress conditions. Additionally, I maintained a comprehensive function test suite to ensure that updates to the AMAC circuit layout align with the specifications.

#### 5.4.1.1 CoCoTB Verification Framework

The CoCoTB (COroutine based COsimulation TestBench) framework is essential for our simulation-based testing of AMAC. It interfaces Python with commercial circuit simulation software to verify VHDL and System Verilog RTL designs. This framework allows for efficient testing under varied scenarios, including radiation-induced SEU/SET events, and supports continuous integration of design updates, with nightly tests to ensure that revisions maintain functionality and robustness. The nightly testing routine covers the compiled RTL, synthesis, and place-and-route (PnR) stages, with automated alerts for any detected failures.

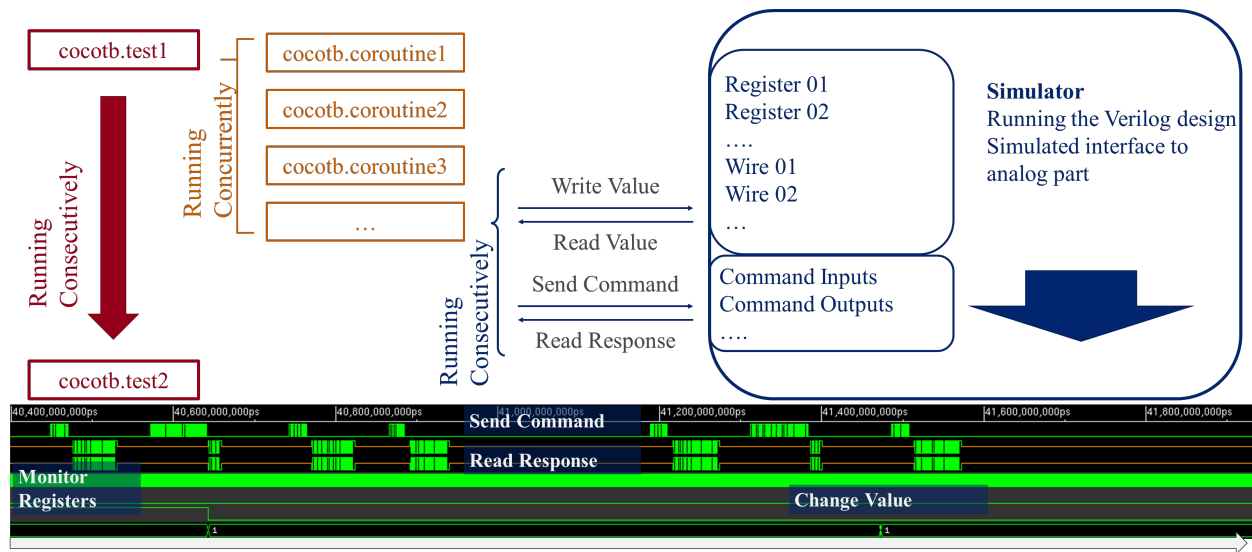


Figure 5.46: The CoCoTB framework for AMAC verification, highlighting test sequences (red) and concurrent coroutines (orange) for assessing AMAC functions like communication and SEU responses. Coroutines enable direct interaction with the simulator for dynamic read/write operations. Waveform examples show external command signals, AMAC responses, and monitored register values, illustrating the framework’s comprehensive testing capabilities.

CoCoTB’s layered test bench structure, as shown in Figure 5.46, includes concurrent coroutines that simulate real-world scenarios, such as command sequences and monitoring responses. The evolution of AMAC’s design has shaped these test routines, ensuring resilience to radiation hazards and alignment with design specifications.

The primary goals of the CoCoTB framework are **comprehensive coverage**(5.4.2)–verifying that AMAC functionalities meet specifications under standard and extreme conditions–and **radiation-**

**hardness testing** (5.4.3) to ensure reliability under intense SEE.

## 5.4.2 Functionality Verification against Specification

### 5.4.2.1 Overview of Functional Simulation Tests

we finalize the AMAC design for manufacturing, verifying that its functional blocks operate precisely according to the specification is essential. The core functionalities of AMAC are verified through targeted simulation tests aligned with the descriptions. The test suite assesses key aspects such as:

- **Communication Block:** Evaluates serial protocols, acceptable frequency range, command-response mechanisms, and register read/write capabilities.
- **Power On, Resets, and Recovery:** Tests soft, hard, and communication resets, along with EFUSE programming and loading.
- **Analog Monitor Ramp and Values:** Verifies the 10-bit input value latching across 16 channels.
- **Interlock Functions:** Examines the interlock system across 5 blocks, with checks for threshold limits, flag logic, and activation of LDO pads based on interlock states.
- **General Triplication and SEU/SET Hardness:** Assesses resilience against SEU/SET to ensure the integrity of triplicated circuits.

The structured testing approach, summarized in Table 5.12, systematically verifies AMAC’s functionality from basic power-on procedures to complex evaluations of serial communication, register mapping, and interlock operations. Each test series incrementally verifies AMAC’s functionality, covering comprehensive device capabilities and robustness against potential failures.

### 5.4.2.2 Example: Verification of EoS Clock Frequency Flexibility

This example demonstrates testing the End of Stave (EoS) clock frequency readability range after modifications to the Ring Oscillator frequency and clock wiring in AMACStar.

Table 5.12: Test Series and Function Blocks. Note: The "Axxx" labels are internal identifiers for organizing tests.

| Test Series        | Function Block                                    |
|--------------------|---------------------------------------------------|
| A0000              | Power On AMAC                                     |
| A0101              | Check AMAC is Responsive                          |
| A0201–A0210        | All Serial Communication Functionality & Features |
| A0301              | Register Map Design (Read/Write/Default)          |
| A0401–A0409        | All Analog Monitor Functionality & Features       |
| A0501, A0509–A0512 | All Flag & Interlock Functionalities              |
| A0602              | EFUSE ID & Comm ID Functionality                  |
| A0701–A0702        | Wiring Check of Other AMAC Functionality          |
| A0801–A0802        | Flag Logic Functionality (3 bit & 8 bit LUT)      |
| A0901–A0922        | Possible Hazards from SEU & SET                   |
| A1001              | All EFUSE functionality                           |

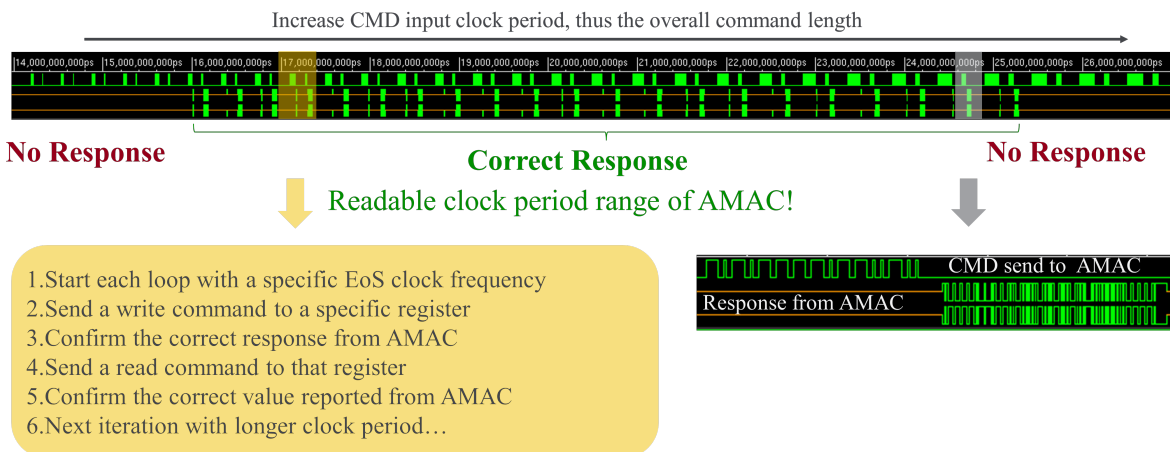


Figure 5.47: CoCoTB verification waveform showcasing the AMAC's response to varying EoS clock frequencies, highlighting the process of extending command durations and analyzing the device's operational frequency range.

The test sequence, shown in Figure 5.47, proceeds from left to right, with an arrow marking a controlled increase in the command input clock period. This increase reduces the frequency and increase the length of the command signal, as can be seen by the expanding green block in the waveform. A zoomed-in view in the grey box shows the AMAC’s response to the commands sent by the testing program. The yellow box on the left outlines the step-by-step interaction between the test bench and AMAC, testing operational bandwidth by varying the clock frequency, issuing commands, and confirming accurate response interpretation.

This test finds the AMAC’s clock frequency readability boundaries by identifying thresholds where the device stops responding. The non-responsive zones at frequency extremes are key indicators of operational limits. A successful response from AMAC within the targeted frequency range confirms compliance with design specifications. Passing this test demonstrates that AMACStar can accurately process clock signals post-modification.

### **5.4.3 Radiation Hardness Verification**

#### **5.4.3.1 Overview of SEE Simulation Tests**

Following the functional verification tests, we developed a suite of SEE injection tests, with a special focus on the interlock mechanism due to its essential responsibility of shutting down electronic components.

The interlock system’s responsibilities include analog monitoring, flag logic, flag latching, and output pad flips. Any SEU/SET affecting these functions could potentially trigger unintended activation or deactivation of vital electronics modules. Therefore, our SEE simulation tests specifically target the interlock’s ability to accurately respond to simulated conditions while withstanding the injected SEU/SET events.

The SEE simulation suite comprises the following tests:

- Intense Interlock Movement (A0903): Tests all possible state transitions within an interlock channel to verify accurate state changes under varying conditions.

- **Interlock Movement Under SEU (A0907 & A0908):** Introduces random SEUs to relevant registers every 5 microseconds. A0908 also tests for double-SEU events, confirming that double SEU on the same component will trigger failures as expected.
- **Intense Interlock Movement Under SET (A0909):** Similar to A0903 but with random SETs on individual wires occurring every clock cycle, testing resilience under high-stress SET conditions.
- **Operational Condition Test Under Intense SET+SEU (A0910):** Simulates a semi-static operational state bombarded with frequent SEUs and SETs to assess AMAC’s ability to avoid catastrophic failures (any unintentional triggering of any interlocks or other resets).
- **SEUstat Register Test (A0911 & A0912):** Verifies AMAC’s capability to log SEUs accurately in the SEUstat registers, which is crucial for tracking radiation-induced register bit-flips.
- **Flag Validation Tests (A0921 & A0922):** Injecting randomness to Analog Monitor’s reported value to simultaneous SEUs and double SEUs, ensuring that the flag validation mechanism can effectively prevent false activations or deactivations.

These simulation tests assess AMAC’s resilience to SEE, particularly focusing on the interlock mechanism’s stability and accuracy. This verification ensures AMAC can reliably operate against the HL-LHC’s challenging radiation environment.

#### 5.4.3.2 Example 1: Interlock Moving Test Under SEE

The Interlock Moving Test is a key part of the radiation hardness verification suite for AMAC, evaluating the interlock state machine’s resilience against Single Event Upsets (SEUs). This test checks that AMAC’s interlock mechanism can maintain accurate operational states, without unintended shutdowns or activations due to SEE impacts. The test runs with two concurrent coroutines:

**Coroutine 1:** Cycles through the interlock state machine’s primary states—OFF (0), ON (1), and LOCK (3)—in response to simulated analog inputs (see Figure 5.48). This part checks if the

interlock transitions correctly under normal conditions.

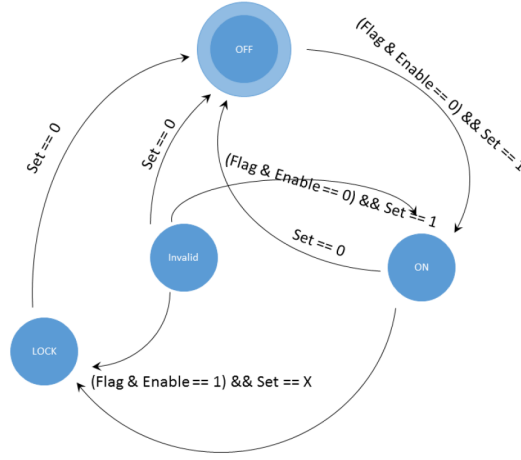


Figure 5.48: AMAC Interlock States. From AMACStar Specification.

**Coroutine 2:** Runs in parallel, applying frequent SEUs to the relevant registers to simulate intense radiation, randomly flipping register values (see Figure 5.49).



Figure 5.49: Example screenshot of SEU effect on flipping the register value, and AMAC's immediate recovery via triplication during an Interlock radiation test simulation. The arrows pointed to instances of SEU recovery via triplication during the simulation, highlighting the system's capacity to self-correct in the face of radiation-induced data corruption.

The main goal of this test is to validate the interlock system's ability to reliably maintain and transition between states, even under intense SEU rates well exceeding typical operating conditions. Successful test completion confirms AMAC's resilience against SEUs, particularly in avoiding unintended shutdowns or activations.

### 5.4.3.3 Example 2: Radiation Saturation Test under Semi-Static Condition

The Semi-Static Condition Radiation Saturation Test evaluates AMAC's resilience to extreme radiation conditions by simulating a high frequency of SEUs and SETs to the maximum, stressing

the system's interlock and LDO outputs (Figure 5.50). This test is essential to verify that AMAC's critical components maintain stability and avoid unintended shutdowns under severe radiation exposure.

Figure 5.50: **Cadence® Simulation Overview:** Visualization of simulated SEEs randomly injected across AMAC's registers and nets, illustrating the aggressive stress test.

The test environment mirrors operational conditions, with key configurations as follows:

**LDO Output Monitoring:** LDO outputs, which control connected ASIC components, are monitored to ensure that neither unexpected shutdowns nor unintentional activations occur, while key registers are checked for staying at a consistent value.



This test was executed in 25 parallel simulation jobs, totaling over 88 million SEE events, averaging 390 SEEs per wire/register, as shown in Figure 5.51.

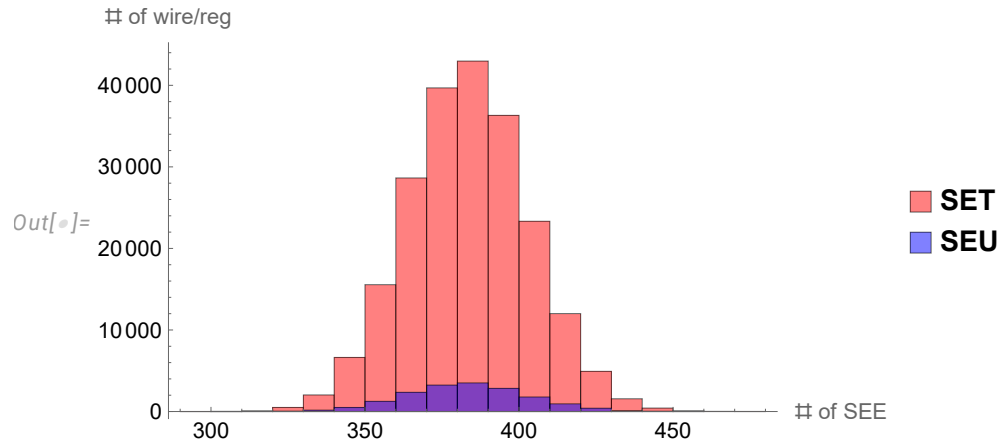


Figure 5.51: **SEE Distribution Summary:** Total of 88.8 million SEEs injected, averaging 390 events per wire/register.

Observed error modes can be classified into benign and malignant cases, only those that require a reset are considered failures:

- **Communication Issues:** Temporary response losses due to a small impact in the communication line were benign and easily recovered. Persistent losses that require a hard reset to re-establish communication are considered malignant.
- **Register Discrepancies:** Expected value changes in SEU logging registers were observed without issue, while unresolved discrepancies in other registers will prompt a reset and is considered bad.
- **Interlock and LDO Pad Activations:** Intermittent LDO pad flips self-resolved as expected within 100ns (if SEE directly hits a connectin wire). Given the physical design of the output PAD line, such incidents won't manifest under normal conditions. Any failure to self-correct required an immediate reset to restore normal operation.

Figure 5.52 presents a comprehensive error log, compiling instances from multiple simulation jobs to provide a holistic view of the AMAC's performance under test conditions. The error log highlights

the following errors:

1. **Temporary LDO Pad Flips:** Numerous temporary LDO pad flips were observed due to SETs impacting output wires. These flips were transient and automatically resolved, showcasing the LDO pads' resilience to brief, radiation-induced disruptions.
2. **Response Lost:** A single lost register response occurred, attributed to an interrupted read. This was quickly resolved by retrying the command, demonstrating AMAC's ability to handle minor interruptions effectively.
3. **Endeavour Reset:** No resets were observed within the Endeavour communication block, underscoring the robustness of AMAC's communication system under high-frequency SEEs.
4. **Register Value Integrity:** Register values remained consistent, with no unexpected changes outside the SEU logging registers, affirming the stability of AMAC's core logic and state.
5. **LDO Pad Flip Followed by Hard Reset Command:** Two initially flagged critical events were identified as false positives. Detailed analysis confirmed these incidents as simulation artifacts rather than actual failures in AMAC's operation.

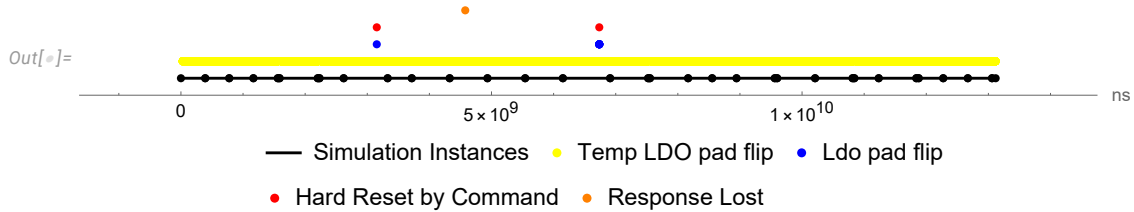


Figure 5.52: **Error Summary Log** capturing key test outcomes: temporary LDO pad flips from simulated SETs, minor register response interruptions, and results of comprehensive register value consistency checks across 124 registers with approximately 850 value validations on each register (no such errors were found). The total record is concatenated from multiple simulation instances (marked by the black dots).

The two false positives include unrealistic scenarios as follows:

- **First LDO Pad Flip:** An SET coincidentally impacted the same output line shortly after a previous flip, leading the testbench to flag a failure. However, this was confirmed to be a

conincidental self-resolved incident, not a persistent fault.

- **Second LDO Pad Flip:** A SET affecting a high-level clock line caused timing violation errors in the simulation, leading to randomized register values and unintended LDO deactivations. This randomization scenario is not possible in actual operations.

These findings affirm AMAC's resilience to extremely intense SEEs, demonstrating its ability to withstand the high-radiation environment of the HL-LHC.

## CHAPTER 6

### Conclusion

During my PhD, I pursued two primary projects that advanced methodologies in high-energy physics: the search for Higgsinos in compressed mass spectra using neural networks, and the design verification of the AMAC ASIC for the ATLAS Upgrade for the High-Luminosity LHC. Additionally, I collaborated on a machine learning project in astrophysics, applying autoencoder models to galaxy spectra analysis.

### 6.1 Summary

#### Search for Higgsinos in Compressed Mass Spectra

The search for Higgsinos addressed the challenge of detecting supersymmetric particles with small mass differences between the lightest supersymmetric particle (LSP) and next-to-lightest supersymmetric particles (NLSPs). Such scenarios result in soft decay products that are difficult to observe and model.

To overcome this, I developed a two-level Fully Connected Neural Network (FCNN) to optimize signal region selection for these events. This approach leveraged modern machine learning techniques to enhance sensitivity while mitigating overfitting and statistical bias. A semi-data-driven background estimation method was implemented, combining Monte Carlo simulations with data-driven corrections using kinematics-dependent reweighting factors. Multiple orthogonal validation regions exploiting the two-level FCNN selection ensured that the VRs had kinematics similar to the SR and minimal signal contamination. Across all 14 orthogonal VRs, the MC and data yields agreed within  $1.1\sigma_{\text{total}}$ , with distribution shapes showing strong agreement across all key kinematic variables.

Key achievements include:

- **Enhanced Sensitivity:** Excluded chargino masses up to approximately 190 GeV with mass splittings between 300 MeV and 1.1 GeV, building on the long-standing constraints at 95 GeV set by LEP.
- **Methodological Innovation:** The cut-based analysis optimized in parallel by the Kyoto team excluded a smaller region, up to 170 GeV with mass splittings between 300 MeV and 0.9 GeV. The NN approach effectively achieved a substantial increase in the dataset size compared to traditional analyses.
- **Robust Background Estimation:** Systematically improved MC modeling of background processes, enhancing the reliability of the results for ML-based analysis.

## Design Verification of the AMAC ASIC

The AMAC ASIC is crucial for monitoring and controlling the operational parameters of the ITk Strip modules, ensuring stable and efficient operation under high-radiation conditions. My contributions to the project included:

- **Prototype Testing and Calibration:** Developed a comprehensive test procedure for device calibration, functionality testing, and performance evaluation. Identified and helped to address multiple design oversights in the AMACv2a prototypes that affected performance and adjustment margins, resulting in a more reliable AMACStar production version.
- **Automated Testing System:** Created an automated Python framework, streamlining data collection and analysis, and integrated test results into the ITk Production Database.
- **Simulation Verification:** Ensured the AMACStar met all specifications through comprehensive simulation tests using the `cocotb` framework, verifying radiation hardness and functionality under extreme Single-Event Effects (SEE).

These efforts contributed to the successful passing of the AMAC's Final Design Reviews, advancing the design to production. By enhancing the reliability of the AMAC ASIC, they support the ITk

detector’s ability to operate effectively under HL-LHC conditions, aiding the pursuit of new physics discoveries in the coming decades.

### **Collaboration on Astrophysics Autoencoder**

In collaboration with Ms. Yan Liang from Princeton Astro Data Lab, I developed the SPENDER autoencoder model to encode Sloan Digital Sky Survey (SDSS) spectroscopic galaxy samples into low-dimensional representations and decode them into realistic spectra. My contributions included:

- **Latent Space Metric & Novel Similarity Loss Term:** Developed a new loss function to create a robust and interpretable latent space that effectively captures the physical properties of galaxies.
- **Applications Enabled by Latent Space Improvements:** Improved robustness in data analysis tasks, such as ensuring redshift invariance, and detecting outliers through clustering similar galaxies and isolating anomalies.

This work demonstrates the potential of physics-informed machine learning to uncover underlying astrophysical processes and has applications in high-energy physics data analysis, such as identifying rare events in LHC experiments.

## **6.2 Future Directions**

Building upon the methodologies and insights developed during my PhD research, several promising avenues for future work emerge in both high-energy physics analysis and detector technology development.

### **6.2.1 Advancements in Machine Learning for High-Energy Physics**

#### **Refining Collider Searches with Graph Neural Networks**

To further improve the detection of beyond-the-Standard-Model (BSM) signals, future research could extend the methodologies developed in this dissertation by employing Graph Neural Net-

works (GNNs). GNNs naturally handle complex relationships between particles in collider events, potentially providing greater sensitivity to diverse event topologies. By incorporating physics symmetries, such as Lorentz invariance, directly into the network architecture, model performance and generalizability might be enhanced. Developing training techniques that are less sensitive to specific signal models could allow for more efficient exploration of vast parameter spaces in BSM theories.

### **Unsupervised Anomaly Detection with Autoencoders**

Given the limited evidence for new physics at colliders, there is a growing interest in model-independent search strategies. Adapting autoencoder concepts from my prior work to graph-based representations of detector data might facilitate unsupervised anomaly detection. By learning efficient latent space representations of normal collision events, autoencoders could identify rare, anomalous events that may indicate new physics. Challenges such as handling inherent degeneracies in collider data and embedding symmetries (e.g., rotational and boost invariance) could be addressed by incorporating domain knowledge into the model architecture as done in the Galaxy Autoencoder project.

## **6.2.2 Enhancements in ASIC Design Verification and Testing**

The increasing complexity of ASIC designs necessitates more robust verification and testing methodologies. Future efforts in this area could be dedicated in some of the following strategies:

### **Advanced Simulation Verification Techniques**

Integrating accessible programming frameworks like Python-based `cocotb` into the simulation verification process can improve efficiency and accessibility. Developing more structured and rigorous functional tests that map directly to design specifications might help identify design oversights and vulnerabilities, including those caused by radiation effects. Establishing systematic feedback loops between simulation and design revisions could lead to more efficient iterations to comprehensively improve the designs of ASIC.

### **Formal Verification and Automated Testing**

Applying mathematically rigorous formal verification methods could provide stronger guarantees of ASIC functionality and reliability. Integrating formal proofs into automated verification tools may enable continuous validation throughout the design process, reducing the risk of costly errors. Leveraging AI-assisted coding and automated test generation might alleviate the human burden and increase the robustness of testing suites.

### **Centralized Knowledge Databases for Collaborative Development**

Developing centralized databases to manage data from design, verification, and testing phases is crucial for large collaborations like ATLAS. Such databases serve as comprehensive repositories, storing test results, design iterations, performance metrics, and calibration settings. However, while we currently have a significant amount of test results stored in the database, interpreting them still requires considerable expertise due to the intricate details and interrelated logic that are not easily accessible. Incorporating AI technologies, such as large language models (LLMs), could address these challenges by enhancing accessibility. Researchers could query the system in natural language, and receive detailed explanations. This approach might aid detector development, enabling broader participation and fostering interdisciplinary collaboration.

## **6.3 Closing Remarks**

This dissertation reflects a journey during my PhD program, addressing challenges in high-energy physics through innovative methods and interdisciplinary collaboration. It encompasses efforts to advance machine learning techniques for supersymmetric particle searches and to improve the reliability of detector components for the High-Luminosity LHC.

As our understanding of fundamental physics continues to evolve, I believe that leveraging computational innovations and fostering cross-disciplinary collaboration will remain crucial in tackling future challenges. I hope the methods and insights presented here contribute to our current understanding and provide a foundation for exploring new frontiers in physics and beyond.



## APPENDIX A

### Collaboration on Astrophysics Auto-encoder Projects

#### A.1 My Involvement in the Galaxy Autoencoder Project

The Galaxy Autoencoder Project was initiated during Ms. Yan Liang’s rotation in the Princeton Astrophysics Department under the supervision of Prof. Peter Melchior. The project aimed to develop an encoder-decoder architecture, SPENDER, for characterizing galaxy types through spectral data and identifying outliers.

My contributions focused on addressing the challenge of encoding degeneracy and introducing a new loss function to define a latent space metric. This work improved the interpretability of unsupervised machine learning analyses of galaxy spectra, laying the groundwork for subsequent advancements. Key outcomes included the development of a full-wavelength rest-frame model, which enabled robust redshift-invariant encoding and revealed correlations between physical quantities and latent space directions. These achievements demonstrated the potential of autoencoders to uncover underlying astrophysical processes from spectral data.

I co-presented a poster on this work at the NeurIPS 2022 Workshop in Machine Learning and the Physical Sciences and am a co-author of the paper *Autoencoding Galaxy Spectra. II. Redshift Invariance and Outlier Detection*, published in *The Astronomical Journal* [82]. Much of the content in this chapter is based on the findings presented in that publication.

This chapter focuses on my involvement, specifically the motivation for the latent space metric and the features introduced through the latent-restframe similarity loss. Detailed training setups, normalizing flow configurations, and outlier detection methods are covered in the referenced paper.

## A.2 Introduction to Galaxy Auto-Encoder

### A.2.1 Galaxy Spectroscopy and Motivation for Using Autoencoders

Spectroscopy is essential for understanding the physical processes that drive galaxy formation and evolution. However, extracting meaningful physical insights from the vast datasets produced by large spectroscopic surveys remains challenging. Existing approaches include:

1. **Theoretical Models:** These involve fitting theoretical models to observed spectral data [83, 84]. While highly interpretable, they often fail to reproduce high-quality galaxy spectra, leading to incomplete and potentially biased interpretations.
2. **Data-Driven Models:** These use linear combinations of templates to reconstruct spectra [85–89]. Although effective at disentangling telluric and redshift effects, these models are limited by template diversity and often require numerous components for accurate reconstruction.
3. **Machine Learning Techniques:** Methods such as unsupervised random forests [90] and self-organizing maps [91] are used for outlier detection. However, these methods cannot reverse the process of reconstructing galaxy spectra from their representations, limiting their utility for generating realistic spectral samples.

### A.2.2 The “spender” Autoencoder Architecture

Autoencoders (AEs) are neural network models that compress high-dimensional data into a low-dimensional latent space and then reconstruct the original data [92]. This approach is particularly suited to capturing the complex, non-linear features of galaxy spectra while facilitating tasks such as classification, clustering, and anomaly detection.

The SPENDER autoencoder (Figure A.1) builds on this concept by enabling redshift-invariant encoding of galaxy spectra [93]. Conventional AEs require galaxy spectra to be de-redshifted and resampled to a common rest frame, limiting the redshift and wavelength range that can be analyzed. In contrast, SPENDER introduces a redshift transformation directly into the decoder, allowing the

entire spectrum of galaxies at all redshifts to be used. This architecture compresses Sloan Digital Sky Survey (SDSS) spectra into a latent space where positions are invariant to redshift and encode galaxy “types.”

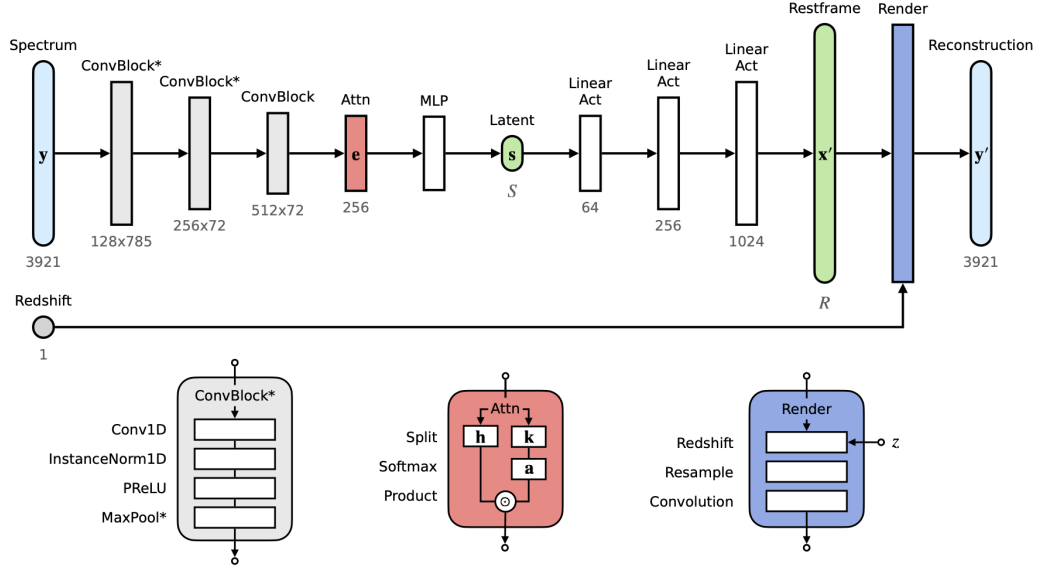


Figure A.1: Neural network architecture of the SPENDER autoencoder [29].

### A.2.3 Challenges in the Previous Architecture

Although the SPENDER architecture aimed to achieve redshift invariance, initial implementations did not consistently meet this goal: the same galaxy spectrum at different redshifts was encoded at scattered latent positions. Furthermore, the latent positions of similar spectra were sensitive to missing features, such as those caused by skyline masks or limited wavelength coverage.

This issue, referred to as “encoding degeneracy,” arises because the neural network’s flexibility allows the autoencoder to map different latent-space positions to similar rest-frame spectra. This resulted in multiple representations for the same galaxy spectrum under varying redshift or missing feature conditions.

My initial involvement focused on analyzing and addressing these challenges. Investigation revealed that while neural networks theoretically benefit from grouping similar spectra into the same latent

position, they often memorize specific features of individual spectra and redshift combinations instead of learning generalized physical patterns. To address this, I proposed a physically motivated solution: a latent space metric designed to enforce “bijectivity” and thus improve interpretability. This metric constrains the model’s flexibility, reducing overfitting and enhancing generalization power.

Details of this solution (Section A.3) and its resulting features (Section A.4) are discussed in the subsequent sections.

## A.3 Latent Space Metric & the Similarity Loss

### A.3.1 Motivation for Latent Space Metric

Before introducing the loss function for neural network training, in this sub-section, we will discuss the physics intuition, mathematical motivation of the latent metric, its implication in neural network training, and the expected features in the training results.

#### A.3.1.1 Physics Intuition: Inherent Galaxy Spectra

To address the challenge of latent space degeneracy and to build a physically interpretable latent space, I proposed a solution based on three key assumptions:

- **Assumption 1:** Galaxy spectra are driven by a few fundamental physical quantities. That is, physically similar galaxies have similar spectra, and vice versa.
- **Assumption 2:** Most galaxies have physically similar counterparts scattered throughout the universe, suggesting a continuum of physical features in observed galaxies.
- **Assumption 3:** The shapes of spectra of intrinsically similar galaxies differ only by their redshifts and possibly dust attenuation along the way.

The motivation behind **Assumption 1** is that: In the astrophysical scale, the dominant features would be driven by generic physical quantities like matter density distribution and molecular com-

position. Given we can only observe the galaxy using spectroscopy which provides limited amount information, we should be able to characterize a galaxy with limited physical quantities inferred from the spectra.

Given the large number of galaxies, and large number of galaxy spectra in the training dataset, based on the preliminary examination, we observed that **Assumption 2** is largely true, and the rare outliers are isolated and identified (See details in Section 5 in the Paper).

**Assumption 3** focuses on the inherent physical similarity of galaxies in their rest frame, advocating for a model that represents galaxy spectra by their physical rest-frame properties and redshifts. In summary, this approach aims to represent galaxy spectra with two components: a data-driven physical rest-frame model and their redshifts.

### A.3.1.2 Mathematics Intuition: Latent Space as Metric Space

To address the issue of physical interpretability in the machine learning context, specifically when using the latent space of an autoencoder, it is useful to adopt a mathematical perspective based on basic topology. To enable meaningful interpretation of the information compressed in the latent space, mappings must be established between the latent space and physical quantities. This requires the latent space to satisfy certain approximate mathematical properties, such as:

1. **Bijectivity:** Ensures that each “point” in the latent space corresponds to a unique type of galaxy spectrum and vice versa.
2. **Connectedness:** The latent position distributions are connected in the latent space. Thus, we are able to create a continuous mapping, allowing for the continual interpretation of physical quantity.
3. **Smoothness:** We can devise the mapping function between the physics-quantity-driven spectrum and the latent space to be smooth, allowing for further physics-informed transformation (interpretation) of the latent space.

Without delving into the detailed physical theories of galaxy formation, I propose modeling the latent space as a metric space and designing the neural network to satisfy these fundamental requirements. This approach ensures that degeneracy is resolved, providing a robust foundation for further interpretation.

### A.3.1.3 Machine Learning Model Training and Expected Features

In training neural networks with numerous spectra and features, the network tends to memorize typical features rather than organize them by physical properties. To counter this, we enforce the grouping of similar spectra by directly incorporating the metric into the training process as an additional **loss function**.

By structuring the latent space and enforcing a metric to group similar galaxies, we aim to improve the identification and classification of different galaxy types and enhance outlier detection. The expected features include:

- **Faithful Reconstruction:** The autoencoder should continue to accurately reconstruct spectra from the latent space, capturing essential features in a low-dimensional space
- **Redshift Invariance:** The autoencoder should reconstruct full-wavelength rest-frame spectra unaffected by redshifts, including unobserved features that are limited by redshifted wavelength range.
- **Correlation with Physical Quantities:** The latent space distribution should correlate with observable physical quantities, even if they are not used in training.

These features were achieved, as demonstrated in Section A.4, after much effort in implementation and tuning by Ms. Yan Liang.

### A.3.2 Building Latent Space Metric with Training Losses

#### A.3.2.1 Reconstruction-Fidelity Loss in “spender”

Our basic training in Melchior *et al.* [93] used a conventional fidelity loss to quantify reconstruction quality, assuming normally distributed noise. This loss measures the mean log-likelihood of the reconstruction of spectral elements averaged over batches of  $N$  spectra with number of wavelength bins  $M$ :

$$L_{\text{fid}} = \frac{1}{2NM} \sum_i^N \mathbf{w}_i \odot (\mathbf{x}_i - \mathbf{x}_i'')^2 \quad (\text{A.1})$$

, where  $\mathbf{x}_i$  is the  $i$ -th input spectrum,  $\mathbf{w}_i$  its inverse variance, and  $\odot$  the element-wise multiplication. The reconstruction loss ensures the autoencoder compresses sufficient information into the latent space to reconstruct rest-frame spectra accurately.

#### A.3.2.2 Simplest Latent Space Metric: Rest-frame Similarity Loss

I proposed the use of  $L_{\text{sim}}$  to enforce proportionality between latent and spectral distances. This ensures that each latent position corresponds to one rest-frame model by linking the distance in latent space  $|\mathbf{s}_1 - \mathbf{s}_2|$  between two spectra to their distance in rest-frame space  $|\mathbf{x}'_1 - \mathbf{x}'_2|$ .

We define a similarity loss  $L_{\text{sim}}$  that operates on the two intermediate stages as shown in A.3. Let  $\mathbf{s} = f_\theta(\mathbf{x})$  be the encoded latent vector and  $\mathbf{x}' = g_\phi(\mathbf{s})$  be the rest-frame model, where  $f_\theta$  and  $g_\phi$  are the parameterized encoder and decoder functions. The simplest bijective requirement demands: if two rest-frame models,  $\mathbf{x}'_i$  and  $\mathbf{x}'_j$ , are similar, their latent positions  $\mathbf{s}_i$  and  $\mathbf{s}_j$  should also be similar. Conversely, distinct models should have well-separated latent positions.

The desired relation will be naturally satisfied if the latent distance is constrained to be proportional to a spectral distance:  $|\mathbf{s}_1 - \mathbf{s}_2|^2 \propto |\mathbf{x}'_1 - \mathbf{x}'_2|^2$ , motivating the following loss term to be set-up:

$$\begin{aligned}
L_{\text{sim}}(\mathbf{S}, k_0, k_1) = & \frac{1}{N^2} \sum_{i,j}^N \text{sigmoid}(k_1 \mathbf{S}_{i,j} - k_0) \\
& + \frac{1}{N^2} \sum_{i,j}^N \text{sigmoid}(-k_1 \mathbf{S}_{i,j} - k_0),
\end{aligned} \tag{A.2}$$

where

$$\mathbf{S}_{i,j} = \frac{1}{S} |\mathbf{s}_i - \mathbf{s}_j|^2 - \frac{1}{M} |\mathbf{w}' \odot (\mathbf{x}'_i - \mathbf{x}'_j)|^2, \tag{A.3}$$

$\mathbf{w}'$  is the inverse-variance weight defined at restframe wavelengths, and  $k_0, k_1$  are adjustable hyper-parameters that control the steepness of the slope (the variation of these hyper-parameters are discussed in later Section A.3.3.2).

$L_{\text{sim}}$  ensures latent distances align proportionally with spectral similarities as defined in Equation A.3. For each randomly-picked batch of  $N$  spectra trained, we compare each restframe spectrum  $\mathbf{x}'_i$  to every other restframe spectrum  $\mathbf{x}'_j$ , and calculate the pairwise distances as a  $N \times N$  matrix. If the restframe models  $\mathbf{x}'_i$  and  $\mathbf{x}'_j$  are similar but have a large latent distance, the first sigmoid term brings them closer in latent space. Conversely, if the restframe models are dissimilar but have a close latent position distance, the second sigmoid term pushes their latent positions apart.

### A.3.2.3 Connecting Similar Galaxies

With the similarity loss, we can connect galaxies with similar physical properties but observed at different distances (redshifts), as shown in Figure A.2. Starting from two spectra from two intrinsically-similar galaxies:

- By restframe similarity loss  $L_{\text{sim}}$ , we connect two similar looking restframe model;
- By reconstruction fidelity loss  $L_{\text{fid}}$ , we connect each spectrum to parts of its restframe model.

With this process, after seeing new spectra, we could put them in the latent position where similar-



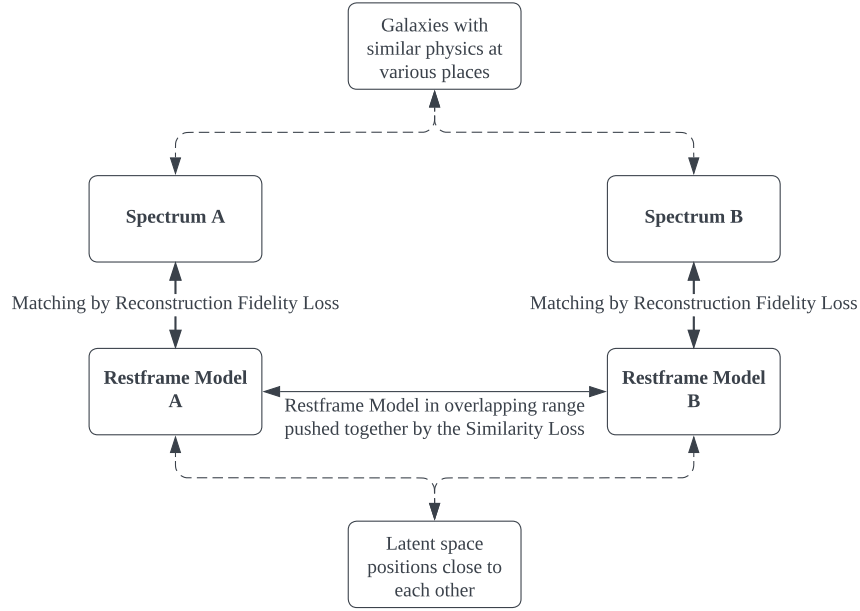


Figure A.2: Neural network mapping of physics to latent space positions, guided by training losses.

looking spectra could look like.

Note that the redshift can cause a galaxy spectrum to be only partially observable on the earth's end. Because of this connection logic, we can use different redshift galaxies to construct a full wavelength range restframe model that corresponds to a single physical origin. This also enables us to extrapolate what the unseen part of a spectrum could look like using other similar galaxies (see SectionA.4.3).

Without the similarity loss, the autoencoder would store information for the same type of galaxy with different redshifts or instrumentation limitations in different parts of the parameter space, losing the connection between them.

### A.3.3 Implementation in the Autoencoder Structure

#### A.3.3.1 Application in “spender” Architecture

Figure A.3 illustrates how  $L_{\text{sim}}$  and  $L_{\text{fid}}$  are integrated across the SPENDER architecture to link latent metrics with rest-frame similarity.

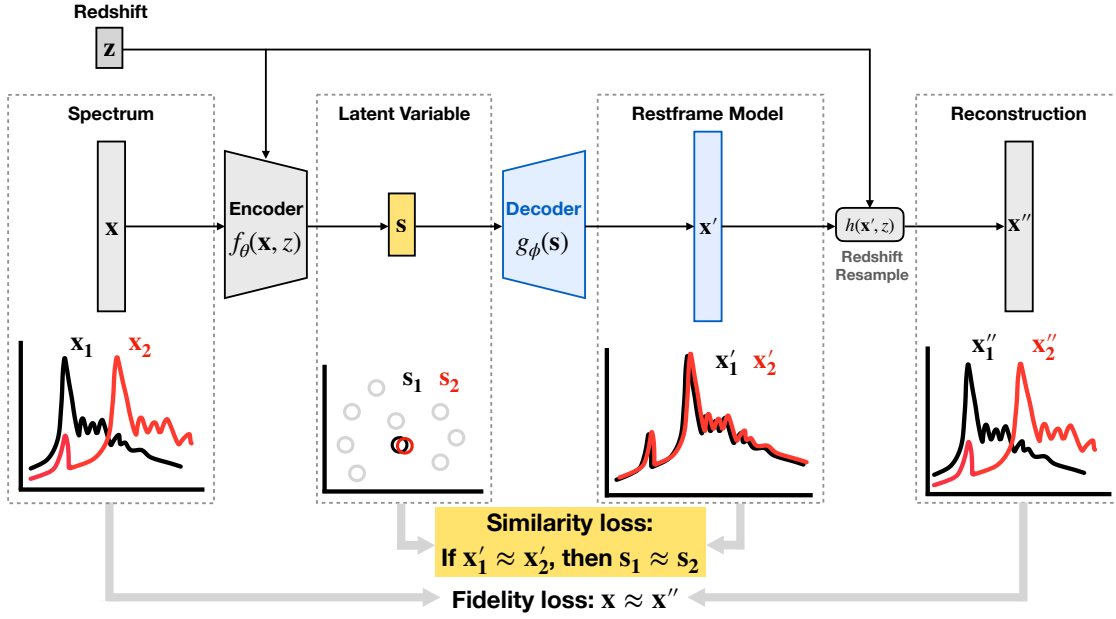


Figure A.3: Autoencoder architecture with new similarity loss function linking the latent space metric to the rest-frame spectral similarity.

The autoencoder architecture consists of an encoder compressing spectral data into a latent space and a decoder reconstructing the spectra from the latent representation. To address encoding degeneracy, the similarity loss term penalizes discrepancies between latent representations of spectra that should be similar, organizing the latent space to reflect true similarities and differences between galaxy types.

#### A.3.3.2 Definition of Loss Functions

Three loss functions are trained together across all four stages shown in Figure A.3

$$L_{\text{total}} = L_{\text{fid}} + L_{\text{sim}} + L_c \quad (\text{A.4})$$

The consistency loss term,  $L_c$ , will be discussed in the next section. Before  $L_c$  is turned on, we optimize  $L_{\text{fid}} + L_{\text{sim}}$  simultaneously, with an “inverse-annealing” cycle to gradually increase the slope  $k_1$ , while keeping  $k_0$  constant, as shown in Figure A.4

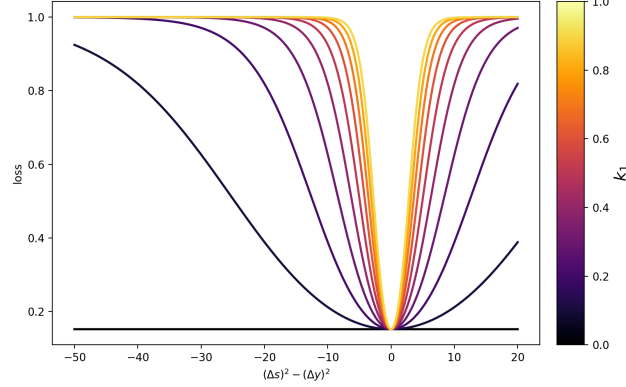


Figure A.4: Annealing with the sigmoid similarity loss function.

### A.3.3.3 Targeting Redshifts: Additional Consistency Loss

To further improve encoding stability, we minimize an additional consistency loss, defined as the latent distance between the input spectrum and its artificially redshifted augment  $|\mathbf{s}_i - \mathbf{s}_{i,\text{aug}}|$ . This redshift augmentation loss helps the model learn redshift invariance by varying the rest-frame model at different redshifts.

Inspired by [94], we add the consistency loss as a more guided form of the similarity loss:

$$L_c = \frac{1}{N} \sum_i \text{sigmoid} \left[ \frac{1}{\sigma_s^2 S} |\mathbf{s}_i - \mathbf{s}_{\text{aug},i}|^2 \right] - 0.5 \quad (\text{A.5})$$

where  $\mathbf{s}_i$  and  $\mathbf{s}_{\text{aug},i}$  are the latent positions of the original and its corresponding augment spectrum, that has been redshifted by a random  $z_{\text{new}}$  from a uniform distribution between  $[0, 0.5]$ .

In practice, we set  $\sigma_s = 0.1$  which provides a good trade-off between the consistency and the overall

scale of the latent distribution. Minimizing  $L_c$  reduces the latent distances between galaxy spectra and their augments, improving the encoding stability against redshift variation. The consistency loss reinforces that physically similar spectra pairs at different redshifts are pulled together in latent space, while dis-similar pairs are moved apart by the (dis)-similarity loss term Equation A.3.

This combination of these losses makes the latent space more expressive by reusing the same encoding and decoding parameter spaces for similar galaxies, rather than memorizing each individually.

It is critical to note that the consistency loss,  $L_c$ , must not be used without  $L_{\text{sim}}$ . Without the similarity loss pushing dissimilar spectra apart, the consistency loss would collapse the latent space indefinitely into a nonsensical distribution.

## A.4 Application in Galaxy Auto-encoder Project

This section demonstrates the successful application of the enhanced autoencoder model, highlighting its improved performance in generating realistic spectra, detecting outliers, and correlating latent space with physical properties.

### A.4.1 Spectra Dataset

We select  $\sim 500,000$  galaxy spectra spanning redshift  $z \in [0, 0.5]$  from Sloan Digital Sky Surveys Data Release 16 [95]. Our sample includes all optical spectra that are classified as galaxies and have redshift error  $z_{\text{err}} < 10^{-4}$ . Approximately 70% of the samples are used for training, 15% for validation, and 15% is held for testing. All spectra are zero-padded to a homogeneous wavelength  $\lambda_{\text{obs}} = 3784 \dots 9332 \text{\AA}$ . We use inverse variance weights and masks provided by SDSS Data Release 16 as flux uncertainties. Additionally, we mask out telluric contamination by assigning zero weights to within  $5 \text{\AA}$  of the top  $\sim 100$  telluric lines, amounting to 12% of the data vectors. All spectra are normalized by the median flux over restframe wavelengths  $\lambda_{\text{rest}} = 5300 \dots 5850 \text{\AA}$ . The restframe normalization is chosen to be relatively quiet and accessible at all redshifts to avoid redshift-dependent amplitudes.

Note that the exact same architecture (including the similarity loss and the consistency loss) was applied to the DESI dataset (see [96]). The DESI dataset analysis identified low-probability objects, discovering outliers with distinctive spectral features and misclassified stars. This work led to a rich catalog of objects with unusual physical properties, such as irregular emission lines, galaxy mergers, and rare quasar types. Additionally, the analysis revealed issues in data processing pipelines, motivating the development of a new star model with the same architecture. These results and pre-trained models are available publicly for further studies.

#### A.4.2 Result 1: Redshift Invariance

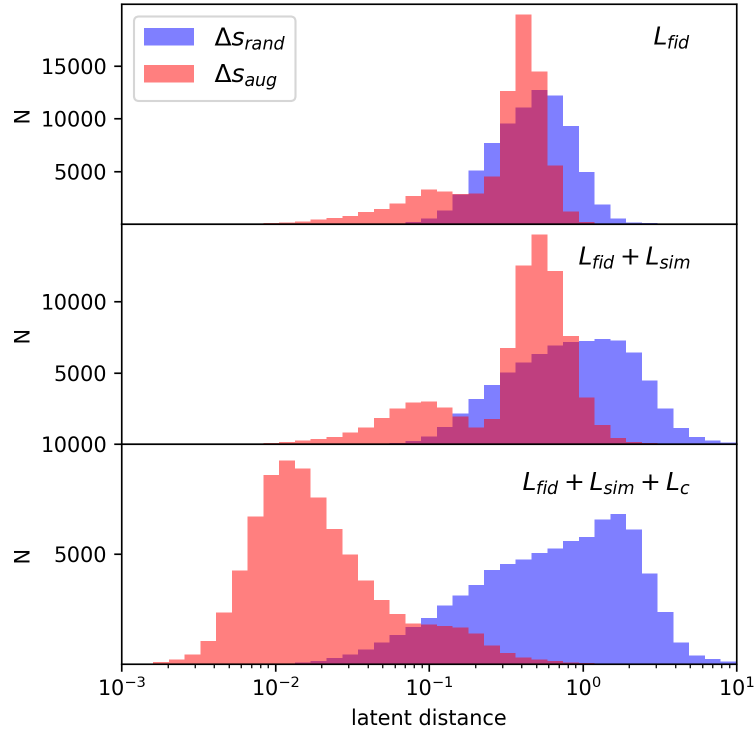


Figure A.5: Euclidean distance distribution in latent space for redshifted augment spectra w.r.t. original spectra  $\Delta s_{aug}$  (red), and randomly selected galaxy pairs  $\Delta s_{rand}$  (blue).

Augmented spectra are created by artificially altering the redshifts of the original spectra. If the encoder is redshift invariant,  $\Delta s_{aug}$  should be close to zero. The three panels in Figure A.5 show the results of training with different terms in the loss function Equation A.4. Optimizing the full loss function (bottom panel) significantly reduces  $\Delta s_{aug}$  while increasing  $\Delta s_{rand}$ , thereby enhancing

the separation of different spectral types in latent space.

Including the similarity loss  $L_{\text{sim}}$  encourages dissimilar spectra pairs to move apart, as seen in the middle panel of Figure A.5, doubling the average latent distance between random spectra pairs. Optimizing  $L_c$  along with  $L_{\text{fid}} + L_{\text{sim}}$  reduces the average latent distance of augmented redshifted spectra by a factor of  $\sim 10$  (Figure A.5, bottom panel). As a result, in the latent space of the best-fit model, the true and augmented spectra are 25 times closer to each other than the average pair-wise distance, while for the fidelity-alone model, the original and augmented spectra are only 1.5 times closer than the average. This order-of-magnitude improvement has been achieved with a very minor decrease in fidelity, suggesting that the autoencoder indeed has sufficient flexibility to accommodate the additional demands to the latent space without sacrificing reconstruction quality.

With the best model, we achieve a desirable redshift-invariant behavior. Figure A.6 shows the reconstructed restframe model and encoded latent position for an example galaxy. The latent positions of the original and redshift-augmented spectra are stably grouped together (colored markers in the right panel).

### A.4.3 Result 2: Reconstructing Un-observed Feature

One of the significant achievements of this project was the development of a full wavelength rest-frame model. This model allows the autoencoder to identify galaxy types with truncated information and extrapolate the intrinsic model to unseen wavelengths, effectively reconstructing missing features. This capability demonstrates the power of autoencoders in handling incomplete data and making accurate predictions about unseen spectral features.

With the all three losses combined together, as discussed in Section A.3.2, we are able to extrapolate unseen features for a partial spectra. As shown in Figure A.6, for the  $z = 0.45$  augment (orange), where the dominant  $\text{H}\alpha$  emission line lies outside the observable wavelength range and is unavailable to the encoder, the reconstruction quality remains robust despite the missing features.

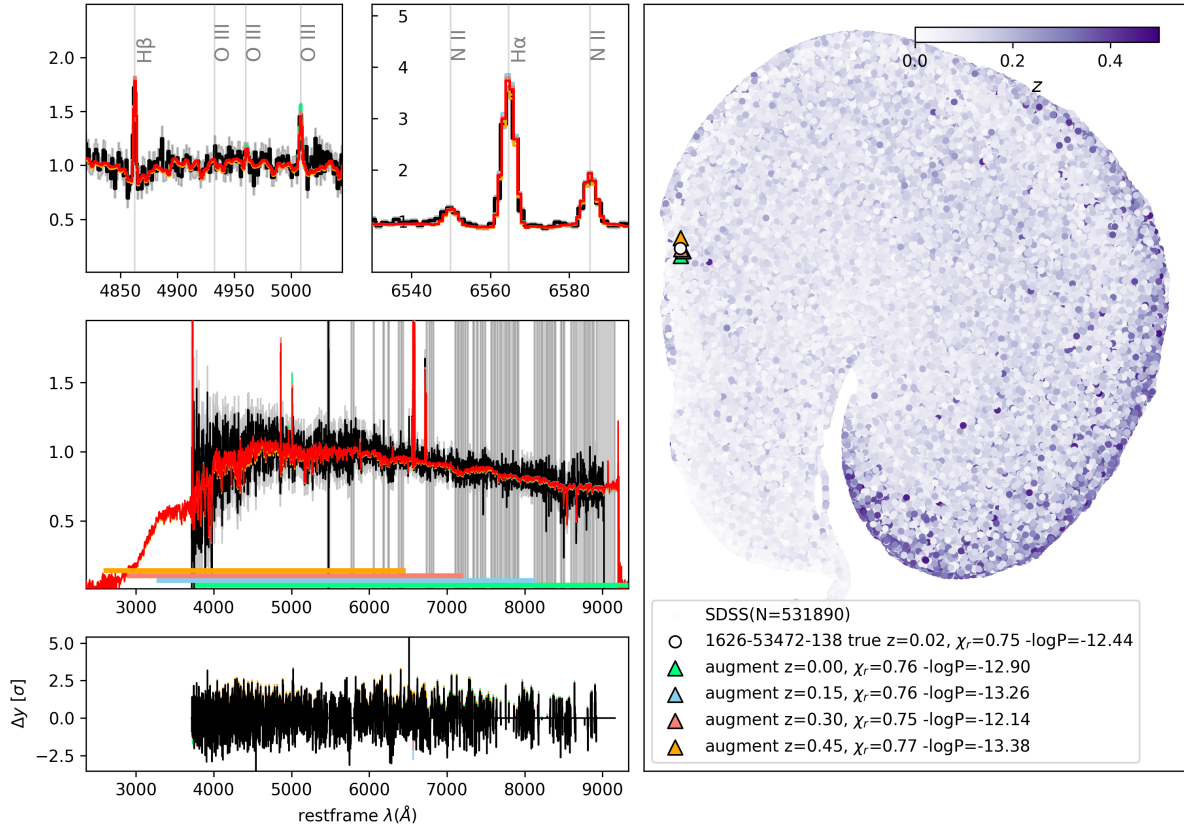


Figure A.6: *Left:* Observed spectrum (black) of a galaxy from the test sample at  $z = 0.02$ , its reconstruction (red), and reconstructions of augmented spectra with artificially altered redshifts (color-coded). Zoomed-in versions are shown on the top. The colored bar in the middle-left shows the observed wavelength range of the augments. *Right:* UMAP-embedded latent space distribution of the entire SDSS galaxy sample. The white circle marks the example spectrum, and the triangles mark its augments.

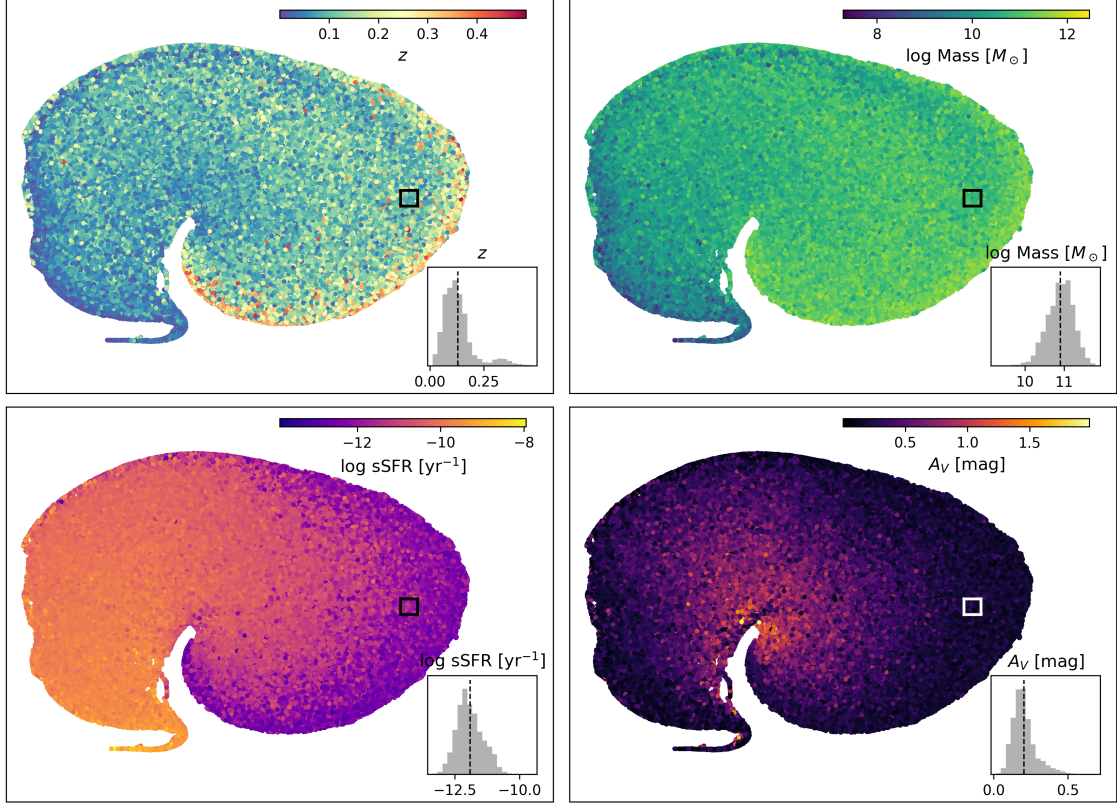


Figure A.7: UMAP embedding of the latent variables for all 531,890 SDSS galaxy spectra, color-coded by redshifts (top left), stellar masses (top right), specific star formation rates (lower left), and dust attenuation in restframe V band (lower right). The lower right histograms show the distribution of physical properties of  $\sim 2000$  samples located inside a small box (marked black/white) in the UMAP space.



#### A.4.4 Result 3: Interpretable Latent Space

Despite not explicitly optimizing for orthogonality in the latent space dimensions, we observed a clear trend correlating physical quantities with specific directions in the latent space. This finding supports our assumption that inherent physical processes in galaxy evolution can be learned from spectra. We utilized the UMAP (Uniform Manifold Approximation and Projection) method to visualize the latent space embedding of the SDSS galaxy dataset. UMAP is known for its computational efficiency, scalability, and ability to preserve both local and global data structure [97]. As shown in Figure A.7, the UMAP embedding of the dataset is continuous and connected. To test our assumption that the latent space encodes the physical properties of the galaxy without our supervision, we plot the stellar masses, star formation rates, and dust attenuation estimates from the GALEX-SDSS-WISE LEGACY CATALOG [98, 99], which covers  $\sim 80\%$  of the SDSS galaxy spectra.

The 2-dimensional embedding of the latent space strongly correlates with each of the physical properties: the specific star formation rate is predominantly following a continuous trend in the counter-clockwise direction, from the most quiescent galaxies to starburst galaxies (bottom left panel). The stellar mass of galaxies correlates with the clockwise direction (top right panel). The galaxies with the strongest dust attenuation seem to cluster around a “locus” where the star-forming and quiescent galaxies are squeezed together, and the attenuation weakens inside-out in the radial direction (bottom right panel).<sup>12</sup>

Although different latent space regions may have similar physical color-coding, they correspond to visually distinct spectra. The three quantities above do not uniquely determine a latent space position, indicating additional physical properties are encoded in the latent space.

By inspecting the latent space structures, we conclude that our latent space is well-behaved and physically informative. One can, for instance, assign an estimate of the physical properties of an SDSS-I spectrum according to its neighbors in latent space (see histograms in the rectangle

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<sup>12</sup>One might notice that the stellar mass appears to correlate with redshift (top left panel). As we have argued in Melchior *et al.* [93], this is an artifact of a magnitude-limited sample. At high-redshift, only the most massive galaxies are observed, while low-mass galaxies can be observed only at low redshifts.

in Figure A.7). This demonstrates that encoded parameters contain valuable information about the physics of a galaxy. This information can be utilized for various diagnostic purposes, such as detecting instrumental or pipeline failures, transforming new data, reducing noise, providing context for spectra, or being adapted to perform new analyses. Without the similarity and consistency loss introduced in subsection A.3.2, the association between latent space position and physical parameters would be subject to random scatter from variations in redshift.

#### A.4.5 Results in Astrophysics

The similarity loss term significantly improved the model’s ability to detect outliers, enabling more accurate identification of anomalies in galaxy spectra. This facilitates a better understanding and analysis of unusual astrophysical phenomena. Despite the apparent simplicity of the UMAP embedding, the latent space has a complex distribution. To address this, we implemented an additional mapping from the SDSS galaxy sample’s latent distribution to a multi-dimensional normal distribution using a normalizing flow.

For comprehensive details and expert interpretations, please refer to our published paper.

### A.5 Summary and Future Directions

The SPENDER autoencoder model successfully recreates highly realistic spectra for the SDSS spectroscopic galaxy sample using six latent parameters, effectively encoding the physical properties probed by the galaxy spectra. Associating the latent space with a physically motivated metric, I introduced a novel loss term that directly relates distances in latent space to distances in rest-frame space. This approach discourages latent-space degeneracies, enabling the decoder to learn a robust and complete underlying rest-frame model across the entire redshift range. As a result, the latent space positions are now robust against missing features.

Training with the similarity loss further enhances the model’s ability to cluster physically similar galaxies in latent space, provided sufficient intermediate galaxies are available to link them. The autoencoder demonstrates the capability to identify galaxy types even with truncated information

and reconstruct features in the unseen wavelengths. Additionally, the similarity loss improves outlier detection by separating anomalous samples from the natural clustering of typical galaxies, facilitating the identification of unusual astrophysical phenomena.

Looking ahead, there are exciting opportunities to enhance and extend this work. Developing more meaningful metrics directly related to physical quantities could provide deeper insights into galaxy properties and evolutionary processes. However, this effort would require extensive calibration and domain expertise to align these metrics with astrophysical interpretations.

Another promising direction involves applying the spectra autoencoder architecture to stellar spectra to disentangle stellar activity from planetary orbital effects on radial velocity measurements of the stars. By compressing the spectrum into low-dimensional activity indices, this approach could advance the search for Earth-like exoplanets via radial velocity measurements, where stellar activity has been a significant challenge. Initial tests on simulated data, as detailed in the AESTRA project, have shown encouraging results. Ongoing work by Ms. Yan Liang includes extending these methods to solar data, with some contributions from my work as well.

## APPENDIX B

### Neural Network Displaced Track Analysis Appendix

#### B.1 Comparison with Similar Higgsino Searches

Figure B.1 shows typical Feynman diagrams for the search targets in different analysis scenarios across different  $\Delta m$  values. The corresponding branching ratio versus  $\Delta m$  can be found in Figure 4.4. The current existing limit for two of the following analyses can be found in Figure 4.1.

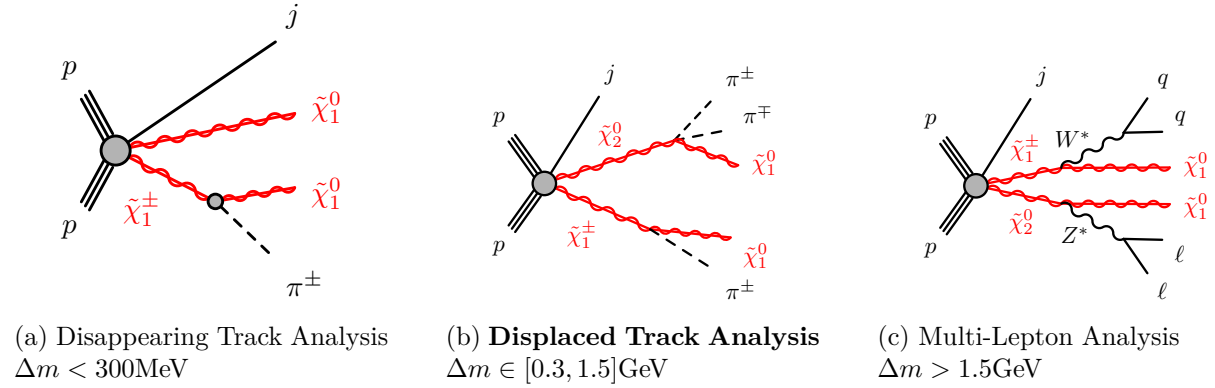


Figure B.1: Typical Feynman diagram of the search target in different analyses covering different mass-splittings  $\Delta m$ . Note that  $j$  denotes an ISR jet here.

The lifetime of  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$  is inversely proportional to their mass splitting, as depicted in Figure 4.3. This relationship implies that smaller mass splittings result in longer lifetimes, allowing particles like the chargino to travel measurable distances before decay, which is crucial for the detection strategies employed in this analysis. This behavior significantly influences the analysis approach, as outlined in Figure B.2, which visualizes how different decay scenarios are investigated based on the  $\Delta m$  value:

- (a) **Disappearing Track Analysis** ( $\Delta m < 300\text{ MeV}$ ): The chargino potentially decays between or beyond the tracker layers, resulting in a disappearing track characterized by minimal energy deposition in the calorimeter after a high momentum trajectory observed in the tracking layer.
- (b) **Displaced Track Analysis** ( $\Delta m \in [0.3, 1.5]\text{ GeV}$ ): In this scenario, the chargino decays before

reaching the first tracking layers. As a result, the track reconstructed by the detector corresponds to a charged pion emerging from a slightly displaced secondary vertex instead of the primary collision along the beam line. This analysis, the focal point of this dissertation, explores these displaced decay signatures.

(c) **Multi-Lepton Analysis** ( $\Delta m > 1.5$  GeV): With larger mass splittings, the chargino decays almost instantaneously after production. The decay predominantly results in leptonic products, which are more easily identified through their energy deposition characters in the calorimeter.

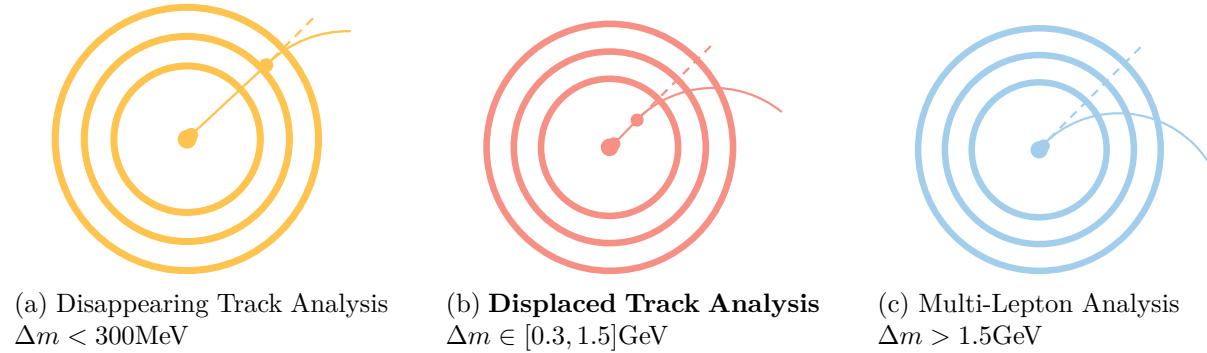


Figure B.2: Visualization of the inner layers of the detector and the decay vertices of  $\tilde{\chi}_1^\pm \rightarrow \tilde{\chi}_1^0$  for different mass splittings  $\Delta m$ . The depiction includes a high-momentum  $\tilde{\chi}_1^\pm$  entering (solid line), a high-momentum  $\tilde{\chi}_1^0$  exiting undetected (dashed line), and a charged pion or lepton with less momentum (curved track) indicating the decay product from a secondary vertex (solid dot).

## B.2 Sample List

The following sample list is directly quoted from the internal note prepared by members of the analysis team: **ANA-SUSY-2020-04**. The note provides detailed documentation of the simulation samples used in this analysis.

### B.2.1 Data and MC Sample List

Information of background samples used in the analysis is summarized in Table B.2.

| Period |         | Chain                       |
|--------|---------|-----------------------------|
| 2015   |         | HLT_xe70_mht                |
| 2016   | A - D3  | HLT_xe90_mht_L1XE50         |
|        | D4 - F1 | HLT_xe100_mht_L1XE50        |
|        | F2 -    | HLT_xe110_mht_L1XE50        |
| 2017   |         | HLT_xe110_pufit_L1XE55      |
| 2018   | B - C5  | HLT_xe110_pufit_xe70_L1XE50 |
|        | C6 -    | HLT_xe110_pufit_xe65_L1XE50 |

Table B.1: Summary of  $E_T^{\text{miss}}$  trigger chain.

### B.2.2 Derivations

The SUSY20 derivation is used for processing data and MC samples for the analysis. The p-tags for data and MC are p5242 and p5241, respectively. There are four types of selection applied in the SUSY20 derivation: two for this analysis and two for the 1 Lepton + 1 Track analysis, which is not documented here. Selections related to this analysis will be explained in detail. The first selection is applied to keep events with  $Z$  + jets,  $W$  + jets and  $\gamma$  + jets processes as well as our target signals:

- Require at least one jet with  $p_T > 200$  GeV and  $|\eta| < 2.8$ .
- Events must pass at least one of the following (lowest unprescaled) triggers :  $E_T^{\text{miss}}$  trigger, single lepton trigger, or single photon trigger.

The other selection is used to keep events from  $t\bar{t}$  for the validation of normalization factors (this selection is not used in the main analyses at the end):

- Require at least one muon with  $p_T > 10$  GeV and  $|\eta| < 2.7$ . The muon is also required to pass the `DFCommonMuonsPreselection`.
- Require at least two b-jets with  $p_T > 25$  GeV and pass the `FixedCut85_DL1r` selection.
- Events must pass at least one of the following (lowest unprescaled) triggers :  $E_T^{\text{miss}}$  trigger, single lepton trigger, or single photon trigger.

| Process        | DSID                    | Sample                                       |
|----------------|-------------------------|----------------------------------------------|
| Multiboson     | 345705 - 345706         | Sherpa_222_NNP30NNLO_ggllll_*                |
|                | 345715, 345718, 345723  | Sherpa_222_NNP30NNLO_ggllvv*                 |
|                | 363355                  | Sherpa_221_NNP30NNLO_ZqqZvv                  |
|                | 363356                  | Sherpa_221_NNP30NNLO_ZqqZll                  |
|                | 363357                  | Sherpa_221_NNP30NNLO_WqqZvv                  |
|                | 363358                  | Sherpa_221_NNP30NNLO_WqqZll                  |
|                | 363359                  | Sherpa_221_NNP30NNLO_WpqqWmlv                |
|                | 363360                  | Sherpa_221_NNP30NNLO_WplvWmqq                |
|                | 363489                  | Sherpa_221_NNP30NNLO_WlvZqq                  |
|                | 363494                  | Sherpa_221_NNP30NNLO_vvvv                    |
|                | 364250                  | Sherpa_222_NNP30NNLO_llll                    |
|                | 364253                  | Sherpa_222_NNP30NNLO_lllv                    |
|                | 364254                  | Sherpa_222_NNP30NNLO_llvv                    |
|                | 364255                  | Sherpa_222_NNP30NNLO_lvvv                    |
|                | 364283                  | Sherpa_222_NNP30NNLO_lllljj                  |
|                | 364284                  | Sherpa_222_NNP30NNLO_lllvjj                  |
|                | 364288                  | Sherpa_222_NNP30NNLO_llll_lowMllPtComplement |
|                | 364289                  | Sherpa_222_NNP30NNLO_lllv_lowMllPtComplement |
|                | 364290                  | Sherpa_222_NNP30NNLO_llvv_lowMllPtComplement |
|                | 364286 - 364287         | Sherpa_222_NNP30NNLO_llvvjj_*                |
|                | 364302                  | Sherpa_222_NNP30NNLO_ggZllZqq                |
|                | 364303                  | Sherpa_222_NNP30NNLO_ggZvvZqq                |
|                | 364304                  | Sherpa_222_NNP30NNLO_ggWmlvWpqq              |
|                | 364305                  | Sherpa_222_NNP30NNLO_ggWplvWmqq              |
| $\gamma$ +jets | 364541 - 364547         | Sherpa_222_NNP30NNLO_SinglePhoton_pty_*      |
| Dijet          | 364702 - 364712         | Pythia8EvtGen_A14NNPDF23LO_jetjet_*          |
| $t\bar{t}$     | 800036                  | Py8EG_A14N23LO_jetjet_JZ1WwithSW             |
|                | 410470 - 410471         | PhPy8EG_A14_ttbar_hdamp258p75_*              |
| Single top     | 345935, 407345 - 407347 | PhPy8EG_A14_ttbarMET*                        |
|                | 410644 - 410647         | PowhegPythia8EvtGen_A14_*                    |
|                | 410658 - 410659         | PhPy8EG_A14_tchan_BW50_lept_*                |
| $Z$ + jets     | 700320 - 700322         | Sh_2211_Zee_maxHTpTV2_*                      |
|                | 700323 - 700325         | Sh_2211_Zmumu_maxHTpTV2_*                    |
|                | 700326 - 700334         | Sh_2211_Ztautau_*_maxHTpTV2_*                |
|                | 700335 - 700337         | Sh_2211_Znunu_pTV2_*                         |
| $W$ + jets     | 700338 - 700340         | Sh_2211_Wenu_maxHTpTV2_*                     |
|                | 700341 - 700343         | Sh_2211_Wmunu_maxHTpTV2_*                    |
|                | 700344 - 700349         | Sh_2211_Wtaunu_*_maxHTpTV2_*                 |

Table B.2: Summary of background sample information

### B.2.3 NTuples

Common ntuples produced for this analysis use the SusySkimAna package. Specific configuration used for this analysis which rely on the **SusySkimAna** package resides in the SusySkimHiggsino package. Specically, the tuple production is configured in MonojetSelector. NTuples were produced with AnalysisBase 21.2.222.

| $\Delta m(\tilde{\chi}_1^\pm, \tilde{\chi}_1^0)$ | width [MeV]           | $\text{BR}(\tilde{\chi}_1^\pm \rightarrow e\nu_e \tilde{\chi}_1^0)$ | $\text{BR}(\tilde{\chi}_1^\pm \rightarrow \mu\nu_\mu \tilde{\chi}_1^0)$ | $\text{BR}(\tilde{\chi}_1^\pm \rightarrow \tau\nu_\tau \tilde{\chi}_1^0)$ | $\text{BR}(\tilde{\chi}_1^\pm \rightarrow \pi^\pm \tilde{\chi}_1^0)$ | $\text{BR}(\tilde{\chi}_1^\pm \rightarrow \pi^\pm \pi^0 \tilde{\chi}_1^0)$ |
|--------------------------------------------------|-----------------------|---------------------------------------------------------------------|-------------------------------------------------------------------------|---------------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------|
| 1.50                                             | $4.80 \cdot 10^{-9}$  | 0.226                                                               | 0.220522                                                                | 0.                                                                        | 0.246745                                                             | 0.306732                                                                   |
| 1.00                                             | $8.17 \cdot 10^{-10}$ | 0.176438                                                            | 0.167033                                                                | 0.                                                                        | 0.428895                                                             | 0.227634                                                                   |
| 0.75                                             | $2.24 \cdot 10^{-10}$ | 0.153102                                                            | 0.138997                                                                | 0.                                                                        | 0.654859                                                             | 0.0530423                                                                  |
| 0.50                                             | $5.09 \cdot 10^{-11}$ | 0.0890595                                                           | 0.0718403                                                               | 0.                                                                        | 0.835566                                                             | 0.00353413                                                                 |
| 0.35                                             | $1.52 \cdot 10^{-11}$ | 0.0502338                                                           | 0.0325023                                                               | 0.                                                                        | 0.917185                                                             | 0.000079166                                                                |
| 0.25                                             | $4.80 \cdot 10^{-12}$ | 0.0296155                                                           | 0.0125164                                                               | 0.                                                                        | 0.957863                                                             | $5.33038 \cdot 10^{-6}$                                                    |

---

| $\Delta m(\tilde{\chi}_2^0, \tilde{\chi}_1^0)$ | width [MeV]           | $\text{BR}(\tilde{\chi}_2^0 \rightarrow ee \tilde{\chi}_1^0)$ | $\text{BR}(\tilde{\chi}_2^0 \rightarrow \mu\mu \tilde{\chi}_1^0)$ | $\text{BR}(\tilde{\chi}_2^0 \rightarrow \tau\tau \tilde{\chi}_1^0)$ | $\text{BR}(\tilde{\chi}_2^0 \rightarrow \nu\nu \tilde{\chi}_1^0)$ | $\text{BR}(\tilde{\chi}_2^0 \rightarrow \pi^0 \tilde{\chi}_1^0)$ | $\text{BR}(\tilde{\chi}_2^0 \rightarrow \pi^+ \pi^- \tilde{\chi}_1^0)$ |
|------------------------------------------------|-----------------------|---------------------------------------------------------------|-------------------------------------------------------------------|---------------------------------------------------------------------|-------------------------------------------------------------------|------------------------------------------------------------------|------------------------------------------------------------------------|
| 3.00                                           | $3.14 \cdot 10^{-8}$  | 0.0681631                                                     | 0.0663985                                                         | 0.                                                                  | 0.406377                                                          | 0.158647                                                         | 0.300414                                                               |
| 2.00                                           | $6.12 \cdot 10^{-9}$  | 0.0466601                                                     | 0.0438824                                                         | 0.                                                                  | 0.27818                                                           | 0.241633                                                         | 0.389645                                                               |
| 1.50                                           | $1.96 \cdot 10^{-9}$  | 0.0349377                                                     | 0.0311588                                                         | 0.                                                                  | 0.208293                                                          | 0.319454                                                         | 0.406156                                                               |
| 1.00                                           | $3.54 \cdot 10^{-10}$ | 0.0256158                                                     | 0.0191733                                                         | 0.                                                                  | 0.152717                                                          | 0.521519                                                         | 0.280975                                                               |
| 0.70                                           | $7.71 \cdot 10^{-11}$ | 0.0198572                                                     | 0.00965133                                                        | 0.                                                                  | 0.118385                                                          | 0.81405                                                          | 0.038056                                                               |
| 0.50                                           | $2.45 \cdot 10^{-11}$ | 0.0116295                                                     | 0.00128466                                                        | 0.                                                                  | 0.0693332                                                         | 0.913858                                                         | 0.00389437                                                             |

Table B.3: Branching ratios for the  $\tilde{\chi}_1^\pm$  (top) and  $\tilde{\chi}_2^0$  (bottom) decay as a function of the  $\Delta m$  with the  $\tilde{\chi}_1^0$ .

## B.3 Displaced Track Analysis: Systematic Uncertainties

The following detailed descriptions of systematic uncertainties were prepared by my collaborators and are taken from the internal note *ANA-SUSY-2020-04-INT1*. These uncertainties were used as part of my analysis framework, and this section is included for completeness.

### B.3.1 Experimental Uncertainties

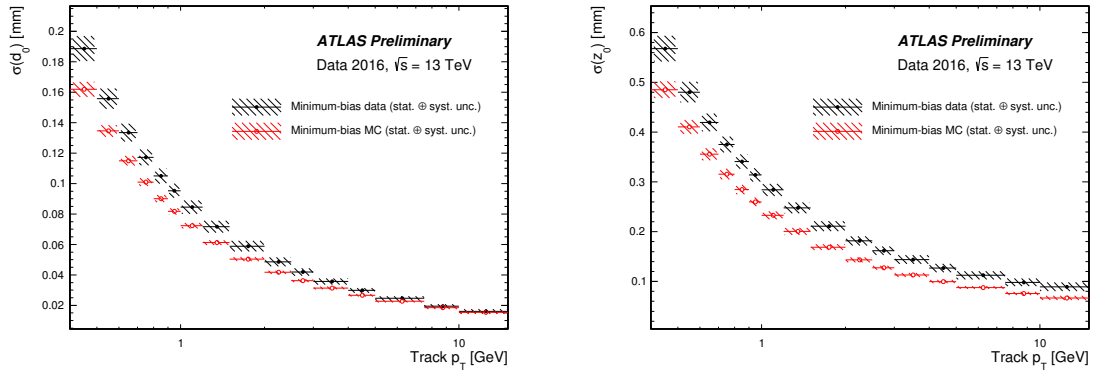
The experimental systematic uncertainties considered in the analysis are described below.

- Electron energy resolution:  $\pm 1\sigma$  variations in the resolution of the electron momentum (EGamma resolution uncertainty).
- Electron energy scale:  $\pm 1\sigma$  variations in the scale of the electron momentum (EGamma scale uncertainty).
- Electron identification efficiency:  $\pm 1\sigma$  variations in the error of the electron identification working-point scale factors.
- Electron reconstruction efficiency:  $\pm 1\sigma$  variations in the error of the electron reconstruction scale factors.



- Electron isolation efficiency:  $\pm 1\sigma$  variations in the error of the electron isolation working-point scale factors.
- Electron trigger efficiency:  $\pm 1\sigma$  variations on the electron trigger efficiency uncertainty.
- Electron trigger SF:  $\pm 1\sigma$  electron trigger scale factors uncertainties.
- Muon ID:  $\pm 1\sigma$  variations in the smearing of the muon ID track.
- Muon MS:  $\pm 1\sigma$  variations in the smearing of the muon MS tracks.
- Muon momentum scale:  $\pm 1\sigma$  variations in the muon momentum scale.
- Muon sagitta resolution:  $\pm 1\sigma$  charge-dependent variations in the scale of the momentum and statistical error associated to the charge-dependent corrections.
- Muon reconstruction efficiency:  $\pm 1\sigma$  variations in the statistical/systematic error on the muon reconstruction scale factors.
- Muon isolation efficiency:  $\pm 1\sigma$  variations in statistical/systematic error on the muon isolation working-point scale factors.
- Muon track to vertex association efficiency: statistical/systematic component of the on the muon TTVA scale factors.
- Muon trigger efficiency: statistical/systematic uncertainty on the muon trigger scale factors.
- Jet energy resolution uncertainties:  $\pm 1\sigma$  variations in the smearing of the MC jets to the data in order to correct the MC resolution. These uncertainties are evaluated from dijet events and zero bias data using random cones.
- Jet energy scale uncertainties:  $\pm 1\sigma$  variations in the scale of the jet momentum. These uncertainties are derived from the dijet eta-intercalibration across eta,  $Z(\rightarrow ee, \mu\mu)$ +jet, Gamma+jet and multijet balance, and the propagation of single particles in high- $p_T$  regimes.

- Jet vertex tagger:  $\pm 1\sigma$  variations accounting for the residual contamination from pile-up jets in the central region.
- MET soft-term resolution: one-sided variations of the MET track soft term resolution parallel/perpendicular to the hard term.
- MET soft-term scale:  $\pm 1\sigma$  variations in the MET track soft term scale obtained by scaling the soft term magnitude in the direction of  $p_T^{\text{Hard}}$ .
- Pile-up:  $\pm 1\sigma$  variations of the pile-up weight used to reweight nominal MC predictions to reproduce the correct distribution of the number of  $pp$  collisions per bunch crossing in the data.
- Track impact parameter resolution: one-sided systematic variations on the impact parameter resolution and its longitudinal component in order to account for any differences with respect to data. These uncertainties are obtained by replacing the nominal impact parameter(s) with a random value taken from a Gaussian distribution whose central value is the original MC impact parameter and whose sigma is taken from dedicated smearing maps from studies on MC/data resolution differences. Track impact parameter resolutions measured in minimum-bias simulation and in 2016 data are shown in Figure B.3.[100]



(a) Transverse impact parameter resolution

(b) Longitudinal impact parameter resolution

Figure B.3: Unfolded transverse and longitudinal impact parameter resolution measured in simulation and data as a function of  $p_T$ .

### B.3.2 Theoretical Uncertainties

Theory uncertainties for all signal and background processes in the analysis is evaluated by using LHE3 weights. Variations of QCD renormalization and factorization scales, parton density functions and strong coupling constant ( $\alpha_S$ ) are considered by combining LHE3 weight variations following the PMG recommendation.

#### QCD renormalization and factorization scales

Renormalisation and factorisation scales ( $\mu_R$  and  $\mu_F$ ) are used to estimate the uncertainty due to missing higher orders in the perturbative expansion of the partonic cross-section corrections. The uncertainty is estimated by varying  $\mu_R$  and  $\mu_F$  by a factor of two resulting in 7-point variations of  $\{\mu_R, \mu_F\} \times \{0.5, 0.5\}$ ,  $\{1.0, 0.5\}$ ,  $\{0.5, 1.0\}$ ,  $\{1.0, 1.0\}$ ,  $\{2.0, 1.0\}$ ,  $\{1.0, 2.0\}$ ,  $\{2.0, 2.0\}$ . 3-point variations of  $\{\mu_R, \mu_F\} \times \{0.5, 0.5\}$ ,  $\{1.0, 1.0\}$ ,  $\{2.0, 2.0\}$  are used when 7-point variations are unavailable which should lead to larger uncertainties compared to independent variations. The envelope of the 7-point (3-point) variations are taken as the overall uncertainty.

#### Parton Density Function (PDF)

PDFs at a given scale ( $Q$ ) are determined by fitting a given functional form to data. The PDF at different energy scales in the MC generator is estimated by DGLAP equations. Therefore, experimental uncertainties in the dataset and uncertainty on the functional form for PDF fits are sources of uncertainties. In addition, missing higher order calculations of DGLAP equations are sources of uncertainties although considered by varying renormalization and factorization scales. Recommended PDF choices for recent generators are summarized in Table B.4.

#### Strong coupling constant ( $\alpha_S$ )

$\alpha_S$  is determined experimentally and quoted at the Z mass scale ( $Q = m_Z$ ).  $\alpha_S$  at different energy scales in the MC generators are predicted by Renormalization Group Equation (RGE) although the calculation is truncated at a given order. Therefore, experimental errors of  $\alpha_S$

and missing higher order calculations of RGE need to be accounted as uncertainties of  $\alpha_S$ . PDF sets with different  $\alpha_S$  values, summarized in Table B.4, are used to estimate uncertainties of  $\alpha_S$ .

PDF and  $\alpha_S$  uncertainties are combined following the PDF4LHC recommendations by taking the quadratic sum of the two uncertainties.

|                       | Pythia8                                   | MG5aMC, Powheg, Herwig7                                         | Sherpa                                                                 |
|-----------------------|-------------------------------------------|-----------------------------------------------------------------|------------------------------------------------------------------------|
| ME order              | LO                                        | LO/NLO                                                          | LO/NLO                                                                 |
| Baseline              | NNPDF23,lo,as,0130,qed (247000)           | NNPDF30,nlo,as,0118 (260000)<br>NNPDF30,nlo,as,0118,mc (260800) | NNPDF30,nnlo,as,0118 (261000)<br>NNPDF30,nnlo,as,0118,hessian (303200) |
| $\alpha_S$ variations | NNPDF23,lo,as,0119,qed (246800)           | NNPDF30,nlo,as,0119 (266000)<br>NNPDF30,nlo,as,0117 (265000)    | NNPDF30,nnlo,as,0119 (270000)<br>NNPDF30,nnlo,as,0117 (269000)         |
| Alternative PDFs      | CT14llo (13205)<br>MMHT2014lo68cl (25000) | CT14nlo (13100)<br>MMHT2014nlo68clas118 (25200)                 | CT14nnlo (13000)<br>MMHT2014nnlo68cl (25300)                           |

Table B.4: PDF list used for each MC generator.

## B.4 Displaced Track Analysis Further Discussion: Comparison with Previous Results

Note that the following results in this section were obtained during the development phase, where different loss functions were tested; while not the final results, they are very close and provide a fair comparison.

The fitted yield table with the NN Semi-data-driven background estimation strategy can be found in Table 4.10 previous section 4.7.6, (which agrees well with the Cut & Count ABCD strategy prediction). We also produced exclusion contours for the cut-based analysis with the NN analysis workflow (background estimation + PyHF fit) with the nominal luminosity and scaled-up luminosity (equivalent to an increased dataset) in Figure B.5, and we could then subsequently quantitatively compare the improvement introduced by using the Neural Network, which covered looser parameter space, and allowed for a more flexible signal region definition to recover more signals.

In order to compare the sensitivity between different analysis strategies quantitatively, we defined a variable called the CLs-equivalent luminosity Increase. We start by evaluating the signal confidence level for the Cut & Count analysis. As we gain increased statistics with a larger dataset, we should expect higher sensitivity, that is lower CLs for the background-only assumption.

Because we are using Monte Carlo simulation-based signal region yield estimate, we can easily extrapolate to higher integrated luminosity, that is, equivalent to a larger dataset. In Figure B.4 we plot the  $x$ -axis as the luminosity scale factor of the cut-based analysis, and plot the decreasing expected nominal CLs value. We then plot the nominal confidence level of the neural network analysis, which, in this particular signal neutralino-chargino mass point combination, intercepts the curve at around 1.869. What it means is: The expected exclusion confidence of NN Signal Region using  $139 \text{ fb}^{-1}$  cumulative data is equal to that of traditional analysis with  $1.869 * 139 \text{ fb}^{-1} = 259 \text{ fb}^{-1}$  cumulative data. That is, using the neural network analysis could mean a sensitivity to doubling the dataset for a cut-based analysis.

In Table B.5, we are summarizing the sensitivity improvement from using the NN-based analysis

for some representative signal mass points, suggesting that the improvement could range from a data increase of up to 326 percent. In particular, beyond the masspoints that can be excluded by the Cut & Count Analysis, we are able to provide exclusion for mass points at (102, 101, 100), (125.7, 125.35, 125), (176.5, 175.75, 175) and (87, 86, 85).

Note that the comparison table for the confidence level ( $CL_s$ ) of Cut & Count analysis from HepData and the proposed Neural Network Analysis can be found in Table B.5.

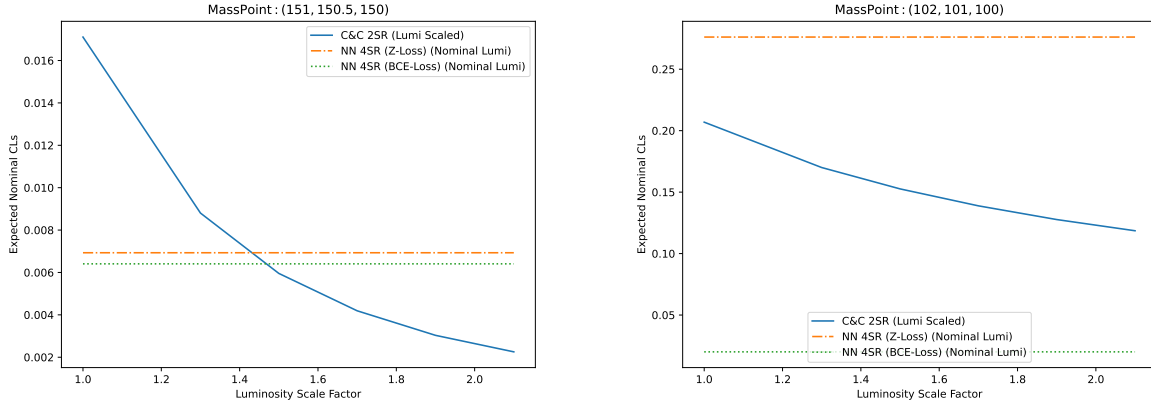
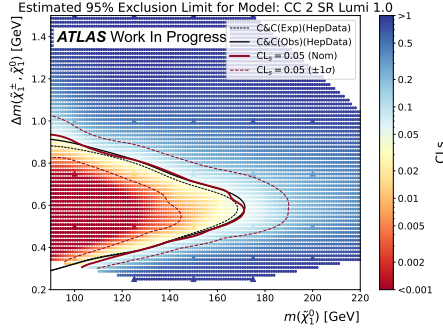


Figure B.4: Nominal expected confidence level improvement of ( $CL_{s,nom}$ ) of Cut & Count analysis given luminosity-increase versus the scale factor (estimated with the semi-data-driven MC weight correction method, with full-systematic fit on example mass points as described in Section 4.9, the intermediate values are linearly interpolated/extrapolated from scale factor of (1.0, 1.3, 1.5, 1.7, 1.9, 2.1)). The corresponding expected  $CL_{s,nom}$  for the 4-SR approach with NN trained BCE-Loss at nominal luminosity ( $139\text{fb}^{-1}$ ) are given by horizontal lines.

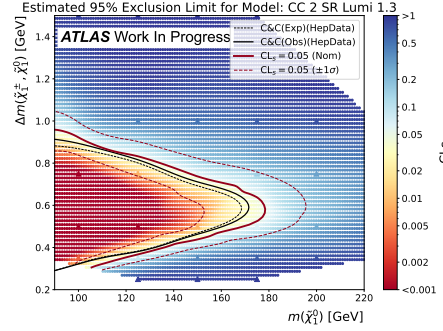
Table B.5: Nominal expected confidence level improvement of ( $\text{CL}_{\text{s,nom}}$ ) of Cut & Count analysis given luminosity-increase versus the scale factor (estimated with the semi-data-driven MC weight correction method, with full-systematic fit on example mass points as described in Section 4.9). The corresponding expected  $\text{CL}_{\text{s,nom}}$  for the 4-SR approach at nominal luminosity ( $139\text{fb}^{-1}$ ) with NN trained by Z-Loss and BCE-Loss and the CLs-equivalent luminosity-increase percentage (extrapolated from Figure B.4) needed for Cut & Count analysis are given in the last columns.

| Sig. Grid [GeV]                                                        | Expected Nom. CLs |        |        |        |        |        |        | CLs-Equiv-Lumi-Increase |
|------------------------------------------------------------------------|-------------------|--------|--------|--------|--------|--------|--------|-------------------------|
| $(m_{\tilde{\chi}_2^0}, m_{\tilde{\chi}_1^\pm}, m_{\tilde{\chi}_1^0})$ | CC Nom            | CC1.3  | CC1.5  | CC1.7  | CC1.9  | CC2.1  | NN-4SR | NN-4SR                  |
| (100.7, 100.35, 100)                                                   | 0.0077            | 0.0035 | 0.0022 | 0.0015 | 0.0010 | 0.0007 | 0.0015 | 70.4%                   |
| (101, 100.5, 100)                                                      | 0.0000            | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 68.2%                   |
| (101.5, 100.75, 100)                                                   | 0.0012            | 0.0004 | 0.0002 | 0.0001 | 0.0001 | 0.0001 | 0.0000 | 129.9%                  |
| (102, 101, 100)                                                        | 0.2069            | 0.1700 | 0.1526 | 0.1388 | 0.1277 | 0.1186 | 0.0201 | 326.2%                  |
| (125.7, 125.35, 125)                                                   | 0.1211            | 0.0897 | 0.0754 | 0.0644 | 0.0558 | 0.0478 | 0.0374 | 135.8%                  |
| (126, 125.5, 125)                                                      | 0.0014            | 0.0005 | 0.0002 | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 60.6%                   |
| (126.5, 125.75, 125)                                                   | 0.0142            | 0.0085 | 0.0065 | 0.0052 | 0.0042 | 0.0034 | 0.0023 | 135.1%                  |
| (151, 150.5, 150)                                                      | 0.0171            | 0.0088 | 0.0060 | 0.0042 | 0.0030 | 0.0023 | 0.0064 | 46.8%                   |
| (151.5, 150.75, 150)                                                   | 0.0864            | 0.0617 | 0.0510 | 0.0431 | 0.0366 | 0.0325 | 0.0180 | 180.6%                  |
| (176, 175.5, 175)                                                      | 0.0944            | 0.0673 | 0.0554 | 0.0450 | 0.0398 | 0.0346 | 0.0406 | 86.9%                   |
| (176.5, 175.75, 175)                                                   | 0.1818            | 0.1460 | 0.1292 | 0.1159 | 0.1039 | 0.0965 | 0.0824 | 148.5%                  |
| (85.7, 85.35, 85)                                                      | 0.0006            | 0.0002 | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0004 | 11.3%                   |
| (87, 86, 85)                                                           | 0.1189            | 0.0910 | 0.0785 | 0.0688 | 0.0613 | 0.0550 | 0.0129 | 244.4%                  |

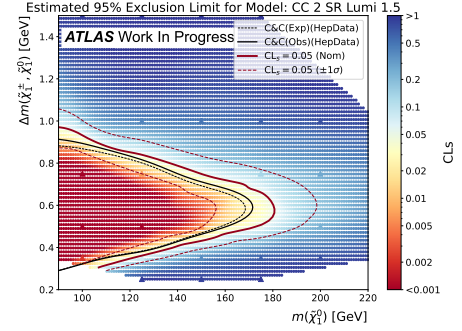




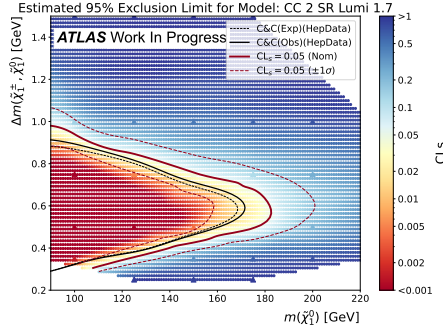
(a) Luminosity Scale Factor: 1.0



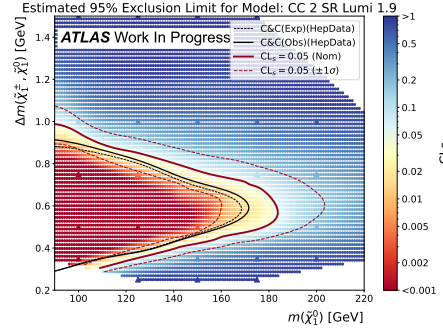
(b) Luminosity Scale Factor: 1.3



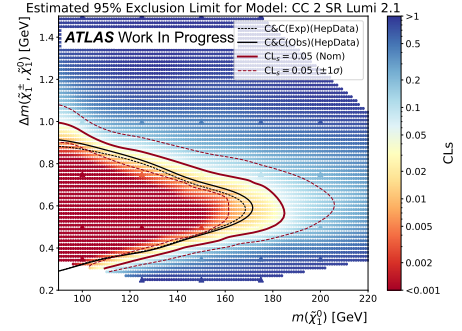
(c) Luminosity Scale Factor: 1.5



(d) Luminosity Scale Factor: 1.7



(e) Luminosity Scale Factor: 1.9



(f) Luminosity Scale Factor: 2.1

Figure B.5: Expected exclusion contour with Cut & Count Signal Regions (High and Low  $S(D_0)$  with Luminosity scaled-up. (Scale factor = 1.0, 1.3, 1.5, 1.7, 1.9, 2.1). The limit of individual mass points can be found in Table B.5).

## B.5 Neural Network Approach: Control Region Histograms

### B.5.1 Event Level Control Region Histograms

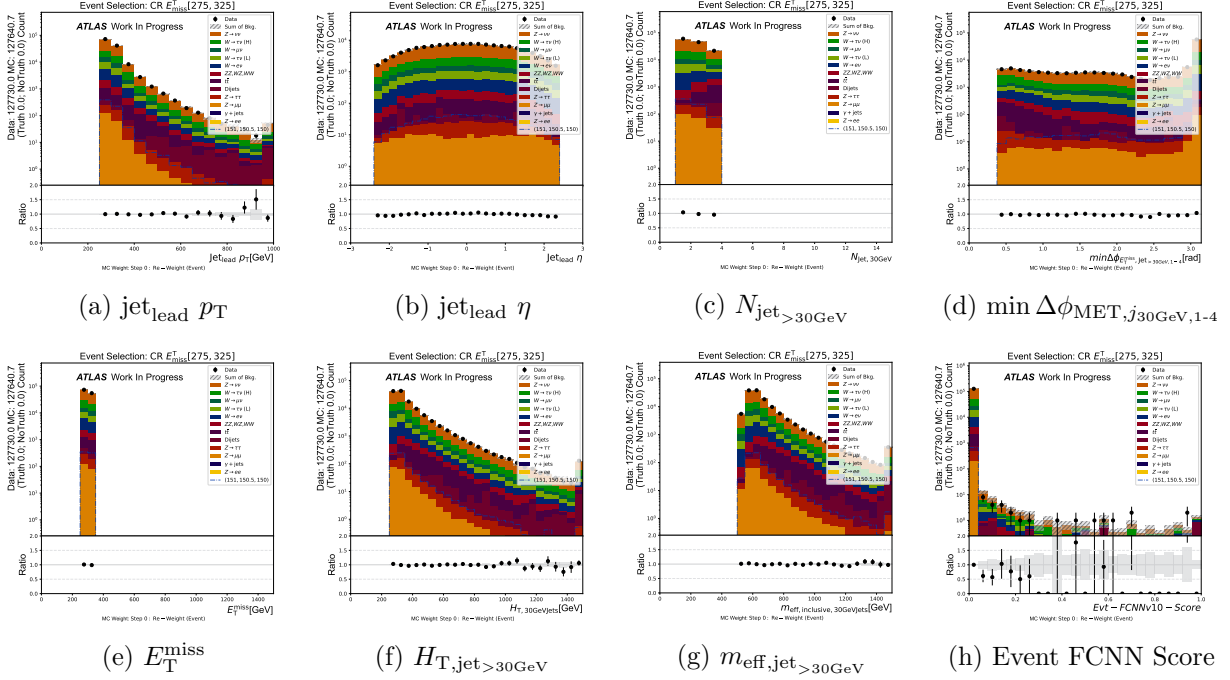


Figure B.6: Event-level kinematics histograms passing the following selection: Event-level:  $\text{CR } E_{\text{miss}}^T [275, 325] \text{ GeV}$

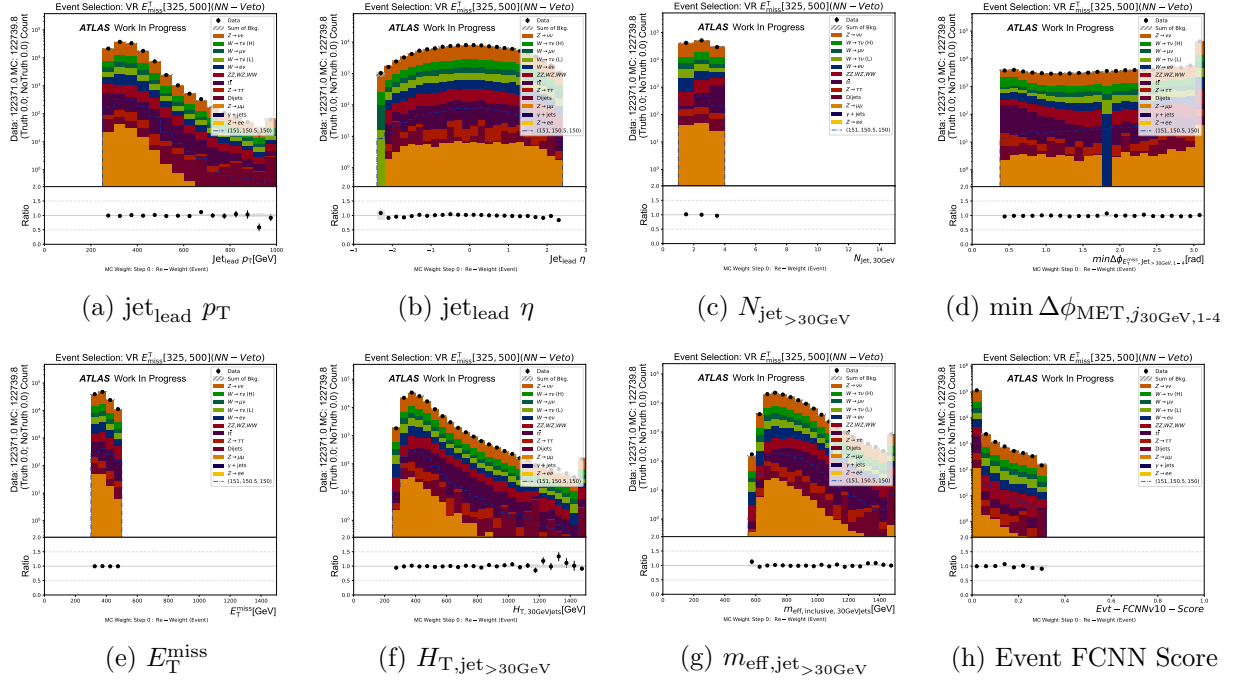


Figure B.7: Event-level kinematics histograms passing the following selection: Event-level: VR  $E_{\text{miss}}^T$  [325, 500] GeV, High Scored Event Veto-ed (to ensure orthogonality).

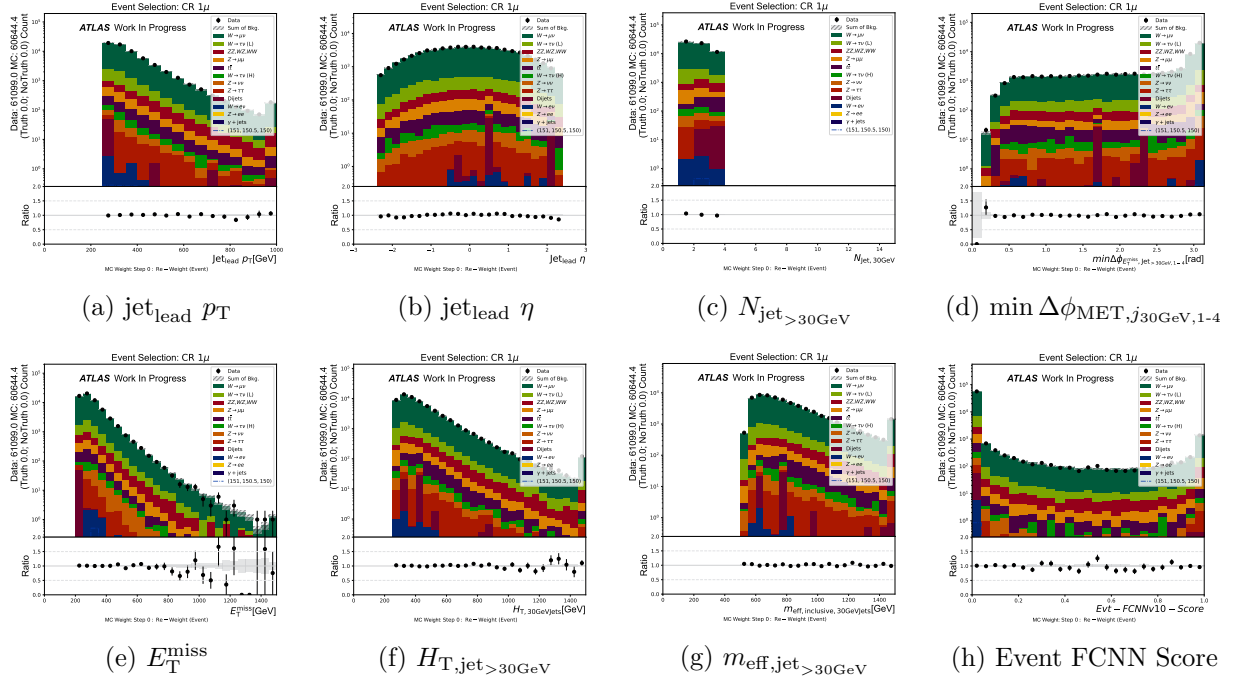


Figure B.8: Event-level kinematics histograms passing the following selection: Event-level: CR  $1\mu$

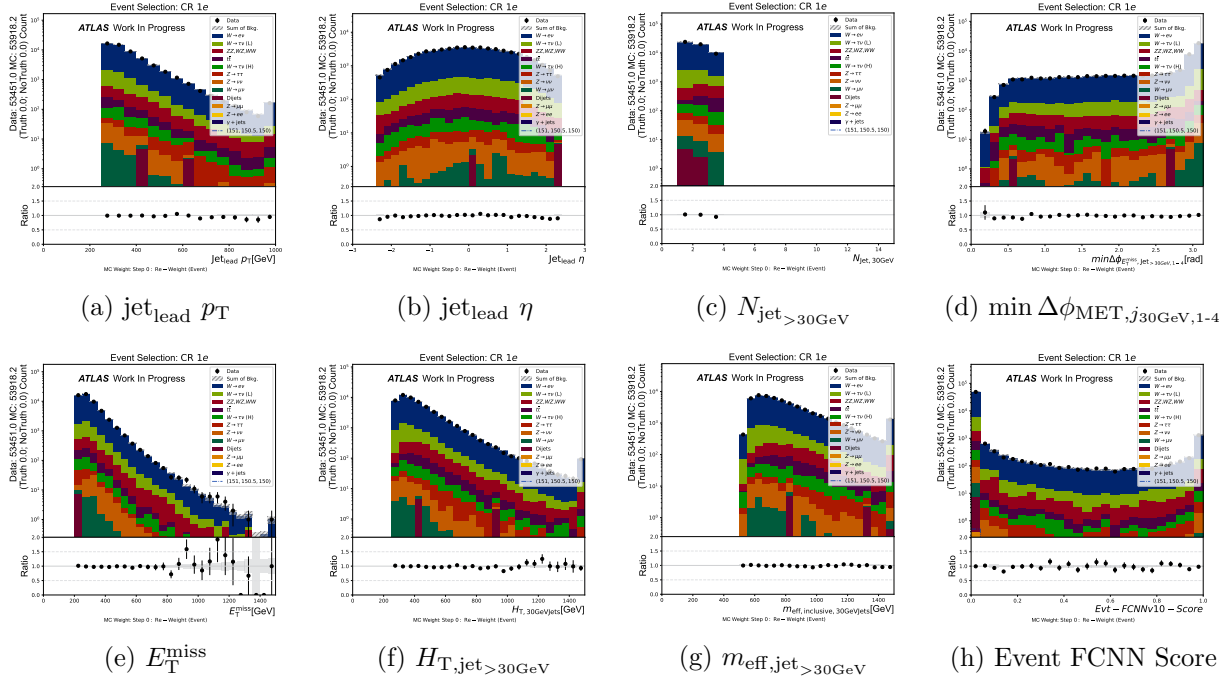


Figure B.9: Event-level kinematics histograms passing the following selection: Event-level: CR 1e

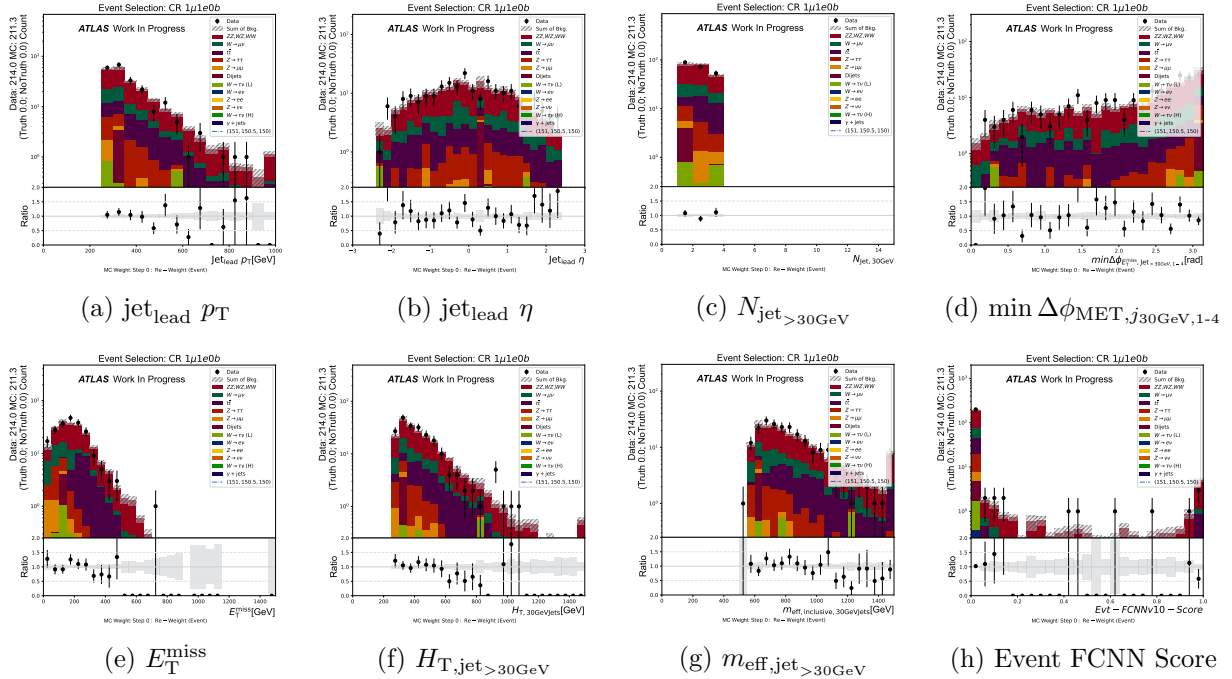


Figure B.10: Event-level kinematics histograms passing the following selection: Event-level: CR  $1\mu 1e$

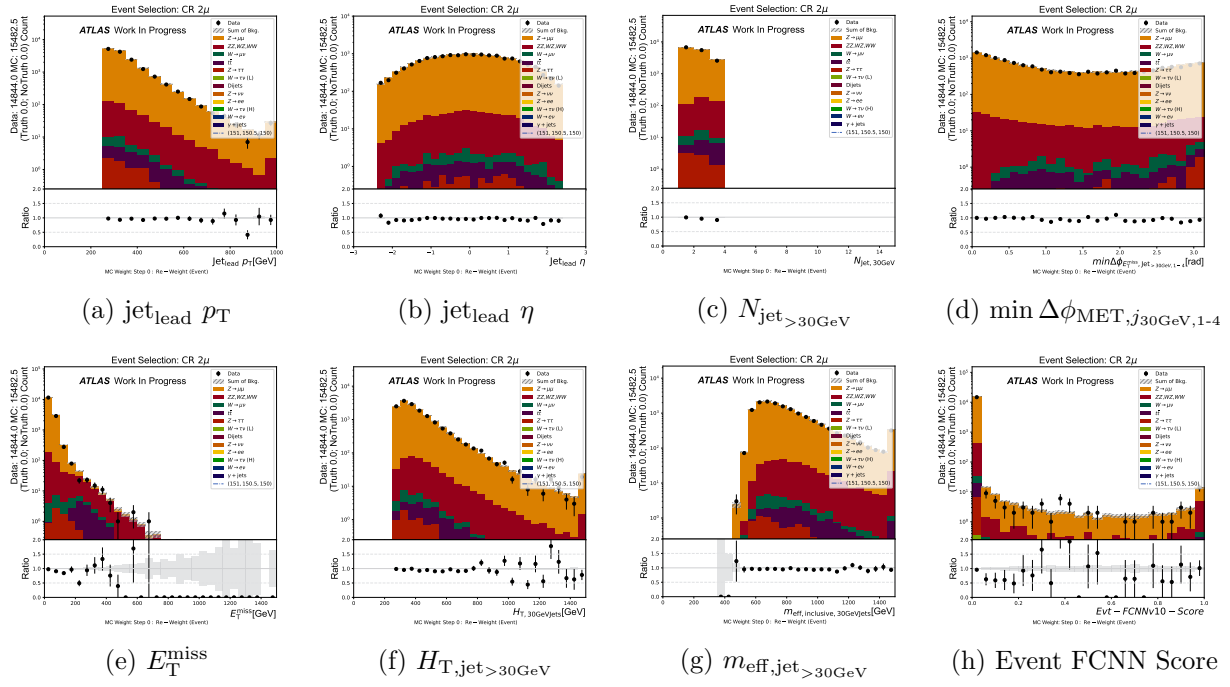


Figure B.11: Event-level kinematics histograms passing the following selection: Event-level: CR  $2\mu$

## B.5.2 Track Level Control Region Histograms (After Step 0)

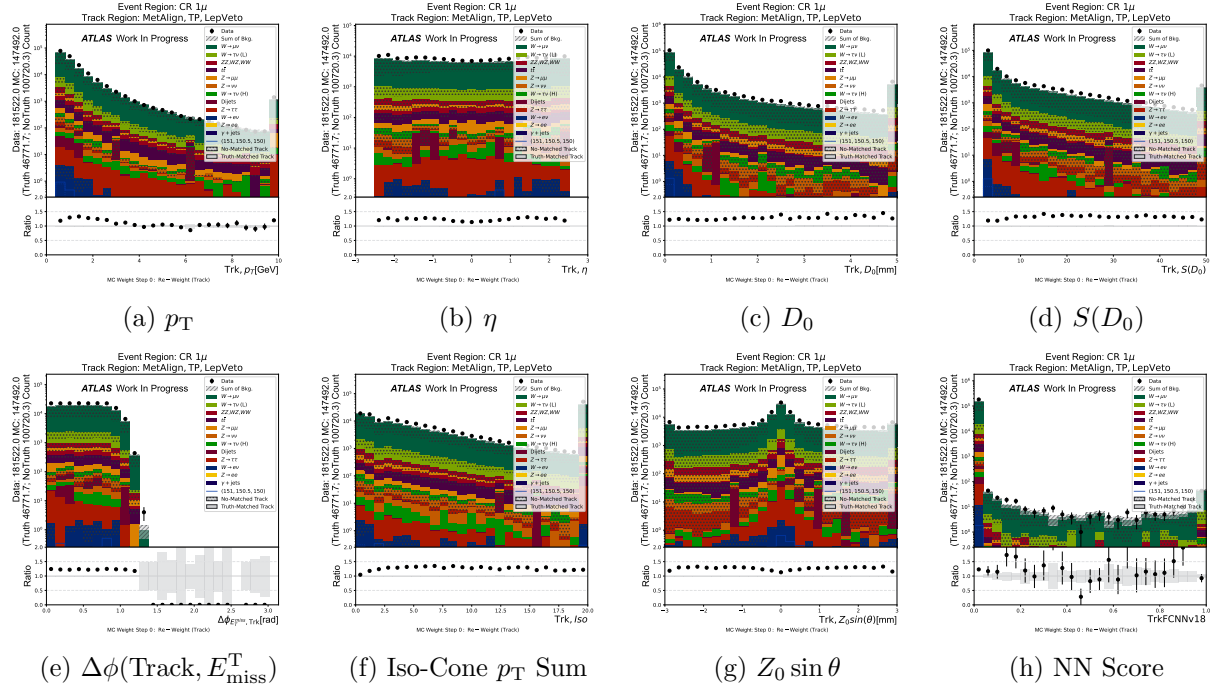
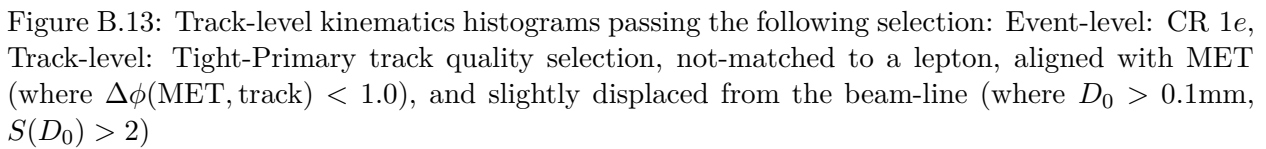
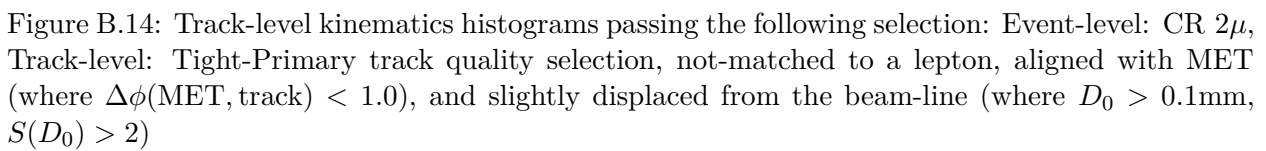


Figure B.12: Track-level kinematics histograms passing the following selection: Event-level: CR  $1\mu$ , Track-level: Tight-Primary track quality selection, not-matched to a lepton, aligned with MET (where  $\Delta\phi(\text{MET}, \text{track}) < 1.0$ ), and slightly displaced from the beam-line (where  $D_0 > 0.1\text{mm}$ ,  $S(D_0) > 2$ )











### B.5.3 Track Level Control Region Histograms (After Step 1)

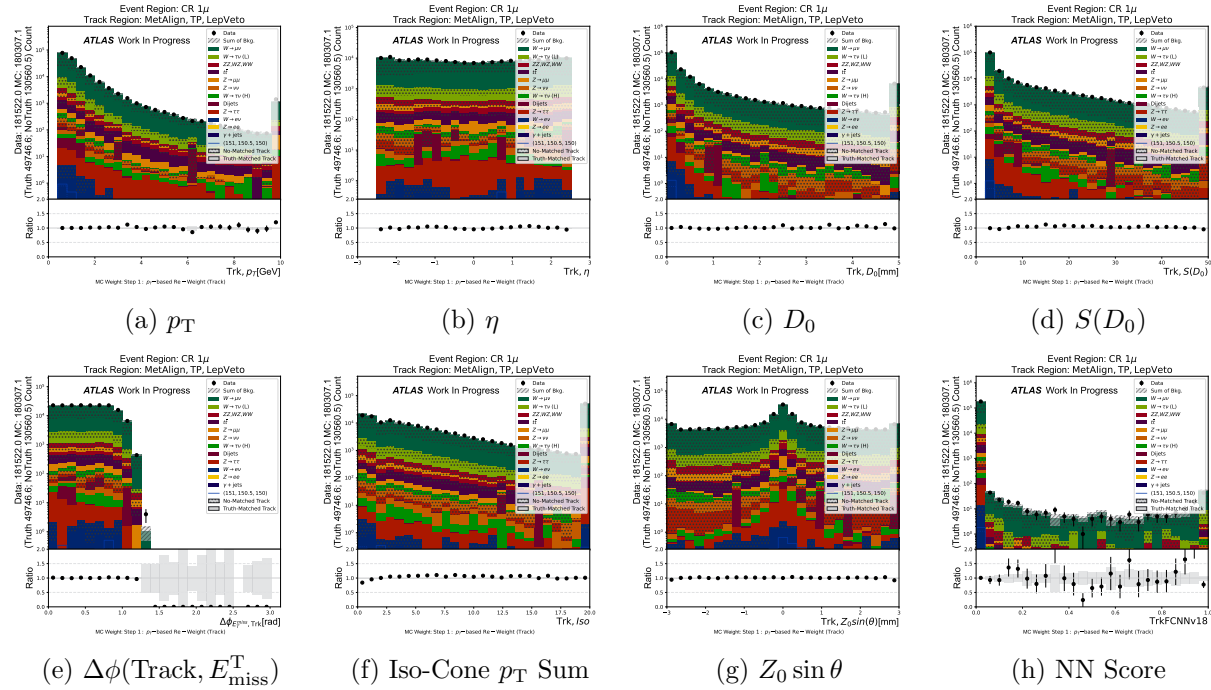


Figure B.16: Track-level kinematics histograms passing the following selection: Event-level: CR  $1\mu$ , Track-level: Tight-Primary track quality selection, not-matched to a lepton, aligned with MET (where  $\Delta\phi(\text{MET}, \text{track}) < 1.0$ ), and slightly displaced from the beam-line (where  $D_0 > 0.1\text{mm}$ ,  $S(D_0) > 2$ )

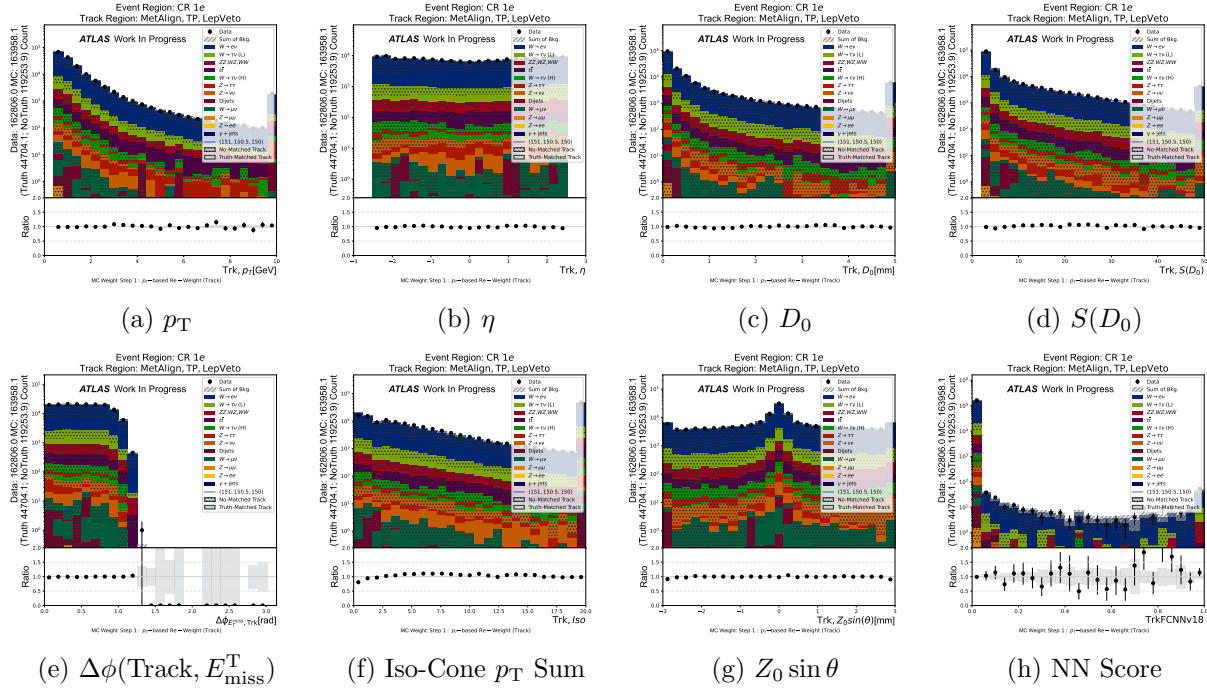
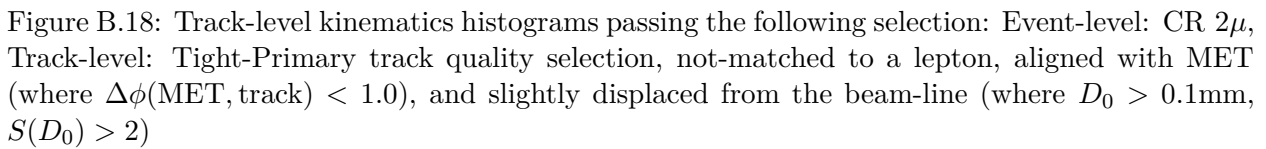


Figure B.17: Track-level kinematics histograms passing the following selection: Event-level: CR 1e, Track-level: Tight-Primary track quality selection, not-matched to a lepton, aligned with MET (where  $\Delta\phi(\text{MET}, \text{track}) < 1.0$ ), and slightly displaced from the beam-line (where  $D_0 > 0.1\text{mm}$ ,  $S(D_0) > 2$ )



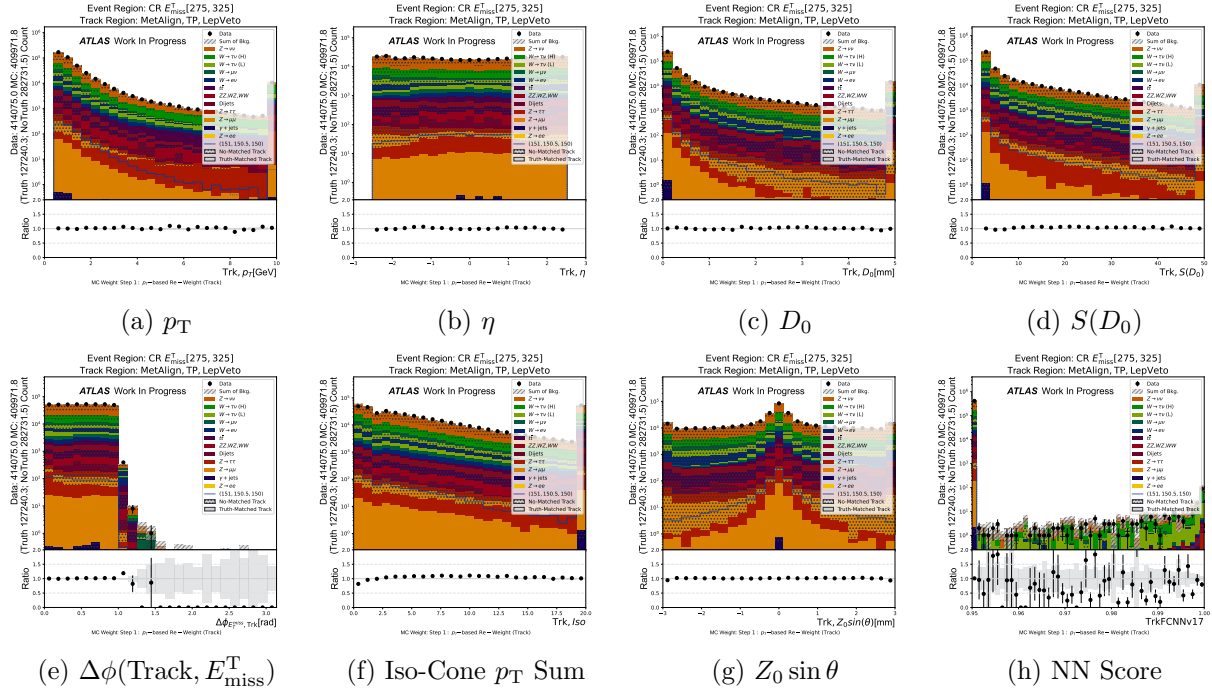


Figure B.19: Track-level kinematics histograms passing the following selection: Event-level:  $CR E_{miss}^T [275, 325]$  GeV, Track-level: Tight-Primary track quality selection, not-matched to a lepton, aligned with MET (where  $\Delta\phi(\text{MET}, \text{track}) < 1.0$ ), and slightly displaced from the beam-line (where  $D_0 > 0.1\text{mm}$ ,  $S(D_0) > 2$ )

#### B.5.4 Track Level Control Region Histograms (After Step 2)

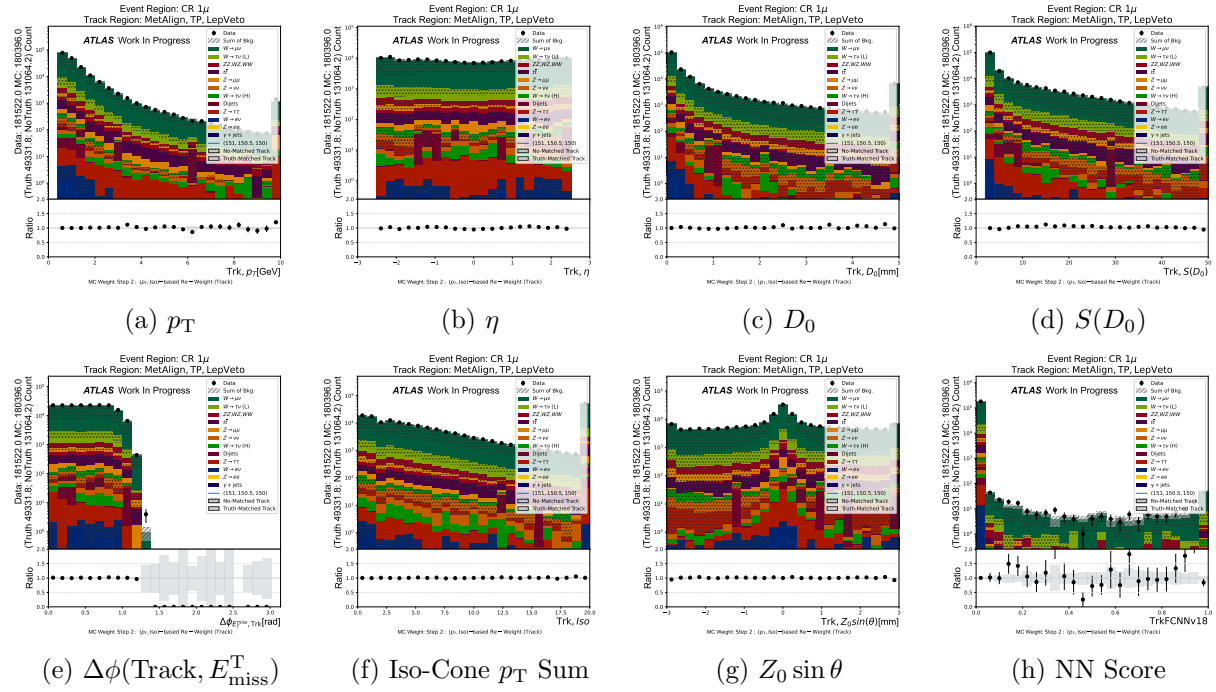
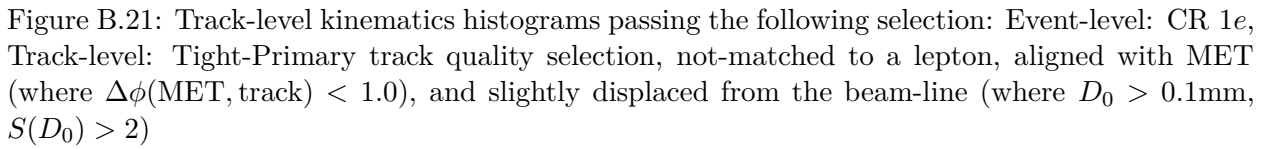
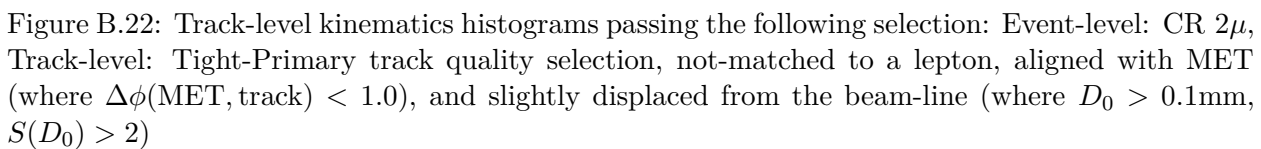


Figure B.20: Track-level kinematics histograms passing the following selection: Event-level: CR  $1\mu$ , Track-level: Tight-Primary track quality selection, not-matched to a lepton, aligned with MET (where  $\Delta\phi(\text{MET}, \text{track}) < 1.0$ ), and slightly displaced from the beam-line (where  $D_0 > 0.1\text{mm}$ ,  $S(D_0) > 2$ )









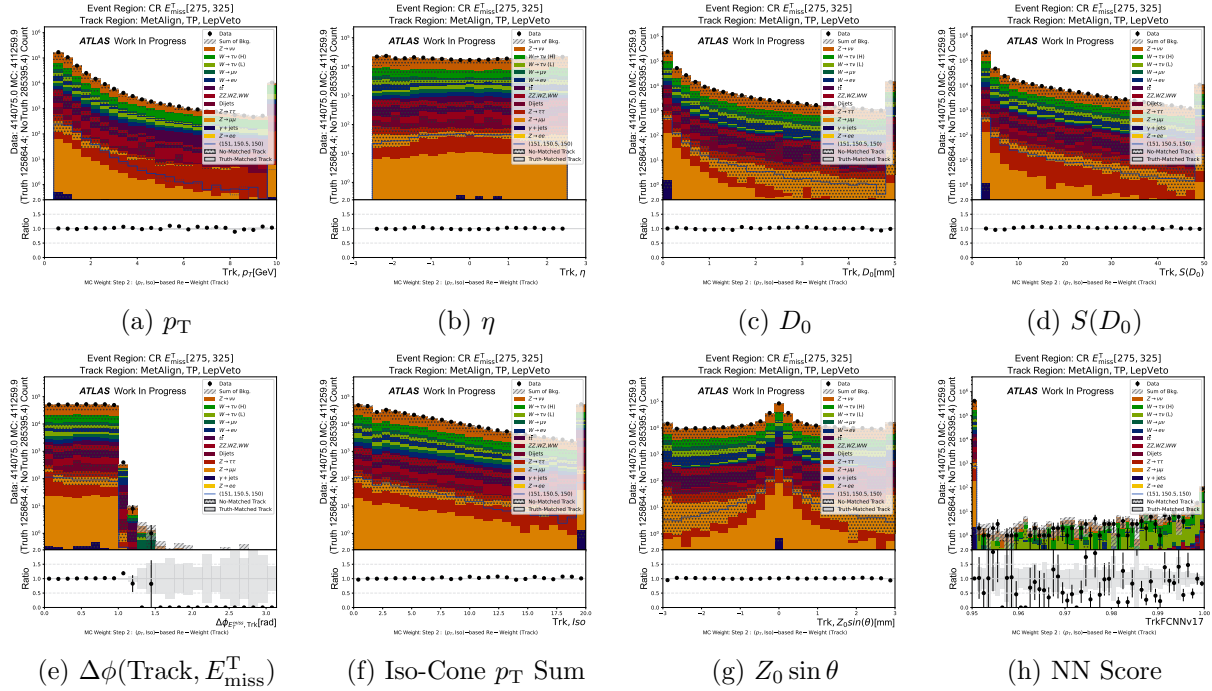


Figure B.23: Track-level kinematics histograms passing the following selection: Event-level:  $\text{CR } E_{\text{miss}}^T [275, 325]$  GeV, Track-level: Tight-Primary track quality selection, not-matched to a lepton, aligned with MET (where  $\Delta\phi(\text{MET}, \text{track}) < 1.0$ ), and slightly displaced from the beam-line (where  $D_0 > 0.1\text{mm}$ ,  $S(D_0) > 2$ )

## B.5.5 Track Level Control Region Histograms (After Step 3)

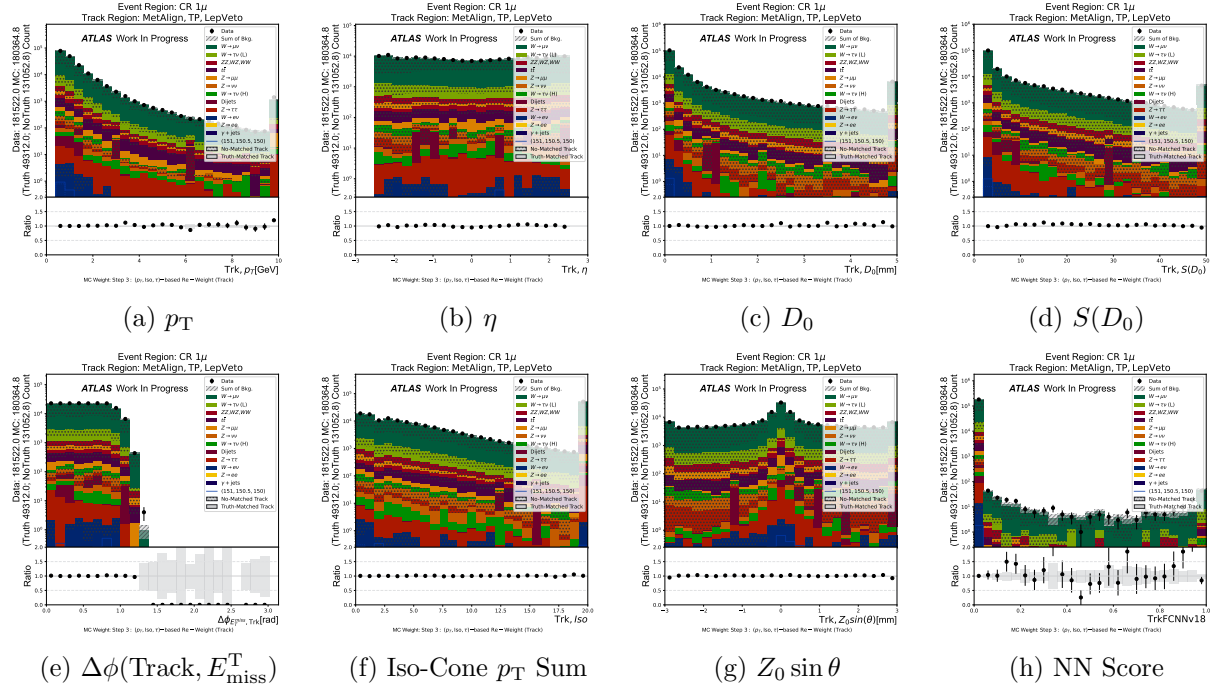


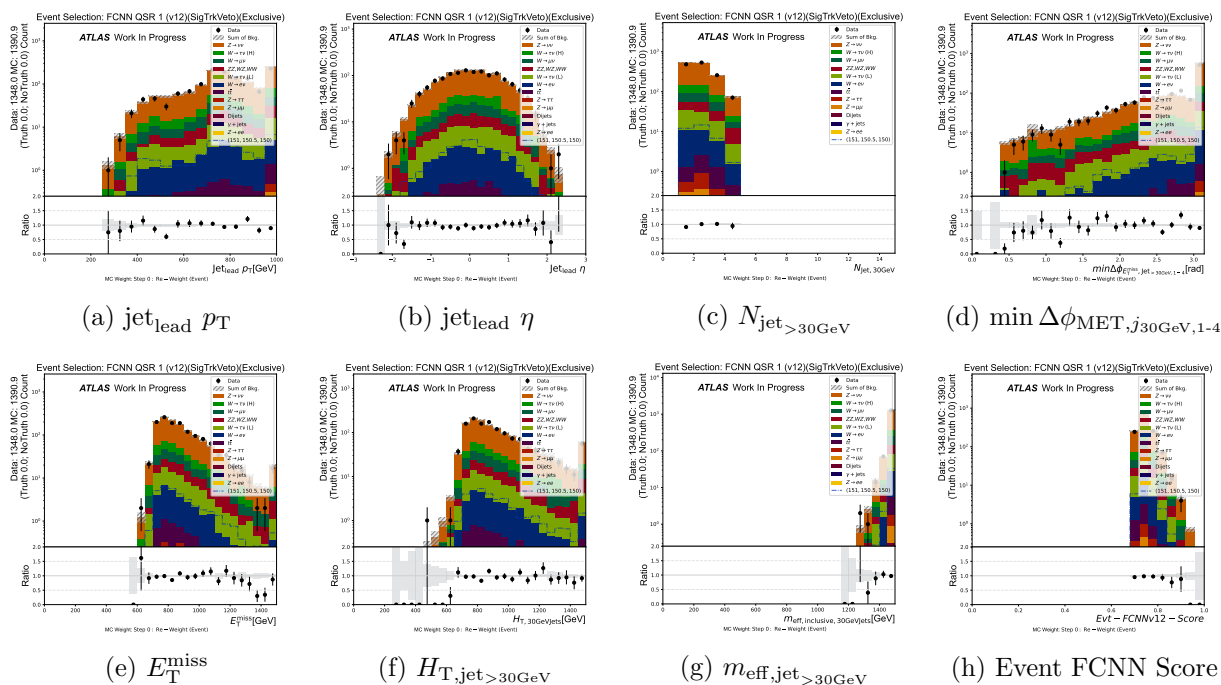
Figure B.24: Track-level kinematics histograms passing the following selection: Event-level: CR  $1\mu$ , Track-level: Tight-Primary track quality selection, not-matched to a lepton, aligned with MET (where  $\Delta\phi(\text{MET}, \text{track}) < 1.0$ ), and slightly displaced from the beam-line (where  $D_0 > 0.1\text{mm}$ ,  $S(D_0) > 2$ )







## B.6 Neural Network Approach: Validation Region Histograms



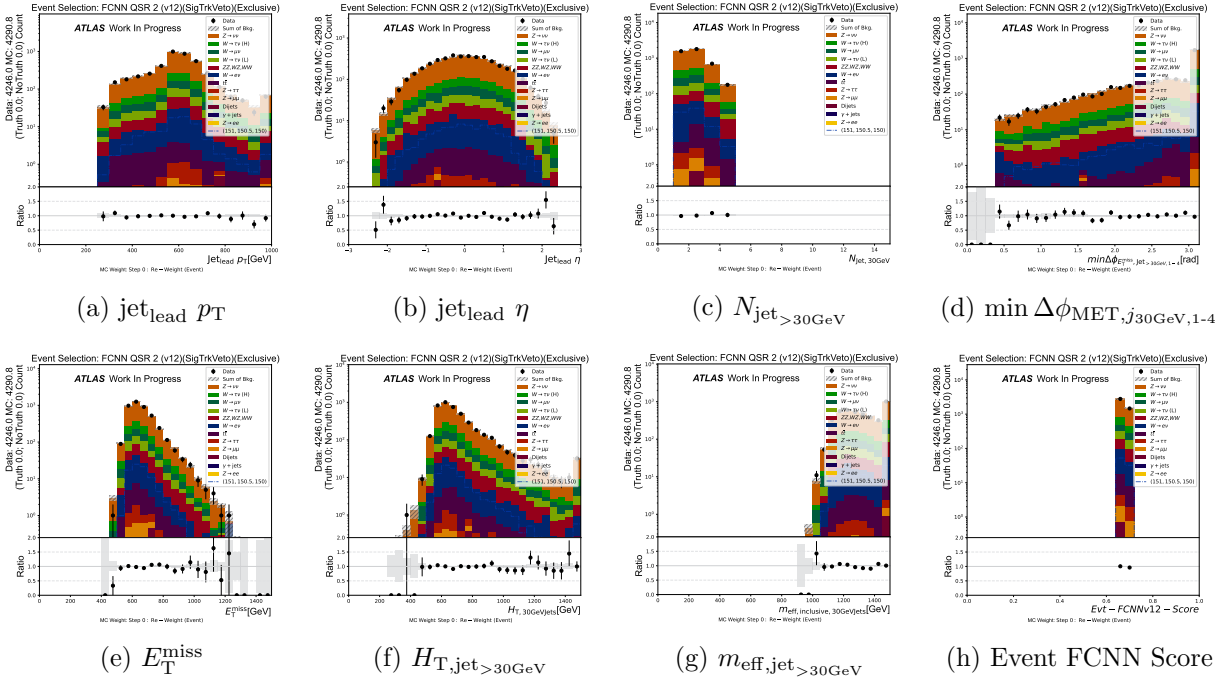


Figure B.29: Event-level kinematics histograms passing the following selection: Event-level: FCNN Signal Region Cut 2, and No Signal-Like Track in the event (e.g. Track with FCNN score greater than 0.00001)(Neural Networks trained with BCE loss)

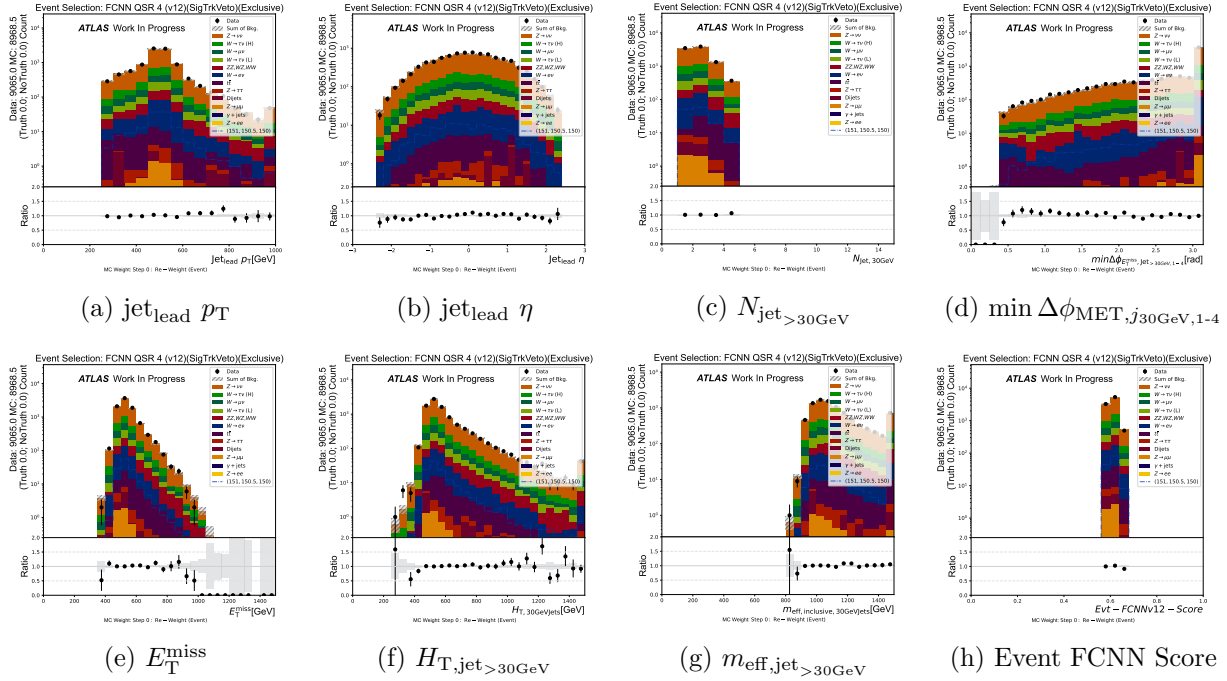


Figure B.30: Event-level kinematics histograms passing the following selection: Event-level: FCNN Signal Region Cut 4, and No Signal-Like Track in the event (e.g. Track with FCNN score greater than 0.00001)(Neural Networks trained with BCE loss)



## B.6.2 Event Level Signal Region Histograms (Blinded)

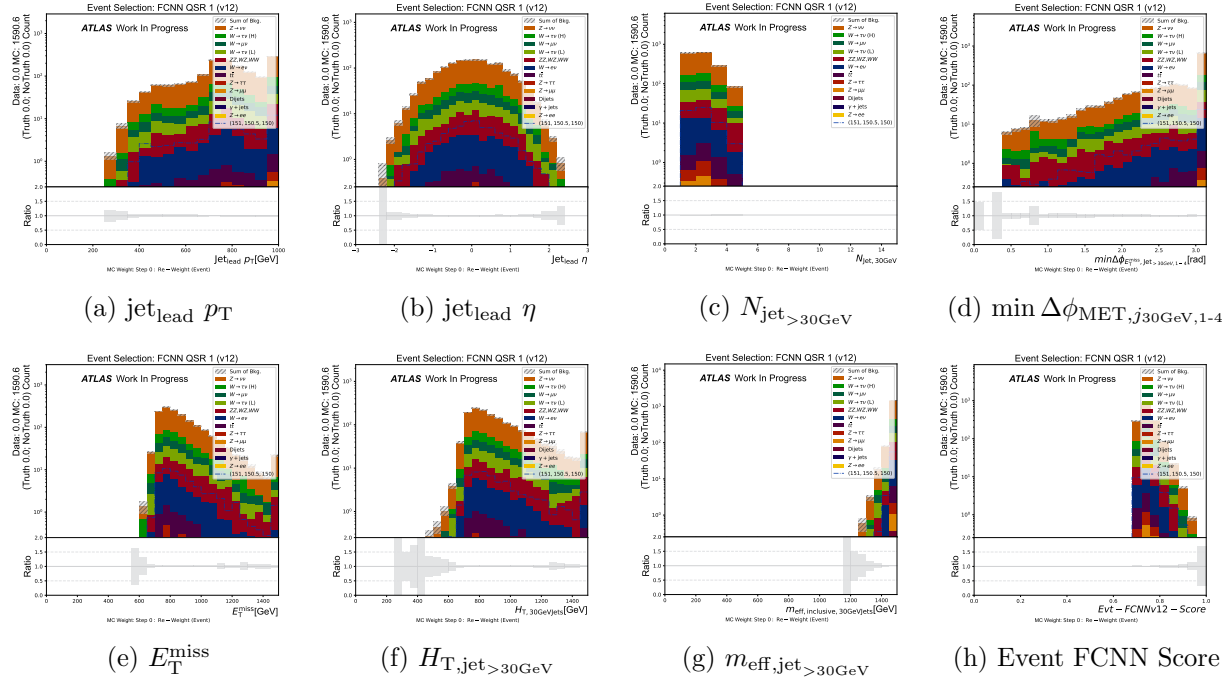


Figure B.31: Event-level kinematics histograms passing the following selection: Event-level: FCNN Signal Region Cut 1(NN trained with BCE loss).

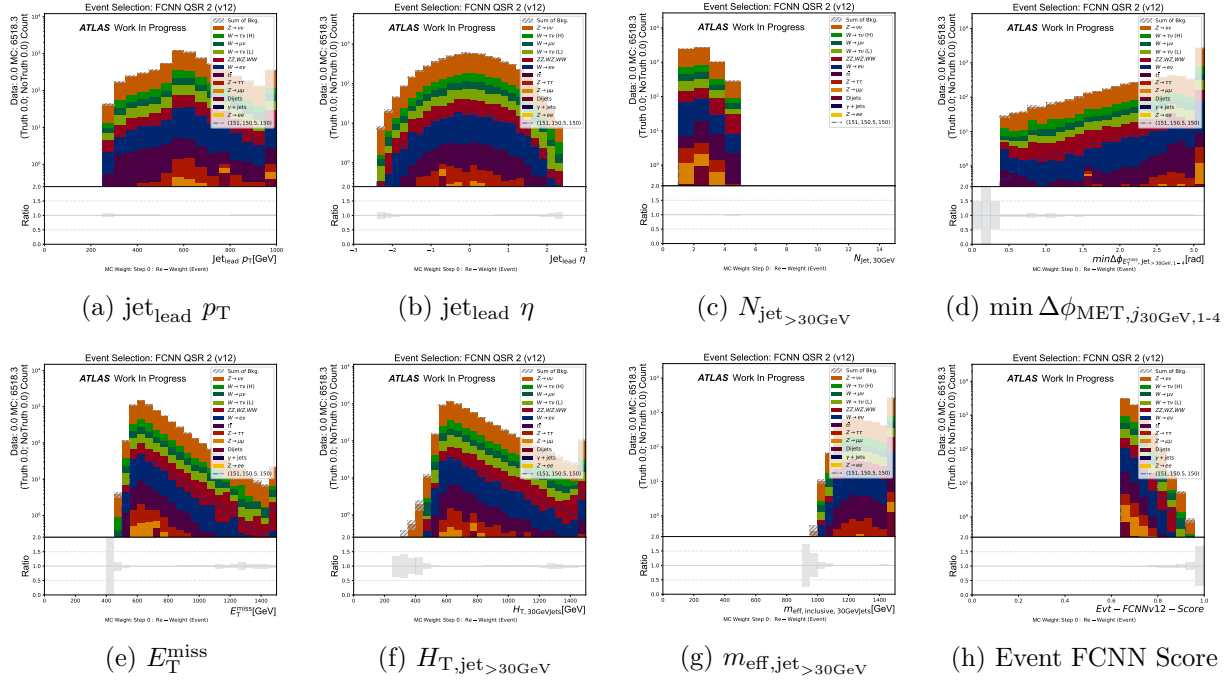


Figure B.32: Event-level kinematics histograms passing the following selection: Event-level: FCNN Signal Region Cut 2(NN trained with BCE loss).

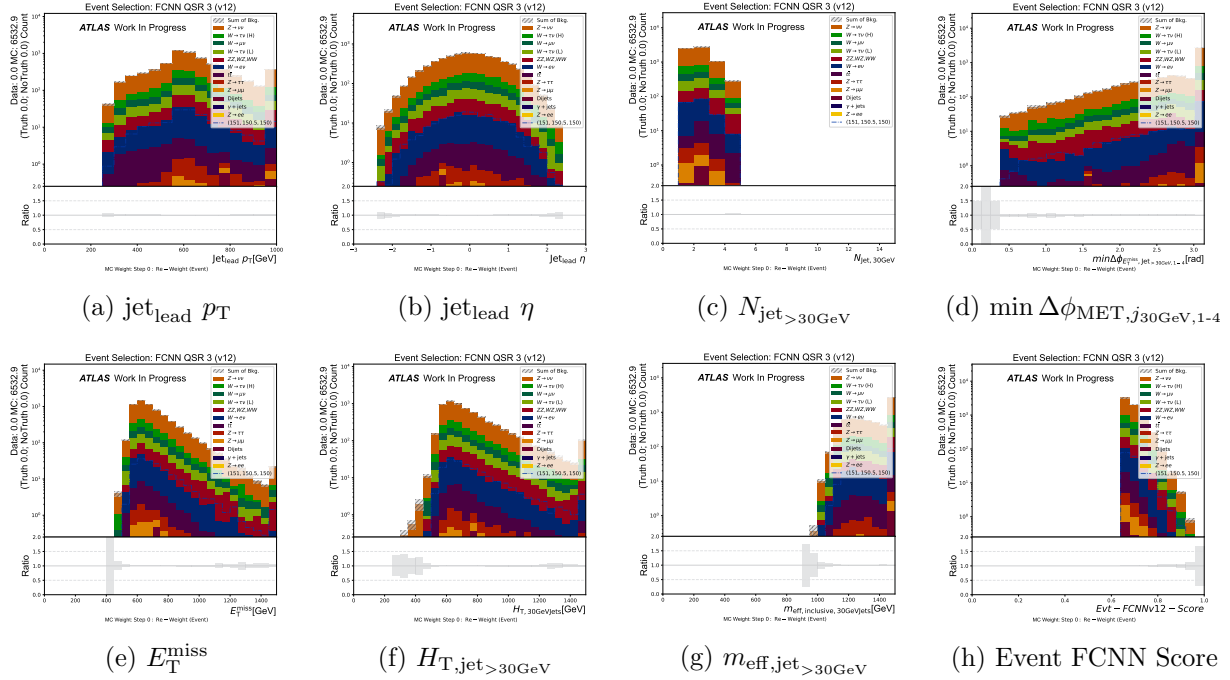


Figure B.33: Event-level kinematics histograms passing the following selection: Event-level: FCNN Signal Region Cut 3(NN trained with BCE loss).



## B.6.3 Track Level Validation Region Histograms

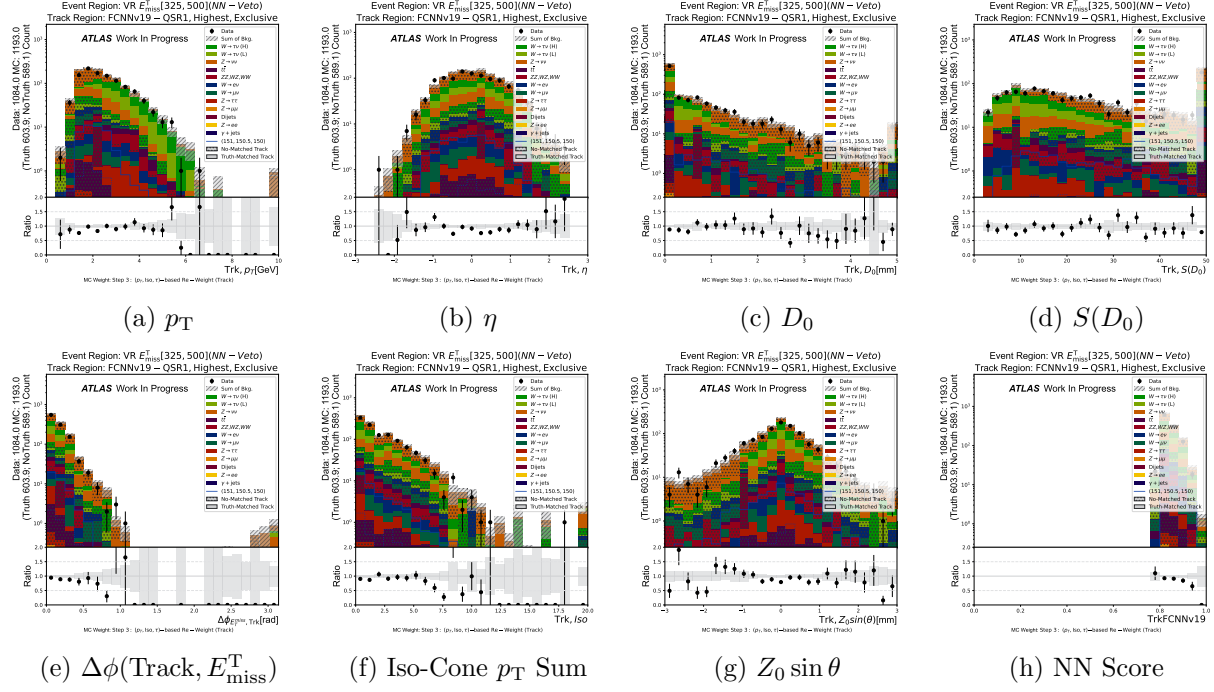


Figure B.35: Track-level kinematics histograms passing the following selection: Event-level: Medium MET Validation Region ([325,500] GeV), Track-level: NN-QSR 1 (Neural Networks trained with BCE loss)

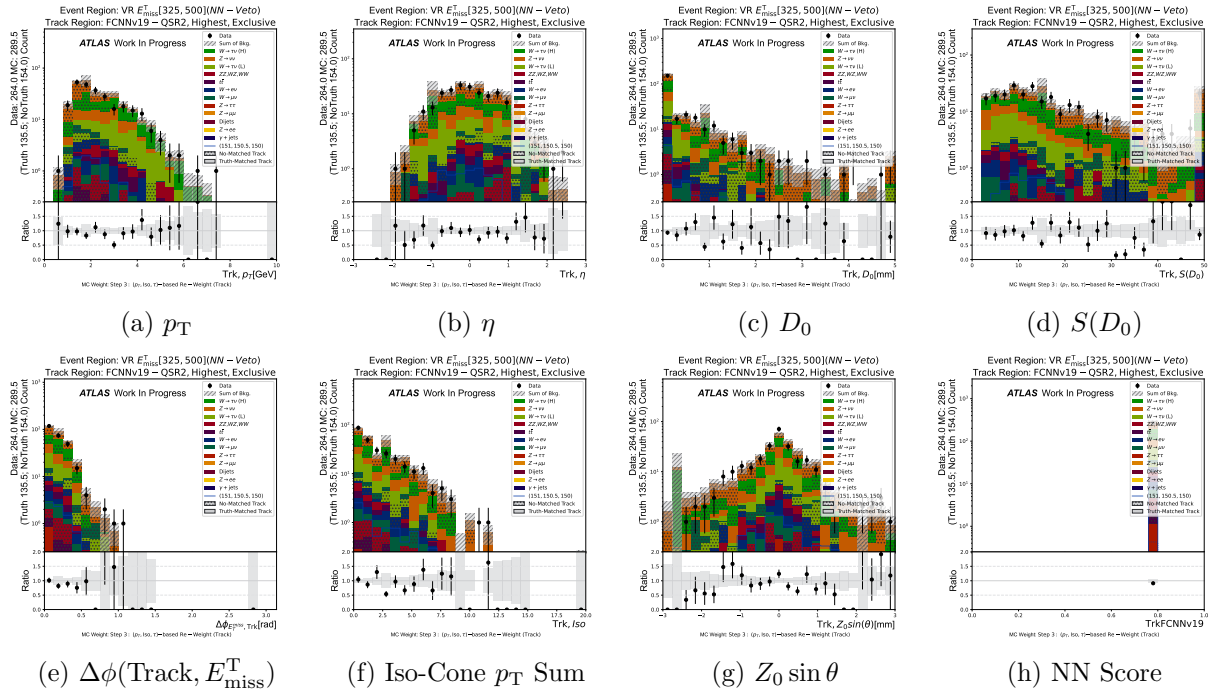


Figure B.36: Track-level kinematics histograms passing the following selection: Event-level: Medium MET Validation Region ( $[325, 500]$  GeV), Track-level: NN-QSR 2 (Neural Networks trained with BCE loss)

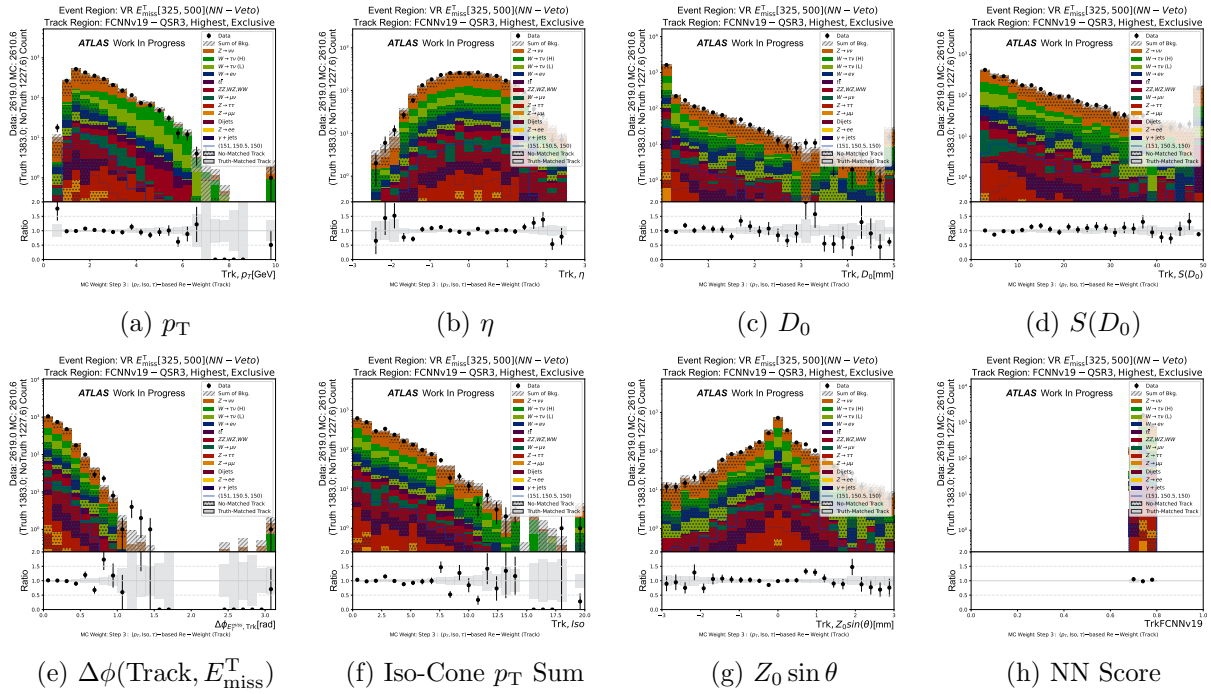


Figure B.37: Track-level kinematics histograms passing the following selection: Event-level: Medium MET Validation Region ([325,500] GeV), Track-level: NN-QSR 3 (Neural Networks trained with BCE loss)

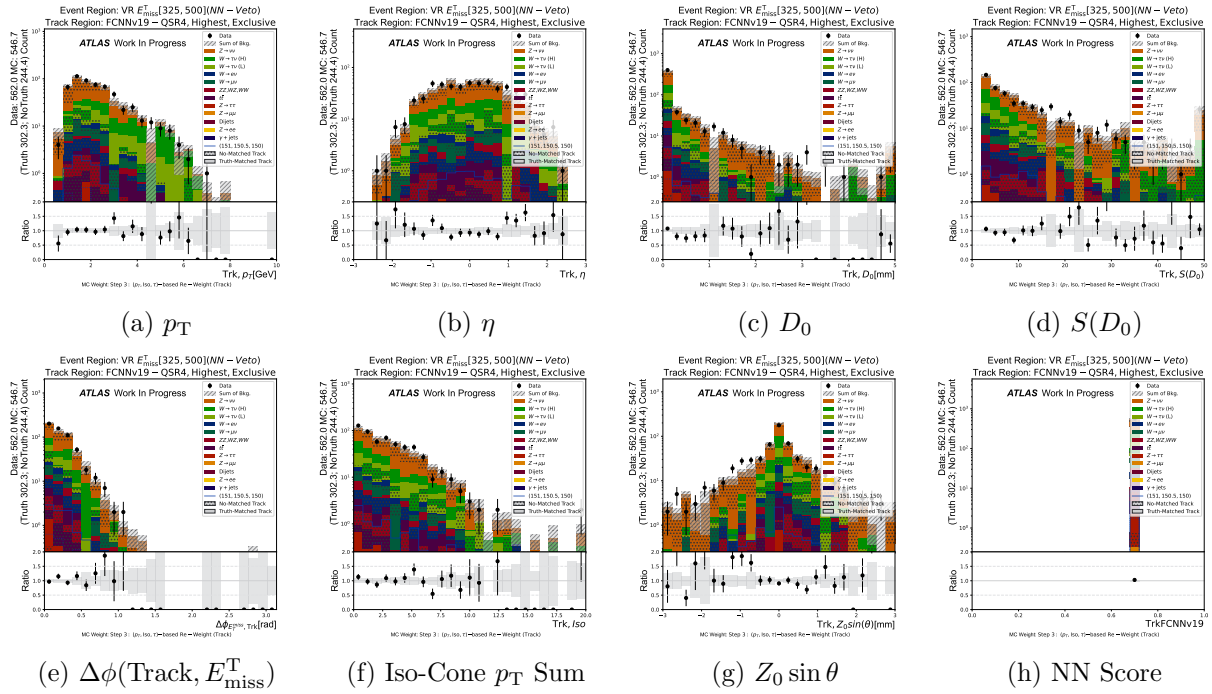


Figure B.38: Track-level kinematics histograms passing the following selection: Event-level: Medium MET Validation Region ([325,500] GeV), Track-level: NN-QSR 4 (Neural Networks trained with BCE loss)

### B.6.4 Track Level Signal Region Histograms (Unblinded)

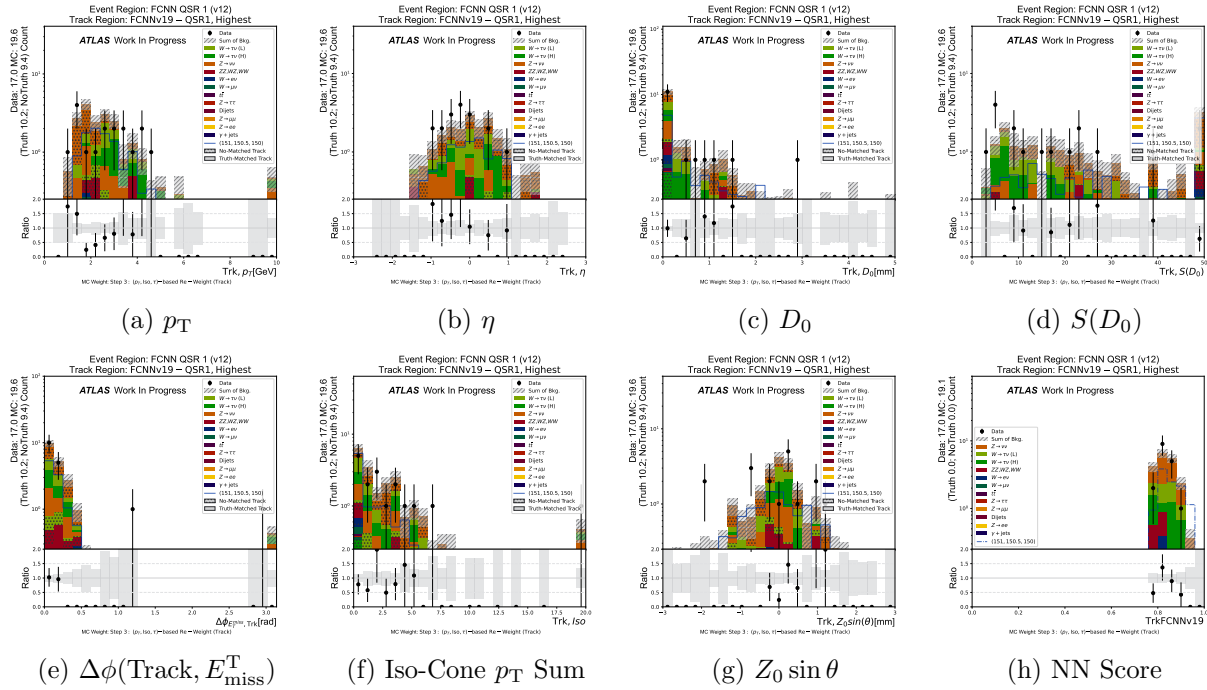


Figure B.39: Track-level kinematics histograms passing the following selection: Event-level: NN-QSR 1, Track-level: NN-QSR 1 (Neural Networks trained with BCE loss)



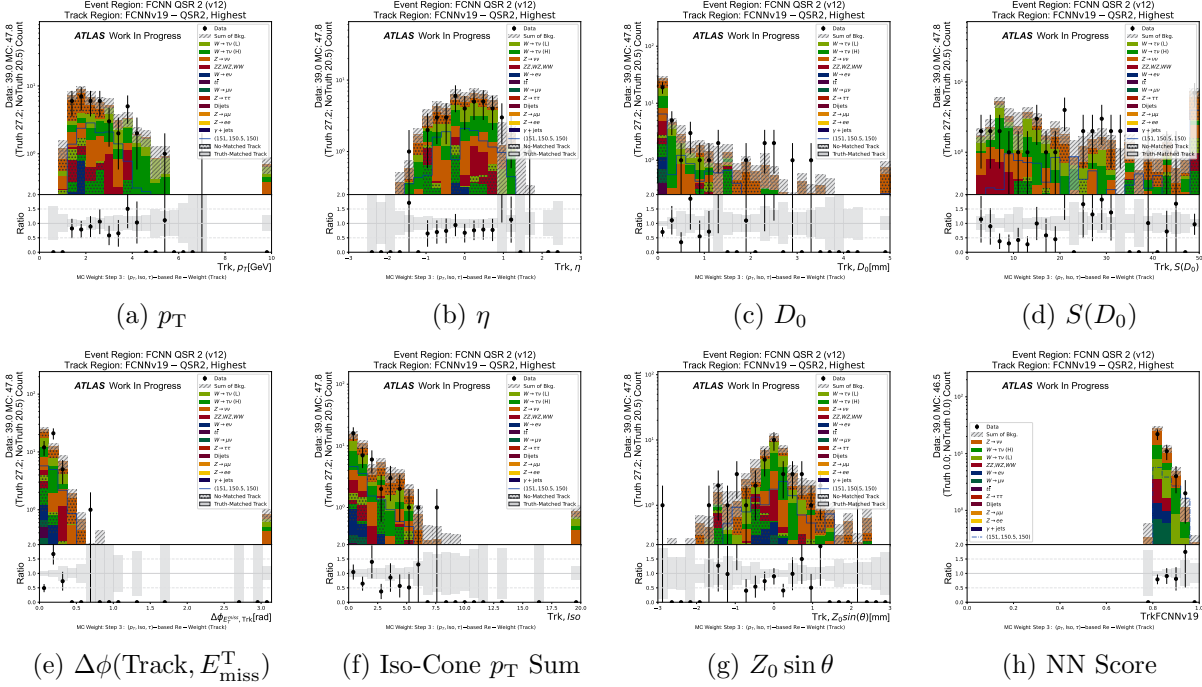


Figure B.40: Track-level kinematics histograms passing the following selection: Event-level: NN-QSR 2, Track-level: NN-QSR 2 (Neural Networks trained with BCE loss)

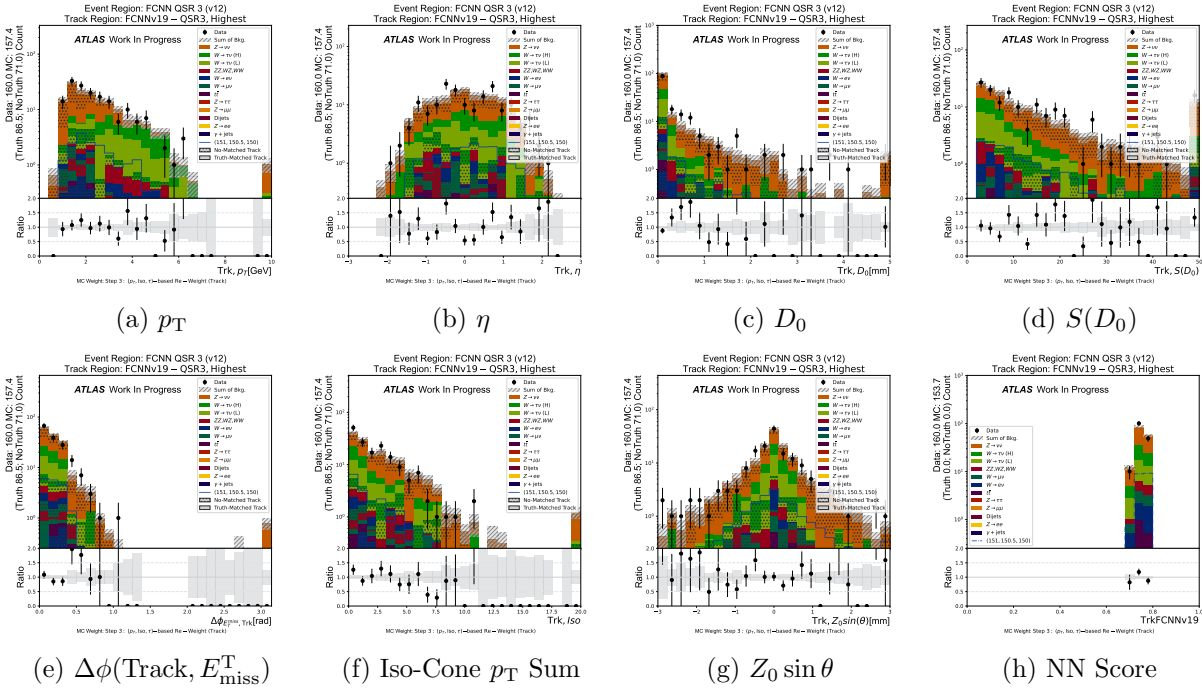


Figure B.41: Track-level kinematics histograms passing the following selection: Event-level: NN-QSR 3, Track-level: NN-QSR 3 (Neural Networks trained with BCE loss)

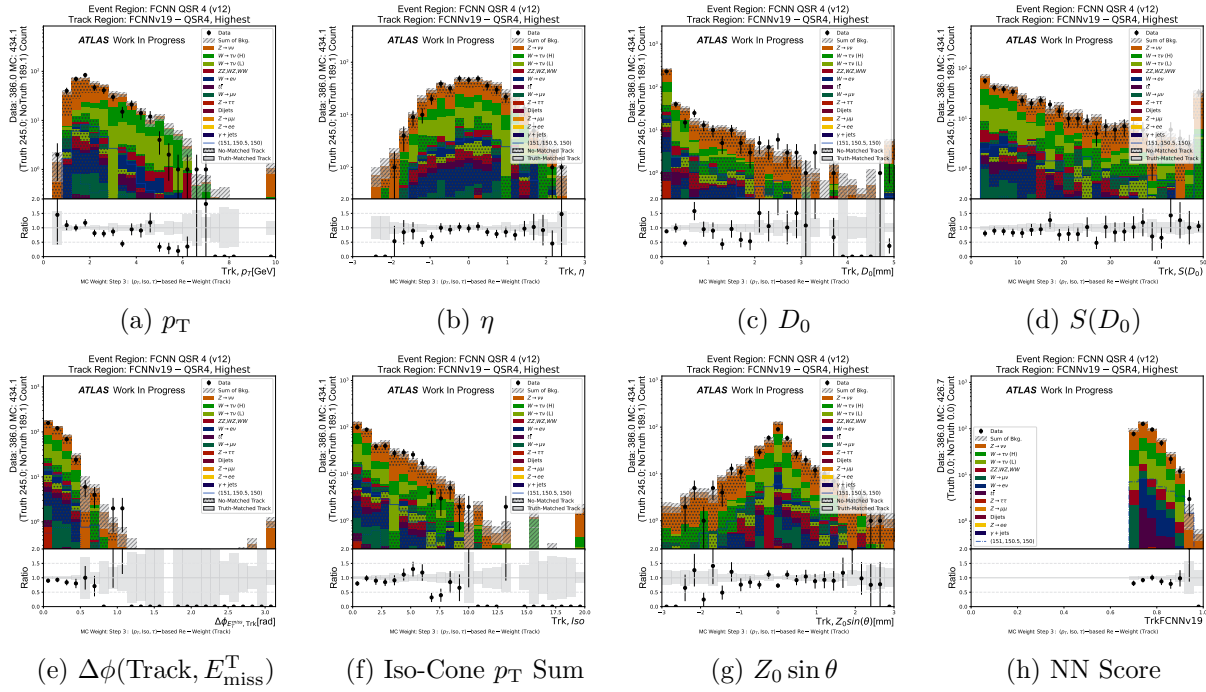


Figure B.42: Track-level kinematics histograms passing the following selection: Event-level: NN-QSR 4, Track-level: NN-QSR 4 (Neural Networks trained with BCE loss)

## B.6.5 Tau-Enriched Validation Region Histograms

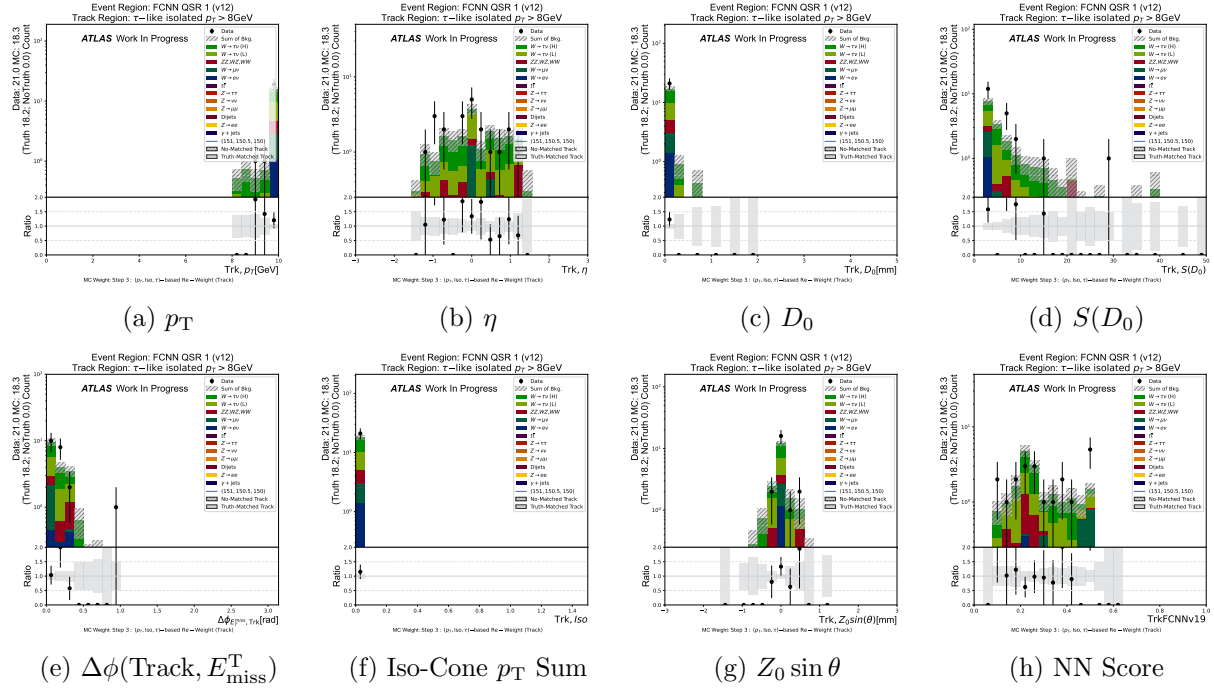
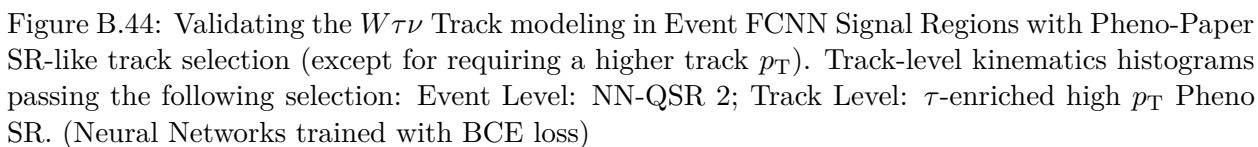
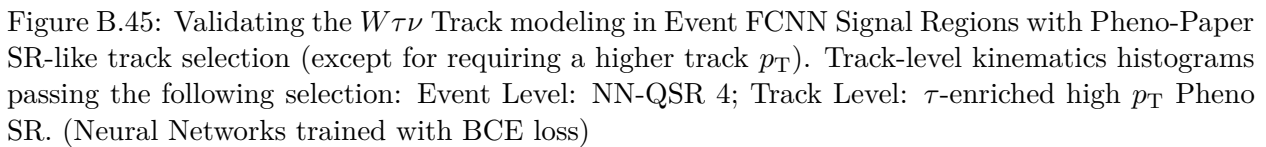


Figure B.43: Validating the  $W\tau\nu$  Track modeling in Event FCNN Signal Regions with Pheno-Paper SR-like track selection (except for requiring a higher track  $p_T$ ). Track-level kinematics histograms passing the following selection: Event Level: NN-QSR 1; Track Level:  $\tau$ -enriched high  $p_T$  Pheno SR. (Neural Networks trained with BCE loss)





## B.7 Neural Network Approach: Statistical Interpretation Appendix

### B.7.1 Benchmarking Improvement with CLs-Equivalent Luminosity Increased Cut & Count Signal Region

Table B.6: Comparison of confidence level ( $CL_{s,nom}$ ) of Cut & Count analysis from HepData and the proposed Neural Network Analysis.

| Sig. Grid [GeV]                                                        | Nom. CLs (CC) |          | Nom. CLs (NN) |             |
|------------------------------------------------------------------------|---------------|----------|---------------|-------------|
| $(m_{\tilde{\chi}_2^0}, m_{\tilde{\chi}_1^\pm}, m_{\tilde{\chi}_1^0})$ | C&C(Exp)      | C&C(Obs) | NN-4SR(Exp)   | NN-4SR(Obs) |
| (100.7, 100.35, 100)                                                   | 0.0203        | 0.0184   | 0.0023        | 0.0003      |
| (101, 100.5, 100)                                                      | 0.0009        | 0.0007   | 0.0000        | 0.0000      |
| (101.5, 100.75, 100)                                                   | 0.0087        | 0.0063   | 0.0000        | 0.0000      |
| (102, 101, 100)                                                        | 0.2166        | 0.1672   | 0.0245        | 0.0078      |
| (103, 101.5, 100)                                                      | 0.8277        | 0.8283   | 0.5851        | 0.4423      |
| (125.5, 125.25, 125)                                                   | 0.9550        | 0.9499   | 0.5665        | 0.4196      |
| (125.7, 125.35, 125)                                                   | 0.1596        | 0.1500   | 0.0573        | 0.0149      |
| (126, 125.5, 125)                                                      | 0.0053        | 0.0046   | 0.0004        | 0.0000      |
| (126.5, 125.75, 125)                                                   | 0.0229        | 0.0181   | 0.0036        | 0.0008      |
| (127, 126, 125)                                                        | 0.5001        | 0.4329   | 0.1583        | 0.0987      |
| (128, 126.5, 125)                                                      | 0.8842        | 0.8963   | 0.6272        | 0.5831      |
| (150.5, 150.25, 150)                                                   | 0.9273        | 0.9225   | 0.6780        | 0.5622      |
| (150.7, 150.35, 150)                                                   | 0.4540        | 0.4370   | 0.1969        | 0.0958      |
| (151, 150.5, 150)                                                      | 0.0298        | 0.0256   | 0.0087        | 0.0021      |
| (151.5, 150.75, 150)                                                   | 0.1050        | 0.0828   | 0.0233        | 0.0081      |
| (152, 151, 150)                                                        | 0.6390        | 0.5786   | 0.2650        | 0.1577      |
| (153, 151.5, 150)                                                      | 0.9121        | 0.9192   | 0.7045        | 0.6738      |
| (175.5, 175.25, 175)                                                   | 0.9698        | 0.9673   | 0.7334        | 0.6693      |
| (175.7, 175.35, 175)                                                   | 0.7048        | 0.6802   | 0.4132        | 0.3017      |
| (176, 175.5, 175)                                                      | 0.1238        | 0.1090   | 0.0570        | 0.0210      |
| (176.5, 175.75, 175)                                                   | 0.1942        | 0.1605   | 0.0922        | 0.0387      |
| (177, 176, 175)                                                        | 0.6871        | 0.6241   | 0.3723        | 0.2928      |
| (178, 176.5, 175)                                                      | 0.9490        | 0.9515   | 0.7587        | 0.7340      |
| (200.7, 200.35, 200)                                                   | 0.8177        | 0.8136   | 0.5261        | 0.4048      |
| (201, 200.5, 200)                                                      | 0.3237        | 0.2919   | 0.1274        | 0.0709      |
| (201.5, 200.75, 200)                                                   | 0.3624        | 0.3128   | 0.1867        | 0.1157      |
| (202, 201, 200)                                                        | 0.8242        | 0.7823   | 0.5659        | 0.4690      |
| (225.7, 225.35, 225)                                                   | 0.9231        | 0.9135   | 0.6796        | 0.5958      |
| (226, 225.5, 225)                                                      | 0.5245        | 0.4935   | 0.2903        | 0.1944      |
| (226.5, 225.75, 225)                                                   | 0.5184        | 0.4592   | 0.3434        | 0.2460      |
| (227, 226, 225)                                                        | 0.8675        | 0.8347   | 0.6629        | 0.6180      |
| (85.7, 85.35, 85)                                                      | 0.0053        | 0.0056   | 0.0011        | 0.0001      |
| (87, 86, 85)                                                           | 0.1638        | 0.1200   | 0.0159        | 0.0032      |
| (88, 86.5, 85)                                                         | 0.8215        | 0.8486   | 0.4614        | 0.3626      |

Table B.7: Nominal expected confidence level improvement of ( $CL_{s,nom}$ ) of Cut & Count analysis given luminosity-increase versus the scale factor (estimated with the semi-data-driven MC weight correction method, with full-systematic fit on example mass points as described in Section 4.9). The corresponding expected  $CL_{s,nom}$  for 4-SR NN approach at nominal luminosity ( $139fb^{-1}$ ) with NN trained by BCE-Loss and the CLs-equivalent luminosity increase percentage (extrapolated from Figure B.4) needed for Cut & Count analysis are given in the last columns.

| Sig. Grid [GeV]                                                        | Expected Nom. CLs |        |        |        |        |        |        | Lumi-Increase |
|------------------------------------------------------------------------|-------------------|--------|--------|--------|--------|--------|--------|---------------|
| $(m_{\tilde{\chi}_2^0}, m_{\tilde{\chi}_1^\pm}, m_{\tilde{\chi}_1^0})$ | CC Nom            | CC1.3  | CC1.5  | CC1.7  | CC1.9  | CC2.1  | NN-4SR | NN-4SR        |
| (100.7, 100.35, 100)                                                   | 0.0077            | 0.0035 | 0.0022 | 0.0015 | 0.0010 | 0.0007 | 0.0015 | 70.4%         |
| (101, 100.5, 100)                                                      | 0.0000            | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 68.2%         |
| (101.5, 100.75, 100)                                                   | 0.0012            | 0.0004 | 0.0002 | 0.0001 | 0.0001 | 0.0001 | 0.0000 | 129.9%        |
| (102, 101, 100)                                                        | 0.2069            | 0.1700 | 0.1526 | 0.1388 | 0.1277 | 0.1186 | 0.0201 | 326.2%        |
| (103, 101.5, 100)                                                      | 0.9270            | 0.9213 | 0.9228 | 0.8965 | 0.9077 | 0.9083 | 0.5557 | -540.4%       |
| (125.5, 125.25, 125)                                                   | 0.9284            | 0.9039 | 0.9154 | 0.9114 | 0.8945 | 0.9056 | 0.5673 | 2171.6%       |
| (125.7, 125.35, 125)                                                   | 0.1211            | 0.0897 | 0.0754 | 0.0644 | 0.0558 | 0.0478 | 0.0374 | 135.8%        |
| (126, 125.5, 125)                                                      | 0.0014            | 0.0005 | 0.0002 | 0.0001 | 0.0001 | 0.0001 | 0.0002 | 60.6%         |
| (126.5, 125.75, 125)                                                   | 0.0142            | 0.0085 | 0.0065 | 0.0052 | 0.0042 | 0.0034 | 0.0023 | 135.1%        |
| (127, 126, 125)                                                        | 0.4594            | 0.4208 | 0.4015 | 0.3853 | 0.3717 | 0.3599 | 0.1441 | 477.0%        |
| (128, 126.5, 125)                                                      | 1.0000            | 1.0000 | 0.9905 | 0.9820 | 1.0000 | 0.9822 | 0.6104 | -74028.4%     |
| (150.5, 150.25, 150)                                                   | 0.8829            | 0.8758 | 0.8670 | 0.8622 | 0.8585 | 0.8563 | 0.6722 | 1808.4%       |
| (150.7, 150.35, 150)                                                   | 0.4353            | 0.3945 | 0.3764 | 0.3586 | 0.3426 | 0.3309 | 0.1720 | 382.9%        |
| (151, 150.5, 150)                                                      | 0.0171            | 0.0088 | 0.0060 | 0.0042 | 0.0030 | 0.0023 | 0.0064 | 46.8%         |
| (151.5, 150.75, 150)                                                   | 0.0864            | 0.0617 | 0.0510 | 0.0431 | 0.0366 | 0.0325 | 0.0180 | 180.6%        |
| (152, 151, 150)                                                        | 0.5360            | 0.5015 | 0.4839 | 0.4686 | 0.4559 | 0.4450 | 0.2488 | 470.7%        |
| (153, 151.5, 150)                                                      | 1.0000            | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.6993 | -inf%         |
| (175.5, 175.25, 175)                                                   | 0.9372            | 0.9326 | 0.9278 | 0.9354 | 0.9248 | 0.9222 | 0.7294 | 1627.0%       |
| (175.7, 175.35, 175)                                                   | 0.6691            | 0.6419 | 0.6277 | 0.6157 | 0.6050 | 0.5922 | 0.4003 | 411.6%        |
| (176, 175.5, 175)                                                      | 0.0944            | 0.0673 | 0.0554 | 0.0450 | 0.0398 | 0.0346 | 0.0406 | 86.9%         |
| (176.5, 175.75, 175)                                                   | 0.1818            | 0.1460 | 0.1292 | 0.1159 | 0.1039 | 0.0965 | 0.0824 | 148.5%        |
| (177, 176, 175)                                                        | 0.6502            | 0.6189 | 0.6031 | 0.5894 | 0.5775 | 0.5686 | 0.3560 | 583.8%        |
| (178, 176.5, 175)                                                      | 0.9591            | 0.9791 | 0.9775 | 0.9720 | 0.9588 | 0.9548 | 0.7485 | 1154.5%       |
| (200.7, 200.35, 200)                                                   | 0.7763            | 0.7567 | 0.7492 | 0.7367 | 0.7288 | 0.7216 | 0.5084 | 706.3%        |
| (201, 200.5, 200)                                                      | 0.2953            | 0.2544 | 0.2327 | 0.2176 | 0.2038 | 0.1902 | 0.1118 | 224.8%        |
| (201.5, 200.75, 200)                                                   | 0.3217            | 0.2814 | 0.2604 | 0.2448 | 0.2311 | 0.2197 | 0.1749 | 188.6%        |
| (202, 201, 200)                                                        | 0.7597            | 0.7381 | 0.7269 | 0.7173 | 0.7087 | 0.6999 | 0.5543 | 440.2%        |
| (225.7, 225.35, 225)                                                   | 0.9016            | 0.8945 | 0.8897 | 0.8860 | 0.8820 | 0.8790 | 0.6661 | 1524.1%       |
| (226, 225.5, 225)                                                      | 0.5125            | 0.4770 | 0.4583 | 0.4427 | 0.4290 | 0.4132 | 0.2716 | 289.8%        |
| (226.5, 225.75, 225)                                                   | 0.4893            | 0.4520 | 0.4332 | 0.4175 | 0.4038 | 0.3906 | 0.3274 | 205.9%        |
| (227, 226, 225)                                                        | 0.8352            | 0.8201 | 0.8114 | 0.8051 | 0.7987 | 0.7929 | 0.6499 | 602.3%        |
| (85.7, 85.35, 85)                                                      | 0.0006            | 0.0002 | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0004 | 11.3%         |
| (87, 86, 85)                                                           | 0.1189            | 0.0910 | 0.0785 | 0.0688 | 0.0613 | 0.0550 | 0.0129 | 244.4%        |
| (88, 86.5, 85)                                                         | 0.9314            | 0.9285 | 0.9048 | 0.9302 | 0.9281 | 0.9214 | 0.4322 | -1659.2%      |

### B.7.2 Per-Track vs Per-Event Counting

In the Neural-Network-based analysis, with Semi-Data-Driven background estimation, all yield calculations are predicated on the counting of weighted tracks within weighted events. However, it is worth noting that we select at most one FCNN Signal Region (SR) Track (the one with the highest score) within each FCNN SR Event. Consequently, the count of SR tracks within SR events is identical to the count of SR events containing at least one SR track.

We performed a verification and established that the total number of FCNN SR events encompassing more than one FCNN SR Track is less than 1% of the total FCNN events which contain FCNN SR Tracks. Furthermore, we engineered a mask designed to retain only the single track possessing the highest FCNN Track-Level score within each event. The effect of this modification on the yield in Signal Regions when shifting from "per-track" to "per-event" counting is depicted in Tables B.8. The transition appears to minimally impact the results, with no observable change in the exclusion contour. Thus, we conclude that there is no significant advantage to be gained by counting more than one track per event and complicating the statistical combination.



Table B.8: Yield difference with "per-event" counting instead of "per-track" counting (i.e. multiple track per event versus at most 1 track per event) in the 4 FCNN SR.

| Sample                      | QSR 1 | QSR 2 | QSR 3 | QSR 4 |
|-----------------------------|-------|-------|-------|-------|
| $\gamma + \text{jets}$      | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| $W \rightarrow e\nu$        | 0.0%  | 1.4%  | 0.0%  | 0.6%  |
| $W \rightarrow \mu\nu$      | 0.0%  | 0.0%  | 0.0%  | 3.0%  |
| $W \rightarrow \tau\nu$ (H) | 2.6%  | 1.7%  | 1.3%  | 0.1%  |
| $W \rightarrow \tau\nu$ (L) | 5.7%  | 1.0%  | 1.7%  | 0.2%  |
| $Z \rightarrow ee$          | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| $Z \rightarrow \mu\mu$      | 0.0%  | -0.0% | -0.0% | 0.0%  |
| $Z \rightarrow \nu\nu$      | 0.7%  | 0.7%  | 0.7%  | 1.4%  |
| $Z \rightarrow \tau\tau$    | 0.0%  | -0.0% | 3.1%  | 0.6%  |
| $ZZ, WZ, WW$                | -0.0% | 0.0%  | 0.0%  | 0.8%  |
| Dijets                      | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| $t\bar{t}$                  | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (100.7, 100.35, 100)        | 0.0%  | 0.4%  | 1.5%  | 0.0%  |
| (101, 100.5, 100)           | 0.0%  | 1.9%  | 2.3%  | 1.5%  |
| (101.5, 100.75, 100)        | 0.0%  | 1.5%  | 0.0%  | 3.0%  |
| (102, 101, 100)             | 16.0% | 0.0%  | 0.0%  | 2.6%  |
| (103, 101.5, 100)           | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (125.5, 125.25, 125)        | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (125.7, 125.35, 125)        | 0.0%  | 4.3%  | 0.0%  | 0.0%  |
| (126, 125.5, 125)           | 1.1%  | 2.4%  | 0.7%  | 2.4%  |
| (126.5, 125.75, 125)        | 0.0%  | 0.0%  | 0.0%  | 1.4%  |
| (127, 126, 125)             | 0.0%  | 0.0%  | 0.0%  | 1.1%  |
| (128, 126.5, 125)           | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (150.5, 150.25, 150)        | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (150.7, 150.35, 150)        | 0.0%  | 0.0%  | 0.0%  | 1.8%  |
| (151, 150.5, 150)           | 0.0%  | 1.4%  | 0.3%  | 2.0%  |
| (151.5, 150.75, 150)        | 0.0%  | 1.0%  | 0.5%  | 2.1%  |
| (152, 151, 150)             | 0.0%  | 0.0%  | 0.0%  | 3.4%  |
| (153, 151.5, 150)           | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (175.5, 175.25, 175)        | 0.0%  | 0.0%  | 0.0%  | 3.1%  |
| (175.7, 175.35, 175)        | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (176, 175.5, 175)           | 0.0%  | 0.8%  | 0.0%  | 1.3%  |
| (176.5, 175.75, 175)        | 0.0%  | 0.0%  | 0.0%  | 3.6%  |
| (177, 176, 175)             | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (178, 176.5, 175)           | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (200.7, 200.35, 200)        | 0.0%  | 1.8%  | 0.0%  | 0.7%  |
| (201, 200.5, 200)           | 0.0%  | 0.0%  | 0.0%  | 1.0%  |
| (201.5, 200.75, 200)        | 0.0%  | 0.0%  | 0.8%  | 0.0%  |
| (202, 201, 200)             | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (225.7, 225.35, 225)        | 0.0%  | 2.4%  | 0.0%  | 0.5%  |
| (226, 225.5, 225)           | 0.0%  | 0.0%  | 0.0%  | 0.6%  |
| (226.5, 225.75, 225)        | 0.0%  | 0.0%  | 0.0%  | 0.2%  |
| (227, 226, 225)             | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (85.7, 85.35, 85)           | 0.0%  | 5.4%  | 2.0%  | 0.0%  |
| (87, 86, 85)                | 0.0%  | 0.0%  | 0.0%  | 0.0%  |
| (88, 86.5, 85)              | 0.0%  | 0.0%  | 0.0%  | 0.0%  |

### B.7.3 Neural Network Approach: MC Systematic Uncertainty Composition

Table B.9: Fitted systematic uncertainties composition and relative percentages. Note that individual source of the uncertainties maybe correlated. Signal Region (NN Trained with BCE-Loss): QSR-1

|              |                                                                       |
|--------------|-----------------------------------------------------------------------|
| Event Region | FCNN QSR 1 (v12)                                                      |
| Track Region | FCNNv19 – QSR1, Highest                                               |
|              | 18.9 (MC Pred. Yield)                                                 |
|              | $\pm 1.4$ (7.4%) ( $\sigma_{\text{MC Stat.}}$ )                       |
|              | $\pm 1.7$ (9.0%) ( $\sigma_{\text{MC Syst.}}$ )                       |
| Order        | MC Syst. Sources                                                      |
| 1            | 1.36 (7.2%) ( $\sigma_{\text{Theory}} (Z \rightarrow ll)$ )           |
| 2            | 1.00 (5.3%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau \nu (L))$ ) |
| 3            | 0.82 (4.3%) ( $\mu_{W \rightarrow \tau \nu (H)}$ )                    |
| 4            | 0.78 (4.1%) (Jet Syst.)                                               |
| 5            | 0.69 (3.6%) ( $\mu_{W \rightarrow \tau \nu (L)}$ )                    |
| 6            | 0.66 (3.5%) ( $\mu_{Z \rightarrow ll}$ )                              |
| 7            | 0.54 (2.8%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau \nu (H))$ ) |
| 8            | 0.48 (2.5%) ( $\mu_{ZZ, WZ, WW}$ )                                    |
| 9            | 0.38 (2.0%) ( $\sigma_{\text{Step 2 ISO RW Factor}}$ )                |
| 10           | 0.31 (1.6%) ( $\sigma_{\text{Step 3 } \tau \text{ RW Factor}}$ )      |
| 11           | 0.27 (1.4%) (Track Resolution)                                        |
| 12           | 0.26 (1.3%) ( $\sigma_{\text{Step 1 } p_T \text{ RW Factor}}$ )       |
| 13           | 0.25 (1.3%) ( $\sigma_{\text{Theory}} (ZZ, WZ, WW)$ )                 |
| 14           | 0.18 (0.9%) ( $\sigma_{\text{Theory}} (W \rightarrow e \nu)$ )        |
| 15           | 0.11 (0.6%) ( $\sigma_{\text{Theory}} (\text{Others})$ )              |
| 16           | 0.09 (0.5%) ( $b$ -Tag)                                               |
| 17           | 0.07 (0.4%) ( $E_T^{\text{miss}}$ Scale)                              |
| 18           | 0.04 (0.2%) ( $\sigma_{\text{Theory}} (W \rightarrow \mu \nu)$ )      |
| 19           | 0.03 (0.2%) ( $\mu_{W \rightarrow \mu \nu}$ )                         |
| 20           | 0.02 (0.1%) (EG Resolution)                                           |
| 21           | 0.01 (0.0%) (JVT Weight)                                              |
| 22           | 0.00 (0.0%) (Muon Syst.)                                              |
| 23           | 0.00 (0.0%) (Lepton Weight)                                           |
| 24           | 0.00 (0.0%) (Trigger Weight)                                          |

Table B.10: Fitted systematic uncertainties composition and relative percentages. Note that individual source of the uncertainties maybe correlated. Signal Region (NN Trained with BCE-Loss): QSR-2

| Event Region | FCNN QSR 2 (v12)                                                              |
|--------------|-------------------------------------------------------------------------------|
| Track Region | FCNNv19 – QSR2, Highest                                                       |
|              | 46.1 (MC Pred. Yield)                                                         |
|              | $\pm 2.8$ (6.1%) ( $\sigma_{\text{MC Stat.}}$ )                               |
|              | $\pm 3.6$ (7.8%) ( $\sigma_{\text{MC Syst.}}$ )                               |
| Order        | MC Syst. Sources                                                              |
| 1            | 2.88 (6.2%) ( $\sigma_{\text{Theory}} (Z \rightarrow ll)$ )                   |
| 2            | 2.77 (6.0%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau \nu \text{ (H)})$ ) |
| 3            | 2.61 (5.7%) ( $\mu_{W \rightarrow \tau \nu \text{ (H)}}$ )                    |
| 4            | 1.82 (4.0%) ( $\mu_{W \rightarrow \tau \nu \text{ (L)}}$ )                    |
| 5            | 1.67 (3.6%) (Jet Syst.)                                                       |
| 6            | 1.38 (3.0%) ( $\mu_{Z \rightarrow ll}$ )                                      |
| 7            | 1.28 (2.8%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau \nu \text{ (L)})$ ) |
| 8            | 1.22 (2.6%) ( $\mu_{ZZ, WZ, WW}$ )                                            |
| 9            | 1.03 (2.2%) ( $\sigma_{\text{Step 3 } \tau \text{ RW Factor}}$ )              |
| 10           | 1.01 (2.2%) ( $\sigma_{\text{Step 2 ISO RW Factor}}$ )                        |
| 11           | 0.58 (1.3%) ( $\sigma_{\text{Step 1 } p_T \text{ RW Factor}}$ )               |
| 12           | 0.37 (0.8%) ( $\sigma_{\text{Theory}} (W \rightarrow e \nu)$ )                |
| 13           | 0.27 (0.6%) (Track Resolution)                                                |
| 14           | 0.25 (0.5%) ( $\sigma_{\text{Theory}} (ZZ, WZ, WW)$ )                         |
| 15           | 0.23 (0.5%) ( $\sigma_{\text{Theory}} \text{ (Others)}$ )                     |
| 16           | 0.21 (0.5%) ( $E_{\text{T}}^{\text{miss}}$ Scale)                             |
| 17           | 0.17 (0.4%) (JVT Weight)                                                      |
| 18           | 0.09 (0.2%) ( $\mu_{W \rightarrow \mu \nu}$ )                                 |
| 19           | 0.05 (0.1%) ( $b$ -Tag)                                                       |
| 20           | 0.04 (0.1%) (EG Resolution)                                                   |
| 21           | 0.03 (0.1%) ( $\sigma_{\text{Theory}} (W \rightarrow \mu \nu)$ )              |
| 22           | 0.00 (0.0%) (Muon Syst.)                                                      |
| 23           | 0.00 (0.0%) (Lepton Weight)                                                   |
| 24           | 0.00 (0.0%) (Trigger Weight)                                                  |

Table B.11: Fitted systematic uncertainties composition and relative percentages. Note that individual source of the uncertainties maybe correlated. Signal Region (NN Trained with BCE-Loss): QSR-3

|              |                                                                             |
|--------------|-----------------------------------------------------------------------------|
| Event Region | FCNN QSR 3 (v12)                                                            |
| Track Region | FCNNv19 – QSR3, Highest                                                     |
|              | 152.2 (MC Pred. Yield)                                                      |
|              | $\pm 4.8$ (3.1%) ( $\sigma_{\text{MC Stat.}}$ )                             |
|              | $\pm 10.0$ (6.6%) ( $\sigma_{\text{MC Syst.}}$ )                            |
| Order        | MC Syst. Sources                                                            |
| 1            | 10.26 (6.7%) ( $\sigma_{\text{Theory}} (Z \rightarrow ll)$ )                |
| 2            | 8.55 (5.6%) ( $\mu_{W \rightarrow \tau\nu} (\text{H})$ )                    |
| 3            | 5.53 (3.6%) ( $\mu_{Z \rightarrow ll}$ )                                    |
| 4            | 5.01 (3.3%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau\nu (\text{L}))$ ) |
| 5            | 4.62 (3.0%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau\nu (\text{H}))$ ) |
| 6            | 4.13 (2.7%) ( $\mu_{W \rightarrow \tau\nu} (\text{L})$ )                    |
| 7            | 3.71 (2.4%) (Jet Syst.)                                                     |
| 8            | 3.15 (2.1%) ( $\sigma_{\text{Step 2 ISO RW Factor}}$ )                      |
| 9            | 2.02 (1.3%) ( $\sigma_{\text{Step 3 } \tau \text{ RW Factor}}$ )            |
| 10           | 2.00 (1.3%) ( $\mu_{ZZ, WZ, WW}$ )                                          |
| 11           | 1.75 (1.2%) ( $\sigma_{\text{Step 1 } p_{\text{T}} \text{ RW Factor}}$ )    |
| 12           | 1.48 (1.0%) ( $\sigma_{\text{Theory}} (W \rightarrow e\nu)$ )               |
| 13           | 1.44 (0.9%) ( $b$ -Tag)                                                     |
| 14           | 1.07 (0.7%) (Track Resolution)                                              |
| 15           | 0.73 (0.5%) ( $\sigma_{\text{Theory}} (ZZ, WZ, WW)$ )                       |
| 16           | 0.60 (0.4%) (JVT Weight)                                                    |
| 17           | 0.37 (0.2%) ( $\sigma_{\text{Theory}} (\text{Others})$ )                    |
| 18           | 0.30 (0.2%) ( $\mu_{W \rightarrow \mu\nu}$ )                                |
| 19           | 0.15 (0.1%) ( $\sigma_{\text{Theory}} (W \rightarrow \mu\nu)$ )             |
| 20           | 0.12 (0.1%) ( $E_{\text{T}}^{\text{miss}}$ Scale)                           |
| 21           | 0.10 (0.1%) (EG Resolution)                                                 |
| 22           | 0.03 (0.0%) (Muon Syst.)                                                    |
| 23           | 0.00 (0.0%) (Lepton Weight)                                                 |
| 24           | 0.00 (0.0%) (Trigger Weight)                                                |

Table B.12: Fitted systematic uncertainties composition and relative percentages. Note that individual source of the uncertainties maybe correlated. Signal Region (NN Trained with BCE-Loss): QSR-4

|              |                                                                               |
|--------------|-------------------------------------------------------------------------------|
| Event Region | FCNN QSR 4 (v12)                                                              |
| Track Region | FCNNv19 – QSR4, Highest                                                       |
|              | 422.0 (MC Pred. Yield)                                                        |
|              | $\pm 10.9$ (2.6%) ( $\sigma_{\text{MC Stat.}}$ )                              |
|              | $\pm 27.1$ (6.4%) ( $\sigma_{\text{MC Syst.}}$ )                              |
| Order        | MC Syst. Sources                                                              |
| 1            | 29.67 (7.0%) ( $\sigma_{\text{Theory}} (Z \rightarrow ll)$ )                  |
| 2            | 26.91 (6.4%) ( $\mu_{W \rightarrow \tau \nu} (\text{H})$ )                    |
| 3            | 18.72 (4.4%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau \nu (\text{H}))$ ) |
| 4            | 14.37 (3.4%) ( $\mu_{Z \rightarrow ll}$ )                                     |
| 5            | 11.63 (2.8%) ( $\mu_{W \rightarrow \tau \nu} (\text{L})$ )                    |
| 6            | 9.45 (2.2%) (Jet Syst.)                                                       |
| 7            | 8.87 (2.1%) ( $\sigma_{\text{Step 2 ISO RW Factor}}$ )                        |
| 8            | 8.77 (2.1%) ( $\sigma_{\text{Theory}} (W \rightarrow \tau \nu (\text{L}))$ )  |
| 9            | 6.63 (1.6%) ( $\sigma_{\text{Step 3 } \tau \text{ RW Factor}}$ )              |
| 10           | 5.61 (1.3%) ( $\mu_{ZZ, WZ, WW}$ )                                            |
| 11           | 4.87 (1.2%) ( $\sigma_{\text{Step 1 } p_{\text{T}} \text{ RW Factor}}$ )      |
| 12           | 3.49 (0.8%) ( $b$ -Tag)                                                       |
| 13           | 3.24 (0.8%) ( $\sigma_{\text{Theory}} (W \rightarrow e \nu)$ )                |
| 14           | 2.20 (0.5%) ( $\sigma_{\text{Theory}} (ZZ, WZ, WW)$ )                         |
| 15           | 1.67 (0.4%) (JVT Weight)                                                      |
| 16           | 1.50 (0.4%) ( $\sigma_{\text{Theory}} (\text{Others})$ )                      |
| 17           | 1.31 (0.3%) (Track Resolution)                                                |
| 18           | 0.96 (0.2%) ( $\mu_{W \rightarrow \mu \nu}$ )                                 |
| 19           | 0.44 (0.1%) ( $\sigma_{\text{Theory}} (W \rightarrow \mu \nu)$ )              |
| 20           | 0.17 (0.0%) ( $E_{\text{T}}^{\text{miss}}$ Scale)                             |
| 21           | 0.11 (0.0%) (EG Resolution)                                                   |
| 22           | 0.05 (0.0%) (Muon Syst.)                                                      |
| 23           | 0.00 (0.0%) (Lepton Weight)                                                   |
| 24           | 0.00 (0.0%) (Trigger Weight)                                                  |

### B.7.4 Neural Network Approach: Control Region Yield & Contamination Check

Table B.13: Post Simultaneous Fit Control Region Yield Tables (sum of all bins). Notice that the expected signal contamination in the control region is quite small.

| Event Region<br>Track Region      | CR $1\mu$         | CR $1\mu 1e0b$ | CR $E_{\text{miss}}^{\text{T}}[275, 325]$ |
|-----------------------------------|-------------------|----------------|-------------------------------------------|
| Others                            | $501 \pm 108$     | $29 \pm 61$    | $1770 \pm 291$                            |
| $W \rightarrow e\nu$              | $5.8 \pm 1.7$     | $0.4 \pm 0.3$  | $6549 \pm 1108$                           |
| $W \rightarrow \mu\nu$            | $52424 \pm 1824$  | $32.9 \pm 2.7$ | $9179 \pm 356$                            |
| $W \rightarrow \tau\nu$ (H)       | $134 \pm 34$      | $0.0 \pm 0.0$  | $23709 \pm 3797$                          |
| $W \rightarrow \tau\nu$ (L)       | $4684 \pm 554$    | $1.4 \pm 3.9$  | $8200 \pm 1387$                           |
| $Z \rightarrow ll$                | $1026 \pm 56$     | $18.4 \pm 1.8$ | $75814 \pm 3341$                          |
| $ZZ, WZ, WW$                      | $1452 \pm 196$    | $128 \pm 30$   | $1982 \pm 1593$                           |
| Sum Bkg. $\pm \sigma_{\text{MC}}$ | $60226 \pm 1920$  | $210 \pm 68$   | $127202 \pm 5611$                         |
| Data $\pm \sigma_{\text{Pois}}$   | $61099 \pm 247.2$ | $214 \pm 14.6$ | $127730 \pm 357.4$                        |
| (151, 150.5, 150)                 | $0.9 \pm 0.3$     | $0.0 \pm 0.0$  | $669 \pm 173$                             |

Table B.14: Post Simultaneous Fit Control Region Yield Tables (sum of all bins). Notice that the expected signal contamination in the control region is quite small. Note that the “Pu” and “Pv” definition can be found in Section 4.7.3.1, and region definition can be found in the beginning of Section 4.7.1.

| Event Region<br>Track Region      | CR $1\mu$<br>MetAlign, TP, LepVeto( $Pu$ ) | CR $1\mu$<br>MetAlign, TP, LepVeto( $Pv$ ) | CR $E_{\text{miss}}^{\text{T}}[275, 325]$<br>$\tau$ -like isolated (ST) |
|-----------------------------------|--------------------------------------------|--------------------------------------------|-------------------------------------------------------------------------|
| Others                            | $974 \pm 199$                              | $316 \pm 69$                               | $34 \pm 16$                                                             |
| $W \rightarrow e\nu$              | $8.2 \pm 2.8$                              | $1.7 \pm 1.0$                              | $84 \pm 14$                                                             |
| $W \rightarrow \mu\nu$            | $89948 \pm 2047$                           | $22227 \pm 462$                            | $73.2 \pm 6.8$                                                          |
| $W \rightarrow \tau\nu$ (H)       | $246 \pm 50$                               | $42 \pm 10$                                | $797 \pm 164$                                                           |
| $W \rightarrow \tau\nu$ (L)       | $8105 \pm 763$                             | $1966 \pm 173$                             | $406 \pm 81$                                                            |
| $Z \rightarrow ll$                | $1567 \pm 87$                              | $362 \pm 21$                               | $199 \pm 23$                                                            |
| $ZZ, WZ, WW$                      | $2457 \pm 226$                             | $635 \pm 45$                               | $36.1 \pm 5.3$                                                          |
| Sum Bkg. $\pm \sigma_{\text{MC}}$ | $103306 \pm 2207$                          | $25551 \pm 501$                            | $1630 \pm 186$                                                          |
| Data $\pm \sigma_{\text{Pois}}$   | $104814 \pm 323.7$                         | $25885 \pm 160.9$                          | $1598 \pm 40.0$                                                         |
| (151, 150.5, 150)                 | $1.0 \pm 0.2$                              | $0.7 \pm 0.2$                              | $3.2 \pm 1.0$                                                           |

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